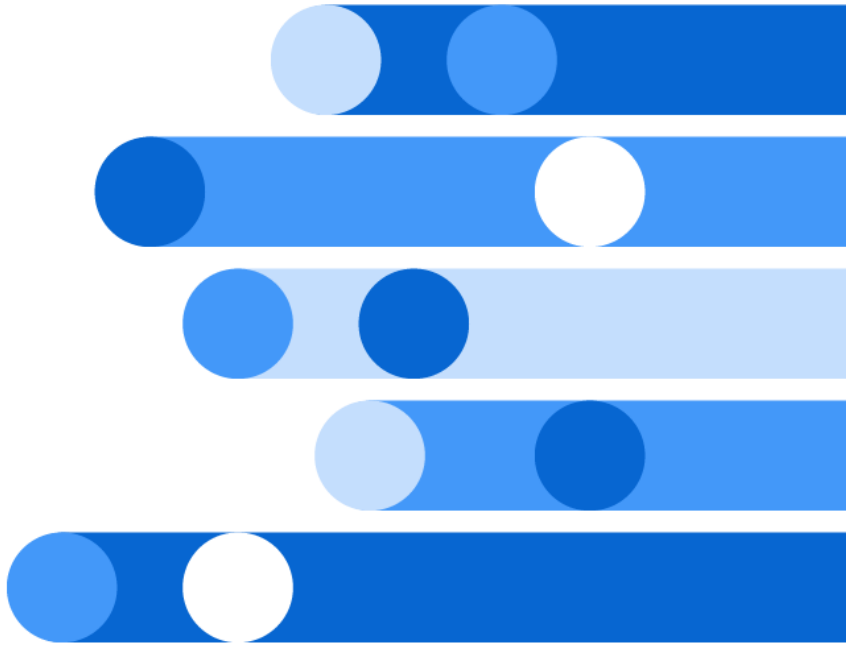
SAS® Forecast Server Procedures User's Guide

2026.03*



* This document might apply to additional versions of the software. Open this document in SAS Help Center and click on the version in the banner to see all available versions.



SAS® Documentation
March 19, 2026

The correct bibliographic citation for this manual is as follows: SAS Institute Inc. 2026. *SAS® Forecast Server Procedures: User's Guide*. Cary, NC: SAS Institute Inc.

SAS® Forecast Server Procedures: User's Guide

Copyright © 2026, SAS Institute Inc., Cary, NC, USA

All Rights Reserved. Produced in the United States of America.

For a hard-copy book: No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, or otherwise, without the prior written permission of the publisher, SAS Institute Inc.

For a web download or e-book: Your use of this publication shall be governed by the terms established by the vendor at the time you acquire this publication.

The scanning, uploading, and distribution of this book via the internet or any other means without the permission of the publisher is illegal and punishable by law. Please purchase only authorized electronic editions and do not participate in or encourage electronic piracy of copyrighted materials. Your support of others' rights is appreciated.

March 2026

SAS® and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration.

Other brand and product names are trademarks of their respective companies.

SAS software may be provided with certain third-party software, including but not limited to open source software, which is licensed under its applicable third-party software license agreement. For license information about third-party software distributed with SAS software, refer to Third-Party Software Reference | SAS Support.

v_006-P1:hpfug

Contents

I General Information **1**
Chapter 1. Introduction 3

II Procedure Reference **19**
Chapter 2. The HPF Procedure 21
Chapter 3. The HPFARIMASPEC Procedure 73
Chapter 4. The HPFDIAGNOSE Procedure 89
Chapter 5. The HPFENGINE Procedure 159
Chapter 6. The HPFESMSPEC Procedure 241
Chapter 7. The HPFEVENTS Procedure 253
Chapter 8. The HPFEXMSPEC Procedure 299
Chapter 9. The HPFIDMSPEC Procedure 305
Chapter 10. The HPFRECONCILE Procedure 317
Chapter 11. The HPFSELECT Procedure 349
Chapter 12. The HPFTEMPRECON Procedure 379
Chapter 13. The HPFUCMSPEC Procedure 411

III Forecasting Details **431**
Chapter 14. Forecasting Process Summary 433
Chapter 15. Forecasting Process Details 461
Chapter 16. Forecast Combination Computational Details 497
Chapter 17. Forecast Model Selection Graph Details 513
Chapter 18. Using Forecasting Model Score Files and DATA Step Functions 529
Chapter 19. Using User-Defined Models 537
Chapter 20. Using External Forecasts 547
Chapter 21. Using Auxiliary Data Sets 551

Part I

General Information

Chapter 1
Introduction

Contents

Overview of SAS Forecast Server Procedures Software **4**
Uses of SAS Forecast Server Procedures Software 5
Contents of SAS Forecast Server Procedures Software 6
About This Book **9**
Chapter Organization 9
Typographical Conventions 10
Options Used in Examples 10
Where to Turn for More Information **12**
Accessing the SAS Forecast Server Procedures Sample Library 12
SAS Technical Support Services 12
Related SAS Software **12**
Base SAS Software 12
SAS/GRAPH Software 15
SAS/STAT Software 15
SAS/IML Software 16
SAS/OR Software 17
SAS/QC Software 17
Other Statistical Tools 18
References **18**

Overview of SAS Forecast Server Procedures Software

SAS Forecast Server Procedures software provides a large-scale automatic forecasting system. The software provides for the automatic selection of time series models for use in forecasting time-stamped data.

Given a time-stamped data set, the software provides the following automatic forecasting process:

1. accumulates the time-stamped data to form a fixed-interval time series
2. diagnoses the time series by using time series analysis techniques
3. creates a list of candidate model specifications that are based on the diagnostics
4. fits each candidate model specification to the time series
5. generates forecasts for each candidate fitted model
6. uses a model selection criterion to select the most appropriate model specification based on either in-sample or holdout-sample forecast performance (fit statistic comparison)
7. refits the selected model specification to the entire range of the time series
8. creates a forecast score from the selected fitted model
9. generate forecasts from the forecast score
10. evaluates the forecast by using in-sample analysis

The software also provides for out-of-sample forecast performance analysis.

For time series data that do not have causal inputs (input variables or calendar events), the HPF procedure provides a single, relatively easy-to-use batch interface that supports the preceding automatic forecasting process. The HPF procedure uses exponential smoothing models and intermittent demand models in an automated way to extrapolate the time series. The HPF procedure is relatively simple to use and requires only one procedure call.

For time series data that either have or do not have causal inputs (input variables or calendar events or both), the software provides several procedures that provide a batch interface that supports the preceding automatic forecasting process with more complicated models. These procedures must be used in the proper sequence in order to get the desired results. Forecasting time series of this nature normally requires more than one procedure call.

Input variables are recorded in the time-stamped data set. These input variables might or might not be incorporated in time series models that are used to generate forecasts.

Calendar events are specified by the HPFEVENTS procedure. These event definitions are used to generate discrete-valued indicator variables or dummy variables. These event definitions are stored in a SAS data set. These indicator variables might or might not be incorporated in time series models that are used to generate forecasts.

Given the specified calendar events and input variables, the HPFDIAGNOSE procedure diagnoses the time series and decides which, if any, of the calendar events or input variables are determined to be useful

in forecasting the time series. The HPFDIAGNOSE procedure automatically generates candidate model specifications and a model selection list by using time series analysis techniques. These model specifications and model selection lists can then be used to automatically generate forecasts.

You can specify model specifications by using one of the following model specification procedures:

- The HPFARIMASPEC procedure enables you to specify one of the family of autoregressive integrated moving average with exogenous inputs models.
- The HPFESMSPEC procedure enables you to specify one of the family of exponential smoothing models.
- The HPFEXMSPEC procedure enables the forecast to be generated by an external source.
- The HPFIDMSPEC procedure enables you to specify one of the family of intermittent demand models.
- The HPFSELECT procedure enables you to specify a model selection list. The model selection list refers to one or more candidate model specifications and specifies how to choose the appropriate model for a given time series.
- The HPFUCMSPEC procedure enables you to specify one of the family of unobserved component models.

Regardless of whether the model specifications or model selection lists are specified or automatically generated, the HPFENGINE procedure uses these files to automatically select an appropriate forecasting model, estimate the model parameters, and forecast the time series.

Most of the computational effort that is associated with automatic forecasting consists of time series analysis, diagnostics, model selection, and parameter estimation. Forecast scoring files summarize the time series model's parameter estimates and the final states (historical time series information). These files can be used to quickly generate the forecasts that are required for the iterative nature of scenario analysis, stochastic optimization, and goal seeking computations. The HPFSCSUB function can be used to score time series information.

Uses of SAS Forecast Server Procedures Software

SAS Forecast Server Procedures software provides tools for a wide variety of applications in business, government, and academia. Major uses of SAS Forecast Server Procedures include forecasting, forecast scoring, market response modeling, and time series data mining.

Contents of SAS Forecast Server Procedures Software

Procedures

SAS Forecast Server Procedures software includes the following procedures:

HPFARIMASPEC — The HPFARIMASPEC procedure creates an autoregressive integrated moving average (ARIMA) model specification file. The output of the procedure is an XML (extensible markup language) file that stores the intended ARIMA model specification. This XML specification file can be used to populate the model repository that the HPFENGINE procedure uses. Likewise, the XML files that are generated by the other model specification procedures in this section can also be used to populate the model repository that PROC HPFENGINE uses. For more information, see Chapter 3, "The HPFARIMASPEC Procedure."

HPFDIAGNOSE — The HPFDIAGNOSE procedure is an automatic modeling procedure that finds the best model among ARIMA models, exponential smoothing models, and unobserved component models.

The HPFDIAGNOSE procedure has the following functionality:

- intermittency test
- functional transformation test
- simple differencing and seasonal differencing test
- tentative simple ARMA order identification
- tentative seasonal ARMA order identification
- outlier detection
- significance test of events
- transfer functions identification
- intermittent demand model
- exponential smoothing model
- unobserved component model

The HPFDIAGNOSE procedure produces output that is compatible with HPFENGINE. As a result, the task of candidate model specification, model selection, and forecasting can be entirely automated by HPFDIAGNOSE and HPFENGINE in combination. For more information, see Chapter 4, "The HPFDIAGNOSE Procedure."

HPFENGINE — The HPFENGINE procedure provides large-scale automatic forecasting of transactional or time series data. The HPFENGINE procedure extends the foundation that is built by the HPF procedure, enabling you to determine the list of models over which automatic selection is performed.

The HPFENGINE procedure supports the following time series model families and forecasting methods:

- ARIMA

- unobserved component models
- exponential smoothing models
- intermittent demand models
- external models
- forecast combinations

Furthermore, you can completely customize the operation by defining your own code to generate forecasts.

For models that have inputs, the STOCHASTIC statement is especially helpful for automatically forecasting inputs that have no future values.

Also supported is the generation of a portable forecast score. The output of the SCORE statement is a file or catalog entry which, when used with the new function HPFSCSUB, can efficiently generate forecasts outside of the HPFENGINE procedure. For more information, see Chapter 5, "The HPFENGINE Procedure."

HPFESMSPEC — The HPFESMSPEC procedure creates an exponential smoothing models (ESM) specification file. The output of the procedure is an XML file that stores the intended ESM specification. For more information, see Chapter 6, "The HPFESMSPEC Procedure."

HPFEVENTS — The HPFEVENTS procedure provides a way to create and manage events that are associated with time series. The procedure can create events, read events from an events data set, write events to an events data set, and create dummy variables that are based on those events, if date information is provided.

A SAS event is used to model any incident that disrupts the normal flow of the process that generated the time series. Examples of commonly used events include natural disasters, retail promotions, strikes, advertising campaigns, policy changes, and data recording errors.

An event has a reference name, a date or dates that are associated with the event, and a set of qualifiers. The event exists separately from any time series; however, the event can be applied to one or more time series. When the event is applied to a time series, a dummy variable is generated that can be used to analyze the impact of the event on the time series.

For more information, see Chapter 7, "The HPFEVENTS Procedure."

HPFEXMSPEC — The HPFEXMSPEC procedure creates an external models (EXM) specification file. The output of the procedure is an XML file that stores the intended EXM specification. For more information, see Chapter 8, "The HPFEXMSPEC Procedure."

HPFIDMSPEC — The HPFIDMSPEC procedure creates an intermittent demand models (IDM) specification file. The output of the procedure is an XML file that stores the intended IDM specification. For more information, see Chapter 9, "The HPFIDMSPEC Procedure."

HPFRECONCILE — The HPFRECONCILE procedure reconciles forecasts of time series data at two different levels of aggregation. Optionally, the HPFRECONCILE procedure can disaggregate forecasts from upper-level forecasts or aggregate forecasts from lower level-forecasts. Additionally, the procedure enables you to specify the

	direction and the method of reconciliation and equality constraints and bounds on the reconciled values at each point in time. For more information, see Chapter 10, "The HPFRECONCILE Procedure."
HPFSCSIG	The HPFSCSIG function generates a sample signature for subsequent use by the HPFSCSUB function. For more information, see Chapter 18, "Using Forecasting Model Score Files and DATA Step Functions," and Chapter 5, "The HPFENGINE Procedure."
HPFSCSUB	The HPFSCSUB function uses score files to produce forecasts outside of the HPFENGINE procedure. Because it is a function, it is particularly well suited for use within other SAS programming contexts (such as the DATA step) or procedures that permit the specification of functions (such as the NLP procedure). The only input required is a reference to the score function, the horizon, and future values of any inputs. For more information, see Chapter 18, "Using Forecasting Model Score Files and DATA Step Functions," and Chapter 5, "The HPFENGINE Procedure."
HPFSELECT	The HPFSELECT procedure creates model lists. A model list contains references to candidate model specifications that are stored in the model repository. A model selection list selects the best model from its set of candidates based on the performance of each model's forecast. A model combination list combines the forecasts from its candidates to generate a combined forecast. The output of the procedure is an XML file that stores the intended model selection list. For more information, see Chapter 11, "The HPFSELECT Procedure."
HPFTEMPRECON	The HPFTEMPRECON procedure reconciles forecasts of time series data that are performed at two different frequencies. A low-frequency forecast serves as a benchmark that is used to perform adjustments to a high-frequency forecast. Constraints are imposed so that the adjusted high-frequency forecasts sum to the corresponding low-frequency forecasts over encompassing time periods. For more information, see Chapter 12, "The HPFTEMPRECON Procedure."
HPFUCMSPEC	The HPFUCMSPEC procedure creates an unobserved component models (UCM) specification file. The output of the procedure is an XML file that stores the intended UCM specification. For more information, see Chapter 13, "The HPFUCMSPEC Procedure."

About This Book

This book is a user's guide to SAS Forecast Server Procedures software. Because this software is a part of the SAS System, this book assumes that you are familiar with Base SAS software and that you have the books *SAS Language: Reference* and *SAS Procedures Guide* available for reference. It also assumes that you are familiar with SAS data sets, the SAS DATA step, and basic SAS procedures such as the PRINT procedure and the SORT procedure.

Chapter Organization

This book is divided into three major parts:

- Part One contains general information to aid you in working with SAS Forecast Server Procedures software.

  The current chapter provides an overview of this software and summarizes related SAS publications, products, and services.

- Part Two, the "Procedure Reference," contains the chapters that explain the procedures that make up SAS Forecast Server Procedures software. The chapters that document each of the procedures appear in alphabetical order by procedure name and are organized as follows:

  1. Each chapter begins with an "Overview" section, which briefly describes the procedure.
  2. The "Getting Started" section provides a brief tutorial introduction about how to use the procedure.
  3. The "Syntax" section is a reference to the SAS statements and options that control the procedure.
  4. The "Details" section discusses various technical details.
  5. The "Examples" section contains additional examples of the use of the procedure.
  6. The "References" section contains technical references on methodology.

- Part Three provides a summary of and computational details about the SAS Forecast Server Procedures software.

Typographical Conventions

This book uses several type styles for presenting information. The following list explains the meaning of the typographical conventions used in this book:

roman	is the standard type style used for most text.
UPPERCASE ROMAN	is used for SAS statements, options, and other SAS language elements when they appear in the text. However, you can enter these elements in your own SAS programs in lowercase, uppercase, or a mixture of the two.
UPPERCASE BOLD	is used in the "Syntax" sections' initial lists of SAS statements and options.
oblique	is used for user-supplied values for options in the syntax definitions.
helvetica	is used for the names of variables and data sets when they appear in the text.
bold	is used to refer to matrices and vectors, and to refer to commands (for example, **end** or **cd**.)
italic	is used for terms that are defined in the text, for emphasis, and for references to publications.
`monospace`	is used for example code. In most cases, this book uses lowercase type for SAS statements.

Options Used in Examples

Output of Examples

For each example, the procedure output is numbered consecutively starting with 1, and each output is given a title. Each page of output produced by a procedure is enclosed in a box.

Most of the output shown in this book is produced with the following SAS System options:

```
options linesize=80 pagesize=200 nonumber nodate;
```

The template STATDOC.TPL is used to create the HTML output that appears in the online (CD) version. A style template controls stylistic HTML elements such as colors, fonts, and presentation attributes. The style template is specified in the ODS HTML statement as follows:

```
ODS HTML style=statdoc;
```

If you run the examples, you might get slightly different output. This is a function of the SAS System options used and the precision used by your computer for floating-point calculations.

Graphics Options

The examples that contain graphical output are created with a specific set of options and symbol statements. The statements you see in the examples creates the color graphics that appear in the online (CD) version of this book. A slightly different set of options and statements is used to create the black-and-white graphics that appear in the printed version of the book.

If you run the examples, you might get slightly different results. This may occur because not all graphic options for color devices translate directly to black-and-white output formats. For complete information about SAS/GRAPH software and graphics options, see *SAS/GRAPH Software: Reference*.

The following GOPTIONS statement is used to create the online (color) version of the graphic output.

```
filename GSASFILE '<file-specification>';

goptions reset=all
         gaccess=GSASFILE    gsfmode=replace
         fileonly
         transparency        dev = gif
         ftext = swiss       lfactor = 1
         htext = 4.0pct      htitle = 4.5pct
         hsize = 5.5in       vsize = 3.5in
         noborder            cback = white
         horigin = 0in       vorigin = 0in ;
```

The following GOPTIONS statement is used to create the black-and-white version of the graphic output, which appears in the printed version of the manual.

```
filename GSASFILE '<file-specification>';

goptions reset=all
         gaccess=GSASFILE    gsfmode=replace
         fileonly
         dev = pslepsf
         ftext = swiss       lfactor = 1
         htext = 3.0pct      htitle = 3.5pct
         hsize = 5.5in       vsize = 3.5in
         border              cback = white
         horigin = 0in       vorigin = 0in;
```

In most of the online examples, the plot symbols are specified as follows:

```
symbol1 value=dot color=white height=3.5pct;
```

The SYMBOL*n* statements used in online examples order the symbol colors as follows: white, yellow, cyan, green, orange, blue, and black.

In the examples that appear in the printed manual, symbol statements specify COLOR=BLACK and order the plot symbols as follows: dot, square, triangle, circle, plus, x, diamond, and star.

Where to Turn for More Information

This section describes other sources of information about the SAS Forecast Server Procedures software.

Accessing the SAS Forecast Server Procedures Sample Library

The sample library includes many examples that illustrate the use of this software, and it includes the examples that are used in this documentation.

To access these sample programs, make the following selections from the **Help** menu:

- **SAS Help and Documentation**
- **SAS Products** (on the **Contents** tab)
- **SAS Forecast Server Procedures**

SAS Technical Support Services

The SAS Technical Support staff is available to respond to problems and answer technical questions regarding the use of procedures in this book. Go to `http://support.sas.com/techsup` for more information.

Related SAS Software

Many features not found in the SAS Forecast Server Procedures software are available in other parts of the SAS System. If you do not find something you need in this software, you might find it in one of the following SAS software products.

Base SAS Software

The features provided by the SAS Forecast Server Procedures software are extensions to the features provided by Base SAS software. Many data management and reporting capabilities you will need are part of Base SAS software. Refer to *SAS Language: Reference* and the *SAS Procedures Guide* for documentation of Base SAS software.

The following sections summarize Base SAS software features of interest to users of SAS Forecast Server Procedures software. See Chapter 3, “Working with Time Series Data” (*SAS/ETS User’s Guide*), for further discussion of some of these topics as they relate to time series data and SAS Forecast Server Procedures software.

SAS DATA Step

The DATA step is your primary tool for reading and processing data in the SAS System. The DATA step provides a powerful general purpose programming language that enables you to perform all kinds of data processing tasks. The DATA step is documented in *SAS Language: Reference*.

Base SAS Procedures

Base SAS software includes many useful SAS procedures. Base SAS procedures are documented in the *SAS Procedures Guide*. The following is a list of Base SAS procedures you might find useful:

CATALOG	for managing SAS catalogs
CHART	for printing charts and histograms
COMPARE	for comparing SAS data sets
CONTENTS	for displaying the contents of SAS data sets
COPY	for copying SAS data sets
CORR	for computing correlations
CPORT	for moving SAS data libraries between computer systems
DATASETS	for deleting or renaming SAS data sets
FREQ	for computing frequency crosstabulations
MEANS	for computing descriptive statistics and summarizing or collapsing data over cross sections
PLOT	for printing scatter plots
PRINT	for printing SAS data sets
RANK	for computing rankings or order statistics
SORT	for sorting SAS data sets
SQL	for processing SAS data sets with structured query language
STANDARD	for standardizing variables to a fixed mean and variance
TABULATE	for printing descriptive statistics in tabular format
TIMEPLOT	for plotting variables over time
TRANSPOSE	for transposing SAS data sets
UNIVARIATE	for computing descriptive statistics

Global Statements

Global statements can be specified anywhere in your SAS program, and they remain in effect until changed. Global statements are documented in *SAS Language: Reference*. You might find the following SAS global statements useful:

FILENAME	for accessing data files
FOOTNOTE	for printing footnote lines at the bottom of each page
%INCLUDE	for including files of SAS statements

LIBNAME	for accessing SAS data libraries
OPTIONS	for setting various SAS system options
RUN	for executing the preceding SAS statements
TITLE	for printing title lines at the top of each page
X	for issuing host operating system commands from within your SAS session

Some Base SAS statements can be used with any SAS procedure, including SAS Forecast Server Procedures procedures. These statements are not global, and they affect only the SAS procedure they are used with. These statements are documented in *SAS Language: Reference*.

The following Base SAS statements are useful with SAS Forecast Server Procedures procedures:

BY	for computing separate analyses for groups of observations
FORMAT	for assigning formats to variables
LABEL	for assigning descriptive labels to variables
WHERE	for subsetting data to restrict the range of data processed or to select or exclude observations from the analysis

SAS Functions

SAS functions can be used in DATA step programs and in the COMPUTAB and MODEL procedures. The following kinds of functions are available:

- character functions, for manipulating character strings
- date and time functions, for performing date and calendar calculations
- financial functions, for performing financial calculations such as depreciation, net present value, periodic savings, and internal rate of return
- lagging and differencing functions, for computing lags and differences
- mathematical functions, for computing data transformations and other mathematical calculations
- probability functions, for computing quantiles of statistical distributions and the significance of test statistics
- random number functions, for simulation experiments
- sample statistics functions, for computing means, standard deviations, kurtosis, and so on

Formats, Informats, and Time Intervals

Base SAS software provides formats to control the printing of data values, informats to read data values, and time intervals to define the frequency of time series.

SAS/GRAPH Software

SAS/GRAPH software includes procedures that create two- and three-dimensional high-resolution color graphics plots and charts. You can generate output that graphs the relationship of data values to one another, enhance existing graphs, or simply create graphics output that is not tied to data. SAS/GRAPH software can produce the following outputs:

- charts
- plots
- maps
- text
- three-dimensional graphs

With SAS/GRAPH software you can produce high-resolution color graphics plots of time series data.

SAS/STAT Software

SAS/STAT software is of interest to users of SAS Forecast Server Procedures software because many econometric and other statistical methods that are not included in SAS Forecast Server Procedures software are provided in SAS/STAT software.

SAS/STAT software includes procedures for a wide range of statistical methodologies, including the following:

- logistic regression
- censored regression
- principal component analysis
- structural equation models using covariance structure analysis
- factor analysis
- survival analysis
- discriminant analysis
- cluster analysis

- categorical data analysis, including log-linear and conditional logistic models
- general linear models
- mixed linear and nonlinear models
- generalized linear models
- response surface analysis
- kernel density estimation
- LOESS regression
- spline regression
- two-dimensional kriging
- multiple imputation for missing values

SAS/IML Software

SAS/IML software gives you access to a powerful and flexible programming language (interactive matrix language) in a dynamic, interactive environment. The fundamental object of the language is a data matrix. You can use SAS/IML software interactively (at the statement level) to see results immediately, or you can store statements in a module and execute them later. The programming is dynamic because necessary activities such as memory allocation and dimensioning of matrices are done automatically.

You can access built-in operators and call routines to perform complex tasks such as matrix inversion or eigenvector generation. You can define your own functions and subroutines with SAS/IML modules. You can perform operations on an entire data matrix. You have access to a wide choice of data management commands. You can read, create, and update SAS data sets from inside SAS/IML software without ever using the DATA step.

SAS/IML software is of interest to users of SAS Forecast Server Procedures software because it enables you to program your own econometric and time series methods in the SAS System. It contains subroutines for time series operators and for general function optimization. If you need to perform a statistical calculation that is not provided as an automated feature by SAS Forecast Server Procedures or other SAS software, you can use SAS/IML software to program the matrix equations for the calculation.

Kalman Filtering and Time Series Analysis in SAS/IML

SAS/IML software includes a library for Kalman filtering and time series analysis. The library provides the following functions:

- generating univariate, multivariate, and fractional time series
- computing likelihood function of ARMA, VARMA, and ARFIMA models
- computing an autocovariance function of ARMA, VARMA, and ARFIMA models

- checking the stationarity of ARMA and VARMA models
- filtering and smoothing of time series models with the Kalman method
- fitting AR, periodic AR, time-varying coefficient AR, VAR, and ARFIMA models
- handling Bayesian seasonal adjustment model

SAS/OR Software

SAS/OR software provides SAS procedures for operations research and project planning and includes a menu-driven system for project management. SAS/OR software has features for the following:

- solving transportation problems
- linear, integer, and mixed-integer programming
- nonlinear programming and optimization
- scheduling projects
- plotting Gantt charts
- drawing network diagrams
- solving optimal assignment problems
- network flow programming

SAS/OR software might be of interest to users of SAS Forecast Server Procedures software for its mathematical programming features. In particular, the NLP procedure in SAS/OR software solves nonlinear programming problems and can be used for constrained and unconstrained maximization of user-defined likelihood functions.

SAS/QC Software

SAS/QC software provides a variety of procedures for statistical quality control and quality improvement. SAS/QC software includes procedures for the following:

- Shewhart control charts
- cumulative sum control charts
- moving average control charts
- process capability analysis
- Ishikawa diagrams

- Pareto charts
- experimental design

SAS/QC software also includes the SQC menu system for interactive application of statistical quality control methods and the ADX Interface for Design of Experiments.

Other Statistical Tools

Many other statistical tools are available in Base SAS, SAS/STAT, SAS/OR, SAS/QC, and SAS/IML software. If you do not find something you need in SAS Forecast Server Procedures software, you might find it in SAS/STAT software or in Base SAS software. If you still do not find it, look in other SAS software products or contact the SAS Technical Support staff.

References

Leonard, M. J. (2000). "Promotional Analysis and Forecasting for Demand Planning: A Practical Time Series Approach." Cary, NC: SAS Institute Inc.

Leonard, M. J. (2002). "Large-Scale Automatic Forecasting: Millions of Forecasts." Cary, NC: SAS Institute Inc.

Leonard, M. J. (2003). "Mining Transactional and Time Series Data." Paper presented at the International Symposium on Forecasting, Merida, Mexico.

Leonard, M. J. (2004). "Large-Scale Automatic Forecasting with Inputs and Calendar Events." Paper presented at the International Symposium on Forecasting, Sydney.

Part II

Procedure Reference

Chapter 2
The HPF Procedure

Contents

Overview: HPF Procedure **22**
Getting Started: HPF Procedure **23**
Syntax: HPF Procedure **26**
- Functional Summary 26
- PROC HPF Statement 28
- BY Statement 31
- FORECAST Statement 32
- ID Statement 36
- IDM Statement 39
- Smoothing Model Specification Options for IDM Statement 41

Details: HPF Procedure **43**
- Accumulation 44
- Missing Value Interpretation 45
- Diagnostic Tests 46
- Model Selection 46
- Transformations 46
- Parameter Estimation 46
- Smoothing Model Parameter Specification Options 46
- Missing Value Modeling Issues 47
- Forecasting 47
- IDM Smoothing Model Forecast Bounds Options 47
- Inverse Transformations 47
- Statistics of Fit 48
- Forecast Summation 48
- Comparison to the Time Series Forecasting System 48
- Data Set Output 48
- OUT= Data Set 49
- OUTEST= Data Set 49
- OUTFOR= Data Set 50
- OUTPROCINFO= Data Set 50
- OUTSTAT= Data Set 51
- OUTSUM= Data Set 53
- OUTSEASON= Data Set 54
- OUTTREND= Data Set 54
- Printed Output 55
- ODS Table Names 56

ODS Graphics 57
Examples: HPF Procedure **59**
Example 2.1: Automatic Forecasting of Time Series Data 59
Example 2.2: Automatic Forecasting of Transactional Data 61
Example 2.3: Specifying the Forecasting Model 63
Example 2.4: Extending the Independent Variables for Multivariate Forecasts 63
Example 2.5: Forecasting Intermittent Time Series Data 65
Example 2.6: Illustration of ODS Graphics 67
References **71**

Overview: HPF Procedure

The HPF procedure provides a quick and automatic way to generate forecasts for many time series or transactional data in one step. The procedure can forecast millions of series at a time, with the series organized into separate variables or across BY groups.

- For typical time series, you can use the following smoothing models:
  - simple
  - double
  - linear
  - damped trend
  - seasonal (additive and multiplicative)
  - Winters method (additive and multiplicative)
- Additionally, transformed versions of these models are provided:
  - log
  - square root
  - logistic
  - Box-Cox
- For intermittent time series (series where a large number of values are zero-valued), you can use an intermittent demand model such as Croston's method and the average demand model.

All parameters associated with the forecast model are optimized based on the data. Optionally, the HPF procedure can select the appropriate smoothing model for you by using holdout sample analysis based on one of several model selection criteria.

The HPF procedure writes the following information to output data sets:

- time series extrapolated by the forecasts

- series summary statistics
- forecasts and confidence limits
- parameter estimates
- fit statistics

The HPF procedure optionally produces printed output for these results by using the Output Delivery System (ODS).

The HPF procedure can forecast time series data, whose observations are equally spaced by a specific time interval (for example, monthly, weekly), and also transactional data, whose observations are not spaced with respect to any particular time interval. Internet, inventory, sales, and similar data are typical examples of transactional data. For transactional data, the data are accumulated based on a specified time interval to form a time series. The HPF procedure can also perform trend and seasonal analysis on transactional data.

Also, the EXPAND procedure can be used for the frequency conversion and transformations of time series. For more information, see Chapter 15, "EXPAND Procedure" (*SAS/ETS User's Guide*).

Getting Started: HPF Procedure

The HPF procedure is simple to use for someone who is new to forecasting, and yet at the same time it is powerful for the experienced professional forecaster who needs to generate a large number of forecasts automatically. It can provide results in output data sets or in other output formats by using the Output Delivery System (ODS). The following examples are more fully illustrated in the section "Examples: HPF Procedure" on page 59.

Given an input data set that contains numerous time series variables recorded at a specific frequency, the HPF procedure can automatically forecast the series as follows:

```
PROC HPF DATA=<input-data-set> OUT=<output-data-set>;
   ID <time-ID-variable> INTERVAL=<frequency>;
   FORECAST <time-series-variables>;
   RUN;
```

For example, suppose that the input data set SALES contains numerous sales data recorded monthly, the variable that represents time is DATE, and the forecasts are to be recorded in the output data set NEXTYEAR. The HPF procedure could be used as follows:

```
proc hpf data=sales out=nextyear;
   id date interval=month;
   forecast _ALL_;
run;
```

The preceding statements automatically select the best fitting model, generate forecasts for every numeric variable in the input data set (SALES) for the next twelve months, and store these forecasts in the output data set (NEXTYEAR). Other output data sets can be specified to store the parameter estimates, forecasts, statistics of fit, and summary data.

If you want to print the forecasts by using the Output Delivery System (ODS), then you need to add PRINT=FORECASTS:

```
proc hpf data=sales out=nextyear print=forecasts;
   id date interval=month;
   forecast _ALL_;
run;
```

Other results can be specified to output the parameter estimates, forecasts, statistics of fit, and summary data by using ODS.

The HPF procedure can forecast time series data, whose observations are equally spaced by a specific time interval (for example, monthly, weekly), and also transactional data, whose observations are not spaced with respect to any particular time interval.

Given an input data set that contains transactional variables not recorded at any specific frequency, the HPF procedure accumulates the data to a specific time interval and forecasts the accumulated series as follows:

```
PROC HPF DATA=<input-data-set> OUT=<output-data-set>;
   ID <time-ID-variable> INTERVAL=<frequency>
      ACCUMULATE=<accumulation>;
   FORECAST <time-series-variables>;
RUN;
```

For example, suppose that the input data set WEBSITES contains three variables (BOATS, CARS, PLANES) that are Internet data recorded on no particular time interval, and the variable that represents time is TIME, which records the time of the Web hit. The forecasts for the total daily values are to be recorded in the output data set NEXTWEEK. The HPF procedure could be used as follows:

```
proc hpf data=websites out=nextweek lead=7;
   id time interval=dtday accumulate=total;
   forecast boats cars planes;
run;
```

The preceding statements accumulate the data into a daily time series, automatically generate forecasts for the BOATS, CARS, and PLANES variables in the input data set (WEBSITES) for the next seven days, and store the forecasts in the output data set (NEXTWEEK).

The HPF procedure can specify a particular forecast model or select from several candidate models based on a selection criterion. The HPF procedure also supports transformed models and holdout sample analysis.

Using the previous WEBSITES example, suppose that you want to forecast the BOATS variable by using the best seasonal forecasting model that minimizes the mean absolute percent error (MAPE), forecast the CARS variable by using the best nonseasonal forecasting model that minimizes the mean square error (MSE) by using holdout sample analysis on the last five days, and forecast the PLANES variable by using the log Winters method (additive). The HPF procedure could be used as follows:

```
proc hpf data=websites out=nextweek lead=7;
   id time interval=dtday accumulate=total;
   forecast boats   / model=bests criterion=mape;
   forecast cars    / model=bestn criterion=mse holdout=5;
   forecast planes  / model=addwinters transform=log;
run;
```

The preceding statements demonstrate how each variable in the input data set can be modeled differently and how several candidate models can be specified and selected based on holdout sample analysis or the entire range of data.

The HPF procedure is also useful in extending independent variables in regression or autoregression models where future values of the independent variable are needed to predict the dependent variable.

Using the WEBSITES example, suppose that you want to forecast the ENGINES variable by using the BOATS, CARS, and PLANES variable as regressor variables. Since future values of the BOATS, CARS, and PLANES variables are needed, the HPF procedure can be used to extend these variables in the future:

```
proc hpf data=websites out=nextweek lead=7;
   id time interval=dtday accumulate=total;
   forecast engines / model=none;
   forecast boats   / model=bests criterion=mape;
   forecast cars    / model=bestn crierion=mse holdout=5;
   forecast planes  / model=addwinters transform=log;
run;

proc autoreg data= nextweek;
   model engines = boats cars planes;
   output out=enginehits p=predicted;
run;
```

The preceding HPF procedure statements generate forecasts for BOATS, CARS, and PLANES in the input data set (WEBSITES) for the next seven days and extend the variable ENGINES with missing values. The output data set (NEXTWEEK) of the PROC HPF statement is used as an input data set for the PROC AUTOREG statement. The output data set of PROC AUTOREG contains the forecast of the variable ENGINE based on the regression model with the variables BOATS, CARS, and PLANES as regressors. For more information about autoregression, see Chapter 8, "AUTOREG Procedure" (*SAS/ETS User's Guide*).

The HPF procedure can also forecast intermittent time series (series where a large number of values are zero-valued). Typical time series forecasting techniques are less effective in forecasting intermittent time series.

For example, suppose that the input data set INVENTORY contains three variables (TIRES, HUBCAPS, LUGBOLTS) that are demand data recorded on no particular time interval, the variable that represents time is DATE, and the forecasts for the total weekly values are to be recorded in the output data set NEXTMONTH. The models requested are intermittent demand models, which can be specified as MODEL=IDM. Two intermittent demand models are compared, the Croston model and the average demand model. The HPF procedure could be used as follows:

```
proc hpf data=inventory out=nextmonth lead=4 print=forecasts;
   id date interval=week accumulate=total;
   forecast tires hubcaps lugbolts / model=idm;
run;
```

In the preceding example, the total demand for inventory items is accumulated on a weekly basis, and forecasts are generated that recommend future stocking levels.

Syntax: HPF Procedure

The following statements are used with the HPF procedure.

PROC HPF *options* **;**
BY *variables* **;**
FORECAST *variable-list / options* **;**
ID *variable INTERVAL= interval options* **;**
IDM *options* **;**

Functional Summary

Table 2.1 summarizes the statements and options that control the HPF procedure.

Table 2.1 PROC HPF Functional Summary

Description	Statement	Option
Statements		
Specifies BY-group processing	BY	
Specifies variables to forecast	FORECAST	
Specifies the time ID variable	ID	
Specifies intermittent demand model	IDM	
Data Set Options		
Specifies the input data set	PROC HPF	DATA=
Specifies to output forecasts only	PROC HPF	NOOUTALL
Specifies the output data set	PROC HPF	OUT=
Specifies the parameter output data set	PROC HPF	OUTEST=
Specifies the forecast output data set	PROC HPF	OUTFOR=
Specifies the forecast procedure information output data set	PROC HPF	OUTPROCINFO=
Specifies the output data set for seasonal statistics	PROC HPF	OUTSEASON=
Specifies the statistics output data set	PROC HPF	OUTSTAT=
Specifies the summary output data set	PROC HPF	OUTSUM=
Specifies trend statistics output data set	PROC HPF	OUTTREND=
Replaces actual values held back	FORECAST	REPLACEBACK
Replaces missing values	FORECAST	REPLACEMISSING
Specifies forecast value type to append for OUT=	FORECAST	USE=
Accumulation and Seasonality Options		
Specifies the accumulation frequency	ID	INTERVAL=
Specifies the length of seasonal cycle	PROC HPF	SEASONALITY=
Specifies the interval alignment	ID	ALIGN=

Description	Statement	Option
Specifies that the time ID variable values are not sorted	ID	NOTSORTED
Specifies the starting time ID value	ID	START=
Specifies the ending time ID value	ID	END=
Specifies the accumulation statistic	ID, FORECAST	ACCUMULATE=
Specifies missing value interpretation	ID, FORECAST	SETMISSING=
Specifies zero value interpretation	ID, FORECAST	ZEROMISS=
Forecasting Horizon, Holdout, Holdback Options		
Specifies data to hold back	PROC HPF	BACK=
Specifies the forecast holdout sample size	FORECAST	HOLDOUT=
Specifies the forecast holdout sample percent	FORECAST	HOLDOUTPCT=
Specifies the forecast horizon or lead	PROC HPF	LEAD=
Specifies the horizon to start summation	PROC HPF	STARTSUM=
Forecasting Model and Selection Options		
Specifies the confidence limit width	FORECAST	ALPHA=
Specifies the model selection criterion	FORECAST	CRITERION=
Specifies intermittency threshold	FORECAST	INTERMITTENT=
Specifies the forecast model	FORECAST	MODEL=
Specifies to use median forecast	FORECAST	MEDIAN
Specifies backcast initialization	FORECAST	NBACKCAST=
Specifies the seasonality test threshold	FORECAST	SEASONTEST=
Specifies the model transformation	FORECAST	TRANSFORM=
Intermittent Demand Model Options		
Specifies the model for average demand	IDM	AVERAGE=
Specifies the base value	IDM	BASE=
Specifies the model for demand intervals	IDM	INTERVAL=
Specifies the model for demand sizes	IDM	SIZE=
Printing and Plotting Control Options		
Specifies the time ID format	ID	FORMAT=
Specifies types of graphical output	PROC HPF	PLOT=
Specifies types of printed output	PROC HPF	PRINT=
Requests detailed printed output	PROC HPF	PRINTDETAILS
Miscellaneous Options		
Requests that analysis variables be processed in sorted order	PROC HPF	SORTNAMES
Limits error and warning messages	PROC HPF	MAXERROR=

PROC HPF Statement

PROC HPF *options* **;**

You can specify the following *options*:

BACK=*n*
specifies the number of observations before the end of the data where the multistep forecasts are to begin, where *n* is an integer. By default, BACK=0.

DATA=*SAS-data-set*
names the *SAS-data-set* that contains the input data for the procedure to forecast. If this option is not specified, the most recently created SAS data set is used.

LEAD=*n*
specifies the number of periods ahead to forecast (forecast lead or horizon), where *n* is relative to the last observation in the input data set and not to the last nonmissing observation of a particular series. Thus, if a series has missing values at the end, the actual number of forecasts computed for that series will be greater than *n*. By default, LEAD=12

MAXERROR=*number*
limits the number of warning and error messages produced during the execution of the procedure to *number*. This option is particularly useful in BY-group processing where it can be used to suppress recurring messages. By default, MAXERROR=50.

NOOUTALL
requests that only forecasts be written to the OUT= and OUTFOR= data sets. This option includes only the final forecast observations in the output data sets, not the one-step forecasts for the data before the forecast period.

The OUT= and OUTFOR= data sets will contain only the forecast results that start at the next period that follows the last observation and go to the forecast horizon that is specified in the LEAD= option.

OUT=*SAS-data-set*
names the output data set to contain the forecasts of the variables that are specified in the subsequent FORECAST statements. If an ID statement is included, the variable specified in it will also be included in the OUT= data set. The values are accumulated based on the ACCUMULATE= option, and forecasts are appended to these values based on the USE= option in the FORECAST statement. The OUT= data set is particularly useful in extending the independent variables when forecasting dependent series associated with regression and autoregression models. If the OUT= option is not specified, a default output data set named DATA*n* is created, where *n* is the next integer greater than the suffix of any other DATA*n* data sets. If you do not want the OUT= data set created, then use OUT=_NULL_.

OUTEST=*SAS-data-set*
names the output data set to contain the model parameter estimates and the associated test statistics and probability values. The OUTEST= data set is particularly useful for evaluating the significance of the model parameters and understanding the model dynamics.

OUTFOR=*SAS-data-set*
names the output data set to contain the forecast time series components (actual, predicted, lower confidence limit, upper confidence limit, prediction error, and prediction standard error). The OUTFOR= data set is particularly useful for displaying the forecasts in tabular or graphical form.

OUTPROCINFO=*SAS-data-set*
names the output data set to contain information in the SAS log, specifically the number of notes, errors, and warnings and the number of series processed, forecasts requested, and forecasts failed.

OUTSEASON=*SAS-data-set*
names the output data set to contain the seasonal statistics. The statistics are computed for each season as specified by the INTERVAL= option or the SEASONALITY= option in the ID statement. The OUTSEASON= data set is particularly useful when analyzing transactional data for seasonal variations.

OUTSTAT=*SAS-data-set*
names the output data set to contain the statistics of fit (or goodness-of-fit statistics). The OUTSTAT= data set is particularly useful for evaluating how well the model fits the series. The statistics of fit are based on the entire range of the time series regardless of whether the HOLDOUT= option is specified.

OUTSUM=*SAS-data-set*
names the output data set to contain the summary statistics and the forecast summation. The summary statistics are based on the accumulated time series when the ACCUMULATE= or SETMISSING= options are specified. The forecast summations are based on the LEAD=, STARTSUM=, and USE= options. The OUTSUM= data set is particularly useful when forecasting large numbers of series and a summary of the results is needed.

OUTTREND=*SAS-data-set*
names the output data set to contain the trend statistics. The statistics are computed for each time period as specified by the ID statement INTERVAL= option. The OUTTREND= data set is particularly useful when analyzing transactional data for trends.

PLOT=*option* | **(***options***)**
specifies the graphical output desired. By default, the HPF procedure produces no graphical output. You can specify the following printing *options*:

ACF plots prediction error autocorrelation function graphics.

ALL is the same as specifying all of the PLOT= options.

BASIC equivalent to specifying PLOT=(CORR ERRORS MODELFORECASTS). In the context of IDM models, the StockingLevelPlot is generated in place of the prediction error correlation panel plot.

CORR plots the prediction error series graphics panel containing the ACF, IACF, PACF, and white noise probability plots. Note in the context of IDM models PLOT=CORR produces no additional output.

ERRORS plots prediction error time series graphics.

FORECASTS plots forecast graphics.

FORECASTSONLY plots the forecast in the forecast horizon only.

IACF plots prediction error inverse autocorrelation function graphics.

LEVELS plots smoothed level component graphics.

MODELFORECASTS plots the one-step ahead model forecast and its confidence bands in the historical period; the forecast and its confidence bands over the forecast horizon.

MODELS plots model graphics.

PACF plots prediction error partial autocorrelation function graphics.

PERIODOGRAM plots prediction error periodogram.

SEASONS plots smoothed seasonal component graphics.

SPECTRUM plots periodogram and smoothed periodogram of the prediction error series in a single graph. The SPECTRUM plot admits the specification of options to control some aspects of the generation of the smoothed periodogram. No options are required to use PLOT=SPECTRUM. To specify options use the following syntax:

SPECTRUM=(*options***)**

Valid options for the SPECTUM plot include:

ALPHA=value specifies the significance level for upper and lower confidence limits about the smoothed periodogram estimates of spectral density. The default is ALPHA=0.4.

CENTER=YES|NO specifies whether mean adjustment is desired for the error series before computation of the smoothed periodogram estimates of spectral density. The default is NO.

TRENDS plots smoothed trend (slope) component graphics.

WN plots white noise graphics.

For example, PLOT=FORECASTS plots the forecasts for each series.

PRINT=*option* | **(***options***)**

specifies the printed output desired. By default, the HPF procedure produces no printed output. The following printing options are available:

ESTIMATES prints the results of parameter estimation (OUTEST= data set).

FORECASTS prints the forecasts (OUTFOR= data set).

PERFORMANCE prints the performance statistics for each forecast.

PERFORMANCESUMMARY prints the performance summary for each BY group.

PERFORMANCEOVERALL prints the performance summary for all of the BY groups.

SEASONS prints the seasonal statistics (OUTSEASON= data set).

STATISTICS prints the statistics of fit (OUTSTAT= data set).

STATES prints the backcast, initial, and final states.

SUMMARY prints the summary statistics for the accumulated time series (OUTSUM= data set).

TRENDS prints the trend statistics (OUTTREND= data set).

ALL is the same as PRINT=(ESTIMATES FORECASTS STATISTICS SUMMARY). PRINT=(ALL TRENDS SEASONS) prints all of the options in the preceding list.

For example, PRINT=FORECASTS prints the forecasts, PRINT=(ESTIMATES FORECASTS) prints the parameter estimates and the forecasts, and PRINT=ALL prints all of the preceding output.

The PRINT= option produces printed output for these results with the Output Delivery System (ODS). The PRINT= option produces results similar to the data sets listed in parenthesis for some of the options in the preceding list.

PRINTDETAILS
specifies that output requested with the PRINT= option be printed in greater detail.

SEASONALITY=*number*
specifies the length of the seasonal cycle. For example, SEASONALITY=3 means that every group of three observations forms a seasonal cycle. The SEASONALITY= option is applicable only for seasonal forecasting models. By default, the length of the seasonal cycle is one (no seasonality) or the length implied by the INTERVAL= option specified in the ID statement. For example, INTERVAL=MONTH implies that the length of the seasonal cycle is 12.

SORTNAMES
specifies that the variables specified in the FORECAST statements be processed in sorted order.

STARTSUM=*n*
specifies the starting forecast lead (or horizon) for which to begin summation of the forecasts specified by the LEAD= option. The STARTSUM= value must be less than the LEAD= value. The default is STARTSUM=1—that is, the sum from the one-step-ahead forecast to the multistep forecast specified by the LEAD= option.

The prediction standard errors of the summation of forecasts take into account the correlation between the multistep forecasts. The section "Details: HPF Procedure" on page 43 describes the STARTSUM= option in more detail.

BY Statement

BY *variables* **;**

A BY statement can be used with PROC HPF to obtain separate analyses for groups of observations defined by the BY variables.

When a BY statement appears, the procedure expects the input data set to be sorted in order of the BY variables.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data by using the SORT procedure with a similar BY statement.
- Specify the NOTSORTED or DESCENDING option in the BY statement for the HPF procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged

in groups (according to values of the BY variables) and that these groups are not necessarily in alphabetical or increasing numeric order.

- Create an index on the BY variables by using the DATASETS procedure.

For more information about the BY statement, see *SAS Language Reference: Concepts*. For more information about the DATASETS procedure, see the discussion in the *Base SAS Procedures Guide.*

FORECAST Statement

FORECAST *variable-list / options* **;**

The FORECAST statement lists the numeric variables in the DATA= data set whose accumulated values represent time series to be modeled and forecast. The options specify which forecast model is to be used or how the forecast model is selected from several possible candidate models.

A data set variable can be specified in only one FORECAST statement. Any number of FORECAST statements can be used. The following options can be used with the FORECAST statement.

ACCUMULATE=*option*

specifies how the data set observations are to be accumulated within each time period for the variables listed in the FORECAST statement. If the ACCUMULATE= option is not specified in the FORECAST statement, accumulation is determined by the ACCUMULATE= option of the ID statement. For more information, see the ID statement ACCUMULATE= option.

ALPHA=*number*

specifies the significance level to use in computing the confidence limits of the forecast. The ALPHA= value must be between 0 and 1. The default is ALPHA=0.05, which produces 95% confidence intervals.

CRITERION=*option*

SELECT=*option*

specifies the model selection criterion (statistic of fit) to be used to select from several candidate models. This option is often used in conjunction with the HOLDOUT= option. The CRITERION= option can also be specified as SELECT=. The default is CRITERION=RMSE.

HOLDOUT=*n*

specifies the size of the holdout sample to be used for model selection. The holdout sample is a subset of actual time series that end at the last nonmissing observation. If the ACCUMULATE= option is specified, the holdout sample is based on the accumulated series. If the holdout sample is not specified, the full range of the actual time series is used for model selection.

For each candidate model specified, the holdout sample is excluded from the initial model fit and forecasts are made within the holdout sample time range. Then, for each candidate model specified, the statistic of fit specified by the CRITERION= option is computed by using only the observations in the holdout sample. Finally, the candidate model, which performs best in the holdout sample, based on this statistic, is selected to forecast the actual time series.

The HOLDOUT= option is used only to select the best forecasting model from a list of candidate models. After the best model is selected, the full range of the actual time series is used for subsequent

model fitting and forecasting. It is possible that one model will outperform another model in the holdout sample but perform less well when the entire range of the actual series is used.

If the MODEL=BESTALL and HOLDOUT= options are used together, the last one hundred observations are used to determine whether the series is intermittent. If the series is determined not to be intermittent, holdout sample analysis is used to select the smoothing model.

HOLDOUTPCT=*number*

specifies the size of the holdout sample as a percentage of the length of the time series. If HOLDOUT=5 and HOLDOUTPCT=10, the size of the holdout sample is $min(5, 0.1T)$ where T is the length of the time series with the beginning and ending missing values removed. The default is 100 (100%).

INTERMITTENT=*number*

specifies a number greater than one which is used to determine whether or not a time series is intermittent. If the average demand interval is greater than this number, then the series is assumed to be intermittent. This option is used with the MODEL=BESTALL option. The default is INTERMITTENT=1.25.

MEDIAN

specifies that the median forecast values are to be estimated. Forecasts can be based on the mean or median. By default the mean value is provided. If no transformation is applied to the actual series by using the TRANSFORM= option, the mean and median forecast values are identical.

MODEL=*model-name*

specifies the forecasting model to be used to forecast the actual time series. A single model can be specified or a group of candidate models can be specified. If a group of models is specified, the model used to forecast the accumulated time series is selected based on the CRITERION= option and the HOLDOUT= option. The default is MODEL=BEST. The following forecasting models are provided:

NONE	no forecast. The accumulated time series is appended with missing values in the OUT= data set. This option is particularly useful when the results stored in the OUT= data set are subsequently used in regression or autoregression analysis where forecasts of the independent variables are needed to forecast the dependent variable.
SIMPLE	simple (single) exponential smoothing
DOUBLE	double (Brown) exponential smoothing
LINEAR	linear (Holt) exponential smoothing
DAMPTREND	damped trend exponential smoothing
ADDSEASONAL|SEASONAL	additive seasonal exponential smoothing
MULTSEASONAL	multiplicative seasonal exponential smoothing
WINTERS	Winters multiplicative method
ADDWINTERS	Winters additive method
BEST	best candidate smoothing model (SIMPLE, DOUBLE, LINEAR, DAMPTREND, ADDSEASONAL, WINTERS, ADDWINTERS)
BESTN	best candidate nonseasonal smoothing model (SIMPLE, DOUBLE, LINEAR, DAMPTREND)

BESTS best candidate seasonal smoothing model (ADDSEASONAL, WINTERS, ADDWINTERS)

IDM|CROSTON intermittent demand model such as Croston's method or average demand model. An intermittent time series is one whose values are mostly zero.

BESTALL best candidate model (IDM, BEST)

The BEST, BESTN, and BESTS options specify a group of models by which the HOLDOUT= option and CRITERION= option are used to select the model used to forecast the accumulated time series based on holdout sample analysis. Transformed versions of the preceding smoothing models can be specified using the TRANSFORM= option.

The BESTALL option specifies that if the series is intermittent, an intermittent demand model such as Croston's method or average demand model (MODEL=IDM) is selected; otherwise, the best smoothing model is selected (MODEL=BEST). Intermittency is determined by the INTERMITTENT= option.

Chapter 15, "Forecasting Process Details," describes the preceding smoothing models and intermittent models in greater detail.

NBACKCAST=*n*

specifies the number of observations used to initialize the backcast states. The default is the entire series.

REPLACEBACK

specifies that actual values excluded by the BACK= option be replaced with one-step-ahead forecasts in the OUT= data set.

REPLACEMISSING

specifies that embedded missing actual values be replaced with one-step-ahead forecasts in the OUT= data set.

SEASONTEST=*option*

specifies the options related to the seasonality test. This option is used with the MODEL=BEST and MODEL=BESTALL options.

The following options are provided:

SEASONTEST=NONE no test

SEASONTEST=(SIGLEVEL=number) significance probability value

Series with strong seasonality have small test probabilities. SEASONTEST=(SIGLEVEL=0) always implies seasonality. SEASONTEST=(SIGLEVEL=1) always implies no seasonality. The default is SEASONTEST=(SIGLEVEL=0.01).

SETMISSING=*option* | *number*

specifies how to assign missing values (either actual or accumulated) in the accumulated time series for variables that are listed in the FORECAST statement. If the SETMISSING= option is not specified in the FORECAST statement, missing values are set based on the SETMISSING= option of the ID statement. For more information, see the SETMISSING= option in the ID statement.

TRANSFORM=*option*

specifies the time series transformation to apply to the actual time series. The following transformations are provided:

NONE	no transformation
AUTO	automatically choose between NONE and LOG based on model selection criteria
BOXCOX(*n***)**	Box-Cox transformation with parameter number (*n*); where *n* is between –5 and 5
LOG	logarithmic transformation
LOGISTIC	logistic transformation
SQRT	square-root transformation

When the TRANSFORM= option is specified, the time series must be strictly positive. After the time series is transformed, the model parameters are estimated by using the transformed series. The forecasts of the transformed series are then computed, and finally the transformed series forecasts are inverse transformed. The inverse transform produces either mean or median forecasts depending on whether the MEDIAN option is specified.

The TRANSFORM= option is not applicable when MODEL=IDM is specified. By default, TRANSFORM=NONE.

USE=*option*

specifies which forecast values to append to the actual values in the OUT= and OUTSUM= data sets. You can specify the following *options*:

PREDICT	The predicted values are appended to the actual values. This option is the default.
LOWER	The lower confidence limit values are appended to the actual values.
UPPER	The upper confidence limit values are appended to the actual values.

Thus, the USE= option enables the OUT= and OUTSUM= data sets to be used for worst-, best-, average-, and median-case decisions. By default, USE=PREDICT.

ZEROMISS=*option*

specifies how to interpret beginning and ending zero values (either actual or accumulated) in the accumulated time series for variables that are listed in the FORECAST statement. If the ZEROMISS= option is not specified in the FORECAST statement, missing values are set based on the ZEROMISS= option in the ID statement. For more information, see the ZEROMISS=option in the ID statement.

ID Statement

ID *variable* **INTERVAL=***interval* < *options* > **;**

The ID statement names a numeric variable that identifies observations in the input and output data sets. The ID variable's values are assumed to be SAS date, time, or datetime values. In addition, the ID statement specifies the (desired) frequency to be associated with the actual time series. The *options* in the ID statement also specify how to accumulate the observations and how to align the time ID values to form the actual time series. Consequently, the specified information affects all variables that are specified in subsequent FORECAST statements. If an ID statement is not specified, the observation number, with respect to the BY group, is used as the time ID.

You must specify the following option:

INTERVAL=*interval*

specifies the frequency of the input time series. For example, if the input data set consists of quarterly observations, then INTERVAL=QTR should be used. If the SEASONALITY= option is not specified, the length of the seasonal cycle is implied by the INTERVAL= option. For example, INTERVAL=QTR implies a seasonal cycle of length 4. If the ACCUMULATE= option is also specified, the INTERVAL= option determines the time periods for the accumulation of observations.

The basic intervals are YEAR, SEMIYEAR, QTR, MONTH, SEMIMONTH, TENDAY, WEEK, WEEKDAY, DAY, HOUR, MINUTE, SECOND. For information about the intervals that can be specified, see Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*).

You can also specify the following *options*:

ACCUMULATE=*option*

specifies how to accumulate the data set observations within each time period. The frequency (width of each time interval) is specified by the INTERVAL= option. The ID *variable* contains the time ID values, each of which corresponds to a specific time period. The accumulated values form the actual time series, which is used in subsequent model fitting and forecasting.

The ACCUMULATE= option is particularly useful when there are zero or more than one input observations that coincide with a particular time period (for example, transactional data). The EXPAND procedure offers additional frequency conversions and transformations that can also be useful in creating a time series.

The following *options* determine how the observations are to be accumulated within each time period based on the ID *variable* and the frequency specified by the INTERVAL= option. By default, ACCUMULATE=NONE.

NONE	does not accumulate observations; the ID variable values must be equally spaced with respect to the frequency.
TOTAL	accumulates observations based on the total sum of their values.
AVERAGE | AVG	accumulates observations based on the average of their values.
MINIMUM | MIN	accumulates observations based on the minimum of their values.
MEDIAN | MED	accumulates observations based on the median of their values.
MAXIMUM | MAX	accumulates observations based on the maximum of their values.

N	accumulates observations based on the number of nonmissing observations.
NMISS	accumulates observations based on the number of missing observations.
NOBS	accumulates observations based on the number of observations.
FIRST	accumulates observations based on the first of their values.
LAST	accumulates observations based on the last of their values.
STDDEV | STD	accumulates observations based on the standard deviation of their values.
CSS	accumulates observations based on the corrected sum of squares of their values.
USS	accumulates observations based on the uncorrected sum of squares of their values.

If the ACCUMULATE= option is specified, the SETMISSING= option is useful for specifying how accumulated missing values are treated. If missing values should be interpreted as zero, then SETMISSING=0 should be used. For more information about accumulation, see the section "Details: HPF Procedure" on page 43.

ALIGN=*option*

controls the alignment of SAS dates used to identify output observations.

You can specify the following *options*:

BEGINNING | BEG | B	represents each time period by using the beginning SAS date or datetime value of the time period.
ENDING | END | E	represents each time period by using the ending SAS date or datetime value of the time period.
MIDDLE | MID | M	represents each time period by using the middle SAS date or datetime value of the time period. The middle is calculated as the average of the beginning and ending values.

By default, ALIGN=BEGINNING.

END=*value*

specifies a SAS date, datetime, or time value that represents the end of the data. If the last time ID variable's value is less than *value*, the series is extended with missing values. If the last time ID variable's value is greater than *value*, the series is truncated. For example, END="&sysdate"D uses the automatic macro variable SYSDATE to extend or truncate the series to the current date. This option and the START= option can be used to ensure that data that are associated with each BY group contain the same number of observations.

FORMAT=*format*

specifies the SAS format for the time ID values. If this option is not specified, the default format is implied by the INTERVAL= option.

NOTSORTED
requests that the time ID values not be in sorted order. The HPF procedure sorts the data with respect to the time ID prior to analysis.

SETMISSING=*option* | *number*
specifies how to assign missing values (either actual or accumulated) in the accumulated time series. If a *number* is specified, missing values are set to *number*. If a missing value indicates an unknown value, do not specify this option. If a missing value indicates no value, specify SETMISSING=0. You would typically use SETMISSING=0 for transactional data because a lack of recorded data usually implies no activity. You can specify the following *options*.

MISSING	sets missing values to missing. If the MODEL= option specifies a smoothing model, the missing observations are smoothed over. If MODEL=IDM is specified, missing values are assumed to be periods of no demand—that is, SETMISSING=MISSING is equivalent to SETMISSING=0.
AVERAGE | AVG	sets missing values to the accumulated average value.
MINIMUM | MIN	sets missing values to the accumulated minimum value.
MEDIAN | MED	sets missing values to the accumulated median value.
MAXIMUM | MAX	sets missing values to the accumulated maximum value.
FIRST	sets missing values to the accumulated first nonmissing value.
LAST	sets missing values to the accumulated last nonmissing value.
PREVIOUS | PREV	sets missing values to the previous accumulated nonmissing value. Missing values at the beginning of the accumulated series remain missing.
NEXT	sets missing values to the next accumulated nonmissing value. Missing values at the end of the accumulated series remain missing.

By default, SETMISSING=MISSING.

START=*value*
specifies a SAS date, datetime, or time value that represents the beginning of the data. If the first time ID variable value is greater than *value*, missing values are added at the beginning of the series. If the first time ID variable value is less than *value*, the series is truncated. This option and the END= option can be used to ensure that data that are associated with each BY group contain the same number of observations.

ZEROMISS=*option*
specifies how to interpret beginning and ending zero values (either actual or accumulated) in the accumulated time series. The following *options* can also be used to determine how beginning and/or ending zero values are assigned:

NONE	does not change beginning and ending zeros.
LEFT	sets beginning zeros to missing.
RIGHT	sets ending zeros to missing.
BOTH	sets both beginning and ending zeros to missing.

If the only values in the accumulated series are missing or zero, the series is not changed. By default, ZEROMISS=NONE

IDM Statement

IDM *options* **;**

The IDM statement specifies an intermittent demand model. An intermittent demand series can be analyzed in two ways: individually modeling both demand interval and size component or jointly modeling these components by using the average demand component (demand size divided by demand interval). The IDM statement specifies the two smoothing models to be used to forecast the demand interval component (INTERVAL= option) and the demand size component (SIZE= option) or specifies the single smoothing model to be used to forecast the average demand component (AVERAGE= option). Therefore, two smoothing models (INTERVAL= and SIZE= options) must be specified or one smoothing model (AVERAGE= option) must be specified. Only one statement can be specified.

The following examples illustrate typical uses of the IDM statement:

```
/* default specification */
idm;

/* demand interval model only specification */
idm interval=(transform=log);

/* demand size model only specification */
idm size=(method=linear);

/* Croston's Method */
idm interval=(method=simple)
    size    =(method=simple);

/* Log Croston's Method */
idm interval=(method=simple transform=log)
    size    =(method=simple transform=log);

/* average demand model specification */
idm average=(method=bestn);
```

The default specification uses both the INTERVAL= option and SIZE= option defaults for the decomposed (Croston's) demand model and the AVERAGE= option defaults for the average demand model.

The following example illustrates how to automatically choose the decomposed demand model by using MAPE as the model selection criterion:

```
idm interval=( method=simple transform=auto criterion=mape )
    size    =( method=simple transform=auto criterion=mape );
forecast sales / model=idm criterion=mape;
```

The preceding statements fit two forecast models (simple and log simple exponential smoothing) to both the demand interval and size components. The forecast model that results in the lowest in-sample MAPE for each component is used to forecast the component.

The following example illustrates how to automatically choose the average demand model by using MAPE as the model selection criterion:

```
idm average=(method=simple transform=auto criterion=mape);
forecast sales / model=idm;
```

The preceding statements fit two forecast models (simple and log simple exponential smoothing) to the average demand component. The forecast model that results in the lowest in-sample MAPE is used to forecast the component.

Combining the two preceding examples, the following example illustrates how to automatically choose between the decomposed demand model and the average demand model by using MAPE as the model selection criterion:

```
idm interval=(method=simple transform=auto criterion=mape)
    size    =(method=simple transform=auto criterion=mape)
    average =(method=simple transform=auto criterion=mape);
forecast sales / model=idm criterion=mape;
```

The preceding statements automatically select between the decomposed demand model and the average demand model as described previously. The forecast model that results in the lowest in-sample MAPE is used to forecast the series.

The following options can be specified in the IDM statement:

AVERAGE=(*smoothing-model-options***)**
specifies the smoothing model used to forecast the demand average component. See the section "Smoothing Model Specification Options for IDM Statement" on page 41.

BASE=AUTO | *number*
specifies the base value of the time series used to determine the demand series components. The demand series components are determined based on the departures from this base value. If a base value is specified, this value is used to determine the demand series components. If BASE=AUTO is specified, the time series properties are used to automatically adjust the time series. For the common definition of Croston's method use BASE=0 which defines departures based on zero. The default is BASE=0.

Given a time series y_t and base value b, the time series is adjusted by the base value to create the base adjusted time series, $x_t = y_t - b$. Demands are assumed to occur when the base adjusted series is nonzero (or when the time series y_t departs from the base value b).

When BASE=AUTO, the base value is automatically determined by the time series median, minimum and maximum values, and the INTERMITTENT= option value of the FORECAST statement.

INTERVAL=(*smoothing-model-options***)**
specifies the smoothing model used to forecast the demand interval component. See the section "Smoothing Model Specification Options for IDM Statement" on page 41.

SIZE=(*smoothing-model-options***)**
specifies the smoothing model used to forecast the demand size component. See the section "Smoothing Model Specification Options for IDM Statement" on page 41.

Smoothing Model Specification Options for IDM Statement

The smoothing model options describe how to forecast the demand interval, size, and average demand components (INTERVAL= option, SIZE= option, and AVERAGE= option).

If the smoothing model options are not specified, the following are the defaults for the demand interval, size, and average components:

```
interval=(transform=auto method=bestn
          levelrest=(0.0001 0.9999)
          trendrest=(0.0001 0.9999)
          damprest =(0.0001 0.9999) criterion=rmse bounds=(1,.));

size    =(transform=auto method=bestn
          levelrest=(0.0001 0.9999)
          trendrest=(0.0001 0.9999)
          damprest =(0.0001 0.9999) criterion=rmse);

average  =(transform=auto method=bestn
          levelrest=(0.0001 0.9999)
          trendrest=(0.0001 0.9999)
          damprest =(0.0001 0.9999) criterion=rmse);
```

The preceding smoothing model options provide the typical automation in intermittent demand model selection.

The following smoothing model options can be specified:

BOUNDS=(*number***, *number*)**
specifies the component forecast bound. See the section "IDM Smoothing Model Forecast Bounds Options" on page 47.

CRITERION=*option*

SELECT=*option*
specifies the model selection criterion (statistic of fit) to be used to select from several candidate models. This option is often used in conjunction with the HOLDOUT= option specified in the FORECAST statement. The CRITERION= option can also be specified as SELECT=. The default is CRITERION=RMSE. The statistics of fit provided are the same as those provided in the FORECAST statement.

DAMPPARM=*number*
specifies the damping weight parameter initial value. See the section "IDM Smoothing Model Forecast Bounds Options" on page 47.

DAMPREST=(*number***, *number*)**
specifies the damping weight parameter restrictions. See the section "IDM Smoothing Model Forecast Bounds Options" on page 47.

LEVELPARM=*number*
specifies the level weight parameter initial value. See the section "IDM Smoothing Model Forecast Bounds Options" on page 47.

LEVELREST=(*number***,** *number***)**
specifies the level weight parameter restrictions. See the section "IDM Smoothing Model Forecast Bounds Options" on page 47.

MEDIAN
specifies that the median forecast values are to be estimated. Forecasts can be based on the mean or median. By default the mean value is provided. If no transformation is applied to the actual series by using the TRANSFORM= option, the mean and median component forecast values are identical.

METHOD=*method-name*
specifies the forecasting model to be used to forecast the demand component. A single model can be specified, or a group of candidate models can be specified. If a group of models is specified, the model used to forecast the accumulated time series is selected based on the CRITERION= option of the IDM statement and the HOLDOUT= option of the FORECAST statement. The default is METHOD=BESTN. The following forecasting models are provided:

SIMPLE	simple (single) exponential smoothing
DOUBLE	double (Brown) exponential smoothing
LINEAR	linear (Holt) exponential smoothing
DAMPTREND	damped trend exponential smoothing
BESTN	best candidate nonseasonal smoothing model (SIMPLE, DOUBLE, LINEAR, DAMPTREND)

NOEST
specifies that the smoothing model parameters are fixed values. To use this option, all of the smoothing model parameters must be explicitly specified. By default, the smoothing model parameters are optimized.

NOSTABLE
specifies that the smoothing model parameters are not restricted to the additive invertible region of the parameter space. By default, the smoothing model parameters are restricted to be inside the additive invertible region of the parameter space.

TRANSFORM=*option*
specifies the time series transformation to be applied to the demand component. The following transformations are provided:

NONE	no transformation
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n***)**	Box-Cox transformation with parameter number *n*, where *n* is between –5 and 5

AUTO automatically choose between NONE and LOG based on model selection criteria. This option is the default.

When the TRANSFORM= option is specified, the demand component must be strictly positive. After the demand component is transformed, the model parameters are estimated by using the transformed component. The forecasts of the transformed component are then computed, and finally the transformed component forecasts are inverse transformed. The inverse transform produces either mean or median forecasts depending on whether the MEDIAN option is specified.

TRENDPARM=*number*
specifies the trend weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 46.

TRENDREST=(*number***,** *number***)**
specifies the trend weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 46.

Details: HPF Procedure

The HPF procedure can be used to perform trend and seasonal analysis on transactional data. For trend analysis, various sample statistics are computed for each time period defined by the time ID variable and INTERVAL= option. For seasonal analysis, various sample statistics are computed for each season defined by the INTERVAL= or the SEASONALITY= option. For example, suppose the transactional data ranges from June 1990 to January 2000, then the trend statistics are computed for every month: June 1990, July 1990, . . . , January 2000. The seasonal statistics are computed for each season: January, February, . . . , December.

The HPF procedure can be used to forecast time series data as well as transactional data. If the data are transactional, then the procedure must first accumulate the data into a time series before the data can be forecast. The procedure uses the sequential steps in Table 2.2 to produce forecasts, with the options that control the step listed to the right.

Table 2.2 PROC HPF Processing Steps and Control Options

Step	Operation	Options	Statements
1	Accumulation	ACCUMULATE=	ID, FORECAST
2	Missing Value Interpretation	SETMISSING=	ID, FORECAST
3	Diagnostic Tests	INTERMITTENT=,	FORECAST
		SEASONTEST=	FORECAST
4	Model Selection	MODEL=,	FORECAST
		HOLDOUT=,	FORECAST
		HOLDOUTPCT=,	FORECAST
		CRITERION=	FORECAST
5	Transformations	TRANSFORM=	FORECAST
6	Parameter Estimation	MODEL=	FORECAST
7	Forecasting	MODEL=,	FORECAST
		LEAD=	PROC HPF

Table 2.2 *continued*

Step	Operation	Options	Statements
8	Inverse Transformation	TRANSFORM=,	FORECAST
		MEDIAN	FORECAST
9	Statistics of Fit	OUTSTAT=	PROC HPF
10	Summation of Forecasts	LEAD=,	PROC HPF
		STARTSUM=	PROC HPF

Each of the steps shown in Table 2.2 is described in the following sections.

Accumulation

If the ACCUMULATE= option is specified, data set observations are accumulated within each time period. The frequency (width of each time interval) is specified by the INTERVAL= option. The ID variable contains the time ID values. Each time ID value corresponds to a specific time period. Accumulation is particularly useful when the input data set contains transactional data, whose observations are not spaced with respect to any particular time interval. The accumulated values form the actual time series, which is used in subsequent analyses.

For example, suppose a data set contains the following observations:

```
19MAR1999    10
19MAR1999    30
11MAY1999    50
12MAY1999    20
23MAY1999    20
```

If the INTERVAL=MONTH is specified, all of the preceding observations fall within three time periods of March 1999, April 1999, and May 1999. The observations are to be accumulated within each time period as follows.

If the ACCUMULATE=NONE option is specified, an error is generated because the ID variable values are not equally spaced with respect to the specified frequency (MONTH).

If the ACCUMULATE=TOTAL option is specified:

```
01MAR1999    40
01APR1999    .
01MAY1999    90
```

If the ACCUMULATE=AVERAGE option is specified:

```
01MAR1999    20
01APR1999    .
01MAY1999    30
```

If the ACCUMULATE=MINIMUM option is specified:

```
O1MAR1999    10
O1APR1999    .
O1MAY1999    20
```

If the ACCUMULATE=MEDIAN option is specified:

```
O1MAR1999    20
01APR1999    .
O1MAY1999    20
```

If the ACCUMULATE=MAXIMUM option is specified:

```
O1MAR1999    30
O1APR1999    .
O1MAY1999    50
```

If the ACCUMULATE=FIRST option is specified:

```
O1MAR1999    10
O1APR1999    .
O1MAY1999    50
```

If the ACCUMULATE=LAST option is specified:

```
O1MAR1999    30
O1APR1999    .
O1MAY1999    20
```

If the ACCUMULATE=STDDEV option is specified:

```
O1MAR1999    14.14
O1APR1999    .
O1MAY1999    17.32
```

As can be seen from the preceding examples, even though the data set observations contained no missing values, the accumulated time series might have missing values.

Missing Value Interpretation

Sometimes missing values should be interpreted as unknown values. The forecasting models used by the HPF procedure can effectively handle missing values (see the section "Missing Value Modeling Issues" on page 47). But sometimes missing values are known (such as when missing values are created from accumulation), and no observations should be interpreted as no (zero) value. In the former case, the SETMISSING= option can be used to interpret how missing values are treated. The SETMISSING=0 option should be used when missing observations are to be treated as no (zero) values. In other cases, missing values should be interpreted as global values, such as minimum or maximum values of the accumulated series. The accumulated and interpreted time series is used in subsequent analyses.

Diagnostic Tests

The INTERMITTENT= option set the thresholds for categorizing a series as intermittent or non-intermittent. The SEASONTEST= option set the thresholds for categorizing a series as seasonal or nonseasonal.

Model Selection

When more than one candidate model is specified, forecasts for each candidate model are compared by using the model selection criterion specified by the CRITERION= option. The selection criterion is computed by using the multistep forecasts in the holdout sample range if the HOLDOUT= or HOLDOUTPCT= options are specified, or by the one-step-ahead forecasts for the full range of the time series if the HOLDOUT= and HOLDOUTPCT= options are not specified. The candidate model with the best selection criterion is selected to forecast the time series.

Transformations

If the TRANSFORM= option is specified, the time series is transformed prior to model parameter estimation and forecasting. Only strictly positive series can be transformed. An error is generated when the TRANSFORM= option is used with a nonpositive series.

Parameter Estimation

All parameters associated with the model are optimized based on the data with the default parameter restrictions imposed. If the TRANSFORM= option is specified, the transformed time series data are used to estimate the model parameters.

Smoothing Model Parameter Specification Options

The parameter options are used to specify smoothing model parameters. If the parameter restrictions are not specified, the default is (0.0001 0.9999), which implies that the parameters are restricted between 0.0001 and 0.9999. Parameters and their restrictions are required to be greater than or equal to –1 and less than or equal to 2. Missing values indicate no lower and/or upper restriction. If the parameter initial values are not specified, the optimizer uses a grid search to find an appropriate initial value.

Missing Value Modeling Issues

The treatment of missing values varies with the forecasting model. For the smoothing models, missing values after the start of the series are replaced with one-step-ahead predicted values, and the predicted values are applied to the smoothing equations. See Chapter 15, "Forecasting Process Details," for greater detail about how missing values are treated in the smoothing models. For MODEL=IDM, specified missing values are assumed to be periods of no demand.

The treatment of missing values can also be specified by the user with the SETMISSING= option, which changes the missing values prior to modeling.

Even though all of the observed data are nonmissing, using the ACCUMULATE= option can create missing values in the accumulated series.

Forecasting

After the model parameters are estimated, one-step-ahead forecasts are generated for the full range of the actual (optionally transformed) time series data, and multistep forecasts are generated from the end of the observed time series to the future time period after the last observation specified by the LEAD= option. If there are missing values at the end of the time series, the forecast horizon will be greater than that specified by the LEAD= option.

IDM Smoothing Model Forecast Bounds Options

These options specify the demand component forecast bounds. The forecast bounds restrict the component forecasts. The default for demand interval forecasts is BOUNDS=1. The lower bound for the demand interval forecast must be greater than one. The default for demand size forecasts is BOUNDS=(.,.), which is equivalent to no bounds. The demand size forecasts bounds are applied after the forecast is adjusted by the base value.

Inverse Transformations

If the TRANSFORM= option is specified, the forecasts of the transformed time series are inverse transformed. By default, the mean (expected) forecasts are generated. If the MEDIAN option is specified, the median forecasts are generated.

Statistics of Fit

The statistics of fit (or goodness-of-fit statistics) are computed by comparing the actual time series data and the generated forecasts. If the TRANSFORM= option is specified, the statistics of fit are based on the inverse transformed forecasts.

Forecast Summation

The multistep forecasts generated by the preceding steps are summed from the STARTSUM= number to the LEAD= number. For example, if STARTSUM=4 and LEAD=6, the 4-step-ahead through 6-step-ahead forecasts are summed. The predictions are simply summed. However, the prediction error variance of this sum is computed by taking into account the correlation between the individual predictions. The upper and lower confidence limits for the sum of the predictions is then computed based on the prediction error variance of the sum.

The forecast summation is particularly useful when it is desirable to model in one frequency yet the forecast of interest is another frequency. For example, if a time series has a monthly frequency (INTERVAL=MONTH) and you want a forecast for the third and fourth future months, a forecast summation for the third and fourth month can be obtained by specifying STARTSUM=3 and LEAD=4.

Variance-related computations are computed only when no transformation is specified (TRANSFORM=NONE).

Comparison to the Time Series Forecasting System

With the exception of model selection, the techniques used in the HPF procedure are identical to the Time Series Forecasting System of SAS/ETS software. For model parameter estimation, the default parameter restrictions are imposed.

Data Set Output

The HPF procedure can create the OUT=, OUTEST=, OUTFOR=, OUTSTAT=, OUTSUM=, OUTSEASON=, and OUTTREND= data sets. In general, these data sets contain the variables listed in the BY statement. In general, if a forecasting step related to an output data step fails, the values of this step are not recorded or are set to missing in the related output data set, and appropriate error and/or warning messages are recorded in the log.

OUT= Data Set

The OUT= data set contains the variables specified in the BY, ID, and FORECAST statements. If the ID statement is specified, the ID variable values are aligned and extended based on the ALIGN= and INTERVAL= options. The values of the variables specified in the FORECAST statements are accumulated based on the ACCUMULATE= option, and missing values are interpreted based on the SETMISSING= option. If the REPLACEMISSING option is specified, embedded missing values are replaced by the one-step-ahead forecasts.

These variable values are then extrapolated based on their forecasts, or they are extended with missing values when the MODEL=NONE option is specified. If USE=LOWER is specified, the variable is extrapolated with the lower confidence limits; if USE=UPPER is specified, the variable is extrapolated using the upper confidence limits; otherwise, the variable values are extrapolated with the predicted values. If the TRANSFORM= option is specified, the predicted values contain either mean or median forecasts depending on whether or not the MEDIAN option is specified.

If any of the forecasting steps fail for particular variable, the variable values are extended by missing values.

OUTEST= Data Set

The OUTEST= data set contains the variables specified in the BY statement as well as the variables listed in this section. For variables listed in FORECAST statements where the option MODEL=NONE is specified, no observations are recorded for these variables. For variables listed in FORECAST statements where the option MODEL=NONE is not specified, the following variables contain observations related to the parameter estimation step:

NAME	variable name
MODEL	forecasting model
TRANSFORM	transformation
PARM	parameter name
EST	parameter estimate
STDERR	standard errors
TVALUE	*t* values
PVALUE	probability values

If the parameter estimation step fails for a particular variable, no observations are recorded.

OUTFOR= Data Set

The OUTFOR= data set contains the variables specified in the BY statement as well as the variables listed in this section. For variables listed in FORECAST statements where the option MODEL=NONE is specified, no observations are recorded for these variables. For variables listed in FORECAST statements where the option MODEL=NONE is not specified, the following variables contain observations related to the forecasting step:

NAME	variable name
TIMEID	time ID values
ACTUAL	actual values
PREDICT	predicted values
STD	prediction standard errors
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors

If the forecasting step fails for a particular variable, no observations are recorded. If the TRANSFORM= option is specified, the values that are listed in this section are the inverse transform forecasts. If the MEDIAN option is specified, the median forecasts are stored; otherwise, the mean forecasts are stored.

OUTPROCINFO= Data Set

The OUTPROCINFO= data set contains information about the run of the HPF procedure. The following variables are present:

SOURCE	name of the procedure, in this case HPF
NAME	name of an item being reported. The item can be the number of errors, notes, or warnings, number of forecasts requested, and so on.
LABEL	descriptive label for the item in _NAME_
STAGE	current stage of the procedure. For HPFENGINE this is set to ALL.
VALUE	value of the item specified in _NAME_

OUTSTAT= Data Set

The OUTSTAT= data set contains the variables specified in the BY statement as well as the variables listed in this section. For variables listed in FORECAST statements where the option MODEL=NONE is specified, no observations are recorded for these variables. For variables listed in FORECAST statements where the option MODEL=NONE is not specified, the following variables contain observations related to the statistics of fit step:

NAME	variable name
REGION	the region in which the statistics are calculated. Statistics calculated in the fit region are indicated by FIT. Statistics calculated in the forecast region, which happens only if the BACK= option is greater than zero, are indicated by FORECAST.
DFE	degrees of freedom error
N	number of observations that were used. This is the number of observations in the block of observations from the first to the last nonmissing error, which includes any embedded missing errors.
NOBS	number of observations
NMISSA	number of missing actuals
NMISSP	number of missing predicted values
NPARMS	number of parameters
TSS	total sum of squares
SST	corrected total sum of squares
SSE	sum of square error
MSE	mean square error
UMSE	unbiased mean square error
RMSE	root mean square error
URMSE	unbiased root mean square error
MAPE	mean absolute percent error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R-square
ADJRSQ	adjusted R-square
AADJRSQ	Amemiya's adjusted R-square
RWRSQ	random walk R-square
AIC	Akaike information criterion
AICC	finite sample corrected AIC
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion

MAXERR	maximum error
MINERR	minimum error
MINPE	minimum percent error
MAXPE	maximum percent error
ME	mean error
MPE	mean percent error
MDAPE	median absolute percent error
GMAPE	geometric mean absolute percent error
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MSPPE	mean predictive percent error
MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median absolute predictive percent error
GMAPPE	geometric mean absolute predictive percent error
MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error
MSPE	mean symmetric percent error
SMAPE	symmetric mean absolute percent error
MDASPE	median absolute symmetric percent error
GMASPE	geometric mean absolute symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error
MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MINAPES	minimum absolute error percent of standard deviation
MAXAPES	maximum absolute error percent of standard deviation
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation

If the statistics-of-fit step fails for particular variable, no observations are recorded. If the TRANSFORM= option is specified, the values that are listed in this section are computed based on the inverse transform forecasts. If the MEDIAN option is specified, the median forecasts are the basis; otherwise, the mean forecasts are the basis.

OUTSUM= Data Set

The OUTSUM= data set contains the variables specified in the BY statement as well as the variables listed in this section. The OUTSUM= data set records the summary statistics for each variable specified in a FORECAST statement. For variables listed in FORECAST statements where the option MODEL=NONE is specified, the values related to forecasts are set to missing. For variables listed in FORECAST statements where the option MODEL=NONE is not specified, the forecast values are set based on the USE= option.

Variables related to summary statistics are based on the ACCUMULATE= and SETMISSING= options:

NAME	variable name
STATUS	forecasting status. Nonzero values imply that no forecast was generated for the series.
NOBS	number of observations
N	number of nonmissing observations
NMISS	number of missing observations
MIN	minimum value
MAX	maximum value
MEAN	mean value
STDDEV	standard deviation

Variables related to forecast summation are based on the LEAD= and STARTSUM= options:

PREDICT	forecast summation predicted values
STD	forecast summation prediction standard errors
LOWER	forecast summation lower confidence limits
UPPER	forecast summation upper confidence limits

Variance-related computations are computed only when no transformation is specified (TRANSFORM=NONE).

Variables related to multistep forecast are based on the LEAD= and USE= options:

LEAD*n* multistep forecast (*n* ranges from one to the value of the LEAD= option). If USE=LOWER, this variable contains the lower confidence limits; if USE=UPPER, this variable contains the upper confidence limits; otherwise, this variable contains the predicted values.

If the forecast step fails for a particular variable, the variables related to forecasting are set to missing. The OUTSUM= data set contains a summary of the (accumulated) time series and optionally its forecasts for all series.

OUTSEASON= Data Set

The OUTSEASON= data set contains the variables specified in the BY statement as well as the variables listed in this section. The OUTSEASON= data set records the seasonal statistics for each variable specified in a FORECAST statement.

Variables related to seasonal statistics are based on the INTERVAL= or SEASONALITY= options:

NAME	variable name
TIMEID	time ID values
SEASON	seasonal index
NOBS	number of observations
N	number of nonmissing observations
NMISS	number of missing observations
MIN	minimum value
MAX	maximum value
RANGE	range value
SUM	summation value
MEAN	mean value
STDDEV	standard deviation
CSS	corrected sum of squares
USS	uncorrected sum of squares
MEDIAN	median value

The preceding statistics are computed for each season.

OUTTREND= Data Set

The OUTTREND= data set contains the variables specified in the BY statement as well as the variables listed in this section. The OUTTREND= data set records the trend statistics for each variable specified in a FORECAST statement.

Variables related to trend statistics are based on the INTERVAL= and SEASONALITY= options:

NAME	variable name
TIMEID	time ID values
SEASON	seasonal index
NOBS	number of observations
N	number of nonmissing observations
NMISS	number of missing observations

MIN	minimum value
MAX	maximum value
RANGE	range value
SUM	summation value
MEAN	mean value
STDDEV	standard deviation
CSS	corrected sum of squares
USS	uncorrected sum of squares
MEDIAN	median value

The preceding statistics are computed for each time period.

Printed Output

The HPF procedure optionally produces printed output for these results by using utilizing the Output Delivery System (ODS). By default, the procedure produces no printed output. All output is controlled by the PRINT= and PRINTDETAILS options associated with the PROC HPF statement. In general, if a forecasting step related to printed output fails, the values of this step are not printed and appropriate error and/or warning messages are recorded in the log. The printed output is similar to the output data set; these similarities are described as follows.

PRINT=SUMMARY

prints the summary statistics and forecast summaries similar to the OUTSUM= data set.

PRINT=ESTIMATES

prints the parameter estimates similar to the OUTEST= data set.

PRINT=FORECASTS

prints the forecasts similar to the OUTFOR= data set. If the MODEL=IDM option is specified, the demand series predictions table is also printed. This table is based on the demand index (when demands occurred).

PRINT=PERFORMANCE

prints the performance statistics.

PRINT=PERFORMANCESUMMARY

prints the performance summary for each BY group.

PRINT=PERFORMANCEOVERALL

prints the performance summary for all BY groups.

PRINT=STATES

prints the backcast, initial, and final smoothed states.

PRINT=SEASONS

prints the seasonal statistics similar to the OUTSEASON= data set.

PRINT=STATISTICS

prints the statistics of fit similar to the OUTSTAT= data set.

PRINT=TRENDS

prints the trend statistics similar to the OUTTREND= data set.

PRINTDETAILS

is the opposite of the NOOUTALL option. Specifically, if PRINT=FORECASTS and the PRINTDETAILS options are specified, the one-step-ahead forecasts throughout the range of the data are printed as well as the information related to a specific forecasting model such as the smoothing states. If the PRINTDETAILS option is not specified, only the multistep forecasts are printed.

ODS Table Names

Table 2.3 relates the PRINT= options to ODS tables.

Table 2.3 ODS Tables Produced in PROC HPF

ODS Table Name	Description	Printing Option
DescStats	Descriptive statistics	PRINT=SUMMARY
DemandSummary	Demand summary	PRINT=SUMMARY (MODEL=IDM option only)
ForecastSummary	Forecast summary	PRINT=SUMMARY
ForecastSummation	Forecast summation	PRINT=SUMMARY
ModelSelection	Model selection	PRINT=ESTIMATES
ParameterEstimates	Parameter estimates	PRINT=ESTIMATES
Forecasts	Forecast	PRINT=FORECASTS
Demands	Demands	PRINT=FORECASTS (MODEL=IDM option only)
Performance	Performance statistics	PRINT=PERFORMANCE
PerformanceSummary	Performance summary	PRINT=PERFORMANCESUMMARY
PerformanceSummary	Performance overall	PRINT=PERFORMANCEOVERALL
SeasonStatistics	Seasonal statistics	PRINT=SEASONS

Table 2.3 (continued)

ODS Table Name	Description	PRINT= Option
SmoothedStates	Smoothed states	PRINT=STATES
DemandStates	Demand states	PRINT=STATES (MODEL=IDM option only)
FitStatistics	Evaluation (in-sample) statistics of fit	PRINT=STATISTICS
PerformanceStatistics	Performance (out-of-sample) statistics of fit	PRINT=STATISTICS
TrendStatistics	Trend statistics	PRINT=TRENDS

The ODS table ForecastSummary is related to all time series within a BY group. The other tables are related to a single series within a BY group.

ODS Graphics

Statistical procedures use ODS Graphics to create graphs as part of their output. ODS Graphics is described in detail in Chapter 24, "Statistical Graphics Using ODS" (*SAS/STAT User's Guide*).

Before you create graphs, ODS Graphics must be enabled (for example, with the ODS GRAPHICS ON statement). For more information about enabling and disabling ODS Graphics, see the section "Enabling and Disabling ODS Graphics" in that chapter.

The overall appearance of graphs is controlled by ODS styles. Styles and other aspects of using ODS Graphics are discussed in the section "A Primer on ODS Statistical Graphics" in that chapter.

This section describes the use of ODS Graphics for creating graphics with the HPF procedure.

ODS Graph Names

PROC HPF assigns a name to each graph it creates by using ODS. You can use these names to refer to the graphs when you use ODS. The names are listed in Table 2.4.

You select the desired plots via the PLOT= option in the HPF statement.

Table 2.4 ODS Graphics Produced by PROC HPF

ODS Graph Name	Plot Description	Statement	PLOT= Option
DemandErrorsPlot	Average demand errors	PROC HPF	PLOT=ERRORS
DemandForecastsPlot	Average demand forecasts	PROC HPF	PLOT=FORECASTS
DemandIntervalHistogram	Demand interval histogram	PROC HPF	PLOT=MODELS
DemandIntervalPlot	Demand interval forecast plot	PROC HPF	PLOT=MODELS
DemandSizeHistogram	Demand size histogram	PROC HPF	PLOT=MODELS
DemandSizePlot	Demand size forecast plot	PROC HPF	PLOT=MODELS

Table 2.4 *continued*

ODS Graph Name	Plot Description	Statement	Option
ErrorACFNORMPlot	Standardized autocorrelation of prediction errors	PROC HPF	PLOT=ACF
ErrorACFPlot	Autocorrelation of prediction errors	PROC HPF	PLOT=ACF
ErrorCorrelationPlots	Prediction error plot panel	PROC HPF	PLOT=CORR
ErrorHistogram	Prediction error histogram	PROC HPF	PLOT=ERRORS
ErrorIACFNORMPlot	Standardized inverse autocorrelation of prediction errors	PROC HPF	PLOT=IACF
ErrorIACFPlot	Inverse autocorrelation of prediction errors	PROC HPF	PLOT=IACF
ErrorPACFNORMPlot	Standardized partial autocorrelation of prediction errors	PROC HPF	PLOT=PACF
ErrorPACFPlot	Partial autocorrelation of prediction errors	PROC HPF	PLOT=PACF
ErrorPeriodogramPlot	Periodogram of prediction errors	PROC HPF	PLOT=PERIODOGRAM
ErrorPlot	Prediction errors	PROC HPF	PLOT=ERRORS
ErrorSpectralDensityPlot	Combined periodogram and spectral density estimate plot	PROC HPF	PLOT=SPECTRUM
ErrorWhiteNoiseLogProbPlot	White noise log probability plot of prediction errors	PROC HPF	PLOT=WN
ErrorWhiteNoiseProbPlot	White noise probability plot of prediction errors	PROC HPF	PLOT=WN
ForecastsOnlyPlot	Forecasts only plot	PROC HPF	PLOT=FORECASTSONLY
ForecastsPlot	Forecasts plot	PROC HPF	PLOT=FORECAST
LevelStatePlot	Smoothed level state plot	PROC HPF	PLOT=LEVELS
ModelForecastsPlot	Model and forecasts plot	PROC HPF	PLOT=MODELFORECAST
ModelPlot	Model plot	PROC HPF	PLOT=MODELS
SeasonStatePlot	Smoothed season state plot	PROC HPF	PLOT=SEASONS
StockingAveragePlot	Stocking average plot	PROC HPF	PLOT=FORECASTS
StockingLevelPlot	Stocking level plot	PROC HPF	PLOT=FORECASTS
TrendStatePlot	Smoothed trend state plot	PROC HPF	PLOT=TRENDS

Examples: HPF Procedure

Example 2.1: Automatic Forecasting of Time Series Data

This example illustrates how the HPF procedure can be used for the automatic forecasting of time series data. Retail sales data is used for this illustration.

The following DATA step creates a data set from data recorded monthly at numerous points of sales. The data set, SALES, contains a variable DATE that represents time and a variable for each sales item. Each value of the DATE variable is recorded in ascending order, and the values of each of the other variables represent a single time series:

```
data sales;
   format date date9.;
   input date : date9. shoes socks laces dresses
                       coats shirts ties belts hats blouses;
   datalines;
01JAN1994 3557 3718 6368.80 575  987 10.8200 15.0000 102.600 12410 15013

   ... more lines ...
```

The following HPF procedure statements automatically forecast each of the monthly time series:

```
proc hpf data=sales out=nextyear;
   id date interval=month;
   forecast _ALL_;
run;
```

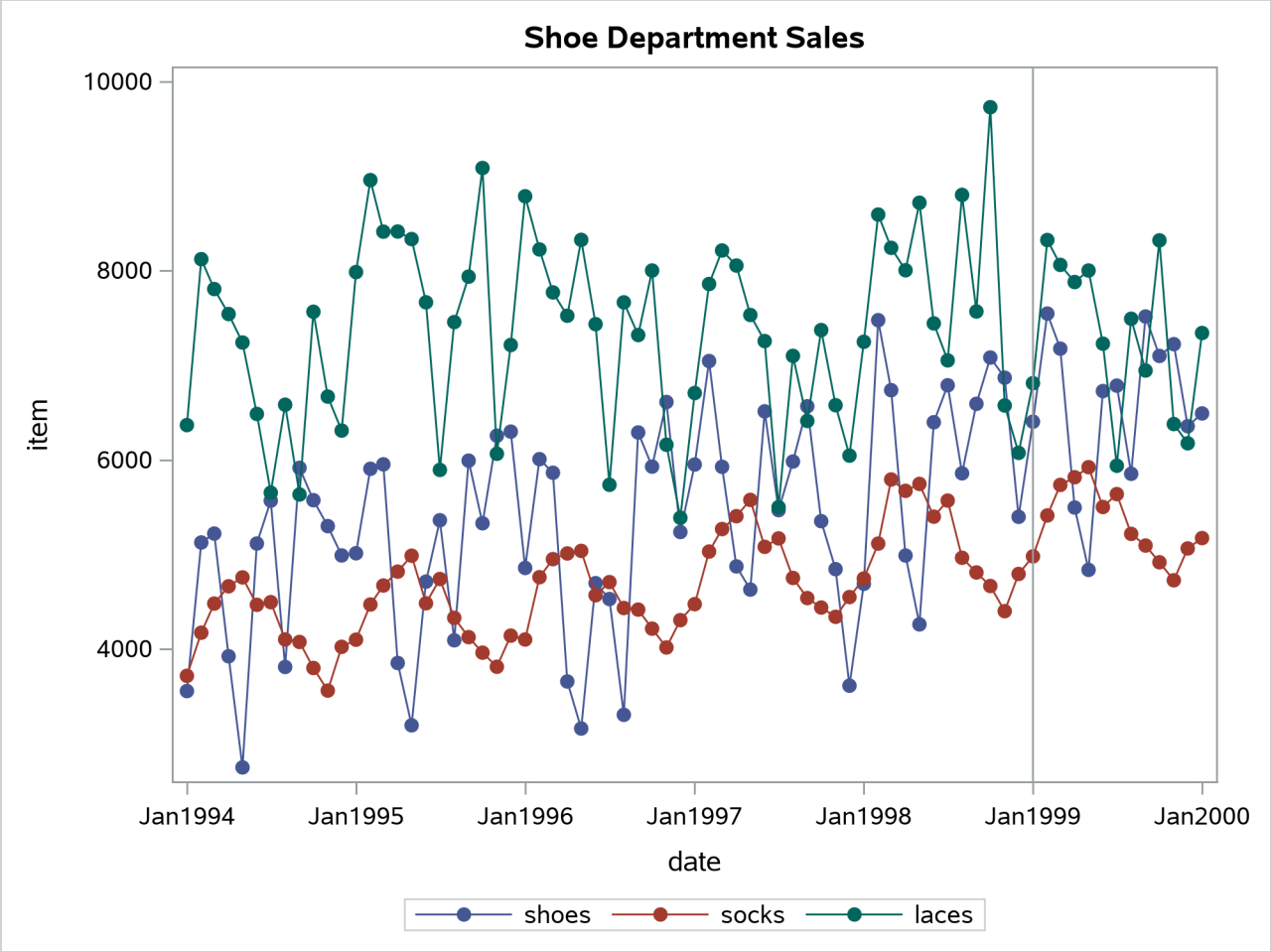
The preceding statements automatically select the best fitting model, generate forecasts for every numeric variable in the input data set (SALES) for the next twelve months, and store these forecasts in the output data set (NEXTYEAR).

The following SGPLOT procedure statements plot the forecasts related to shoe sales:

```
title1 "Shoe Department Sales";
proc sgplot data=nextyear;
   series x=date y=shoes / markers
      markerattrs=(symbol=circlefilled) lineattrs=(pattern=1);
   series x=date y=socks / markers
      markerattrs=(symbol=circlefilled) lineattrs=(pattern=1);
   series x=date y=laces / markers
      markerattrs=(symbol=circlefilled) lineattrs=(pattern=1);
   xaxis values=('01JAN1994'd to '01DEC2000'd by year);
   yaxis label='item';
   refline '01JAN1999'd / axis=x;
run;
```

The SGPLOT procedure results are shown in Output 2.1.1. The historical data is shown to the left of the vertical reference line, and the forecasts for the next twelve monthly periods is shown to the right.

Output 2.1.1 Retail Sales Forecast Plots



The following HPF procedure statements are identical to the preceding statements except that the PRINT=FORECASTS option is specified:

```
proc hpf data=sales out=nextyear print=forecasts;
   id date interval=month;
   forecast _ALL_;
run;
```

In addition to automatically forecasting each of the monthly time series, the preceding statements print the forecasts by using the Output Delivery System (ODS), which is partially shown in Output 2.1.2. This output shows the predictions, prediction standard errors, and the upper and lower confidence limits for the next twelve monthly periods.

Output 2.1.2 Forecast Tables

Shoe Department Sales

The HPF Procedure

Forecasts for Variable shoes

Obs	Time	Forecasts	Standard Error	95% Confidence Limits	
62	FEB1999	7548.0041	607.5238	6357.2792	8738.7289
63	MAR1999	7177.1472	699.4400	5806.2701	8548.0244
64	APR1999	5497.5595	780.7609	3967.2964	7027.8227
65	MAY1999	4838.2001	854.5169	3163.3778	6513.0224
66	JUN1999	6728.4521	922.5244	4920.3375	8536.5668
67	JUL1999	6786.1094	985.9738	4853.6362	8718.5826
68	AUG1999	5853.9650	1045.6953	3804.4399	7903.4900
69	SEP1999	7517.0144	1102.2949	5356.5561	9677.4728
70	OCT1999	7100.2489	1156.2315	4834.0769	9366.4210
71	NOV1999	7224.6449	1207.8618	4857.2793	9592.0106
72	DEC1999	6357.1556	1257.4701	3892.5594	8821.7518
73	JAN2000	6492.2657	1305.2871	3933.9500	9050.5815

Example 2.2: Automatic Forecasting of Transactional Data

This example illustrates how the HPF procedure can be used to automatically forecast transactional data. Internet data is used for this illustration.

The data set WEBSITES contains data recorded at several Internet Web sites. WEBSITES contains a variable TIME and the variables BOATS, CARS, and PLANES that represent Internet Web site data. Each value of the TIME variable is recorded in ascending order, and the values of each of the other variables represent a transactional data series.

The following HPF procedure statements automatically forecast each of the transactional data series:

```
proc hpf data=websites out=nextweek lead=7;
   id time interval=dtday accumulate=total;
   forecast boats cars planes;
run;
```

The preceding statements accumulate the data into a daily time series, automatically generate forecasts for the BOATS, CARS, and PLANES variables in the input data set (WEBSITES) for the next week, and store the forecasts in the output data set (NEXTWEEK).

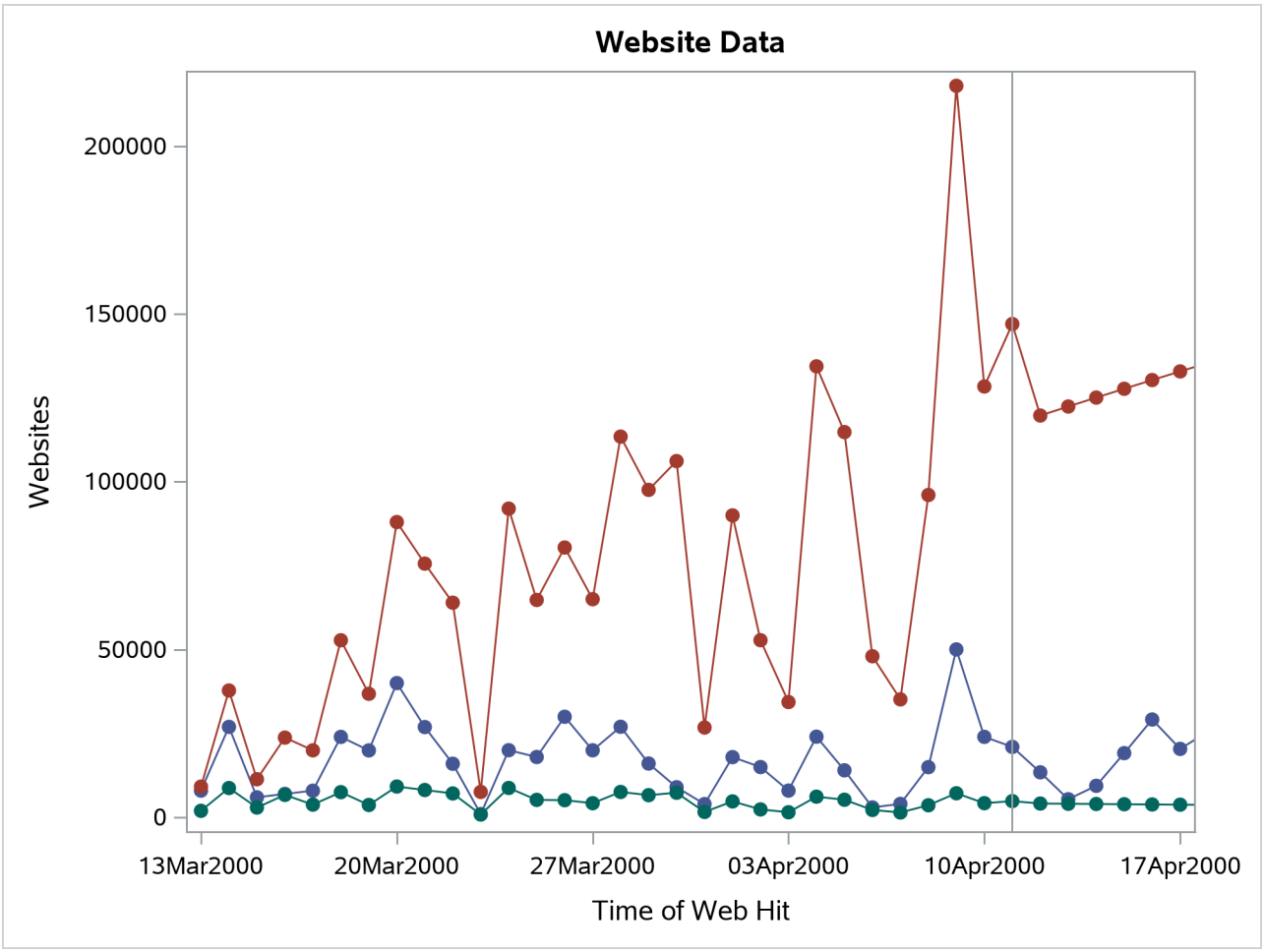
The following SGPLOT procedure statements plot the forecasts related to the Internet data:

```
title1 "Website Data";
proc sgplot data=nextweek noautolegend;
   series x=time y=boats / markers
      markerattrs=(symbol=circlefilled) lineattrs=(pattern=1);
   series x=time y=cars / markers
      markerattrs=(symbol=circlefilled) lineattrs=(pattern=1);
   series x=time y=planes / markers
```

```
      markerattrs=(symbol=circlefilled) lineattrs=(pattern=1);
   xaxis values=('13MAR2000:00:00:00'dt to '18APR2000:00:00:00'dt by dtweek);
   yaxis label='Websites';
   refline '11APR2000:00:00:00'dt / axis=x;
run;
```

The SGPLOT procedure results are shown in Output 2.2.1. The historical data is shown to the left of the vertical reference line, and the forecasts for the next twelve monthly periods are shown to the right.

Output 2.2.1 Internet Data Forecast Plots



Example 2.3: Specifying the Forecasting Model

In the previous example, the HPF procedure was used to automatically select the appropriate forecasting model by using the root mean square error (RMSE) as the default selection criterion. This example illustrates how the HPF procedure can be used to more narrowly specify the possible candidate models. Internet data from the previous example are used for this illustration.

This example forecasts the BOATS variable by using the best seasonal forecasting model (BESTS) that minimizes the mean absolute percent error (MAPE), forecasts the CARS variable by using the best nonseasonal forecasting model (BESTN) that minimizes the mean square error (MSE) using holdout sample analysis, and forecasts the PLANES variable by using the log Winters (additive) method. The following HPF procedure statements forecast each of the transactional data series based on these requirements:

```
proc hpf data=websites out=nextweek lead=7;
   id time interval=dtday accumulate=total;
   forecast boats   / model=bests criterion=mape;
   forecast cars    / model=bestn criterion=mse holdout=5;
   forecast planes  / model=addwinters transform=log;
run;
```

Example 2.4: Extending the Independent Variables for Multivariate Forecasts

In the previous example, the HPF procedure was used to forecast several transactional series variables by using univariate models. This example illustrates how the HPF procedure can be used to extend the independent variables associated with a multiple regression forecasting problem. Specifically, PROC HPF is used to extend the independent variables for use in forecasting a regression model.

This example accumulates and forecasts the BOATS, CARS, and PLANES variables as illustrated in the previous example. In addition, it accumulates the ENGINES variable to form a time series that is then extended with missing values within the forecast horizon with the specification of MODEL=NONE.

```
proc hpf data=websites out=nextweek lead=7;
   id time interval=dtday accumulate=total;
   forecast engines / model=none;
   forecast boats   / model=bests criterion=mape;
   forecast cars    / model=bestn criterion=mse holdout=5;
   forecast planes  / model=winters transform=log;
run;
```

The following AUTOREG procedure statements are used to forecast the ENGINES variable by regressing on the independent variables (BOATS, CARS, and PLANES).

```
proc autoreg data=nextweek;
   model engines = boats cars planes / noprint;
   output out=enginehits p=predicted;
run;
```

The output data set (NEXTWEEK) of the PROC HPF statement is used as an input data set for the PROC AUTOREG statement. The output data set of PROC AUTOREG contains the forecast of the variable ENGINES based on the regression model with the variables BOATS, CARS, and PLANES as regressors. For

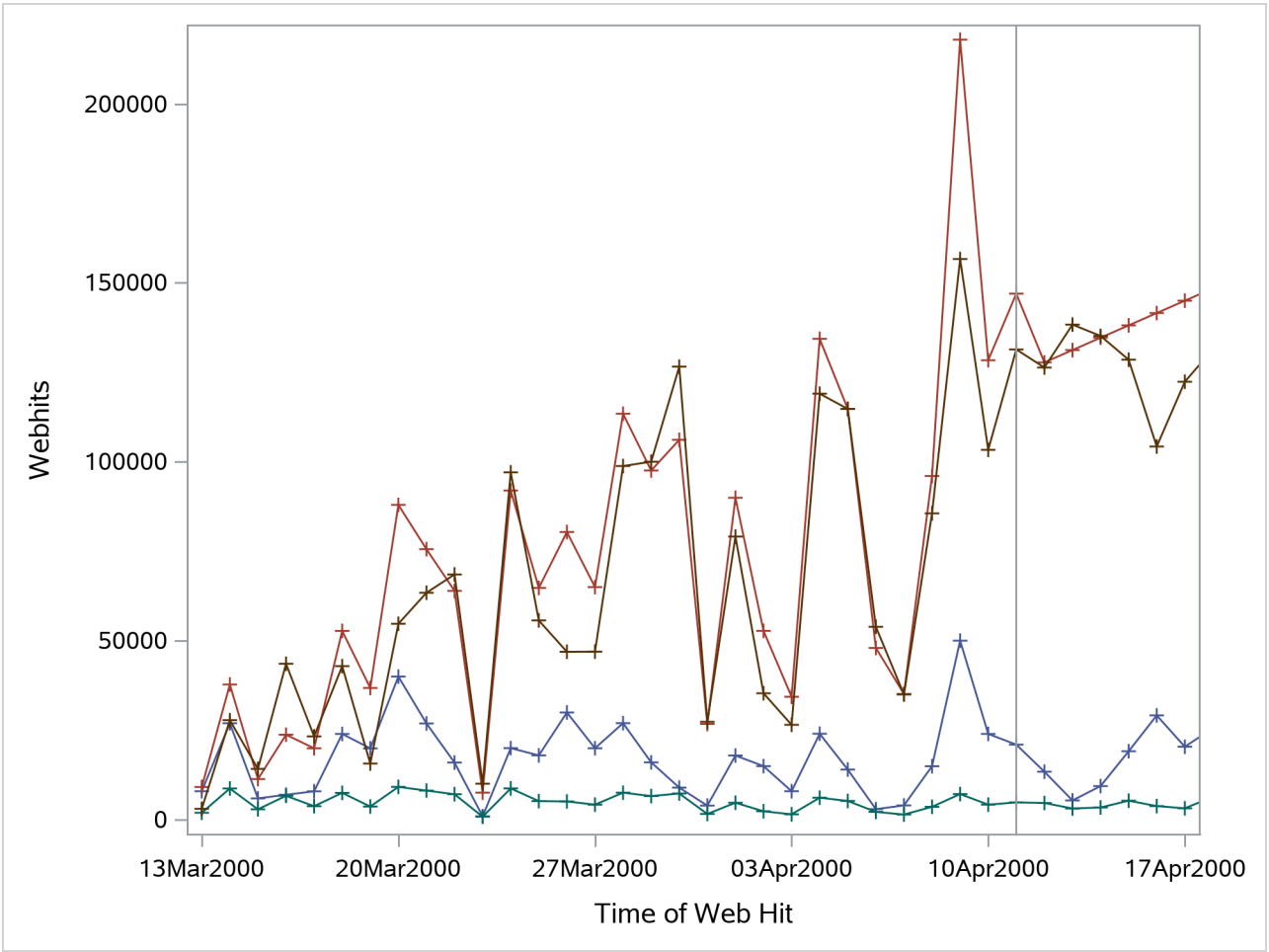
more information about autoregression models, see Chapter 8, "AUTOREG Procedure" (*SAS/ETS User's Guide*).

The following SGPLOT procedure statements plot the forecasts related to the ENGINES variable:

```
proc sgplot data=enginehits noautolegend;
   series x=time y=boats / markers
      markerattrs=(symbol=plus) lineattrs=(pattern=1);
   series x=time y=cars / markers
      markerattrs=(symbol=plus) lineattrs=(pattern=1);
   series x=time y=planes / markers
      markerattrs=(symbol=plus) lineattrs=(pattern=1);
   series x=time y=predicted / markers
      markerattrs=(symbol=plus) lineattrs=(pattern=1);
   xaxis values=('13MAR2000:00:00:00'dt to '18APR2000:00:00:00'dt by dtweek);
   yaxis label='Webhits';
   refline '11APR2000:00:00:00'dt / axis=x;
run;
```

The SGPLOT procedure results are shown in Output 2.4.1. The historical data is shown to the left of the vertical reference line, and the forecasts for the next four weekly periods is shown to the right.

Output 2.4.1 Internet Data Forecast Plots



Example 2.5: Forecasting Intermittent Time Series Data

This example illustrates how the HPF procedure can be used to forecast intermittent time series data. Inventory demand is used for this illustration.

The following DATA step creates a data set from inventory data recorded at no particular frequency. The data set INVENTORY contains a variable DATE that represents time and the demand variables (TIRES, HUBCAPS, and LUGBOLTS), which represent inventory items. Each value of the DATE variable is recorded in ascending order, and the values of each of the other variables represent a transactional data series.

```
data inventory;
   format date date9.;
   input date : date9. tires hubcaps lugbolts;
datalines;
01JUN1997  0  0  0
01JUL1997  0  1  5
01AUG1997  0  0  0

   ... more lines ...
```

The following HPF procedure statements forecast each of the transactional data series by using an intermittent demand model:

```
proc hpf data=inventory out=nextmonth lead=4 print=forecasts;
   id date interval=week accumulate=total;
   forecast tires hubcaps lugbolts / model=idm;
run;
```

The preceding statements accumulate the data into a weekly time series, generate forecasts for the TIRES, HUBCAPS, and LUGBOLTS variables in the input data set (INVENTORY) for the four weekly periods, and store the forecasts in the output data set (NEXTMONTH). The PRINT=FORECAST option produces results which are partially shown in Output 2.5.1. The first two tables record the demand series and predictions. The third table represents forecasts or recommended stocking levels.

Output 2.5.1 Forecast Tables

The HPF Procedure

Demands for Variable tires

Demand		Demand Intervals					Demand Size				
Index	Time	Actual	Predicted	Std	95% Confidence Limits	Error	Actual	Predicted	Std	95% Confidence Limits	Error
1	Sun, 31 Aug 1997	14	14.0000	.	. .	.	6.00000	4.42151	2.18902	0.13110 8.71191	1.57849
2	Sun, 26 Oct 1997	8	14.0000	6.6736	0.9200 27.0800	-6.0000	4.00000	4.74216	2.18902	0.45176 9.03257	-0.74216
3	Sun, 1 Mar 1998	18	12.8920	6.6736	-0.1880 25.9720	5.1080	2.00000	4.59140	2.18902	0.30100 8.88180	-2.59140
4	Sun, 26 Apr 1998	8	13.8353	6.6736	0.7553 26.9153	-5.8353	2.00000	4.06498	2.18902	-0.22542 8.35539	-2.06498
5	Sun, 31 May 1998	5	12.7577	6.6736	-0.3223 25.8377	-7.7577	2.00000	3.64550	2.18902	-0.64490 7.93591	-1.64550
6	Sun, 27 Sep 1998	17	11.3251	6.6736	-1.7549 24.4051	5.6749	6.00000	3.31123	2.18902	-0.97917 7.60164	2.68877
7	Sun, 3 Jan 1999	14	12.3731	6.6736	-0.7069 25.4531	.	.	3.85743	2.18902	-0.43297 8.14783	.

Stock = (Interval Actual)*(Predict) - (Size Actual)

Demands for Variable tires

Demand		Estimate of Mean Demand per Period						
Index	Time	Actual	Predict	Std	95% Confidence Limits	Error	Stock
1	Sun, 31 Aug 1997	0.42857	0.31582	.	. .	0.1127495	-1.578494
2	Sun, 26 Oct 1997	0.50000	0.33873	0.22476	-0.10180 0.77926	0.1612742	-1.290193
3	Sun, 1 Mar 1998	0.11111	0.35614	0.25064	-0.13510 0.84738	-.2450321	4.410578
4	Sun, 26 Apr 1998	0.25000	0.29381	0.21241	-0.12251 0.71013	-.0438128	0.350503
5	Sun, 31 May 1998	0.40000	0.28575	0.22756	-0.16026 0.73176	0.1142508	-0.571254
6	Sun, 27 Sep 1998	0.35294	0.29238	0.25893	-0.21512 0.79987	0.0605614	-1.029543
7	Sun, 3 Jan 1999	.	0.27553	0.20420	-0.12470 0.67576	.	.

Stock = (Interval Actual)*(Predict) - (Size Actual)

Forecasts for Variable tires

Obs	Time	Forecasts	Standard Error	95% Confidence Limits	
84	Sun, 3 Jan 1999	0.27553	0.20420	-0.12470	0.67576
85	Sun, 10 Jan 1999	0.27553	0.20420	-0.12470	0.67576
86	Sun, 17 Jan 1999	0.27553	0.20420	-0.12470	0.67576
87	Sun, 24 Jan 1999	0.27553	0.20420	-0.12470	0.67576

Example 2.6: Illustration of ODS Graphics

This example illustrates the use of ODS graphics.

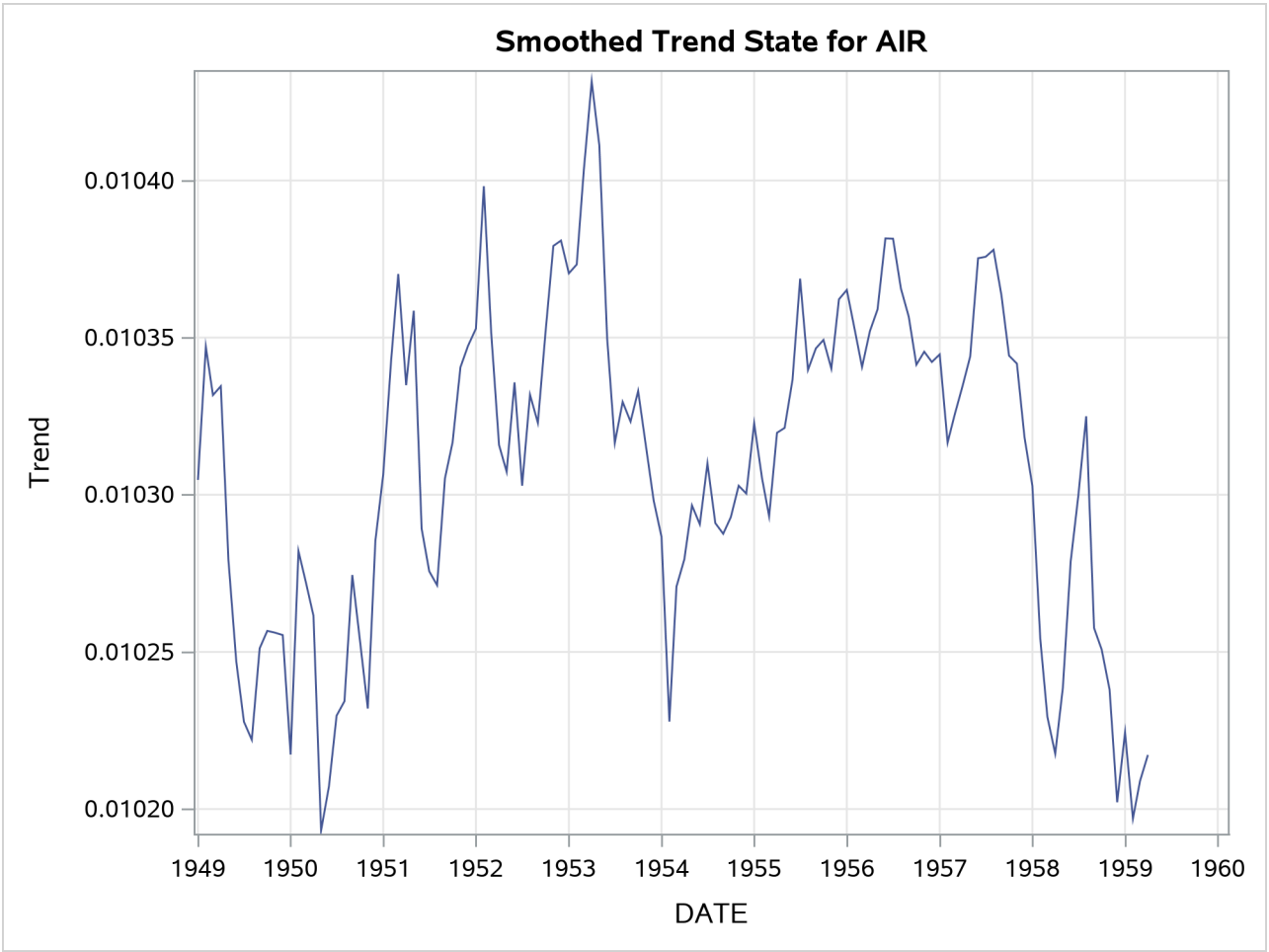
The following statements use the SASHELP.AIR data set to automatically forecast the time series of international airline travel.

The graphical displays are requested by specifying the PLOT= option in the PROC HPF statement. In this case, all plots are requested. Output 2.6.1 through Output 2.6.5 show a selection of the plots created.

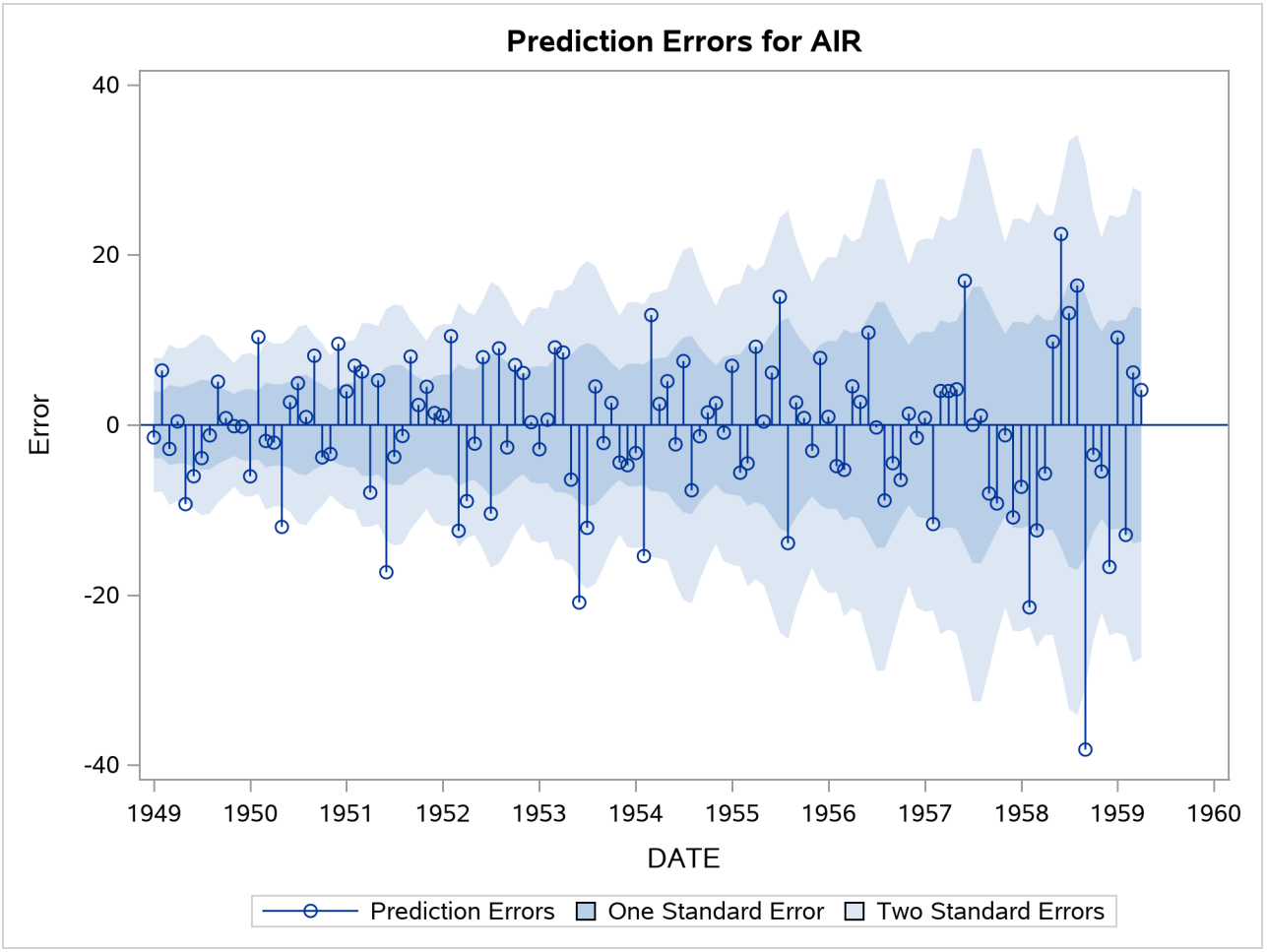
For specific information about the graphics available in the HPF procedure, see the "ODS Graphics" on page 57 section.

```
proc hpf data=sashelp.air out=_null_
         lead=20
         back=20
         print=all
         plot=all;
   id date interval=month;
   forecast air / model=best transform=auto criterion=mape;
run;
```

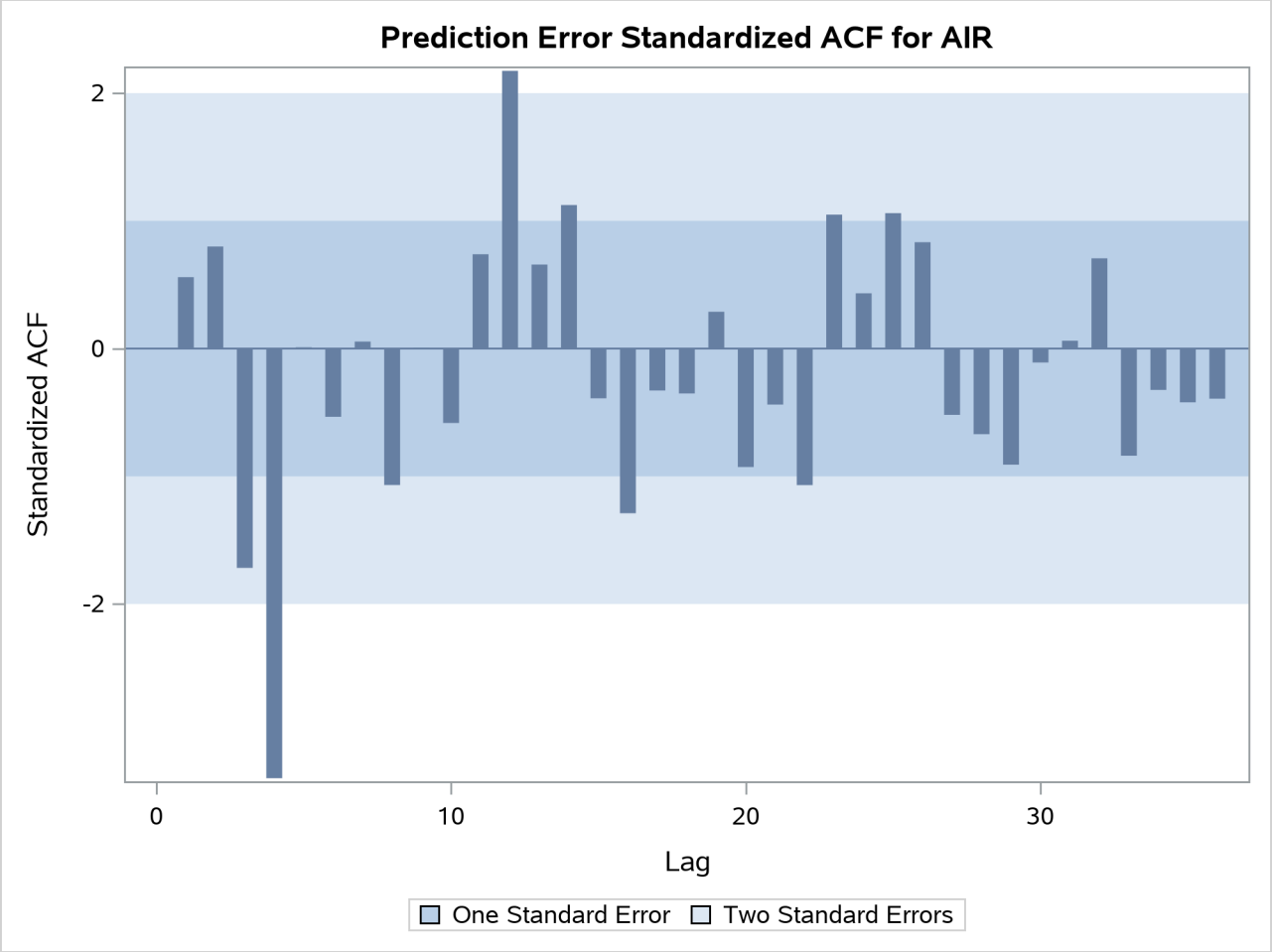
Output 2.6.1 Smoothed Trend Plot



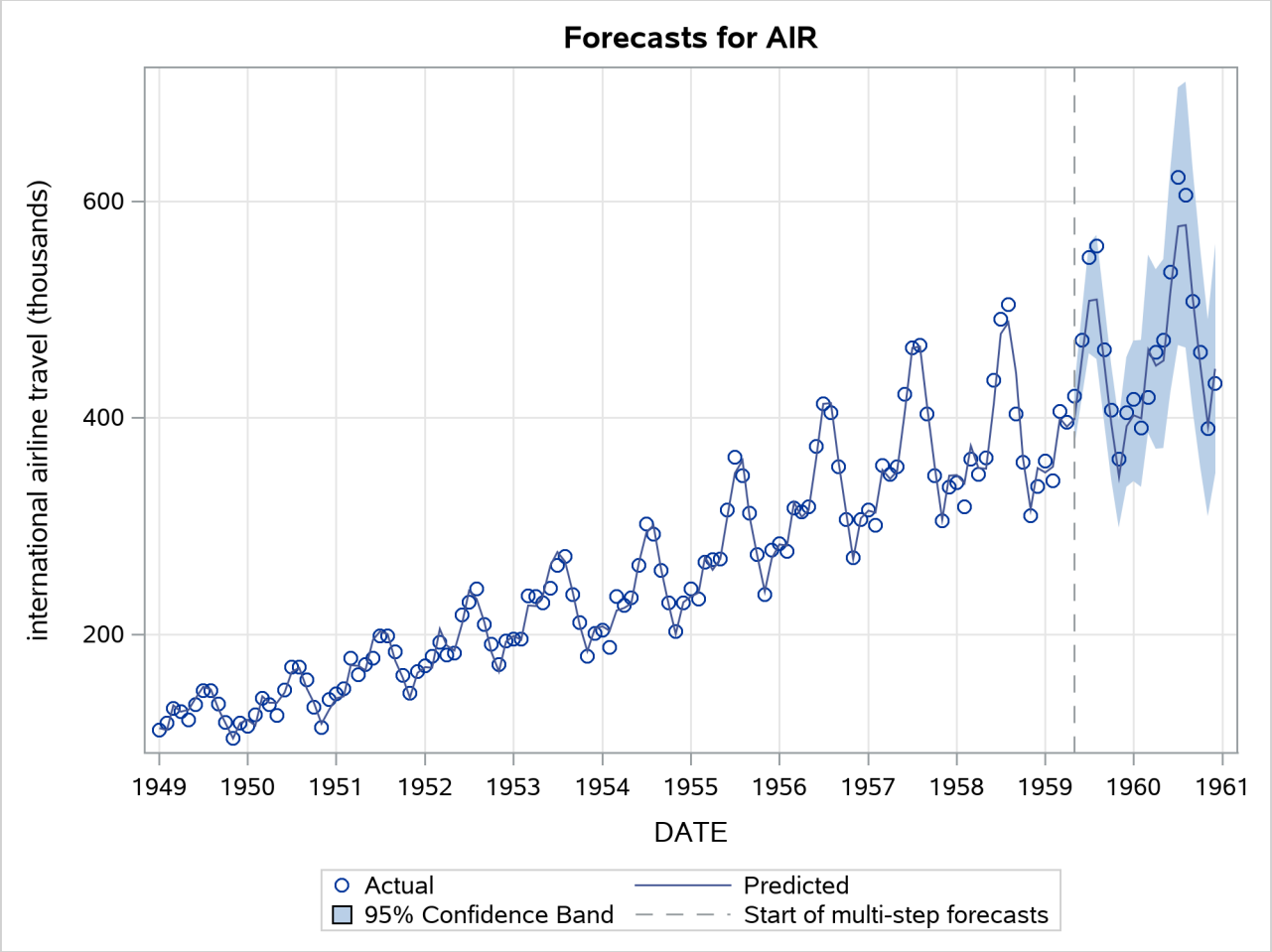
Output 2.6.2 Prediction Error Plot



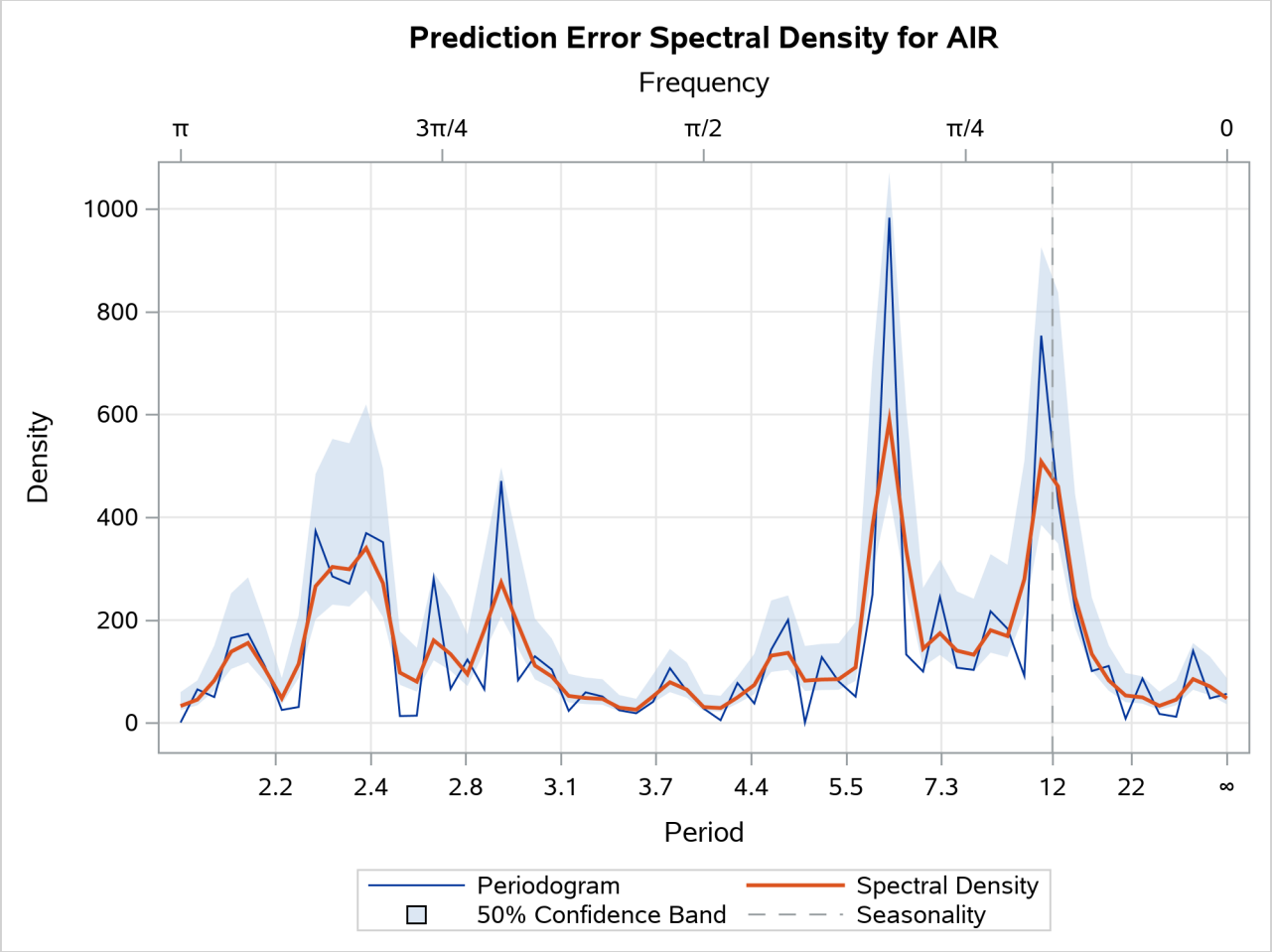
Output 2.6.3 Prediction Error Standardized ACF Plot



Output 2.6.4 Forecast Plot



Output 2.6.5 Prediction Error Spectral Density



References

Pyle, D. (1999). *Data Preparation for Data Mining*. San Francisco: Morgan Kaufmann.

Chapter 3
The HPFARIMASPEC Procedure

Contents

Overview: HPFARIMASPEC Procedure **73**
Getting Started: HPFARIMASPEC Procedure **74**
Syntax: HPFARIMASPEC Procedure **75**
Functional Summary 75
PROC HPFARIMASPEC Statement 76
FORECAST Statement 77
INPUT Statement 79
ESTIMATE Statement 81
Examples: HPFARIMASPEC Procedure **82**
Example 3.1: Some HPFARIMASPEC Syntax Illustrations 82
Example 3.2: How to Include ARIMA Models in a Model Selection List 83
Example 3.3: A Generic Seasonal Model Specification Suitable for Different Season Lengths 85
References **87**

Overview: HPFARIMASPEC Procedure

The HPFARIMASPEC procedure is used to create an ARIMA (autoregressive integrated moving average) model specification file. The output of this procedure is an XML file that stores the intended ARIMA model specification. This XML specification file can be used for different purposes—for example, to populate the model repository used by the HPFENGINE procedure (see Chapter 5, "The HPFENGINE Procedure"). You can specify very general ARIMA models with this procedure. In particular, any model that can be analyzed with the ARIMA procedure can be specified; see Chapter 7, "ARIMA Procedure" (*SAS/ETS User's Guide*). Moreover, the model specification can include series transformations such as log or Box-Cox transformations.

Getting Started: HPFARIMASPEC Procedure

The following example shows how to create an ARIMA model specification file. In this example the specification for an Airline model with one input is created.

```
proc hpfarimaspec repository=work.arima
                  name=Airline1
                  label="Airline model with one input";
   forecast symbol=Y q=(1)(12) dif=(1, 12) noint
            transform=log;
   input symbol=X dif=(1, 12);
   estimate method=ml;
run;
```

The options in the PROC HPFARIMASPEC statement are used to specify the location of the specification file that will be output. Here the REPOSITORY= option specifies that the output file be placed in the catalog WORK.ARIMA, the NAME= option specifies that the name of the file be Airline1.xml, and the LABEL= option specifies a label for this catalog member. The other statements in the procedure specify the ARIMA model and the options used to control the parameter estimation process for the model. The model specification begins with the FORECAST statement that specifies the following:

- transformation, such as log or Box-Cox, and the differencing orders associated with the variable that is to be forecast
- autoregressive and moving average polynomials
- presence or absence of the constant in the model

According to the FORECAST statement, the model contains no constant term and has a two-factor moving average polynomial of orders 1 and 12. The forecast variable is log transformed and differenced with differencing orders 1 and 12. The SYMBOL= option in the FORECAST statement can be used to provide a convenient name for the forecast variable. This name is only a placeholder, and a proper data variable is associated with this name when this model specification is used in actual data analysis.

Next, the INPUT statement provides the transfer function specification associated with the input variable in the model. In the INPUT statement you can specify the following:

- transformation, such as log or Box-Cox, and the lagging and differencing orders associated with the input variable
- numerator and denominator polynomials associated with the transfer function input

In this case the input variable is differenced with differencing orders 1 and 12, and it enters the model as a simple regressor. Here again the SYMBOL= option can be used to supply a convenient name for the input variable. If a model contains multiple input variables, then each input variable has to be specified with a separate INPUT statement.

Lastly, the ESTIMATE statement specifies that the model be estimated using the ML method of estimation.

Syntax: HPFARIMASPEC Procedure

The HPFARIMASPEC procedure uses the following statements.

PROC HPFARIMASPEC *options* ;
FORECAST *options* ;
INPUT *options* ;
ESTIMATE *options* ;

Functional Summary

Table 3.1 summarizes the statements and options that control the HPFARIMASPEC procedure.

Table 3.1 PROC HPFARIMASPEC Functional Summary

Description	Statement	Option
Model Repository Options		
Specifies the model repository	PROC HPFARIMASPEC	REPOSITORY=
Specifies the model specification name	PROC HPFARIMASPEC	NAME=
Specifies the model specification label	PROC HPFARIMASPEC	LABEL=
Options for Specifying Symbolic Series Names		
Specifies a symbolic name for the response series	FORECAST	SYMBOL=
Specifies a symbolic name for the input series	INPUT	SYMBOL=
Specifies a predefined trend as the input series	INPUT	PREDEFINED=
Options for Specifying the Model		
Specifies the response series transformation	FORECAST	TRANSFORM=
Specifies the response series transformation options	FORECAST	TRANSOPT=
Specifies the response series differencing orders	FORECAST	DIF=
Specifies the input series transformation	INPUT	TRANSFORM=
Specifies the input series differencing orders	INPUT	DIF=
Specifies the input series lagging order	INPUT	DELAY=
Specifies the ARIMA part of the model	FORECAST	
Specifies the AR polynomial	FORECAST	P=
Specifies autoregressive starting values	FORECAST	AR=
Specifies the MA polynomial	FORECAST	Q=
Specifies moving average starting values	FORECAST	MA=
Suppresses the constant term in the model	FORECAST	NOINT

Table 3.1 *continued*

Description	Statement	Option
Specifies a starting value for the mean parameter	FORECAST	MU=
Specifies the NOISE variance	FORECAST	NOISEVAR=
Specifies the transfer function part of the model	INPUT	
Specifies the numerator polynomial of a transfer function	INPUT	NUM=
Specifies the starting values for the numerator polynomial coefficients	INPUT	NC=
Specifies the starting value for the zero degree numerator polynomial coefficient	INPUT	NZ=
Specifies the denominator polynomial of a transfer function	INPUT	DEN=
Specifies the starting values for the denominator polynomial coefficients	INPUT	DC=
Options to Control the Parameter Estimation		
Specifies the estimation method	ESTIMATE	METHOD=
Suppress the iterative estimation process	ESTIMATE	NOEST
Specifies the maximum number of iterations	ESTIMATE	MAXITER=
Specifies the convergence criterion	ESTIMATE	CONVERGE=

PROC HPFARIMASPEC Statement

PROC HPFARIMASPEC *options* **;**

The following options can be used in the PROC HPFARIMASPEC statement.

LABEL=*SAS-label*
specifies a descriptive label for the model specification to be stored in the SAS catalog or external file reference. The LABEL= option can also be specified as SPECLABEL=.

NAME=*SAS-name*
names the model specification to be stored in the SAS catalog or external file reference. The NAME= option can also be specified as SPECNAME=.

REPOSITORY=*SAS-catalog-name*

REPOSITORY=*SAS-file-reference*
names the SAS catalog or external file reference to contain the model specification. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=.

FORECAST Statement

FORECAST *options* **;**

The FORECAST statement specifies the operations to be performed on the response series as well as the autoregressive and moving average polynomials in the model. The presence or absence of a constant in the model is also specified here.

The following options are used in the FORECAST statement.

SYMBOL=*variable*

VAR=*variable*

specifies a symbolic name for the dependent series. This symbol specification is optional. If the SYMBOL= option is not specified, *Y* is used as a default symbol.

DIF=*order*

DIF=*(order1, order2, . . .)*

specifies the differencing orders for the dependent series. For example, DIF= (1 12) specifies that the series be differenced using the operator $(1 - B)(1 - B^{12})$. The differencing orders can be positive integers or they can be "s", which indicates a placeholder that will be substituted later with an appropriate value. The use of placeholders is explained further in Example 3.3.

P=*order*

P=(*lag, . . . , lag* **) . . . (***lag, . . . , lag* **)**

P=(*lag, . . . , lag* **)<** s_1 **> . . . (***lag, . . . , lag* **)<** s_k **>**

specifies the autoregressive part of the model. By default, no autoregressive parameters are fit.

P=($l_1, l_2, \ldots, l_k$) defines a model with autoregressive parameters at the specified lags. P= *order* is equivalent to P=(1, 2, . . . , *order*).

A concatenation of parenthesized lists specifies a factored model. For example, P=(1,2,5)(6,12) specifies the autoregressive model

$$(1 - \phi_{1,1}B - \phi_{1,2}B^2 - \phi_{1,3}B^5)(1 - \phi_{2,1}B^6 - \phi_{2,2}B^{12})$$

Optionally, you can specify *multipliers* after the parenthesized lists. For example, P=(1)(1)12 is equivalent to P=(1)(12), and P=(1,2)4(1)12(1,2)24 is equivalent to P=(4,8)(12)(24,48). These multipliers can either be positive integers or they can be "s", which indicates a placeholder that will be substituted later with an appropriate value. The use of placeholders in the multiplier specification is explained in Example 3.3.

Q=*order*

Q=(*lag, . . . , lag* **) . . . (***lag, . . . , lag* **)**

Q=(*lag, . . . , lag* **)<** s_1 **> . . . (***lag, . . . , lag* **)<** s_k **>**

specifies the moving average part of the model. By default, no moving average parameters are fit.

The manner of specification of the moving average part is identical to the specification of the autoregressive part described in the P= option.

AR=*value* **...**
lists starting values for the autoregressive parameters.

MA=*value* **...**
lists starting values for the moving average parameters.

NOCONSTANT
NOINT
suppresses the fitting of a constant (or intercept) parameter in the model. (That is, the parameter μ is omitted.)

MU=*value*
specifies the MU parameter.

NOISEVAR=*value*
specifies the noise variance. This is useful only if you want to specify an externally published model that is fully specified.

TRANSFORM=*option*
specifies the transformation to be applied to the time series. The following transformations are provided:

NONE	no transformation applied
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5

When the TRANSFORM= option is specified, the intended time series must be strictly positive.

TRANSOPT=*option*
specifies that mean or median forecasts be estimated. The following options are provided:

MEAN	Mean forecasts are estimated. This is the default.
MEDIAN	Median forecasts are estimated.

If no transformation is applied to the actual series with the TRANSFORM= option, the mean and median time series forecast values are identical.

INPUT Statement

INPUT *options* **;**

The INPUT statements specify the transfer function inputs in the model. A separate INPUT statement is needed for each of the transfer function inputs. In this statement you can specify all the features of the transfer function associated with the input variable under consideration. The following options are used in the INPUT statement.

(SYMBOL|VAR)=*variable*

specifies a symbolic name for the transfer function input series. This symbol specification is optional. If the SYMBOL= option or the PREDEFINED= option is not specified, then *X* is used as a default symbol. If there are multiple INPUT statements, then an attempt is made to generate a unique set of input symbols.

PREDEFINED=*option*

associates a predefined trend or a set of seasonal dummy variables with this transfer function. The SYMBOL=, and PREDEFINED= options are mutually exclusive.

In the following list of options, let t represent the observation count from the start of the period of fit for the model, and let X_t be the value of the time trend variable at observation t.

LINEAR	a linear trend, with $X_t = t - c$
QUADRATIC	a quadratic trend, with $X_t = (t - c)^2$
CUBIC	a cubic trend, with $X_t = (t - c)^3$
INVERSE	an inverse trend, with $X_t = 1/t$
SEASONAL	seasonal dummies. For a seasonal cycle of length s, the seasonal dummy regressors include $X_{i,t} : 1 \le i \le (s-1), 1 \le t \le n$ for models that include an intercept term, and $X_{i,t} : 1 \le i \le (s), 1 \le t \le n$ for models that do not include an intercept term.

Each element of a seasonal dummy regressor is either zero or one, based on the following rule:

$$X_{i,t} = \begin{cases} 1 & \text{when } i = t \\ 0 & \text{otherwise} \end{cases}$$

Note that if the model includes an intercept term, the number of seasonal dummy regressors is one less than s to ensure that the linear system is full rank.

DIF=*order*

DIF=*(order1, order2, . . .)*

specifies the differencing orders for the input series. See the DIF= option of the FORECAST statement for additional information.

DIF=SAME
specifies that the differencing orders from the FORECAST statement be used.

DELAY=*order*
specifies the delay (or lag) order for the input series.

NUM=*order*

NUM= (*lag, . . . , lag* **) . . . (***lag, . . . , lag* **)**

NUM= (*lag, . . . , lag* **)<** s_1 **> . . . (***lag, . . . , lag* **)<** s_k **>**
specifies the numerator polynomial of the transfer function. See the P= option of the FORECAST statement for additional information about the polynomial order specification.

DEN=*order*

DEN= (*lag, . . . , lag* **) . . . (***lag, . . . , lag* **)**

DEN= (*lag, . . . , lag* **)<** s_1 **> . . . (***lag, . . . , lag* **)<** s_k **>**
specifies the denominator polynomial of the transfer function. See the P= option of the FORECAST statement for additional information about the polynomial order specification.

NC=*value* **. . .**
lists starting values for the numerator polynomial coefficients.

DC=*value* **. . .**
lists starting values for the denominator polynomial coefficients.

NZ=*value*
specifies the scale parameter—that is, the zero degree coefficient of the numerator.

TRANSFORM=*option*
specifies the transformation to be applied to the time series. The following transformations are provided:

NONE	no transformation applied
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5

When the TRANSFORM= option is specified, the intended time series must be strictly positive.

ESTIMATE Statement

ESTIMATE *options* **;**

This is an optional statement in the procedure. Here you can specify the estimation method or whether to hold the model parameters fixed to their starting values. You can also specify some parameters that control the nonlinear optimization process.

The following options are available.

METHOD=ML

METHOD=ULS

METHOD=CLS

specifies the estimation method to use. METHOD=ML specifies the maximum likelihood method. METHOD=ULS specifies the unconditional least squares method. METHOD=CLS specifies the conditional least squares method. METHOD=CLS is the default.

NOEST

uses the values specified with the AR=, MA=, and so on, as final parameter values. The estimation process is suppressed except for the estimation of the residual variance. The specified parameter values are used directly by the next FORECAST statement. Use of NOEST requires that all parameters be specified via the AR=, MA=, and so on. Partially specified models will cause an error when used by the HPFENGINE procedure. When NOEST is specified, standard errors, t values, and the correlations between estimates are displayed as 0 or missing. (The NOEST option is useful, for example, when you wish to generate forecasts that correspond to a published model.)

CONVERGE=*value*

specifies the convergence criterion. Convergence is assumed when the largest change in the estimate for any parameter is less than the CONVERGE= option value. If the absolute value of the parameter estimate is greater than 0.01, the relative change is used; otherwise, the absolute change in the estimate is used. The default is CONVERGE=0.001.

DELTA=*value*

specifies the perturbation value for computing numerical derivatives. The default is DELTA=0.001.

MAXITER=*n*

MAXIT=*n*

specifies the maximum number of iterations allowed. The default is MAXITER=50.

NOLS

begins the maximum likelihood or unconditional least squares iterations from the preliminary estimates rather than from the conditional least squares estimates that are produced after four iterations.

NOSTABLE

specifies that the autoregressive and moving average parameter estimates for the noise part of the model not be restricted to the stationary and invertible regions, respectively.

SINGULAR=*value*

specifies the criterion for checking singularity. If a pivot of a sweep operation is less than the SINGULAR= value, the matrix is deemed singular. Sweep operations are performed on the Jacobian matrix during final estimation and on the covariance matrix when preliminary estimates are obtained. The default is SINGULAR=1E–7.

Examples: HPFARIMASPEC Procedure

Example 3.1: Some HPFARIMASPEC Syntax Illustrations

The following statements illustrate the PROC HPFARIMASPEC syntax for some of the commonly needed modeling activities. Suppose that a variety of ARIMA models are to be fit to a data set that contains a sales series as the forecast variable and several promotional events as predictor series. In all these cases the model repository is kept the same, work.arima, and the models are named as *model1, model2,* and so on, to ensure uniqueness. Note that in a given repository, the models must have unique names. The symbols for the forecast and input variables are *sales* and *promo1, promo2,* and so on, respectively.

```
/* Two transfer functions */
proc hpfarimaspec repository=work.arima
                  name=model1;
   forecast symbol=sales transform=log
            q=(1)(12) dif=(1,12) noint;
   input symbol=promo1 dif=(1, 12) den=2;
   input symbol=promo2 num=2 delay=3;
run;

/* Box-Cox transform and Estimation Method=ML */

proc hpfarimaspec repository=work.arima
                  name=model2;
   forecast symbol=sales transform=BoxCox(0.8) p=2;
   estimate method=ml;
run;

/* suppress parameter estimation: in this    */
/* case all the parameters must be specified */

proc hpfarimaspec repository=work.arima
                  name=model3;
   forecast symbol=sales transform=log
            p=2 ar=0.1 0.8 mu=3.5;
   estimate noest method=ml;
run;

/* Supply starting values for the parameters */

proc hpfarimaspec repository=work.arima
                  name=model4;
```

```
   forecast symbol=sales transform=log
            p=2 ar=0.1 0.8 mu=3.5;
   input symbol=promo1
         den=1 dc=0.1 nz=-1.5;
run;

/* Create a generic seasonal Airline model with one input
   that is applicable for different season lengths */

proc hpfarimaspec repository=work.arima
                  name=model5
                  label="Generic Airline Model with One Input";
   forecast symbol=Y q=(1)(1)s dif=(1, s) noint
            transform= log;
   input symbol=X dif=(1, s);
run;
```

Example 3.2: How to Include ARIMA Models in a Model Selection List

One of the primary uses of the HPFARIMASPEC procedure is to add candidate ARIMA models to a model selection list that can be used by the HPFENGINE procedure (see Chapter 5, "The HPFENGINE Procedure"). The HPFARIMASPEC procedure is used to create the ARIMA model specifications, and the HPFSELECT procedure is used to add the specifications to a model selection list (see Chapter 11, "The HPFSELECT Procedure"). This example illustrates this scenario.

Here the Gas Furnace Data, "Series J" from Box and Jenkins (1976), is used. This data set contains two series, Input Gas Rate and Output CO2. The goal is to forecast the output CO2, using the input Gas Rate as a predictor if necessary.

The following DATA step statements read the data in a SAS data set.

```
data seriesj;
   input GasRate CO2 @@;
   date = intnx( 'day', '01jan1950'd, _n_-1 );
   format date DATE.;
datalines;
-0.109  53.8  0.000  53.6  0.178  53.5  0.339  53.5
 0.373  53.4  0.441  53.1  0.461  52.7  0.348  52.4
 0.127  52.2 -0.180  52.0 -0.588  52.0 -1.055  52.4

... more lines ...
```

Three candidate models are specified, *m1, m2*, and *m3*. Out of these three models, *m1* is known to be a good fit to the data. It is a transfer function model that involves the input Gas Rate. The other two models are simplified versions of *m1*. The following syntax shows how to specify these models and how to create a selection list that combines them by using the HPFSELECT procedure. In the HPFSELECT procedure note the use of the INPUTMAP option in the SPEC statement. It ties the symbolic variable names used in the HPFARIMASPEC procedure with the actual variable names in the data set. If the symbolic names were appropriate to start with, then the INPUTMAP option is not necessary.

```
* make spec1;
proc hpfarimaspec repository=work.mycat
                  name=m1;
   forecast symbol=y p=2;
   input symbol=x delay=3 num=(1,2) den=1;
   estimate method=ml;
run;

* make spec2;
proc hpfarimaspec repository=work.mycat name=m2;
   forecast symbol=y p=2;
   input symbol=x delay=3;
   estimate method=ml;
run;

* make spec3;
proc hpfarimaspec repository=work.mycat
                  name=m3;
   forecast symbol=y p=2;
   estimate method=ml;
run;

* make a selection list that includes m1, m2 and m3;
proc hpfselect repository=work.mycat
               name=myselect;

   spec m1 / inputmap(symbol=y var=co2)
             inputmap(symbol=x var=gasrate);

   spec m2 / inputmap(symbol=y var=co2)
             inputmap(symbol=x var=gasrate);

   spec m3 / inputmap(symbol=y var=co2);
run;
```

This selection list can now be used in the HPFENGINE procedure for various types of analyses. The following syntax shows how to compare these models based on the default comparison criterion, mean absolute percentage error (MAPE). As expected, model *m1* turns out to be the best of the three compared (see Figure 3.2.1).

```
proc hpfengine data=seriesj
               repository=work.mycat
               globalselection=myselect
               lead=0
               print=(select);
   forecast co2;
   input    gasrate;
run;
```

Output 3.2.1 Model Selection Based on the MAPE Criterion

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
M1	0.31478330	Yes	ARIMA: Y ~ P = 2 + INPUT: Lag(3) X NUM = 2 DEN = 1
M2	0.50671996	No	ARIMA: Y ~ P = 2 + INPUT: Lag(3) X
M3	0.53295590	No	ARIMA: Y ~ P = 2

Example 3.3: A Generic Seasonal Model Specification Suitable for Different Season Lengths

In the case of many seasonal model specifications, it is possible to describe a generic specification that is applicable in a variety of situations just by changing the season length specifications at appropriate places. As an example, consider the Airline model, which is very useful for modeling seasonal data. The Airline model for a monthly series can be specified using the following syntax:

```
proc hpfarimaspec repository=work.specs
                  name=MonthlyAirline
     label="Airline Model For A Series With Season Length 12";
   forecast symbol=Y q=(1)(1)12 dif=(1, 12) noint
            transform= log;
run;
```

It is easy to see that the same syntax is applicable to a quarterly series if the multiplier in the MA specification is changed from 12 to 4 and the seasonal differencing order is similarly changed from 12 to 4. A generic specification that allows for late binding of season lengths can be generated by the following syntax:

```
proc hpfarimaspec repository=work.specs
                  name=GenericAirline
                  label="Generic Airline Model";
    forecast symbol=Y q=(1)(1)s dif=(1, s) noint
             transform= log;
run;
```

In this syntax the multiplier in the MA specification is changed from 12 to "s", and similarly the seasonal differencing order 12 is changed to "s". This syntax creates a template for the Airline model that is applicable to different season lengths. When the HPFENGINE procedure, which actually uses such model specifications to estimate the model and produce the forecasts, encounters such "generic" specification it automatically creates a proper specification by replacing the placeholders for the seasonal multiplier and the seasonal differencing order with the value implied by the ID variable or its SEASONALITY= option. The following example illustrates the use of this generic spec. It shows how the same spec can be used for monthly and quarterly series. The parameter estimates for monthly and quarterly series are given in Output 3.3.1 and Output 3.3.2, respectively.

```
/* Create a selection list that contains
   the Generic Airline Model */

proc hpfselect repository=work.specs
```

```
                name=genselect;
   spec GenericAirline;
run;

/* Monthly interval */

proc hpfengine data=sashelp.air
                repository=work.specs
                globalselection=genselect
                print=(estimates);
   id date interval=month;
   forecast air;
run;
```

Output 3.3.1 Parameter Estimates for the Monthly Series

The HPFENGINE Procedure

Parameter Estimates for GENERICAIRLINE Model

Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
AIR	MA1_1	0.37727	0.08196	4.60	<.0001
AIR	MA2_12	0.57236	0.07802	7.34	<.0001

```
/* Create a quarterly series to illustrate
   accumulating the monthly Airline series to quarterly*/

proc timeseries data=sashelp.air out=Qair;
   id date interval=quarter;
   var air / accumulate=total;
run;

/* Quarterly interval */

proc hpfengine data=Qair
                repository= work.specs
                globalselection=genselect
                print=(estimates);
   id date interval=quarter;
   forecast air;
run;
```

Output 3.3.2 Parameter Estimates for the Quarterly Series

The HPFENGINE Procedure

Parameter Estimates for GENERICAIRLINE Model

Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
AIR	MA1_1	0.05892	0.15594	0.38	0.7075
AIR	MA2_4	0.50558	0.14004	3.61	0.0008

References

Box, G. E. P., and Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control*. Rev. ed. San Francisco: Holden-Day.

Chapter 4
The HPFDIAGNOSE Procedure

Contents

Overview: HPFDIAGNOSE Procedure **90**
Getting Started: HPFDIAGNOSE Procedure **91**
Default Settings 94
The Role of the IDM Statement 95
Syntax: HPFDIAGNOSE Procedure **96**
Functional Summary 96
PROC HPFDIAGNOSE Statement 100
ADJUST Statement 107
ARIMAX Statement 108
BY Statement 111
COMBINE Statement 112
ESM Statement 116
EVENT Statement 117
FORECAST Statement 118
ID Statement 119
IDM Statement 120
INPUT Statement 122
TRANSFORM Statement 123
TREND Statement 124
UCM Statement 125
Details: HPFDIAGNOSE Procedure **126**
Adjustment Operations 126
Data Preparation 126
Functional Transformation 128
Stationarity Test 129
ARMA Order Selection 131
Transfer Functions in an ARIMAX Model 133
Outliers 134
Intermittent Demand Model 135
Exponential Smoothing Model 136
Unobserved Components Model 137
Values of Status 139
Holdout Sample 140
Events 141
Thread Usage in PROC HPFDIAGNOSE 143
Relationship with PROC HPFENGINE 144

Data Set Input/Output 145
ODS Table Names 150
Examples: HPFDIAGNOSE Procedure **151**
Example 4.1: Selection of Input Variables 151
Example 4.2: Selection of Events and Input Variables 152
Example 4.3: Intermittent Demand Series 154
Example 4.4: Exponential Smoothing Model 154
Example 4.5: Unobserved Components Model 155
Example 4.6: Automatic Model Combination 156
References **157**

Overview: HPFDIAGNOSE Procedure

The HPFDIAGNOSE procedure provides a comprehensive set of tools for automated univariate time series model identification. Time series data can have outliers, structural changes, and calendar effects. In the past, finding a good model for time series data usually required experience and expertise in time series analysis.

The HPFDIAGNOSE procedure automatically diagnoses the statistical characteristics of time series and identifies appropriate models. The models that HPFDIAGNOSE considers for each time series include autoregressive integrated moving average with exogenous inputs (ARIMAX), exponential smoothing, and unobserved components models. Log transformation and stationarity tests are automatically performed. The ARIMAX model diagnostics find the autoregressive (AR) and moving average (MA) orders, detect outliers, and select the best input variables. The unobserved components model (UCM) diagnostics find the best components and select the best input variables.

The HPFDIAGNOSE procedure provides the following functionality:

- intermittency (or interrupted series) test
- functional transformation test
- simple differencing and seasonal differencing tests
- tentative simple ARMA order identification
- tentative seasonal ARMA order identification
- outlier detection
- significance test of events (indicator variables)
- transfer function identification
  - intermittency test
  - functional transformation for each regressor
  - simple differencing order and seasonal differencing order for each regressor
  - time delay for each regressor

  - simple numerator and denominator polynomial orders for each regressor

- intermittent demand model (automatic selection)
- exponential smoothing model (automatic selection)
- unobserved components model (automatic selection)

PROC HPFDIAGNOSE can be abbreviated as PROC HPFDIAG.

Getting Started: HPFDIAGNOSE Procedure

This section outlines the use of the HPFDIAGNOSE procedure and shows examples of how to create ARIMA, ESM, and UCM model specifications.

The following example prints the diagnostic tests of an ARIMA model. In the HPFDIAGNOSE statement, the SEASONALITY=12 option specifies the length of the seasonal cycle of the time series, and the PRINT=SHORT option prints the chosen model specification. The FORECAST statement specifies the dependent variable (Air). The ARIMAX statement specifies that an ARIMA model is to be diagnosed.

```
proc hpfdiagnose data=sashelp.air
                 seasonality=12
                 print=short;
   forecast air;
   transform;
   arimax;
run;
```

Figure 4.1 shows the ARIMAX model specification. The log transformation test and trend test are conducted by default. The log transformation was applied to the dependent series and the seasonal ARIMA $(1,1,0)(0,1,1)_{12}$ model was selected. The default model selection criterion (RMSE) was used. The STATUS column explains warnings or errors during diagnostic tests. STATUS=OK indicates that the model was successfully diagnosed.

Figure 4.1 ARIMAX Specification

The HPFDIAGNOSE Procedure

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	Status
AIR	LOG	NO	1	1	0	0	1	1	12	RMSE	10.8353	OK

The following example prints the diagnostic tests of an ESM for airline data. The ID statement INTERVAL=MONTH option specifies an implied seasonality of 12. The ESM statement specifies that an exponential smoothing model is to be diagnosed.

```
proc hpfdiagnose data=sashelp.air print=short;
   id date interval=month;
   forecast air;
   transform;
   esm;
run;
```

Figure 4.2 shows the ESM specification. The chosen model specification applied the log transformation and selected a multiplicative seasonal model with a trend component (WINTERS).

Figure 4.2 ESM Specification

The HPFDIAGNOSE Procedure

Exponential Smoothing Model Specification

Variable	Functional Transform	Selected Model	Component	Model Criterion	Statistic
AIR	LOG	WINTERS	LEVEL	RMSE	10.6521
			TREND		
			SEASONAL		

The following example prints the diagnostic tests of a UCM for airline data. The UCM statement specifies that an unobserved component model is to be diagnosed.

```
proc hpfdiagnose data=sashelp.air print=short;
   id date interval=month;
   forecast air;
   transform;
   ucm;
run;
```

When the column SELECTED=YES, as shown in Figure 4.3, the component is significant. When the column SELECTED=NO, the component is insignificant.

When SELECTED=YES, the STOCHASTIC column has either YES or NO. STOCHASTIC=YES indicates that a component has a statistically significant variance, indicating the component is changing over time; STOCHASTIC=NO indicates that the variance of a component is not statistically significant, but the component itself is still significant.

Figure 4.3 shows that the irregular, level, slope, and seasonal components are selected. The irregular, level, and seasonal components have statistically significant variances. The slope component is constant over the time.

Figure 4.3 Select Components

The HPFDIAGNOSE Procedure

Unobserved Components Model(UCM) Specification

Variable	Functional Transform	Component	Selected	Stochastic	Seasonality	Model Criterion	Statistic	Status
AIR	LOG	IRREGULAR	YES	YES		RMSE	10.9801	OK
		LEVEL	YES	YES				
		SLOPE	YES	NO				
		SEASON	YES	YES	12			

The following example shows how to pass a model specification created by the HPFDIAGNOSE procedure to the HPFENGINE procedure.

An ARIMAX model specification file, a model selection list, and a model repository Sasuser.Mycat are created by the HPFDIAGNOSE procedure. The ARIMAX model specification file and the model selection list are contained in the Sasuser.Mycat repository.

The OUTEST= data set is used to transmit the diagnostic results to the HPFENGINE procedure by the INEST= option. The Work.Est_One data set contains the information about the data set variable and the model selection list.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor mycat;
run;

proc hpfdiagnose data=sashelp.air outest=est_one
             modelrepository=sasuser.mycat criterion=MAPE;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;

proc hpfengine data=sashelp.air print=(select)
               modelrepository=sasuser.mycat inest=est_one;
   forecast air;
   id date interval=month;
run;
```

Figure 4.4 shows the DIAG0 model specification created by the HPFDIAGNOSE procedure in the previous example. The model specification is labeled DIAG0 because the HPFDIAGNOSE procedure uses BASENAME=DIAG by default.

Figure 4.4 Model Selection from the HPFENGINE Procedure

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
diag0	2.9422734	Yes	ARIMA: Log(AIR) ~ P = 1 D = (1,12) Q = (12) NOINT

The following example shows how the HPFDIAGNOSE and HPFENGINE procedures can be used to select a single model specification from among multiple candidate model specifications.

In this example the HPFDIAGNOSE procedure creates three model specifications and adds them to the model repository SASUSER.MYCAT created in the previous example.

```
proc hpfdiagnose data=sashelp.air outest=est_three
             modelrepository=sasuser.mycat;
   id date interval=month;
   forecast air;
   transform;
   arimax;
   esm;
```

```
   ucm;
run;

proc hpfengine data=sashelp.air print=(select)
               modelrepository=sasuser.mycat inest=est_three;
   forecast air;
   id date interval=month;
run;
```

If new model specification files are added to a model repository that already exists, then the suffixed number of the model specification file name and the model selection list file name are sequential.

This example adds three model specification files (DIAG2, DIAG3, and DIAG4) to the model repository Sasuser.Mycat which already contains DIAG0 and DIAG1.

Figure 4.5 shows the three model specifications (DIAG2, DIAG3, DIAG4) found by the HPFDIAGNOSE procedure.

Figure 4.5 Model Selection

The HPFENGINE Procedure

Model Selection Criterion = RMSE			
Model	**Statistic**	**Selected**	**Label**
diag2	10.835333	No	ARIMA: Log(AIR) ~ P = 1 D = (1,12) Q = (12) NOINT
diag3	10.652082	Yes	Log Winters Method (Multiplicative)
diag4	10.980119	No	UCM: Log(AIR) = TREND + SEASON + ERROR

Default Settings

The following example shows the HPFDIAGNOSE procedure with the default settings. The data sets Aaa, Bbb, and Ccc are not specific data sets.

```
proc hpfdiagnose data=aaa print=all;
   id date interval=month;
   forecast y;
run;
```

The HPFDIAGNOSE procedure always performs the intermittency test first. If the HPFDIAGNOSE procedure determines that the series is intermittent, then the preceding example is equivalent to the following statements:

```
proc hpfdiagnose data=aaa print=all;
   id date interval=month;
   forecast y;
   idm intermittent=2 base=auto;
run;
```

However, if the HPFDIAGNOSE procedure determines that the series is not intermittent, then the default settings are equivalent to the following statements:

```
proc hpfdiagnose data=aaa print=all siglevel=0.05
             criterion=rmse holdout=0 holdoutpct=0 prefilter=yes
             back=0 errorcontrol=(severity=all stage=all);
   id date interval=month;
   forecast y;
   transform type=none;
   trend dif=auto sdif=auto;
   arimax method=minic p=(0:5)(0:2) q=(0:5)(0:2) perror=(5:10)
      outlier=(detect=maybe maxnum=2 maxpct=2
               siglevel=0.01 filter=full);
   esm method=best;
run;
```

The Role of the IDM Statement

The HPFDIAGNOSE procedure always performs the intermittency test first regardless of which model statement is specified. The IDM statement controls only the intermittency test by using the INTERMITTENT= and BASE= options.

The following example specifies the IDM statement to control the intermittency test. If the HPFDIAGNOSE procedure determines that the series is intermittent, then an intermittent demand model is fitted to the data.

However, if the series is not intermittent, ARIMAX and exponential smoothing models are fitted to the data, even though the IDM statement is specified.

```
proc hpfdiagnose data=bbb print=all;
   id date interval=month;
   forecast x;
   idm intermittent=2.5 base=auto;
run;
```

The following example specifies the ESM statement. If the series is intermittent, an intermittent demand model is fitted to the data, even though the ESM statement is specified. But if the series is not intermittent, an ESM is fitted to the data. The same is true when the ARIMAX and UCM statements are specified.

```
proc hpfdiagnose data=ccc print=all;
   id date interval=month;
   forecast z;
   esm;
run;
```

Syntax: HPFDIAGNOSE Procedure

The HPFDIAGNOSE procedure uses the following statements:

```
PROC HPFDIAGNOSE options ;
    ADJUST variable = ( variable-list ) / options ;
    ARIMAX options ;
    BY variables ;
    COMBINE options ;
    ESM option ;
    EVENT event-names ;
    FORECAST variables ;
    ID variable INTERVAL=interval options ;
    IDM options ;
    INPUT variables ;
    TRANSFORM options ;
    TREND options ;
    UCM options ;
```

Functional Summary

Table 4.1 summarizes the statements and options that control the HPFDIAGNOSE procedure.

Table 4.1 PROC HPFDIAGNOSE Functional Summary

Description	Statements	Option
Statements		
Specifies BY-group processing	BY	
Specifies model combination options	COMBINE	
Specifies event definitions	EVENT	
Specifies variables to be forecast	FORECAST	
Specifies the time ID variable	ID	
Specifies input variables	INPUT	
Specifies log transform test and other functional transformation types	TRANSFORM	
Specifies the differencing test	TREND	
Specifies ARIMAX model options	ARIMAX	
Specifies the exponential smoothing model	ESM	
Specifies the intermittent demand model options	IDM	
Specifies the unobserved components model	UCM	
Specifies that the dependent values be adjusted	ADJUST	

Table 4.1 *continued*

Description	Statements	Option
Model Repository Options		
Specifies the model repository	PROC HPFDIAGNOSE	REPOSITORY=
Respects the CHOOSE= option in PROC HPFSELECT	PROC HPFDIAGNOSE	RETAINCHOOSE=
Specifies the base name for all specification files	PROC HPFDIAGNOSE	BASENAME=
Specifies the base name for combined model list files	PROC HPFDIAGNOSE	COMBINEBASE=
Specifies the base name for model selection list files	PROC HPFDIAGNOSE	SELECTBASE=
Specifies the base name for model specification files	PROC HPFDIAGNOSE	SPECBASE=
Data Set Options		
Specifies the auxiliary input data sets	PROC HPFDIAGNOSE	AUXDATA=
Specifies the input data set	PROC HPFDIAGNOSE	DATA=
Specifies the mapping output data set	PROC HPFDIAGNOSE	OUTEST=
Specifies the events data set	PROC HPFDIAGNOSE	INEVENT=
Specifies the events data set organized by BY groups	PROC HPFDIAGNOSE	EVENTBY=
Specifies the output data set that contains the outliers	PROC HPFDIAGNOSE	OUTOUTLIER=
Specifies the output data set that contains the information in the SAS log	PROC HPFDIAGNOSE	OUTPROCINFO=
Accumulation Options		
Specifies the length of the seasonal cycle	PROC HPFDIAGNOSE	SEASONALITY=
Specifies the accumulation frequency	ID	INTERVAL=
Specifies the interval alignment	ID	ALIGN=
Specifies the starting time ID value	ID	START=
Specifies the ending time ID value	ID	END=
Specifies the accumulation statistic	ID, FORECAST, INPUT, ADJUST	ACCUMULATE=
Specifies the missing value interpretation	ID, FORECAST, INPUT, ADJUST	SETMISSING=
Specifies the zero value interpretation	ID, FORECAST, INPUT, ADJUST	ZEROMISS=
Specifies how missing values are trimmed	ID, FORECAST, INPUT, ADJUST	TRIMMISS=
Transformation Test Options		
Specifies the type of the functional transformation	TRANSFORM	TYPE=

Table 4.1 *continued*

Description	Statements	Option
Specifies the method of the forecasts of the transformed series	TRANSFORM	TRANSOPT=
Trend Test Options		
Specifies simple differencing	TREND	DIFF=
Specifies seasonal differencing	TREND	SDIFF=
Specifies the AR order for the augmented unit root test	TREND	P=
ARIMAX Model Options		
Specifies the ARMA order selection criterion	ARIMAX	CRITERION=
Specifies the range of the AR orders for obtaining the error series used in the MINIC method	ARIMAX	PERROR=
Specifies the range of the AR orders	ARIMAX	P=
Specifies the range of the MA orders	ARIMAX	Q=
Specifies the range of the denominator orders of the transfer function	ARIMAX	DEN=
Specifies the range of the numerator orders of the transfer function	ARIMAX	NUM=
Specifies the tentative order identification method	ARIMAX	METHOD=
Specifies the outlier detection	ARIMAX	OUTLIER=
Specifies the identification order of the components	ARIMAX	IDENTIFYORDER=
Suppresses the intercept (constant) term	ARIMAX	NOINT
Unobserved Components Model Option		
Specifies the components to test for inclusion in the UCM	UCM	COMPONENT=
Exponential Smoothing Model Option		
Specifies the method of the ESM	ESM	METHOD=
Model Combination Options		
Specifies the combination weight method	COMBINE	METHOD=
Specifies the encompassing test	COMBINE	ENCOMPASS=
Specifies the forecast combination criterion	COMBINE	CRITERION=
Specifies the percentage of missing forecast values	COMBINE	MISSPERCENT=
Specifies the percentage of missing horizon values	COMBINE	HORMISSPERCENT=
Specifies the combination of missing forecast values	COMBINE	MISSMODE=

Table 4.1 *continued*

Description	Statements	Option
Significance Level Option		
Specifies the significance level for diagnostic tests	PROC HPFDIAGNOSE, TRANSFORM, TREND, ARIMAX, UCM	SIGLEVEL=
Specifies the significance level to control confidence limits in the model selection list files	PROC HPFDIAGNOSE	ALPHA=
Event Variable Control Option		
Specifies the maximum number of events to be selected	PROC HPFDIAGNOSE	SELECTEVENT=
Specifies a hint for event inclusion in the generated model	EVENT	REQUIRED=
Input Variable Control Options		
Specifies the maximum number of input variables to be selected	PROC HPFDIAGNOSE	SELECTINPUT=
Specifies the transformation and differencing of the input variables	PROC HPFDIAGNOSE	TESTINPUT=
Specifies the maximum missing percentage of the input variables	PROC HPFDIAGNOSE	INPUTMISSINGPCT=
Specifies a hint for input variable inclusion in the generated model	INPUT	REQUIRED=
Model Selection Options		
Specifies the model selection criterion	PROC HPFDIAGNOSE	CRITERION=
Specifies the forecast holdout sample size	PROC HPFDIAGNOSE	HOLDOUT=
Specifies the forecast holdout sample percentage	PROC HPFDIAGNOSE	HOLDOUTPCT=
Specifies data to hold back	PROC HPFDIAGNOSE	BACK=
Specifies the minimum number of observations needed to fit a trend or seasonal model	PROC HPFDIAGNOSE	MINOBS=
Specifies the threshold of forward selection of inputs and events	PROC HPFDIAGNOSE	ENTRYPCT=
Printing Options		
Specifies printed output for only the model specifications	PROC HPFDIAGNOSE	PRINT=SHORT
Specifies printed output for PRINT=SHORT and summary of the transformation and trend tests	PROC HPFDIAGNOSE	PRINT=LONG
Specifies detailed printed output	PROC HPFDIAGNOSE	PRINT=ALL
Specifies control of message printing in the log	PROC HPFDIAGNOSE	ERRORCONTROL=

Table 4.1 *continued*

Description	Statements	Option
Data Prefilter Option		
Specifies how to handle missing and extreme values prior to diagnostic tests	PROC HPFDIAGNOSE	PREFILTER=
Miscellaneous Options		
Specifies control of exception handling	PROC HPFDIAGNOSE	EXCEPTIONS=

PROC HPFDIAGNOSE Statement

PROC HPFDIAGNOSE *options* **;**

PROC HPFDIAG *options* **;**

The following options can be used in the PROC HPFDIAGNOSE or HPFDIAG statement.

ALPHA=*value*

specifies the confidence level size to use in computing the confidence limits in the model selection list files. The ALPHA= value must be between (0, 1). The default is ALPHA=0.05, which produces 95% confidence intervals.

AUXDATA=*SAS-data-set*

names a SAS data set that contains auxiliary input data for the procedure to use for supplying explanatory variables in a forecast. See section "AUXDATA= Data Set" on page 146 for more information.

BACK=*number*

specifies the number of observations before the end of the data. If BACK=n and the number of observations is T, then the first $T - n$ observations are used to diagnose a series. The default is BACK=0.

BASENAME=*SAS-name*

prefixes any generated XML specification file name in the absence of other contextual base name options(i.e. COMBINEBASE=, SPECBASE=, SELECTBASE=). If the BASENAME=MYSPEC, then the generated specification files are named MYSPEC0, . . . , MYSPEC9999999999. The default *SAS-name* uses the prefix DIAG and generates file names DIAG0, . . . , DIAG9999999999. The generated files are stored in the model repository defined by the REPOSITORY= option.

COMBINEBASE=*SAS-name*

prefixes the combined model list file name. If you specify COMBINEBASE=MYCOMB, the automatically generated combined model list files are named MYCOMB0, MYCOMB1, and so on. If not specified, combined model list files are named according to the rules for the BASENAME= option. Combined model list files are stored in the model repository defined by the REPOSITORY= option. You should note that automatic model combinations are only generated when you specify the

COMBINE statement as part of the HPFDIAGNOSE procedure statement block, otherwise, specifying this option has no effect.

CRITERION=*option*

specifies the model selection criterion to select the best model. This option is often used in conjunction with the HOLDOUT= and HOLDOUTPCT= options. The default is CRITERION=RMSE. The following statistics of fit are provided:

SSE	sum of square error
MSE	mean squared error
RMSE	root mean squared error
UMSE	unbiased mean squared error
URMSE	unbiased root mean squared error
MAXPE	maximum percent error
MINPE	minimum percent error
MPE	mean percent error
MAPE	mean absolute percent error
MDAPE	median percent error
GMAPE	geometric mean percent error
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MPPE	mean predictive percent error
MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median predictive percent error
GMAPPE	geometric mean predictive percent error
MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error
MSPE	mean symmetric percent error
SMAPE	symmetric mean absolute percent error
MDASPE	median symmetric percent error
GMASPE	geometric mean symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error

MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MAXERR	maximum error
MINERR	minimum error
ME	mean error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R-square
ADJRSQ	adjusted R-square
AADJRSQ	Amemiya's adjusted R-square
RWRSQ	random walk R-square
AIC	Akaike information criterion
AICC	Akaike information corrected criterion
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion

DATA=*SAS data set*

specifies the name of the SAS data set that contains the time series. If the DATA= option is not specified, the most recently created SAS data set is used.

DELAYEVENT=*number*

specifies the delay lag for the events. If the option is not specified, the delay lag for the events is set to zero by default.

DELAYINPUT=*number*

specifies the delay lag for the inputs. If the option is not specified, the delay lag for the inputs is appropriately chosen by the procedure.

ENTRYPCT=*number*

specifies a threshold to check the percentage increment of the criterion between two candidate models. The ENTRYPCT=value should be in (0,100); the default is ENTRYPCT=0.1.

ERRORCONTROL=(SEVERITY= (*severity-options***) STAGE= (** *stage-options***) MAXMESSAGE=***number***)**

allows finer control of message printing. The error severity level and the HPFDIAGNOSE procedure processing stages are set independently. The MAXMESSAGE=*number* option controls the number of messages printed. A logical 'and' is taken over all the specified options and any message.

Available *severity-options* are as follows:

LOW	specifies low severity, minor issues
MEDIUM	specifies medium severity problems

HIGH	specifies severe errors
ALL	specifies all severity levels of LOW, MEDIUM, and HIGH options
NONE	specifies that no messages from PROC HPFDIAGNOSE are printed

Available *stage-options* are as follows:

PROCEDURELEVEL	specifies that the procedure stage is option processing and validation
DATAPREP	specifies the accumulation of data and the application of SETMISS= and ZEROMISS= options
DIAGNOSE	specifies the diagnostic process
ALL	specifies all PROCEDURELEVEL, DATAPREP, and DIAGNOSE options

Examples are as follows.

The following statement prints high- and moderate-severity errors at any processing stage of PROC HPFDIAGNOSE:

```
errorcontrol=(severity=(high medium) stage=all)
```

The following statement prints high-severity errors only during the data preparation:

```
errorcontrol=(severity=high stage=dataprep)
```

The following statement turns off messages from PROC HPFDIAGNOSE:

```
errorcontrol=(severity=none stage=all)
errorcontrol=(maxmessage=0)
```

Each of the following statements specifies the default behavior:

```
errorcontrol=( severity=(high medium low)
               stage=(procedurelevel dataprep diagnose) )


errorcontrol=(severity=all stage=all)
```

EVENTBY=*SAS data set*

specifies the name of the event data set that contains the events for specific BY groups that are created by DATA steps. The events in the EVENT statement are used in all BY groups, but the events in the EVENTBY= data set are used in the specific BY group.

EXCEPTIONS=*except-option*

specifies the desired handling of arithmetic exceptions during the run. You can specify *except-option* as one of the following:

IGNORE specifies that PROC HPFDIAGNOSE stop on an arithmetic exception. No recovery is attempted. This is the default behavior if the EXCEPTIONS= option is not specified.

CATCH specifies that PROC HPFDIAGNOSE skip the generation of diagnostic output for the variable that produces the exception in the current BY group. PROC HPFDIAGNOSE generates a record to the OUTEST= data set with a blank select list name in the _SELECT_ column. The blank select list name reflects the handled exception on that combination of variable and BY group.

HOLDOUT=*number*

specifies the size of the holdout sample to be used for model selection. The holdout sample is a subset of the dependent time series that ends at the last nonmissing observation. The statistics of a model selection criterion are computed using only the holdout sample. The default is HOLDOUT=0.

HOLDOUTPCT=*value*

specifies the size of the holdout sample as a percentage of the length of the dependent time series. If HOLDOUT=5 and HOLDOUTPCT=10, the size of the holdout sample is $min(5, 0.1T)$ where T is the length of the dependent time series with beginning and ending missing values removed. The default is HOLDOUTPCT=0.

INEST=*SAS data set*

contains information that maps forecast variables to models or selection lists, and data set variables to model variables.

INEVENT=*SAS data set*

specifies the name of the event data set that contains the event definitions created by the HPFEVENTS procedure. If the INEVENT= data set is not specified, only SAS predefined event definitions can be used in the EVENT statement.

For more information about the INEVENT= option, see Chapter 7, "The HPFEVENTS Procedure."

INPUTMISSINGPCT=*value*

specifies the size of the missing observation as a percentage of the length of the input time series. If INPUTMISSINGPCT=50, then the input time series that has more than 50% missing data is ignored in the model. The default is INPUTMISSINGPCT=10.

INSELECTNAME=*SAS-name*

specifies the name of a catalog entry that serves as a model selection list. This is the selection list that includes existing model specification files. A selection list created by the HPFDIAGNOSE procedure includes the existing model specification files.

MINOBS=(SEASON=*number* **TREND=***number***)**

SEASON= specifies that no seasonal model is fitted to any series with fewer nonmissing observations than *number* × (season length). The value of *number* must be greater than or equal to 1. The default is *number* = 2.

TREND= specifies that no trend model is fitted to any series with fewer nonmissing observations than *number* . The value of *number* must be greater than or equal to 1. The default is *number* = 1.

NODIAGNOSE
specifies that the series is not diagnosed. If the INSELECTNAME= option and OUTEST= option are specified, the existing model specification files are written to the OUTEST data set.

NOINESTOPTS
specifies that the selection lists referred to by the INEST= option are not used in the diagnosed version.

OUTEST=*SAS data set*
contains information that maps data set variables to model symbols and references model specification files and model selection list files.

OUTOUTLIER=*SAS data set*
contains information that is associated with the detected outliers.

OUTPROCINFO=*SAS-data-set*
names the output data set to contain the summary information of the processing done by PROC HPFDIAGNOSE. This option is particularly useful for easy programmatic assessment of the status of the procedure's execution via a data set instead of looking at or parsing the SAS log.

PREFILTER=MISSING | YES | EXTREME | BOTH
specifies how missing and extreme values are handled prior to diagnostic tests.

MISSING specifies that smoothed values for missing data are applied for tentative order selection and missing values are used for the final diagnostics.

YES specifies that smoothed values for missing data are applied to overall diagnoses. This option is the default.

EXTREME specifies that extreme values are set to missing for a tentative ARIMA model and extreme values are used for the final ARIMAX model diagnostics.

BOTH is equivalent to both YES and EXTREME.

If the input variables have missing values, they are always smoothed for the diagnostics.

PRINT=NONE | SHORT | LONG | ALL
specifies the print option.

NONE suppresses the printed output. This option is the default.

SHORT prints the model specifications. This option also prints only the significant input variables, events, and outliers.

LONG prints the summary of the transform, the stationarity test, and the determination of ARMA order in addition to all of the information printed by PRINT=SHORT.

ALL prints the details of the stationarity test and the determination of ARMA order. This option prints the detail information about all input variables and events under consideration.

REPOSITORY=*catalog*

contains information about model specification files and model selection list files. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=. The default model repository is Sasuser.Hpfdflt.

RETAINCHOOSE=YES | NO

RETAINCHOOSE=TRUE | FALSE

specifies that the CHOOSE= option in the HPFSELECT procedure is respected when re-diagnosing series. The default is RETAINCHOOSE=NO.

SEASONALITY=*number*

specifies the length of the seasonal cycle. The *number* should be a positive integer. For example, SEASONALITY=3 means that every group of three observations forms a seasonal cycle. By default, the length of the seasonal cycle is 1 (no seasonality) or the length implied by the INTERVAL= option specified in the ID statement. For example, INTERVAL=MONTH implies that the length of the seasonal cycle is 12.

SELECTINPUT=SELECT | ALL | *number*

specifies the maximum number of the input variables to select.

SELECT selects the input variables that satisfy the criteria (noncollinearity, nonnegative delay, smaller AIC). This option is the default.

ALL selects the input variables that satisfy the criteria (noncollinearity, nonnegative delay).

number selects the best *number* input variables that satisfy the criteria (noncollinearity, nonnegative delay).

SELECTEVENT=SELECT | ALL |*number*

specifies the maximum number of events to select.

SELECT selects the events that satisfy the criteria (noncollinearity, smaller AIC). This option is the default.

ALL selects the events that satisfy the criteria (noncollinearity).

number selects the best *number* of events that satisfy the criteria (noncollinearity).

SIGLEVEL=*value*

specifies the cutoff value for all diagnostic tests such as log transformation, stationarity, tentative ARMA order selection, and significance of UCM components. The SIGLEVEL=value should be between (0,1) and SIGLEVEL=0.05 is the default. The SIGLEVEL options in TRANSFORM, TREND, ARIMAX, and UCM statements control testing independently.

SELECTBASE=*SAS-name*

prefixes the model selection list file name. If the SELECTBASE=MYSELECT, then the model selection list files are named MYSELECT0, MYSELECT1, and so on. If not specified, model selection list files are named according to the rules defined for the BASENAME= option. Model selection list files are stored in the model repository defined by the REPOSITORY= option.

SPECBASE=*SAS-name*

prefixes the model specification file name. If the SPECBASE=MYSPEC, then the model specification files are named MYSPEC0, MYSPECT1, and so on. If not specified, model specification files are named according to the rules defined for the BASENAME= option. Model specification files are stored in the model repository defined by the REPOSITORY= option.

TESTINPUT=TRANSFORM | TREND | BOTH

TRANSFORM	specifies that the log transform testing of the input variables is applied independently of the variable to be forecast.
TREND	specifies that the trend testing of the input variables is applied independently of the variable to be forecast.
BOTH	specifies that the log transform and trend testing of the input variables are applied independently of the variable to be forecast.

If this option is not specified, the same differencing is applied to the input variables as is used for the variable to be forecast, and no transformation is applied to the input variables.

ADJUST Statement

ADJUST *variable = (variable-list) / options* **;**

The ADJUST statement lists the numeric variables in the DATA= data set whose accumulated values are used to adjust the dependent values. Adjustments are performed before diagnostics.

The numeric variable listed is the variable to which adjustments specified in that statement applies. This variable must appear in a FORECAST statement.

The numeric variables used as the source of the adjustments are listed following the parentheses. For more information see the section "Adjustment Operations" on page 126 section.

The following options can be used with the ADJUST statement.

OPERATION=*option*

specifies how the adjustments are applied to the forecast variable. The option determines how the adjustment variables are applied to the dependent variable prior to diagnostics.

Computations with missing values are handled differently in the ADJUST statement than in other parts of SAS. If any of the adjustment operations result in a nonmissing dependent value being added to, subtracted from, divided by, or multiplied by a missing value, the nonmissing dependent value is left unchanged. Division by zero produces a missing value.

The following predefined adjustment operations are provided:

NONE	No adjustment operation is performed. This is the default.
ADD	Variables listed in the adjustment statement are added to the dependent variable.
SUBTRACT	Variables listed in the adjustment statement are subtracted from the dependent variable.
MULTIPLY	Dependent variable is multiplied by variables listed in the adjustment statement.
DIVIDE	Dependent variable is divided by variables listed in the adjustment statement.
MIN	Dependent variable is set to the minimum of the dependent variable and all variables listed in the adjustment statement.
MAX	Dependent variable is set to the maximum of the dependent variable and all variables listed in the adjustment statement.

ACCUMULATE=*option*
See the ACCUMULATE= option in the section "ID Statement" on page 119 for more details.

SETMISSING=*option* | *number*
See the SETMISSING= option in the section "ID Statement" on page 119 for more details.

TRIMMISS=*option*
See the TRIMMISS= option in the section "ID Statement" on page 119 for more details.

ZEROMISS=*option*
See the ZEROMISS= option in the section "ID Statement" on page 119 for more details.

ARIMAX Statement

ARIMAX < *options* > **;**

An ARIMAX statement can be used to find an appropriate ARIMAX specification.

The HPFDIAGNOSE procedure performs the intermittency test first. If the series is intermittent, an intermittent demand model is fitted to the data and the ARIMAX statement is not applicable. If the series is not intermittent, an ARIMAX model is fitted to the data.

If a model statement is not specified, the HPFDIAGNOSE procedure diagnoses ARIMAX and exponential smoothing models if the series is not intermittent, but diagnoses an intermittent demand model if the series is intermittent.

The following options can be used in the ARIMAX statement.

PERROR=(*number* **:** *number***)**
specifies the range of the AR order for obtaining the error series used in the MINIC method. The default is (maxp:maxp+maxq).

P=(*number* **:** *number***) (***number* **:** *number***)**
specifies the range of the nonseasonal and seasonal AR orders. The default is (0:5)(0:2).

Q=(*number* **:** *number***) (***number* **:** *number***)**
specifies the range of the nonseasonal and seasonal MA orders. The default is (0:5)(0:2).

DEN=(*number* **:** *number***)**
specifies the range of the denominator order of the transfer function. The default is (0:2).

NUM=(*number* **:** *number***)**
specifies the range of the numerator order of the transfer function. The default is (0:2).

CRITERION=AIC | SBC
specifies the criterion for the tentative ARMA order selection. The default is CRITERION=SBC.

SIGLEVEL=*value*
specifies the significance level to use as a cutoff value to decide the AR and MA orders. The SIGLEVEL=value should be in (0,1). The SIGLEVEL= option overrides the value of SIGLEVEL= option in the HPFDIAGNOSE statement.

ESTMETHOD=CLS | ULS | ML
specifies the method for choosing the tentative ARMA orders (Choi 1992; Tsay and Tiao 1984).

CLS	conditional least squares method. This option is the default.
ULS	unconditional least squares method
ML	maximum likelihood method

METHOD=ESACF | MINIC | SCAN
specifies the method for choosing the tentative ARMA orders (Choi 1992; Tsay and Tiao 1984).

ESACF	extended sample autocorrelation function
MINIC	minimum information criterion. This option is the default.
SCAN	smallest canonical correlation analysis

OUTLIER=(*options***)**
specifies outlier detection in an ARIMAX model (De Jong and Penzer 1998).

DETECT=YES includes outliers detected in a model if the model that includes the outliers is successfully diagnosed.

DETECT=MAYBE includes outliers detected in a model if the model that includes the outliers is successfully diagnosed and has a smaller criterion than the model without outliers. This option is the default.

DETECT=NO no outlier detection is performed.

FILTER=FULL | SUBSET chooses a model for outlier detection. If FILTER=FULL, then use a full model. If FILTER=SUBSET, then use a subset model that includes nonseasonal AR and MA filters only. If the data have no seasonality, then the outlier detection is not affected by the FILTER= option. FILTER=FULL is the default.

MAXNUM=*number* includes up to MAXNUM= value outliers in a model. MAXNUM=2 is the default.

MAXPCT=*value* includes up to MAXPCT= value outliers in a model. MAXPCT=2 is the default. If MAXNUM=5 and MAXPCT=10, the number of the outliers is $min(5, 0.1T)$ where T is the length of the time series with beginning and ending missing values removed.

TYPE=*option* | (*options*) specifies the type of outliers. If the TYPE= option is not specified, then both AO and LS types are searched for outliers. The *options* are as follows.

AO specifies additive outliers.

LS specifies level shift outliers.

TLS(*value,...,value*) specifies temporary level shift outliers. The value is a duration of a temporary level shift and should be greater than or equal to 2. Examples are TYPE=TLS(2) and TYPE=TLS(3,9,15).

SIGLEVEL=*value* specifies the cutoff value for outlier detection. The SIGLEVEL=value should be in (0,1). The SIGLEVEL=0.01 is the default. The SIGLEVEL= option overrides the value of SIGLEVEL= option in the HPFDIAGNOSE statement.

ENTRYPCT=*number* specifies a threshold to check the percentage increment of the criterion between two candidate models. The ENTRYPCT=value should be in (0,100); the default is ENTRYPCT=0.1. The ENTRYPCT= option overrides the value of the ENTRYPCT= option in the HPFDIAGNOSE statement.

If the OUTLIER= option is not specified, the HPFDIAGNOSE performs the outlier detection with the OUTLIER=(DETECT=MAYBE MAXNUM=2 MAXPCT=2 SIGLEVEL=0.01) option as default.

If the PREFILTER=EXTREME option is specified in the PROC HPFDIAGNOSE statement and extreme values are found, then these values are potential outliers. With the PREFILTER=EXTREME option, outliers might be detected even if the DETECT=NO option is specified and more than *n* number of outliers can be detected even if the MAXNUM=*n* option is specified.

IDENTIFYORDER=ARIMA | REG | BOTH

IDENTIFY=ARIMA | REG | BOTH

specifies the identification order when inputs and events are specified.

ARIMA finds an ARIMA model for the error series first and then chooses significant inputs and events. This option is the default.

REG finds a regression model first and then decides the AR and MA polynomial orders.

BOTH fits models by using the two methods and determines the better model.

REFINEPARMS=(*options* **)**

specifies to refine insignificant parameters of the final model, identify the factors to refine, and identify the order of factors.

SIGLEVEL= specifies the cutoff value for all refining insignificant parameters. The SIGLEVEL=value should be between (0,1); SIGLEVEL=0.4 is the default.

FACTOR=ALL refines the parameters for all factors. This option is the default.

FACTOR=ARMA refines the parameters for ARMA factor.

FACTOR=EVENT refines the parameters for EVENT factor.

FACTOR=INPUT refines the parameters for INPUT factor.

Using parentheses, more than one option can be specified. For example, the option FACTOR=(ARMA EVENT) refines the parameters for ARMA and EVENT.

The FIRST= and SECOND= options take one of the factors ARMA, EVENT, and INPUT.

FIRST= specifies the factor that refines first.

SECOND= specifies the factor that refines second.

The default order of refining is ARMA, EVENT, INPUT.

If you omit the REFINEPARMS= option, PROC HPFDIAGNOSE does not refine insignificant parameters of the final autogenerated ARIMAX model. Also, if you specify the keyword REFINEPARMS without any additional arguments, the procedure refines insignificant parameters of the final model with the REFINEPARMS=(SIGLEVEL=0.4 FACTOR=ALL FIRST=ARMA SECOND=EVENT) option as the default.

NOINT

NOCONSTANT

suppresses the intercept (constant) term.

BY Statement

BY *variables* **;**

A BY statement can be used with PROC HPFDIAGNOSE to obtain separate dummy variable definitions for groups of observations defined by the BY variables.

When a BY statement appears, the procedure expects the input data set to be sorted in order of the BY variables.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data by using the SORT procedure with a similar BY statement.
- Specify the NOTSORTED or DESCENDING option in the BY statement for the HPFDIAGNOSE procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged in groups (according to values of the BY variables) and that these groups are not necessarily in alphabetical or increasing numeric order.
- Create an index on the BY variables by using the DATASETS procedure.

For more information about the BY statement, see *SAS Language Reference: Concepts*. For more information about the DATASETS procedure, see the discussion in the *Base SAS Procedures Guide.*

COMBINE Statement

COMBINE *options* **;**

The COMBINE statement serves two purposes. Foremost, it causes PROC HPFDIAGNOSE to automatically generate a combined model for the set of time series models it generates from its diagnosis of each series during the run. Additionally, through the various options in the COMBINE statement, you define the desired combination semantics for the combined model it generates.

The following example illustrates a typical use of the COMBINE statement:

```
proc hpfdiagnose
     data=sales.data
     rep=work.diagcomb1
     outest=diagest;
  by region store product;
  id date interval=month;
  forecast Nunits;
  input Unit_Price/required=yes;
  esm;
  arimax;
  combine method=average encompass=ols misspercent=25 hormisspercent=10;
run;
```

The presence of the COMBINE statement in the PROC HPFDIAGNOSE statement block causes the automatic generation of a combined model list that includes the time series models generated from the diagnosis of the Nunits series for each BY group. The custom model selection list generated for each BY group includes a reference to another XML specification that instructs PROC HPFENGINE to generate a combined forecast from the forecasts of the individual time series models. This is strictly an XML generation process in the context of PROC HPFDIAGNOSE. No additional computational overhead is incurred in the context of PROC HPFDIAGNOSE to generate this additional combined model list. Computational details for how PROC HPFENGINE interprets the combined model list to produce combined forecasts can be found in Chapter 16, "Forecast Combination Computational Details."

A combined model list is generated for each diagnosed series when all of the following are true:

- A COMBINE statement is specified in the PROC HPFDIAGNOSE statement block.
- The number of models generated from the series diagnosis is more than 1.
- None of the generated models is an IDM model.

The following options affect the evaluation of the combined forecast produced by the combined model list. The COMBINE statement syntax is identical to that of the HPFSELECT procedure.

CRITERION=*option*

specifies the forecast combination criterion (statistic of fit) to be used when ranking forecast candidates in the context of the COMBINE statement. This option is often used in conjunction with the ENCOMPASS= and METHOD=RANKWGT options. The default is CRITERION=RMSE. See "Valid Statistic of Fit Names" on page 364 for valid values for *option*.

ENCOMPASS=NONE

ENCOMPASS=*test-name***(***test-options***)**

specifies whether a forecast encompassing test be performed, and if so which type of test. The encompassing test attempts to eliminate forecasts from consideration that fail to add significant information to the final forecast. The default is ENCOMPASS=NONE, which specifies that no encompassing test be performed.

You can specify the following values for *test-name* and *test-options*:

OLS(ALPHA=*number*) uses an OLS-based regression test to estimate pairwise encompassing between candidate forecasts. Candidates are ranked from best to worst using the CRITERION= values. Iterating from best to worst, inferior candidates are tested with the best of the untested candidates for retention in the combined set. The significance level for the test is given by specifying ALPHA=*number* option. The default value is ALPHA=0.05 when the simple form ENCOMPASS=OLS is specified. The range is 0 to 1.

HLN(ALPHA=*number*) uses the Harvey-Leybourne-Newbold (HLN) test to estimate pairwise encompassing between candidate forecasts. Candidates are ranked from best to worst using the CRITERION= values. Iterating from best to worst, inferior candidates are tested with the best of the untested candidates for retention in the combined set. The significance level for the test is given by specifying ALPHA=*number* option. The default value is ALPHA=0.05 when the simple form ENCOMPASS=HLN is specified. The range is 0 to 1.

HORMISSPERCENT=*number*

specifies a threshold for the percentage of missing forecast values in the combination horizon used to exclude a candidate forecast from consideration in the final combination. By default, no horizon missing percentage test is performed on candidate forecasts. If specified, the admissible range is 1 to 100. The forecast horizon is the region of time in which multistep forecasts are generated. This test and the MISSPERCENT test operate independent of each other. One or both can be specified.

METHOD=*weight-method***(***method-options***)**

specifies the method for determining the combination weights used in the weighted average of the candidate forecasts in the combination list. The default method is METHOD=AVERAGE. The simple form METHOD=*weight-method* can be used when no weight-specific options are desired.

The following values for *weight-method* and *method-options* can be specified:

AICC(*AICC-opts*) computes the combination weights based on corrected AIC weights. See Chapter 16, "Forecast Combination Computational Details," for the mathematical details of this process. Frequently there is considerable disparity between the weights because of the exponential weighting scheme, so options are allowed to affect the scaling and to cull low-scoring candidates from consideration for computational efficiency. By default, all AICC scored candidate forecasts are combined.

Possible values for *AICC-opts* include:

ABSWGT=*number* omits computed weights with values less than the specified value. The range is 0 to 1 inclusive. The remaining weights are normalized to sum to 1.

BESTPCT=*number* retains the best N of the candidates as a percentage of the total number weighted, where

$$N = \max\{\lfloor \frac{\textit{number} \cdot M}{100} \rfloor, 1\} \tag{4.1}$$

and M denotes the number of candidate models in the combination after any specified forecast exclusion tests have been performed.

The N remaining weights are normalized to sum to 1.

BESTN=*N* retains the best N of the candidates as a percentage of the total number weighted. The N remaining weights are normalized to sum to 1.

LAMBDA=*number* specifies the scale factor used in the computation of the AICC weights. The default is LAMBDA=1.0, which results in the usual Akaike weights.

AVERAGE computes the simple average of the forecasts selected for combination. This is the default.

ERLS(*NLP-opts*) computes the combination weights based on a constrained least squares problem to minimize the ℓ_2 norm of the combined forecast residuals subject to the constraint that the weights sum to 1.

LAD(*LAD-opts*) computes the weights based on a least absolute deviations measure of fit for the combined forecast. A linear program is formulated according to the *LAD-opts* to minimize an objective function expressed in terms of a absolute values of a loss series subject to constraints that the weights sum to 1 and be nonnegative. Options permitted in *LAD-opts* include OBJTYPE and ERRTYPE.

The form of the objective can be specified by the OBJTYPE= option as:

OBJTYPE=L1 specifies that the objective is an ℓ_1 norm involving loss series.

OBJTYPE=LINF specifies that the objective is an ℓ_∞ norm involving the loss series.

The form of the loss series in the objective can be specified as:

ERRTYPE=ABS specifies loss series terms are deviations.

ERRTYPE=APE specifies loss series terms are percentage deviations.

ERRTYPE=RAE specifies loss series terms are relative error deviations.

NERLS(*NLP-opts*) computes the combination weights based on a constrained least squares problem to minimize the ℓ_2 norm of the combined forecast residuals subject to the constraints that the weights sum to 1 and be nonnegative.

NRLS(*NLP-opts*) computes the combination weights based on a constrained least squares problem to minimize the ℓ_2 norm of the combined forecast residuals subject to the constraints that the weights be nonnegative.

OLS computes the combination weights that result from the ordinary least squares problem to minimize the ℓ_2 norm of the combined forecast residuals.

RANKWGT*(W1,...,Wn)* assigns weights by using the rank of the candidate forecasts at the time the combination is performed as determined by the COMBINE statement CRITERION= values. These weights must sum to 1. If not, they are normalized and a warning is issued. The number of values specified must agree with the number of specification names declared in the SPECIFICATION statements in the PROC HPFDIAGNOSE statement block. The weights are assigned by ranking the candidate forecasts from best to worst. The best uses the first weight, W1, and so on. The set of weights used is normalized to account for candidates that fail to forecast or for candidates that are omitted from the final combination because of any of the COMBINE statement exclusion tests.

RMSEWGT computes the combination weights based on the RMSE statistic of fit for the forecast contributors. The weights are normalized to sum to 1. See Chapter 16, "Forecast Combination Computational Details," for details.

USERDEF*(W1,...,Wn)* assigns weights by using the list of user-specified values. These weights must sum to 1. If not, they are normalized and a warning is issued. The number of values specified must agree with the number of specification names declared in the SPECIFICATION statements in the PROC HPFDIAGNOSE statement block. The weights correspond with the order of the names in the SPECIFICATION statements. The set of weights used is normalized to account for candidates that fail to forecast or for candidates that are omitted from the final combination due to any of the COMBINE statement exclusion tests.

MISSMODE=*miss-method*

specifies a method for treating missing values in the forecast combination. In a given time slice across the combination ensemble, one or more combination contributors can have a missing value. This setting determines the treatment of those in the final combination for such time indices.

The following values for *miss-method* can be specified:

RESCALE rescales the combination weights for the nonmissing contributors at each time index to sum to 1.

MISSING generates a missing combined forecast at each time index with one or more missing contributors.

The default behavior is determined by the weight method selected as follows:

- MISSMODE=RESCALE is the default for simple average, user-specified weights, ranked user weights, ranked weights, and RMSE weights.
- MISSMODE=MISSING is the default for AICC weights, OLS weights, restricted least squares weights, and LAD weights. For OLS and NRLS you cannot specify MISSMODE=RESCALE since the estimated weights are not constrained to sum to one.

MISSPERCENT=*number*

specifies a threshold for the percentage of missing forecast values in the combination estimation region that is used to exclude a candidate forecast from consideration in the final combination. By default, no missing percentage test is performed on candidate forecasts. If specified, the admissible range is 1 to 100. This test and the HORMISSPERCENT test operate independent of each other. One or both can be specified.

STDERR=*stderr-method*(*stderr-options*)

SEMODE=*stderr-method*(*stderr-options*)

specifies the method for computing the prediction error variance series. This series is used to compute the prediction standard error, which in turn is used to compute confidence bands on the combined forecast.

The simple form STDERR=*stderr-method* can be used when no method-specific options are desired.

The following values for *stderr-method* and *stderr-options* can be specified:

STDERR=DIAG computes the prediction error variance by assuming the forecast errors at time t are uncorrelated so that the simple diagonal form of Σ_t is used. This is the default method for computing prediction error variance.

STDERR=ESTCORR computes the prediction error variance by using estimates of $\rho_{i,j,t}$, the sample cross-correlation between $e_{i,t}$ and $e_{j,t}$ over the time span $t = 1, \ldots, T$, where t denotes the last time index of the actual series y_t. Of course, this option implies that the error series $e_{i,t}$ and $e_{j,t}$ are assumed to be jointly stationary.

STDERR=ESTCORR(TAU=τ) is similar to STDERR=ESTCORR except that the cross-correlation estimates are localized to a time window of τ steps. The time span $t = 1, \ldots, T$ is quantized into segments of τ steps working from t backwards for in-sample cross-correlation estimates. The cross-correlation estimates from the interval $[T - \tau, T]$ are used for the period of multistep forecasts that extend beyond time t.

ESM Statement

ESM < *option* > **;**

An ESM statement can be used to find an appropriate exponential smoothing model specification based on the model selection criterion (McKenzie 1984).

The HPFDIAGNOSE procedure performs the intermittency test first. If the series is intermittent, an intermittent demand model is fitted to the data and the ESM statement is not applicable. If the series is not intermittent, an ESM is fitted to the data.

The ESM method is one of the default methods that the HPFDIAGNOSE procedure uses to fit a model. If you do not specify a modeling statement, such as an ESM, ARIMAX, IDM, or UCM statement, and if you do not specify the REPOSITORY= option in the HPFDIAGNOSE statement, then the HPFDIAGNOSE procedure diagnoses ARIMAX and exponential smoothing models for a nonintermittent series and an intermittent demand model for an intermittent series.

METHOD=BEST | BESTN | BESTS

specifies the method to be used to select an appropriate forecast model. You can specify the following methods:

BEST uses seasonal properties of the data to choose between the BESTN and BESTS methods. If the data consist of a single seasonal cycle, the BESTN method is used. Otherwise, a seasonality test is performed on both the original data and the original data after one nonseasonal difference is taken. If seasonality is present in either

the original or differenced series, the series is considered to be seasonal. If the data are seasonal, the BESTS method is used. If neither seasonality test indicates seasonality, the BESTN method is used. The results of the seasonality test are summarized in Table 4.2. You can specify the significance level for the seasonality test by using the SIGLEVEL option in the PROC HPFDIAGNOSE statement. The default value of the SIGLEVEL option is 0.05. For more information about the seasonality test, see the SEASONTEST function of the time series analysis (TSA) package.

BESTN fits the best candidate nonseasonal smoothing model (SIMPLE, DOUBLE, LINEAR, or DAMPTREND).

BESTS fits the best candidate seasonal smoothing model (SEASONAL, WINTERS, or ADDWINTERS).

By default, METHOD=BEST.

Table 4.2 Results of BEST Method of the ESM Statement

Number of Seasonal Cycles	Result of Seasonality Test	Method Used
< 2	Test is not performed	BESTN
≥ 2	Test indicates seasonality	BESTS
≥ 2	Test does not indicate seasonality	BESTN

EVENT Statement

EVENT *event-names* **;**

The EVENT statement names either event names or _ALL_. The event names identify the events in the INEVENT= data set or are the SAS predefined event keywords. _ALL_ is used to indicate that all simple events in the INEVENT= data set should be included in processing. If combination events exist in the INEVENT= data set and are to be included, then they must be specified in a separate EVENT statement. The HPFDIAGNOSE procedure does not currently process group events, although if the simple events associated with the group are defined in the INEVENT= data set, they can be included in processing, either by event name or by using _ALL_.

The EVENT statement requires the ID statement.

For more information about the EVENT statement, see Chapter 7, "The HPFEVENTS Procedure."

The following option can be used in the EVENT statement:

REQUIRED=YES | MAYBE | NO

YES	specifies that the events be included in the model as long as the model does not fail to be diagnosed.
MAYBE	specifies that the events be included in the model as long as the parameters of events are significant.
NO	specifies that the events be included in the model as long as the parameters of events are significant and the increment of the value of criterion exceeds a threshold. The default is REQUIRED=NO.

The same differencing is applied to the events as is used for the variables to be forecast. No functional transformations are applied to the events.

FORECAST Statement

FORECAST *variables* / < / *options* > **;**

Any number of FORECAST statements can be used in the HPFDIAGNOSE procedure. The FORECAST statement lists the variables in the DATA= data set to be diagnosed. The variables are dependent or response variables that you want to forecast in the HPFENGINE procedure.

The following options can be used in the FORECAST statement.

ACCUMULATE=*option*
See the ACCUMULATE= option in the section "ID Statement" on page 119 for more details.

SETMISSING=*option* |*number*
See the SETMISSING= option in the section "ID Statement" on page 119 for more details.

TRIMMISS=*option*
See the TRIMMISS= option in the section "ID Statement" on page 119 for more details.

ZEROMISS=*option*
See the ZEROMISS= option in the section "ID Statement" on page 119 for more details.

ID Statement

ID *variable options* **;**

The ID statement names a numeric variable that identifies observations in the input and output data sets. The ID variable's values are assumed to be SAS date, time, or datetime values. In addition, the ID statement specifies the (desired) frequency associated with the time series. The ID statement options also specify how the observations are accumulated and how the time ID values are aligned to form the time series. The information specified affects all variables specified in subsequent FORECAST statements. If the ID statement is specified, the INTERVAL= option must also be specified. If an ID statement is not specified, the observation number (with respect to the BY group) is used as the time ID.

For more information about the ID statement, see the section "ID Statement" on page 184 in the HPFENGINE procedure.

ACCUMULATE=*option*

specifies how the data set observations are accumulated within each time period for the variables listed in the FORECAST statement. If the ACCUMULATE= option is not specified in the FORECAST statement, accumulation is determined by the ACCUMULATE= option of the ID statement. The ACCUMULATE= option accepts the following values: NONE, TOTAL, AVERAGE | AVG, MINIMUM | MIN, MEDIAN | MED, MAXIMUM | MAX, N, NMISS, NOBS, FIRST, LAST, STDDEV | STD, CSS, USS. The default is NONE.

ALIGN=*option*

controls the alignment of SAS dates used to identify output observations. The ALIGN= option accepts the following values: BEGINNING | BEG | B, MIDDLE | MID | M, and ENDING | END | E. BEGINNING is the default.

END=*option*

specifies a SAS date, datetime, or time value that represents the end of the data. If the last time ID variable value is less than the END= value, the series is extended with missing values. If the last time ID variable value is greater than the END= value, the series is truncated. For example, END="&sysdate" uses the automatic macro variable SYSDATE to extend or truncate the series to the current date. This option and the START= option can be used to ensure that data associated with each BY group contains the same number of observations.

INTERVAL=*interval*

specifies the frequency of the input time series. For example, if the input data set consists of quarterly observations, then INTERVAL=QTR should be used. If the SEASONALITY= option is not specified, the length of the seasonal cycle is implied by the INTERVAL= option. For example, INTERVAL=QTR implies a seasonal cycle of length 4. If the ACCUMULATE= option is also specified, the INTERVAL= option determines the time periods for the accumulation of observations. See *SAS/ETS User's Guide* for the intervals that can be specified.

SETMISSING=*option* | *number*

specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for variables listed in the FORECAST statement. If the SETMISSING= option is not specified in the FORECAST statement, missing values are set based on the SETMISSING= option of the ID statement. The SETMISSING= option accepts the following values: MISSING, AVERAGE | AVG, MINIMUM |

MIN, MEDIAN | MED, MAXIMUM | MAX, FIRST, LAST, PREVIOUS | PREV, NEXT. The default is MISSING.

START=*option*
specifies a SAS date, datetime, or time value that represents the beginning of the data. If the first time ID variable value is greater than the START= value, the series is prefixed with missing values. If the first time ID variable value is less than the END= value, the series is truncated. This option and the END= option can be used to ensure that data associated with each BY group contains the same number of observations.

TRIMMISS=*option*
specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the FORECAST statement. The following options are provided:

NONE	No missing value trimming is applied.
LEFT	Beginning missing values are trimmed.
RIGHT	Ending missing values are trimmed.
BOTH	Both beginning and ending missing value are trimmed. This option is the default.

If the TRIMMISS= option is not specified in the FORECAST statement, missing values are set based on the TRIMMISS= option of the ID statement.

ZEROMISS=*option*
specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the FORECAST statement. If the ZEROMISS= option is not specified in the FORECAST statement, missing values are set based on the ZEROMISS= option of the ID statement. The following options are provided:

NONE	Beginning and/or ending zeros unchanged. This option is the default.
LEFT	Beginning zeros are set to missing.
RIGHT	Ending zeros are set to missing.
BOTH	Both beginning and ending zeros are set to missing.

IDM Statement

IDM < *options* > **;**

An IDM statement is used to control the intermittency test. The HPFDIAGNOSE procedure performs the intermittency test first.

If the series is intermittent, an intermittent demand model is fitted to the data based on the model selection criterion. However, if the series is not intermittent, ARIMAX and exponential smoothing models are fitted to the data.

If a model statement is not specified, the HPFDIAGNOSE procedure diagnoses ARIMAX and exponential smoothing models if the series is not intermittent, but diagnoses an intermittent demand model if the series is intermittent.

INTERMITTENT=*number*

specifies a number greater than one that is used to determine whether or not a time series is intermittent. If the median demand interval is equal to or greater than this number, then the series is assumed to be intermittent. The default is INTERMITTENT=2.

BASE=AUTO | *value*

specifies the base value of the time series used to determine the demand series components. The demand series components are determined based on the departures from this base value. If a base value is specified, this value is used to determine the demand series components. If BASE=AUTO is specified, the time series properties are used to automatically adjust the time series. For the common definition of Croston's method, use BASE=0, which defines departures based on zero. The default is BASE=AUTO.

METHOD=CROSTON | AVERAGE | BEST

specifies the smoothing model of the time series.

CROSTON	The two smoothing models are used to fit the demand interval component and the demand size component.
AVERAGE	The single smoothing model is used to fit the average demand component.
BEST	Both CROSTON and AVERAGE methods are used to fit the intermittent series. The default is METHOD=BEST.

TRANSFORM=AUTO | LOG | NONE | SQRT | LOGISTIC | BOXCOX*(value)*

specifies the type of functional transformation. The following transformations are provided:

AUTO	Automatically choose between NONE and LOG based on model selection criteria. The default is TYPE=AUTO.
LOG	logarithmic transformation
NONE	No transformation is applied.
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*value*)	Box-Cox transformation with a parameter value where the value is between –5 and 5. The default is BOXCOX(1).

INPUT Statement

INPUT *variables* < / *options* > **;**

Any number of INPUT statements can be used in the HPFDIAGNOSE procedure. The INPUT statement lists the variables in the DATA= data set to be diagnosed as regressors. The variables are independent or predictor variables to be used to forecast dependent or response variables.

The following options can be used in the INPUT statement.

REQUIRED=YES | MAYBE | NO

YES	specifies that the input variables be included in the model as long as the model does not fail to be diagnosed.
MAYBE	specifies that the input variables be included in the model as long as their parameters are significant.
NO	specifies that the input variables be included in the model as long as their parameters are significant and the increment of the value of criterion exceeds a threshold. The default is REQUIRED=NO.

The same differencing is applied to the REQUIRED=YES variables as is used for the variables to be forecast. No functional transformations are applied to the REQUIRED=YES variables. The delay and numerator and denominator orders of the REQUIRED=YES variables are set to zero.

The functional transform and differencing of the REQUIRED=MAYBE or REQUIRED=NO variables depends on the request of the TESTINPUT option in the PROC HPFDIAGNOSE statement.

Either the POSITIVE or NEGATIVE option with parentheses can follow the REQUIRED= option. For example, specifying REQUIRED=YES(POSITIVE) drops the input variable from the model if its coefficient is negative, while specifying REQUIRED=YES(NEGATIVE) implies the opposite. The specification of POSITIVE or NEGATIVE does not mean that constraints are imposed during the estimation of the variable's coefficient in the model.

ACCUMULATE=*option*

See the ACCUMULATE= option in the section "ID Statement" on page 119 for more details.

SETMISSING=*option* |*number*

See the SETMISSING= option in the section "ID Statement" on page 119 for more details.

TRIMMISS=*option*

See the TRIMMISS= option in the section "ID Statement" on page 119 for more details.

ZEROMISS=*option*

See the ZEROMISS= option in the section "ID Statement" on page 119 for more details.

TRANSFORM Statement

TRANSFORM < *options* > **;**

A TRANSFORM statement can be used to specify the functional transformation of the series.

The following options can be used in the TRANSFORM statement.

SIGLEVEL=*value*

specifies the significance level to use as a cutoff value to decide whether or not the series requires a log transformation. The SIGLEVEL=value should be in (0,1). The SIGLEVEL= option overrides the value of SIGLEVEL= option in the HPFDIAGNOSE statement.

TRANSOPT=MEAN | MEDIAN

specifies whether mean or median forecasts are produced. If no transformation is applied to the series, then the mean and median forecasts are identical.

MEAN	The inverse transform produces mean forecasts. This is the default.
MEDIAN	The inverse transform produces median forecasts.

TYPE=AUTO | LOG | NONE | SQRT | LOGISTIC | BOXCOX*(value)*

specifies the type of functional transformation. The following transformations are provided:

AUTO	Automatically choose between NONE and LOG based on model selection criteria. If the TRANSFORM statement is specified but the TYPE= option is not specified, then TYPE=AUTO is the default.
LOG	logarithmic transformation
NONE	No transformation is applied. If the TRANSFORM statement is not specified, TYPE=NONE is the default.
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*value*)	Box-Cox transformation with a parameter value where the value is between –5 and 5. The default is BOXCOX(1).

TREND Statement

TREND < *options* > **;**

A TREND statement can be used to test whether the dependent series requires simple or seasonal differencing, or both. The augmented Dickey-Fuller test (Dickey and Fuller 1979) is used for the simple unit root test.

If the seasonality is less than or equal to 12, the seasonal augmented Dickey-Fuller (ADF) test (Dickey, Hasza, and Fuller 1984) is used for the seasonal unit root test. Otherwise, an AR(1) seasonal dummy test is used.

The joint simple and seasonal differencing test uses the Hasza-Fuller test (Hasza and Fuller 1979, 1984) in the special seasonality. Otherwise, proceed with the ADF test and the season dummy test.

The following options can be used in the TREND statement.

DIFF=AUTO | NONE | *number* **| (0 :** *number***)**

AUTO	tests for simple differencing. This option is the default.
NONE	specifies that no simple differencing be used.
number	specifies the simple differencing order. The option *number*=1 means $(1-B)y_t$ and *number*=2 means $(1-B)^2 y_t$.
(0 : *number*)	specifies the range of simple differencing order for testing. The option *number* can be 0, 1, or 2.

SDIFF=AUTO | NONE | *number*

AUTO	tests for seasonal differencing. This option is the default.
NONE	specifies that no seasonal differencing be used.
number	specifies the seasonal differencing order. The option *number*=1 means $(1-B^s)y_t$ and *number*=2 means $(1-B^s)^2 y_t$ where s is the seasonal period.

P=*number*

specifies the autoregressive order for the augmented unit root tests and a seasonality test. The default is P=$\min(5, [T/10])$ where t is the number of observations.

SIGLEVEL=*value*

specifies the significance level to use as a cutoff value to decide whether or not the series needs differencing. The SIGLEVEL=value should be in (0,1). The SIGLEVEL= option overrides the value of SIGLEVEL= option in the HPFDIAGNOSE statement.

UCM Statement

UCM < *options* > **;**

A UCM statement can be used to find an appropriate unobserved component model specification (Harvey 1989, 2001; Durbin and Koopman 2001).

The HPFDIAGNOSE procedure performs the intermittency test first. If the series is intermittent, an intermittent demand model is fitted to the data and the UCM statement is not applicable. If the series is not intermittent, an unobserved component model is fitted to the data.

The following options can be used in the UCM statement.

COMPONENT=(*components***)**

ALL	tests which components and/or variances are significant in the model. This option is the default. When the series has the seasonality information, the IRREGULAR, LEVEL, SLOPE, and SEASON components are included. Otherwise, the IRREGULAR, LEVEL, SLOPE, and CYCLE components are included.
AUTOREG	tests if an autoregressive component is significant in the model.
CYCLE	tests if two cycle components are significant in the model. The two CYCLE components are included and the LEVEL component is added. When the series has the seasonality information, the CYCLE component is not tested.
DEPLAG	tests if a dependent lag component is significant in the model. Only the order 1 is included.
IRREGULAR	tests if an irregular component is significant in the model.
LEVEL	tests if a level component is significant in the model.
SEASON	tests if a season component is significant in the model. When the series has the seasonality information, the SEASON component is not tested.
SLOPE	tests if a slope component is significant in the model. The LEVEL component is added.

SIGLEVEL=*value*

specifies the significance level to use as a cutoff value to decide which component and/or variances are significant. The SIGLEVEL=value should be in (0,1). The SIGLEVEL= option overrides the value of SIGLEVEL= option in the HPFDIAGNOSE statement.

REFINEPARMS= (SIGLEVEL= | FACTOR=(ALL | EVENT | INPUT) | FIRST=EVENT | INPUT)

specifies to refine insignificant parameters of the final model, identify the factors to refine, and identify the order of factors.

SIGLEVEL=	specifies the cutoff value for all refining insignificant parameters. The SIGLEVEL=value should be between (0,1); SIGLEVEL=0.4 is the default.
FACTOR=ALL	refines the parameters for all factors. This option is the default.
FACTOR=EVENT	refines the parameters for EVENT factor.

FACTOR=INPUT refines the parameters for INPUT factor.

Using parentheses, more than one option can be specified. For example, the option FACTOR=(EVENT INPUT) refines the parameters for EVENT and INPUT.

FIRST= specifies the factor which refines first.

The default order of refining is EVENT, INPUT.

If you omit the REFINEPARMS= option, PROC HPFDIAGNOSE does not refine insignificant parameters of the final autogenerated UCM. Also, if you specify the keyword REFINEPARMS without any additional arguments, the procedure refines insignificant parameters of the final model with the REFINEPARMS=(SIGLEVEL=0.4 FACTOR=ALL FIRST=EVENT) option as the default.

Details: HPFDIAGNOSE Procedure

Adjustment Operations

Preadjustment variables can be used to adjust the dependent series prior to model diagnostics.

If y_t is the dependent series and $z_{i,t}$ for $i = 1, \ldots, M$ are the M adjustment series, then the adjusted dependent series, w_t, is

$$\begin{aligned} w_t^1 &= op_i(y_t, z_{i,t}) \\ w_t^i &= op_i(w_t^{i-1}, z_{i,t}) \text{ for } 1 < i \leq M \\ w_t &= w_t^{\boldsymbol{M}} \end{aligned}$$

where op_i represents the ith preadjustment operator and w_t^i is the ith adjusted dependent series. The preadjustment operators are nested and applied sequentially from $i = 1, \ldots, M$.

Data Preparation

The HPFDIAGNOSE procedure does not use missing data at the beginning and/or end of the series.

Missing values in the middle of the series to be forecast would be handled with the PREFILTER=MISSING or PREFILTER=YES option. The PREFILTER=MISSING option uses smoothed values for missing data for tentative order selection in the ARIMAX modeling and for tentative components selection in the UCM modeling, but it uses the original values for the final diagnostics. The PREFILTER=YES option uses smoothed values for missing data and for all diagnostics.

Extreme values in the middle of the series to be forecast can be handled with the PREFILTER=EXTREME option in the ARIMA modeling. The HPFDIAGNOSE procedure replaces extreme values with missing values when determining a tentative ARIMA model, but it uses the original values for the final diagnostics.

The PREFILTER=EXTREME option detects extreme values if the absolute values of residuals are greater than 3 × STDDEV from a proper smoothed model.

If there are missing values in the middle of data for the input series, the procedure uses an interpolation method based on exponential smoothing to fill in the missing values.

The following data set provides a scenario for explaining the PREFILTER=EXTREME option.

```
data air_extreme;
   set sashelp.air;
   if _n_ = 30  then air = 500;
   if _n_ = 50  then air = 500;
   if _n_ = 100 then air = 700;
run;
```

In the following SAS statements, the HPFDIAGNOSE procedure diagnoses the new data set Air_Extreme without the PREFILTER=EXTREME option.

```
proc hpfdiagnose data=air_extreme print=short;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;
```

In Figure 4.6, the ARIMA$(0,1,1)(2,0,0)_{12}$ model is diagnosed for the time series. The diagnosed model has no seasonal differencing and is quite different from the model in Figure 4.1. The three extreme values mislead the model diagnostic tests.

Figure 4.6 ARIMAX Model Specification without Outliers

The HPFDIAGNOSE Procedure

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	Status
AIR	LOG	YES	0	1	1	2	0	0	12	RMSE	56.6436	OK

In the following SAS statements, the HPFDIAGNOSE procedure diagnoses the new data set Air_Extreme with the PREFILTER=EXTREME option.

```
proc hpfdiagnose data=air_extreme
                 prefilter=extreme
                 print=short;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;
```

In Figure 4.7, the ARIMA$(0,1,1)(0,1,1)_{12}$ model is diagnosed for the time series. The required seasonal differencing is detected.

Figure 4.7 ARIMAX Model Specification without Outliers

The HPFDIAGNOSE Procedure

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	Status
AIR	LOG	NO	0	1	1	0	1	1	12	RMSE	53.9316	OK

Figure 4.8 shows that the three extreme values are detected as outliers.

Figure 4.8 Outlier Information

ARIMA Outlier Selection

Variable	Type	Obs	Time	Chi-Square	Approx Pr > ChiSq
AIR	AO	30	JUN1951	223.88	<.0001
	AO	50	FEB1953	291.81	<.0001
	AO	100	APR1957	261.52	<.0001

After the three extreme values are included in the ARIMAX model, Figure 4.9 shows that the statistic of the model selection criterion drops substantially.

Figure 4.9 ARIMAX Model Specification with Outliers

ARIMA Model Specification After Adjusting for Outliers

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Outlier	Model Criterion	Statistic	Status
AIR	LOG	NO	0	1	1	0	1	1	12	3	RMSE	10.7626	OK

Functional Transformation

The log transform test compares the MSE or MAPE value after fitting an AR(p) model to the original data and to the logged data. If the MSE or MAPE value is smaller for the AR(p) model fitted to the logged data, then the HPFDIAGNOSE procedure performs the log transformation.

The next two sets of SAS statements specify the same log transformation test.

```
proc hpfdiagnose data=sashelp.air print=all;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;

proc hpfdiagnose data=sashelp.air print=all;
   id date interval=month;
   forecast air;
   arimax;
   transform type=auto;
run;
```

The "Functional Transformation Test" table shown in Figure 4.10 states that the airline data requires a log transformation.

Figure 4.10 Log Transformation Test

The HPFDIAGNOSE Procedure

Functional Transformation Test	
Variable	Functional Transform
AIR	LOG

Stationarity Test

The stationarity test decides whether the data requires differencing. Note that d is the simple differencing order, and D is the seasonal differencing order.

The next two sets of SAS statements specify the same trend test.

```
proc hpfdiagnose data=sashelp.air print=all;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;

proc hpfdiagnose data=sashelp.air print=all;
   id date interval=month;
   forecast air;
   transform;
   arimax;
   trend diff=auto sdiff=auto;
run;
```

Simple Differencing Order

The simple augmented Dickey-Fuller test is used to determine the simple differencing order.

If there is no unit root, then the HPFDIAGNOSE procedure sets $d = 0$.

If there is a unit root, then the double unit root test is applied. If there is a double unit root, then the HPFDIAGNOSE procedure sets $d = 2$; otherwise, $d = 1$.

Figure 4.11 and Figure 4.12 show that the series needs simple differencing because the null hypothesis test probability is greater than SIGLEVEL=0.05.

Figure 4.11 Dickey-Fuller Unit Root Test

Dickey-Fuller Unit Root Test				
Type	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	0.22	0.7335	1.38	0.9580
Single Mean	-2.42	0.7255	-1.11	0.7118
Trend	294.41	0.9999	-6.42	<.0001

Figure 4.12 Summary of Dickey-Fuller Unit Root Test

Dickey-Fuller Unit Root Test Summary				
Variable	**Seasonality**	**Zero Mean**	**Mean**	**Trend**
AIR	1	YES	YES	NO

Seasonal Differencing Order

The seasonal augmented Dickey-Fuller test is used to identify the seasonal differencing order. If the seasonality is greater than 12, the season dummy regression test is used. If there is no seasonal unit root, the HPFDIAGNOSE procedure sets $D = 0$. If there is a seasonal unit root, the HPFDIAGNOSE procedure sets $D = 1$.

Figure 4.13 and Figure 4.14 show that the series needs seasonal differencing because the null hypothesis test probability is greater than SIGLEVEL=0.05.

Figure 4.13 Seasonal Dickey-Fuller Unit Root Test

Seasonal Dickey-Fuller Unit Root Test(Seasonality=12)				
Type	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	-0.47	0.5112	-0.13	0.4970
Single Mean	-6.51	0.2186	-1.59	0.1101

Figure 4.14 Summary of Seasonal Dickey-Fuller Unit Root Test

Seasonal Dickey-Fuller Unit Root Test Summary				
Variable	**Seasonality**	**Zero Mean**	**Mean**	**Trend**
AIR	12	YES	YES	

Joint Differencing Orders

Hasza and Fuller (1979, 1984) proposed the joint unit roots test. If the seasonality is less than or equal to 12, use these tests. If there is a joint unit root, then the HPFDIAGNOSE procedure sets $D = 1$ and $d = 1$.

Figure 4.15 and Figure 4.16 show that the series needs both simple and seasonal differencing because the null hypothesis test probability is greater than SIGLEVEL=0.05.

Figure 4.15 Joint Unit Root Test

Joint Unit Root Test

		Critical Values			
Type	F Value	90%	95%	99%	Approx Pr > F
Zero Mean	3.2684	2.5695	3.2600	4.8800	0.0466
Single Mean	3.8360	5.1409	6.3473	8.8400	0.1476
Trend	3.0426	7.2635	8.6820	10.7600	0.2896

Figure 4.16 Summary of Joint Unit Root Test

Joint Unit Root Test Summary

Variable	Seasonality	Zero Mean	Mean	Trend
AIR	1, 12	NO	YES	

Seasonal Dummy Test

If the seasonality is greater than 12, the seasonal dummy test is used to decide the seasonal differencing order.

The seasonal dummy test compares the criterion (AIC) of two AR(1) models and the joint significance of the seasonal dummy parameters, where one has seasonal dummy variables and the other does not have the seasonal dummy variables.

ARMA Order Selection

Tentative Simple Autoregressive and Moving-Average Orders

The tentative simple autoregressive and moving-average orders (AR=p^* and MA=q^*) are found using the ESACF, MINIC, or SCAN method.

The next two sets of SAS statements result in the same diagnoses.

```
proc hpfdiagnose data=sashelp.air print=all;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;
```

```
proc hpfdiagnose data=sashelp.air print=all;
   id date interval=month;
   forecast air;
   transform;
   arimax method=minic p=(0:5) q=(0:5) criterion=sbc;
run;
```

Figure 4.17 shows the minimum information criterion among the AR and MA orders. The AR=3 and MA=0 element has the smallest value in the table.

Figure 4.17 Minimum Information Criterion

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	-6.20852	-6.30537	-6.29093	-6.3145	-6.28459	-6.26408
AR 1	-6.31395	-6.28157	-6.26557	-6.28327	-6.25263	-6.23399
AR 2	-6.29952	-6.26759	-6.24019	-6.24605	-6.21542	-6.20335
AR 3	-6.33026	-6.29846	-6.26559	-6.23155	-6.2356	-6.22296
AR 4	-6.31801	-6.28102	-6.24678	-6.24784	-6.21578	-6.19315
AR 5	-6.29745	-6.2603	-6.22433	-6.2265	-6.19536	-6.15861

Simple Autoregressive and Moving-Average Orders

The simple autoregressive and moving-average orders (p and q) are found by minimizing the SBC/AIC values from the models among $0 \leq p \leq p^*$ and $0 \leq q \leq q^*$ where p^* and q^* are the tentative simple autoregressive and moving-average orders.

Seasonal Autoregressive and Moving-Average Orders

The seasonal AR and MA orders (p and Q) are found by minimizing the SBC/AIC values from the models among $0 \leq P \leq 2$ and $0 \leq Q \leq 2$.

Constant

In order to determine whether the model has a constant, two models are fitted: $(p,d,q)(P,D,Q)_s$ and $C + (p,d,q)(P,D,Q)_s$. The model with the smaller SBC/AIC value is chosen.

Estimation Method

The ARIMA model uses the conditional least squares estimates for the parameters.

Figure 4.18 shows that the simple AR and MA orders are reduced to $p = 1$ and $q = 0$ from $p^* = 3$ and $q^* = 0$. The seasonal AR and MA orders are $P = 0$ and $Q = 1$. The selected model does not have a constant term.

Figure 4.18 ARIMAX Specification

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	Status
AIR	LOG	NO	1	1	0	0	1	1	12	RMSE	10.8353	OK

Transfer Functions in an ARIMAX Model

A transfer function filter has delay, numerator, and denominator parameters. Set (b, k, r) where b is the delay, k is the numerator order, and r is the denominator order.

Functional Transformation for Input Variables

The default of functional transformation for the inputs is no transformation. The TESTINPUT=TRANSFORM option specifies that the same functional transformation is applied to the inputs as is used for the variable to be forecast.

Using the TESTINPUT=TRANSFORM option, you can test whether the log transformation is applied to the inputs.

Simple and Seasonal Differencing Orders for Input Variables

The default of the simple and seasonal differencing for the inputs is the same as the simple and seasonal differencing applied to the variable to be forecast.

Using the TESTINPUT=TREND option, you can test whether the differencing is applied to the inputs.

Cross-Correlations between Forecast and Input Variables

The cross-correlations between the variable y_t to be forecast and each input variable x_{it} are used to identify the delay parameters. The following steps are used to prewhiten the variable to be forecast in order to identify the delay parameter b.

1. Find an appropriate ARIMA model for x_{it} and estimate the residual of x_{it} (e^x_{it}).
2. Prewhiten y_t using this model and get the residual of y_t (e^y_{it}).
3. Compute the cross-correlations between e^x_{it} and e^y_{it} and find the first significant lag that is zero or larger. If no delay lag is significant, the variable x_{it} is not included in the model.

Simple Numerator and Denominator Orders

The high-order lag regression model and the transfer function model are compared to identify the simple numerator and denominator orders.

Fit the high-order lag regression model (lag=15) and get the coefficients. Fit the transfer function $C + (b, k, r)$ where C is a constant term, b is the delay parameter found in the previous section, $0 \leq k \leq 2$, and $0 \leq r \leq 2$, and get the impulse weight function (lag=15) of the transfer model. Compare the pattern of the coefficients from the high-order regression model and the transfer model.

The following SAS statements shows how to select significant input variables.

```
proc hpfdiagnose data=sashelp.citimon(obs=141) print=all;
   forecast conb;
   input cciutc eec eegp exvus fm1 fm1d82;
   transform;
   arimax;
```

```
run;
```

The "ARIMA Input Selection" table shown in Figure 4.19 states that the Eegp input variable is selected in the model with difference $d = 1$ and delay $b = 8$. Other input variables are not selected because of either unstable or insignificant status.

Figure 4.19 ARIMA Input Selection

The HPFDIAGNOSE Procedure

ARIMA Input Selection

Input Variable	Selected	Functional Transform	d	Delay	Numerator	Denominator	Status
CCIUTC	NO	NONE	1	2	0	0	Not Improved
EEC	NO						Not Causal
EEGP	YES	NONE	1	8	0	0	OK
EXVUS	NO						Not Causal
FM1	NO						Not Causal
FM1D82	NO						Not Causal

Outliers

Outlier detection is the default in the ARIMAX modeling.

There are two types of outliers: the additive outlier (AO) and the level shift (LS). For each detected outlier, dummy regressors or indicator variables are created. The ARIMAX model and the dummy regressors are fitted to the data.

The detection of outliers follows a forward method. First find a significant outlier. If there are no other significant outliers, detecting outlier stops at this point. Otherwise, include this outlier into a model as an input and find another significant outlier.

The same functional differencing is applied to the outlier dummy regressors as is used for the variable to be forecast.

The following data come from Hillmer, Larcker, and Schroeder (1983).

```
data hardware;
   input hardware @@;
   label hardware="Wholesale Sales of Hardware";
   date=intnx('month','01jan67'd,_n_-1);
   format date monyy.;
datalines;
 626  614  689  686  723  778  711  824  793  831  775  689

   ... more lines ...
```

The next two sets of SAS statements result in the same outlier analysis.

```
proc hpfdiagnose data=hardware print=short;
   id date interval=month;
   forecast hardware;
   transform;
   arimax;
run;

proc hpfdiagnose data=hardware print=short;
   id date interval=month;
   forecast hardware;
   transform;
   arimax outlier=(detect=maybe maxnum=2 maxpct=2 siglevel=0.01);
run;
```

Figure 4.20 shows that the two level shifts (LS) occurred at the 96th (DEC1974) and 99th (MAR1975) observations.

Figure 4.20 Outlier Information

The HPFDIAGNOSE Procedure

ARIMA Outlier Selection

Variable	Type	Obs	Time	Chi-Square	Approx Pr > ChiSq
hardware	LS	99	MAR1975	25.73	<.0001
	LS	96	DEC1974	29.64	<.0001

Figure 4.21 shows the ARIMA model specification with two outliers included in the model.

Figure 4.21 ARIMAX Specification

ARIMA Model Specification After Adjusting for Outliers

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Outlier	Model Criterion	Statistic	Status
hardware	NONE	NO	2	1	1	2	1	1	12	2	RMSE	45.9477	OK

Intermittent Demand Model

The HPFDIAGNOSE procedure selects an appropriate intermittent demand model (IDM) based on the model selection criterion.

If a series is intermittent or interrupted, a proper IDM is selected by either individually modeling both the demand interval and size component or by jointly modeling these components by using the average demand component (demand size divided by demand interval).

The following example prints the diagnostics of an intermittent demand series. The options INTERMITTENT=2.5 and BASE=0 are specified.

```
data sales;
   input hubcaps @@;
datalines;
0 1 0 0 0 1 0 0 0 0 0 2 0 4 0 0 0 0 1 0
;

proc hpfdiagnose data=sales print=all;
   forecast hubcaps;
   transform;
   idm intermittent=2.5 base=0;
run;
```

Output 4.22 shows that the variable to be forecast is an intermittent demand series. The interval/size demand model and average demand model were diagnosed for the time series. The value of the model selection criterion of the interval/size demand model is smaller than that of the average demand model.

Figure 4.22 Intermittent Demand Model Specification

The HPFDIAGNOSE Procedure

Intermittent Demand Model Specification

Variable	Demand Model	Functional Transform	Selected Model	Component	Model Criterion	Statistic
hubcaps	INTERVAL	NONE	SIMPLE	LEVEL	RMSE	0.8428
	SIZE	LOG	SIMPLE	LEVEL		
	AVERAGE	LOG	SIMPLE	LEVEL		0.8736

Exponential Smoothing Model

The HPFDIAGNOSE procedure selects an appropriate exponential smoothing model (ESM) based on the model selection criterion.

The following statements print the ESM specification.

```
proc hpfdiagnose data=sashelp.gnp print=short;
   id date interval=qtr;
   forecast gnp;
   transform;
   esm;
run;
```

The ESM specification in Figure 4.23 states that the damp-trend exponential smoothing model was automatically selected.

Figure 4.23 ESM Specification

The HPFDIAGNOSE Procedure

Exponential Smoothing Model Specification

Variable	Functional Transform	Selected Model	Component	Model Criterion	Statistic
GNP	NONE	DAMPTREND	LEVEL	RMSE	22.0750
			TREND		
			DAMP		

Unobserved Components Model

The UCM statement is used to find the proper components among the level, trend, seasonal, cycles, and regression effects.

Differencing Variables in a UCM

The variable to be forecast and the events are not differenced regardless of the result of the TREND statement. Differencing of the input variables follows the result of the option TESTINPUT=TREND or TESTINPUT=BOTH.

Transfer Function in a UCM

The functional transformation, simple and seasonal differencing, and delay parameters for the transfer function in a UCM are the same as those that are used for the transfer function in an ARIMAX model.

The series that consists of the yearly river flow readings of the Nile, recorded at Aswan (Cobb 1978), is studied. The data consist of readings from the years 1871 to 1970.

The following DATA step statements read the data in a SAS data set and create dummy inputs for the shift in 1899 and the unusual years 1877 and 1913.

```
data nile;
   input riverFlow @@;
   year = intnx( 'year', '1jan1871'd, _n_-1 );
   format year year4.;
datalines;
1120 1160  963 1210 1160 1160  813 1230 1370 1140

   ... more lines ...
```

The series is known to have had a shift in the level starting at the year 1899, and the years 1877 and 1913 are suspected to be outlying points. The following SAS statements create the Nile_Data data set with the Shift1899, Event1877, and Event1913 variables.

```
data nile_data;
   set nile;
   if year >= '1jan1899'd then
      Shift1899 = 1.0;
```

```
   else
      Shift1899 = 0;
   if year = '1jan1913'd then
      Event1913 = 1.0;
   else
      Event1913 = 0;
   if year = '1jan1877'd then
      Event1877 = 1.0;
   else
      Event1877 = 0;
run;
```

The following SAS statements print the diagnoses of the UCM specification.

```
proc hpfdiagnose data=nile_data print=short;
   id year interval=year;
   forecast riverFlow;
   input Shift1899 Event1913 Event1877;
   transform;
   ucm;
run;
```

Figure 4.24 shows the three significant inputs chosen.

Figure 4.24 UCM Input Selection

The HPFDIAGNOSE Procedure

UCM Input Selection

Input Variable	Selected	Functional Transform	d	Delay
Shift1899	YES	NONE	0	0
Event1913	YES	NONE	0	0
Event1877	YES	NONE	0	2

Figure 4.25 shows the UCM specification for the Nile data. The data have significant irregular and level components, along with three significant inputs.

Figure 4.25 UCM Specification

Unobserved Components Model(UCM) Specification

Variable	Functional Transform	Component	Selected	Stochastic	Period	Model Criterion	Statistic	Status
riverFlow	NONE	IRREGULAR	YES	YES		RMSE	117.13	OK
		LEVEL	YES	NO				
		SLOPE	NO					
		CYCLE1	NO					
		CYCLE2	NO					
		INPUT	3					

The following example has the same results as Figure 4.24. The COMPONENTS= option in the UCM statement requests that level and irregular components only be considered. Figure 4.26 shows the result from the execution of this example.

```
proc hpfdiagnose data=nile_data print=short;
   id year interval=year;
   forecast riverFlow;
   transform;
   input Shift1899 Event1913 Event1877;
   ucm component=(level irregular);
run;
```

Figure 4.26 UCM Specification

The HPFDIAGNOSE Procedure

Unobserved Components Model(UCM) Specification

Variable	Functional Transform	Component	Selected	Stochastic	Model Criterion	Statistic	Status
riverFlow	NONE	IRREGULAR	YES	YES	RMSE	117.13	OK
		LEVEL	YES	NO			
		INPUT	3				

Values of Status

The meaning of the different values of status in the output is summarized as follows:

OK	The model fits successfully.
All Missing Obs	All series values are missing.
All Same Values	All series values are identical.
Collinearity	Multi-collinearity between input series.
Not Causal	A delay parameter is negative.
Insignificant	Some of the parameters are insignificant.
X Model Failed	Prewhitening model of input series failed.
Y Model Failed	The g(y)=f(x) model failed.
Not Improved	Input series does not improve benchmarking model.
Not One of Best	When the SELECTINPUT=*n* and SELECTEVENT=*n* are specified, it is not one of the best first *n* inputs and events.
Unstable Model	The model is unstable.
May Not Converge	The model might not converge.
Small Variance	The series values have very small variance.
Singularity	The model is singular.
Modeling Error	A model cannot be fitted to the data.
Extreme Value	The series values are extremely large.
Error Transform	The data transformation failed.
Lack of Memory	The memory is insufficient.

Not Enough Data The number of observations is insufficient.

Bad Arguments The arguments are incorrect.

Non Positive Obs The series values are either zero or negative.

The following are the messages for the intermittent model:

No Demand There is no recorded demand.

Not Fitted Model The model cannot be fitted to the data.

Not Selected The model cannot be selected.

Not Predicted The model cannot be predicted.

Not Initialized The model cannot be initialized.

Negative Demand The demand size is negative.

Holdout Sample

A holdout sample is useful to find models that have better out-of-sample forecasts. If the HOLDOUT= or HOLDOUTPCT= option is specified, the model selection criterion is computed using only the holdout sample region.

```
proc hpfdiagnose data=sashelp.air print=short holdout=10;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;
```

The ARIMA model specification in Figure 4.27 shows that the log test, trend test, and selection of ARMA orders use only the first part of the series and exclude the last 10 observations that were specified as the holdout sample. The statistic of the model selection criterion is computed using only the last 10 observations that were specified as the holdout sample.

Figure 4.27 Use HOLDOUT= Option

The HPFDIAGNOSE Procedure

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	HoldOut Sample	Status
AIR	LOG	NO	1	1	0	0	1	1	12	RMSE	16.3008	10	OK

Events

Calendar effects such as holiday and trading day are defined by the HPFEVENTS procedure or predefined event keywords.

The HPEVENTS procedure creates the OUT= data set for the event definitions, and the HPFDIAGNOSE procedure uses these event definitions by specifying the INEVENT= option in the ARIMAX or UCM model.

Events in an ARIMAX Model

The simple and seasonal differencing for the events in an ARIMAX are the same as those that are used for the variable to be forecast.

No functional transformations are applied to the events.

Events in a UCM

The simple and seasonal differencing for the events in a UCM are not applied to the events.

No functional transformations are applied to the events.

The following SAS statements show how the HPEVENTS procedure can be used to create the event data set, OUT=Eventdata.

```
proc hpfevents data=nile;
   id year interval=year;
   eventkey Shift1899 = LS01JAN1899D;
   eventkey Event1913 = AO01JAN1913D;
   eventkey Event1877 = AO01JAN1877D;
   eventdata out=eventdata;
run;
```

The following SAS statements show that the HPFDIAGNOSE procedure uses these event data by specifying the INEVENT=EVENTDATA option. The EVENT statement specifies the name of events defined in the INEVENT=EVENTDATA.

```
proc hpfdiagnose data=nile print=short inevent=eventdata;
   id year interval=year;
   forecast riverFlow;
   event Shift1899 Event1913 Event1877;
   transform;
   ucm component=(level cycle);
run;
```

Figure 4.28 shows that two significant events are chosen.

Figure 4.28 UCM Event Selection

The HPFDIAGNOSE Procedure

UCM Event Selection

Event Name	Selected
SHIFT1899	YES
EVENT1913	YES

Figure 4.29 shows the UCM specification for the Nile data. The data have significant irregular and level components, along with two significant events.

Figure 4.29 UCM Specification

Unobserved Components Model(UCM) Specification

Variable	Functional Transform	Component	Selected	Stochastic	Period	Model Criterion	Statistic	Status
riverFlow	NONE	IRREGULAR	YES	YES		RMSE	117.13	OK
		LEVEL	YES	NO				
		CYCLE1	NO					
		CYCLE2	NO					
		EVENT	2					

The following SAS code generates the same results as the previous example without specifying an INEVENT= data set. In this example, SAS predefined event keywords are specified in the EVENT statement. Figure 4.30 shows the results from this example.

```
proc hpfdiagnose data=nile print=short;
   id year interval=year;
   forecast riverFlow;
   event LS01JAN1899D AO01JAN1913D AO01JAN1877D;
   transform;
   ucm component=(level irregular);
run;
```

Figure 4.30 UCM Specification

The HPFDIAGNOSE Procedure

Unobserved Components Model(UCM) Specification

Variable	Functional Transform	Component	Selected	Stochastic	Model Criterion	Statistic	Status
riverFlow	NONE	IRREGULAR	YES	YES	RMSE	117.13	OK
		LEVEL	YES	NO			
		EVENT	2				

Thread Usage in PROC HPFDIAGNOSE

The HPFDIAGNOSE procedure can make use of threads to speed up different aspects of model identification. There are no special options beyond those present in the SAS System to control thread usage in PROC HPFDIAGNOSE. You can use the OPTIONS statement to specify the following SAS options:

THREADS | NOTHREADS controls whether threading is allowed in PROC HPFDIAGNOSE.

CPUCOUNT= controls the maximum number of threads to be used by PROC HPFDIAGNOSE.

When threading is allowed, the thread budget for the PROC HPFDIAGNOSE step is determined by the CPUCOUNT option setting. Threaded execution is considered only when the CPUCOUNT setting is more than 1.

PROC HPFDIAGNOSE can use threads in certain phases of its computations within each BY group that it processes. When threading is allowed, PROC HPFDIAGNOSE can make use of threads in these computational processes:

- model identification by model family
- preliminary predictor qualification

PROC HPFDIAGNOSE can use threads to perform model identification for different model families concurrently. You control the model families to be considered in the PROC HPFDIAGNOSE step by the following statements:

ARIMAX allocates one or two threads depending on the value of the IDENTIFYORDER= option. The identification orders ARIMA and REG are performed concurrently when both are requested.

ESM allocates one thread.

UCM allocates one thread.

It is possible to have up to four model identification steps executing concurrently for each BY group. This is a very coarse level of threading, but it can provide some of the most dramatic improvement in elapsed time over nonthreaded execution for the added CPU time expenditure. Obviously, the elapsed time improvement for each BY group is effectively determined by the longest time of the respective model families that are performed concurrently.

PROC HPFDIAGNOSE can use threads as part of its variable selection process within ARIMAX and UCM model identification. When you specify predictors for consideration for these models, a preliminary qualification process is performed to determine whether a particular predictor improves the AIC or SBC of the model that is being generated. Because this step considers each predictor in isolation from the others, it represents a good opportunity for exploiting parallelism. Predictors that are considered in each BY group arise from EVENT statements, from INPUT statements, or from the EVENTBY= data set that is specified in the PROC HFDIAGNOSE step. Elapsed time reduction here depends strongly on the number of predictors to be considered in each model family. For threads to be beneficial, each thread must service a minimum number of predictors to justify the overhead for the threads (the minimum depends on whether the predictor is an EVENT or INPUT, and EVENT variables generally require less time per variable to qualify than INPUT

variables). An estimate of the useful thread count for predictor qualification is used to govern the use of threads in this context.

The thread budget (CPUCOUNT) that is allowed for the PROC HPFDIAGNOSE step is dynamically shared between coarse threading of the model families and threading of predictor qualification. Each of the specified ARIMAX (ARIMA and REG) and UCM model families execute concurrently, and each of those considers all of the declared predictors for inclusion in the respective model identification process.

Relationship with PROC HPFENGINE

The HPFDIAGNOSE procedure diagnoses, and the HPFENGINE procedure forecasts.

There are two ways to communicate between the HPFDIAGNOSE procedure and the HPFENGINE procedure. One way is that the OUTEST= data set specified in the HPFDIAGNOSE procedure is specified as the INEST= data set in the HPFENGINE procedure. The other way is that the HPFSELECT procedure is used to communicate between the HPFDIAGNOSE procedure and the HPFENGINE procedure.

The ALPHA=, CRITERION=, HOLDOUT=, and HOLDOUTPCT= options can be changed using the HPFSELECT procedure before these options are transmitted to the HPFENGINE procedure. Otherwise, the values specified in the HPFDIAGNOSE procedure are transmitted directly to the HPFENGINE procedure.

Missing values in the input series are handled differently in the HPFDIAGNOSE procedure than in the HPFENGINE procedure. The HPFDIAGNOSE procedure uses the smoothed missing values for inputs, but the HPFENGINE procedure does not include the inputs that have missing values. This difference can produce different statistical results between the two procedures.

The model specification files created by the HPFDIAGNOSE procedure can be compared with benchmark model specifications by using the HPFESMSPEC, HPFIDMSPEC, HPFARIMASPEC, and HPFUCMSPEC procedures.

The following example shows how to combine these procedures to diagnose a time series.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor mymodel;
run;
```

Create a diagnosed model specification.

```
proc hpfdiagnose data=sashelp.air outest=est
             modelrepository=sasuser.mymodel;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;
```

Create an ARIMA$(0,1,1)(0,1,1)_s$ model specification.

```
proc hpfarimaspec modelrepository=sasuser.mymodel
                  specname=benchModel;
   forecast var=dep1 dif=1 12 q=(1)(12) noint transform=log;
run;
```

Create a model selection list that includes a diagnosed model (DIAG0) and a specified model (BENCHMODEL).

```
proc hpfselect modelrepository=sasuser.mymodel
               selectname=arimaSpec;
   select criterion=mape;
   spec diag0 / eventmap(symbol=_none_ event=ao135obs)
                eventmap(symbol=_none_ event=ao29obs);
   spec benchModel / inputmap(symbol=dep1 data=air);
run;
```

Select a better model from the model specification list.

```
proc hpfengine data=sashelp.air print=(select)
               modelrepository=sasuser.mymodel
               globalselection=arimaSpec;
   forecast air;
   id date interval=month;
run;
```

Figure 4.31 shows the DIAG0 and BENCHModel model specifications. The DIAG0.XML is created by the HPFDIAGNOSE procedure, and the BENCHModel is created by the HPFARIMASPEC procedure.

Figure 4.31 Model Selection from the HPFENGINE Procedure

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
DIAG0	2.7094770	Yes	ARIMA: Log(AIR) ~ P = 1 D = (1,12) Q = (12) NOINT
BENCHMODEL	2.8979097	No	ARIMA: Log(DEP1) ~ D = (1,12) Q = ((1)(12)) NOINT

The following statements delete the SAS catalogs.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor mymodel;
run;
```

Data Set Input/Output

The AUXDATA= option specifies auxiliary input data for the HPFDIAGNOSE procedure.

The EVENTBY= and INEVENT= data sets can be specified to supply event-related inputs for the HPFDIAGNOSE procedure.

The HPFDIAGNOSE procedure can create the OUTEST=, OUTOUTLIER=, and OUTPROCINFO= data sets. In general, if diagnostics for a particular time series fail, the output that corresponds to this series is not recorded or is set to missing in the relevant output data set, and appropriate error messages or warning messages or both are recorded in the log.

AUXDATA= Data Set

PROC HPFDIAGNOSE supports the AUXDATA= option to supply variables that are used in a forecast but are not physically part of the primary data set supplied via the DATA= option. For example, you could use AUXDATA to share a data set with explanatory variables across multiple projects, or you could use AUXDATA to separate out explanatory variables that are redundant below some level in a BY-variable hierarchy or that might not need BY-variable qualification at all. Although you can specify only one DATA= option, you can specify the AUXDATA= option multiple times in the PROC statement to supply more than one auxiliary data set for PROC HPFDIAGNOSE to use during its run. For more information and examples, see Chapter 21, "Using Auxiliary Data Sets."

EVENTBY= Data Set

The EVENTBY= data set contains information that maps predefined events to specific BY groups and variables to be forecast. Instead of mapping predefined events to all forecast series and all BY groups, you can assign the specific events to the specific BY groups and the specific forecast series. This data set is created by a SAS DATA step.

The EVENTBY= data set has the following columns:

BY variable name contains BY variables that organize the results in BY groups.

NAME contains one or more variables to be forecast.

EVENT contains event names.

REQUIRED indicates whether the event is included in a model.

Figure 4.32 shows an example EVENTBY= data set created by a SAS DATA step. In this example, the EVENTBY= data set contains two BY variables (REGION with two groups, R1 and R2, and STORE with three groups, S1, S2, and S3), three forecast series (Y1, Y2, and Y3), and three events (EASTER, AO11JAN2004D, and AO25JAN2008D). The data set also assigns the event EASTER to REGION=R1, STORE=S1 for the forecast variable Y3, and it assigns EASTER to REGION=R2, STORE=S3 for the forecast variable Y3.

Figure 4.32 EVENTBY= Data Set

Obs	region	store	_NAME_	_EVENT_	_REQUIRED_
1	R1	S1	Y3	EASTER	YES
2	R1	S1	Y3	AO11JAN2004D	MAYBE
3	R1	S1	Y3	AO25JAN2008D	MAYBE
4	R1	S2	Y1	AO11JAN2004D	MAYBE
5	R1	S2	Y1	AO25JAN2008D	YES
6	R2	S3	Y1	AO11JAN2004D	MAYBE
7	R2	S3	Y1	AO25JAN2008D	MAYBE
8	R2	S3	Y3	EASTER	MAYBE
9	R2	S3	Y3	AO11JAN2004D	MAYBE

INEVENT= Data Set

The INEVENT= data set contains information that describes predefined events. This data set is usually created by the HPFEVENTS procedure and is required only if events are included in a model. For more information about creating this data set, see the section "EVENTDATA Statement" on page 263

OUTEST= Data Set

The OUTEST= data set contains information that maps data set variables to model symbols and references the model specification file and model selection list files for each variable to be forecast. This information is used by the HPFENGINE procedure for further model selection, parameter estimation, and forecasts.

In addition, this information can be used by the HPFSELECT procedure to create customized model specification files.

The OUTEST= data set has the following columns:

BY variable name contains BY variables that organize the results in BY groups.

NAME contains one or more variables to be forecast.

SELECT contains model selection list file names.

The model selection list file contains the information of the values of CRITERION=, ALPHA=, HOLDOUT=, and HOLDPCT= options, EVENT and OUTLIER information, and model specification file names.

MODEL is not applicable in the HPFDIAGNOSE procedure.

SCORE is not applicable in the HPFDIAGNOSE procedure.

MODELVAR specifies the model symbol.

DSVAR specifies the data set variable name.

VARTYPE specifies the variable type.

Here are two examples. The first example has one model specification file with a model selection list file; the second example has two model select list files and four model specification files.

The first example uses the BASENAME=AIRSPEC and the new model repository Sasuser.Mymodel.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor mymodel;
run;

proc hpfdiagnose data=sashelp.air outest=est_air
             modelrepository=sasuser.mymodel
             basename=airSpec;
   id date interval=month;
   forecast air;
   transform;
   arimax;
run;
proc print data=est_air;
run;
```

Figure 4.33 shows _SELECT_=AIRSPEC1 since BASENAME=AIRSPEC is specified. Because the new model repository Sasuser.Mymodel is created, the suffix number followed by AIRSPEC starts from 0. AIRSPEC0 is the model specification file, and AIRSPEC1 is the model selection list file.

Figure 4.33 OUTEST1

Obs	_NAME_	_SELECT_	_MODEL_	_SCORE_	_MODELVAR_	_DSVAR_	_VARTYPE_	_STATUS_
1	AIR	AIRSPEC1		Y		AIR	DEPENDENT	0

The following statements delete the SAS catalogs.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor mymodel;
run;
```

The next example uses the new BASENAME=GNPSPEC and the new model repository Sasuser.Mygnp. The ESM and ARIMAX statement request that two variables to be forecast.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor mygnp;
run;

proc hpfdiagnose data=sashelp.gnp outest=est_gnp
             modelrepository=sasuser.mygnp
             basename=gnpSpec;
   id date interval=qtr;
   forecast consump invest;
   transform;
   esm;
   arimax;
run;

proc print data=est_gnp;
run;
```

Figure 4.34 shows two observations. Because the model repository Sasuser.Mygnp is newly created, the suffix number followed by GNPSPEC starts from 0.

The model selection list GNPSPEC2 contains the two model specifications, GNPSPEC0 is the ARIMAX model specification, and GNPSPEC1 is the ESM specification for the variable to be forecast, Consump.

The model selection list GNPSPEC5 contains the two model specifications, GNPSPEC3 is the ARIMAX model specification, and GNPSPEC4 is the ESM specification for the variable to be forecast, Invest.

Figure 4.34 OUTEST2

Obs	_NAME_	_SELECT_	_MODEL_	_SCORE_	_MODELVAR_	_DSVAR_	_VARTYPE_	_STATUS_
1	CONSUMP	GNPSPEC2		Y		CONSUMP	DEPENDENT	0
2	INVEST	GNPSPEC5		Y		INVEST	DEPENDENT	0

The following SAS statements delete the SAS catalogs.

```
proc datasets lib=sasuser mt=catalog nolist;
   delete hpfscor myGNP;
run;
```

OUTOUTLIER= Data Set

The OUTOUTLIER= data set contains information about the outliers and has the following variables:

BY variable name contains BY variables that organize the results in BY groups.

NAME contains variables to be forecast.

TYPE contains a type, either AO for an additive outlier or LS for a level shift.

DIRECTION contains a direction, either UP for a positive effect or DOWN for a negative effect.

OBS contains the number of the observation where the outlier happens.

SASDATE contains the SAS date when the outlier happens.

EVENT contains the outlier's event name.

ESTIMATE contains the coefficient estimate.

CHISQ contains the chi-square statistic of the coefficient estimate.

PVALUE contains the p -value of the coefficient estimate.

IDSTEP contains the step name where the outlier diagnosis occurred. Valid values include:

- ARIMA indicates that the outlier event comes from an ARIMA model with no predictors.
- ARIMA_REG indicates that the outlier event comes from a model generated by ARIMA order selection first, followed by the selection of significant inputs.
- REG_ARIMA indicates that the outlier event comes from a model generated by the selection of significant inputs first, followed by ARIMA order selection.

The following SAS statements and Figure 4.35 show the OUTOUTLIER= data set that contains information associated with the output in Figure 4.20.

```
proc hpfdiagnose data=hardware outoutlier=outl;
   id date interval=month;
   forecast hardware;
   transform;
   arimax;
run;

proc print data=outl;
run;
```

Figure 4.35 OUTOUTLIER= Data Set

Obs	_NAME_	_TYPE_	_DIRECTION_	_OBS_	_SASDATE_	_EVENT_	_ESTIMATE_	_CHISQ_	_PVALUE_	_IDSTEP_
1	hardware	LS	DOWN	99	01MAR75	LS01MAR1975D	-125.695	25.7273	.000000393	ARIMA
2	hardware	LS	DOWN	96	01DEC74	LS01DEC1974D	-115.714	29.6352	.000000052	ARIMA

OUTPROCINFO= Data Set

The OUTPROCINFO= data set contains the following variables:

SOURCE	The source procedure that produces this data set
STAGE	Stage of the procedure execution for which the summary variable is reported
NAME	Name of the summary variable
LABEL	Description of the summary variable
VALUE	Value of the summary variable

ODS Table Names

The HPFDIAGNOSE procedure assigns a name to each table it creates. You can use these names to refer to the table when you use the Output Delivery System (ODS) to select tables and create output data sets. These names are listed in Table 4.3:

Table 4.3 ODS Tables Produced Using the HPFDIAGNOSE Procedure

ODS Table Name	Description	Statement	Options
ODS Tables Created by the PRINT=SHORT Option			
ARIMAEventSelect	ARIMA event selection	EVENT	
ARIMAInputSelect	ARIMA input selection	INPUT	
ARIMASpec	ARIMA model specification	ARIMAX	
BestmodelSpec	Selected model specification		
ESMSpec	Exponential smoothing model specification	ESM	
FinalARIMASpec	Final ARIMA model specification	ARIMAX	
IDMSpec	Intermittent model specification	IDM	
OutlierInfo	ARIMA outlier selection	ARIMAX	
UCMEventSelect	UCM event selection	EVENT	
UCMInputSelect	UCM input selection	INPUT	
UCMSpec	Unobserved components model specification	UCM	
VariableInfo	Forecast variable information		
Additional ODS Tables Created by the PRINT=LONG Option			
DFTestSummary	Dickey-Fuller unit root test	TREND	DIFF
JointTestSummary	Joint unit root test	TREND	DIFF, SDIFF
SeasonDFTestSummary	Seasonal Dickey-Fuller unit root test	TREND	SDIFF

Table 4.3 *continued*

ODS Table Name	Description	Statement	Options
Transform	Functional transformation test	TRANSFORM	TYPE=AUTO
Additional ODS Tables Created by the PRINT=ALL Option			
DFTest	Dickey-Fuller unit root test	TREND	DIFF
ESACF	Extended sample autocorrelation function	ARIMAX	ESACF
ESACFPValues	*p*-values of ESACF	ARIMAX	ESACF
JointTest	Joint unit root test	TREND	DIFF, SDIFF
MINIC	Minimum information criterion	ARIMAX	MINIC
SCAN	Squared canonical correlation estimates	ARIMAX	SCAN
SCANPValues	*p*-values of SCAN	ARIMAX	SCAN
SeasonDFTest	Seasonal Dickey-Fuller unit root test	TREND	SDIFF

Examples: HPFDIAGNOSE Procedure

Example 4.1: Selection of Input Variables

This example requests testing of the transformation and differencing of the input variables independent of the variable to be forecast.

```
proc hpfdiagnose data=sashelp.citimon(obs=141)
     testinput=both selectinput=all print=all;
   forecast conb;
   input cciutc eec eegp exvus fm1 fm1d82;
   transform;
   arimax;
run;
```

Output 4.1.1 shows that the ARIMA $(0, 1, 0)$ model is diagnosed for the variable (Conb) to be forecast.

Output 4.1.1 ARIMAX Specification before Input Selection

The HPFDIAGNOSE Procedure

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	Model Criterion	Statistic	Status
CONB	NONE	NO	0	1	0	RMSE	2363.79	OK

Output 4.1.2 shows that one input variable (Eegp) is selected. The input variable needs a simple differencing.

Output 4.1.2 ARIMA Input Selection

ARIMA Input Selection

Input Variable	Selected	Functional Transform	d	Delay	Numerator	Denominator	Status
CCIUTC	NO	NONE	1	2	0	0	Not Improved
EEC	NO						Not Causal
EEGP	YES	NONE	1	8	0	0	OK
EXVUS	NO						Not Causal
FM1	NO						Not Causal
FM1D82	NO						Not Causal

Output 4.1.3 shows that the RMSE model selection criterion with inputs is smaller than the model selection criterion without inputs and outliers.

Output 4.1.3 ARIMAX Specification after Input Selection

ARIMA Model Specification After Adjusting for Inputs and Outliers

Variable	Functional Transform	Constant	p	d	q	Outlier	Input	Model Criterion	Statistic	Status
CONB	NONE	NO	0	1	0	1	1	RMSE	2171.06	OK

Example 4.2: Selection of Events and Input Variables

This example demonstrates how to select events and input variables.

```
proc hpfevents data=sashelp.gnp;
   id date interval=qtr;
   eventkey shock=AO1050BS;
   eventkey shift=LS850BS;
   eventdata out=eventdata;
run;

proc hpfdiagnose data=sashelp.gnp print=all inevent=eventdata
             testinput=trend;
   id date interval=qtr;
   forecast gnp;
   input consump invest exports govt;
   event shock shift;
   transform;
   arimax outlier=(detect=no);
run;
```

Output 4.2.1 shows the seasonal ARIMA (1, 1, 1) model diagnosed for the variable (Gnp) to be forecast.

Output 4.2.1 ARIMAX Specification before Event Input Selection

The HPFDIAGNOSE Procedure

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	Status
GNP	NONE	NO	1	1	1	0	0	0	4	RMSE	22.1611	OK

Output 4.2.2 shows that the SHIFT event is significant.

Output 4.2.2 ARIMA Event Selection

ARIMA Event Selection

Event Name	Selected	d	D	Status
SHOCK	NO	1	0	Not Improved
SHIFT	YES	1	0	OK

Output 4.2.3 shows that the input variable Consump is selected in the model.

Output 4.2.3 ARIMA Input Selection

ARIMA Input Selection

Input Variable	Selected	Functional Transform	d	D	Delay	Numerator	Denominator	Status
CONSUMP	YES	NONE	1	0	0	2	1	OK
INVEST	NO	NONE	1	0	0	0	0	Unstable Model
EXPORTS	NO							Not Causal
GOVT	NO	NONE	1	0	0	2	0	Unstable Model

Output 4.2.4 shows that the RMSE model selection criterion with the events and input is smaller than that without the events and input.

Output 4.2.4 ARIMAX Specification after Event Input Selection

ARIMA Model Specification After Adjusting for Events and Inputs

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Input	Event	Model Criterion	Statistic	Status
GNP	NONE	NO	1	1	1	0	0	0	4	1	1	RMSE	15.3900	OK

Example 4.3: Intermittent Demand Series

This example shows that the data are an intermittent demand series.

```
data inventory;
   input tires @@;
datalines;
0 0 0 6 0 4 0 0 0 2 0 2 2 0 0 0 6 0 0 0
;

proc hpfdiagnose data=inventory print=all;
   forecast tires;
   transform;
run;
```

Output 4.3.1 shows that the variable (Tires) to be forecast is an intermittent demand series. The interval/size demand model and average demand model were diagnosed to the data. The value of model selection criterion (RMSE) of the average demand model is smaller than that of the interval/size demand model.

Output 4.3.1 Intermittent Demand Model Specification

The HPFDIAGNOSE Procedure

Intermittent Demand Model Specification

Variable	Demand Model	Functional Transform	Selected Model	Component	Model Criterion	Statistic
tires	INTERVAL	NONE	SIMPLE	LEVEL	RMSE	0.6690
	SIZE	NONE	SIMPLE	LEVEL		
	AVERAGE	NONE	SIMPLE	LEVEL		0.5919

Example 4.4: Exponential Smoothing Model

This example illustrates the use of exponential smoothing models (ESM).

```
data investment;
   input inv @@;
   label inv="Gross Investment";
datalines;
33.1 45. 77.2 44.6 48.1 74.4 113. 91.9 61.3 56.8 93.6
159.9 147.2 146.3 98.3 93.5 135.2 157.3 179.5 189.6
;

proc hpfdiagnose data=investment print=all;
   forecast inv;
   transform;
   esm;
run;
```

Output 4.4.1 shows that the variable (Inv) to be forecast diagnosed the damped-trend exponential smoothing model.

Output 4.4.1 Exponential Smoothing Model Specification

The HPFDIAGNOSE Procedure

Exponential Smoothing Model Specification

Variable	Functional Transform	Selected Model	Component	Model Criterion	Statistic
inv	NONE	DAMPTREND	LEVEL	RMSE	26.2492
			TREND		
			DAMP		

Example 4.5: Unobserved Components Model

This example illustrates the use of the UCM statement in the HPFDIAGNOSE procedure.

```
data ozone;
   input ozone @@;
   label ozone  = 'Ozone Concentration'
         x1     = 'Intervention for post 1960 period'
         summer = 'Summer Months Intervention'
         winter = 'Winter Months Intervention';
   date = intnx( 'month', '31dec1954'd, _n_ );
   format date monyy.;
   month = month( date );
   year = year( date );
   x1 = year >= 1960;
   summer = ( 5 < month < 11 ) * ( year > 1965 );
   winter = ( year > 1965 ) - summer;
datalines;

   ... more lines ...


proc hpfdiagnose data=ozone print=all;
   id date interval=month;
   forecast ozone;
   input x1 summer winter;
   transform;
   ucm;
run;
```

Output 4.5.1 shows that the input Winter is selected in the model.

Output 4.5.1 UCM Input Selection

The HPFDIAGNOSE Procedure

UCM Input Selection

Input Variable	Selected	Functional Transform	d	D	Delay	Status
x1	NO	NONE	0	0	11	Insignificant
summer	NO					Not Causal
winter	YES	NONE	0	0	4	OK

Output 4.5.2 shows that the forecast variable (Ozone) is explained by the irregular and season components, along with the single input variable.

Output 4.5.2 Unobserved Components Model Specification

Unobserved Components Model(UCM) Specification								
Variable	Functional Transform	Component	Selected	Stochastic	Seasonality	Model Criterion	Statistic	Status
ozone	NONE	IRREGULAR	YES	YES		RMSE	1.0110	OK
		LEVEL	YES	NO				
		SLOPE	NO					
		SEASON	YES	NO	12			
		INPUT	1					

Example 4.6: Automatic Model Combination

This example illustrates the automatic model combination feature of the HPFDIAGNOSE procedure.

The following statements run PROC HPFDIAGNOSE to generate model combinations for the automatic models it formulates from its diagnosis of the input series. The combined forecast is produced using a simple average of the candidate forecasts. The COMBINE statement specifies an OLS encompassing test and tests to access forecast quality with an estimation region missing percentage of 25% and a horizon missing percentage of 50%.

```
proc hpfdiagnose
     data=sashelp.air
     rep=work.diagcomb1
     outest=diagest;
   id date interval=month;
   forecast air;
   esm;
   arimax;
   combine method=average encompass=ols misspercent=25 hormisspercent=50;
run;
```

The OUTEST= data set and model repository from HPFDIAGNOSE are fed into the HPFENGINE procedure to perform model selection and forecast generation as follows:

```
proc hpfengine data=sashelp.air
     rep=work.diagcomb1
     inest=diagest
     out=outcomb
     outfor=forcomb
     outest=estcomb
     outstatselect=selcomb
     print=(select estimates)
     lead=4;
   id date interval=month;
   forecast air;
run;
```

Output 4.6.1 shows that the combined forecast is selected from this run.

Output 4.6.1 Model Selection Statistics

The HPFENGINE Procedure

Model Selection Criterion = RMSE			
Model	**Statistic**	**Selected**	**Label**
diag0	10.695241	No	ARIMA: AIR ~ P = 1 D = (1,12) NOINT
diag1	10.579085	No	Winters Method (Multiplicative)
diag2	9.571806	Yes	COMBINE: AVERAGE(diag0,diag1)

References

Box, G. E. P., and Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control*. Rev. ed. San Francisco: Holden-Day.

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control*. 3rd ed. Englewood Cliffs, NJ: Prentice-Hall.

Choi, B. (1992). *ARMA Model Identification*. New York: Springer-Verlag.

Cobb, G. W. (1978). "The Problem of the Nile: Conditional Solution to a Change Point Problem." *Biometrika* 65:243–251.

De Jong, P., and Penzer, J. (1998). "Diagnosing Shocks in Time Series." *Journal of the American Statistical Association* 93:796–806.

Dickey, D. A., and Fuller, W. A. (1979). "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74:427–431.

Dickey, D. A., Hasza, D. P., and Fuller, W. A. (1984). "Testing for Unit Roots in Seasonal Time Series." *Journal of the American Statistical Association* 79:355–367.

Durbin, J., and Koopman, S. J. (2001). *Time Series Analysis by State Space Methods*. Oxford: Oxford University Press.

Harvey, A. C. (1989). *Forecasting, Structural Time Series Models, and the Kalman Filter*. Cambridge: Cambridge University Press.

Harvey, A. C. (2001). "Testing in Unobserved Components Models." *Journal of Forecasting* 20:1–19.

Hasza, D. P., and Fuller, W. A. (1979). "Estimation for Autoregressive Processes with Unit Roots." *Annals of Statistics* 7:1106–1120.

Hasza, D. P., and Fuller, W. A. (1984). "Testing for Nonstationary Parameter Specifications in Seasonal Time Series Models." *Annals of Statistics* 10:1209–1216.

Hillmer, S. C., Larcker, D. F., and Schroeder, D. A. (1983). "Forecasting Accounting Data: A Multiple Time-Series Analysis." *Journal of Forecasting* 2:389–404.

McKenzie, E. (1984). "General Exponential Smoothing and the Equivalent ARMA Process." *Journal of Forecasting* 3:333–344.

Tsay, R. S., and Tiao, G. C. (1984). "Consistent Estimates of Autoregressive Parameters and Extended Sample Autocorrelation Function for Stationary and Nonstationary ARMA Models." *Journal of the American Statistical Association* 79:84–96.

Chapter 5
The HPFENGINE Procedure

Contents

Overview: HPFENGINE Procedure **160**
Getting Started: HPFENGINE Procedure **161**
Syntax: HPFENGINE Procedure **163**
- Functional Summary 164
- PROC HPFENGINE Statement 166
- ADJUST Statement 178
- BY Statement 180
- CONTROL Statement 181
- EXTERNAL Statement 182
- FORECAST Statement 183
- ID Statement 184
- INPUT Statement 187
- SCORE Statement 188
- STOCHASTIC Statement 189

Details: HPFENGINE Procedure **191**
- Accumulation 191
- Missing Value Interpretation 193
- Adjustment Operations 193
- Diagnostic Tests 195
- Model Selection 195
- IDM Model Combinations 196
- Transformations 197
- Parameter Estimation 197
- Missing Value Modeling Issues 197
- Forecasting 198
- Inverse Transformations 198
- Statistics of Fit 198
- Thread Usage in PROC HPFENGINE 198
- Data Set Input/Output 199
- ODS Table Names 209
- ODS Graphics 211

Examples: HPFENGINE Procedure **213**
- Example 5.1: The TASK= Option 213
- Example 5.2: Different Types of Input 215
- Example 5.3: Incorporating Events 218
- Example 5.4: Using the SCORE Statement 223

Example 5.5: HPFENGINE and HPFDIAGNOSE Procedures 227
Example 5.6: The ADJUST Statement 230
Example 5.7: Multiple Repositories 232
Example 5.8: ODS Graphics 233
Example 5.9: Combining Judgmental Forecasts 238
References **240**

Overview: HPFENGINE Procedure

The HPFENGINE procedure provides an automatic way to generate forecasts for many time series or transactional data in one step. The procedure can automatically choose the best forecast model from a user-defined model list or a default model list. Specifications for the candidate forecast models are independent of any data series. You can generate the specifications or choose them from a default set. Supported model families include the following:

- smoothing
- intermittent demand
- unobserved component
- ARIMA

Additionally, you can provide user-defined forecasts with data drawn from a SAS data set or through the use of user-written functions.

All parameters associated with the forecast model are optimized based on the data. The HPFENGINE procedure selects the appropriate model for each data series based on one of several model selection criteria.

The procedure operates in a variety of modes. At its most comprehensive, all appropriate candidate models from a list are fit to a particular series, and the model that produces the best fit (based on a user-determined criterion) is determined. Forecasts are then produced from this model. It is also possible to skip the selection process and fit a particular model and produce subsequent forecasts. Finally, given a set of parameter estimates and model specifications, the procedure can bypass the fit stage entirely and calculate forecasts directly.

The HPFENGINE procedure writes the time series extrapolated by the forecasts, the series summary statistics, the forecasts and confidence limits, the parameter estimates, and the fit statistics to output data sets.

The HPFENGINE procedure can forecast both time series data (whose observations are equally spaced at a specific time interval) and transactional data (whose observations are not spaced at any particular time interval). For transactional data, the data are accumulated at a specified time interval to form a time series.

Getting Started: HPFENGINE Procedure

In its simplest usage, the HPFENGINE procedure produces results similar to those of the HPF procedure:

```
proc hpfengine data=sashelp.air
               print=(select summary);
   id date interval=month;
   forecast air;
run;
```

The GLOBALSELECTION= and REPOSITORY= options assume their respective default values. Therefore automatic selection is performed for the AIR series in SASHELP.AIR by using the models specified in the BEST selection list. The selection list BEST is found, together with the smoothing models it references, in SASHELP.HPFDFLT.

The results of the automatic model selection are displayed in Output 5.1. A summary of the forecast is shown in Output 5.2.

Figure 5.1 Selection Results

The HPFENGINE Procedure

Model Selection Criterion = RMSE			
Model	**Statistic**	**Selected**	**Label**
SMSIMP	.	Removed	Simple Exponential Smoothing
SMDAMP	.	Removed	Damped-Trend Exponential Smoothing
SMLIN	.	Removed	Linear Exponential Smoothing
SMADWN	12.245596	No	Winters Method (Additive)
SMWINT	10.579085	Yes	Winters Method (Multiplicative)
SMSEAS	14.169905	No	Seasonal Exponential Smoothing

Figure 5.2 Forecast Summary

Forecast Summary											
Variable	**Value**	**JAN1961**	**FEB1961**	**MAR1961**	**APR1961**	**MAY1961**	**JUN1961**	**JUL1961**	**AUG1961**	**SEP1961**	**OCT1961**
AIR	Predicted	445.2972	418.1426	464.0889	494.0261	504.9584	572.5947	662.7040	653.7742	545.8935	487.7147

Forecast Summary		
Variable	**NOV1961**	**DEC1961**
AIR	415.2594	459.6067

The first four models in the selection list are nonseasonal smoothing models. The HPFENGINE procedure determined that the series AIR in SASHELP.AIR was seasonal and attempted to fit only seasonal models.

The multiplicative Winters method produced a fit with the smallest root mean squared error (RMSE).

As another example, consider the problem of comparing the performance of multiple ARIMA models for a particular series. This is done by using the HPFARIMASPEC procedure as follows to specify the models.

```
proc hpfarimaspec repository=sasuser.repository
                  name=arima1;
   dependent symbol=air q=1
             diflist=(1 12) noint transform=log;
run;

proc hpfarimaspec repository=sasuser.repository
                  name=arima2;
   dependent symbol=air q=(1,12)
             diflist=(1 12) noint transform=log;
run;
```

The model specifications are grouped together in a selection list. Selection lists are built with the HPFSELECT procedure.

```
proc hpfselect repository=sasuser.repository
               name=myselect;
   spec arima1 arima2;
run;
```

The HPFENGINE procedure uses the GLOBALSELECTION= option to reference the selection list that contains the two ARIMA models. Selection /results are shown in Output 5.3, and the forecast plot is shown in Figure 5.4.

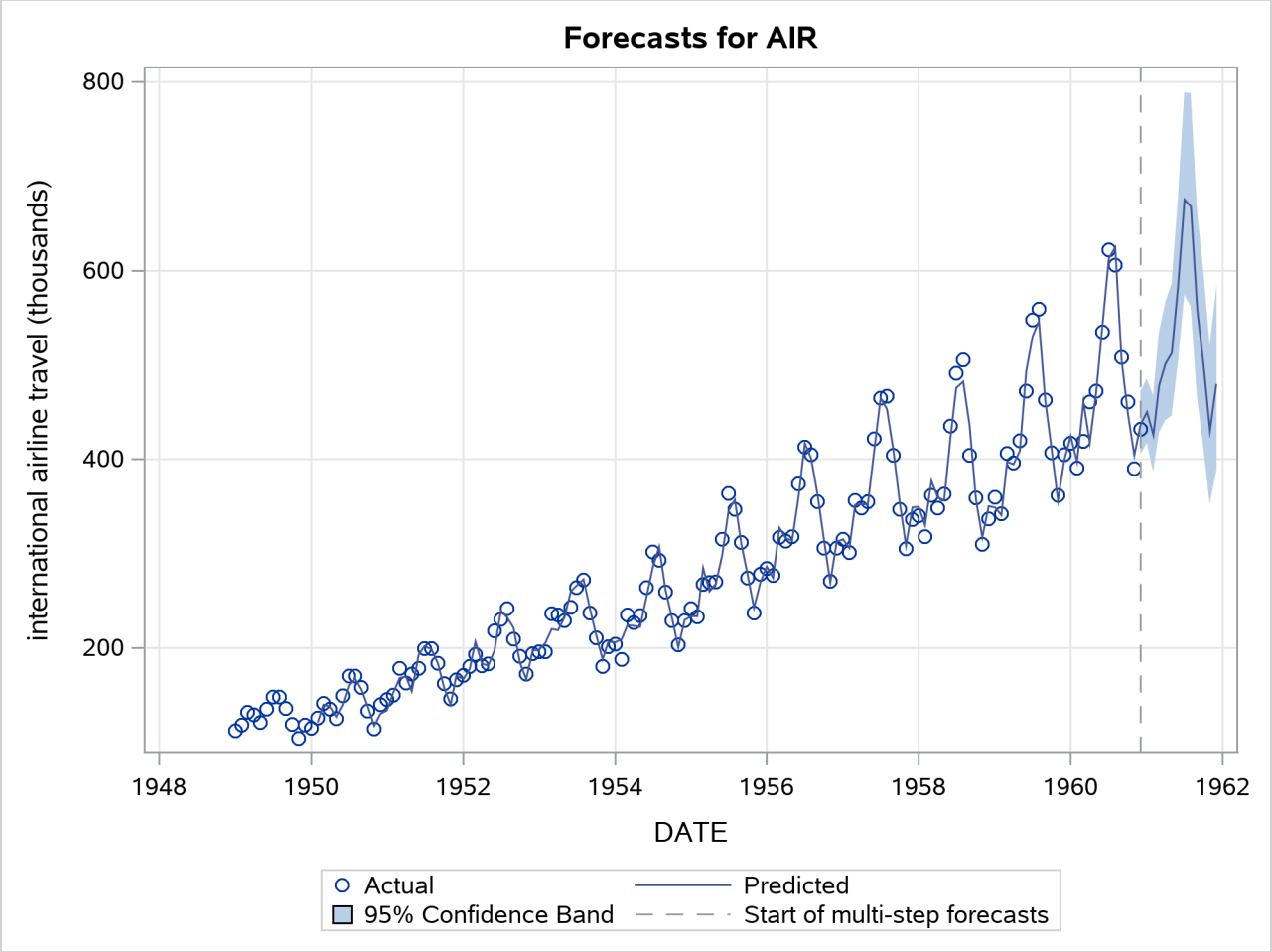
```
proc hpfengine data=sashelp.air
               repository=sasuser.repository
               globalselection=myselect
               print=(select forecasts)
               plot=forecasts;
   id date interval=month;
   forecast air;
run;
```

Figure 5.3 Selection and Forecast Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
ARIMA1	3.2553815	No	ARIMA: Log(AIR) ~ D = (1,12) Q = 1 NOINT
ARIMA2	2.9672282	Yes	ARIMA: Log(AIR) ~ D = (1,12) Q = (1,12) NOINT

Figure 5.4 Forecasts



Syntax: HPFENGINE Procedure

The following statements are used with the HPFENGINE procedure:

PROC HPFENGINE *options* ;
ADJUST *variable = (variable-list) / options* ;
BY *variables* ;
CONTROL *variable-list / options* ;
EXTERNAL *variable-list / options* ;
FORECAST *variable-list / options* ;
ID *variable INTERVAL= interval options* ;
INPUT *variable-list / options* ;
SCORE ;
STOCHASTIC *variable-list / options* ;

Functional Summary

Table 5.1 summarizes the statements and options that control the HPFENGINE procedure.

Table 5.1 PROC HPFENGINE Functional Summary

Description	Statements	Option
Statements		
Specifies BY-group processing	BY	
Specifies variables to forecast	FORECAST	
Specifies the time ID variable	ID	
Specifies input variables	INPUT	
Specifies input variables	STOCHASTIC	
Specifies input variables	CONTROL	
Specifies input forecasts, bounds, PIs	EXTERNAL	
Requests creation of score files	SCORE	
Model Selection Options		
Specifies location of model repository	PROC HPFENGINE	REPOSITORY=
Specifies model selection list	PROC HPFENGINE	GLOBALSELECTION=
Data Sets		
Specifies the auxiliary input data sets	PROC HPFENGINE	AUXDATA=
Specifies the input data sets	PROC HPFENGINE	DATA=
Specifies the data set containing mapping and estimate data	PROC HPFENGINE	INEST=
Specifies the events data set	PROC HPFENGINE	INEVENT=
Specifies the output data set	PROC HPFENGINE	OUT=
Specifies the accumulation mode output data set	PROC HPFENGINE	OUTACCDATA=
Specifies the forecast component output data set	PROC HPFENGINE	OUTCOMPONENT=
Specifies the output data set to store mapping and estimate data	PROC HPFENGINE	OUTEST=
Specifies the forecast output data set	PROC HPFENGINE	OUTFOR=
Specifies the output data set to store independent variable time series	PROC HPFENGINE	OUTINDEP=
Specifies the detailed model information output data set	PROC HPFENGINE	OUTMODELINFO=
Specifies the forecast procedure run information output data set	PROC HPFENGINE	OUTPROCINFO=
Specifies the forecast model statistics-of-fit output data set	PROC HPFENGINE	OUTSTAT=
Specifies the candidate model statistics-of-fit output data set	PROC HPFENGINE	OUTSTATSELECT=
Specifies the summary output data set	PROC HPFENGINE	OUTSUM=

Table 5.1 *continued*

Description	Statements	Option
Accumulation Options		
Specifies the accumulation frequency	ID	INTERVAL=
Specifies the length of seasonal cycle	PROC HPFENGINE	SEASONALITY=
Specifies the interval alignment	ID	ALIGN=
Specifies the starting time ID value	ID	START=
Specifies the starting time ID of forecast horizon	ID	HORIZONSTART=
Specifies the ending time ID value	ID	END=
Specifies the date format	ID	FORMAT=
Specifies that the time ID values might not be in sorted order	ID	NOTSORTED
Specifies the accumulation statistic	ID, FORECAST, INPUT, STOCHASTIC, CONTROL, EXTERNAL	ACCUMULATE=
Specifies the missing value interpretation	ID, FORECAST, INPUT, STOCHASTIC, CONTROL, EXTERNAL	SETMISSING=
Specifies the zero value interpretation	ID, FORECAST, INPUT, STOCHASTIC, CONTROL, EXTERNAL	ZEROMISS=
Specifies the trim missing values	ID, FORECAST, INPUT, STOCHASTIC, CONTROL, EXTERNAL	TRIMMISS=
Forecasting Horizon Options		
Specifies data to hold back	PROC HPFENGINE	BACK=
Modifies the holdback behavior for insufficient data	PROC HPFENGINE	FORCEBACK
Specifies forecast horizon or lead	PROC HPFENGINE	LEAD=
Forecasting Control Options		
Specifies forecasting control options	PROC HPFENGINE	TASK=
Replaces missing values in OUTFOR=	FORECAST	REPLACEMISSING
Does not replace missing values in OUTFOR=	FORECAST	NOREPLACE
Scoring Options		
Specifies the location of the score repository	PROC HPFENGINE	SCOREREPOSITORY=
Printing and Plotting Options		
Specifies graphical output	PROC HPFENGINE	PLOT=
Specifies printed output	PROC HPFENGINE	PRINT=

Table 5.1 *continued*

Description	Statements	Option
Specifies detailed printed output	PROC HPFENGINE	PRINTDETAILS
Miscellaneous Options		
Specifies error printing options	PROC HPFENGINE	ERRORCONTROL=
Specifies exception handling	PROC HPFENGINE	EXCEPTIONS=
Specifies control for statistics-of-fit computation	PROC HPFENGINE	STAT=
Specifies that analysis variables are processed in sorted order	PROC HPFENGINE	SORTNAMES

PROC HPFENGINE Statement

PROC HPFENGINE *options* **;**

The PROC HPFENGINE statement invokes the HPFENGINE procedure. You can specify the following *options*:

AUXDATA=*SAS-data-set*
names a SAS data set that contains auxiliary input data for the procedure to use for supplying explanatory variables in a forecast. See the section "AUXDATA= Data Set" on page 200 for more information.

BACK=*n*
specifies the number of observations before the end of the data where the multistep forecasts are to begin. This option is often used to obtain performance statistics. See the PRINT= option details about printing performance statistics. The default is BACK=0.

COMPONENTS=INTEGRATE
requests that the component series in the OUTCOMPONENT= data set be of the "integrated" type. The integrated type components might not satisfy the summability constraint. This option affects only the components that are produced by ARIMA models that include differencing. By default, the ARIMA components are generated with the summability constraint. For more information, see "ARIMA Model Based Series Decomposition" in the section "ARIMA Models" on page 478.

DATA=*SAS-data-set*
names the SAS data set that contains the input data for the procedure to forecast. If the DATA= option is not specified, the most recently created SAS data set is used.

ERRORCONTROL=(SEVERITY=(*severity-options***) STAGE= (***stage-options***) MAXMESSAGE=***number***)**
enables finer control of message printing. The error severity level and HPFENGINE procedure processing stages are set independently. A logical 'and' is taken over all the specified options, and any message that tests true against the results of the 'and' is printed.

Available *severity-options* are as follows:

LOW specifies that only low-severity, minor issues be printed.

MEDIUM specifies that only medium-severity problems be printed.

HIGH specifies that only severe errors be printed.

ALL specifies that errors of all severity levels (LOW, MEDIUM, and HIGH) be printed.

NONE specifies that no messages from the HPFENGINE procedure be printed.

Available *stage-options* are as follows:

PROCEDURELEVEL specifies that only errors that occur during option processing and validation be printed.

DATAPREP specifies that only errors that occur during the accumulation of data and the application of SETMISS= and ZEROMISS= options be printed.

SELECTION specifies that only errors that occur during the model selection process be printed.

ESTIMATION specifies that only errors that occur during the model parameter estimation process be printed.

FORECASTING specifies that only errors that occur during the model evaluation and forecasting process be printed.

ALL is the same as specifying all PROCEDURELEVEL, DATAPREP, SELECTION, ESTIMATION, and FORECASTING options.

Examples are as follows:

```
errorcontrol=(severity=(high medium) stage=all);
```

prints high- and moderate-severity errors at any processing stage of PROC HPFENGINE.

```
errorcontrol=(severity=high stage=dataprep);
```

prints high-severity errors only during the data preparation.

```
errorcontrol=(severity=none stage=all);
```

turns off messages from PROC HPFENGINE.

```
errorcontrol=(severity=(high medium low)
              stage=(procedurelevel dataprep selection
                     estimation forecasting));
```

specifies the default behavior. Also the following statement specifies the default behavior:

```
errorcontrol=(severity=all stage=all)
```

EXCEPTIONS=*except-option*

specifies the desired handling of arithmetic exceptions during the run. You can specify *except-option* as one of the following:

IGNORE specifies that PROC HPFENGINE stop on an arithmetic exception. No recovery is attempted. This is the default behavior if the EXCEPTIONS= option is not specified.

CATCH(ESM) specifies that PROC HPFENGINE generate a forecast based on using its default exponential smoothing model for the variable that produces the arithmetic exception in the current BY group. The ESM model is equivalent to the default model used by the HPFESMSPEC procedure with no modifications.

CATCH(RW) specifies that PROC HPFENGINE generate a forecast based on a zero-drift random walk model for the variable that produces the exception in the current BY group.

CATCH(MISSING) specifies that PROC HPFENGINE generate a forecast of missing values for the variable that produces the exception in the current BY group.

The order of CATCH handling corresponds to the order of the preceding list. If CATCH(ESM) handling produces an arithmetic exception, it attempts to generate a forecast by using CATCH(RW) semantics. Likewise, if CATCH(RW) handling produces an arithmetic exception, it generates a missing value forecast.

FORCEBACK

specifies alternate behavior for hold back when there is insufficient data to fit any model and honor the requested hold back sample size. The default behavior dynamically resets to no hold back samples for the current BY group if excluding the requested number of hold back samples leaves insufficient non-missing observations to fit any model. This allows PROC HPFENGINE to make an absolute effort to generate a statistical forecast for each BY group regardless of the condition of the input data set. Sometimes it can be desirable to sacrifice this behavior in order to preserve a consistent time base across the BY groups in the OUT= and OUTFOR= data sets. This is the purpose of FORCEBACK. It alters the default behavior of PROC HPFENGINE to ensure that a consistent hold back sample size is used across all BY groups of the input data set. If a series has insufficient observations to permit a model fit after excluding hold back samples, a missing value forecast is generated over the range of time ID's corresponding to the complete forecast horizon including the hold back region. Additionally, for both OUTSUM= and OUTEST= data sets, the _STATUS_ variable is set to indicate the excepted forecast produced by the presence of FORCEBACK.

GLOBALSELECTION=*catalog-name*

specifies the name of a catalog entry that serves as a model selection list. This is the selection list used to forecast all series if no INEST= data set is provided. It is also the selection list used if individual model selections are missing in the INEST= data set when INEST= is provided. If REPOSITORY= is not present, GLOBALSELECTION defaults to BEST, specified in SASHELP.HPFDFLT.

IGNORECHOOSE

specifies that the CHOOSE= option in the HPFSELECT procedure be ignored when selecting a model in the candidate model list. The best model is selected regardless of the model chosen in the CHOOSE= option in the HPFSELECT procedure.

INEST=*SAS-data-set*
contains information that maps forecast variables to models or selection lists, and data set variables to model variables. It can also contain parameter estimates used if the TASK=FORECAST or TASK=UPDATE options are present. INEST= is optional. See the description of the GLOBALSELECTION= option for more information.

INEVENT=*SAS-data-set*
contains information that describes predefined events. This data set is usually created by the HPFEVENTS procedure. This option is only used if events are included in a model.

LEAD=*n*
specifies the number of periods ahead to forecast (forecast lead or horizon). The default is LEAD=12.

The LEAD= value is relative to the last observation in the input data set and not to the last nonmissing observation of a particular series. Thus, if a series has missing values at the end, the actual number of forecasts computed for that series will be greater than the LEAD= value.

OUT=*SAS-data-set*
names the output data set to contain the forecasts of the variables specified in the subsequent FORECAST statements. If an ID variable is specified, it will also be included in the OUT= data set. The values are accumulated based on the ACCUMULATE= option and forecasts are appended to these values. If the OUT= data set is not specified, a default output data set DATA*n* is created. If you do not want the OUT= data set created, then use OUT=_NULL_.

OUTACCDATA=*SAS-data-set*
names the output data set to store accumulation mode used for each forecast variable specified for the HPFENGINE procedure. This data set is commonly used to transfer information to the HPFTEMPRECON procedure so it can properly affect constraint formulation for the benchmarking process.

OUTCOMPONENT=*SAS-data-set*
names the output data set to contain the forecast components. The components included in the output depend on the model.

OUTEST=*SAS-data-set*
contains information that maps forecast variables to model specifications, and data set variables to model variables and parameter estimates.

An OUTEST= data set will frequently be used as the INEST= data set for subsequent invocations of PROC HPFENGINE. In such a case, if the PROC HPFENGINE statement option TASK=FORECAST is used, forecasts are generated using the parameter estimates found in this data set and are not reestimated.

OUTFOR=*SAS-data-set*
names the output data set to contain the forecast time series components (actual, predicted, lower confidence limit, upper confidence limit, prediction error, and prediction standard error). The OUTFOR= data set is particularly useful for displaying the forecasts in tabular or graphical form.

OUTINDEP=*SAS-data-set*
names the output data set to contain input in the forecasting process. This information is useful if future values of input variables are automatically supplied by the HPFENGINE procedure. Such a case would occur if one or more input variables are listed in either the STOCHASTIC or the CONTROLLABLE statement and if there are missing future values of these input variables.

OUTMODELINFO=*SAS-data-set*
names the output data set to contain detailed information about the selected forecast model. The data set has information such as the model family, presence or absence of inputs, events and outliers, and so forth.

OUTPROCINFO=*SAS-data-set*
names the output data set to contain information in the SAS log, specifically the number of notes, errors, and warnings and the number of series processed, forecasts requested, and forecasts failed.

OUTSTAT=*SAS-data-set*
names the output data set to contain the statistics of fit (or goodness-of-fit statistics). The OUTSTAT= data set is useful for evaluating how well the model fits the series. The statistics of fit are based on the entire range of the time series.

OUTSTATSELECT=*SAS-data-set*
names the output data set to contain statistics of fit for all of the candidate models fit during model selection. The OUTSTATSELECT= data set is useful for comparing the performance of various models.

OUTSUM=*SAS-data-set*
names the output data set to contain the summary statistics and the forecast summation. The summary statistics are based on the accumulated time series for the dependent variables acquired from the DATA= data set. The forecast summations are based on the LEAD= option setting. The OUTSUM= data set is particularly useful when forecasting large numbers of series and a summary of the results is needed.

PLOT <(*global-plot-options***)> =***plot-request* *< (options) >*

PLOT <(*global-plot-options***)> =(***plot-request* *< (options) >* **< . . .** *plot-request* *< (options) >* **>)**
specifies the graphical output that you want. By default, the HPFENGINE procedure produces no graphical output.

Any specified *global-plot-options* are available to all of the requested plots. They are interpreted by the individual plots that are requested, so it is possible to specify *global-plot-options* that have no effect for a particular set of plot requests. Each of the following *global-plot-options* description includes the set of plots for which it has some effect.

You can specify the following *global-plot-options*:

NLAGS=*number*
specifies the number of lags to include in various error series plots. This option affects the ACF, IACF, PACF, and WN plots. The default number of lags is given by

$$\mathrm{NLAGS} = \begin{cases} \min\{120, \max\{3 \times \mathrm{SEASONALITY}, 24\}\} & \text{if } \mathrm{SEASONALITY} > 1 \\ 24 & \text{if } \mathrm{SEASONALITY} = 0 \end{cases}$$

In all cases, NLAGS is automatically limited to half of the number of observations in the error series.

You can specify the following *plot-requests*:

ACF plots the prediction error autocorrelation function.

ALL is equivalent to specifying PLOT=(ACF COMPONENTS ERRORS FORECASTCYCLES FORECASTS FORECASTSONLY IACF MODELFORECASTS MODELS PERIODOGRAM SPECTRUM WN).

BASIC is equivalent to specifying PLOT=(CORR ERRORS MODELFORECASTS). In the context of IDM models, the stocking level plot is generated in place of the prediction error correlation panel plot.

CANDIDATES plots model (forecast) and error series for each candidate model that is fit to the dependent series.

COMPONENTS plots the forecast components.

CORR plots the prediction error series graphics panel that contains the ACF, IACF, PACF, and white noise probability plots. In the context of IDM models, PLOT=CORR produces no additional output.

ERRORS=<(SMOOTH=*method*)> plots prediction error time series. You can specify the following *method* values:

NONE specifies that no smoothed error series overlay be applied to the plot.

LOESS specifies that a LOESS fit be used to generate a smoothed error series overlay for the plot.

PLOT=ERRORS is equivalent to PLOT=ERRORS(SMOOTH=LOESS).

FORECASTCYCLES plots the forecast seasonal cycles.

FORECASTS plots the actual time series and its one-step-ahead forecast over the historical period; plots the forecast and its confidence bands over the forecast horizon.

FORECASTSONLY plots the forecast and its confidence bands over the forecast horizon only.

IACF plots the prediction error inverse autocorrelation function.

MODELFORECASTS plots the one-step-ahead model forecast and its confidence bands in the historical period; plots the forecast and its confidence bands over the forecast horizon.

MODELS plots the one-step-ahead model forecast and its confidence bands in the historical period.

PACF plots the prediction error partial autocorrelation function.

PERIODOGRAM plots periodogram of the prediction error series.

SPECTRUM=<(*spectrum-options*)> plots the periodogram and the smoothed periodogram of the prediction error series in a single graph.

You can specify the following *spectrum-options*:

ALPHA=*value* specifies the significance level for upper and lower confidence limits around the smoothed periodogram estimates of spectral density. By default, ALPHA=0.4.

CENTER=YES | NO specifies whether mean adjustment is desired for the error series before computation of the smoothed periodogram estimates of spectral density. By default, CENTER=NO.

PLOT=SPECTRUM is equivalent to PLOT=SPECTRUM(ALPHA=0.4 CENTER=NO).

WN plots white noise graphics.

For example, PLOT=FORECASTS plots the forecasts for each series; PLOT(NLAGS=12)=(ACF IACF) produces the prediction error autocorrelation and inverse autocorrelation plots for which the number of lags restricted to 12.

PRINT=*option* | **(***options* **)**

specifies printed output. By default, the HPFENGINE procedure produces no printed output.

The following printing options are available:

ALL is the same as specifying PRINT=(ESTIMATES SELECT FORECASTS STATISTICS BIAS DESCSTATS). PRINT=(ALL CANDIDATES COMPONENTS PERFORMANCE PERFORMANCESUMMARY PERFORMANCEOVERALL) prints all the options listed.

BIAS prints model bias information.

CANDIDATES prints parameter estimates for each candidate model evaluated during the model selection step.

COMPONENTS prints forecast model components.

DESCSTATS prints descriptive statistics the series forecast series.

ESTIMATES prints parameter estimates for the selected model.

FORECASTS prints the forecasts.

PERFORMANCE prints the performance statistics for each forecast.

PERFORMANCESUMMARY prints the performance summary for each BY group.

PERFORMANCEOVERALL prints the performance summary for all of the BY groups.

SELECT prints the label and fit statistics for each model in the selection list.

STATISTICS prints the statistics of fit.

SUMMARY prints the forecast summary.

PRINTDETAILS

specifies that output requested with the PRINT= option be printed in greater detail.

REPOSITORY=*catalog-name*
is a two-level SAS catalog name that specifies the location of the model repository. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=. The default for this option is Sashelp.Hpfdflt.

SCOREREPOSITORY=*catalog-name*
is a two-level SAS catalog name that specifies the location of the model score repository. Score files are written to this repository if the SCORE statement is used in the HPFENGINE procedure. There is no default score repository. The presence of a SCORE statement requires that the SCOREREPOSITORY= option also be present.

SEASONALITY=*n*
specifies the length of the seasonal cycle. For example, SEASONALITY=3 means that every group of three observations forms a seasonal cycle. The SEASONALITY= option is applicable only for seasonal forecasting models. By default, the length of the seasonal cycle is 1 (no seasonality) or the length implied by the INTERVAL= option specified in the ID statement. For example, INTERVAL=MONTH implies that the length of the seasonal cycle is 12.

SORTNAMES
specifies that the variables specified in the FORECAST statement be processed in sorted order.

STAT=ADJUST | NOADJUST
specifies whether the statistics of fit be computed before or after the forecast dependent series is post-adjusted.

ADJUST specifies that statistics of fit be computed after the forecast series is post-adjusted. This is the default.

NOADJUST specifies that statistics of fit be computed before the forecast series is post-adjusted.

TASK=*action*(*override-options*)
controls the model selection and parameter estimation process. The following *action* values are valid. All *override-options* are admissible for any *action*. See section "TASK= Option Details" on page 174 for details.

SELECT performs model selection, estimates parameters of the selected model, and produces forecasts. This is the default.

SELECT(*override-options*) performs model selection, estimates parameters of the selected model, produces forecasts, and potentially overrides settings in the model selection list. If a selection list does not specify a particular item and that item is specified with a TASK=SELECT option, the value as set in TASK=SELECT is used. If an option is specified in selection list, the corresponding value set in TASK=SELECT is not used unless the OVERRIDE option is also present. See section "TASK= Option Details" on page 174 for possible values of *override-options* and other details.

FIT estimates parameters by using the model specified in the INEST= data set, and then forecasts. No model selection is performed. New parameter estimates are saved if an OUTEST= data set is specified. See section "TASK= Option Details" on page 174 for details.

FIT(*override-options*) performs the same action as TASK=FIT supplemented by any *override-options* specified. See section "TASK= Option Details" on page 174 for details.

UPDATE estimates parameters by using the model specified in the INEST= data set, and then forecasts. TASK=UPDATE differs from TASK=FIT in that the parameters found in the INEST= data set are used as starting values in the estimation. No model selection is performed. New parameter estimates are saved if an OUTEST= data set is specified. See section "TASK= Option Details" on page 174 for details.

UPDATE(*override-options*) performs the same action as TASK=UPDATE supplemented by any *override-options* specified. See section "TASK= Option Details" on page 174 for details.

FORECAST forecasts using model and parameters specified in the INEST= data set. No parameter estimation nor model selection occurs. See section "TASK= Option Details" on page 174 for details.

FORECAST(*override-options*) performs the same action as TASK=FORECAST supplemented by any *override-options* specified. See section "TASK= Option Details" on page 174 for details.

TASK= Option Details

This section describes the *override-options* that can be specified in any TASK=*action* context. Many of these settings are used only during the model selection phase of PROC HPFENGINE processing (that is, during the processing performed when you specify TASK=SELECT). However, there can be a need for them in any TASK=*action* context. PROC HPFENGINE can generate special placeholder forecasts for some of the time series it encounters during a TASK=SELECT run. These are generally the result of nominal data that prohibits PROC HPFENGINE from performing an evaluation of the model selection list for the series. As such, these forecasts represent excepted cases. Many of these cases are triggered from various *override-options* in effect during the TASK=SELECT run. For example, if you specified TASK=SELECT(MINOBS=6), any series with fewer than six nonmissing observations would trigger a forecast using the _MEAN_ model. Another example would be the _ZERO_ model that arises from use of the ENDZEROS= option. PROC HPFENGINE recognizes these excepted cases when processing the information from its INEST= data set that is saved as the OUTEST= data set from a previous PROC HPFENGINE run. When recognized in this way, PROC HPFENGINE attempts to perform model selection processing on those excepted cases regardless of the TASK=*action* requested. To deal with any such cases properly and ensure consistent behavior, you should specify the same set of *override-options* for your PROC HPFENGINE runs without regard to the *action* value specified.

You can specify these *override-options* in the context of any admissible *action* for TASK=.

ALPHA=*number* specifies the significance level to use in computing the confidence limits of the forecast. The ALPHA= value must be between 0 and 1. For example, ALPHA=0.05 produces 95% confidence intervals.

If a selection list does not specify ALPHA and ALPHA is specified in TASK=, the value that is specified takes effect. If ALPHA is specified in the selection list, the corresponding value specified in TASK= is not used unless the OVERRIDE option is also present.

CRITERION=*option* specifies the model selection criterion (statistic of fit) to be used to select from several candidate models. The following list shows the valid values for the CRITERION=*option* and its corresponding statistic of fit:

SSE	sum of square error
MSE	mean square error
RMSE	root mean squared error
UMSE	unbiased mean squared error
URMSE	unbiased root mean squared error
MAXPE	maximum percent error
MINPE	minimum percent error
MPE	mean percent error
MAPE	mean absolute percent error
MDAPE	median absolute percent error
GMAPE	geometric mean absolute percent error
MINAPES	minimum absolute error percent of standard deviation
MAXAPES	maximum absolute error percent of standard deviation
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MPPE	mean predictive percent error
MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median absolute predictive percent error
GMAPPE	geometric mean absolute predictive percent error
MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error
MSPE	mean symmetric percent error
SMAPE	symmetric mean absolute percent error
MDASPE	median absolute symmetric percent error
GMASPE	geometric mean absolute symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error
MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MAXERR	maximum error

MINERR	minimum error
ME	mean error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R square
ADJRSQ	adjusted R square
AADJRSQ	Amemiya's adjusted R square
RWRSQ	random walk R square
AIC	Akaike information criterion
AICC	finite sample corrected AIC
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion

ENDZEROS=(MAXNUM=*number* MAXPCT=*percent* MINOBS=*number*) specifies criteria that control the use of a _ZERO_ model for a series. A _ZERO_ model is used when the number of trailing zero values in the series fails to indicate that a nonzero model is appropriate. (By default, no _ZERO_ model testing is performed.) If CHOOSE= is specified in the model selection list that is used for a series, these options have no effect and the chosen model is used.

You can specify the following suboptions:

MAXNUM=*number* specifies the count of trailing zero values needed in order to consider a nonzero model. If the series has *number* or fewer trailing zero observations, then a nonzero model is considered. For example, if you specify ENDZEROS=(MAXNUM=10), then a nonzero model is considered only if the series has 10 or fewer trailing zero values.

MAXPCT=*P* specifies the maximum percentage of trailing zero values relative to the number of nonzero values in the entire series. If the number of trailing zero observations in the series is fewer than or equal to *P*% of the nonmissing and nonzero values of the entire series, then a nonzero model is considered. The value of *P* is in the range (0,100). If you specify ENDZEROS=(MAXPCT=20), then a nonzero model is considered only if the number of trailing zero values is fewer than or equal to 20% of the number of nonmissing and nonzero values of the entire series.

MINOBS=*number* specifies the minimum series length that is required to perform the _ZERO_ model test. For example, if you specify MINOBS=8, then the _ZERO_ model test is not performed on any series whose length is fewer than eight observations. By default, MINOBS=0, which implies no minimum length exclusion.

If MAXNUM=0 and MAXPCT=100 or MAXPCT=0, then a nonzero model is always considered. You can specify a combination of the MAXNUM= and MAXPCT= options. If you specify ENDZEROS=(MAXNUM=10 MAXPCT=20), then a nonzero model is

considered only if the series has 10 or fewer trailing zero values and if the number of trailing zero values is fewer than or equal to 20% of the number of nonmissing and nonzero values of the entire series.

When a series fails to use a nonzero model by the criteria specified in this option, the _ZERO_ model is used. In the OUTEST= data set, the _MODEL_ variable is set to _ZERO_, and the remaining data set variables that are associated with the parameter estimates are set to missing.

HOLDOUT=*n* specifies the size of the holdout sample to be used for model selection. The holdout sample is a subset of actual time series that ends at the last nonmissing observation.

HOLDOUTPCT=*number* specifies the size of the holdout sample as a percentage of the length of the time series. If HOLDOUT=5 and HOLDOUTPCT=10, the size of the holdout sample is $min(5, 0.1T)$, where T is the length of the time series with beginning and ending missing values removed.

INTERMITTENT=*number* specifies a number greater than 1 that is used to determine whether or not a time series is intermittent. If the median demand interval is equal to or greater than this number, then the series is assumed to be intermittent.

MINOBS=(TREND=*n*) specifies that no trend model be fit to any series with fewer than *n* nonmissing values. Normally the models in a selection list are not subset by trend.

Incorporation of a trend is checked only for smoothing, UCM, and ARIMA models. For the smoothing case, only simple smoothing is a non-trend model. For UCM, the absence of a slope component qualifies it as a non-trend model. For ARIMA, there must be no differencing of the dependent variable for PROC HPFENGINE to consider it a non-trend model.

The value of *n* must be greater than or equal to 1. The default is TREND=1.

MINOBS=(SEASON=*n*) specifies that no seasonal model be fit to any series with fewer observations than *n* multiplied by the seasonal cycle length. The value of *n* must be greater than or equal to 1. The default is SEASON=2.

MINOBS=*n* specifies that any series with fewer than *n* nonmissing values not be fit using the models in the selection list, but instead be forecast as the mean of the observations in the series. The forecast is recorded as using the _MEAN_ model in the OUTEST= data set _MODEL_ variable. The value of *n* must be greater than or equal to 1. The default is MINOBS=1.

NOALTLIST disables the default action and sets the forecast to missing if no models can be fit from the initial selection list. (By default, if none of the models in a selection list can be successfully fit to a series, PROC HPFENGINE returns to the selection list Sashelp.Hpfdflt.Best and restarts the selection process.) There will be an observation in OUTSUM=, if requested, that corresponds to the variable and BY group in question, and the _STATUS_ variable will be nonzero.

OVERRIDE forces the use of any options listed.

SEASONTEST=*option* specifies the options related to the seasonality test.

The following values for the SEASONTEST= option are allowed:

NONE no test

(SIGLEVEL=*number*) specifies the significance probability value to use in testing whether seasonality is present in the time series. The value must be between 0 and 1. A smaller value of the SIGLEVEL= option means that stronger evidence of a seasonal pattern in the data is required before PROC HPFENGINE uses seasonal models to forecast the time series.

The default is SEASONTEST=(SIGLEVEL=0.01).

The following details apply to the usage of SEASONTEST=(SIGLEVEL=*number*):

- If the HPFDIAGNOSE procedure is used to identify a single model, and that model is input to the HPFENGINE procedure by using the REPOSITORY= option and the INEST= option, then SEASONTEST(SIGLEVEL=) does not apply. Note that the default SIGLEVEL= value for PROC HPFDIAGNOSE is 0.05.
- If no model is specified for PROC HPFENGINE, then the procedure chooses a model from the list of default smoothing models. In this case, SEASONTEST(SIGLEVEL=) does apply, and SIGLEVEL=0.01 is the default value for choosing between a seasonal and nonseasonal model.
- If a model that is included in the PROC HPFENGINE selection list is created using the METHOD=BEST option of the ESM statement in the HPFESMSPEC procedure, then the significance level for including seasonal components in the model is fixed at 0.05. The SEASONTEST(SIGLEVEL=) value in PROC HPFENGINE does not affect the identification of seasonal components in the BEST model when you use this method.

ADJUST Statement

ADJUST *variable = (variable-list) / options* **;**

The ADJUST statement lists the numeric variables in the DATA= data set whose accumulated values are used to adjust the dependent values. Adjustments can be performed before or after forecasting (or both). A particular forecast variable can be referenced by multiple ADJUST statements.

The first variable specified is the variable to be adjusted. This variable must appear in a FORECAST statement. The numeric variables used as the source of the adjustments are listed following the parentheses. Options determine which adjustments are applied and when they are applied. More information about the use of adjustments is in the section "Details: HPFENGINE Procedure" on page 191.

The following options can be used with the ADJUST statement:

OPERATION=(*preadjust***,** *postadjust* **)**

specifies how the adjustments are applied to the forecast variable. The *preadjust* option determines how the adjustment variables are applied to the dependent variable prior to forecasting. The *postadjust* option determines how the adjustment variables are applied to the forecast results.

Computations with missing values are handled differently in the adjustment statement than in other parts of SAS. If any of the adjustment operations result in a nonmissing dependent value being added

to, subtracted from, divided by, or multiplied by a missing value, the nonmissing dependent value is left unchanged. Division by zero produces a missing value.

The following predefined adjustment operations are provided:

NONE	No adjustment operation is performed. This is the default.
ADD	Variables listed in the adjustment statement are added to the dependent variable.
SUBTRACT	Variables listed in the adjustment statement are subtracted from the dependent variable.
MULTIPLY	Dependent variable is multiplied by variables listed in the adjustment statement.
DIVIDE	Dependent variable is divided by variables listed in the adjustment statement.
MIN	Dependent variable is set to the minimum of the dependent variable and all variables listed in the adjustment statement.
MAX	Dependent variable is set to the maximum of the dependent variable and all variables listed in the adjustment statement.

It is important to note that pre-adjustment operations are applied in the order defined by the sequence of ADJUST statements but post-adjustment operations are applied in the reverse order. For example, suppose you specify the following sequence of ADJUST statements:

```
ADJUST AIR=(BIAS)  / OPERATION = (SUBTRACT,ADD);
ADJUST AIR=(SCALE) / OPERATION = (DIVIDE,MULTIPLY)
```

When PROC HPFENGINE performs its pre-adjustment, the value of BIAS is subtracted from the forecast variable AIR and that result is then divided by the value of SCALE to produce the pre-adjusted AIR series used by HPFENGINE to generate a forecast. Then that forecast series is post-adjusted using the specified *postadjust* operators in the reverse order of the ADJUST statements: the forecast series is multiplied by the value of SCALE and that result is added to the value of BIAS to produce the final forecast series output from HPFENGINE.

ACCUMULATE=*option*

specifies how the data set observations are accumulated within each time period for the variables listed in the ADJUST statement. If the ACCUMULATE= option is not specified in the CONTROL statement, accumulation is determined by the ACCUMULATE= option of the ID statement. See the ID statement ACCUMULATE= option for more details.

SETMISSING=*option* | *number*

specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for variables listed in the ADJUST statement. If the SETMISSING= option is not specified in the ADJUST statement, missing values are set based on the SETMISSING= option of the ID statement. See the ID statement SETMISSING= option for more details.

TRIMMISS=*option*
specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the ADJUST statement.

If the TRIMMISS= option is not specified in the ADJUST statement, missing values are set based on the TRIMMISS= option of the ID statement. See the ID statement TRIMMISS= option for more details.

ZEROMISS=*option*
specifies how beginning and ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the ADJUST statement. If the ZEROMISS= option is not specified in the ADJUST statement, missing values are set based on the ZEROMISS= option of the ID statement. See the ID statement ZEROMISS= option for more details.

BY Statement

BY *variables* **;**

A BY statement can be used with PROC HPFENGINE to obtain separate dummy variable definitions for groups of observations defined by the BY variables.

When a BY statement appears, the procedure expects the input data set to be sorted in order of the BY variables.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data by using the SORT procedure with a similar BY statement.
- Specify the option NOTSORTED or DESCENDING in the BY statement for the HPF procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged in groups (according to values of the BY variables) and that these groups are not necessarily in alphabetical or increasing numeric order.
- Create an index on the BY variables by using the DATASETS procedure.

For more information about the BY statement, see *SAS Language Reference: Concepts*. For more information about the DATASETS procedure, see the discussion in the *Base SAS Procedures Guide.*

CONTROL Statement

CONTROL *variable-list / options* **;**

The CONTROL statement lists the numeric variables in the DATA= data set whose accumulated values are used as input in the forecasting process. The future values of the control variables in the forecast statement are determined by the EXTEND= option. Only input values used in a CONTROL statement are adjustable in the score evaluation subroutine HPFSCSUB.

The following options can be used with the CONTROL statement:

ACCUMULATE=*option*

specifies how the data set observations are accumulated within each time period for the variables listed in the CONTROL statement. If the ACCUMULATE= option is not specified in the CONTROL statement, accumulation is determined by the ACCUMULATE= option of the ID statement. See the ID statement ACCUMULATE= option for more details.

EXTEND=*option*

specifies how future values of the control variables are set. The following options are provided:

NONE	Future values are set to missing.
AVERAGE	Future values are set to the mean of the values in the fit range. This is the default.
FIRST	Future values are set to the first value found in the fit range.
LAST	Future values are set to the last value found in the fit range.
MINIMUM	Future values are set to the minimum of the values in the fit range.
MAXIMUM	Future values are set to the maximum of the values in the fit range.
MEDIAN	Future values are set to the median of the values in the fit range.
STOCHASTIC	Future values are forecast using the best suited exponential smoothing model. See STOCHASTIC statement for details.

REPLACEMISSING

specifies that embedded missing actual values over the fit range be replaced with values obtained by applying the method specified in the EXTEND= option. For EXTEND=STOCHASTIC, the replacement values are the one-step-ahead forecasts obtained over the fit range.

SETMISSING=*option* | *number*

specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for variables listed in the CONTROL statement. If the SETMISSING= option is not specified in the CONTROL statement, missing values are set based on the SETMISSING= option of the ID statement. See the ID statement SETMISSING= option for more details.

TRIMMISS=*option*

specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the CONTROL statement.

If the TRIMMISS= option is not specified in the CONTROL statement, missing values are set based on the TRIMMISS= option of the ID statement. See the ID statement TRIMMISS= option for more details.

ZEROMISS=*option*

specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the CONTROL statement. If the ZEROMISS= option is not specified in the CONTROL statement, missing values are set based on the ZEROMISS= option of the ID statement. See the ID statement ZEROMISS= option for more details.

EXTERNAL Statement

EXTERNAL *variable-list / options* **;**

The EXTERNAL statement lists the numeric variables in the DATA= data set whose accumulated values are used as predicted values for an external model. It can also list prediction standard errors and lower and upper confidence intervals.

Any variables used in an EXMMAP in a selection list, as specified by PROC HPFSELECT, must appear in an EXTERNAL statement.

The following options can be used with the EXTERNAL statement:

SETMISSING=*option* | *number*

specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for variables listed in the EXTERNAL statement. If the SETMISSING= option is not specified in the EXTERNAL statement, missing values are set based on the SETMISSING= option of the ID statement. See the ID statement SETMISSING= option for more details.

TRIMMISS=*option*

specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the EXTERNAL statement.

If the TRIMMISS= option is not specified in the EXTERNAL statement, missing values are set based on the TRIMMISS= option of the ID statement. See the ID statement TRIMMISS= option for more details.

ZEROMISS=*option*

specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the ADJUST statement. If the ZEROMISS= option is not specified in the EXTERNAL statement, missing values are set based on the ZEROMISS= option of the ID statement. See the ID statement ZEROMISS= option for more details.

FORECAST Statement

FORECAST *variable-list / options* **;**

The FORECAST statement lists the numeric variables in the DATA= data set whose accumulated values represent time series to be modeled and forecast.

A data set variable can be specified in only one FORECAST statement. Any number of FORECAST statements can be used.

The following options can be used with the FORECAST statement.

ACCUMULATE=*option*
specifies how the data set observations are accumulated within each time period for the variables listed in the FORECAST statement. If the ACCUMULATE= option is not specified in the FORECAST statement, accumulation is determined by the ACCUMULATE= option of the ID statement. See the ID statement ACCUMULATE= option for more details.

NOREPLACE
specifies that the forecast value in the OUTFOR= data set be set to missing when a corresponding historical value is missing. For example, consider historical data spanning 01JAN1980 through 01DEC1985. If the dependent variable that corresponds to 01MAR1983 is missing, the forecast variable in the OUTFOR= data set at time ID 01MAR1983 is usually replaced by the one-step-ahead forecast. The NOREPLACE option prevents that one-step-ahead forecast from being written in the OUTFOR= data set. The inverse behavior of this option, applied to the OUT= data set, is REPLACEMISSING.

REPLACEMISSING
specifies that embedded missing actual values be replaced with one-step-ahead forecasts in the OUT= data set. The inverse behavior of this option, applied to the OUTFOR= data set, is NOREPLACE.

SETMISSING=*option* | *number*
specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for variables listed in the FORECAST statement. If the SETMISSING= option is not specified in the FORECAST statement, missing values are set based on the SETMISSING= option of the ID statement. See the ID statement SETMISSING= option for more details.

TRIMMISS=*option*
specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the FORECAST statement. If the TRIMMISS= option is not specified in the FORECAST statement, missing values are set based on the TRIMMISS= option of the ID statement. See the ID statement TRIMMISS= option for more details.

ZEROMISS=*option*
specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the FORECAST statement. If the ZEROMISS= option is not specified in the FORECAST statement, missing values are set based on the ZEROMISS= option of the ID statement. See the ID statement ZEROMISS= option for more details.

ID Statement

ID *variable* < *options* > **;**

The ID statement names a numeric variable that identifies observations in the input and output data sets. The ID variable's values are assumed to be SAS date, time, or datetime values. In addition, the ID statement specifies the (desired) frequency associated with the actual time series. The ID statement options also specify how the observations are accumulated and how the time ID values are aligned to form the actual time series. The information specified affects all variables specified in subsequent FORECAST statements. If the ID statement is specified, the INTERVAL= option must also be specified. If an ID statement is not specified, the observation number (with respect to the BY group) is used as the time ID.

The following options can be used with the ID statement.

ACCUMULATE=*option*

specifies how the data set observations are accumulated within each time period. The frequency (width of each time interval) is specified by the INTERVAL= option. The ID variable contains the time ID values. Each time ID variable value corresponds to a specific time period. The accumulated values form the actual time series, which is used in subsequent model fitting and forecasting.

The ACCUMULATE= option is particularly useful when there are zero or more than one input observations that coincide with a particular time period (for example, transactional data). The EXPAND procedure offers additional frequency conversions and transformations that can also be useful in creating a time series.

Duplicate time ID variable values within a BY group can cause unexpected results. If your data might contain such duplicate values, specify an *option* other than NONE to remove any duplicates.

The following *option* values determine how the observations are accumulated within each time period on the basis of the ID variable and the frequency that you specify in the INTERVAL= option:

NONE	No accumulation occurs; the ID variable values must be equally spaced with respect to the frequency. This is the default *option*.
TOTAL	Observations are accumulated based on the total sum of their values.
AVERAGE | AVG	Observations are accumulated based on the average of their values.
MINIMUM | MIN	Observations are accumulated based on the minimum of their values.
MEDIAN | MED	Observations are accumulated based on the median of their values.
MAXIMUM | MAX	Observations are accumulated based on the maximum of their values.
N	Observations are accumulated based on the number of nonmissing observations.
NMISS	Observations are accumulated based on the number of missing observations.
NOBS	Observations are accumulated based on the number of observations.
FIRST	Observations are accumulated based on the first of their values.
LAST	Observations are accumulated based on the last of their values.

STDDEV | STD	Observations are accumulated based on the standard deviation of their values.
CSS	Observations are accumulated based on the corrected sum of squares of their values.
USS	Observations are accumulated based on the uncorrected sum of squares of their values.

If you specify the ACCUMULATE= option, the SETMISSING= option is useful for specifying how accumulated missing values are treated. If missing values should be interpreted as zero, then specify SETMISSING=0. The section "Details: HPFENGINE Procedure" on page 191 describes accumulation in greater detail.

ALIGN=*option*

controls the alignment of SAS dates that are used to identify output observations. You can specify the following values: BEGINNING | BEG | B, MIDDLE | MID | M, and ENDING | END | E. By default, ALIGN=BEGINNING.

END=*option*

specifies a SAS date, datetime, or time value that represents the end of the data. If the last time ID variable value is less than the END= value, the series is extended with missing values. If the last time ID variable value is greater than the END= value, the series is truncated. For example, END="&sysdate"D uses the automatic macro variable SYSDATE to extend or truncate the series to the current date.

FORMAT=*option*

specifies a SAS format that is used for the DATE variable in the output data sets. The default format is the same as that of the DATE variable in the DATA= data set.

HORIZONSTART=*option*

specifies a SAS date, datetime, or time value that represents the start of the forecast horizon. If the specified HORIZONSTART= date falls beyond the end of the historical data, then forecasts are computed from the last observation with a nonmissing dependent variable value until LEAD= intervals from the HORIZONSTART= data. Therefore, the effective forecast horizon for any particular BY group might differ from another due to differences in the lengths of the historical data across the BY groups, but all forecasts will end at the same date as determined by the HORIZONSTART= and LEAD= options.

An important feature of the HORIZONSTART= option is that it truncates values only in forecast variables. Any future values of input variables are retained.

INTERVAL=*interval*

specifies the frequency of the input time series. For example, if the input data set consists of quarterly observations, then specify INTERVAL=QTR. If the SEASONALITY= option is not specified, the length of the seasonal cycle is implied from the INTERVAL= option. For example, INTERVAL=QTR implies a seasonal cycle of length 4. If the ACCUMULATE= option is also specified, the INTERVAL= option determines the time periods for the accumulation of observations. See the *SAS/ETS User's Guide* for the intervals that can be specified.

NOTSORTED

specifies that the time ID variable values might not be in sorted order. If you specify this option, then prior to analysis, the HPFENGINE procedure sorts the data in ascending order of time ID variable values.

If you omit this option, you must ensure that the data are sorted in ascending order of time ID variable values.

If you specify the BY statement, then the sorting requirements are applicable within each BY group.

SETMISSING=*option* | *number*

specifies how to treat missing values (either actual or accumulated) in the accumulated time series. If you specify a *number*, missing values are set to that number. If a missing value indicates an unknown value, this option should not be used. If a missing value indicates no value, specify SETMISSING=0. You would typically specify SETMISSING=0 for transactional data because the absence of recorded data usually implies no activity. You can also specify the following *options* to determine how to treat missing values:

MISSING	Missing values are set to missing. This is the default *option*.
AVERAGE | AVG	Missing values are set to the accumulated average value.
MINIMUM | MIN	Missing values are set to the accumulated minimum value.
MEDIAN | MED	Missing values are set to the accumulated median value.
MAXIMUM | MAX	Missing values are set to the accumulated maximum value.
FIRST	Missing values are set to the accumulated first nonmissing value.
LAST	Missing values are set to the accumulated last nonmissing value.
PREVIOUS | PREV	Missing values are set to the previous accumulated nonmissing value. Missing values at the beginning of the accumulated series remain missing.
NEXT	Missing values are set to the next accumulated nonmissing value. Missing values at the end of the accumulated series remain missing.

If you specify SETMISSING=MISSING and the MODEL= option specifies a smoothing model, the missing observations are smoothed over. If MODEL=IDM is specified, missing values are assumed to be periods of no demand; that is, SETMISSING=MISSING is equivalent to SETMISSING=0.

START=*option*

specifies a SAS date, datetime, or time value that represents the beginning of the data. If the first time ID variable value is greater than the START= value, the series is prefixed with missing values. If the first time ID variable value is less than the END= value, the series is truncated. This option and the END= option can be used to ensure that data associated with each BY group contain the same number of observations.

TRIMMISS=*option*

specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the FORECAST statement. You can also specify the following *options*:

NONE	No missing value trimming is applied.
LEFT	Beginning missing values are trimmed.

RIGHT	Ending missing values are trimmed.
BOTH	Both beginning and ending missing values are trimmed. This is the default.

ZEROMISS=*option*
specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series. You can also specify the following *options* to determine how beginning and/or ending zero values are assigned:

NONE	Beginning and/or ending zeros are unchanged. This is the default.
LEFT	Beginning zeros are set to missing.
RIGHT	Ending zeros are set to missing.
BOTH	Both beginning and ending zeros are set to missing.

If the accumulated series is all missing and/or zero, the series is not changed.

INPUT Statement

INPUT *variable-list / options* **;**

The INPUT statement lists the numeric variables in the DATA= data set whose accumulated values are used as deterministic input in the forecasting process.

Future values for input variables must be supplied. If future values are unknown, consider using either the STOCHASTIC statement or the CONTROL statement. If it will be necessary to later modify future values using the forecast score function HPFSCSUB, use the CONTROL statement.

A data set variable can be specified in only one INPUT statement. Any number of INPUT statements can be used.

The following options can be used with the INPUT statement:

ACCUMULATE=*option*
specifies how the data set observations are accumulated within each time period for the variables listed in the INPUT statement. If the ACCUMULATE= option is not specified in the INPUT statement, accumulation is determined by the ACCUMULATE= option of the ID statement. See the ID statement ACCUMULATE= option for more details.

REQUIRED=YES | NO
enables or disables a check of inputs to models. The kinds of problems checked include the following:

- errors in functional transformation
- an input consisting of only a constant value or all missing values
- errors introduced by differencing
- multicollinearity among inputs

If REQUIRED=YES, these checks are not performed and no inputs are dropped from a model. The model might subsequently fail to fit during parameter estimation or forecasting for any of the reasons in the preceding list.

If REQUIRED=NO, inputs are checked and those with errors, or those judged collinear, are dropped from the model for the current series and task only. No changes are kept in the model specification.

This option has no effect on models with no inputs.

The default is REQUIRED=YES.

SETMISSING=*option* | *number*
specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for the variables listed in the INPUT statement. If the SETMISSING= option is not specified in the INPUT statement, missing values are set based on the SETMISSING= option of the ID statement. See the ID statement SETMISSING= option for more details.

TRIMMISS=*option*
specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the INPUT statement.

If the TRIMMISS= option is not specified in the INPUT statement, missing values are set based on the TRIMMISS= option of the ID statement. See the ID statement TRIMMISS= option for more details.

ZEROMISS=*option*
specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the INPUT statement. If the ZEROMISS= option is not specified in the INPUT statement, missing values are set based on the ZEROMISS= option of the ID statement. See the ID statement ZEROMISS= option for more details.

SCORE Statement

SCORE *options* **;**

The SCORE statement, used in conjunction with one or more FORECAST statements, causes the generation of score files. The score files are written to the catalog specified by the SCOREREPOSITORY= option. One score file is generated for each forecast variable within each BY group. Score file names are constructed by appending a sequence number to a base name to create a unique entry in the score repository. Sequence numbers start from 0. You can determine the name of the score file used for each forecast variable within each BY group by referring to the _SCORE_ column in the OUTEST= data set.

The SCORE statement supports the following option:

BASENAME=*SAS-name*
prefixes the score file name with the specified value. For example, if you specify BASENAME=SALE, the score files are named SALE0, SALE1, ... The default BASENAME for the SCORE statement is 'SCOR'. If you forecast more than one variable in the PROC HPFENGINE run, score file names all use the same prefix regardless of the dependent variable. Use the OUTEST= data set to determine the score file generated for each variable and BY group combination.

Also note, the BASENAME= value is limited to 22 characters to ensure that the entire range of score file names can be generated if needed. If you specify a value that exceeds this limit, a warning is printed to the SAS log and the value is truncated.

For examples that demonstrate use of the SCORE statement, see Example 5.4.

STOCHASTIC Statement

STOCHASTIC *variable-list / options* **;**

The STOCHASTIC statement lists the numeric variables in the DATA= data set whose accumulated values are used as stochastic input in the forecasting process.

Future values of stochastic inputs do not need to be provided. By default, they are automatically forecast using one of the following smoothing models:

- simple
- double
- linear
- damped trend
- seasonal
- Winters method (additive and multiplicative)

The model with the smallest in-sample MAPE is used to forecast the future values of the stochastic input. Information on the model selected for the independent variables can be found in the OUTEST data set.

A data set variable can be specified in only one STOCHASTIC statement. Any number of STOCHASTIC statements can be used.

The following options can be used with the STOCHASTIC statement:

ACCUMULATE=*option*
specifies how the data set observations are accumulated within each time period for the variables listed in the STOCHASTIC statement. If the ACCUMULATE= option is not specified in the STOCHASTIC statement, accumulation is determined by the ACCUMULATE= option of the ID statement. See the ID statement ACCUMULATE= option for more details.

SELECTION=*option*
specifies the selection list used to forecast the stochastic variables. The default is BEST, found in SASHELP.HPFDFLT.

REQUIRED=YES | NO
enables or disables a check of inputs to models. The kinds of problems checked include the following:

- errors in functional transformation
- an input consisting of only a constant value or all missing values
- errors introduced by differencing
- multicollinearity among inputs

If REQUIRED=YES, these checks are not performed and no inputs are dropped from a model. The model might subsequently fail to fit during parameter estimation or forecasting for any of the reasons in the preceding list.

If REQUIRED=NO, inputs are checked and those with errors, or those judged collinear, are dropped from the model for the current series and task only. No changes are kept in the model specification.

This option has no effect on models with no inputs.

The default is REQUIRED=YES.

REPLACEMISSING
specifies that embedded missing actual values be replaced with one-step-ahead forecasts in the STOCHASTIC variables.

SETMISSING=*option* | *number*
specifies how missing values (either actual or accumulated) are assigned in the accumulated time series for variables listed in the STOCHASTIC statement. If the SETMISSING= option is not specified in the STOCHASTIC statement, missing values are set based on the SETMISSING= option of the ID statement. See the ID statement SETMISSING= option for more details.

TRIMMISS=*option*
specifies how missing values (either actual or accumulated) are trimmed from the accumulated time series for variables listed in the STOCHASTIC statement.

If the TRIMMISS= option is not specified in the STOCHASTIC statement, missing values are set based on the TRIMMISS= option of the ID statement. See the ID statement TRIMMISS= option for more details.

ZEROMISS=*option*
specifies how beginning and/or ending zero values (either actual or accumulated) are interpreted in the accumulated time series for variables listed in the FORECAST statement. If the ZEROMISS= option is not specified in the STOCHASTIC statement, missing values are set based on the ZEROMISS= option of the ID statement. See the ID statement ZEROMISS= option for more details.

Details: HPFENGINE Procedure

The HPFENGINE procedure can be used to forecast time series data as well as transactional data. If the data are transactional, then the procedure must first accumulate the data into a time series before the data can be forecast. The procedure uses the following sequential steps to produce forecasts:

1. accumulation
2. missing value interpretation
3. pre-forecast adjustment
4. diagnostic tests
5. model selection
6. transformations
7. parameter estimation
8. forecasting
9. inverse transformation
10. post-forecast adjustment
11. statistics of fit

These steps are described in the following sections.

Accumulation

If the ACCUMULATE= option is specified, data set observations are accumulated within each time period. The frequency (width of each time interval) is specified by the INTERVAL= option. The ID variable contains the time ID values. Each time ID value corresponds to a specific time period. Accumulation is particularly useful when the input data set contains transactional data, whose observations are not spaced with respect to any particular time interval. The accumulated values form the actual time series, which is used in subsequent analyses.

For example, suppose a data set contains the following observations:

```
19MAR1999    10
19MAR1999    30
11MAY1999    50
12MAY1999    20
23MAY1999    20
```

If the INTERVAL=MONTH is specified, all of the preceding observations fall within the three time periods of March 1999, April 1999, and May 1999. The observations are accumulated within each time period as follows:

If the ACCUMULATE=NONE option is specified:

```
01MAR1999      D
01APR1999      .
01MAY1999      D
```

There are input observations with time stamps that resolve to the same period in the uniform time ID sequence. This creates an indeterminate situation for ACCUMULATE=NONE; therefore, the accumulated values for the offending time stamps are flagged with 'D' missing values. When you specify ACCUMULATE=NONE, those input observations that do not require accumulation are preserved.

If the ACCUMULATE=TOTAL option is specified:

```
01MAR1999    40
01APR1999    .
01MAY1999    90
```

If the ACCUMULATE=AVERAGE option is specified:

```
01MAR1999    20
01APR1999    .
01MAY1999    30
```

If the ACCUMULATE=MINIMUM option is specified:

```
01MAR1999    10
01APR1999    .
01MAY1999    20
```

If the ACCUMULATE=MEDIAN option is specified:

```
01MAR1999    20
01APR1999    .
01MAY1999    20
```

If the ACCUMULATE=MAXIMUM option is specified:

```
01MAR1999    30
01APR1999    .
01MAY1999    50
```

If the ACCUMULATE=FIRST option is specified:

```
01MAR1999    10
01APR1999    .
01MAY1999    50
```

If the ACCUMULATE=LAST option is specified:

```
01MAR1999    30
01APR1999    .
01MAY1999    20
```

If the ACCUMULATE=STDDEV option is specified:

```
01MAR1999    14.14
01APR1999    .
01MAY1999    17.32
```

As can be seen from the preceding examples, even though the data set observations contained no missing values, the accumulated time series might have missing values.

Missing Value Interpretation

Sometimes missing values should be interpreted as unknown values. The forecasting models used by the HPFENGINE procedure can handle missing values effectively. But sometimes missing values are known (such as when missing values are created from accumulation), and no observations should be interpreted as no (zero) value. In the former case, the SETMISSING= option can be used to interpret how missing values are treated. The SETMISSING=0 option should be used when missing observations are to be treated as no (zero) values. In other cases, missing values should be interpreted as global values, such as minimum or maximum values of the accumulated series. The accumulated and interpreted time series is used in subsequent analyses.

Adjustment Operations

Pre-adjustment variables can be used to adjust the dependent series prior to model parameter estimation, evaluation, and forecasting. After the predictions of the adjusted dependent series are obtained from the forecasting mode, the post-adjustment variables can be used to adjust these forecasts to obtain predictions that more closely match the original dependent series.

Pre-adjustment (Before Forecasting) Step

If y_t is the dependent series and $x_{i,t}$ for $i = 1, \ldots, M$ are the M adjustment series, the adjusted dependent series w_t is as follows:

$$\begin{aligned} w_{i,t} &= op_i^b(y_t, x_{i,t-k_i}) \text{ for } i = 1 \\ w_{i,t} &= op_i^b(w_{i-1,t}, x_{i,t-k_i}) \text{ for } 1 < i \leq M \\ w_t &= w_{i,t} \text{ for } i = M \end{aligned}$$

where op_i^b represents the pre-adjustment operator and k_i is the time shift for the adjustment series $x_{i,t}$.

As can be seen, the pre-adjustment operators are nested and applied sequentially from $i = 1, \ldots, M$.

Pre-adjustment is performed on the historical data only.

Adjusted Forecast Step

$$\begin{aligned} w_t &= \hat{F}(w_t) + \varepsilon_t \text{ historical data} \\ \hat{w}_t &= \hat{F}(w_t) \text{ historical data and forecast horizon} \end{aligned}$$

where $\hat{F}()$ represents the fitted forecasting function.

Post-adjustment (After Forecasting) Step

$$
\begin{aligned}
\hat{w}_{i,t} &= op_i^a(\hat{w}_t, x_{i,t-k_i}) \text{ for } i = M \\
\hat{w}_{i,t} &= op_i^a(\hat{w}_{i+1,t}, x_{i,t-k_i}) \text{ for } 1 \leq i < M \\
\hat{y}_t &= \hat{w}_{i,t}
\end{aligned}
$$

where op_i^a represents the post-adjustment operator for the adjustment series $x_{i,t}$.

As can be seen, the post-adjustment operators are nested and applied sequentially from $i = M, \ldots, 1$, which is the reverse of the pre-adjustment step.

Post-adjustment is performed on the historical data as well as the forecast horizon.

Notes

Typically the pre-adjustment operator op_i^b and post-adjustment operator op_i^a are inverses of each other; that is, $op_i^a = inverse(op_i^b)$.

For example, if the pre-adjustment operator is subtraction, the post-adjustment operator is addition, as shown in the following:

$$
\begin{aligned}
w_t &= y_t - \sum_{i=1}^{M} x_{i,t} \\
\hat{y}_t &= \hat{w}_t + \sum_{i=1}^{M} x_{i,t}
\end{aligned}
$$

For example, if the pre-adjustment operator is division, the post-adjustment operator is multiplication, as shown in the following:

$$
\begin{aligned}
w_t &= y_t \prod_{i=1}^{M} \frac{1}{x_{i,t}} \\
\hat{y}_t &= \hat{w}_t \prod_{i=1}^{M} x_{i,t}
\end{aligned}
$$

Pre-adjustment is often followed by post-adjustment, but the inverse operation is not required. It is acceptable to pre-adjust, but not post-adjust, and vice versa.

As an example, the following statement adds, before forecasting, the values contained in the variables firstadj and scndadj to the dependent variable air. After forecasting air, there is no post-adjustment. The variable air must be specified in a FORECAST statement.

```
ADJUST air=(firstadj scndadj) / OPERATION = (ADD,NONE);
```

Diagnostic Tests

Diagnostic test control is specified in the model selection list and can be set by using the HPFSELECT procedure. The INTERMITTENT= option in the HPFSELECT procedure's DIAGNOSE statement sets the threshold for categorizing a series as intermittent or nonintermittent. Likewise, the SEASONTEST= option in the HPFSELECT procedure's DIAGNOSE statement sets the threshold for categorizing a series as seasonal or nonseasonal.

These diagnostic categorizations are used during the model selection process to ensure that only appropriate models are fit to a given series.

Model Selection

PROC HPFENGINE applies a model selection list to each series it processes. When more than one candidate model is specified in a model selection list, forecasts for each candidate model are compared by using the model selection criterion specified via the CRITERION= option in the SELECT statement in the HPFSELECT procedure.

The selection criterion is computed using the multistep forecasts in the holdout sample range if the HOLDOUT= or HOLDOUTPCT= option is specified, or the one-step-ahead forecasts for the full range of the time series if the HOLDOUT= and HOLDOUTPCT= option is not specified.

The candidate model with the best selection criterion is selected to forecast the time series.

Not all model specifications in a model selection list are necessarily used as candidates during the selection process. Diagnostic tests might tag some model specifications as unsuitable. Generally, if a time series is judged as seasonal by the diagnostic tests, only seasonal models in the model selection list are candidates. Likewise, if a time series is nonseasonal, only nonseasonal models are fit. If the seasonal characteristics of a time series do not match those of any models in a selection list, the seasonal diagnostic test is turned off and the selection process is restarted.

Characteristics that make a model seasonal vary according to the family of model. Those characteristics are listed here by model family:

Smoothing models	The Winters, additive Winters, and seasonal smoothing models are considered seasonal. Linear, simple, double, and damped trend models smoothing are considered nonseasonal.
ARIMA models	An ARIMA model is considered seasonal if there is a difference of order equal to the seasonal cycle length of the time ID. The presence of MA or AR terms with lags equal to the seasonal cycle length also qualifies a model as seasonal. The presence of a predefined seasonal input is another factor that tags a model as seasonal.
UCM	An unobserved component model is seasonal if a seasonal component is present, specified by the SEASON statement in the HPFUCMSPEC procedure, or if there is a predefined seasonal input.

Similar subsetting of selection lists occurs after an intermittency diagnostic test. The HPFENGINE procedure avoids direct comparison of results from intermittent models and nonintermittent models. If the diagnostic tests deem a time series intermittent, only intermittent models are used as candidates during the selection process. If a series is nonintermittent, only nonintermittent series are used.

The topology of the model selection process can be more complex than this brief overview describes. Combined models and mixtures of lists with time series models in the overall selection process can be evaluated by the HPFENGINE procedure. This enables more complex model selection decision topologies. Details of the full model selection process are described in Chapter 17, "Forecast Model Selection Graph Details." See Chapter 16, "Forecast Combination Computational Details," for mathematical details related to combined models. See also Chapter 11, "The HPFSELECT Procedure," for information related to defining these more complex model selection topologies.

IDM Model Combinations

Intermittent demand model (IDM) forecasts present special problems when considering the combination of those IDM forecasts with forecasts from other non-IDM models, in addition to combinations of forecasts that arise from different IDM models. IDM models work in a transform domain of demand-indexed observations. The demand domain represents observations in the series that have values different from the IDM model's base value. Non-base demands are collapsed into contiguous observations for purposes of modeling the demand series. See Chapter 15, "Forecasting Process Details," for more information about IDM models.

For a given series, the model selection process in PROC HPFENGINE never mixes models from the IDM and non-IDM families. If IDM models are present in the list, those are run first. If one or more of them are successful in classifying the series as intermittent, then any non-IDM models in the list are automatically removed from consideration in the remainder of the selection list processing.

A combined model list that contains IDM models follows this same scheme. If any IDM model in the combination list is successful, the list is restricted to combinations of IDM model forecasts that use the same IDM base value. The first successful IDM model in the combination list defines the reference IDM base for the list. Any subsequent IDM model in the combined model list that uses a different base value is excluded from the combination.

A combination of base-compatible IDM forecasts is further restricted in terms of elements of the COMBINE statement functionality. These restrictions are related to operations that depend on the use of time-based residuals in some way. They affect the following COMBINE statement options:

- Combination weight methods are restricted to METHOD=AVG and METHOD=USERDEF.
- Encompassing tests are not permitted.
- Standard error modes for prediction errors are not permitted.

When a combined model list that uses IDM forecasts is processed in PROC HPFENGINE, checks are performed to ensure that the settings for the WEIGHT= and ENCOMPASS= options are consistent with the listed restrictions. If not, messages are issued to the SAS log to indicate that the respective option settings are being ignored and changed for the particular series instance and combined model list pairing.

Transformations

If a forecasting model specifies a transformation of the dependent series, the time series is transformed prior to model parameter estimation and forecasting. Only strictly positive series can be transformed.

Parameter Estimation

All parameters associated with the model are optimized based on the data with the default parameter restrictions imposed. The starting point for parameter estimation, either automatically chosen by the optimizer or supplied programmatically, can be controlled using the TASK= option.

If a forecasting model specifies a transformation of the dependent series, the transformed time series data are used to estimate the model parameters.

NOTE: For moving average models, the minimum data requirement for n is p+2. In other words, the number of observations, n, must be greater than or equal to the number of potential parameters, p, + 2.

NOTE: After any differencing is performed, at least six (6) observations are required for ARIMA models. If you do not have the required 6 observations after differencing then you may see WARNING messages such as:

"Insufficient data for parameter estimation"

"No model was chosen from the selection list"

Missing Value Modeling Issues

The treatment of missing values varies with the forecasting model. For the intermittent demand models, specified missing values are assumed to be periods of no demand. For other models, missing values after the start of the series are replaced with one-step-ahead predicted values, and the predicted values are applied to the smoothing equations. See the section "Forecasting" on page 198 for more information about how missing values are treated in the smoothing models.

You can also specify the treatment of missing values with the SETMISSING= option, which changes the missing values prior to modeling. The ZEROMISS= option replaces zero values with missing values at either the beginning or end of a series. In such cases the SETMISSING= option is applied after the ZEROMISS= option.

Even though all of the observed data are nonmissing, using the ACCUMULATE= option can create missing values in the accumulated series.

Forecasting

After the model parameters are estimated, one-step-ahead forecasts are generated for the full range of the actual (optionally transformed) time series data, and multistep forecasts are generated from the end of the observed time series to the future time period after the last observation specified by the LEAD= option. If there are missing values at the end of the time series, the forecast horizon will be greater than that specified by the LEAD= option. Options such as HORIZONSTART= might implicitly add missing values to the end of a series and also cause forecast horizons greater than that specified by LEAD=.

Inverse Transformations

If a forecasting model specifies a transformation of the dependent series, the forecasts of the transformed time series are inverse transformed. By default, the mean (expected) forecasts are generated. If the MEDIAN option is specified the model specification procedures, the median forecasts are generated.

Statistics of Fit

The statistics of fit (or goodness-of-fit statistics) are computed by comparing the actual time series data and the generated forecasts. If the dependent series was transformed according to the model specification, the statistics of fit are based on the inverse transformed forecasts.

Thread Usage in PROC HPFENGINE

The HPFENGINE procedure can make use of threads to speed up different aspects of model selection and forecasting. There are no special options beyond SAS system options to control thread usage in PROC HPFENGINE. You can use the OPTIONS statement to specify the following SAS options:

THREADS | NOTHREADS controls whether threading is allowed in PROC HPFENGINE.

CPUCOUNT= controls the maximum number of threads to be used PROC HPFENGINE.

When threading is allowed, the thread budget for the PROC HPFENGINE step is determined by the value of the CPUCOUNT= option. Threaded execution is considered only when the CPUCOUNT= value is greater than 1.

PROC HPFENGINE can thread certain phases of its computations within each BY group that it processes. When threading is allowed, PROC HPFENGINE can make use of threads in the following computational processes:

- FORECAST statement variables (also called FORECAST variable)
- model execution

At a coarse level, PROC HPFENGINE can use threads to process different FORECAST statement variables concurrently. If you specify more than one FORECAST variable in a single PROC HPFENGINE step and

threading is allowed, then those variables are processed concurrently for the TASK= option that is specified. When this coarse threading can be applied, it provides a maximum benefit in terms of reducing elapsed time with respect to nonthreaded execution for the additional CPU resources expended, and it produces gains without regard to the model selection list complexity or the TASK= mode that is specified for the step.

Within the scope of each FORECAST variable, PROC HPFENGINE can use threads as part of its model selection process. All of the time series models to be considered in the forecast model selection graph are submitted for concurrent execution. Subject to the availability of the CPUCPOUNT= resources after accounting for coarse-grained parallelism at the FORECAST variable level, the available threads execute time series models concurrently. When the models complete, the decision process as defined by the forecast model selection graph is evaluated to select the best performing model (forecast). If the selected model (forecast) uses a model combination, concurrent model execution can also occur during the generation of the final forecast. This obviously has the greatest opportunity for improvement when TASK=SELECT is performed for a model selection graph that has several time series models to be executed. Invocations that specify a TASK=FIT, UPDATE, or FORECAST option have much less opportunity for the use of threads at the FORECAST variable scope because the set of time series models to be executed is frequently only the one that was selected from a previous TASK=SELECT run.

The thread budget that is allowed for the PROC HPFENGINE step is dynamically shared between coarse threading of the FORECAST variables and threaded execution of the time series models.

Data Set Input/Output

The following input data sets supply series data, selection list mapping information and/or parameter estimates, and event data base information, respectively:

- AUXDATA=
- DATA=
- INEST=
- INEVENT=

Additionally, the HPFENGINE procedure can create the following data sets:

- OUT=
- OUTACCDATA=
- OUTCOMPONENT=
- OUTEST=
- OUTFOR=
- OUTINDEP=
- OUTMODELINFO=

- OUTPROCINFO=
- OUTSTAT=
- OUTSTATSELECT=
- OUTSUM=

In general, if the forecasting process for a particular time series fails, the output that corresponds to this series is not recorded or is set to missing in the relevant output data set, and appropriate error and/or warning messages are recorded in the log.

AUXDATA= Data Set

PROC HPFENGINE supports the AUXDATA= option to supply variables that are used in a forecast run but are not physically part of the primary data set supplied via the DATA= option. For example, you could use AUXDATA to share a data set with explanatory variables across multiple projects, or to separate out explanatory variables that are redundant below some level in a BY group hierarchy or that might not need BY-variable qualification at all. Unlike the DATA= option, you can specify the AUXDATA= option multiple times in the PROC statement to supply more than one auxiliary data set for PROC HPFENGINE to use during its run. For more information and examples, see Chapter 21, "Using Auxiliary Data Sets."

DATA= Data Set

The DATA= data set supplies the input data for the procedure to forecast. It optionally contains any time ID variable, adjustment variables, explanatory variables, and BY group variables needed for PROC HPFENGINE to run successfully. If the DATA= option is not specified, the most recently created SAS data set is used. See also AUXDATA= for related information.

INEST= Data Set

The INEST= data set supplies mapping information that associates individual time series with model selection lists. It can optionally include information about model parameter estimates. Parameter estimates might be required depending on the setting of the TASK= option. This data set is typically created by either the HPFDIAGNOSE procedure or a prior invocation of the HPFENGINE procedure with the OUTEST= option.

The INEST= data set is not required. If not present, a model selection list can be supplied for use by all dependent series by using the GLOBALSELECTION= option. In the absence of both the INEST= data set and the GLOBALSELECTION= option, a default selection list is used.

If the INEST= data set is supplied but there are some forecast variables that have no mapping in INEST=, those unmatched variables are forecast using model specifications found either by using the GLOBALSELECTION= option or in the default list.

The INEST= data set contains the variables specified in the BY statement as well as the following variables:

NAME	variable name
SELECT	name of selection list
MODEL	name of model
MODELVAR	model variable mapping

DSVAR	data set variable mapping
VARTYPE	role of variable: DEPENDENT, INPUT, or EVENT

The referenced selection lists, taken together with the data set to model variable mappings, drive the forecasting process.

If the HPFENGINE statement TASK= option is specified and set to either FORECAST or UPDATE, other variables should be present in INEST=. The additional variables are as follows:

TRANSFORM	transformation applied
COMPONENT	model component (for example, AR, MA, trend, and so on)
COMPMODEL	model portion of an intermittent demand component
FACTOR	model factor
LAG	lag of input
SHIFT	shift
PARM	parameter name
LABEL	parameter label
EST	parameter estimate
STDERR	parameter estimate standard error
TVALUE	parameter estimate t value
PVALUE	parameter estimate p-value
STATUS	indicates success/failure in estimating parameter. See "_STATUS_ Values" on page 208 for details.

INEVENT= Data Set

The INEVENT= contains information that describes predefined events. This data set is usually created by the HPFEVENTS procedure and is required only if events are included in a model. For more information, see Chapter 7, "The HPFEVENTS Procedure."

OUT= Data Set

The OUT= data set contains the variables specified in the BY, ID, and FORECAST statements. If the ID statement is specified, the ID variables are aligned and extended based on the ALIGN= and INTERVAL= options. The values of the variables specified in the FORECAST statements are accumulated based on the ACCUMULATE= option, and missing values are interpreted based on the SETMISSING= option. If the REPLACEMISSING option is specified, embedded missing values are replaced by the one-step-ahead forecasts. If any of the forecasting steps fail for a particular variable, the variable values are extended by missing values.

OUTACCDATA= Data Set

The OUTACCDATA contains one row for each forecast variable in the HPFENGINE run. It contains the following variables:

NAME	variable name
ACCUMULATE	accumulation mode used for the variable

OUTCOMPONENT= Data Set

The contents of the OUTCOMPONENT set vary depending upon the forecast model. See Chapter 15, "Forecasting Process Details," for information about specific model components.

The OUTCOMPONENT= data set contains the variables specified in the BY statement as well as the following variables:

NAME	variable name
COMP	name of the component
TIME	time ID
ACTUAL	dependent series value
PREDICT	component forecast
LOWER	lower confidence limit
UPPER	upper confidence limit
STD	prediction standard error

OUTEST= Data Set

The OUTEST= data set contains the variables specified in the BY statement as well as the following variables:

NAME	variable name
SELECT	name of selection list
MODEL	name of model
MODELVAR	model variable mapping
DSVAR	data set variable mapping
TRANSFORM	transformation applied
COMPONENT	model component (for example, AR, MA, trend, and so on)
COMPMODEL	model portion of an intermittent demand component
FACTOR	model factor
LAG	lag of input
SHIFT	shift
PARM	parameter name
LABEL	parameter label

EST	parameter estimate
STDERR	parameter estimate standard error
TVALUE	parameter estimate *t* value
PVALUE	parameter estimate *p*-value
STATUS	indicates success/failure in estimating parameter. See "_STATUS_ Values" on page 208 for details.

An OUTEST= data set is frequently used as the INEST= data set for subsequent invocations of PROC HPFENGINE. In such a case, if the option TASK=FORECAST is used, forecasts are generated using the parameter estimates found in this data set as opposed to being reestimated. If the option TASK=UPDATE is used, the parameters are estimated again, this time using the supplied estimates as starting values for the optimization process.

OUTFOR= Data Set

The OUTFOR= data set contains the variables specified in the BY statement as well as the following variables:

NAME	variable name
TIMEID	time ID values
PREDICT	predicted values
STD	prediction standard errors
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors

If the forecasting step fails for a particular variable, no observations are recorded.

Procedures that define model specifications have TRANSFORM= and MEDIAN options used to apply functional transformations to series and the subsequent inverse transformation of forecast results. If the TRANSFORM= option is specified, the values in the preceding variables are the inverse transformed forecasts. If the MEDIAN option is specified, the median forecasts are stored; otherwise, the mean forecasts are stored.

OUTINDEP= Data Set

The OUTINDEP= data set contains data used as input in the forecasting process. This information is useful if future values of input variables are automatically supplied by the HPFENGINE procedure. Such a case would occur if one or more input variables are listed in either the STOCHASTIC or CONTROLLABLE statement and if there are missing future values of these input variables.

The OUTINDEP= data set contains the variables specified in the BY statement as well as the following variables:

NAME	variable name
TIMEID	time ID values
_X_	values of the input variable _NAME_

OUTMODELINFO= Data Set

The OUTMODELINFO= data set provides information about the selected forecast model and contains the following variables.

NAME	variable name
MODEL	model specification name
MODELTYPE	model specification type, either ARIMA, COMBINED, ESM, UCM, IDM, EXTERNAL, or INACTIVE
DEPTRANS	name of transform applied to dependent variable or NONE if no transform
SEASONAL	set to 1 if the model is seasonal, 0 otherwise
TREND	set to 1 if the model has a trend, 0 otherwise
INPUTS	set to 1 if one or more inputs are present, 0 otherwise
EVENTS	set to 1 if one or more events are present, 0 otherwise
OUTLIERS	set to 1 if one or more outliers are present, 0 otherwise
STATUS	forecasting status. Nonzero values imply that no forecast was generated for the series. See "_STATUS_ Values" on page 208 for details.
SOURCE	set to the model source based on the extended description element in the model's XML. This value corresponds to the SOURCE= attribute in the XML. The _SOURCE_ value for models generated from HPFDIAGNOSE is 'HPFDIAGNOSE'. The _SOURCE_ value for models generated from the HPF XML procedures is 'USERSPECIFIED'.

Characteristics that make a model seasonal vary according to the family of model. Those characteristics are listed here by model family.

Smoothing models	The Winters, additive Winters, and seasonal smoothing models are considered seasonal. Linear, simple, double, and damped trend models smoothing are considered nonseasonal.
ARIMA models	An ARIMA model is considered seasonal if there is a difference with order equal to the seasonal cycle length of the time ID. The presence of MA or AR terms with lags equal to the seasonal cycle length also qualifies a model as seasonal. The presence of a predefined seasonal input is another factor that tags a model as seasonal.
Combined models	A combined model is considered seasonal if any of its contributing candidates is seasonal.
UCM	An unobserved component model is seasonal if there is a seasonal component present, specified by the SEASON statement in the HPFUCMSPEC procedure, or if there is a predefined seasonal input.
IDM	Intermittent demand models are always considered nonseasonal.

Likewise, characteristics of a model that indicate a trend vary according to the family of model.

Smoothing models	The simple and seasonal smoothing models do not have a trend. Linear, double, damped trend models, and multiplicative and additive Winters models do have a trend.
ARIMA models	An ARIMA model is considered to have a trend if there is a first- or second-order difference applied to the dependent variable. A predefined trend in an input statement also qualifies the model as having a trend component.
Combined models	A combined model has a trend if any of its contributing candidates has a trend component.
UCM	An unobserved component model has a trend if there is a slope component or a predefined trend in an input statement.
IDM	Intermittent demand models do have a trend.

Additionally, a combined model has its other OUTMODELINFO attributes set as follows:

DEPTRANS	set to the common transform applied to all of the contributing candidate forecasts, or set to UNKNOWN if the contributing candidate forecasts use a mixture of transform types
INPUTS	set to 1 if any of the contributing candidate forecasts has inputs, 0 otherwise
EVENTS	set to 1 if any of the contributing candidate forecasts has events, 0 otherwise
OUTLIERS	set to 1 if any of the contributing candidate forecasts has outliers, 0 otherwise

OUTPROCINFO= Data Set

The OUTPROCINFO= data set contains information about the run of the HPFENGINE procedure. The following variables are present:

SOURCE	set to the name of the procedure, in this case HPFENGINE
NAME	name of an item being reported; can be the number of errors, notes, or warnings, number of forecasts requested, and so on
LABEL	descriptive label for the item in _NAME_
STAGE	set to the current stage of the procedure; for HPFENGINE this is set to ALL
VALUE	value of the item specified in _NAME_

OUTSTAT= Data Set

The OUTSTAT= data set contains the variables specified in the BY statement as well as the following variables. The following variables contain observations related to the statistics-of-fit step:

NAME	variable name
REGION	region in which the statistics are calculated. Statistics calculated in the fit region are indicated by FIT. Statistics calculated in the forecast region, which happens only if the BACK= option is greater than zero, are indicated by FORECAST.
DFE	degrees of freedom error

N	number of observations that were used. This is the number of observations in the block of observations from the first to the last nonmissing error, which includes any embedded missing errors.
NOBS	number of observations
NMISSA	number of missing actuals
NMISSP	number of missing predicted values
NPARMS	number of parameters
TSS	total sum of squares
SST	corrected total sum of squares
SSE	sum of square error
MSE	mean square error
UMSE	unbiased mean square error
RMSE	root mean square error
URMSE	unbiased root mean square error
MAPE	mean absolute percent error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R square
ADJRSQ	adjusted R square
AADJRSQ	Amemiya's adjusted R square
RWRSQ	random walk R square
AIC	Akaike's information criterion
AICC	finite sample corrected AIC
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion
MAXERR	maximum error
MINERR	minimum error
MINPE	minimum percent error
MAXPE	maximum percent error
ME	mean error
MPE	mean percent error
MDAPE	median absolute percent error
GMAPE	geometric mean absolute percent error
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MSPPE	mean predictive percent error

MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median absolute predictive percent error
GMAPPE	geometric mean absolute predictive percent error
MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error
MSPE	mean symmetric percent error
SMAPE	symmetric mean absolute percent error
MDASPE	median absolute symmetric percent error
GMASPE	geometric mean absolute symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error
MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation

If the statistics-of-fit step fails for a particular variable, no observations are recorded.

OUTSTATSELECT= Data Set

The OUTSTATSELECT= data set contains the same variables as the OUTSTAT= data set with the addition of the following:

MODEL model specification name

SELECT name of model selection list to which _MODEL_ belongs

SELECTED whether or not this model was chosen to forecast the dependent series or used by the chosen forecast in the case when the chosen forecast is a combined model. Values set in the _SELECTED_ variable include:

- YES indicates the associated _MODEL_ is the primary model selected for the forecast
- USED indicates the associated _MODEL_ is used by the primary model in producing the final forecast
- USED_SELECT indicates the associated _MODEL_ is used by the primary model in the model selection region, but is not used in producing the final forecast
- NO indicates the associated _MODEL_ is neither selected nor used

OUTSUM= Data Set

The OUTSUM= data set contains the variables specified in the BY statement as well as the variables listed in this section. The OUTSUM= data set records the summary statistics for each variable specified in a FORECAST statement and its multistep forecasts as determined by the LEAD= option specified.

Variables related to summary statistics are based on the ACCUMULATE= and SETMISSING= options:

NAME	variable name
STATUS	forecasting status. Nonzero values imply that no forecast was generated for the series. See "_STATUS_ Values" on page 208 for details.
NOBS	number of observations
N	number of nonmissing observations
NMISS	number of missing observations
MIN	minimum value
MAX	maximum value
MEAN	mean value
STDDEV	standard deviation

Variables related to multistep forecast are based on the LEAD= option:

LEAD*n*	multistep forecast (*n* ranges from one to the value of the LEAD= option).

If the forecast step fails for a particular variable, the variables related to forecasting are set to missing.

STATUS Values

Values common to all _STATUS_ variables in various PROC HPFENGINE output data sets are listed here along with brief explanations of their meaning:

0	The forecast was successfully completed.
3000	Model selection could not be completed. Forecast values are set to missing.
3001	Model selection could not be completed and NOALTLIST prohibits use of default exponential smoothing. Forecast values are set to missing.
3002	The forecast was completed subject to qualification that one or more input variables were omitted from the selected model. This can only occur in the context of ARIMAX or UCM models.
3003	The desired model could not be forecast. The forecast reverted to the default exponential smoothing model.
3004	The attempt to forecast the desired model produced an arithmetic exception. The forecast is generated by CATCH(ESM) processing.
3005	The attempt to forecast the desired model produced an arithmetic exception. The forecast is generated by CATCH(RW) processing.

3006	The attempt to forecast the desired model produced an arithmetic exception. The forecast is generated by CATCH(MISSING) processing.
3007	The mean value forecast is generated as a result of the MINOBS criterion.
3008	There were insufficient non-missing observations in the variable to be forecast. A missing value forecast is produced.
3009	There were insufficient non-zero observations in the variable to be forecast. A zero-valued forecast is produced.

ODS Table Names

Table 5.2 ODS Tables Produced in PROC HPFENGINE

ODS Table Name	Description	Specific Models
ODS Tables Created by the PRINT=DESCSTATS Option		
Variable	Forecast variable information	
DescStats	Descriptive statistics	
ODS Tables Created by the PRINT=SUMMARY Option		
Variable	Forecast variable information	
ForecastSummary	Forecast summary	
ODS Tables Created by the PRINT=ESTIMATES Option		
Variable	Forecast variable information	
ParameterEstimates	Parameter estimates	
ODS Tables Created by the PRINT=SELECT Option		
Variable	Forecast variable information	
ModelSelection	Model selection statistics	
ODS Tables Created by the PRINT=FORECASTS Option		
Variable	Forecast variable information	
Forecasts	Forecast	
Demands	Demands	IDM models only
DemandSummary	Demand summary	IDM models only
ODS Tables Created by the PRINT=STATISTICS Option		
Variable	Forecast variable information	
FitStatistics	Statistics of fit	
PerformanceStatistics	Performance statistics	BACK= option only
ODS Tables Created by the PRINT=BIAS Option		
Variable	Forecast variable information	
BiasEstimates	Bias test model parameter estimates	
TestUnbiasedness	Bias test	

Table 5.2 *continued*

ODS Table Name	Description	Specific Models
ODS Tables Created by the PRINT=CANDIDATES Option		
Variable	Forecast variable information	
ParameterEstimates	Parameter estimates	
ODS Tables Created by the PRINT=COMPONENTS Option		
Variable	Forecast variable information	
ComponentEstimates	Parameter estimates	
ODS Tables Created by the PRINT=PERFORMANCE Option		
Variable	Forecast variable information	
Performance	Performance	BACK= option only
ODS Tables Created by the PRINT=PERFORMANCESUMMARY Option		
Variable	Forecast variable information	
PerformanceSummary	Performance summary	BACK= option only
ODS Tables Created by the PRINT=PERFORMANCEOVERALL Option		
Variable	Forecast variable information	
PerformanceSummary	Performance overall	BACK= option only
ODS Tables Created by the PRINT=ALL Option		
DataSet	Input data set	
Variable	Forecast variable information	
DescStats	Descriptive statistics	
Demands	Demands	IDM models only
DemandSummary	Demand summary	IDM models only
ModelSelection	Model selection statistics	
ParameterEstimates	Parameter estimates	
Forecasts	Forecast	
BiasEstimates	Bias test model parameter estimates	
TestUnbiasedness	Bias test	
FitStatistics	Statistics of fit	
PerformanceStatistics	Performance statistics	BACK= option only
Performance	Performance	BACK= option only
ForecastSummary	Forecast summary	

The ODS table ForecastSummary is related to all time series within a BY group. The other tables are related to a single series within a BY group.

ODS Graphics

Statistical procedures use ODS Graphics to create graphs as part of their output. ODS Graphics is described in detail in Chapter 24, "Statistical Graphics Using ODS" (*SAS/STAT User's Guide*).

Before you create graphs, ODS Graphics must be enabled (for example, with the ODS GRAPHICS ON statement). For more information about enabling and disabling ODS Graphics, see the section "Enabling and Disabling ODS Graphics" in that chapter.

The overall appearance of graphs is controlled by ODS styles. Styles and other aspects of using ODS Graphics are discussed in the section "A Primer on ODS Statistical Graphics" in that chapter.

This section describes the use of ODS for creating graphics with the HPFENGINE procedure.

ODS Graph Names

PROC HPFENGINE assigns a name to each graph it creates using ODS. You can use these names to refer to the graphs when using ODS. The names are listed in Table 5.3.

You must specify the PLOT= option in the PROC HPFENGINE statement to select the desired plots. By default, no plots are generated.

Table 5.3 ODS Graphs Produced by PROC HPFENGINE

ODS Graph Name	Plot Description	Statement	PLOT= Option
CandidateErrorHoldoutPlot	Candidate model errors with holdout	PROC HPFENGINE	CANDIDATES
CandidateErrorPlot	Candidate model errors	PROC HPFENGINE	CANDIDATES
CandidateModelHoldoutPlot	Candidate models with holdout	PROC HPFENGINE	CANDIDATES
CandidateModelPlot	Candidate models	PROC HPFENGINE	CANDIDATES
ComponentEstimatesPlot	Component estimates	PROC HPFENGINE	COMPONENTS
DemandErrorsPlot	Average demand errors	PROC HPFENGINE	ERRORS
DemandForecastsPlot	Average demand forecasts	PROC HPFENGINE	FORECASTS
DemandIntervalHistogram	Demand interval histogram	PROC HPFENGINE	ALL
DemandIntervalPlot	Demand interval forecast plot	PROC HPFENGINE	ALL
DemandSizeHistogram	Demand size histogram	PROC HPFENGINE	MODELS
DemandSizePlot	Demand size forecast plot	PROC HPFENGINE	MODELS
ErrorACFNORMPlot	Standardized autocorrelation of prediction errors	PROC HPFENGINE	ACF
ErrorACFPlot	Autocorrelation of prediction errors	PROC HPFENGINE	ACF
ErrorCorrelationPlots	Prediction error panel	PROC HPFENGINE	CORR

Table 5.3 *continued*

ODS Graph Name	Plot Description	Statement	PLOT= Option
ErrorHistogram	Prediction error histogram	PROC HPFENGINE	ERRORS
ErrorIACFNORMPlot	Standardized inverse autocorrelation of prediction errors	PROC HPFENGINE	IACF
ErrorIACFPlot	Inverse autocorrelation of prediction errors	PROC HPFENGINE	IACF
ErrorPACFNORMPlot	Standardized partial autocorrelation of prediction errors	PROC HPFENGINE	PACF
ErrorPACFPlot	Partial autocorrelation of prediction errors	PROC HPFENGINE	PACF
ErrorPeriodogram	Periodogram of prediction errors	PROC HPFENGINE	PERIODOGRAM
ErrorSpectralDensityPlot	Spectral density estimates of prediction errors	PROC HPFENGINE	SPECTRUM
ErrorPlot	Prediction errors	PROC HPFENGINE	ERRORS
ErrorWhiteNoiseLogProbPlot	White noise log probability plot of prediction errors	PROC HPFENGINE	WN
ErrorWhiteNoisePlot	White noise plot of prediction errors	PROC HPFENGINE	ALL
ErrorWhiteNoiseProbPlot	White noise probability plot of prediction errors	PROC HPFENGINE	WN
ForecastSeasonalCyclePlot	Forecast seasonal cycles	PROC HPFENGINE	FORECASTCYCLES
ForecastsOnlyPlot	Forecasts only	PROC HPFENGINE	FORECASTSONLY
ForecastsPlot	Forecasts	PROC HPFENGINE	FORECAST
ModelForecastsPlot	Model and forecasts	PROC HPFENGINE	ALL
ModelPlot	Model only	PROC HPFENGINE	ALL
StockingAveragePlot	Stocking average	PROC HPFENGINE	FORECASTS
StockingLevelPlot	Stocking level	PROC HPFENGINE	FORECASTS

Examples: HPFENGINE Procedure

Example 5.1: The TASK= Option

The default selection list is used in this example. The first call to the HPFENGINE procedure, which follows, uses the default TASK=SELECT option. A model is selected from the default list, parameters are estimated, and a forecast is produced. Selection results are shown in Output 5.1.1.

```
proc hpfengine data=sashelp.citimon
               outfor=outfor
               print=select;
   id date interval=month;
   forecast eec;
run;
```

Output 5.1.1 Selection and Forecast Results

The HPFENGINE Procedure

Model Selection Criterion = RMSE			
Model	**Statistic**	**Selected**	**Label**
SMSIMP	.	Removed	Simple Exponential Smoothing
SMDAMP	.	Removed	Damped-Trend Exponential Smoothing
SMLIN	.	Removed	Linear Exponential Smoothing
SMADWN	0.16293237	No	Winters Method (Additive)
SMWINT	0.17985708	No	Winters Method (Multiplicative)
SMSEAS	0.16291415	Yes	Seasonal Exponential Smoothing

The second call to the HPFENGINE procedure follows. It demonstrates how to use the same model specifications but alter the selection criterion and add a holdout. It is not necessary to create a new selection list to make these changes, since the TASK=SELECT option can override the settings in an existing list. Selection results are shown in Output 5.1.2.

```
proc hpfengine data=sashelp.citimon
               outfor=outfor
               outest=outest
               print=select
               task=select(criterion=mape holdout=24 override);
   id date interval=month;
   forecast eec;
run;
```

Output 5.1.2 Selection and Forecast Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
SMSIMP	.	Removed	Simple Exponential Smoothing
SMDAMP	.	Removed	Damped-Trend Exponential Smoothing
SMLIN	.	Removed	Linear Exponential Smoothing
SMADWN	2.2881620	Yes	Winters Method (Additive)
SMWINT	2.9441207	No	Winters Method (Multiplicative)
SMSEAS	2.5775447	No	Seasonal Exponential Smoothing

Perhaps there are revisions to recent historical data and there is a need to forecast using the updated information but with the same model used to forecast earlier data. This is done easily with the TASK=UPDATE option. The following DATA step is used to simulate revision to the data.

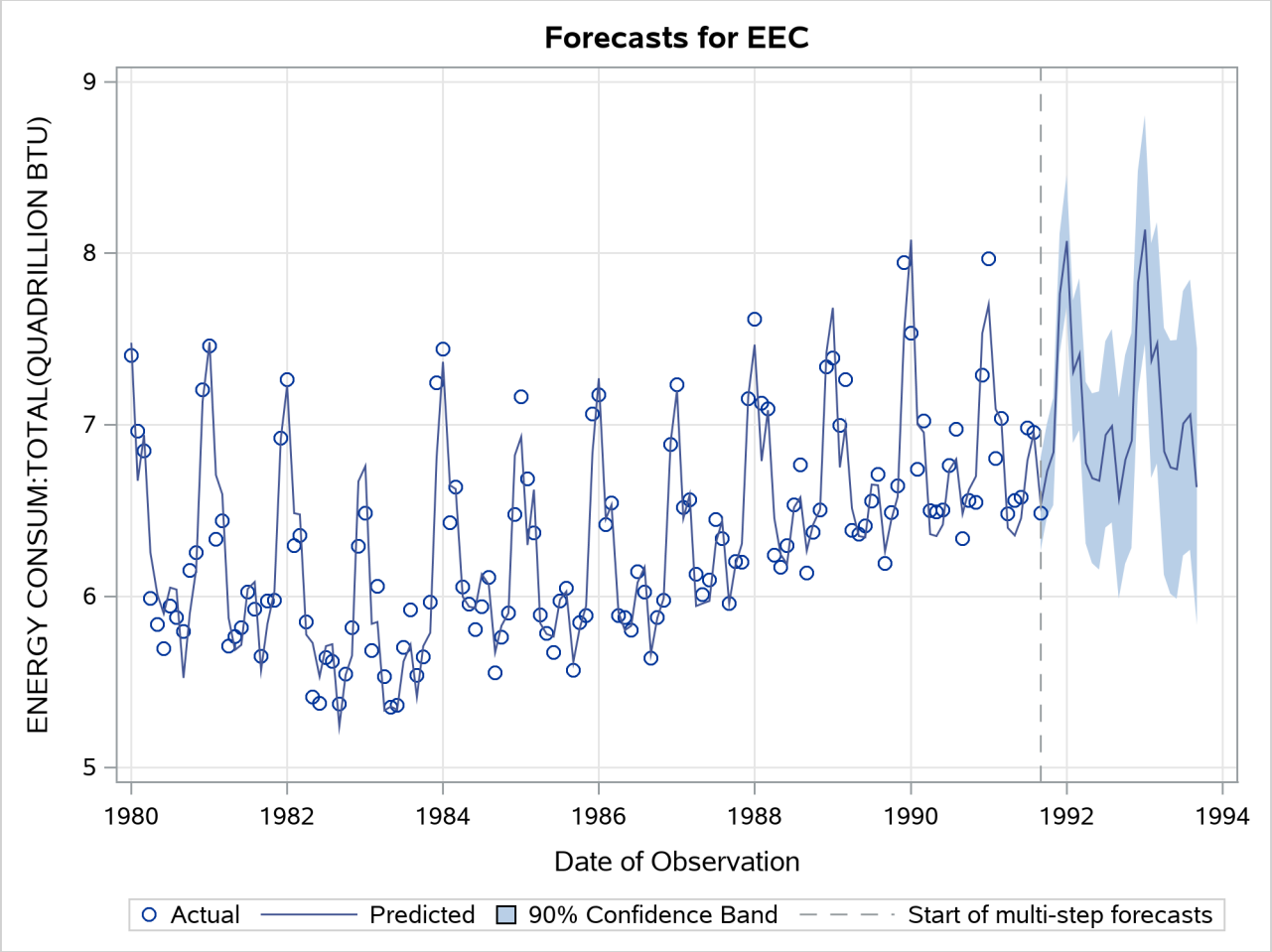
```
data citimon;
   set sashelp.citimon;
   if date ge '01JAN1991'd then eec = eec + 0.1;
run;
```

In the following statements, the HPFENGINE procedure is called with TASK=UPDATE. The additional instruction to change the confidence interval to 90%. The forecast model is the same as was used in the previous call of the HPFENGINE procedure. A reference to this model, together with estimates of its parameters, is found in the OUTEST= data set. The parameters are estimated again using the full range of data, and the prior parameter estimates are used as starting points in the optimization of the new estimates.

```
proc hpfengine data=citimon
               outfor=outfor
               inest=outest
               plot=forecasts
               lead=24
               task=update(alpha=.1 override);
   id date interval=month;
   forecast eec;
run;
```

Figure 5.1.3 shows the forecast plot from the PLOT=FORECASTS option.

Output 5.1.3 Forecasts



Example 5.2: Different Types of Input

This example demonstrates the use of different input types in the HPFENGINE procedure.

The following statements read Input Gas Rate and Output CO2 from a gas furnace. (Data values are not shown. See "Series J" in (Box, Jenkins, and Reinsel 1994) for the values.)

```
data seriesj;
   input x y @@;
   label x = 'Input Gas Rate'
         y = 'Output CO2';
   date = intnx( 'day', '01jan1950'd, _n_-1 );
   format Date DATE.;
datalines;
-0.109  53.8  0.000  53.6  0.178  53.5  0.339  53.5

... more lines ...
```

Begin by creating an ARIMA model specification using the HPFARIMASPEC procedure as follows. The new model specification is then placed into a model selection list by using the HPFSELECT procedure.

```
proc hpfarimaspec repository=sasuser.repository
                  name=arimasp;
   dependent symbol=Y p=2;
   input     symbol=X num=2 den=1 lag=3;
run;

proc hpfselect repository=sasuser.repository
               name=myselect;
   spec arimasp;
run;
```

There are no future values of the independent variables given in the seriesj data set. For this example a DATA step is used as follows to set the last few observations of the dependent value to missing. Values of the independent variable are left intact. This ensures that some future values of the independent variable are available for forecasting the dependent variable between 17OCT1950 and the end of the data set.

```
data seriesj_trunc;
   set seriesj;
   if (date >= '17oct1950'd) then y = .;
run;
```

In the following statements, the HPFENGINE procedure is called using the INPUT statement to identify the data set variable "x" as input. No missing future values, even if required, are computed for "x". The OUTINDEP= data set contains values of the input variable used in the forecast.

```
proc hpfengine data=seriesj_trunc
               outfor=outfor
               outindep=outindep
               repository=sasuser.repository
               globalselection=myselect
               lead=7;
   id date interval=day;
   forecast y;
   input    x;
run;

proc print data=outindep(where=(date >= '17oct1950'd)) label noobs;
var date x;
run;

proc print data=outfor(where=(date >= '17oct1950'd)) label noobs;
   var date predict upper lower;
run;
```

The user-supplied future values of the input variable used in the forecast as well as the forecasts themselves are shown in Output 5.2.1 and Output 5.2.2.

Output 5.2.1 Future Values of X Supplied by the User

date	Input Values
17OCT1950	0.204
18OCT1950	0.253
19OCT1950	0.195
20OCT1950	0.131
21OCT1950	0.017
22OCT1950	-0.182
23OCT1950	-0.262

Output 5.2.2 Forecasts for Y

date	Predicted Values	Upper Confidence Limits	Lower Confidence Limits
17OCT1950	57.0684	57.5116	56.6252
18OCT1950	56.4050	57.1793	55.6306
19OCT1950	55.3430	56.3381	54.3480
20OCT1950	54.1844	55.2923	53.0765
21OCT1950	53.2288	54.3756	52.0820
22OCT1950	52.6228	53.7750	51.4705
23OCT1950	52.3789	53.5315	51.2263

To demonstrate use of the STOCHASTIC statement, a DATA step is used as follows to eliminate future values of the input variable.

```
data seriesj_trunc;
   set seriesj;
   if (date < '17oct1950'd);
run;
```

In the following statements, the HPFENGINE procedure identifies the input variable using the STOCHASTIC statement and automatically forecasts the input variable.

```
proc hpfengine data=seriesj_trunc
               outfor=outfor
               outindep=outindep
               repository=sasuser.repository
               globalselection=myselect
               lead=7;
   id date interval=day;
   forecast   y;
   stochastic x;
run;

proc print data=outindep(where=(date >= '17oct1950'd)) label noobs;
var date x;
run;
```

```
proc print data=outfor(where=(date >= '17oct1950'd)) label noobs;
   var date predict upper lower;
run;
```

The future values of the input variable, automatically forecast, are shown in Output 5.2.3. The forecasts of the dependent variable are shown in Output 5.2.4.

Output 5.2.3 Future Values of X Automatically Forecast

date	Input Values
17OCT1950	0.21222
18OCT1950	0.34557
19OCT1950	0.44535
20OCT1950	0.52002
21OCT1950	0.57588
22OCT1950	0.61769
23OCT1950	0.64897

Output 5.2.4 Forecasts for Y

date	Predicted Values	Upper Confidence Limits	Lower Confidence Limits
17OCT1950	57.0684	57.5116	56.6252
18OCT1950	56.4050	57.1793	55.6306
19OCT1950	55.3430	56.3381	54.3480
20OCT1950	54.1798	55.2877	53.0719
21OCT1950	53.1713	54.3181	52.0244
22OCT1950	52.4125	53.5647	51.2602
23OCT1950	51.9055	53.0581	50.7528

Example 5.3: Incorporating Events

This example creates an event called PROMOTION. The event is added as a simple regressor to each ARIMA specification in the selection list.

First a DATA step is used to generate a data set with a shift beginning at “01OCT1980”.

```
data shifted;
   set sashelp.workers;
   if date >= '01oct80'd then Y = electric+100;
   else Y = electric;
   drop masonry electric;
run;
```

Next the HPFEVENTS procedure is used to create an events database. The database will contain the definition of an event named “promotion,” a level shift beginning at “01OCT1980.”

```
proc hpfevents data=shifted lead=12;
   id date interval=month;
   eventdef   promotion='01oct80'd / TYPE=LS;
   eventdata  out= evdsout1;
   eventdummy out= evdumout1;
run;
```

Then two ARIMA model specification are created as follows. Both of them will be added to a selection list for use by the HPFENGINE procedure.

```
proc hpfarimaspec repository=sasuser.repository
                  name=sp1
                  label="ARIMA(0,1,2)(0,1,1)_12 No Intercept";
   dependent symbol=Y q=(1,2)(12) diflist=1 12 noint;
run;

proc hpfarimaspec repository=sasuser.repository
                  name=sp2
                  label="ARIMA(2,1,0)(1,1,0)_12 No Intercept";
   dependent symbol=Y p=(1, 2)(12) diflist=1 12 noint;
run;
```

The HPFSELECT procedure then creates a new selection list that contains the two ARIMA specifications and uses the EVENTMAP option to add the "promotion" event to each of them, as follows.

```
proc hpfselect repository=sasuser.repository
               name=myselect
               label="My Selection List";
   select select=mape;
   spec sp1 sp2 /
        eventmap(symbol=_NONE_ event=promotion);
run;
```

The HPFENGINE procedure fits both ARIMA models to the data with the "promotion" event, as follows.

```
proc hpfengine data=shifted
               globalselection=myselect
               repository=sasuser.repository
               inevent=evdsout1
               print=(select estimates)
               plot=forecasts;
   id date interval=month;
   forecast y;
run;
```

The results of the model selection are shown in Output 5.3.1. Parameter estimates for the selected model are shown in Output 5.3.2.

Output 5.3.1 Model Selection Results

The HPFENGINE Procedure

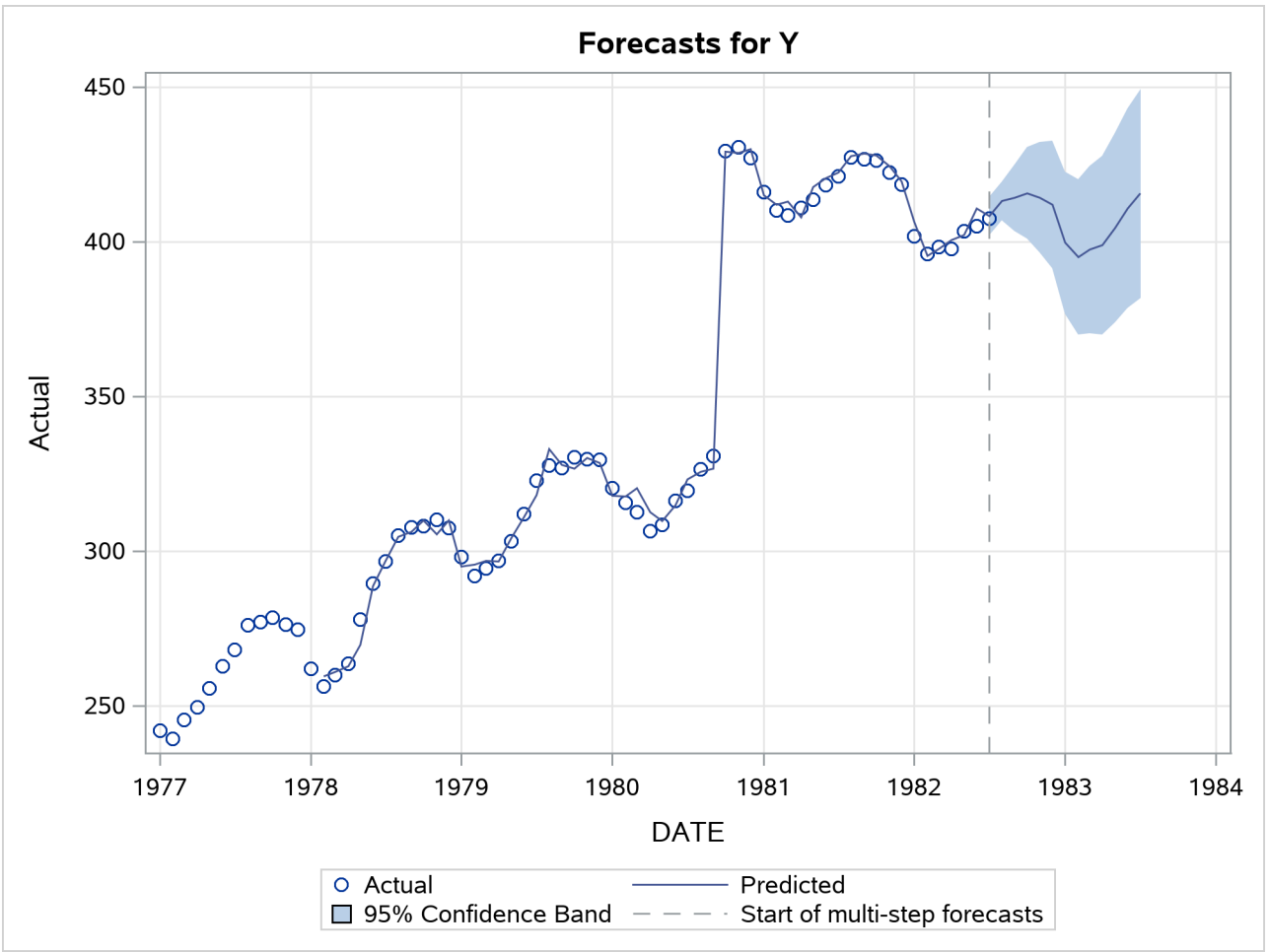
Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
SP1	0.70600173	Yes	ARIMA(0,1,2)(0,1,1)_12 No Intercept
SP2	0.76609476	No	ARIMA(2,1,0)(1,1,0)_12 No Intercept

Output 5.3.2 Parameter Estimates of Selected Model

Parameter Estimates for SP1 Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Y	**MA1_1**	-0.41281	0.14173	-2.91	0.0053
Y	**MA1_2**	-0.21826	0.14382	-1.52	0.1354
Y	**MA2_12**	0.80211	0.11064	7.25	<.0001
PROMOTION	**SCALE**	94.91032	2.91440	32.57	<.0001

Figure 5.3.3 shows the forecast plot from the PLOT=FORECASTS option.

Output 5.3.3 Forecasts



An alternate way to include inputs is to refer to the dummy variable in the data set created by the EVENTDUMMY statement in the HPFEVENTS procedure, as shown in the following statements.

The ARIMA models are different in this case because the event data are explicitly added as an input. In order to produce the same results as the EVENTMAP method of handling events, the input variables are differenced in the same manner as the dependent variable.

```
proc hpfarimaspec repository=sasuser.repository
                  name=sp1
                  label="ARIMA(0,1,2)(0,1,1)_12 No Intercept";
   dependent symbol=Y q=(1,2)(12) diflist=1 12 noint;
   input     symbol=promotion diflist=1 12;
run;

proc hpfarimaspec repository=sasuser.repository
                  name=sp2
                  label="ARIMA(2,1,0)(1,1,0)_12 No Intercept";
   dependent symbol=Y p=(1, 2)(12) diflist=1 12 noint;
   input     symbol=promotion diflist=1 12;
run;
```

Again, the HPFSELECT procedure creates a new selection list that contains the two ARIMA specifications, as follows. This time no EVENTMAP option is required.

```
proc hpfselect repository=sasuser.repository
               name=myselect
               label="My Selection List";
   select select=mape;
   spec sp1 sp2;
run;
```

The HPFENGINE procedure needs to find the "promotion" variable in the input data set. A DATA step is used as follows to merge the input variable with the data set that contains the dependent variable.

```
   data shifted;
      merge shifted evdumout1(drop=y);
      by date;
   run;
```

The HPFENGINE procedure fits both ARIMA models to the data with the "promotion" input, as follows. The results of the model selection are shown in Output 5.3.4. Notice that the results are the same as the results of using the EVENTMAP option in the HPFSELECT procedure. This technique of avoiding the EVENTMAP option and including the event is useful if events need to enter the forecast model through more complex transfer functions.

```
proc hpfengine data=shifted
               globalselection=myselect
               repository=sasuser.repository
               inevent=evdsout1
               print=(select estimates)
               plot=forecasts;
   id date interval=month;
   forecast y;
   input promotion;
run;
```

Output 5.3.4 Model Selection Results

The HPFENGINE Procedure

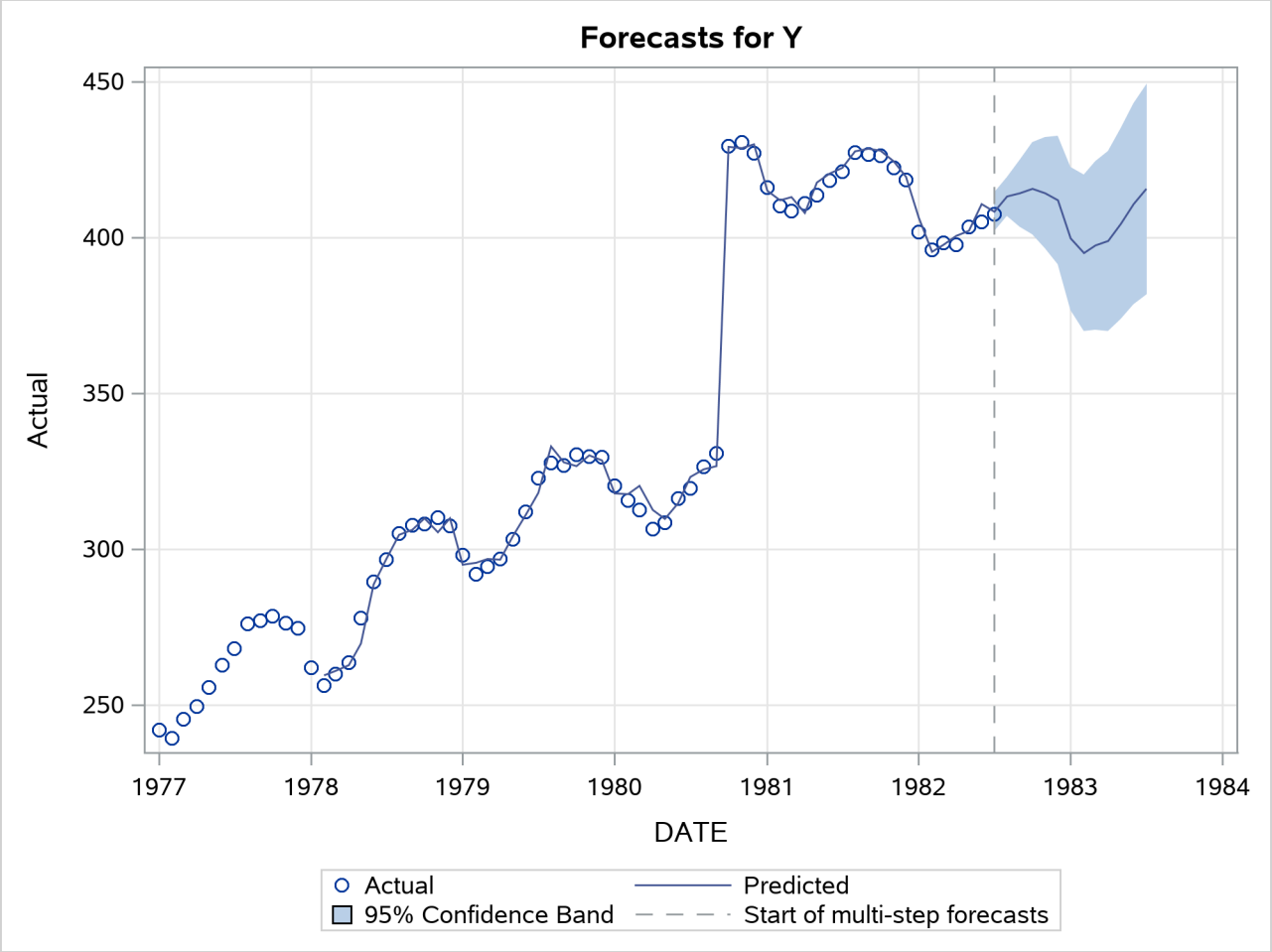
Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
SP1	0.70600173	Yes	ARIMA(0,1,2)(0,1,1)_12 No Intercept
SP2	0.76609476	No	ARIMA(2,1,0)(1,1,0)_12 No Intercept

Parameter estimates for the selected model are in Output 5.3.5. The forecast is displayed in Figure 5.3.6.

Output 5.3.5 Parameter Estimates of Selected Model

Parameter Estimates for SP1 Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
Y	**MA1_1**	-0.41281	0.14173	-2.91	0.0053
Y	**MA1_2**	-0.21826	0.14382	-1.52	0.1354
Y	**MA2_12**	0.80211	0.11064	7.25	<.0001
promotion	**SCALE**	94.91032	2.91440	32.57	<.0001

Output 5.3.6 Forecasts



Example 5.4: Using the SCORE Statement

This example demonstrates the use of the SCORE statement to create a forecast score file. Score files are used by the HPFSCSUB function to produce forecasts outside of the HPFENGINE procedure.

In this particular case price and sales data are present. A forecast score file is produced with price as a controllable input. The NLP procedure is used to maximize a simple expression of total revenue in the forecast horizon, in the way that the optimizer adjusts the price inputs of the forecast function. The input values found by the NLP procedure are then used in the HPFENGINE procedure again to create a forecast plot.

The following DATA step uses data from a single BY group in the SASUSER.PRICEDATA data set.

```
data pricedata;
   set sashelp.pricedata(where=(product=1));
   keep date sale price;
run;
```

An ARIMAX model specification is created as follows, together with a selection list that references this specification.

```
proc hpfarimaspec repository=work.repository name=arimax;
   forecast symbol=sale q=(12) diflist=12 noint;
   input symbol=price diflist=12;
run;

proc hpfselect repository=work.repository name=select;
   spec arimax;
run;
```

The HPFENGINE procedure then creates a forecast score file by using the controllable input variable price, as follows. The designation of this input as "controllable" means that the input can be manipulated in the HPFSCSUB function.

```
proc hpfengine data=pricedata
               repository=work.repository
               scorerepository=work.repository
               globalselection=select
               print=estimates
               plot=forecasts;
   id date interval=month;
   forecast sale;
   controllable price / extend=last;
   score;
run;
```

The parameter estimates of the model are shown in Output 5.4.1. A plot of the forecast results is produced and shown in Figure 5.4.2.

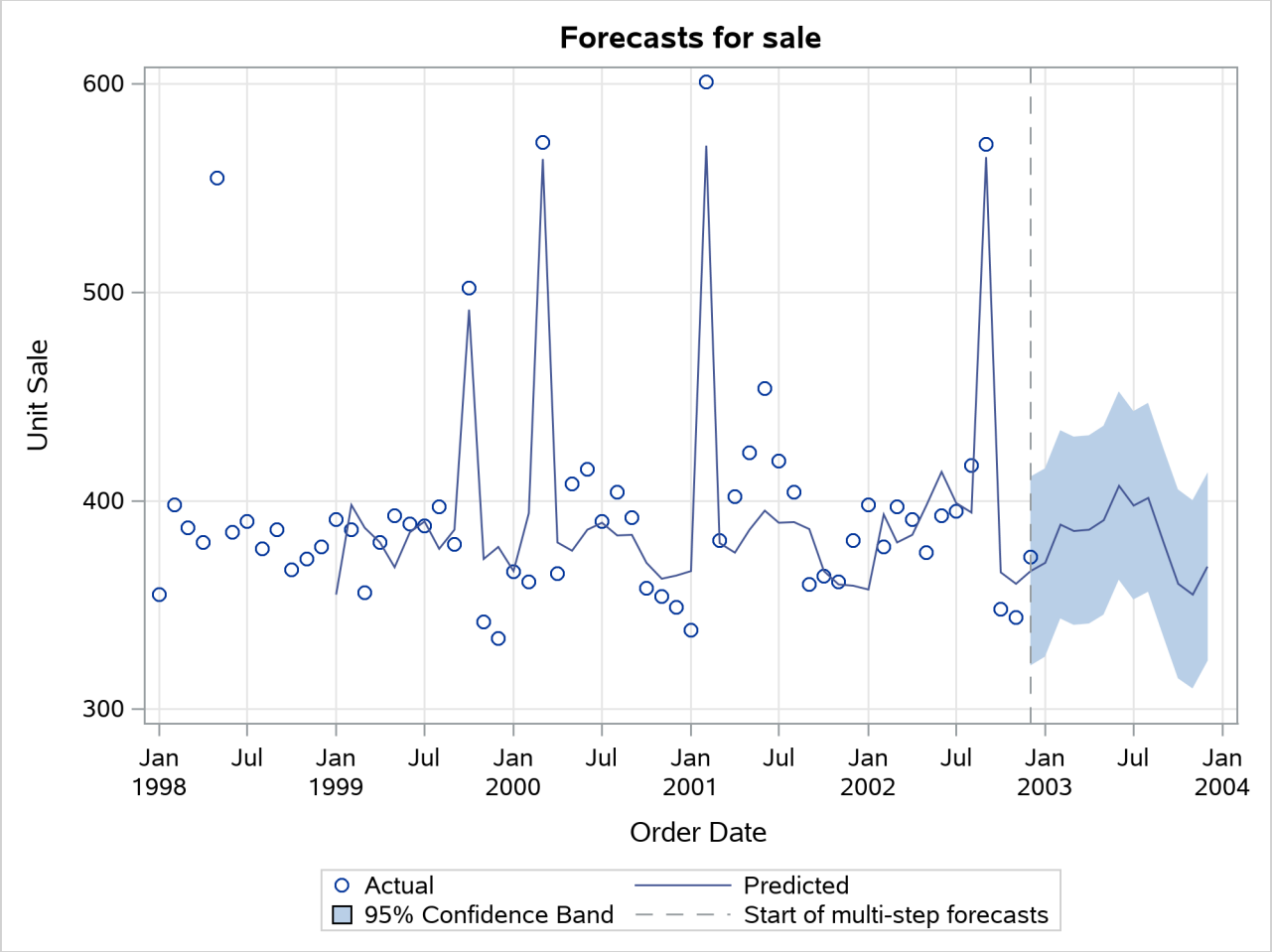
Output 5.4.1 Parameter Estimates of Selected Model

The HPFENGINE Procedure

Parameter Estimates for ARIMAX Model

Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
sale	MA1_12	0.68351	0.13905	4.92	<.0001
price	SCALE	-23.82518	1.34147	-17.76	<.0001

Output 5.4.2 Forecasts



The NLP procedure is used as follows to maximize an objective function whose definition depends on forecasts from the score file. Some lower bounds are set on the price for certain months.

```
filename score catalog "work.repository.scor0.xml";
proc nlp tech=nmsimp noprint out=outnlp(keep=p1-p6);
   max trev;
   parms p1-p6;
   bounds p3 p4 >= 20.0;
   bounds p1 p2 p5 p6 >= 52.3;
   initial = 52.3;
   q1 = .; q2 = .; q3 = .;
   q4 = .; q5 = .; q6 = .;
   call HPFSCSUB('score', 6, 'price', p1, p2, p3, p4, p5, p6,
                 'predict', q1, q2, q3, q4, q5, q6);
   trev = q1*p1 + q2*p2 + q3*p3 + q4*p4 + q5*p5 +q6*p6;
run;
```

Some manipulation of the output from the NLP procedure is needed before the HPFENGINE procedure is called again with the new future price values. In the following statements, the new price data are transposed and a date variable is added. The result is shown in Output 5.4.3.

```
proc transpose data=outnlp out=outnlp;
   var p1-p6;
run;

data outnlp;
   drop _name_;
   format date date9.;
   set outnlp(rename=(col1=price));
   date = intnx('month', '01dec02'd, _n_);
run;

proc print data=outnlp noobs;
run;
```

Output 5.4.3 Future Values of Price

date	price
01JAN2003	52.3000
01FEB2003	52.3000
01MAR2003	34.2393
01APR2003	34.2512
01MAY2003	52.3000
01JUN2003	52.3000

The original data set is now extended, with proper date information, and merged with the results of the optimization, as follows.

```
data pricedataExtend;
   set pricedata;
   drop i;
   output;
   if _n_ ge 60 then do;
      sale = .;
      do i=1 to 6;
         date = intnx('month', '01dec02'd, i);
         output;
      end;
   end;
run;

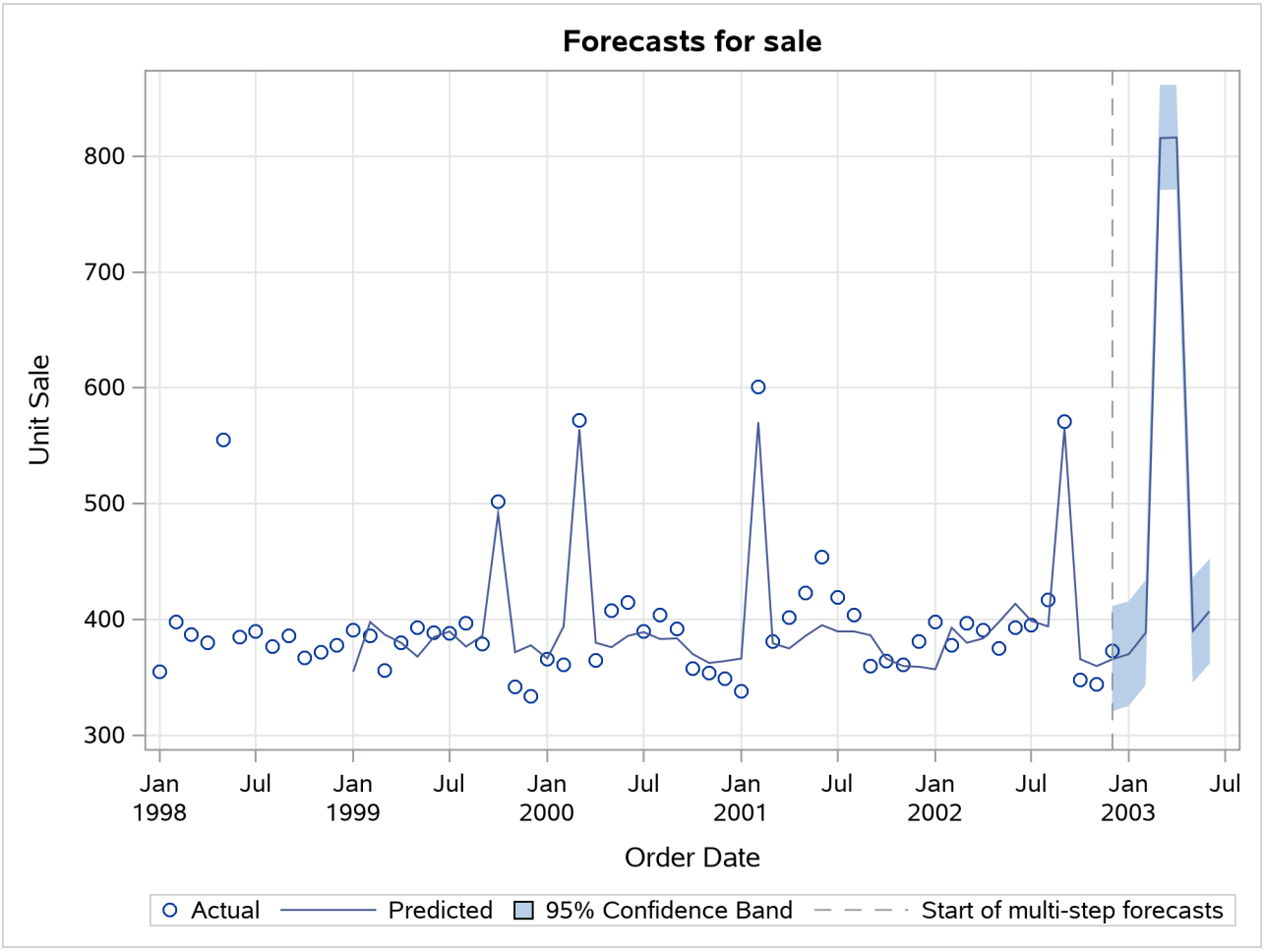
data pricedataExtend;
   merge pricedataExtend outnlp;
   by date;
run;
```

The HPFENGINE procedure then uses the optimized price input to forecast future sales, as follows. A plot of the forecasts is shown in Figure 5.4.4.

```
proc hpfengine data=pricedataExtend
               repository=work.repository
               globalselection=select
               plot=forecasts;
   id date interval=month;
```

```
   forecast sale;
   input price;
run;
```

Output 5.4.4 Forecasts



Example 5.5: HPFENGINE and HPFDIAGNOSE Procedures

The HPFDIAGNOSE procedure is often used in conjunction with the HPFENGINE procedure. This example demonstrates the most basic interaction between the two. In the following statements, model specifications are created by the HPFDIAGNOSE procedure and are those specifications are then fit to the data by using the HPFENGINE procedure.

```
proc hpfdiagnose data=sashelp.air
                 repository=work.repository
                 outest=est;
   id date interval=month;
   forecast air;
run;
proc hpfengine data=sashelp.air
               inest=est outest=outest
```

```
                repository=work.repository
                print=(select estimates summary)
                plot=forecasts;
    id date interval=month;
    forecast air;
run;
```

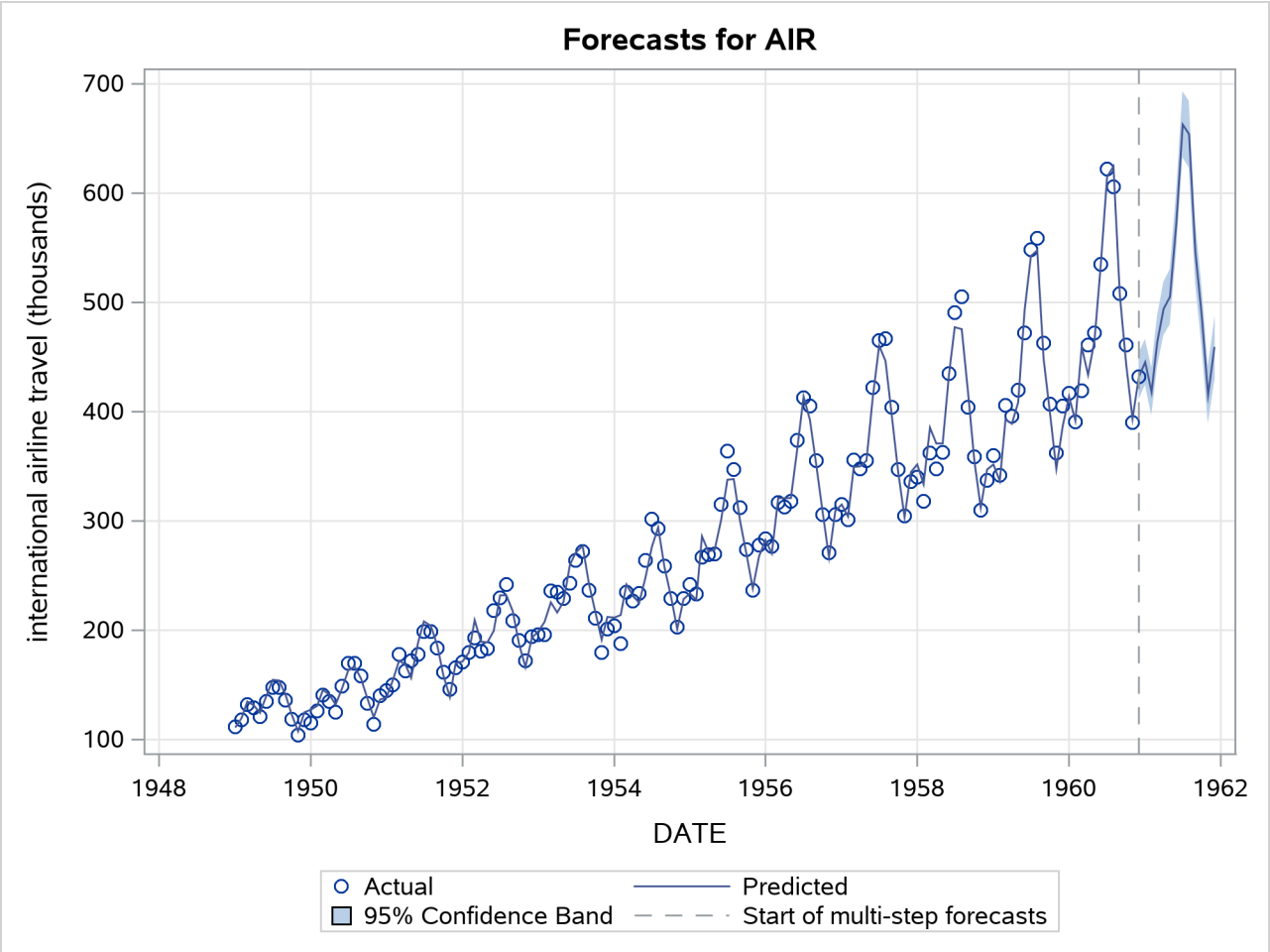
The HPFENGINE procedure output is shown in Output 5.5.1. Forecasts are shown in Figure 5.5.2.

Output 5.5.1 Selection and Forecast Results

The HPFENGINE Procedure

Model Selection Criterion = RMSE			
Model	**Statistic**	**Selected**	**Label**
diag0	10.695241	No	ARIMA: AIR ~ P = 1 D = (1,12) NOINT
diag1	10.579085	Yes	Winters Method (Multiplicative)

Output 5.5.2 Forecasts



It is also possible to compare the performance of model specifications that you create with those automatically generated by the HPFDIAGNOSE procedure.

In the following statements, two model specifications are created, together with a selection list to reference those specifications.

```
proc hpfarimaspec repository=work.repository name=myarima;
   forecast symbol=sale transform=log q=(1 12) diflist=(1 12) noint;
run;

proc hpfucmspec repository=work.repository name=myucm;
   forecast symbol=sale transform=log;
   irregular;
   level;
   season length=12;
run;

proc hpfselect repository=work.repository name=select;
   spec myarima myucm;
run;
```

The model selection list is passed to the HPFDIAGNOSE procedure by using the INSELECTNAME= option as follows. The new selection list ultimately created by the HPFDIAGNOSE procedure includes all model specifications in the INSELECTNAME= selection list together with automatically generated model specifications.

```
proc hpfdiagnose data=sashelp.air
                 inselectname=select
                 repository=work.repository
                 outest=est
                 criterion=mape;
   id date interval=month;
   forecast air;
run;
```

The HPFENGINE procedure selects the best-fitting model as follows. Selection results are shown in Figure 5.5.3, parameter estimates of the selected model are shown in Figure 5.5.4, and the forecast summary is shown in Figure 5.5.5.

```
proc hpfengine data=sashelp.air
               inest=est
               repository=work.repository
               print=(select estimates summary)
               plot=forecasts;
   id date interval=month;
   forecast air;
run;
```

Output 5.5.3 Model Selection Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
diag3	3.1212192	No	ARIMA: AIR ~ P = 1 D = (1,12) NOINT
diag4	3.0845016	No	Winters Method (Multiplicative)
MYARIMA	2.9672282	Yes	ARIMA: Log(SALE) ~ D = (1,12) Q = (1,12) NOINT
MYUCM	3.1842031	No	UCM: Log(SALE) = LEVEL + SEASON + ERROR

Output 5.5.4 Parameter Estimates of Selected Model

Parameter Estimates for MYARIMA Model					
Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
AIR	MA1_1	0.24576	0.07364	3.34	0.0011
AIR	MA1_12	0.50641	0.07676	6.60	<.0001

Output 5.5.5 Forecast Summary

Forecast Summary											
Variable	Value	JAN1961	FEB1961	MAR1961	APR1961	MAY1961	JUN1961	JUL1961	AUG1961	SEP1961	OCT1961
AIR	Predicted	450.3513	425.6158	478.6340	501.0466	512.5109	584.8311	674.9025	667.8935	558.3906	499.4696

Forecast Summary		
Variable	NOV1961	DEC1961
AIR	430.1668	479.4592

Example 5.6: The ADJUST Statement

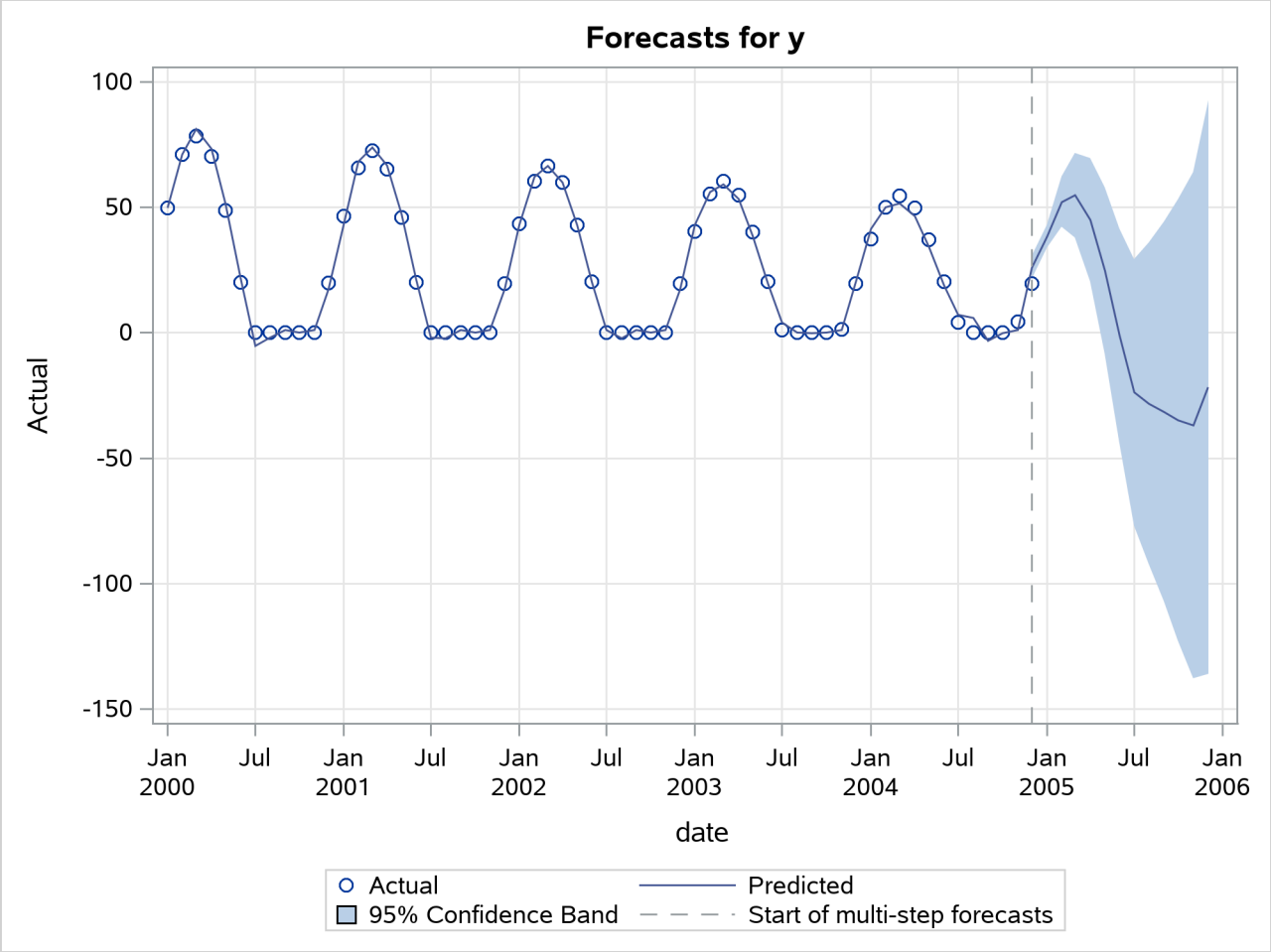
This example illustrates the use of adjustment operations. The following statements create seasonal test data with the in-season data trending downward. When the data are forecast, note that the out-of-season range in the forecast horizon is negative, due to the trend. (See the plot in Figure 5.6.1.)

```
data test;
   do i=1 to 60;
      y = (60-i/2)*sin(2*3.14*i/12) + 20;
      if y lt 0 then do;
         y =0;
         inseason = 0;
      end;
      else do;
         inseason = 1;
      end;
      date = intnx('month', '01jan2000'd, i-1);
      output;
   end;
   do i=61 to 72;
      y = .;
      date = intnx('month', '01jan2000'd, i-1);
      if i le 66 then inseason = 1;
      else inseason = 0;
      output;
   end;
run;

proc hpfengine data=test
               plot=forecasts;
   id date interval=month;
   forecast y;
```

```
run;
```

Output 5.6.1 Forecasts

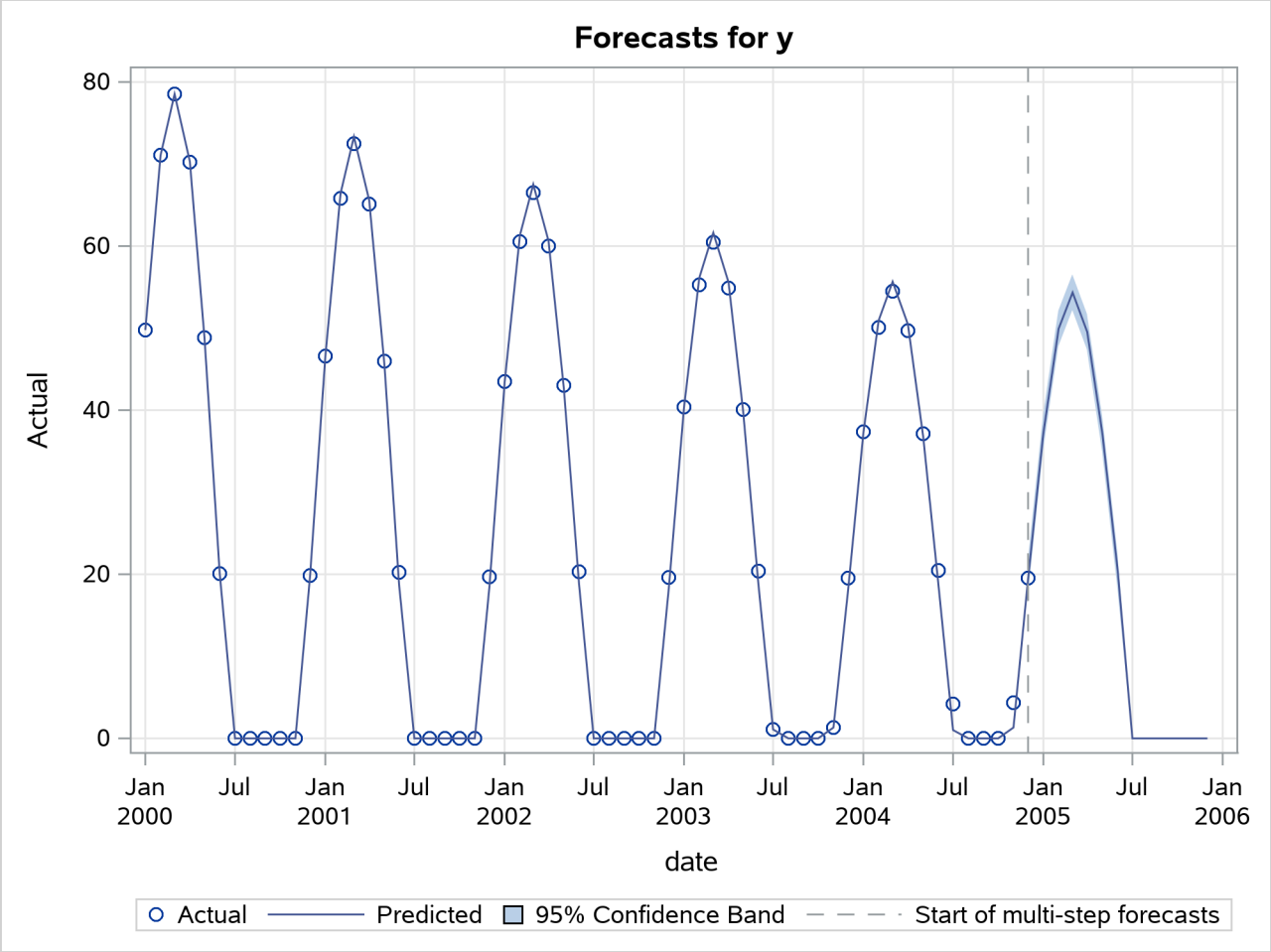


The seasonal indicator variable inseason can be used to fix this situation. Division by zero in the adjustment operation replaces the dividend by a missing value. Subsequent multiplication by zero sets the dividend to zero, especially helpful in the forecast horizon.

Running the HPFENGINE procedure again with the adjustment statement, as follows, produces the forecast shown in Output 5.6.2.

```
proc hpfengine data=test
               print=(select estimates)
               plot=forecasts;
   id date interval=month;
   forecast y;
   adjust y=(inseason) / operation=(divide, multiply);
run;
```

Output 5.6.2 Forecasts



Example 5.7: Multiple Repositories

This example demonstrates how to use the HPFENGINE procedure to access model specifications and model selection lists in multiple repositories.

In the following statements, three model specifications are created, one in SASUSER.REPOS1 and the other two in SASUSER.REPOS2.

```
proc hpfarimaspec repository=sasuser.repos1 name=myarima;
   forecast symbol=y transform=log q=(1 12) diflist=(1 12) noint;
run;

proc hpfucmspec repository=sasuser.repos2 name=myucm;
   forecast symbol=y transform=log;
   irregular;
   level;
   slope;
   season length=12;
run;
```

```
proc hpfesmspec repository=sasuser.repos2 name=mywinters;
   esm method=winters transform=log;
run;
```

A selection list is then created by using the HPFSELECT procedure and placed in the repository named SASUSER.REPOS3, as follows.

```
proc hpfselect repository=sasuser.repos3 name=mylist;
   spec myarima myucm mywinters;
run;
```

Because the HPFENGINE procedure has only one REPOSITORY option, it would not normally be possible for the procedure to locate the selection list and all three models. The CATNAME statement is used as follows to create a logical concatenation of multiple catalogs; this offers the solution to this problem.

```
catname sasuser.cataloglist (sasuser.repos1 sasuser.repos2 sasuser.repos3);
```

When the HPFENGINE procedure is called, the concatenated name is used in the REPOSITORY= option, as follows. The results of the model selection are shown in Output 5.7.1.

```
proc hpfengine data=sashelp.air
               repository=sasuser.cataloglist
               globalselection=mylist
               print=select;
   id date interval=month;
   forecast air;
run;
```

Output 5.7.1 Model Selection Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
MYARIMA	2.9672282	No	ARIMA: Log(Y) ~ D = (1,12) Q = (1,12) NOINT
MYUCM	3.2601060	No	UCM: Log(Y) = TREND + SEASON + ERROR
MYWINTERS	2.7138783	Yes	Log Winters Method (Multiplicative)

Example 5.8: ODS Graphics

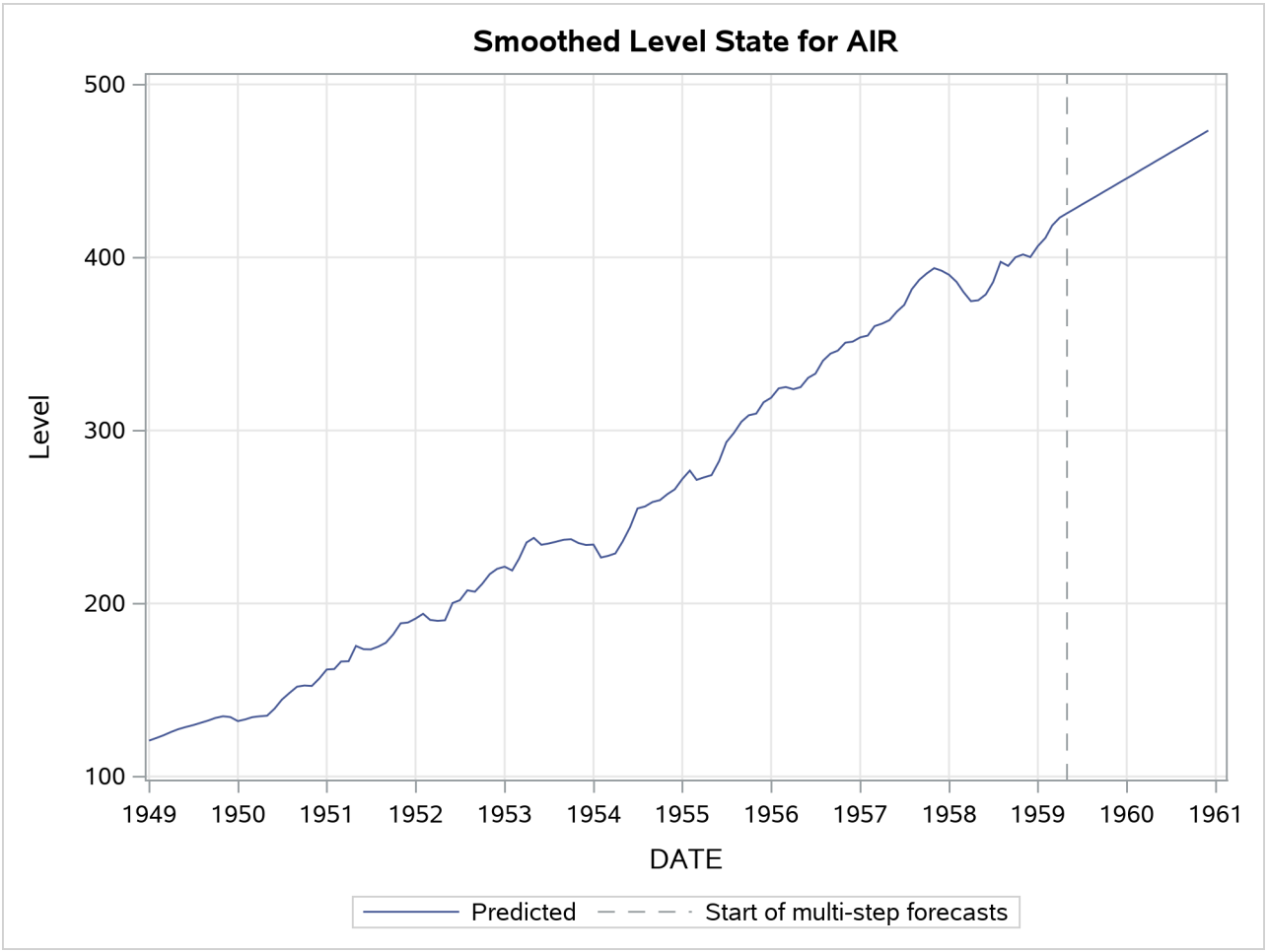
This example illustrates the use of ODS Graphics. The following statements use the SASHELP.AIR data set to automatically forecast the time series of international airline travel.

The graphical displays are requested by specifying the PLOT= option in the PROC HPFENGINE statement. In this case, all plots are requested. Figures Output 5.8.1 through Output 5.8.5 show a selection of the plots created.

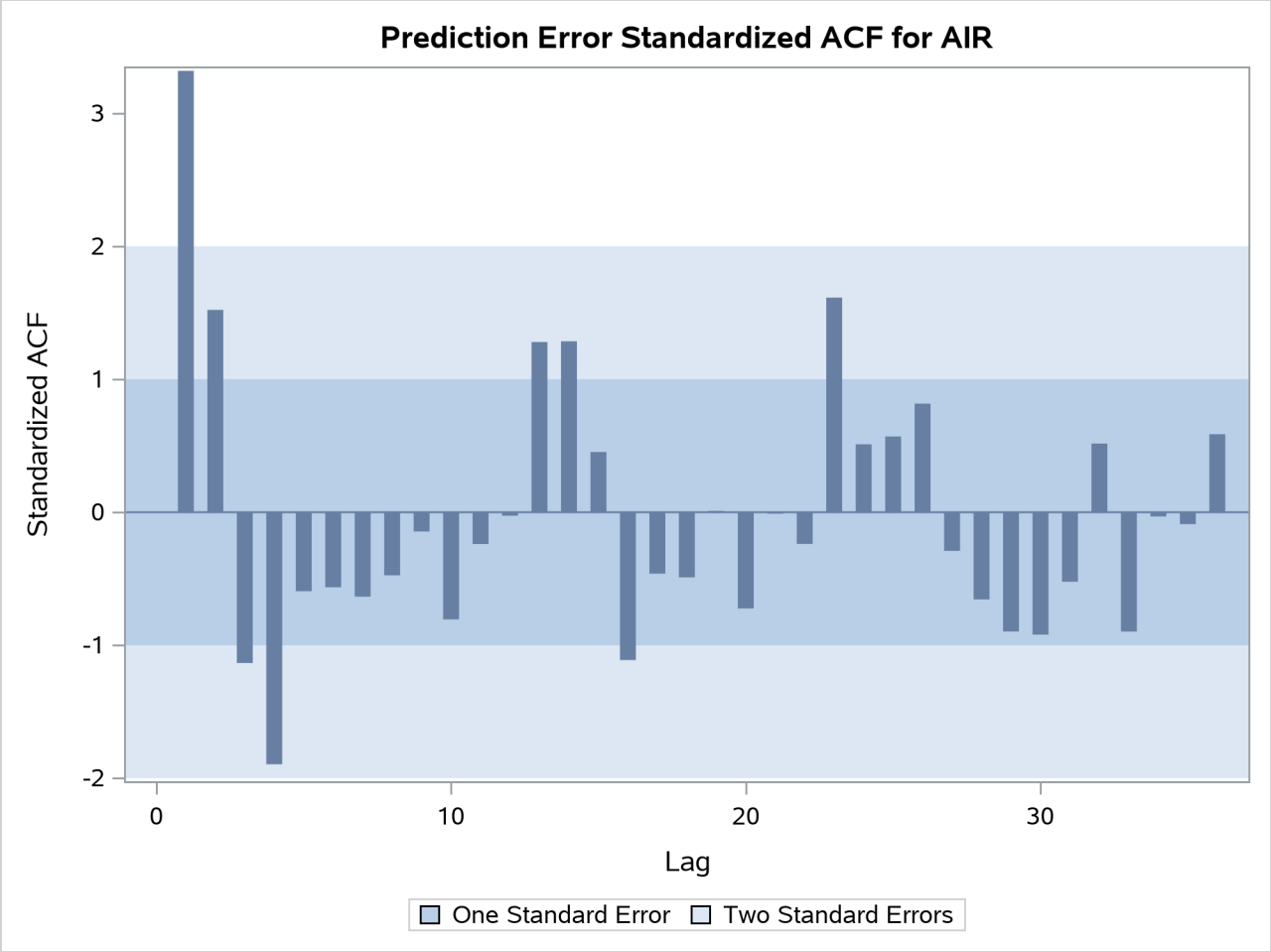
For information about the graphics available in the HPFENGINE procedure, see the “ODS Graphics” on page 211 section.

```
proc hpfengine data=sashelp.air
               out=_null_
               lead=20
               back=20
               plot=all;
   id date interval=month;
   forecast air;
run;
```

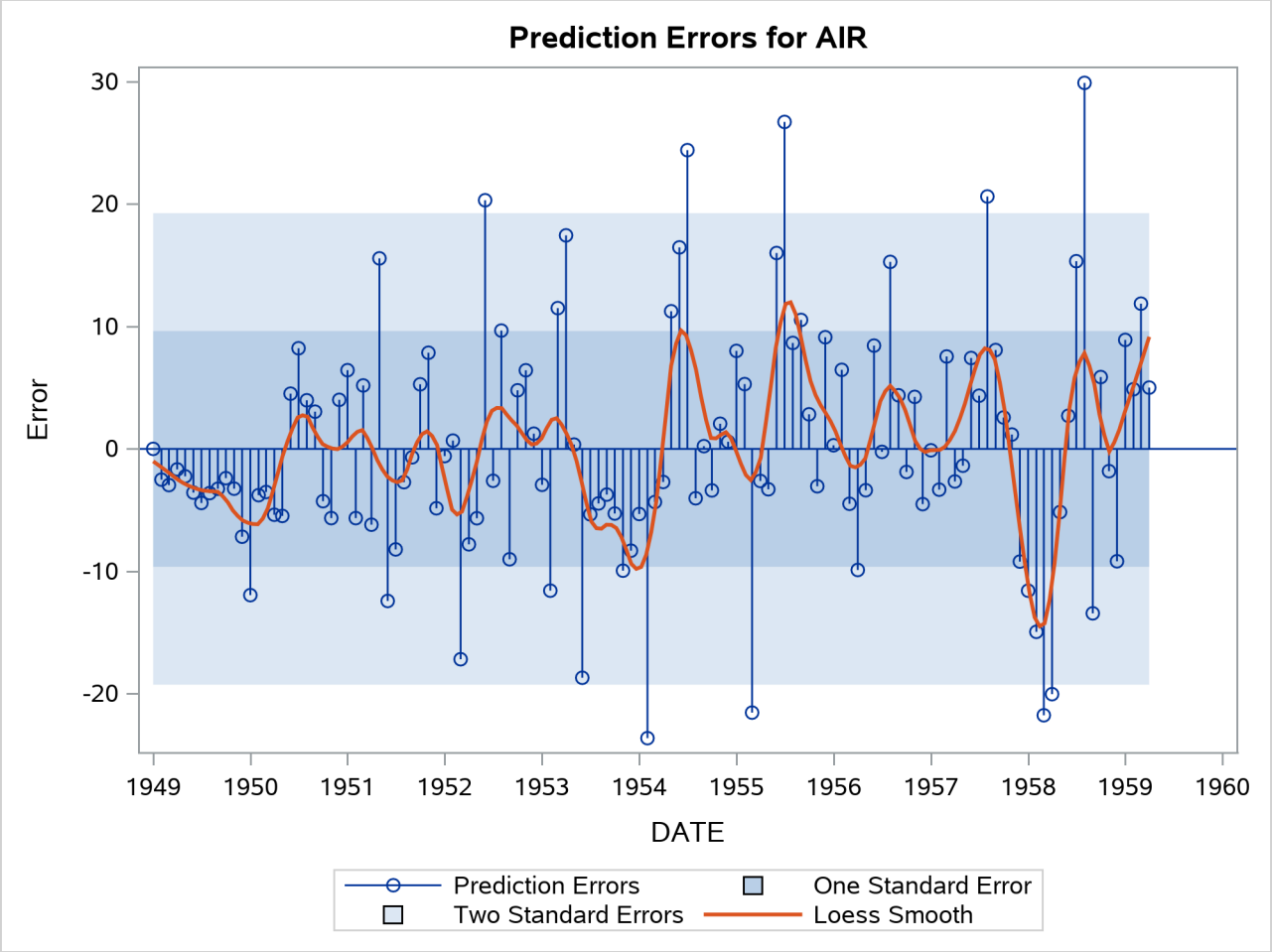
Output 5.8.1 Component Estimates



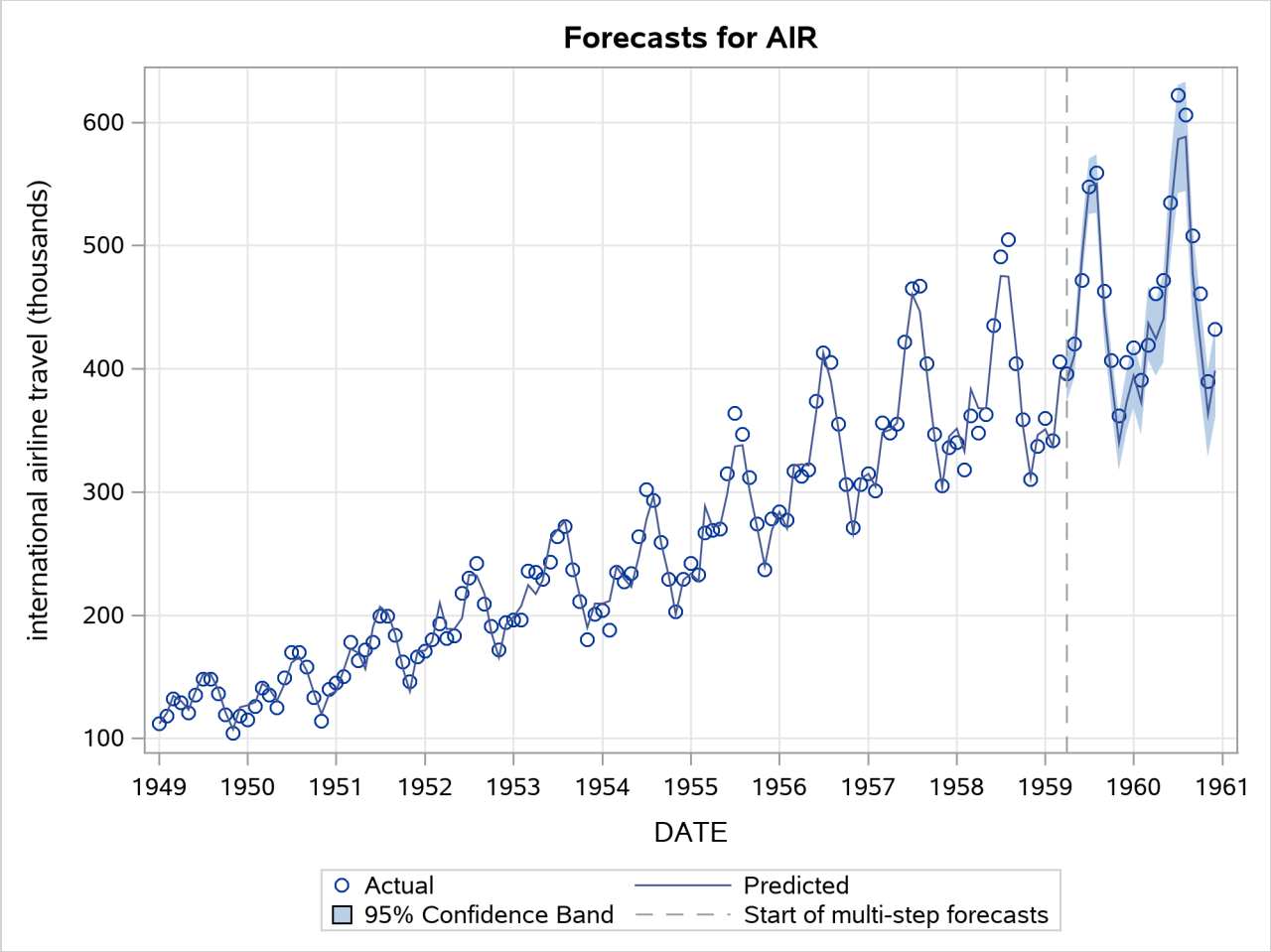
Output 5.8.2 Standardized Autocorrelation of Prediction Errors



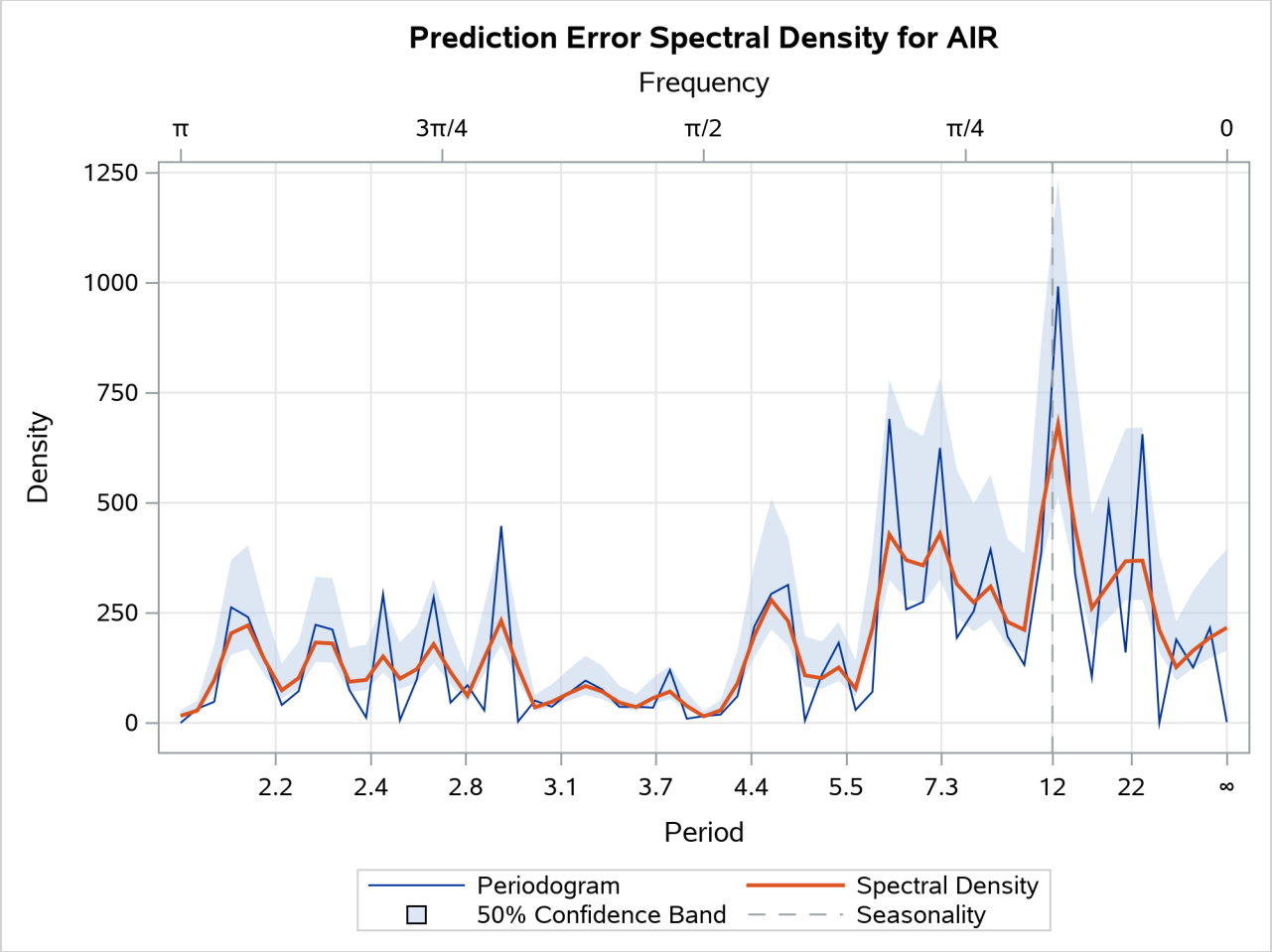
Output 5.8.3 Prediction Errors



Output 5.8.4 Forecasts



Output 5.8.5 Prediction Error Spectral Density



Example 5.9: Combining Judgmental Forecasts

Externally specified models enable forecasts from external sources to be included in the model selection process in the HPFENGINE procedure. Because ensemble models operate on forecasts, you might naturally expect a combination of forecasts from externally specified models to function in this setting. This simple example demonstrates such a scenario.

For the data set Sashelp.Pricedata, suppose you have sales forecasts that arise from the judgment of three independent sources. Suppose you want to compare a weighted combination of those judgmental forecasts against the sales forecast from the best exponential smoothing model (BESTESM), where the weighted combination assigns predetermined weights to the combination candidates. This example assumes that the external forecasts are contained in a separate data set, Perm.External, where the variables Salef1-Salef3 denote the three judgmental forecasts to be combined. This example also demonstrates the use of the AUXDATA= option for supporting auxiliary data set access.

First, you create three separate external models to identify each of the combined forecast contributors (named XF1, XF2, and XF3). Then you combine those with the combined model list COMBXF. Combination weights of 0.5, 0.3, and 0.2 are assigned to XF1, XF2, and XF3, respectively. You must map each external

model specification to the data set variable that supplies its forecast. Finally, you create the model selection list XFSELECT that uses MAPE to define the comparison between BESTESM and COMBXF over a holdout region of six months:

```
proc hpfesmspec rep=work.rep specname=bestesm;
   esm method=best;
run;

proc hpfexmspec rep=work.rep specname=xf1;
  exm;
run;

proc hpfexmspec rep=work.rep specname=xf2;
  exm;
run;

proc hpfexmspec rep=work.rep specname=xf3;
  exm;
run;

proc hpfselect rep=work.rep name=combxf label="USERDEF(XF1,XF2,XF3)";
   combine method=userdef(0.5,0.3,0.2);
   spec xf1 /exmmap(predict=salef1);
   spec xf2 /exmmap(predict=salef2);
   spec xf3 /exmmap(predict=salef3);
run;

proc hpfselect rep=work.rep name=xfselect;
   select holdout=6 criterion=mape;
   spec combxf bestesm;
run;
```

You now run the HPFENGINE procedure on the primary data set Sashelp.Pricedata with the external forecasts in Perm.External. PROC HPFENGINE constructs the forecast model selection graph as directed by the GLOBALSELECTION= option and runs it for each BY group in Sashelp.Pricedata. PROC HPFENGINE selects the best forecast for each BY group independently from the candidates that are evaluated in the forecast model selection graph.

```
proc hpfengine data=sashelp.pricedata
               auxdata=perm.external
               rep=work.rep
               globalselection=xfselect
               out=out3 outfor=for3
               outmodelinfo=minfo3
               outstatselect=oss3
               outstat=stat3
               outest=est3
               lead=12;
   by region line product;
   id date interval=month horizonstart='01jan2003'd end='01dec2003'd;
   forecast sale;
   external salef1 salef2 salef3;
run;
```

Sashelp.Pricedata contains 17 BY groups for the hierarchy Region, Line, Product. Figure 5.9.1 shows a summary of the MAPE statistics for the selected models over the BY groups on the basis of whether a combined judgmental forecast was selected.

Output 5.9.1 MAPE Summary Statistics for Combined versus Best ESM

Combined judgment vs. BESTESM

The MEANS Procedure

Analysis Variable : MAPE Mean Absolute Percent Error						
CombSelected	N Obs	N	Mean	Std Dev	Minimum	Maximum
NO	11	11	6.5339736	2.4822563	3.4681708	11.6676137
YES	6	6	6.1907580	2.2840940	4.3111761	9.9540557

References

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control*. 3rd ed. Englewood Cliffs, NJ: Prentice-Hall.

Chapter 6
The HPFESMSPEC Procedure

Contents

Overview: HPFESMSPEC Procedure **241**
Getting Started: HPFESMSPEC Procedure **242**
Syntax: HPFESMSPEC Procedure **242**
Functional Summary 242
PROC HPFESMSPEC Statement 243
ESM Statement 244
Details: HPFESMSPEC Procedure **248**
Smoothing Model Parameter Specification Options 248
Examples: HPFESMSPEC Procedure **248**
Example 6.1: Various Kinds of ESM Model Specifications 248
Example 6.2: Selecting the Best ESM Model 251

Overview: HPFESMSPEC Procedure

The HPFESMSPEC procedure creates model specifications files for exponential smoothing models (ESM).

You can specify many types of exponential models with this procedure. In particular, any model that can be analyzed using the HPF procedure can be specified.

Getting Started: HPFESMSPEC Procedure

The following example shows how to create an exponential smoothing model specification file. In this example, a model specification for a Winters method is created.

```
proc hpfesmspec repository=sasuser.mymodels
                name=mywinters
                label="Winters Method";
   esm method=winters;
run;
```

The options in the PROC HPESMSPEC statement are used to specify the location of the specification file that will be output. Here the REPOSITORY= option specifies that the output file be placed in a catalog "sasuser.mymodels,", the NAME= option specifies that the name of the file be "mywinters.xml," and the LABEL= option specifies a label for this catalog member. The ESM statement in the procedure specifies the exponential smoothing model and the options used to control the parameter estimation process for the model.

Syntax: HPFESMSPEC Procedure

The following statements are used with the HPFESMSPEC procedure.

PROC HPFESMSPEC *options* **;**
ESM *options* **;**

Functional Summary

Table 6.1 summarizes the statements and options that control the HPFESMSPEC procedure.

Table 6.1 PROC HPFESMSPEC Functional Summary

Description	Statement	Option
Statements		
Specifies the exponential smoothing model	ESM	
Model Repository Options		
Specifies the model repository	PROC HPFESMSPEC	REPOSITORY=
Specifies the model specification name	PROC HPFESMSPEC	NAME=
Specifies the model specification label	PROC HPFESMSPEC	LABEL=
Exponential Smoothing Model Options		
Specifies the model selection criterion	ESM	CRITERION=
Specifies the damping weight parameter initial value	ESM	DAMPPARM=

Description	Statement	Option
Specifies the damping weight parameter restrictions	ESM	DAMPREST=
Specifies the level weight parameter initial value	ESM	LEVELPARM=
Specifies the level weight parameter restrictions	ESM	LEVELREST=
Specifies median forecasts	ESM	MEDIAN
Specifies the time series forecasting model	ESM	METHOD=
Specifies that the smoothing model parameters are fixed values	ESM	NOEST
Specifies that stable parameter estimates are not required	ESM	NOSTABLE
Specifies the season weight parameter initial value	ESM	SEASONPARM=
Specifies the season weight parameter restrictions	ESM	SEASONREST=
Specifies the time series transformation	ESM	TRANSFORM=
Specifies the trend weight parameter initial value	ESM	TRENDPARM=
Specifies the trend weight parameter restrictions	ESM	TRENDREST=

PROC HPFESMSPEC Statement

PROC HPFESMSPEC *options* **;**

The following options can be used in the PROC HPFESMSPEC statement.

LABEL=*"specification label"*

SPECLABEL=*"specification label"*

specifies a descriptive label for the model specification to be stored in the SAS catalog or external file reference. The LABEL= option can also be specified as SPECLABEL=.

NAME=*SAS-name*

SPECNAME=*SAS-name*

names the model specification to be stored in the SAS catalog or external file reference. The NAME= option can also be specified as SPECNAME=.

REPOSITORY=*SAS-catalog-name* | *SAS-file-reference*

names the SAS catalog or external file reference to contain the model specification. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=.

ESM Statement

ESM *options* **;**

The ESM statement is used to specify an exponential smoothing model.

The default specification selects the best exponential smoothing model without transformation (METHOD=BEST TRANSFORM=NONE).

The following options can be specified in the ESM statement.

CRITERION=*option*

SELECT=*option*

specifies the model selection criterion (statistic of fit) to be used to select from several candidate models. This option is often used in conjunction with the HOLDOUT= option. The CRITERION= option can also be specified as SELECT=. The default is CRITERION=RMSE.

The following list shows the valid values for the CRITERION= option and the statistics of fit these option values specify:

SSE	sum of squared error
MSE	mean squared error
RMSE	root mean squared error
UMSE	unbiased mean squared error
URMSE	unbiased root mean squared error
MAXPE	maximum percent error
MINPE	minimum percent error
MPE	mean percent error
MAPE	mean absolute percent error
MDAPE	median absolute percent error
GMAPE	geometric mean absolute percent error
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MPPE	mean predictive percent error
MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median absolute predictive percent error
GMAPPE	geometric mean absolute predictive percent error
MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error

MSPE	mean symmetric percent error
SMAPE	symmetric mean absolute percent error
MDASPE	median absolute symmetric percent error
GMASPE	geometric mean absolute symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error
MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MAXERR	maximum error
MINERR	minimum error
ME	mean error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R-square
ADJRSQ	adjusted R-square
AADJRSQ	Amemiya's adjusted R-square
RWRSQ	random walk R-square
AIC	Akaike information criterion
AICC	finite sample corrected AIC
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion

DAMPPARM=*number*
specifies the damping weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 248.

DAMPREST=(*number***,** *number* **)**
specifies the damping weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 248.

LEVELPARM=*number*
specifies the level weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 248.

LEVELREST=(*number***,** *number* **)**
specifies the level weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 248.

MEDIAN
specifies that the median forecast values be estimated. Forecasts can be based on the mean or median. By default the mean value is provided. If no transformation is applied to the actual series with the TRANSFORM= option, the mean and median time series forecast values are identical.

METHOD=*method-name*
specifies the type of exponential smoothing model to use as a candidate for model selection. The selected model is used to forecast the time series. A single method can be specified, or multiple methods can be specified. If multiple methods are specified, the model used to forecast the accumulated time series is selected based on the CRITERION= option of the ESM statement and the HOLDOUT= option of the FORECAST statement. The default is METHOD=BEST. The following forecasting models are provided:

SIMPLE	simple (single) exponential smoothing
DOUBLE	double (Brown) exponential smoothing
LINEAR	linear (Holt) exponential smoothing
DAMPTREND	damped trend exponential smoothing
ADDSEASONAL	additive seasonal exponential smoothing
MULTSEASONAL	multiplicative seasonal exponential smoothing
SEASONAL	same as ADDSEASONAL
WINTERS	Winters multiplicative method
ADDWINTERS	Winters additive method
BEST	uses seasonal properties of the data to choose between the BESTN and BESTS methods. If the data consist of a single seasonal cycle, the BESTN method is used. Otherwise, a seasonality test is performed on both the original data and the original data after one nonseasonal difference is taken. If seasonality is present in either the original or differenced series, the series is considered to be seasonal. If the data are seasonal, the BESTS method is used. If neither seasonality test indicates seasonality, the BESTN method is used. The results of the seasonality test are summarized in Table 6.2. The significance level for the seasonality test is specified by the model diagnostic routine. If you use the HPFDIAGNOSE procedure as the model diagnostic routine, you can specify the SIGLEVEL option in the PROC HPFDIAGNOSE statement. For more information about the seasonality test, see the SEASONTEST function of the time series analysis (TSA) package.
BESTN	best candidate nonseasonal smoothing model (SIMPLE, LINEAR, or DAMPTREND)
BESTS	best candidate seasonal smoothing model (ADDSEASONAL, ADDWINTERS, or WINTERS)

NOEST
specifies that the smoothing model parameters are fixed values. To use this option, all of the smoothing model parameters must be explicitly specified. By default, the smoothing model parameters are optimized.

NOSTABLE
specifies that the smoothing model parameters are not restricted to the additive invertible region of the parameter space. By default, the smoothing model parameters are restricted to be inside the additive invertible region of the parameter space.

SEASONPARM=*number*
specifies the season weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 248.

SEASONREST=(*number***,** *number* **)**
specifies the season weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 248.

TRANSFORM=*option*
specifies the time series transformation to be applied to the time series. The following transformations are provided:

NONE	no transformation. This option is the default.
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5
AUTO	automatically choose between NONE and LOG based on model selection criteria

When the TRANSFORM= option is specified, the time series must be strictly positive. Once the time series is transformed, the model parameters are estimated using the transformed time series. The forecasts of the transformed time series are then computed, and finally the transformed time series forecasts are inverse transformed. The inverse transform produces either mean or median forecasts depending on whether the MEDIAN option is specified.

TRENDPARM=*number*
specifies the trend weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 248.

TRENDREST=(*number***,** *number* **)**
specifies the trend weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 248.

Table 6.2 Results of BEST Method of the ESM Statement

Number of Seasonal Cycles	Result of Seasonality Test	Method Used
< 2	Test is not performed	BESTN
≥ 2	Test indicates seasonality	BESTS
≥ 2	Test does not indicate seasonality	BESTN

Details: HPFESMSPEC Procedure

Smoothing Model Parameter Specification Options

The parameter options are used to specify smoothing model parameters. If the parameter restrictions are not specified, the default is (0.0001 0.9999), which implies that the parameters are restricted between 0.0001 and 0.9999. Parameters and their restrictions are required to be greater than or equal to –1 and less than or equal to 2. Missing values indicate no lower and/or upper restriction. If the parameter initial values are not specified, the optimizer uses a grid search to find an appropriate initial value.

Examples: HPFESMSPEC Procedure

Example 6.1: Various Kinds of ESM Model Specifications

The following statements illustrate typical uses of the ESM statement:

```
proc hpfesmspec repository=mymodels
                name=model1
                label="Default Specification";
   esm;
run;

proc hpfesmspec repository=mymodels
                name=model2
                label="Simple Exponential Smoothing";
   esm method=simple;
run;

proc hpfesmspec repository=mymodels
                name=model3
                label="Double Exponential Smoothing";
   esm method=double;
```

```
run;

proc hpfesmspec repository=mymodels
                name=model4
                label="Linear Exponential Smoothing";
   esm method=linear;
run;

proc hpfesmspec repository=mymodels
                name=model5
                label="Damp-Trend Exponential Smoothing";
   esm method=damptrend;
run;

proc hpfesmspec repository=mymodels
                name=model6
                label="Seasonal Exponential Smoothing";
   esm method=addseasonal;
run;

proc hpfesmspec repository=mymodels
                name=model7
                label="Winters Method";
   esm method=winters;
run;

proc hpfesmspec repository=mymodels
                name=model8
                label="Additive-Winters Method";
   esm method=addwinters;
run;

proc hpfesmspec repository=mymodels
                name=model9
                label="Best Smoothing Model";
   esm method=best;
run;

proc hpfesmspec repository=mymodels
                name=model10
                label="Best Non-Seasonal Smoothing Model";
   esm method=bestn;
run;

proc hpfesmspec repository=mymodels
                name=model11
                label="Best Seasonal Smoothing Model";
   esm method=bests;
run;

proc hpfesmspec repository=mymodels
                name=model12
                label="Log Simple Exponential Smoothing";
   esm method=simple transform=log;
```

```
run;

proc hpfesmspec repository=mymodels
                name=model13
                label="Log Double Exponential Smoothing";
   esm method=double transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model14
                label="Log Linear Exponential Smoothing";
   esm method=linear transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model15
                label="Log Damp-Trend Exponential Smoothing";
   esm method=damptrend transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model16
                label="Log Seasonal Exponential Smoothing";
   esm method=addseasonal transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model16
                label="Log Winters Method";
   esm method=winters transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model18
                label="Log Additive-Winters Method";
   esm method=addwinters transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model19
                label="Best Log Smoothing Model";
   esm method=best transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model20
                label="Best Log Non-Seasonal Smoothing Model";
   esm method=bestn transform=log;
run;

proc hpfesmspec repository=mymodels
                name=model21
                label="Best Log Seasonal Smoothing Model";
   esm method=bests transform=log;
```

```
run;

title "Models Added to MYMODELS Repository";
proc catalog catalog=mymodels;
   contents;
run;
```

Output 6.1.1 Listing of Models in MYMODELS Repository

Models Added to MYMODELS Repository

Contents of Catalog WORK.MYMODELS

#	Name	Type	Create Date	Modified Date	Description
1	MODEL1	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Default Specification
2	MODEL10	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Best Non-Seasonal Smoothing Model
3	MODEL11	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Best Seasonal Smoothing Model
4	MODEL12	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Log Simple Exponential Smoothing
5	MODEL13	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Log Double Exponential Smoothing
6	MODEL14	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Log Linear Exponential Smoothing
7	MODEL15	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Log Damp-Trend Exponential Smoothing
8	MODEL16	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Log Winters Method
9	MODEL18	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Log Additive-Winters Method
10	MODEL19	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Best Log Smoothing Model
11	MODEL2	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Simple Exponential Smoothing
12	MODEL20	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Best Log Non-Seasonal Smoothing Model
13	MODEL21	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Best Log Seasonal Smoothing Model
14	MODEL3	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Double Exponential Smoothing
15	MODEL4	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Linear Exponential Smoothing
16	MODEL5	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Damp-Trend Exponential Smoothing
17	MODEL6	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Seasonal Exponential Smoothing
18	MODEL7	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Winters Method
19	MODEL8	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Additive-Winters Method
20	MODEL9	XML	08/06/2020 03:20:02	08/06/2020 03:20:02	Best Smoothing Model

Example 6.2: Selecting the Best ESM Model

This example illustrates how to define model specifications that automatically choose the best exponential smoothing model by using MAPE as the model selection criterion.

The following statements fit two forecast models (simple and log simple exponential smoothing) to the time series. The forecast model that results in the lowest MAPE is used to forecast the time series.

```
proc hpfesmspec repository=mymodels
                name=best_simple;
   esm method=simple transform=auto criterion=mape;
run;
```

The following statements fit two forecast models (seasonal and log seasonal exponential smoothing) to the time series. The forecast model that results in the lowest MAPE is used to forecast the time series.

```
proc hpfesmspec repository=mymodels
                name=best_seasonal;
   esm method=addseasonal transform=auto criterion=mape;
run;
```

The following statements fit 14 forecasting models (best and log best exponential smoothing) to the time series. The forecast model that results in the lowest MAPE is used to forecast the time series.

```
proc hpfesmspec repository=mymodels
                name=best;
   esm method=best transform=auto criterion=mape;
run;
```

Chapter 7
The HPFEVENTS Procedure

Contents

Overview: HPFEVENTS Procedure **254**
Getting Started: HPFEVENTS Procedure **255**
Syntax: HPFEVENTS Procedure **259**
Functional Summary 260
PROC HPFEVENTS Statement 261
BY Statement 261
EVENTCOMB Statement 262
EVENTDATA Statement 263
EVENTDEF Statement 263
EVENTDUMMY Statement 266
EVENTGROUP Statement 267
EVENTKEY Statement 268
ID Statement 268
VAR Statement 270
Details: HPFEVENTS Procedure **271**
Event Definitions 271
Using the EVENTKEY Statement 282
Using the EVENTDS= System Option to Customize Holiday Predefined Date Keywords 285
Missing Value Interpretation 285
Input and Output Data Sets 286
Printed Output 288
Examples: HPFEVENTS Procedure **288**
Example 7.1: Using Multiple Timing Values in a Single Event versus Using Multiple Events and the EVENTCOMB Statement 288
Example 7.2: Using a DATA Step to Construct an Events Data Set 289
Example 7.3: Preparing a Data Set for PROC HPFENGINE 292
Example 7.4: Using Predefined SAS Event Keywords Directly in Other SAS Procedures 294
Example 7.5: Viewing Dummy Variables by Using the SGPLOT Procedure 295
References **297**

Overview: HPFEVENTS Procedure

The HPFEVENTS procedure enables you to create and manage event definitions that are associated with time series so that the events can be analyzed further by other procedures. PROC HPFEVENTS can create event definitions, read events from an events data set, write events to an events data set, and create dummy variables that are based on those events if date information is provided.

An event definition is used to model any incident that disrupts the normal flow of the process that generated the time series. Examples of commonly used event definitions include natural disasters, retail promotions, strikes, advertising campaigns, policy changes, and data recording errors.

An event definition has a reference name, a date or dates that are associated with the event, and a set of qualifiers. The event definition exists separate from any time series; however, the event definition can be applied to one or more time series. When the event definition is applied to a time series, a dummy variable is generated that can be used to analyze the impact of the event definition on the time series. You can use the HPFEVENTS procedure to apply one or more event definitions to a time series, create one or more dummy variables, and save the dummy variables in a data set. However, you do not need to save the dummy variables if you plan to use the HPFENGINE or HPFDIAGNOSE procedure to evaluate the time series and the events. You only need to supply the event definition data set that PROC HPFEVENTS creates, and then PROC HPFENGINE and PROC HPFDIAGNOSE create and store the dummy variables in memory for you.

The HPFEVENTS procedure offers the following advantages:

- Dummy variables that are generated by PROC HPFEVENTS are automatically extended, shortened, or changed as observations are added and deleted from a time series. Thus, you can use a single event definition for several time series or for different spans of the same series.
- You can define dummy variables that function equally well for time series of various intervals, such as weekly or monthly data. The same event definition can model daily data or weekly totals.
- You can store event definitions in a data set. You can change event definitions later, add new events, or generate additional dummy variables from an existing data set.
- You can pass event definitions that are stored in a data set directly to PROC HPFENGINE and PROC HPFDIAGNOSE. For more information, see Chapter 5, "The HPFENGINE Procedure," and Chapter 4, "The HPFDIAGNOSE Procedure."
- You can access predefined SAS event definitions directly from PROC HPFENGINE and PROC HPFDIAGNOSE. For a list of predefined SAS event definitions, see the section "Using the EVENTKEY Statement" on page 282. Example 7.4 illustrates this feature.
- You can generate a data set that can be used in other procedures such as PROC REG. For more information, see Chapter 105, "The REG Procedure" (*SAS/STAT User's Guide*). As data are added or deleted from the time series, PROC HPFEVENTS can automatically generate new dummy variables as required.
- PROC HPFEVENTS recognizes predefined variables and dates. Thus, events that involve holidays such as Easter and Thanksgiving can be modeled easily, even though the dates of the events change from year to year.

Getting Started: HPFEVENTS Procedure

The HPFEVENTS procedure is simple to use. It provides results in output data sets that can be interpreted in other SAS procedures.

The following statements create event definitions and dummy variables. Then they output the event definitions to a data set named EVDSOUT1 and dummy variables to a data set named EVDUMOUT1. More examples are shown in the section "Examples: HPFEVENTS Procedure" on page 288.

```
proc hpfevents data=sashelp.air ;
   var air;
   id date interval=month end='31Dec1952'D;
   eventdef laborday=labor / value=2 ;
   eventdef summer= '01Jun1900'D to '01Jun2005'D by year /
                  after=(duration=2) label='jun jul aug';
   eventdef yr1950= '01Jan1950'D / pulse=year ;
   eventdef levelshift= '01Jan1950'D / type=ls ;
   eventdef novdec= christmas / before=(duration=1)
                              pulse=month;
   eventdef first10obs= 1 to 10;
   eventdef everyotherobs= 1 to 200 by 2;
   eventdef saturday= '01Jan1950'D to '31Jan1950'D by week.7;
   eventkey ao15obs;
   eventkey ls01Jan1950D / after=(duration=5) ;
   eventkey garbage ;
   eventdata  out=evdsout1(label='list of events');
   eventdummy  out=evdumout1(label='dummy variables');
run;
```

The EVENTDEF statements create the following event definitions:

LABORDAY — PROC HPFEVENTS recognizes that "LABOR" is a date keyword. When PROC HPFEVENTS creates a dummy variable for this event, it generates a timing value for each Labor Day that falls in the span of the time series. Each observation that matches the date of Labor Day has a value of 2.

SUMMER — The string `'01Jun1900'D to '01Jun2005'D by year` is a "do-list" that generates 106 timing values for June 1 for each year from 1900 to 2005. The AFTER=(DURATION=2) option requests that the pulse for each timing value last for three observations (the observation that matches June 1 and the two following). For monthly data, this AFTER= value generates a pulse for June 1, July 1, and August 1 of each year from 1900 to 2005. If you add PULSE=MONTH to this statement, then the event always specifies June, July, and August, regardless of the interval of the data. If you specify only the timing value `'01Jun1900'D` and you add PERIOD=YEAR, then you have the same effect for all years, even years before 1900 and after 2005.

YR1950 — When you specify a timing value within the year 1950 and use PULSE=YEAR, this event is a pulse for any observations within the year 1950.

LEVELSHIFT — When TYPE=LS, the default value of the AFTER= option is AFTER=(DURATION=ALL). The pulse begins at the observation that matches January 1, 1950, and continues to the

end of the series. A special missing value of "A" is shown in the _DUR_AFTER_ variable of the events definition data set to represent AFTER=(DURATION=ALL).

NOVDEC Compare this to the SUMMER event. Here the date keyword CHRISTMAS is used. CHRISTMAS produces the same result as a timing value of `'25Decyyyy'D` and PERIOD=YEAR. BEFORE=(DURATION=1) and PULSE=MONTH specify the months of November and December for any year in the span of the series. If you want to specify certain months of the year, this syntax is preferable to the syntax used in SUMMER.

FIRST10OBS Integers in the timing list always specify observation numbers. This dummy variable is always a pulse from observation 1 to observation 10, regardless of the value of the timing ID variable.

EVERYOTHEROBS Like FIRST10OBS, this dummy variable always specifies every other observation starting at observation 1 and ending at observation 199.

SATURDAY WEEK.7 in the do-list specifies Saturday dates. The do-list produces timing values that are the Saturdays in January 1950. If the data are daily, there are four pulses in January 1950, one on each Saturday. If the data are weekly, a pulse is formed for four successive observations in January 1950. If the data are monthly and RULE= ADD (which is the default), then the observation for January 1950 counts the number of Saturdays in January.

The first two EVENTKEY statements in the preceding statements alter predefined SAS event definitions, and the last EVENTKEY statement is ignored, as follows:

AO15OBS AO15OBS is recognized as an event keyword; it is a predefined event that means a pulse that is placed on the 15th observation.

LS01JAN1950D LS01JAN1950D is recognized as an event keyword; it is a predefined event that means a level shift that begins at `'01Jan1950'D`. The qualifier AFTER=(DURATION=5) modifies the predefined event.

GARBAGE EVENTKEY GARBAGE is ignored because GARBAGE is not an event keyword. A warning is printed to the log.

The following statements display the EVDSOUT1 output data set (which is created by the EVENTDATA statement). The data set is shown in Figure 7.1.

```
proc print data=evdsout1;
run;
```

Figure 7.1 Event Definition Data Set That Shows All Variables Related to Event Definitions

Obs	_LOCALE_	_NAME_	_CLASS_	_KEYNAME_	_STARTDATE_	_ENDDATE_	_DATEINTRVL_	_STARTDT_
1	.	laborday	SIMPLE	LABOR	.	.	.	.
2	.	summer	SIMPLE	.	01JUN1900	01JUN2005	YEAR.6	.
3	.	yr1950	SIMPLE	.	01JAN1950	.	.	.
4	.	levelshift	SIMPLE	.	01JAN1950	.	.	.
5	.	novdec	SIMPLE	CHRISTMAS	.	.	.	.
6	.	first10obs	SIMPLE	.	.	.	.	.
7	.	everyotherobs	SIMPLE	.	.	.	.	.
8	.	saturday	SIMPLE	.	07JAN1950	28JAN1950	WEEK1.7	.
9	.	ao15obs	SIMPLE	.	.	.	.	.
10	.	ls01Jan1950D	SIMPLE	.	01JAN1950	.	.	.

Obs	_ENDDT_	_DTINTRVL_	_STARTOBS_	_ENDOBS_	_OBSINTRVL_	_TYPE_	_VALUE_	_PULSE_	_DUR_BEFORE_
1	.	.	.	.	.	POINT	2	.	0
2	.	.	.	.	.	POINT	1	.	0
3	.	.	.	.	.	POINT	1	YEAR	0
4	.	.	.	.	.	LS	1	.	0
5	.	.	.	.	.	POINT	1	MONTH	1
6	.	.	1	10	1	POINT	1	.	0
7	.	.	1	199	2	POINT	1	.	0
8	.	.	.	.	.	POINT	1	.	0
9	.	.	15	.	.	POINT	1	.	0
10	.	.	.	.	.	LS	1	.	0

Obs	_DUR_AFTER_	_SLOPE_BEF_	_SLOPE_AFT_	_SHIFT_	_TCPARM_	_RULE_	_PERIOD_	_LABEL_
1	0	GROWTH	GROWTH	0	0.5	ADD	.	.
2	2	GROWTH	GROWTH	0	0.5	ADD	.	jun jul aug
3	0	GROWTH	GROWTH	0	0.5	ADD	.	.
4	A	GROWTH	GROWTH	0	0.5	ADD	.	.
5	0	GROWTH	GROWTH	0	0.5	ADD	.	.
6	0	GROWTH	GROWTH	0	0.5	ADD	.	.
7	0	GROWTH	GROWTH	0	0.5	ADD	.	.
8	0	GROWTH	GROWTH	0	0.5	ADD	.	.
9	0	GROWTH	GROWTH	0	0.5	ADD	.	.
10	5	GROWTH	GROWTH	0	0.5	ADD	.	.

The following statements display the EVDUMOUT1 output data set (which is created by the EVENT-DUMMY statement). The data set is shown in Figure 7.2.

```
proc print data=evdumout1(obs=10);
run;
```

Figure 7.2 Event Dummy Data Set

Obs	DATE	AIR	laborday	summer	yr1950	levelshift	novdec	first10obs	everyotherobs
1	JAN1949	112	0	0	0	0	0	1	1
2	FEB1949	118	0	0	0	0	0	1	0
3	MAR1949	132	0	0	0	0	0	1	1
4	APR1949	129	0	0	0	0	0	1	0
5	MAY1949	121	0	0	0	0	0	1	1
6	JUN1949	135	0	1	0	0	0	1	0
7	JUL1949	148	0	1	0	0	0	1	1
8	AUG1949	148	0	1	0	0	0	1	0
9	SEP1949	136	2	0	0	0	0	1	1
10	OCT1949	119	0	0	0	0	0	1	0

Obs	saturday	ao15obs	ls01Jan1950D
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0

Often a set of event definitions has only a few variables that apply. For example, in the preceding statements, no datetime timing values are specified, so the variables _STARTDT_, _ENDDT_, and _DTINTRVL_ have all missing values. In such a case, you can specify the CONDENSE option in the EVENTDATA statement. When the CONDENSE option is specified, PROC HPFEVENTS automatically determines whether any variables in the event definition data set contain only the default values; those variables are not included in the output data set. In the following statements, in addition to the missing datetime values, the variables _SLOPE_BEF_, _SLOPE_AFT_, _TCPARM_, _RULE_, and _PERIOD_ also contain default values and are omitted from the condensed data set, which is shown in Figure 7.3.

```
proc hpfevents data=sashelp.air ;
   id date interval=month end='31Dec1952'D;
   eventdata  in= evdsout1;
   eventdata  out= evdsout2 condense;
run;

proc print data=evdsout2;
run;
```

Figure 7.3 Event Definition Data Set in Condensed Format

Obs	_NAME_	_KEYNAME_	_STARTDATE_	_ENDDATE_	_DATEINTRVL_	_STARTOBS_	_ENDOBS_
1	laborday	LABOR	.	.	.	.	.
2	summer	.	01JUN1900	01JUN2005	YEAR.6	.	.
3	yr1950	.	01JAN1950	.	.	.	.
4	levelshift	.	01JAN1950	.	.	.	.
5	novdec	CHRISTMAS	.	.	.	.	.
6	first10obs	.	.	.	.	1	10
7	everyotherobs	.	.	.	.	1	199
8	saturday	.	07JAN1950	28JAN1950	WEEK1.7	.	.
9	ao15obs	.	.	.	.	15	.
10	ls01Jan1950D	.	01JAN1950	.	.	.	.

Obs	_OBSINTRVL_	_TYPE_	_VALUE_	_PULSE_	_DUR_BEFORE_	_DUR_AFTER_	_LABEL_
1	.	POINT	2	.	0	0	.
2	.	POINT	1	.	0	2	jun jul aug
3	.	POINT	1	YEAR	0	0	.
4	.	LS	1	.	0	A	.
5	.	POINT	1	MONTH	1	0	.
6	1	POINT	1	.	0	0	.
7	2	POINT	1	.	0	0	.
8	.	POINT	1	.	0	0	.
9	.	POINT	1	.	0	0	.
10	.	LS	1	.	0	5	.

When PROC HPFEVENTS reads a data set, any variables not in the data set are automatically set to the default value. Thus, it is not necessary to specify CONDENSE when you use the IN= option in the EVENTDATA statement. PROC HPFEVENTS automatically reads condensed data sets. For more information about the CONDENSE option, see the section "EVENTDATA Statement OUT= Data Set" on page 286.

Syntax: HPFEVENTS Procedure

The following statements are available in the HPFEVENTS procedure:

PROC HPFEVENTS < *options* > ;
BY *variables* ;
EVENTCOMB *variable=variable-list* < / *options* > ;
EVENTDATA *options* ;
EVENTDEF *SAS-variable-name=timing-value-list* < / *qualifier-options* > ;
EVENTDUMMY OUT=*SAS-data-set* ;
EVENTGROUP < *variable=* > *event-group-keyword* ;
EVENTKEY < *variable=* > *event-keyword* < / *qualifier-options* > ;
ID *variable* **INTERVAL=***interval* < *options* > ;
VAR *variables* ;

Functional Summary

Table 7.1 summarizes the statements and options that control the HPFEVENTS procedure.

Table 7.1 PROC HPFEVENTS Functional Summary

Description	Statement	Option
Statements		
Specifies BY-group processing	BY	
Specifies an event combination	EVENTCOMB	
Specifies the event definition	EVENTDEF	
Specifies a group of events	EVENTGROUP	
Uses a predefined event definition	EVENTKEY	
Specifies the event data set	EVENTDATA	
Specifies the dummy variable data set	EVENTDUMMY	
Specifies the time ID variable	ID	
Specifies the variables to be copied to the dummy variable data set	VAR	
Data Set Options		
Specifies the input data set	PROC HPFEVENTS	DATA=
Specifies an events input data set	EVENTDATA	IN=
Specifies an events output data set	EVENTDATA	OUT=
Condenses the events output data set	EVENTDATA	CONDENSE
Specifies a dummy variable output data set	EVENTDUMMY	OUT=
Specifies a starting time ID value	ID	START=
Specifies an ending time ID value	ID	END=
Specifies the format of the ID variable	ID	FORMAT=
Dummy Variable Format Options		
Extends dummy variables past the end of the series	PROC HPFEVENTS	LEAD=
Specifies how to interpret missing values	ID	SETMISSING=
Specifies the frequency of the dummy variables	ID	INTERVAL=
Specifies interval alignment	ID	ALIGN=
Miscellaneous Options		
Requests that variables in output data sets be in sorted order	PROC HPFEVENTS	SORTNAMES
Limits error and warning messages	PROC HPFEVENTS	MAXERROR=

PROC HPFEVENTS Statement

PROC HPFEVENTS < *options* > **;**

You can specify the following *options* in the PROC HPFEVENTS statement.

DATA=*SAS-data-set*
names the SAS data set that contains the variables that are used in the VAR, ID, and BY statements. If you do not specify this option, PROC HPFEVENTS uses the most recently created SAS data set.

LEAD=*n*
specifies the number of periods by which to extend the dummy variable beyond the time series, where *n* is relative to the last observation in the input data set and not to the last nonmissing observation of a particular series. Thus, if a series has missing values at the end, the actual number of dummy values beyond the last nonmissing value is greater than *n*.

By default, LEAD=0.

MAXERROR=*number*
limits the number of warning and error messages that are produced during the execution of the procedure to the specified *number*. This option is particularly useful in BY-group processing, where it can be used to suppress the recurring messages.

By default, MAXERROR=25.

SORTNAMES
requests that the events and variables in the output data sets be printed in alphabetical order within their respective groups. (By default, the input variables are printed in the same order as they appear in the input data set, and events are printed in the order in which they are created.)

BY Statement

BY *variables* **;**

You can use a BY statement to obtain separate dummy variable definitions for groups of observations that are defined by the *variables*.

When you include a BY statement, PROC HPFEVENTS expects the input data set to be sorted in order of the *variables*.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data by using the SORT procedure with a similar BY statement.
- Specify the NOTSORTED or DESCENDING option in the BY statement for the HPFEVENTS procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged in groups (according to the values of the BY *variables*) and that these groups are not necessarily in alphabetical or increasing numeric order.
- Create an index on the BY *variables* by using the DATASETS procedure.

For more information about the BY statement, see *SAS Language Reference: Concepts*. For more information about the DATASETS procedure, see the discussion in the *Base SAS Procedures Guide.*

EVENTCOMB Statement

EVENTCOMB *variable=variable-list* < */ options* > **;**

The EVENTCOMB statement creates a new event from one or more events that have previously been defined.

You can specify the following *options*:

LABEL='*SAS-label*'
specifies a label for the dummy variable for this event. *SAS-label* is a quoted text string of up to 256 characters. The label is also stored as a description in the data set that is specified in the OUT= option in the EVENTDATA statement. If you do not specify a *SAS-label*, then "." is displayed in the EVENTDATA OUT= data set, but the default label is still used for the dummy variable.

The default label is 'Dummy Variable for Event <*variable*>'.

LOCALE='*POSIX-locale*'
specifies a locale that is associated with the event. The locale should be a POSIX locale value. By default, no locale is associated with the event.

RULE=ADD | MAX | MIN | MINMAG | MINNZ | MULT
specifies the action to take when the events are combined. You can specify the following values:

ADD	adds the values.
MAX	uses the maximum value.
MIN	uses the minimum value.
MINMAG	uses the value whose magnitude is the lowest.
MINNZ	uses the minimum nonzero value.
MULT	multiplies the values.

Example 7.1 shows how PROC HPFEVENTS interprets the RULE= option in the EVENTDEF and EVENTCOMB statements.

By default, RULE=ADD.

EVENTDATA Statement

EVENTDATA *options* **;**

The EVENTDATA statement inputs events from an events data set or outputs events to an events data set.

You must specify either the IN= option or the OUT= option:

IN=*SAS-data-set*
names an input data set that contains event definitions. The *SAS-data-set* can be condensed or not. PROC HPFEVENTS inputs all data sets that are specified in IN= options before it processes other statements.

OUT=*SAS-data-set*
names the output data set to contain the event definitions as specified in the data set that is specified in the IN= option and as specified in the EVENTDEF, EVENTKEY, and EVENTCOMB statements. This output data set can then be used in other SAS procedures to define events.

In addition, you can specify the following *option*:

CONDENSE
condenses the output data set that is specified in the OUT= option by omitting any variables that contain only default values. For more information, see the section "EVENTDATA Statement OUT= Data Set" on page 286.

EVENTDEF Statement

EVENTDEF *SAS-variable-name=timing-value-list* **<** */ qualifier-options* **>** **;**

The EVENTDEF statement defines an event that can be included in forecasting models.

You must specify a variable name and a timing value list as follows:

SAS-variable-name
specifies a valid SAS variable name.

timing-value-list
specifies one or more timing values. Each value can be a SAS date keyword, an integer, a SAS date, a SAS datetime, or a do-list. For more information, see the section "Event Definitions" on page 271.

You can specify the following *qualifier-options*:

AFTER=(< DURATION=*number* **> < SLOPE=DECAY | GROWTH >)**
specifies options that control the event definition after the timing value. You can specify the following suboptions within the parentheses:

DURATION=*number*
specifies the event duration after the timing value.

SLOPE=DECAY | GROWTH
controls the slope after the timing value. You can specify either of the following values:

DECAY creates a slope away from the peak value.

GROWTH creates a slope toward the peak value.

This suboption is ignored unless TYPE=RAMP, TYPE=TR, TYPE=TEMPRAMP, or TYPE=TC; it is also ignored if DURATION=0. For more information, see the section "Details of Event Specifications" on page 279.

By default, SLOPE=GROWTH in all cases except TYPE=TC. When TYPE=TC, the default is AFTER=(SLOPE=DECAY).

BEFORE=(< DURATION=*number* **> < SLOPE=DECAY | GROWTH >)**
specifies options that control the event definition before the timing value. You can specify the following suboptions within the parentheses:

DURATION=*number*
specifies the event duration before the timing value.

SLOPE=DECAY | GROWTH
controls the slope before the timing value.

You can specify either of the following values:

DECAY creates a slope away from the peak value.

GROWTH creates a slope toward the peak value.

This suboption is ignored unless TYPE=RAMP, TYPE=TR, TYPE=TEMPRAMP, or TYPE=TC; it is also ignored if DURATION=0. For more information, see the section "Details of Event Specifications" on page 279.

By default, SLOPE=GROWTH in all cases except TYPE=TC. When TYPE=TC, the default is BEFORE=(SLOPE=GROWTH).

LABEL='*SAS-label***'**
specifies a label for the dummy variable for this event definition, where *SAS-label* is a quoted text string of up to 256 characters. The label is also stored as a description in the data set that is specified in the OUT= option in the EVENTDATA statement. If you do not specify this option, then "." is displayed in the data set that is specified in the OUT=option in the EVENTDATA statement, but the default label ('Dummy Variable for Event *variable-name*,' where *variable-name* is the name specified in the EVENT statement) is still used for the dummy variable.

LOCALE='*POSIX-locale***'**
specifies a locale that is associated with the event. The locale should be a POSIX locale value. By default, no locale is associated with the event.

PERIOD=*interval*
specifies the interval for the frequency of the event. For example, PERIOD=YEAR should produce a dummy value that is periodic in a yearly pattern. If you do not specify this option, the event is not periodic. The PERIOD= option also does not apply to observation numbers (which are not periodic) or to date keywords (which have their own periodicity). For information about which intervals you can specify, see Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*).

PULSE=*interval*
specifies the interval to be used, which along with the DURATION= suboption in either the AFTER= option or in the BEFORE= option determines the width of the event. The default pulse is one observation. If you specify this option but you do not specify any DURATION= values, the DURATION= values are set to 0. For information about which intervals you can specify, see Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*).

RULE=ADD | MAX | MIN | MINMAG | MINNZ | MULT
specifies the action to take when the defined event has multiple timing values that overlap. When the timing values do not overlap, this option has no impact because only the one defined value for an observation is always used. You can specify the following values:

ADD	adds the values.
MAX	uses the maximum value.
MIN	uses the minimum value.
MINMAG	uses the value whose magnitude is the lowest.
MINNZ	uses the minimum nonzero value.
MULT	multiplies the values.

By default, RULE=ADD.

Because the range of the event that is associated with a timing value might not include all the observations in the series, this option can be interpreted differently when you use multiple timing values in one EVENTDEF statement than when you define a combination event by using the EVENTCOMB statement. Thus, the dummy variables TWOTIMING and TWOEVENTS that are defined in the following statements are different:

```
eventdef xmasrp= christmas / before=(slope=growth duration=3)
                             type=ramp rule=min ;
eventdef easterrp= easter  / before=(slope=growth duration=3)
                             type=ramp rule=min ;
eventdef twotiming= easter christmas /
                             before=(slope=growth duration=3)
                             type=ramp rule=min ;
eventcomb twoevents= easterrp xmasrp / rule=min ;
```

Example 7.1 shows how PROC HPFEVENTS interprets each of these statements.

SHIFT=δ

specifies the number of pulses (δ) by which to shift the timing value. When you specify this option, all timing values in the list (including those generated by date keywords) are shifted. Thus, you can use this option with EASTER to specify ecclesiastical holidays that are based on Easter. Definitions for some moveable Christian holidays based on Easter are given in Reingold and Dershowitz (2001, p. 122). For example, the following statement specifies Good Friday, which is defined as two days before Easter:

```
EVENTDEF GoodFriday= EASTER / SHIFT=-2 PULSE=DAY;
```

By default, SHIFT=0, which does not shift the timing value.

TCPARM=*number*

specifies a *number*, $0 \leq$ *number* ≤ 1, that represents the rate of growth or decay. This *number* is used as ϕ in the growth/decay equation for TYPE=TC, as shown in Table 7.7. A larger *number* causes faster growth or decay. This option is ignored unless TYPE=TC. By default, TCPARM=0.5.

TYPE=*type*

specifies the type of the event variable. Each type uses a different formula to create the dummy variables. The formula for each TYPE= option is dependent on other *qualifier-options* that are specified in this statement. The formula is applied to each timing value that is specified in the timing-value list. You can specify the following values for *type*: POINT | LS | RAMP | TR | TEMPRAMP | TC | LIN | LINEAR | QUAD | CUBIC | INV | INVERSE | LOG | LOGARITHMIC. Table 7.8 and Table 7.9 illustrate the basic shape for each TYPE= value. By default, TYPE=POINT.

VALUE=ν

specifies the event indicator value. Table 7.7 provides details about the effect of ν on the dummy variables. However, for event definitions that have TYPE=POINT | LS | RAMP | TR | TC events and consist of a single timing value that has finite duration, you can think of the event indicator value as the maximum amplitude: the values of the dummy variable should be bounded below by 0 and above by ν. For trend events (TYPE = LINEAR | QUAD | CUBIC | INV | LOG), ν is the coefficient of the term.

By default, VALUE=1.

EVENTDUMMY Statement

EVENTDUMMY OUT= *SAS-data-set* **;**

The EVENTDUMMY statement outputs dummy variables for events to a data set.

You must specify the following option:

OUT=*SAS-data-set*

names the output data set to contain the dummy variables for the specified events for the time period and frequency that are specified in the ID statement. The *SAS-data-set* also includes variables as specified in the VAR, BY, and ID statements.

EVENTGROUP Statement

EVENTGROUP < *variable=* > *event-group-keyword* **;**

EVENTGROUP *variable=(variable-list)* < */ option* > **;**

You can use the EVENTGROUP statement to do either of the following:

- Use EVENTGROUP *event-group-keyword* to make a predefined event group available for processing.
- Use EVENTGROUP *variable=(variable-list)* to create an event group. In this case, PROC HPFEVENTS constructs a complex event, which is an event that is represented by multiple dummy variables. For example, seasonal effects usually require multiple dummy variables.

Each predefined *event-group-keyword* has a predefined set of event keywords that are associated with the predefined group. Table 7.2 shows the predefined *event-group-keywords*. The default SAS *variable* for the predefined event group is the predefined *event-group-keyword*, but you can specify a SAS variable name for the event. For example, you can change the name of the DAYS predefined event group to TD by using the following statement:

```
eventgroup td=days;
```

Table 7.2 describes the predefined SAS event group keywords. The SEASONAL group is a predefined complex event, which is interpreted to be one of the other SEASONAL groups at the time that dummy variables are created based on the ID statement that is associated with either PROC HPFEVENTS or PROC HPFENGINE.

Table 7.2 Definitions for Predefined Event Group Keywords

event-group-keyword	**Description**	**Associated Event Keywords**
SEASONAL	Seasonal	Depending on ID statement: SECOND_1, . . . , SECOND_60 or MINUTE_1, . . . , MINUTE_60 or HOUR_1, . . . , HOUR_24 or SUNDAY, . . . , SATURDAY or WEEK_1, . . . , WEEK_53 or TENDAY_1, . . . , TENDAY_36 or SEMIMONTH_1, . . . , SEMIMONTH_24 or JANUARY, . . . , DECEMBER or QTR_1, QTR_2, QTR_3, QTR_4 or SEMIYEAR_1, SEMIYEAR_2
SECONDS	Seasonal	SECOND_1, . . . , SECOND_60
MINUTES	Seasonal	MINUTE_1, . . . , MINUTE_60
HOURS	Seasonal	HOUR_1, . . . , HOUR_24
DAYS	Seasonal	SUNDAY, . . . , SATURDAY
WEEKDAYS	Seasonal	MONDAY, . . . , FRIDAY (FRIDAY includes SATURDAY and SUNDAY)
WEEKS	Seasonal	WEEK_1, . . . , WEEK_53

Table 7.2 *continued*

event-group-keyword	**Description**	**Associated Event Keywords**
TENDAYS	Seasonal	TENDAY_1, . . . , TENDAY_36
SEMIMONTHS	Seasonal	SEMIMONTH_1, . . . , SEMIMONTH_24
MONTHS	Seasonal	JANUARY, . . . , DECEMBER
QTRS	Seasonal	QTR_1, QTR_2, QTR_3, QTR_4
SEMIYEARS	Seasonal	SEMIYEAR_1, SEMIYEAR_2
CUBICTREND	Trend	LINEAR, QUAD, CUBIC
QUADTREND	Trend	LINEAR, QUAD

Table 7.10 provides more information about the seasonal and trend predefined SAS events that are included in the event groups.

You can specify the following *option*:

LABEL='*SAS-label***'**
specifies a description to be stored in the data set that is specified in the OUT= option in the EVENTDATA statement. If you do not specify this option, then "." is displayed in that data set.

LOCALE='*POSIX-locale***'**
specifies a locale that is associated with the event. The locale should be a POSIX locale value. By default, no locale is associated with the event.

EVENTKEY Statement

EVENTKEY < *variable*= > *event-keyword* < / *qualifier-options* > **;**

You can use the EVENTKEY statement to alter a user-defined simple event or a predefined SAS event or to create a new event.

For more information about the EVENTKEY statement, see the section "Using the EVENTKEY Statement" on page 282.

ID Statement

ID *variable* **INTERVAL=***interval* < *options* > **;**

The ID statement names a numeric *variable* that identifies observations in the input and output data sets. The values of *variable* are assumed to be SAS date, time, or datetime values. In addition, the ID statement specifies the (desired) frequency to be associated with the actual time series. The specified information affects all dummy variables that are output by using the EVENTDUMMY statements. If no dummy variables are requested, the ID statement has no impact on processing, because the definitions that are specified in the EVENTDEF statement are independent of the time identification values of a time series.

If you specify the ID statement, you must also specify the INTERVAL= option. If you do not specify an ID statement, PROC HPFEVENTS uses the observation number (with respect to the BY group) as the time ID.

When the observation number is used as the time ID, only event timing values that are based on observation numbers are applied to the time series to create dummy variables; timing values based on SAS date or datetime values are ignored.

You must specify the following argument:

INTERVAL=*interval*
specifies the frequency of the input time series. For example, if the input data set consists of quarterly observations, then specify INTERVAL=QTR. For information about the intervals that you can specify, see Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*).

You can also specify the following *options*:

ALIGN=BEGINNING | MIDDLE | END
controls the alignment of SAS dates that are used to identify output observations. You can specify the following values:

BEGINNING
aligns the SAS dates at the beginning. You can abbreviate BEGINNING as BEG or B.

MIDDLE
aligns the SAS dates at the middle. You can abbreviate MIDDLE as MID or M.

ENDING
aligns the SAS dates at the end. You can abbreviate ENDING as END or E.

By default, ALIGN=BEGINNING.

END=*value*
specifies a SAS date, time, or datetime value that represents the end of the data. If the value of the last observation of the time ID variable is less than *value*, the series is extended with missing values. If the value of the last observation of the time ID variable is greater than *value*, the series is truncated. For example, END="&sysdate"D uses the automatic macro variable SYSDATE to extend or truncate the series to the current date. You can use the END= option and the START= option to ensure that data that are associated with each BY group contain the same range of observations. If you omit the END= option, the default depends on the values of the START= option and the last observation of the time ID variable. The default is the value of the last observation of the time ID variable if either of the following is true:

- The START= option is omitted.
- The value of the last observation of the time ID variable is greater than or equal to the START= option value.

Otherwise, the default is the same as the START= option value.

FORMAT=*format*
specifies the SAS format for the time ID values. If you do not specify the FORMAT= option, the default format is implied from the INTERVAL= option.

SETMISSING=*number* | **MISSING** | **SKIP**

specifies how missing values are assigned in the time series that is copied to the dummy variable data set when no observation matches the time ID in the input data set. If you specify a *number*, missing values are set to *number*. Do not specify this option if a missing value indicates an unknown value. If a missing value indicates no value, specify SETMISSING=0. You would usually specify SETMISSING=0 for transactional data because no recorded data usually implies no activity.

Instead of specifying a *number*, you can specify one of the following values:

MISSING sets missing values to missing.

SKIP skips the corresponding observation in the dummy variable data set if the observation for the time ID value is missing in the input data set. This value can be useful if dummy variables are to be used as predictor values and you want to apply the ACCUMULATION option in the PROC HPFENGINE statement to the dummy data.

By default, SETMISSING=MISSING.

START=*value*

specifies a SAS date, time, or datetime value that represents the beginning of the data. If the value of the first observation of the time ID variable is greater than *value*, the series is prefixed with missing values. If the value of the first observation of the time ID variable is less than *value*, the series is truncated. You can specify this option and the END= option to ensure that data that are associated with each BY group contain the same range of observations. If you omit the START= option, the default depends on the values of the END= option and the first observation of the time ID variable. The default is the value of the first observation of the time ID variable if either of the following is true:

- The END= option is omitted.
- The value of the first observation of the time ID variable is less than or equal to the END= option value.

Otherwise, the default is the same as the END= option value.

VAR Statement

VAR *variables* **;**

The VAR statement copies input variables to the output dummy variables data set. The *variables* must be numeric. If the VAR statement is omitted, all numeric variables are selected except those that appear in a BY or ID statement.

Details: HPFEVENTS Procedure

Event Definitions

This section describes the use of the EVENTDEF statement.

Although an event occurs at one or more time values, the event definition is independent of the time ID; that is, the event is a function that operates on a time ID variable. After you define an event, you can output it by specifying the OUT= option in the EVENTDATA statement. You can output a dummy variable for the event by specifying the OUT= option in the EVENTDUMMY statement. The dummy variable is created by evaluating the event with respect to the time ID. If you do not specify a time ID in the ID statement, then the BY-group observation number is used as the time ID. You can specify more than one EVENTDEF statement.

After you define an event, you can refer to it by its SAS variable name. When you output the event by using the EVENTDATA statement, the event is identified by its SAS variable name. When you create a dummy variable by using the event definition, the dummy variable name is the same as the event SAS variable name.

Each event must have a unique SAS variable name. If two event definitions have the same name, the following rules apply:

- If two EVENTDEF statements use the same name, the later statement is used.
- If an event is defined both in an EVENTDEF statement and in a data set that is specified in an EVENTDATA statement, the definition in the EVENTDEF statement is used.
- Any event that is defined in an EVENTDEF or EVENTDATA statement is used rather than a predefined SAS event.

Timing Value List

Each EVENTDEF statement must include one or more event timing values. The timing values can be specified in a list. Using parentheses to enclose the list and using commas to separate list items are optional.

Each item in the list can be a SAS date keyword, an integer, a SAS date, a SAS datetime, or a do-list. For example, the following EVENTDEF statement specifies timing values that use each of these methods in the order listed:

```
EVENTDEF EVENT1= USINDEPENDENCE 10 '25Dec2000'D
                 '01Mar1990:15:03:00'DT
                 '01Jan2000'D to '01Mar2000'D by month;
```

The timing values are interpreted as follows: any July 4 in the series; the 10th observation; December 25, 2000; March 1, 1990, at 3:03 p.m.; January 1, 2000; February 1, 2000; and March 1, 2000.

The following two EVENTDEF statements specify identical timing values:

```
EVENTDEF MYFIRSTEVENT= '01Jan2000'D to '01Mar2000'D by month;
EVENTDEF MYNEXTEVENT= ( '01Jan2000'D, '01Feb2000'D, '01Mar2000'D );
```

Numbers are always interpreted as observation numbers. A do-list can be based on observation numbers, SAS dates, or SAS datetimes, but the first and second values in the list must be of the same type. SAS grammar always expects the type of the second value to be the same as the type of the first value and tries to interpret the statement in that fashion. You should never mix date, datetime, and integer types in a do-list. The following statement yields erratic results and causes PROC HPFEVENTS either to produce a list much longer than expected or to run out of memory:

```
EVENTDEF BADEVENT= '01Jan2000'D to '01Mar2000:00:00:00'DT by month;
```

Table 7.3 shows the SAS default date keywords that you can use in a timing value list and their definitions. For information about customizing the SAS date keywords, see the section "Using the EVENTDS= System Option to Customize Holiday Predefined Date Keywords" on page 285.

Table 7.3 Default Holiday Date Keywords and Definitions

Date Keyword	Definition
BOXING	December 26
CANADA	July 1
CANADAOBSERVED	July 1, or July 2 if July 1 is a Sunday
CHRISTMAS	December 25
COLUMBUS	Second Monday in October
EASTER	Easter Sunday
FATHERS	Third Sunday in June
HALLOWEEN	October 31
JUNETEENTH	June 19th
JUNETEENTHUSG	Juneteenth date observed by US government for Monday–Friday schedule
JUNETEENTHUSPS	Juneteenth date observed by US government for Monday–Saturday schedule (US Postal Service)
LABOR	First Monday in September
MEMORIAL	Last Monday in May
MLK	Third Monday in January
MOTHERS	Second Sunday in May
N<*n*>W<*w*><MON>YR	Date specified by NWKDOM(*n*, *w*, *m*, *year*), where *m* corresponds to the month specified by MON and *year* is any year relevant to the data (example: N4W5NOVYR is the same as THANKSGIVING)
NEWYEAR	January 1
THANKSGIVING	Fourth Thursday in November
THANKSGIVINGCANADA	Second Monday in October
USINDEPENDENCE	July 4
USPRESIDENTS	Third Monday in February (since 1971)

Table 7.3 *continued*

Date Keyword	Definition
VALENTINES	February 14
VETERANS	November 11
VETERANSUSG	US government observed date for Monday–Friday schedule
VETERANSUSPS	US government observed date for Monday–Saturday schedule (US Postal Service)
VICTORIA	Monday on or preceding May 24

The date of Easter is calculated using a method described by Meeus (1998, pp. 67–68).

Table 7.4 shows the seasonal date keywords that can be used in a timing value list and their definitions.

Table 7.4 Seasonal Date Keywords and Definitions

Date Keyword	Definition
SECOND_1, . . . , SECOND_60	The specified second
MINUTE_1, . . . , MINUTE_60	The beginning of the specified minute
HOUR_1, . . . , HOUR_24	The beginning of the specified hour
SUNDAY, . . . , SATURDAY	All Sundays, and so on, in the time series
WEEK_1, . . . , WEEK_53	The first day of the nth week of the year; PULSE=WEEK.n shifts this date for $n \neq 1$
TENDAY_1, . . . , TENDAY_36	The 1st, 11th, or 21st of the appropriate month
SEMIMONTH_1, . . . , SEMIMONTH_24	The 1st or 16th of the appropriate month
JANUARY, . . . , DECEMBER	The 1st of the specified month
QTR_1, QTR_2, QTR_3, QTR_4	The first date of the quarter; PULSE=QTR.n shifts this date for $n \neq 1$
SEMIYEAR_1, SEMIYEAR_2	The first date of the semiyear; PULSE=SEMIYEAR.n shifts this date for $n \neq 1$

When PROC HPFEVENTS creates dummy variables, it evaluates each timing value with respect to the time ID. Take care to choose event timing values that are consistent with the time ID. In particular, date and datetime timing values are ignored when the time ID is based on the observation number.

The *qualifier options* in an EVENTDEF or EVENTKEY statement define a function to be applied at each timing value.

Event Types

The TYPE= option in the EVENTDEF statement specifies the type of the defined event. These event types are POINT, LS, RAMP, TR (TEMPRAMP), TC, LIN (LINEAR), QUAD, CUBIC, INV (INVERSE), and LOG (LOGARITHMIC).

Table 7.5, Table 7.6, and Table 7.7 show the formulas that are used to calculate the dummy variables for the event. Table 7.6 shows the formula that is used for each type of event when the event extends infinitely both before and after the timing value. Table 7.7 shows the formula that is used for each type of event for finite duration values.

To calculate the dummy values, PROC HPFEVENTS first expands the list of timing values, if applicable, with respect to the PERIOD option and the time series ID values. Then, if the SHIFT= option has a nonzero value, the timing values are shifted according to the value of the SHIFT= and PULSE= options. In the formulas, t_i is the observation that is specified by the ith (shifted) timing value in the expanded timing value list, VALUE=v, TCPARM=ϕ, AFTER=(DURATION=n SLOPE=s_a), BEFORE=(DURATION=m SLOPE=s_b), and PULSE=*interval*. Table 7.5 shows how to calculate t_b and t_e, which are the beginning and ending observations, respectively, of the event definition and are based on the values of the DURATION= option. (For TYPE=RAMP, the ramp persists beyond the top of the ramp, either before t_b or after t_e.) For more information about matching SAS date values to observations, see Chapter 3, "Working with Time Series Data" (*SAS/ETS User's Guide*), and Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*).

When PROC HPFEVENTS evaluates multiple timing values (because either the PERIOD= option was specified or multiple values were specified), it calculates observations within the range of the function according to the formulas in the tables. Observations that are not in the range of the functions are left undefined. When the ranges from two timing values overlap, the RULE= option applies. After PROC HPFEVENTS has evaluated all timing values, it sets the undefined values to 0.

Specifying one finite value and another infinite value in DURATION= options is equivalent to extending the finite portion of the event infinitely in one direction. This principle can be understood by examining the results of the following EVENTDEF statements. Example 7.5 shows how PROC HPFEVENTS interprets each of these statements.

```
eventdef monlygg= '01Jun1951'D  /  TYPE=RAMP
         BEFORE=(SLOPE=GROWTH DURATION=4);
eventdef minfgg= '01Jun1951'D  /  TYPE=RAMP
         BEFORE=(SLOPE=GROWTH DURATION=4)
         AFTER=(SLOPE=GROWTH DURATION=ALL) ;
eventdef minfgd= '01Jun1951'D  /  TYPE=RAMP
         BEFORE=(SLOPE=GROWTH DURATION=4)
         AFTER=(SLOPE=DECAY DURATION=ALL) ;
```

Table 7.5 Calculating the Beginning and Ending Observation for Events

BEFORE= (DURATION= Value)	**PULSE= Value**	**Definition of t_b**
ALL	N/A	$t_b = 1$, the first observation in the data set, or $t_b =$ the observation that is specified in the START= option
0	Not specified	$t_b = t_i$, the observation that is specified by the shifted timing value
$m > 0$	Not specified	$t_b = t_i - m$
$m \geq 0$	*interval*	$t_b =$ the observation that is specified by the date INTNX(*interval*, *timing-value*, *–m*, 'begin')
AFTER= (DURATION= Value)	**PULSE= Value**	**Definition of t_e**
ALL	N/A	$t_e =$ the last observation in the data set, or $t_e =$ the observation that is specified in the END= option
0	Not specified	$t_e = t_i$, the observation that is specified by the shifted timing value
$n > 0$	Not specified	$t_e = t_i + n$
$n \geq 0$	*interval*	$t_e =$ the observation that is specified by the date INTNX(*interval*, *timing-value*, n, 'end')

Table 7.6 Event Types for Infinite Durations (m=ALL and n=ALL)

Type	**Description**	**Definition**
POINT	Point or pulse	$\xi_{it} = \nu$ for all t
LS	Level shift	$\xi_{it} = \nu$ for all t
RAMP	Ramp	
	SLOPE=GROWTH	$\xi_{it} = \nu(t - t_i)$ for all t
	SLOPE=DECAY	$\xi_{it} = \nu(t_i - t)$ for all t
	$s_b =$ GROWTH	$\xi_{it} = \nu(t - t_i)$ if $t \leq t_i$
	$s_a =$ DECAY	$\xi_{it} = \nu(t_i - t)$ if $t_i \leq t$
	$s_b =$ DECAY	$\xi_{it} = \nu(t_i - t)$ if $t \leq t_i$
	$s_a =$ GROWTH	$\xi_{it} = \nu(t - t_i)$ if $t_i \leq t$
TEMPRAMP	Temporary ramp	TEMPRAMP is the same as

Table 7.6 *continued*

Type	Description	Definition
(TR)		RAMP for infinite cases
TC	Temporary change	
	SLOPE=GROWTH	$\xi_{it} = \nu\phi^{(t_i - t)}$ for all t
	SLOPE=DECAY	$\xi_{it} = \nu\phi^{(t - t_i)}$ for all t
	s_b = GROWTH s_a = DECAY	$\xi_{it} = \nu\phi^{(t_i - t)}$ if $t \leq t_i$ $\xi_{it} = \nu\phi^{(t - t_i)}$ if $t_i \leq t$
	s_b = DECAY s_a = GROWTH	$\xi_{it} = \nu\phi^{(t - t_i)}$ if $t \leq t_i$ $\xi_{it} = \nu\phi^{(t_i - t)}$ if $t_i \leq t$
LINEAR (LIN)	Linear trend SLOPE= does not apply	$\xi_{it} = \nu(t - t_i)$ for all t
QUAD	Quadratic trend SLOPE= does not apply	$\xi_{it} = \nu(t - t_i)^2$ for all t
CUBIC	Cubic trend SLOPE= does not apply	$\xi_{it} = \nu(t - t_i)^3$ for all t
INVERSE (INV)	Inverse trend SLOPE= does not apply	$\xi_{it} = \nu/t$ for all t
LOGARITHMIC (LOG)	Log trend SLOPE= does not apply	$\xi_{it} = \nu \log(t)$ for all t

Table 7.7 Event Types (for Finite m,n)

Type	Description	Definition
POINT	Point or pulse	$\xi_{it} = \nu$ if $t_b \leq t \leq t_e$ ξ_{it} = undefined otherwise
LS	Level shift	$\xi_{it} = \nu$ if $t_b \leq t \leq t_e$ ξ_{it} = undefined otherwise
RAMP	Ramp	

Table 7.7 *continued*

Type	Description	Definition
	$m = n = 0$ PULSE=*interval* ≤ width of an observation	$\xi_{it} = 0$ if $t = t_i$ ξ_{it} = undefined otherwise
	SLOPE=GROWTH	$\xi_{it} = \nu(t - t_b)/(t_e - t_b)$ if $t_b \leq t \leq t_e$ $\xi_{it} = \nu$ if $t > t_e$ ξ_{it} = undefined otherwise
	SLOPE=DECAY	$\xi_{it} = \nu$ if $t < t_b$ $\xi_{it} = \nu(t_e - t)/(t_e - t_b)$ if $t_b \leq t \leq t_e$ ξ_{it} = undefined otherwise
	s_b = GROWTH s_a = DECAY $m > 0, n > 0$	$\xi_{it} = \nu(t - t_b)/(t_i - t_b)$ if $t_b \leq t \leq t_i$ $\xi_{it} = \nu(t_e - t)/(t_e - t_i)$ if $t_i \leq t \leq t_e$ ξ_{it} = undefined otherwise
	s_b = DECAY s_a = GROWTH $m > 0, n > 0$	$\xi_{it} = \nu$ if $t < t_b$ $\xi_{it} = \nu(t_i - t)/(t_i - t_b)$ if $t_b \leq t \leq t_i$ $\xi_{it} = \nu(t - t_i)/(t_e - t_i)$ if $t_i \leq t \leq t_e$ $\xi_{it} = \nu$ if $t > t_e$
TEMPRAMP (TR)	Temporary ramp $m = n = 0$ PULSE=*interval* ≤ width of an observation	$\xi_{it} = 0$ if $t = t_i$ ξ_{it} = undefined otherwise
	SLOPE=GROWTH	$\xi_{it} = \nu(t - t_b)/(t_e - t_b)$ if $t_b \leq t \leq t_e$ ξ_{it} = undefined otherwise
	SLOPE=DECAY	$\xi_{it} = \nu(t_e - t)/(t_e - t_b)$ if $t_b \leq t \leq t_e$ ξ_{it} = undefined otherwise
	s_b = GROWTH s_a = DECAY $m > 0, n > 0$	$\xi_{it} = \nu(t - t_b)/(t_i - t_b)$ if $t_b \leq t \leq t_i$ $\xi_{it} = \nu(t_e - t)/(t_e - t_i)$ if $t_i \leq t \leq t_e$ ξ_{it} = undefined otherwise
	s_b = DECAY s_a = GROWTH $m > 0, n > 0$	$\xi_{it} = \nu(t_i - t)/(t_i - t_b)$ if $t_b \leq t \leq t_i$ $\xi_{it} = \nu(t - t_i)/(t_e - t_i)$ if $t_i \leq t \leq t_e$ ξ_{it} = undefined otherwise
TC	Temporary change SLOPE=GROWTH	$\xi_{it} = \nu\phi^{(t_e - t)}$ if $t_b \leq t \leq t_e$ ξ_{it} = undefined otherwise

Table 7.7 *continued*

Type	Description	Definition
	SLOPE=DECAY	$\xi_{it} = \nu\phi^{(t-t_b)}$ if $t_b \le t \le t_e$ ξ_{it} = undefined otherwise
	s_b = GROWTH s_a = DECAY $m > 0, n > 0$	$\xi_{it} = \nu\phi^{(t_i-t)}$ if $t_b \le t \le t_i$ $\xi_{it} = \nu\phi^{(t-t_i)}$ if $t_i \le t \le t_e$ ξ_{it} = undefined otherwise
	s_b = DECAY s_a = GROWTH $0 < m \le n$	$\xi_{it} = \nu\phi^{((t_e-t_i)+(t-t_i))}$ if $t_b \le t \le t_i$ $\xi_{it} = \nu\phi^{(t_e-t)}$ if $t_i \le t \le t_e$ ξ_{it} = undefined otherwise
	s_b = DECAY s_a = GROWTH $0 < n \le m$	$\xi_{it} = \nu\phi^{(t-t_b)}$ if $t_b \le t \le t_i$ $\xi_{it} = \nu\phi^{((t_i-t_b)+(t_i-t))}$ if $t_i \le t \le t_e$ ξ_{it} = undefined otherwise
LINEAR (LIN)	Linear trend SLOPE= does not apply	$\xi_{it} = \nu(t - t_i)$ if $t_b \le t \le t_e$
QUAD	Quadratic trend SLOPE= does not apply	$\xi_{it} = \nu(t - t_i)^2$ if $t_b \le t \le t_e$
CUBIC	Cubic trend SLOPE= does not apply	$\xi_{it} = \nu(t - t_i)^3$ if $t_b \le t \le t_e$
INVERSE (INV)	Inverse trend SLOPE= does not apply	$\xi_{it} = \nu/(t - t_b + 1)$ if $t_b \le t \le t_e$
LOGARITHMIC (LOG)	Log trend SLOPE= does not apply	$\xi_{it} = \nu \log(t - t_b + 1)$ if $t_b \le t \le t_e$

Undefined values are set to 0 after all timing values have been evaluated. For more information about evaluating overlapping timing values, see the RULE= option.

Details of Event Specifications

The event always occurs at the timing value, and you use the DURATION= suboption in the BEFORE and AFTER options to indicate how many observations you want to include before and after, respectively. For example, the following statement specifies three observations before the timing value, one observation at the timing value, and four observations after the timing value for a total of eight observations (3 + 1 + 4 = 8):

```
EVENTDEF E1= '01JAN1950'D / BEFORE=(DURATION=3)
                            AFTER=(DURATION=4);
```

You can use the PULSE= option to specify when observations occur. For example, the following statement specifies three weeks before the timing value, the week of the timing value, and four weeks after the timing value:

```
EVENTDEF E1= '01JAN1950'D / BEFORE=(DURATION=3)
                            AFTER=(DURATION=4)
                            PULSE=WEEK;
```

You can also use the SLOPE= suboption in the BEFORE or AFTER option to control the slope before or after the timing value. The following statement specifies a ramp up, followed by a ramp down:

```
EVENTDEF E1= '01JAN1950'D / BEFORE=(DURATION=3 SLOPE=GROWTH)
                            AFTER=(DURATION=4 SLOPE=DECAY)
                            TYPE=RAMP;
```

The event dummy observations that immediately precede the timing value contain the following values: 0, $\frac{1}{3}$, $\frac{2}{3}$. The observation at the timing value has a value of 1. The observations immediately after the timing value are $\frac{3}{4}$, $\frac{2}{4}$, $\frac{1}{4}$, 0.

BEFORE(DURATION=ALL) implies that the event should be extended to the beginning of the series, and AFTER(DURATION=ALL) implies that the event should be extended to the end of the series.

The following list describes the default values for the DURATION= option:

- If you specify a DURATION= value in either the BEFORE option or the AFTER option (but not both), the other value is assumed to be 0.
- When you specify the PULSE= option but you do not specify a DURATION= value in either the BEFORE or AFTER option, both DURATION= values are set to 0.
- When you do not specify either a DURATION= value or the PULSE= option, then both DURATION= values are assigned default values that are based on the TYPE= option.
- For polynomial trend events (TYPE=LINEAR | QUAD | CUBIC), the default DURATION= value is ALL for both the BEFORE= option and the AFTER= option.
- For other events, the default value for the BEFORE= option is always 0, and the default event duration for the AFTER= option depends on the TYPE= option.

Table 7.8 and Table 7.9 show default duration values by TYPE= value and show how the basic event shape depends on the duration value. DURATION=ALL is represented in the event definition data set as a special missing value, which is displayed as "A." For more information about special missing values, see the section "SAS System Concepts" in *SAS Programmers Guide: Essentials*.

Table 7.8 Default DURATION= Values for Non-trend Types

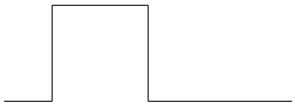
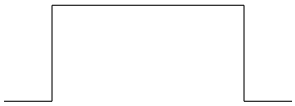
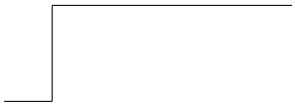
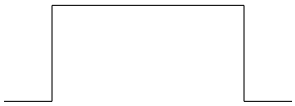
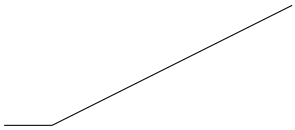
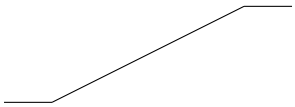
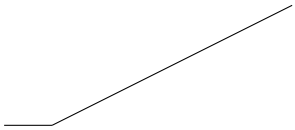
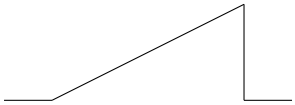
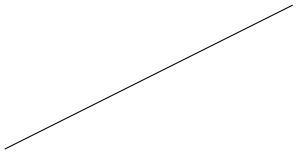
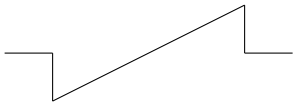
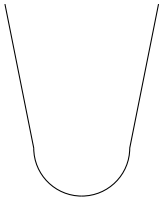
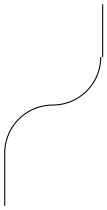
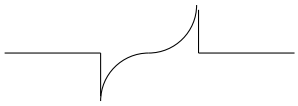
Non-trend TYPE= (BEFORE= Default Is 0)	AFTER= (DURATION=) Default	Default Shape	Shape When Finite AFTER= Duration > 0
POINT	Zero		
LS	ALL (end of series)		
RAMP	ALL (end of series)		
TEMPRAMP	ALL (end of series)		
TC	ALL (end of series)		
INVERSE	ALL (end of series)		

Table 7.8 *continued*

Non-trend TYPE= (BEFORE= Default Is 0)	AFTER= (DURATION=) Default	Default Shape	Shape When Finite AFTER= Duration > 0
LOGARITHMIC	ALL (end of series)		

Table 7.9 Default DURATION= Values for Trend Types

Trend TYPE=	BEFORE= and AFTER= (DURATION=) Default	Default Shape	Shape When Finite BEFORE= and AFTER= Duration > 0
LINEAR TYPE=LIN	ALL (entire series)		
QUAD	ALL (entire series)		
CUBIC	ALL (entire series)		

Using the EVENTKEY Statement

You can use an EVENTKEY statement to make a predefined SAS event available for processing. The EVENTKEY statement constructs a simple SAS event for each predefined SAS event keyword. The predefined SAS events are also available directly through the HPFDIAGNOSE and HPFENGINE procedures. Each predefined event keyword that is specified in the EVENTKEY statement has an associated predefined set of timing values and *qualifier-options*. The *qualifier-options* are the same as in the EVENTDEF statement and can be used to redefine the qualifiers that are associated with the predefined event. As shown in the section "Getting Started: HPFEVENTS Procedure" on page 255, the default SAS variable name for the predefined event is the predefined event keyword. However, you can specify a SAS name for the event. For example, the following statement changes the name of the predefined event definition, CHRISTMAS, to XMAS:

```
eventkey xmas= christmas;
```

Because any user definition takes precedence over a predefined SAS definition, redefining the qualifiers that are associated with a predefined SAS event but not renaming the event has the impact of redefining the predefined SAS event. The following statements produce the event FALLHOLIDAYS, which has a pulse of one day at Halloween and a pulse of one month at Thanksgiving:

```
eventkey thanksgiving / pulse=month;
eventcomb fallholidays= halloween thanksgiving;
```

Predefined SAS events are based on a SAS date keyword, a trend keyword, or an additive outlier or level shift that is based on a timing value. Table 7.10 describes how to construct a predefined SAS event keyword and shows the default *qualifier-options* for those predefined events.

You can use an EVENTKEY statement in a similar manner to modify or clone a user-defined simple event. In the following example, the EVENTDEF statement defines a simple event named SPRING, the EVENTKEY statement modifies the SPRING event definition, and then another EVENTKEY statement creates a new event named SPRINGBREAK that is based on the previously defined user event named SPRING. So the example defines a total of two events, SPRING and SPRINGBREAK. (You can use the EVENTKEY statement to modify the qualifiers, but you cannot use it to modify the timing values.)

```
eventdef spring = '20mar2005'd;
eventkey spring / pulse=day;
eventkey SPRINGBREAK = spring / pulse=week;
```

Suppose the preceding events are stored in a data set named SPRINGHOLIDAYS. The first EVENTKEY statement in the following example clones SPRING as an event named FirstDayOfSpring. The second EVENTKEY statement changes the case of the SPRINGBREAK event name.

```
eventdata in=springholidays;
eventkey FirstDayOfSpring = spring;
eventkey Springbreak = springbreak;
```

Event names that refer to a previously defined event are not case-sensitive. However, the case of event names that are used to create a new event is preserved in the _NAME_ variable of the data set that is specified in the OUT= option in the EVENTDATA statement and in the variable name that is specified in the OUT= option in the EVENTDUMMY statement.

Table 7.10 Definitions for Predefined Event Keywords in the EVENTKEY Statement

Variable Name or Variable Name Format	Description	Qualifier-Options
AO<*obs*>OBS AO<*date*>D AO<*datetime*>DT	Outlier	TYPE=POINT VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=0)
LS<*obs*>OBS LS<*date*>D LS<*datetime*>DT	Level shift	TYPE=LS VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=ALL)
TLS<*obs*>OBS<*n*> TLS<*date*>D<*n*> TLS<*datetime*>DT<*n*>	Temporary level shift	TYPE=LS VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=<n>)
NLS<*obs*>OBS NLS<*date*>D NLS<*datetime*>DT	Negative level shift	TYPE=LS VALUE=–1 BEFORE=(DURATION=0) AFTER=(DURATION=ALL)
CBLS<*obs*>OBS CBLS<*date*>D CBLS<*datetime*>DT	US Census Bureau level shift	TYPE=LS VALUE=–1 SHIFT=–1 BEFORE=(DURATION=ALL) AFTER=(DURATION=0)
TC<*obs*>OBS TC<*date*>D TC<*datetime*>DT	Temporary change	TYPE=TC VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=ALL)
<date keyword>	Date pulse	TYPE=POINT VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=0) PULSE=DAY
LINEAR QUAD CUBIC	Polynomial Trends	TYPE=LIN TYPE=QUAD TYPE=CUBIC VALUE=1 BEFORE=(DURATION=ALL) AFTER=(DURATION=ALL) The default timing value is the 0 observation.

Table 7.10 *continued*

Variable Name or Variable Name Format	Description	Qualifier-Options
INVERSE LOG	Trends	TYPE=INV TYPE=LOG VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=ALL) The default timing value is the 0 observation.
<seasonal keywords>	Seasonal	TYPE=POINT PULSE= depends on keyword VALUE=1 BEFORE=(DURATION=0) AFTER=(DURATION=0) Timing values are based on keyword.

The date keywords that are described in Table 7.3 can be used as predefined SAS event keywords in the EVENTDEF statement. The timing values are defined in Table 7.3, and the default qualifiers are shown in Table 7.10. Table 7.4 shows the seasonal keywords that can be used as predefined SAS event keywords. The default qualifiers for seasonal keywords are shown in Table 7.10. Table 7.11 describes in more detail how date and observation numbers are encoded into predefined events when the value of the TYPE= option in the EVENTDEF statement is AO, LS, TLS, NLS, CBLS, or TC.

Table 7.11 Details for Encoding Date Information into AO, LS, TLS, NLS, CBLS, and TC Type EVENTKEY Variable Names

Variable Name Format	Example	Refers To
AO<*int*>OBS	AO15OBS	15th observation
AO<*date*>D	AO01JAN2000D	`'01JAN2000'D`
AO<*date*>h<*hr*>m<*min*>s<*sec*>DT	AO01Jan2000h12m34s56DT	`'01Jan2000:12:34:56'DT`
TLS<*int*>OBS<*n*>	TLS15OBS10	15th observation
TLS<*date*>D<*n*>	TLS01JAN2000D10	`'01JAN2000'D`
TLS<*date*>h<*hr*>m<*min*>s<*sec*>DT<*n*>	TLS01Jan2000h12m34s56DT10	`'01Jan2000:12:34:56'DT`

Several types of predefined level shifts are available. The parameter for the negative level shift is the same as the parameter for the level shift, but with the opposite sign. If the parameter for a level shift is negative, then replacing the level shift with a negative level shift results in a positive parameter value. The US Census Bureau level shift is defined in the same manner as the level shift in the US Bureau of the Census X-13ARIMA-SEATS seasonal adjustment program (US Bureau of the Census 2013). The advantage of the US Census Bureau level shift is that as historical observations are dropped and the point of the level shift is no longer within the span of the series, the constant term of the series does not change.

Using the EVENTDS= System Option to Customize Holiday Predefined Date Keywords

You can use the DATEKEYS procedure and the EVENTDS= system option to construct user-defined date keywords. The following example constructs the user-defined date keyword GoodFriday:

```
proc datekeys;
   datekeydef GoodFriday = EASTER / SHIFT=-2 PULSE=DAY;
   datekeydata out=MyHolidays;
run;

options eventds=(MyHolidays);

proc hpfevents;
   eventkey GoodFriday;
   eventdata out=MyEvents condense;
run;
```

Missing Value Interpretation

When you use the EVENTDUMMY statement to create dummy variables, you might need to specify how to handle observations that correspond to a time ID but are missing from the input data set. In this case, the input data set does not contain a value for the variables to be copied to the data set that is specified in the OUT= option in the EVENTDUMMY statement. You can use the SETMISSING= option as follows to handle these missing values:

- Sometimes missing values should be interpreted as unknown values. The forecasting models that the HPFENGINE procedure uses can effectively handle missing values. (For more information, see Chapter 5, "The HPFENGINE Procedure.") In this case, you can specify SETMISSING=MISSING.
- Sometimes missing values are known, such as when no observation should be interpreted as no (zero) value. In this case, specify SETMISSING=0.
- In other cases, missing time IDs should be skipped, such as when the data are to be accumulated at a later time. In this case, specify SETMISSING=SKIP.

Input and Output Data Sets

The IN= option in the EVENTDATA statement specifies a data set that contains saved event definitions for input into the HPFEVENTS procedure.

PROC HPFEVENTS creates an output data set in the following cases:

- If you specify the OUT= option in the EVENTDATA statement, the resulting data set contains the event definitions that can be used as input to another SAS procedure.
- If you specify the OUT= data set in the EVENTDUMMY statement, the resulting data set contains the variables that are listed in the BY statement, the ID variable, any variables that are defined by the VAR statement, and any dummy variables that are generated by the procedure.

EVENTDATA Statement IN= Data Set

The IN= option in the EVENTDATA statement inputs a data set that has usually been created by a previous run of PROC HPFEVENTS, in which the OUT= option was specified in the EVENTDATA statement. The input data set can also be created in a prior DATA step, provided that the data set contains the same variables and attributes as those written to the OUT= data set in the EVENTDATA statement. If any variables that are listed in this OUT= data set are omitted from the data set to be read using the IN= option, then the default values for the omitted variables are used. This can occur, for example, when the CONDENSE option is specified in the PROC HPFEVENTS step in which this OUT= data set was created. Whenever a condensed data set is specified in the IN= option in the EVENTDATA statement, the default settings of the omitted variables are assumed.

If the IN= data set contains any extraneous variables that are not usually written to the OUT= data set in the EVENTDATA statement, then those variables are ignored.

All observations that are associated with a particular event should be recorded in contiguous observations in the data set. If a previously defined event is referenced in a subsequent observation in the IN= data set in the EVENTDATA statement, then PROC HPFEVENTS produces a warning to indicate that a duplicate event name was found and replaces the previous definition of the event with the definition in one or more of the latter observations.

EVENTDATA Statement OUT= Data Set

The OUT= option in the EVENTDATA statement specifies a data set to contain the following variables. The default values for the CONDENSE option are also shown. When all the observations in the variable are equal to the default value, the variable can be omitted from the event definition data set.

LOCALE is the POSIX locale value that is associated with the event. The _LOCALE_ variable is not required; there is no default.

NAME is the event variable name, which is displayed with the case preserved. Because _NAME_ is a SAS variable name, the event can be referenced using any case. The _NAME_ variable is required; there is no default.

CLASS is the class of event: SIMPLE, COMBINATION, or PREDEFINED. The default is SIMPLE.

KEYNAME is one of the following: a date keyword (simple event) or a predefined event variable name (predefined event) or an event name (combination event). All _KEYNAME_ values are displayed in uppercase. However, if the _KEYNAME_ value refers to an event name, then the actual name can be mixed case. The default is no keyname, designated by a period (“.”).

STARTDATE is either the date timing value or the first date timing value to use in a do-list. The default is no date, designated by a missing value.

ENDDATE is the last date timing value to use in a do-list. The default is no date, designated by a missing value.

DATEINTRVL is the interval for the date do-list. The default is no interval, designated by a period (“.”).

STARTDT is either the datetime timing value or the first datetime timing value to use in a do-list. The default is no datetime, designated by a missing value.

ENDDT is the last datetime timing value to use in a do-list. The default is no datetime, designated by a missing value.

DTINTRVL is the interval for the datetime do-list. The default is no interval, designated by a period (“.”).

STARTOBS is either the observation number timing value or the first observation number timing value to use in a do-list. The default is no observation number, designated by a missing value.

ENDOBS is the last observation number timing value to use in a do-list. The default is no observation number, designated by a missing value.

OBSINTRVL is the interval length of the observation number do-list. The default is no interval, designated by a period (“.”).

TYPE is the type of EVENT. The default is POINT.

VALUE is the value for a nonzero observation. The default is 1.0.

PULSE is the interval that defines the units for the DURATION values. The default is no interval (one observation), designated by a period (“.”).

_DUR_BEFORE_ is the number of durations before the timing value. The default is 0.

_DUR_AFTER_ is the number of durations after the timing value. The default is 0.

_SLOPE_BEFORE_ determines whether the curve before the timing value is GROWTH or DECAY for TYPE=RAMP, TYPE=RAMPP, and TYPE=TC. The default is GROWTH.

_SLOPE_AFTER_ determines whether the curve after the timing value is GROWTH or DECAY for TYPE=RAMP, TYPE=RAMPP, and TYPE=TC. The default is GROWTH unless TYPE=TC; then the default is DECAY.

SHIFT is the number of PULSE= intervals by which to shift the timing value. The shift can be positive (forward in time) or negative (backward in time). If PULSE= is not specified, then the shift is in observations. The default is 0.

TCPARM is the parameter for an event of TYPE=TC. The default is 0.5.

RULE is the rule to use when events are combined or when timing values of an event overlap. The default is ADD.

PERIOD is the frequency interval at which the event should be repeated. If this value is missing, then the event is not periodic. The default is no interval, designated by a period (“.”).

LABEL is the label or description for the event. If you do not specify a label, then the default label value is displayed as a period (“.”). However, the default label in a data set that is specified in an OUT= option in an EVENTDUMMY statement is “Dummy Variable for Event *variable-name*.”

For more information about the default label, see the LABEL= option.

Printed Output

The HPFEVENTS procedure has no printed output other than warning and error messages that are recorded in the log.

Examples: HPFEVENTS Procedure

Example 7.1: Using Multiple Timing Values in a Single Event versus Using Multiple Events and the EVENTCOMB Statement

This example illustrates how the HPFEVENTS procedure interprets multiple timing values that overlap. It also illustrates the results of combining the same timing values that are used in separate EVENTDEF statements into one combination event by specifying the EVENTCOMB statement. Airline sales data are used for this illustration.

```
   data a(Label='Box-Jenkins Series G: International Airline Data');
     set sashelp.air;
     t = intnx( 'month', '01jan1949'd, _n_-1 );
     format t DATE.;
   run;

proc hpfevents data=sashelp.air ;
   var air;
   id date interval=month start='01Jan1949'D end='01Feb1950'D;
   eventdef xmasrp= christmas / before=(slope=growth duration=3)
                                type=ramp rule=min ;
   eventdef easterrp= easter / before=(slope=growth duration=3)
                               type=ramp rule=min ;
   eventdef twotiming= easter christmas /
                               before=(slope=growth duration=3)
                               type=ramp rule=min ;
   eventcomb twoevents= easterrp xmasrp / rule=min ;
   eventdata  out= evdsout1 (label='EASTER and CHRISTMAS Ramps');
   eventdummy  out= evdumout1 (label='Combining Timing Values');
run;
```

```
proc print data=evdumout1;
run;
```

The preceding statements produce Output 7.1.1.

Output 7.1.1 Multiple Timing Values versus Multiple Events

Obs	DATE	AIR	xmasrp	easterrp	twotiming	twoevents
1	JAN1949	112	0.00000	0.00000	0.00000	0.00000
2	FEB1949	118	0.00000	0.33333	0.33333	0.00000
3	MAR1949	132	0.00000	0.66667	0.66667	0.00000
4	APR1949	129	0.00000	1.00000	1.00000	0.00000
5	MAY1949	121	0.00000	1.00000	1.00000	0.00000
6	JUN1949	135	0.00000	1.00000	1.00000	0.00000
7	JUL1949	148	0.00000	1.00000	1.00000	0.00000
8	AUG1949	148	0.00000	1.00000	1.00000	0.00000
9	SEP1949	136	0.00000	1.00000	0.00000	0.00000
10	OCT1949	119	0.33333	1.00000	0.33333	0.33333
11	NOV1949	104	0.66667	1.00000	0.66667	0.66667
12	DEC1949	118	1.00000	1.00000	1.00000	1.00000
13	JAN1950	115	1.00000	0.00000	0.00000	0.00000
14	FEB1950	126	1.00000	0.33333	0.33333	0.33333

In this example, the ramp for Christmas is defined for observations 9 through 14. When XMASRP is evaluated, the undefined values in observations 1 through 8 are replaced with zeros. The ramp for Easter is defined for the entire time series, as shown in the variable EASTERRP. When both timing values are used in one EVENTDEF statement for the variable TWOTIMING, the values from the Easter ramp are used in observations 1 through 8, and the RULE=MIN option is applied to observations 9 through 14. For the EVENTCOMB statement that defines the variable TWOEVENTS, the RULE=MIN option applies to all observations in the series.

Example 7.2: Using a DATA Step to Construct an Events Data Set

The following DATA step automatically constructs potential outliers that are related to the price data in the data set Sashelp.Pricedata:

```
data orders(keep=date region line product sale);
   set sashelp.pricedata;
   format date monyy.;
run;
```

The following SAS statements construct a data set for potential outliers (identified as sale > 450). Only the _NAME_ and _STARTDATE_ variables are needed.

```
data outliers(keep=_name_ _startdate_  );
   set orders;
   if (sale > 450) then do;
      _name_ = trim('ao')||trim(left(put(year(date),8.)))||'_'
               ||trim(left(put(month(date),8.)));
```

```
         _startdate_=date;
         end;
      else delete;
      format _startdate_ monyy.;
   run;
```

The next DATA step identifies which outliers apply to each product:

```
   data product_event_list (keep= region line product _name_);
      set orders;
      if (sale > 450) then do;
         _name_ = trim('ao')||trim(left(put(year(date),8.)))||'_'
                  ||trim(left(put(month(date),8.)));
         end;
      else delete;
   run;
```

The potential outliers in the data set Outl_Reg1_Line1_Prod1 apply to Region 1, Line 1, and Product 1.

```
   data outl_reg1_line1_prod1;
      set product_event_list;
      if ((region ~= 1) | (line ~= 1) | (product ~= 1)) then delete;
   run;
```

The following statements create dummy variables and eliminate duplicate outlier events from the events definition data set:

```
proc hpfevents data=orders ;
   id date interval=month;
   by region line product;
   eventdata  in=outliers ;
   eventdata  out=outldatabase(label='outlier definitions')
              condense;
   eventdummy out=dummies(label='dummy variables');
run;

proc print data=outldatabase(obs=10);
run;

proc print data=outl_reg1_line1_prod1;
run;
```

Examining the data set Outl_Reg1_Line1_Prod1 shows that you might want to look for outliers for May 1998, October 1999, March 2000, February 2001, June 2001, and September 2002.

The preceding statements produce Output 7.2.1.

Output 7.2.1 Potential Outliers for Region 1, Line 1, and Product 1

Obs	region	line	product	_name_
1	1	1	1	ao1998_5
2	1	1	1	ao1999_10
3	1	1	1	ao2000_3
4	1	1	1	ao2001_2
5	1	1	1	ao2001_6
6	1	1	1	ao2002_9

PROC HPFEVENTS produces the data set shown in Output 7.2.2, which is condensed and has eliminated the duplicate events.

Output 7.2.2 Event Definition Data Set

Obs	_NAME_	_STARTDATE_
1	ao1999_1	01JAN1999
2	ao1999_11	01NOV1999
3	ao2000_12	01DEC2000
4	ao2002_1	01JAN2002
5	ao1998_10	01OCT1998
6	ao1999_8	01AUG1999
7	ao2000_4	01APR2000
8	ao2001_1	01JAN2001
9	ao2001_12	01DEC2001
10	ao2002_12	01DEC2002

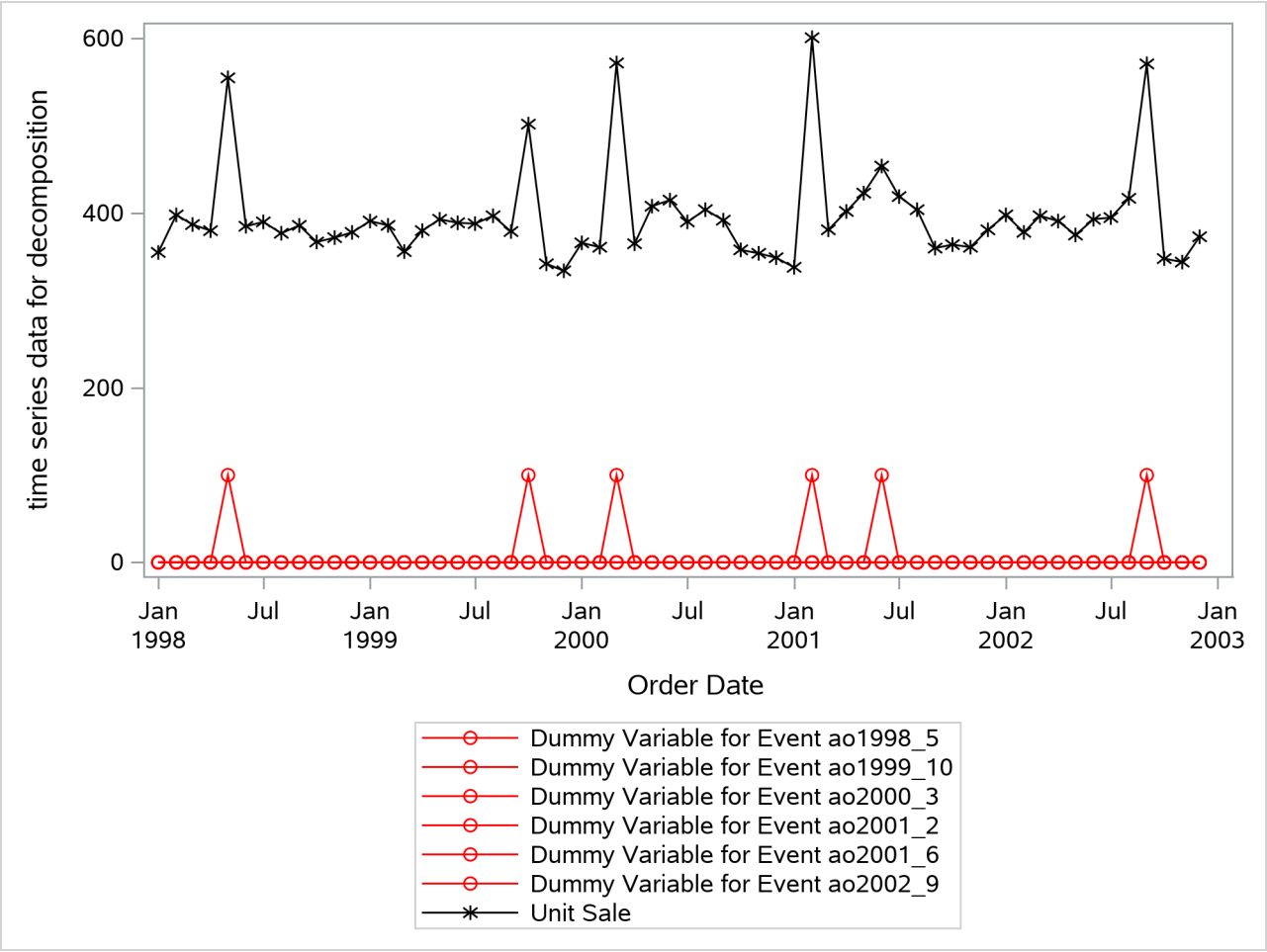
The following statements select the observations that are related to Region 1, Line 1, and Product 1, and they scale the dummy variables that apply so that they are visible when plotted with the original data:

```
data pid1;
   set dummies;
   if ((region ~= 1) | (line ~= 1) | (product ~= 1)) then delete;
   else do;
      AO1998_5  = 100 * AO1998_5;
      AO1999_10 = 100 * AO1999_10;
      AO2000_3  = 100 * AO2000_3;
      AO2001_2  = 100 * AO2001_2;
      AO2001_6  = 100 * AO2001_6;
      AO2002_9  = 100 * AO2002_9;
   end;
run;
```

The following statements use PROC SGPLOT to visually verify that these potential outliers are appropriate for the original data, as shown in Output 7.2.3:

```
proc sgplot data=pid1;
   series x=date y=AO1998_5 / markers markerattrs=(symbol=circle color=red)
    lineattrs=(pattern=1 color=red);
   series x=date y=AO1999_10 / markers markerattrs=(symbol=circle color=red)
    lineattrs=(pattern=1 color=red);
   series x=date y=AO2000_3 / markers markerattrs=(symbol=circle color=red)
    lineattrs=(pattern=1 color=red);
   series x=date y=AO2001_2 / markers markerattrs=(symbol=circle color=red)
    lineattrs=(pattern=1 color=red);
   series x=date y=AO2001_6 / markers markerattrs=(symbol=circle color=red)
    lineattrs=(pattern=1 color=red);
   series x=date y=AO2002_9 / markers markerattrs=(symbol=circle color=red)
    lineattrs=(pattern=1 color=red);
   series x=date y=sale / markers markerattrs=(symbol=asterisk color=black)
    lineattrs=(pattern=1 color=black);
   yaxis label='time series data for decomposition';
run;
```

Output 7.2.3 Plot of Amount and Dummy Variables



Example 7.3: Preparing a Data Set for PROC HPFENGINE

This example illustrates how you can use the HPFEVENTS procedure to include events in the automatic forecasting of time series data. The data have been altered by adding a level shift of 100 that begins at the observation that occurs in October 1980. PROC HPFEVENTS creates an event named Promotion as a level shift that represents a change in level that begins on October 1, 1980. PROC HPFENGINE identifies the parameter of the event Promotion as 97.6728, as shown in Output 7.3.1. This parameter is used in conjunction with the model named SP1, which is described as "ARIMA(0, 1, 1) No Intercept."

```
data work_intv;
   set sashelp.workers;
   if date >= '01oct80'd then electric = electric+100;
   drop masonry;
run;
```

```
* define event 'promotion';
proc hpfevents data=work_intv lead=12;
   id date interval=month;
   eventdef promotion=  '01oct80'd / TYPE=LS;
   eventdata out= evdsout1 (label='list of events');
run;

proc hpfarimaspec modelrepository=sasuser.mycat
                  specname=sp1
                  speclabel="ARIMA(0,1,1) No Intercept";
   dependent symbol=Y q=1 diflist=1 noint;
run;

proc hpfarimaspec modelrepository=sasuser.mycat
                   specname=sp2
                   speclabel="ARIMA(0,1,2)(0,1,1)_12 No Intercept";
   dependent symbol=Y q=(1,2)(12) diflist=1 12 noint;
run;

proc hpfselect modelrepository=sasuser.mycat
               selectname=myselect
               selectlabel="My Selection List";
   select select=mape holdout=12;
   spec sp1 sp2 /
        inputmap(symbol=y var=electric)
        eventmap(symbol=_none_ event=promotion)
        ;
run;

proc hpfengine data=work_intv lead=12 outest=outest
               globalselection=myselect
               modelrepository=sasuser.mycat
               inevent=evdsout1;
   id date interval=month;
   forecast electric / task = select;
run;

proc print data=outest; run;
```

The preceding statements produce Output 7.3.1.

Output 7.3.1 Model Selection Using Events

Obs	_NAME_	_SELECT_	_MODEL_	_MODELVAR_	_DSVAR_	_VARTYPE_	_TRANSFORM_
1	ELECTRIC	MYSELECT	SP1	Y	ELECTRIC	DEPENDENT	NONE
2	ELECTRIC	MYSELECT	SP1	PROMOTION	PROMOTION	EVENT	NONE

Obs	_COMPONENT_	_COMPMODEL_	_FACTOR_	_LAG_	_SHIFT_	_PARM_	_LABEL_	_SCORE_
1	MA		1	1	0	MA1_1	ARIMA(0,1,1) No Intercept	
2	SCALE		0	0	0	SCALE	ARIMA(0,1,1) No Intercept	

Obs	_EST_	_STDERR_	_TVALUE_	_PVALUE_	_STATUS_
1	-0.5260	0.10798	-4.8718	.000007605	0
2	97.6728	4.28766	22.7800	2.0879E-32	0

Example 7.4: Using Predefined SAS Event Keywords Directly in Other SAS Procedures

You can modify the SAS statements in Example 7.3 to use the events system directly without using PROC HPFEVENTS. Instead of creating an event named Promotion, you can use the SAS predefined event keyword LS01OCT1980D. The following statements use the data set from Example 7.3 and the EVENT statement in PROC HPFDIAGNOSE to illustrate this method:

```
proc hpfdiag data=work_intv
             seasonality=12
             print=all;
   id date interval=month;
   forecast electric;
   event LS01OCT1980D;
   trend diff=1 sdiff=1;
   arimax;
run;
```

The output from PROC HPFDIAGNOSE shows that the selected model includes the level shift that represents a change in level that begins on October 1980, as shown in Output 7.4.1.

Output 7.4.1 Using the EVENT Statement in PROC HPFDIAGNOSE

The HPFDIAGNOSE Procedure

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	5.883729	5.949528	6.02335	6.096772	6.170614	6.241918
AR 1	5.949355	6.023199	6.096221	6.169567	6.243324	6.314554
AR 2	6.023143	6.096346	6.170056	6.24107	6.314917	6.38698
AR 3	6.096554	6.169837	6.240963	6.314829	6.387728	6.459893
AR 4	6.170396	6.243647	6.314666	6.387965	6.461478	6.533759
AR 5	6.241435	6.314684	6.386682	6.459847	6.533716	6.60647

ARIMA Model Specification

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Model Criterion	Statistic	Status
ELECTRIC	NONE	NO	0	1	0	0	1	1	12	RMSE	13.6804	OK

ARIMA Event Selection

Event Name	Selected	d	D	Status
LS01OCT1980D	YES	1	1	OK

ARIMA Model Specification After Adjusting for Events

Variable	Functional Transform	Constant	p	d	q	P	D	Q	Seasonality	Event	Model Criterion	Statistic	Status
ELECTRIC	NONE	NO	0	1	0	0	1	1	12	1	RMSE	3.3460	OK

Example 7.5: Viewing Dummy Variables by Using the SGPLOT Procedure

This example illustrates how you can use the HPFEVENTS procedure to create dummy variables. You can then use the SGPLOT procedure to view these dummy variables. This example also shows the behavior of ramp variables when you use them with the SLOPE= option.

```
proc hpfevents data=sashelp.air ;
   var air;
   id date interval=month start='01jan1951'd end='31dec1951'd;
   eventdef infgg= '01jun1951'd  /  type=ramp before=(slope=growth duration=all)
                                    after=(slope=growth duration=all);
   eventdef infgd= '01jun1951'd  /  type=ramp before=(slope=growth duration=all)
                                    after=(slope=decay duration=all) ;
   eventdef infdg= '01jun1951'd  /  type=ramp before=(slope=decay duration=all)
                                    after=(slope=growth duration=all)  ;
   eventdef infdd= '01jun1951'd  /  type=ramp before=(slope=decay duration=all)
                                    after=(duration=all slope=decay) ;
   eventdef minfgg= '01jun1951'd  /  type=ramp before=(slope=growth duration=4)
                                     after=(slope=growth duration=all) ;
   eventdef minfgd= '01jun1951'd  /  type=ramp before=(slope=growth duration=4)
                                     after=(slope=decay duration=all) ;
   eventdef minfdg= '01jun1951'd  /  type=ramp before=(slope=decay duration=4)
                                     after=(slope=growth duration=all);
   eventdef minfdd= '01jun1951'd  /  type=ramp before=(slope=decay duration=4)
                                     after=(slope=decay duration=all) ;
   eventdef monlygg= '01jun1951'd  /  type=ramp before=(slope=growth duration=4);
   eventdef monlygd= '01jun1951'd  /  type=ramp before=(slope=growth duration=4)
                                      after=(slope=decay);
   eventdef monlydg= '01jun1951'd  /  type=ramp before=(slope=decay duration=4)
                                      after=(slope=growth) ;
   eventdef monlydd= '01jun1951'd  /  type=ramp before=(slope=decay duration=4)
                                      after=(slope=decay);
   eventdef ninfgg= '01jun1951'd  /  type=ramp before=(slope=growth duration=all)
                                     after=(slope=growth duration=2) ;
   eventdef ninfgd= '01jun1951'd  /  type=ramp before=(slope=growth duration=all)
                                     after=(slope=decay duration=2) ;
   eventdef ninfdg= '01jun1951'd  /  type=ramp before=(slope=decay duration=all)
                                     after=(slope=growth duration=2) ;
   eventdef ninfdd= '01jun1951'd  /  type=ramp before=(slope=decay duration=all)
                                     after=(slope=decay duration=2) ;
   eventdef nonlygg= '01jun1951'd  /  type=ramp after=(slope=growth duration=2);
   eventdef nonlygd= '01jun1951'd  /  type=ramp after=(slope=decay duration=2)
                                      before=(slope=growth) ;
   eventdef nonlydg= '01jun1951'd  /  type=ramp before=(slope=decay)
                                      after=(slope=growth duration=2) ;
   eventdef nonlydd= '01jun1951'd  /  type=ramp before=(slope=decay)
                                      after=(slope=decay duration=2) ;
   eventdef mngg= '01jun1951'd  /  type=ramp before=(slope=growth duration=4)
                                   after=(slope=growth duration=2) ;
   eventdef mngd= '01jun1951'd  /  type=ramp before=(slope=growth duration=4)
                                   after=(slope=decay duration=2) ;
   eventdef mndg= '01jun1951'd  /  type=ramp before=(slope=decay duration=4)
```

```
                                    after=(slope=growth duration=2) ;
   eventdef mndd= '01jun1951'd  /   type=ramp before=(slope=decay duration=4)
                                    after=(slope=decay duration=2) ;
   eventdata  out= rampds (label='Ramps Using DURATION= and SLOPE=');
   eventdummy out= rampdummies (label='Dummy Variables for Ramps');
run;

proc print data=rampdummies(obs=10);
run;
```

The preceding statements produce Output 7.5.1.

Output 7.5.1 Ramp Dummy Variables

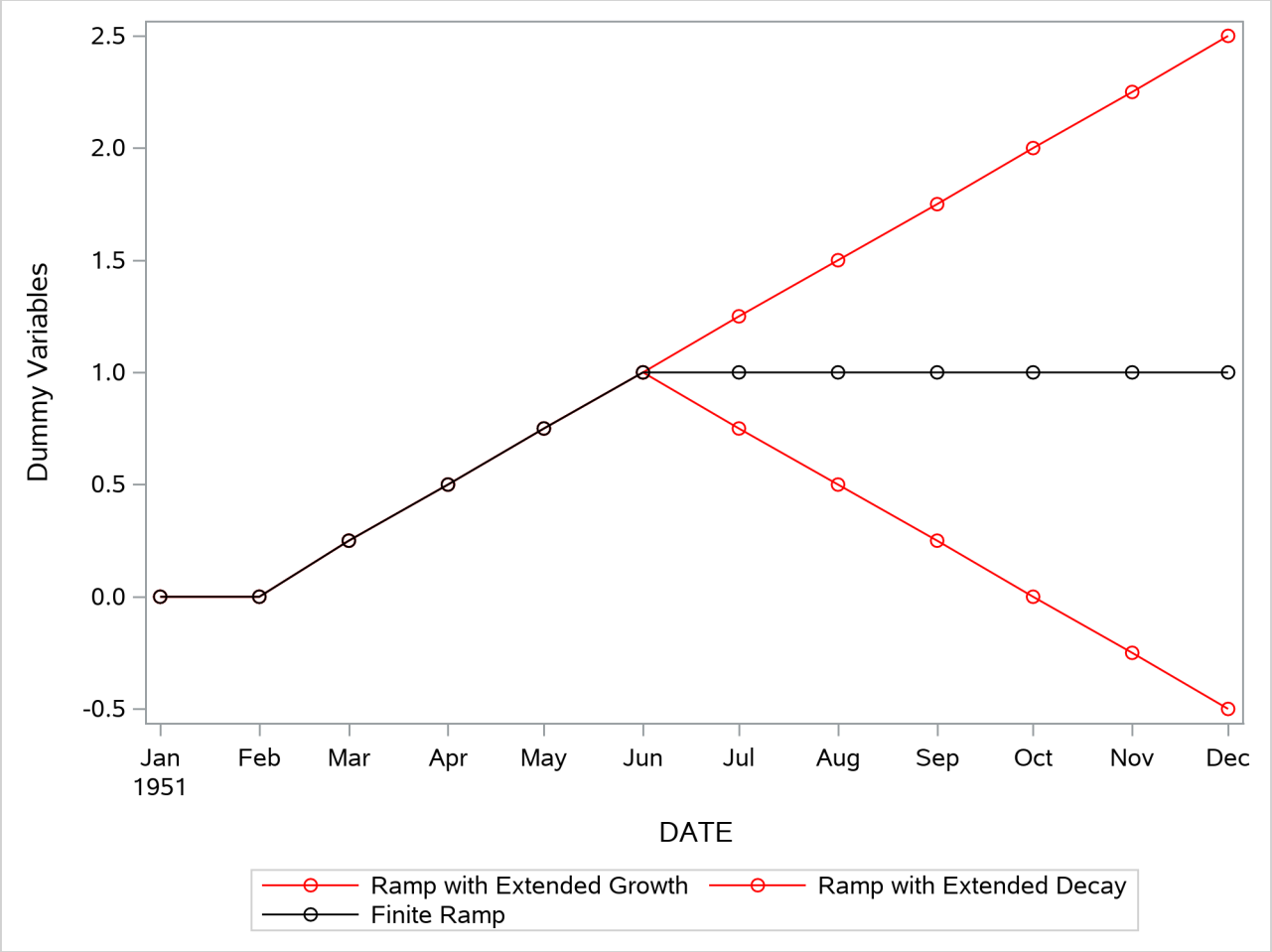
Obs	DATE	AIR	infgg	infgd	infdg	infdd	minfgg	minfgd	minfdg	minfdd	monlygg	monlygd	monlydg	monlydd
1	JAN1951	145	-5	-5	5	5	0.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00
2	FEB1951	150	-4	-4	4	4	0.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00
3	MAR1951	178	-3	-3	3	3	0.25	0.25	0.75	0.75	0.25	0.25	0.75	0.75
4	APR1951	163	-2	-2	2	2	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
5	MAY1951	172	-1	-1	1	1	0.75	0.75	0.25	0.25	0.75	0.75	0.25	0.25
6	JUN1951	178	0	0	0	0	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00
7	JUL1951	199	1	-1	1	-1	1.25	0.75	0.25	-0.25	1.00	1.00	0.00	0.00
8	AUG1951	199	2	-2	2	-2	1.50	0.50	0.50	-0.50	1.00	1.00	0.00	0.00
9	SEP1951	184	3	-3	3	-3	1.75	0.25	0.75	-0.75	1.00	1.00	0.00	0.00
10	OCT1951	162	4	-4	4	-4	2.00	0.00	1.00	-1.00	1.00	1.00	0.00	0.00

Obs	ninfgg	ninfgd	ninfdg	ninfdd	nonlygg	nonlygd	nonlydg	nonlydd	mngg	mngd	mndg	mndd
1	-2.5	-1.5	2.5	3.5	0.0	1.0	0.0	1.0	0.00000	0.00	1.00	1.00000
2	-2.0	-1.0	2.0	3.0	0.0	1.0	0.0	1.0	0.00000	0.00	1.00	1.00000
3	-1.5	-0.5	1.5	2.5	0.0	1.0	0.0	1.0	0.16667	0.25	0.75	0.83333
4	-1.0	0.0	1.0	2.0	0.0	1.0	0.0	1.0	0.33333	0.50	0.50	0.66667
5	-0.5	0.5	0.5	1.5	0.0	1.0	0.0	1.0	0.50000	0.75	0.25	0.50000
6	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.66667	1.00	0.00	0.33333
7	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.83333	0.50	0.50	0.16667
8	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.00000	0.00	1.00	0.00000
9	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.00000	0.00	1.00	0.00000
10	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.00000	0.00	1.00	0.00000

```
proc sgplot data=rampdummies;
   series x=date y=minfgg / markers markerattrs=(color=red)
    lineattrs=(pattern=1 color=red) legendlabel='Ramp with Extended Growth';
   series x=date y=minfgd / markers markerattrs=(color=red)
    lineattrs=(pattern=1 color=red) legendlabel='Ramp with Extended Decay';
   series x=date y=monlygg / markers markerattrs=(color=black)
    lineattrs=(pattern=1 color=black) legendlabel='Finite Ramp';
   yaxis label='Dummy Variables';
run;
```

The preceding statements produce Output 7.5.2.

Output 7.5.2 Plot of Finite and Extended Dummy Variables



References

Meeus, J. (1998). *Astronomical Algorithms*. 2nd ed. Richmond, VA: Willmann-Bell.

Reingold, E. M., and Dershowitz, N. (2001). *Calendrical Calculations*. New York: Cambridge University Press.

US Bureau of the Census (2013). *X-13ARIMA-SEATS Reference Manual, Version 1.1*. US Bureau of the Census, Washington, DC. https://www2.census.gov/software/x-13arima-seats/x13as/unix-linux/documentation/docx13ashtml.pdf.

Chapter 8
The HPFEXMSPEC Procedure

Contents

Overview: HPFEXMSPEC Procedure **299**
Getting Started: HPFEXMSPEC Procedure **300**
Syntax: HPFEXMSPEC Procedure **300**
Functional Summary 300
PROC HPFEXMSPEC Statement 301
EXM Statement 301
Examples: HPFEXMSPEC Procedure **303**
Example 8.1: Various EXM Model Specifications 303

Overview: HPFEXMSPEC Procedure

The HPFEXMSPEC procedure creates model specifications files for external models (EXM). External model specifications are used for forecasts that are provided external to the system. These external forecasts might have originated from an external statistical model from another software package, might have been provided by an outside organization (for example, a marketing organization or government agency), or might be based on judgment.

External forecasts might or might not provide prediction standard errors. If the prediction standard errors are not provided, they must be computed from the prediction errors and additional information. To properly compute the prediction standard errors, the autocovariances of model residuals and information about any transformations applied to the actual time series are needed. Since the autocovariances or transformations are not known to the system, this information must be specified by the user or approximated from the actual time series or the prediction errors.

External forecasts might or might not provide lower and upper confidence limits. If lower and upper confidence limits are not provided, they must be computed from the prediction standard errors.

The external model specification is a means by which the user can specify information about how external forecasts were created so that the prediction standard errors or confidence limits or both can be approximated when they are not provided with the external forecasts.

Getting Started: HPFEXMSPEC Procedure

The following example shows how to create an external model specification file.

```
proc hpfexmspec repository=sasuser.mymodels
                name=myexternal
                label="My External Model";
   exm method=wn;
run;
```

The options in the PROC HPFEXMSPEC statement are used to specify the location of the specification file that will be output. Here the REPOSITORY= option specifies that the output file be placed in a catalog "sasuser.mymodels," the NAME= option specifies that the name of the file be "myexternal.xml," and the LABEL= option specifies a label for this catalog member. The EXM statement in the procedure specifies the external model and the options used to control the parameter estimation process for the model.

Syntax: HPFEXMSPEC Procedure

The following statements are used with the HPFEXMSPEC procedure.

PROC HPFEXMSPEC *options* **;**
EXM *options* **;**

Functional Summary

Table 8.1 summarizes the statements and options that control the HPFEXMSPEC procedure.

Table 8.1 PROC HPFEXMSPEC Functional Summary

Description	Statement	Option
Model Repository Options		
Specifies the model specification label	PROC HPFEXMSPEC	LABEL=
Specifies the model specification name	PROC HPFEXMSPEC	NAME=
Specifies the model repository	PROC HPFEXMSPEC	REPOSITORY=
External Model Options		
Specifies median forecasts	EXM	MEDIAN
Specifies the method of creating forecast standard errors	EXM	METHOD=
Specifies the number of time lags used to compute the autocorrelations	EXM	NLAGPCT=
Specifies that the external model parameters be fixed values	EXM	NOEST
Specifies the number of parameters used to create the external forecast	EXM	NPARMS=

Table 8.1 *continued*

Description	Statement	Option
Specifies the prediction standard error for the external model	EXM	SIGMA=
Specifies the time series transformation	EXM	TRANSFORM=

PROC HPFEXMSPEC Statement

PROC HPFEXMSPEC *options* **;**

The following options can be used in the PROC HPFEXMSPEC statement.

LABEL=*SAS-label*
labels the model specification to be stored in the SAS catalog or external file reference. The LABEL= option can also be specified as SPECLABEL=.

NAME=*SAS-name*
names the model specification to be stored in the SAS catalog or external file reference. The NAME= option can also be specified as SPECNAME=.

REPOSITORY=*SAS-catalog-name* | *SAS-file-reference*
names the SAS catalog or external file reference to contain the model specification. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=.

EXM Statement

EXM *options* **;**

The EXM statement specifies an external model that is used to generate the external forecasts. These options are not needed if the prediction standard errors and confidence limits are provided.

The following examples illustrate typical uses of the EXM statement.

```
/* default specification */
exm;

/* Actual Series Autocorrelation */
exm method=acf;

/* Prediction Error Autocorrelation */
exm method=erroracf;
```

The following options can be specified in the EXM statement.

MEDIAN
specifies that the median forecast values were used to generate the external forecasts. The external forecasts can have been based on the mean or median. By default the mean value is assumed. If no transformation was used by the external forecasting method, as specified by the TRANSFORM=NONE option, the mean and median prediction standard errors and confidence limits are identical.

METHOD=*method-name*
specifies the external model to be used to approximate the prediction standard errors. The default is METHOD=PERFECT. The following forecasting models are provided:

NONE	No prediction error autocorrelation is used.
WN	Prediction error autocorrelation is white noise.
ACF	Autocorrelation is used.
ERRORACF	Prediction error autocorrelation is used.
PERFECT	Perfect autocorrelation is assumed.

NLAGPCT=*number*
specifies the number of time lags as a percentage of the number of computed predictions errors. The default is NLAGPCT=0.25.

NOEST
specifies that the external model parameters are fixed values. To use this option, all of the external model parameters must be explicitly specified. By default, the external model parameters are optimized.

NPARMS=*n*
specifies the number of parameters used by the external model to generate the forecasts. The default is NPARMS=0.

SIGMA=*number*
specifies the prediction standard error for the external model. If the SIGMA= option is specified with the NOEST option, the prediction mean square error specified by the SIGMA= option is used. Otherwise, the prediction mean square error is computed from the prediction errors by using the NPARMS= option.

TRANSFORM=*option*
specifies the time series transformation that was applied to the actual time series when generating the external forecast. The following transformations are provided:

NONE	no transformation
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5

When the TRANSFORM= option is specified, the actual time series must be strictly positive. After the time series is transformed, the model parameters are estimated using the transformed time series. The forecasts of the transformed time series are then computed, and finally the transformed time series

forecasts are inverse transformed. The inverse transform produces either mean or median forecasts depending on whether the MEDIAN option is specified.

Examples: HPFEXMSPEC Procedure

Example 8.1: Various EXM Model Specifications

The following statements illustrate typical uses of the EXM statement:

```
proc hpfexmspec repository=mymodels
                name=model1
                label="Default Specification";
   exm;
run;

proc hpfexmspec repository=mymodels
                name=model2
                label="Actual Series Autocorrelation";
   exm method=acf;
run;

proc hpfexmspec repository=mymodels
                name=model3
                label="Prediction Error Autocorrelation";
   exm method=erroracf;
run;

title "Models Added to MYMODELS Repository";
proc catalog catalog=mymodels;
   contents;
run;
```

Output 8.1.1 Listing of Models in MYMODELS Repository

Models Added to MYMODELS Repository

Contents of Catalog WORK.MYMODELS

#	Name	Type	Create Date	Modified Date	Description
1	MODEL1	XML	08/06/2020 03:20:27	08/06/2020 03:20:27	Default Specification
2	MODEL2	XML	08/06/2020 03:20:27	08/06/2020 03:20:27	Actual Series Autocorrelation
3	MODEL3	XML	08/06/2020 03:20:27	08/06/2020 03:20:27	Prediction Error Autocorrelation

Chapter 9
The HPFIDMSPEC Procedure

Contents

Overview: HPFIDMSPEC Procedure **305**
Getting Started: HPFIDMSPEC Procedure **306**
Syntax: HPFIDMSPEC Procedure **306**
Functional Summary 306
PROC HPFIDMSPEC Statement 307
IDM Statement 308
Smoothing Model Suboptions for IDM Statement Options 309
Details: HPFIDMSPEC Procedure **313**
Smoothing Model Parameter Specification Options 313
Smoothing Model Forecast Bounds Options 313
Examples: HPFIDMSPEC Procedure **313**
Example 9.1: Various Kinds of IDM Model Specifications 313
Example 9.2: Automatically Choosing the Best Decomposed Demand Model 315

Overview: HPFIDMSPEC Procedure

The HPFIDMSPEC procedure creates model specifications files for intermittent demand models (IDM).

You can specify many types of intermittent demand models with this procedure. In particular, any model that can be analyzed using the HPF procedure can be specified.

Getting Started: HPFIDMSPEC Procedure

The following example shows how to create an intermittent demand model specification file. In this example, a model specification for Croston's method is created.

```
proc hpfidmspec repository=mymodels
                name=mycroston
                label="Croston Method";
   idm  interval=( method=simple )
        size=( method=simple ) ;
run;
```

The options in the PROC HPFIDMSPEC statement are used to specify the location of the specification file that will be output. Here the REPOSITORY= option specifies that the output file be placed in a catalog "sasuser.mymodels," the NAME= option specifies that the name of the file be "mycroston.xml," and the LABEL= option specifies a label for this catalog member. The IDM statement in the procedure specifies the intermittent demand model and the options used to control the parameter estimation process for the model.

Syntax: HPFIDMSPEC Procedure

The following statements are used with the HPFIDMSPEC procedure.

PROC HPFIDMSPEC *options* **;**
IDM *options* **;**

Functional Summary

Table 9.1 summarizes the statements and options that control the HPFIDMSPEC procedure.

Table 9.1 PROC HPFFIDMSPEC Functional Summary

Description	Statement	Option
Statements		
Specifies the intermittent demand model	IDM	
Model Repository Options		
Specifies the model specification label	PROC HPFIDMSPEC	LABEL=
Specifies the model specification name	PROC HPFIDMSPEC	NAME=
Specifies the model repository	PROC HPFIDMSPEC	REPOSITORY=
Intermittent Demand Model Options		
Specifies the model for average demand	IDM	AVERAGE=
Specifies the base value	IDM	BASE=
Specifies the model for demand intervals	IDM	INTERVAL=

Table 9.1 *continued*

Description	Statement	Option
Specifies the model for demand sizes	IDM	SIZE=
Exponential Smoothing Model Options		
Specifies the model selection criterion	IDM	CRITERION=
Specifies the damping weight parameter initial value	IDM	DAMPPARM=
Specifies the damping weight parameter restrictions	IDM	DAMPREST=
Specifies the level weight parameter initial value	IDM	LEVELPARM=
Specifies the level weight parameter restrictions	IDM	LEVELREST=
Specifies median forecasts	IDM	MEDIAN
Specifies the time series forecasting model	IDM	METHOD=
Specifies that the smoothing model parameters are fixed values	IDM	NOEST
Specifies that stable parameter estimates are not required	IDM	NOSTABLE
Specifies the time series transformation	IDM	TRANSFORM=
Specifies the trend weight parameter initial value	IDM	TRENDPARM=
Specifies the trend weight parameter restrictions	IDM	TRENDREST=

PROC HPFIDMSPEC Statement

PROC HPFIDMSPEC *options* **;**

The following options can be used in the PROC HPFIDMSPEC statement.

LABEL=*SAS-label*
specified a descriptive label for the model specification to be stored in the SAS catalog or external file reference. The LABEL= option can also be specified as SPECLABEL=.

NAME=*SAS-name*
names the model specification to be stored in the SAS catalog or external file reference. The NAME= option can also be specified as SPECNAME=.

REPOSITORY=*SAS-catalog-name* | *SAS-file-reference*
names the SAS catalog or external file reference to contain the model specification. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=.

IDM Statement

IDM *options* **;**

The IDM statement is used to specify an intermittent demand model. An intermittent demand series can be analyzed in two ways: individually modeling both demand interval and size component, or jointly modeling these components by using the average demand component (demand size divided by demand interval). The IDM statement specifies the two smoothing models to be used to forecast the demand interval component (INTERVAL= option) and the demand size component (SIZE= option), or specifies the single smoothing model to be used to forecast the average demand component (AVERAGE= option). Therefore, two smoothing models (INTERVAL= and SIZE= options) must be specified or one smoothing model (AVERAGE= option) must be specified. Only one IDM statement can be specified.

The following options can be specified in the IDM statement.

AVERAGE=(*smoothing-model-options* **)**
specifies the smoothing model used to forecast the demand average component. See the section "Smoothing Model Suboptions for IDM Statement Options" on page 309.

BASE=AUTO | *number*
specifies the base value of the time series used to determine the demand series components. The demand series components are determined based on the departures from this base value. If a base value is specified, this value is used to determine the demand series components. If BASE=AUTO is specified, the time series properties are used to automatically adjust the time series. For the common definition of Croston's method, use BASE=0, which defines departures based on zero. The default is BASE=AUTO.

Given a time series y_t and base value b the time series is adjusted by the base value to create the base adjusted time series, $x_t = y_t - b$. Demands are assumed to occur when the base adjusted series is nonzero (or when the time series y_t departs from the base value b).

When BASE=AUTO, the base value is automatically determined by the time series median, minimum, and maximum value and the INTERMITTENT= option value of the FORECAST statement.

INTERVAL=(*smoothing-model-options* **)**
specifies the smoothing model used to forecast the demand interval component. See the section "Smoothing Model Suboptions for IDM Statement Options" on page 309.

SIZE=(*smoothing-model-options* **)**
specifies the smoothing model used to forecast the demand size component. See the section "Smoothing Model Suboptions for IDM Statement Options" on page 309.

Smoothing Model Suboptions for IDM Statement Options

The smoothing model options are specified as suboptions of the INTERVAL= option, SIZE= option, and AVERAGE= options. They describe how to forecast the demand interval, demand size, and average demand components, respectively.

The following describes the smoothing model options.

BOUNDS=(*number***,** *number* **)**
specifies the component forecast bound. See the section "Smoothing Model Parameter Specification Options" on page 313.

CRITERION=*option*

SELECT=*option*
specifies the model selection criterion (statistic of fit) to be used to select from several candidate models. This option is often used in conjunction with the HOLDOUT= option specified in the FORECAST statement. The CRITERION= option can also be specified as SELECT=. The default is CRITERION=RMSE.

The following list shows the valid values for the CRITERION= option and the statistics of fit these option values specify:

SSE	sum of square error
MSE	mean square error
RMSE	root mean square error
UMSE	unbiased mean square error
URMSE	unbiased root mean square error
MAXPE	maximum percent error
MINPE	minimum percent error
MPE	mean percent error
MAPE	mean absolute percent error
MDAPE	median absolute percent error
GMAPE	geometric mean absolute percent error
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MPPE	mean predictive percent error
MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median absolute predictive percent error
GMAPPE	geometric mean absolute predictive percent error

MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error
MSPE	mean symmetric percent error
SMAPE	symmetric mean absolute percent error
MDASPE	median absolute symmetric percent error
GMASPE	geometric mean absolute symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error
MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MAXERR	maximum error
MINERR	minimum error
ME	mean error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R-square
ADJRSQ	adjusted R-square
AADJRSQ	Amemiya's adjusted R-square
RWRSQ	random walk R-square
AIC	Akaike information criterion
AICC	finite sample corrected AIC
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion

DAMPPARM=*number*
specifies the damping weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 313.

DAMPREST=(*number***,** *number* **)**
specifies the damping weight parameter restrictions. SSee the section "Smoothing Model Parameter Specification Options" on page 313.

LEVELPARM=*number*
specifies the level weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 313.

LEVELREST=(*number***,** *number* **)**
specifies the level weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 313.

MEDIAN
specifies that the median forecast values are to be estimated. Forecasts can be based on the mean or median. By default the mean value is provided. If no transformation is applied to the actual series with the TRANSFORM= option, the mean and median component forecast values are identical.

METHOD=*method-name*
specifies the forecasting model to be used to forecast the demand component. A single model can be specified, or a group of candidate models can be specified. If a group of models is specified, the model used to forecast the accumulated time series is selected based on the CRITERION= option of the IDM statement and the HOLDOUT= option of the FORECAST statement. The default is METHOD=BESTN. The following forecasting models are provided:

SIMPLE	simple (single) exponential smoothing
DOUBLE	double (Brown) exponential smoothing
LINEAR	linear (Holt) exponential smoothing
DAMPTREND	damped trend exponential smoothing
BESTN	best candidate nonseasonal smoothing model (SIMPLE, LINEAR, DAMPTREND)

NOEST
specifies that the smoothing model parameters are fixed values. To use this option, all of the smoothing model parameters must be explicitly specified. By default, the smoothing model parameters are optimized.

NOSTABLE
specifies that the smoothing model parameters are not restricted to the additive invertible region of the parameter space. By default, the smoothing model parameters are restricted to be inside the additive invertible region of the parameter space.

TRANSFORM=*option*
specifies the time series transformation to be applied to the demand component. The following transformations are provided:

NONE	no transformation
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5
AUTO	Automatically choose between NONE and LOG based on model selection criteria. This option is the default.

When the TRANSFORM= option is specified, the demand component must be strictly positive. After the demand component is transformed, the model parameters are estimated using the transformed

component. The forecasts of the transformed component are then computed, and finally the transformed component forecasts are inverse transformed. The inverse transform produces either mean or median forecasts depending on whether the MEDIAN option is specified.

TRENDPARM=*number*
specifies the trend weight parameter initial value. See the section "Smoothing Model Parameter Specification Options" on page 313.

TRENDREST=(*number*, *number* **)**
specifies the trend weight parameter restrictions. See the section "Smoothing Model Parameter Specification Options" on page 313.

The following shows the defaults values of the smoothing model options that are used when the options are not specified.

For the demand interval component the defaults are:

```
interval=( transform=auto
           method=bestn
           levelrest=(0.001 0.999)
           trendrest=(0.001 0.999)
           damprest =(0.001 0.999)
           criterion=rmse
           bounds=(1,.)
         )
```

For the demand size component the defaults are:

```
size=(    transform=auto
          method=bestn
          levelrest=(0.001 0.999)
          trendrest=(0.001 0.999)
          damprest =(0.001 0.999)
          criterion=rmse
        )
```

For the average demand component the defaults are:

```
average=( transform=auto
          method=bestn
          levelrest=(0.001 0.999)
          trendrest=(0.001 0.999)
          damprest =(0.001 0.999)
          criterion=rmse
        )
```

Details: HPFIDMSPEC Procedure

Smoothing Model Parameter Specification Options

The parameter options are used to specify smoothing model parameters. If the parameter restrictions are not specified the default is (0.001 0.999), which implies that the parameters are restricted between 0.001 and 0.999. Parameters and their restrictions are required to be greater than or equal to –1 and less than or equal to 2. Missing values indicate no lower and/or upper restriction. If the parameter initial values are not specified, the optimizer uses a grid search to find an appropriate initial value.

Smoothing Model Forecast Bounds Options

Specifies the demand component forecast bounds. The forecast bounds restrict the component forecasts. The default for demand interval forecasts is BOUNDS=1. The lower bound for the demand interval forecast must be greater than one. The default for demand size forecasts is BOUNDS=(.,.) or no bounds. The demand size forecasts bounds are applied after the forecast is adjusted by the base value.

Examples: HPFIDMSPEC Procedure

Example 9.1: Various Kinds of IDM Model Specifications

The following statements illustrate typical uses of the IDM statement:

```
proc hpfidmspec repository=mymodels
                name=model1
                label="Default Specification";
   idm;
run;

proc hpfidmspec repository=mymodels
                name=model2
                label="Demand Interval model only specification";
   idm interval=( transform=log );
run;

proc hpfidmspec repository=mymodels
                name=model3
                label="Demand Size model only specification";
   idm size=( method=linear );
run;

proc hpfidmspec repository=mymodels
                name=model4
```

```
                label="Croston's Method";
   idm interval=( method=simple )
       size    =( method=simple );
run;

proc hpfidmspec repository=mymodels
                name=model5
                label="Log Croston's Method";
   idm interval=( method=simple transform=log )
       size    =( method=simple transform=log );
run;

proc hpfidmspec repository=mymodels
                name=model6
                label="Average demand model specification";
   idm average=(method=bestn);
run;

title "Models Added to MYMODELS Repository";
proc catalog catalog=mymodels;
   contents;
run;
```

The default specification uses both the INTERVAL= option and SIZE= option defaults for the decomposed (Croston's) demand model and the AVERAGE= option defaults for the average demand model.

The models added to the model repository are shown in Output 9.1.1.

Output 9.1.1 Listing of Models in MYMODELS repository

Models Added to MYMODELS Repository

Contents of Catalog WORK.MYMODELS

#	Name	Type	Create Date	Modified Date	Description
1	MODEL1	XML	08/06/2020 03:16:06	08/06/2020 03:16:06	Default Specification
2	MODEL2	XML	08/06/2020 03:16:06	08/06/2020 03:16:06	Demand Interval model only specification
3	MODEL3	XML	08/06/2020 03:16:06	08/06/2020 03:16:06	Demand Size model only specification
4	MODEL4	XML	08/06/2020 03:16:06	08/06/2020 03:16:06	Croston's Method
5	MODEL5	XML	08/06/2020 03:16:06	08/06/2020 03:16:06	Log Croston's Method
6	MODEL6	XML	08/06/2020 03:16:06	08/06/2020 03:16:06	Average demand model specification
7	MYCROSTON	XML	08/06/2020 03:16:05	08/06/2020 03:16:05	Croston Method

Example 9.2: Automatically Choosing the Best Decomposed Demand Model

This example illustrates how to automatically choose the decomposed demand model by using mean absolute percent error (MAPE) as the model selection criterion.

```
proc hpfidmspec repository=mymodels
                name=auto1
                label="Automatically Selected Best IDM Model";
   idm interval=( method=simple transform=auto criterion=mape )
       size    =( method=simple transform=auto criterion=mape );
run;
```

The preceding model statements cause PROC HPFENGINE to fit two forecast models (simple and log simple exponential smoothing) to both the demand interval and size components. The forecast model that results in the lowest in-sample MAPE for each component is used to forecast the component.

The following statements illustrate how to automatically choose the average demand model by using MAPE as the model selection criterion.

```
proc hpfidmspec repository=mymodels
                name=auto2
                label="Automatically Selected Best IDM Model";
   idm average=( method=simple transform=auto criterion=mape );
run;
```

The preceding statements cause PROC HPFENGINE to fit two forecast models (simple and log simple exponential smoothing) to the average demand component. The forecast model that results in the lowest in-sample MAPE is used to forecast the component.

Combining the preceding two examples, the following example illustrates how to automatically choose between the decomposed demand model and the average demand model by using MAPE as the model selection criterion:

```
proc hpfidmspec repository=mymodels
                name=auto3
                label="Automatically Selected Best IDM Model";
   idm interval=( method=simple transform=auto criterion=mape )
       size    =( method=simple transform=auto criterion=mape )
       average =( method=simple transform=auto criterion=mape );
run;
```

The preceding model specification causes PROC HPFENGINE to automatically select between the decomposed demand model and the average demand model as described previously. The forecast model that results in the lowest in-sample MAPE is used to forecast the series.

Chapter 10
The HPFRECONCILE Procedure

Contents

Overview: HPFRECONCILE Procedure **318**
Getting Started: HPFRECONCILE Procedure **318**
Syntax: HPFRECONCILE Procedure **320**
Functional Summary 320
PROC HPFRECONCILE Statement 322
AGGBY Statement 326
AGGDATA Statement 326
BY Statement 327
DISAGGDATA Statement 327
ID Statement 328
Details: HPFRECONCILE Procedure **329**
Notation 329
Top-Down Reconciliation 330
Bottom-Up Reconciliation 334
Data Set Input/Output 335
Examples: HPFRECONCILE Procedure **342**
Example 10.1: Reconciling a Hierarchical Tree 342
Example 10.2: Aggregating Forecasts 345
Example 10.3: Disaggregating Forecasts 345
Example 10.4: Imposing Constraints 347

Overview: HPFRECONCILE Procedure

When the data are organized in a hierarchical fashion, there are often accounting constraints that link series at different levels of the hierarchy. For example, the total sales of a product by a retail company are the sum of the sales of the same product in all stores that belong to the company. It seems natural to require that the same constraints hold for the predicted values as well. Imposing such constraints during the forecasting process can be difficult or impossible. Therefore, the series are often forecast independently at different levels. The resulting forecasts, however, do not abide by the constraints that bind the original series. The after-the-fact process through which such constraints are enforced is called *reconciliation*.

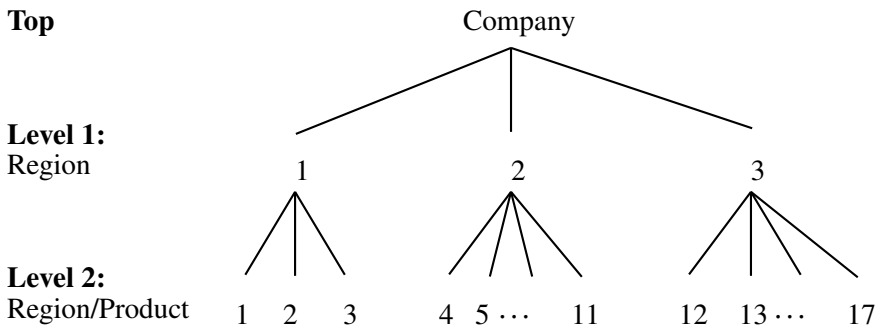
The HPFRECONCILE procedure reconciles forecasts of time series data at two different levels of a hierarchy. Optionally, the HPFRECONCILE procedure can disaggregate forecasts from upper-level forecasts or aggregate forecasts from lower-level forecasts. The procedure enables the user to specify the direction and the method of reconciliation, equality constraints, and bounds on the reconciled values.

Getting Started: HPFRECONCILE Procedure

This section outlines the use of the HPFRECONCILE procedure.

Consider the following hierarchical structure of the SASHELP.PRICEDATA data set.

Figure 10.1 Hierarchical Structure of SASHELP.PRICEDATA



Forecasts for the dependent variable sale are generated first at level 2, region / product , and then at level 1, region. The separate forecasts are then reconciled in a bottom-up manner by using the HPFRECONCILE procedure as shown in the following statements:

```
    /* Forecast series at level 2 (region/product) */

* Step 1: model selection;
proc hpfdiagnose data=sashelp.pricedata
                 outest=lvl2est
                 modelrepository=work.mymodels
                 prefilter=both
                 criterion=mape;
   id date interval=month;
   by region product;
   forecast sale;
```

```
   input price;
run;

* Step 2: estimation and forecasting ;
proc hpfengine data=sashelp.pricedata
               inest=lvl2est
               out=_null_
               outest=lvl2fest
               modelrepository=mymodels
               outfor=lvl2for;
   id date interval=month;
   by region product;
   forecast sale / task=select ;
   stochastic price;
run;

* Forecast aggregated series at level 1 (region);

* Step 1: model selection;
proc hpfdiagnose data=sashelp.pricedata
                 outest=lvl1est
                 modelrepository=work.mymodels
                 prefilter=both
                 criterion=mape;
   id date interval=month notsorted;
   by region;
   forecast sale / accumulate=total;
   input price / accumulate=average;
run;

* Step 2: estimation and forecasting;
proc hpfengine data=sashelp.pricedata
               inest=lvl1est
               out=_null_
               outest=lvl1fest
               modelrepository=mymodels
               outfor=lvl1for;
   id date interval=month notsorted;
   by region;
   forecast sale / task=select accumulate=total;
   stochastic price /accumulate=average;
run;

* Reconcile forecasts bottom up with default settings;
proc hpfreconcile disaggdata=lvl2for
                  aggdata=lvl1for
                  direction=BU
                  outfor=lvl1recfor;
   id date interval=month;
   by region product;
run;
```

Syntax: HPFRECONCILE Procedure

The HPFRECONCILE procedure is controlled by the following statements:

```
PROC HPFRECONCILE < options > ;
    AGGBY variables < / option > ;
    AGGDATA < options > ;
    BY variables < / option > ;
    DISAGGDATA < options > ;
    ID variable INTERVAL=interval < / options > ;
```

Functional Summary

The statements and options used with the HPFRECONCILE procedure are summarized in Table 10.1.

Table 10.1 PROC HPFRECONCILE Functional Summary

Description	Statement	Option
Statements		
Specify the AGGBY variables	AGGBY	
Name variables in the AGGDATA= data set	AGGDATA	
Specify the BY variables	BY	
Name variables in the DISAGGDATA= data set	DISAGGDATA	
Specify the time ID variable	ID	
Time ID Options		
Specify the alignment of time ID values	ID	ALIGN=
Specify the ending time ID value	ID	END=
Specify the date format	ID	FORMAT=
Specify the frequency	ID	INTERVAL=
Specify whether to allow for irregularities in the ID variable frequency	ID	IRREGULAR=
Specify the starting time ID value	ID	START=
Data Set Options		
Specify that the DISAGGDATA= data set is sorted by the BY variables	DISAGGDATA	BYVARSSORTED
Specify the disaggregated input data set (child level in the hierarchy)	PROC HPFRECONCILE	DISAGGDATA=
Specify the aggregated input data set (parent level in the hierarchy)	PROC HPFRECONCILE	AGGDATA=
Specify the output data set that contains the reconciled forecasts	PROC HPFRECONCILE	OUTFOR=
Specify the output data set that contains information regarding the infeasible problems	PROC HPFRECONCILE	OUTINFEASIBLE=

Table 10.1 *continued*

Description	Statement	Option
Specify the output data set that contains summary information	PROC HPFRECONCILE	OUTPROCINFO=
Specify the data set that contains constraints on the reconciled forecasts	PROC HPFRECONCILE	CONSTRAINT=
Specify that constraints be forced on the *predict* variable in the OUTFOR= data set when it conflicts with the aggregation constraint	PROC HPFRECONCILE	FORCECONSTRAINT
Specify that the OUTFOR= data set contains the RECDIFF variable	PROC HPFRECONCILE	RECDIFF
Name the variable that contains the actual values in the DISAGGDATA= data set	DISAGGDATA	ACTUAL=
Name the variable that contains the actual values in the AGGDATA= data set	AGGDATA	ACTUAL=
Name the variable that contains the predicted values in the DISAGGDATA= data set	DISAGGDATA	PREDICT=
Name the variable that contains the predicted values in the AGGDATA= data set	AGGDATA	PREDICT=
Name the variable that contains the lower confidence limit in the DISAGGDATA= data set	DISAGGDATA	LOWER=
Name the variable that contains the lower confidence limit in the AGGDATA= data set	AGGDATA	LOWER=
Name the variable that contains the upper confidence limit in the DISAGGDATA= data set	DISAGGDATA	UPPER=
Name the variable that contains the upper confidence limit in the AGGDATA= data set	AGGDATA	UPPER=
Name the variable that contains the prediction error in the DISAGGDATA= data set	DISAGGDATA	ERROR=
Name the variable that contains the prediction error in the AGGDATA= data set	AGGDATA	ERROR=
Name the variable that contains the standard error in the DISAGGDATA= data set	DISAGGDATA	STD=
Name the variable that contains the standard error in the AGGDATA= data set	AGGDATA	STD=
Error Message Options		
Specify the resolution of error and warning messages	HPFRECONCILE	ERRORTRACE=
Analysis Options		
Specify the aggregation method	PROC HPFRECONCILE	AGGREGATE=
Specify the confidence level	PROC HPFRECONCILE	ALPHA=
Specify method for confidence limits	PROC HPFRECONCILE	CLMETHOD=
Specify the reconciliation direction	PROC HPFRECONCILE	DIRECTION=
Specify the disaggregation function	PROC HPFRECONCILE	DISAGGREGATION=

Table 10.1 *continued*

Description	Statement	Option
Specify that `'.F'` missing values in PREDICT be treated as regular `'.'` missing values	PROC HPFRECONCILE	IGNOREMISSF
Specify that zeros forecasts be left unchanged	PROC HPFRECONCILE	LOCKZERO
Specify the maximum number of iteration of the optimizer	PROC HPFRECONCILE	MAXITER
Specify that only the prediction be reconciled	PROC HPFRECONCILE	PREDICTONLY
Specify sign constraint on the reconciled series	PROC HPFRECONCILE	SIGN=
Specify the method of computing standard errors	PROC HPFRECONCILE	STDMETHOD=
Specify bounds for the standard error	PROC HPFRECONCILE	STDDIFBD=
Specify that the loss function be weighted by the inverse of the prediction variances	PROC HPFRECONCILE	WEIGHTED

PROC HPFRECONCILE Statement

PROC HPFRECONCILE *options* **;**

The following options can be used in the PROC HPFRECONCILE statement.

Options Related to the Input Data Sets

AGGDATA=*SAS-data-set*

specifies the name of the SAS data set that contains the forecasts of the aggregated time series data. Typically, the AGGDATA= data set is generated by the OUTFOR= statement of the HPFENGINE procedure. If the AGGDATA= data set is not specified, only bottom-up reconciliation is allowed.

The AGGDATA= data set must contain a proper subset, possibly empty, of the BY variables present in the DISAGGDATA= data set. Such BY variables are called AGGBY variables. See the section "BY Statement" on page 327 for more details about BY and AGGBY variables.

See the section "AGGDATA= Data Set" on page 335 for more details about the AGGDATA= data set.

CONSTRAINT=*SAS-data-set*

specifies the name of the SAS data set that contains the constraints for the reconciled series. See the section "CONSTRAINT= Data Set" on page 337 for more details.

DISAGGDATA | DATA=*SAS-data-set*

specifies the name of the SAS data set that contains the forecast of the disaggregated time series data. Typically, the DISAGGDATA= data set is generated by the OUTFOR= statement of the HPFENGINE procedure.

If the DISAGGDATA= data set is not specified, the data set last opened is used. The dimensions of the DISAGGDATA= data set are greater than the dimensions of the AGGDATA= data set.

See the section "DISAGGDATA= Data Set" on page 336 for more details.

Options Related to the Output Data Sets

FORCECONSTRAINT
specifies whether the user-specified constraints should be forced on the PREDICT variable in the OUTFOR= data set when the problem is infeasible because the constraints are incompatible with the aggregation constraint. The default is to leave the input unmodified.

OUTFOR=*SAS-data-set*
specifies the name of the output SAS data set that contains the reconciled values.

OUTINFEASIBLE=*SAS-data-set*
specifies the name of the SAS data set that contains a summary of the nodes for which reconciliation failed because of a conflict between the constraints imposed by the user and the aggregation constraint.

OUTPROCINFO=*SAS-data-set*
names the output data set to contain the summary information of the processing done by PROC HPFRECONCILE. When you write a program to assess the status of the procedure's execution, it is easier to parse a data set than it is to look at or parse the SAS log.

RECDIFF
If the RECDIFF option is specified, the OUTFOR= data sets will contain a variable named RECDIFF that is the difference between the reconciled forecasts and the original forecasts.

Options Related to Error Messages

ERRORTRACE=*option*
specifies how often the error and warning messages should be printed to the log.

The following values are allowed:

DATASET	Messages are printed only one time at the end of the procedure run.
AGGBY	Messages are printed for each AGGBY group.
ID	Messages are printed for each ID value.

The default is ERRORTRACE=DATASET.

Options Related to the Analysis

AGGREGATE=TOTAL | AVERAGE
specifies whether the dependent variable in the AGGDATA= data set is the total sum or the average over the BY groups of the dependent variable in the DISAGGDATA= data set. The default is AGGREGATE=TOTAL.

ALPHA=*n*
specifies the level of the confidence limits when CLMETHOD=GAUSSIAN. The ALPHA= value must be between 0.0001 and 0.9999. When you specify ALPHA=α, the upper and lower confidence limits will have a $1-\alpha$ confidence level. The default is ALPHA=0.05, which produces 95% confidence intervals.

CLMETHOD=*option*
specifies the method used to compute confidence limits for the reconciled forecasts.

The following methods are provided:

GAUSSIAN	The confidence intervals are computed by assuming that the forecasts are approximately Gaussian.
SHIFT	The confidence intervals are computed by re-centering the original confidence intervals around the new forecasts.

The default value is CLMETHOD=SHIFT. See the section "Details: HPFRECONCILE Procedure" on page 329 for more information about the methods of computing confidence intervals.

DIRECTION= *reconciliation-direction*
specifies the reconciliation direction.

The following reconciliation values are allowed:

BU	bottom-up reconciliation
TD	top-down reconciliation

If the AGGDATA= data set is not specified, only DIRECTION=BU is allowed.

The default value is DIRECTION=BU.

See the section "Details: HPFRECONCILE Procedure" on page 329 for more information about the reconciliation directions available in PROC HPFRECONCILE.

DISAGGREGATION=DIFFERENCE | PROPORTIONS
specifies the type of loss function for top-down reconciliation.

DISAGGREGATION=PROPORTIONS is available only when all the forecasts at a given ID value share the same sign. See the section "Details: HPFRECONCILE Procedure" on page 329 for more information about the expressions of the loss function.

The default value is DISAGGREGATION=DIFFERENCE.

IGNOREMISSF
specifies that `'.F'` missing values in the PREDICT variable be treated as regular `'.'` missing values. If the IGNOREMISSF option is not specified, a `'.F'` missing value is interpreted as a failed forecast, and PROC HPFRECONCILE generates `'.F'` missing values for all forecasting variables in the OUTFOR= data set if that value is needed for computing the reconciled forecasts. If the IGNOREMISSF option is specified, observations that correspond to `'.F'` missing values are considered to belong to inactive series and therefore are not included in the reconciliation process.

LOCKZERO
specifies that zero values of the PREDICT variable in the DISAGGDATA= data be considered locked equalities. This option is available only when DIRECTION=TD. When the LOCKZERO option is active, a zero value for PREDICT in the DISAGGDATA= set implies a zero value for the corresponding observation in the OUTFOR= data set. However, if constraints are specified in the CONSTRAINT= data set for that observation, these constraints have precedence over the LOCKZERO option. Note that an unlocked equality constraint in the CONSTRAINT= data also has precedence over the LOCKZERO

option. Similarly, an unlocked equality whose value is zero is not converted to a locked equality, even though the LOCKZERO option is specified.

MAXITER=*k*
specifies the maximum number of predictor-corrector iterations performed by the interior point algorithm. The value *k* is an integer between 1 and the largest four-byte, signed integer, $2^{31} - 1$. The default value is MAXITER=100.

PREDICTONLY
specifies that only the predicted value be reconciled.

SIGN=*option*
specifies the sign constraint on the reconciled series.

Valid values are as follows:

MIXED	if the output series can have any sign. This is the default.
NONNEGATIVE | POSITIVE	if the output series are supposed to be nonnegative.
NONPOSITIVE | NEGATIVE	if the output series are supposed to be nonpositive.

STDMETHOD=*option*
specifies the method used to compute standard errors for the reconciled forecasts.

The following methods are provided:

UNCHANGED	Reconciled standard errors are the original standard errors.
AGG	Reconciled standard errors are proportional to the original aggregated standard errors.
DISAGG	Reconciled standard errors are proportional to the original disaggregated standard errors.

The default values are STDMETHOD=UNCHANGED. See the section "Details: HPFRECONCILE Procedure" on page 329 for more information about the methods of computing standard errors.

STDDIFBD=*n*
specifies a positive number that defines boundaries for the percentage difference between the original standard error and the reconciled standard error. If the percentage difference is greater than the values specified in the STDDIFBD= option, the reconciled standard error will be equal to the boundary value. For example, if STDDIFBD=0.3, the reconciled standard errors will be within a 30% band of the original standard errors.

The default value is STDDIFBD=0.25.

WEIGHTED
specifies that the loss function for top-down reconciliation be weighted by the inverse of the variance of the input forecasts.

AGGBY Statement

AGGBY *variables* **;**

When DIRECTION=BU and the AGGDATA= data set is not specified, the AGGBY statement can be used to specify the AGGBY variables, which is a proper subset of the BY variables that should appear in the OUTFOR= data set.

When DIRECTION=BU and neither the AGGDATA= data set nor the AGGBY statement is specified, the OUTFOR= data set contains no BY variables.

If the AGGDATA= data set is specified, the AGGBY statement is ignored. Note that when DIRECTION=TD, the AGGDATA= data set must be specified. Hence, the AGGBY statement is valid only when DIRECTION=BU.

AGGDATA Statement

AGGDATA < *options* > **;**

The AGGDATA statement enables the user to specify custom names for forecasting variables in the AGGDATA= data set. The default names are ACTUAL, PREDICT, LOWER, UPPER, ERROR, and STD.

The following options can be specified in the AGGDATA statement.

ACTUAL=*variable-name*
specifies the name of the variable in the AGGDATA= data set that contains the actual values.

PREDICT=*variable-name*
specifies the name of the variable in the AGGDATA= data set that contains the predicted values.

LOWER=*variable-name*
specifies the name of the variable in the AGGDATA= data set that contains the lower confidence limit values.

UPPER=*variable-name*
specifies the name of the variable in the AGGDATA= data set that contains the upper confidence limit values.

ERROR=*variable-name*
specifies the name of the variable in the AGGDATA= data set that contains the error values.

STD=*variable-name*
specifies the name of the variable in the AGGDATA= data set that contains the standard error values.

BY Statement

BY *variables* < *NOTSORTED* > **;**

The BY statement defines separate groups of observations for the DISAGGDATA= data set. BY variables can be either character or numeric.

All BY variables must exist in the DISAGGDATA= data set. Conversely, only a strict subset of or none of the BY variables must be present in the AGGDATA= data set. The BY variables that are present in the AGGDATA= data set are called AGGBY variables. Since the AGGBY variables form a proper subset of the BY variables, their number must be less than the number of BY variables. PROC HPFRECONCILE finds the AGGBY variables by comparing the variables in the BY statement with the variables in the AGGDATA= data set. When DIRECTION=BU and the AGGDATA= data set is not specified, the AGGBY statement can be used to specify AGGBY variables. See the section "AGGBY Statement" on page 326 for more details.

A group of observations with the same combination of values for the AGGBY variables is called an AGGBY group. The AGGBY groups must follow the same sorting order in both the DISAGGDATA= and the AGGDATA= data sets. However, some groups can be missing from either data set if the NOTSORTED option is not specified. When the NOTSORTED option is specified, all AGGBY groups must be present in both data sets and must follow the same order.

DISAGGDATA Statement

DISAGGDATA < *options* > **;**

The DISAGGDATA statement enables you to specify names for forecasting variables in the DISAGGDATA= data set. The default names are ACTUAL, PREDICT, LOWER, UPPER, ERROR, and STD.

The following options can be specified in the DISAGGDATA statement.

ACTUAL=*variable-name*
specifies the name of the variable in the DISAGGDATA= data set that contains the actual values.

PREDICT=*variable-name*
specifies the name of the variable in the DISAGGDATA= data set that contains the predicted values.

LOWER=*variable-name*
specifies the name of the variable in the DISAGGDATA= data set that contains the lower confidence limit values.

UPPER=*variable-name*
specifies the name of the variable in the DISAGGDATA= data set that contains the upper confidence limit values.

ERROR=*variable-name*
specifies the name of the variable in the DISAGGDATA= data set that contains the error values.

STD=*variable-name*
specifies the name of the variable in the DISAGGDATA= data set that contains the standard error values.

BYVARSSORTED
specifies that the DISAGGDATA= data set be sorted by the BY variables. This option improves input/output performance when there is an index defined on the BY variables. Use of an index degrades the performance as compared to processing a sorted data set. If the BYVARSSORTED option is not specified, PROC HPFRECONCILE uses only the index for processing and disregards the sorting order. If you specify the BYVARSSORTED option in the DISAGGDATA statement, PROC HPFRECONCILE exploits the sorting order to achieve better performance and uses the index minimally.

ID Statement

ID *variable INTERVAL=interval </options>* **;**

The ID statement names a numeric variable that identifies observations in the input and output data sets. The ID variable's values are assumed to be SAS date, time, or datetime values. In addition, the ID statement specifies the frequency associated with the time series. If the ID statement is specified, the INTERVAL= option must also be specified, and the ID variable must be present and must have the same frequency in both the DISAGGDATA= data set and the AGGDATA= data set. If an ID statement is not specified, then a number derived from the observation number, with respect to the BY group, is used as the time ID. The number is derived so as to align the last observations of all BY groups.

The following options can be used in the ID statement.

ALIGN=*option*
controls the alignment of SAS dates used to identify output observations. Internal processing uses aligned versions of the values of START= and END= options (if specified) and values of ID variable in input observations. The ALIGN= option accepts the following values: BEGIN, MIDDLE, and END. BEGIN is the default.

END=*option*
specifies a SAS date, datetime, or time value that represents the date at which the reconciliation should end. If the largest time ID variable value is less than the END= value, this option has no effect.

FORMAT=*option*
specifies a SAS format used for the DATE variable in the output data sets. The default format is the same as that of the DATE variable in the DATA= data set.

INTERVAL=*interval*
specifies the frequency of the input time series. The frequency must be the same for all input data sets. For example, if the input data sets consist of quarterly observations, then INTERVAL=QTR should be used. See the *SAS/ETS User's Guide* for the intervals that can be specified.

IRREGULAR
specifies whether to allow for irregularities in the ID variable frequency. By default, irregularities are not allowed. That is, all ID values that correspond to the INTERVAL= frequency must be present between the START= and END= values in both AGGDATA= and DISAGGDATA= data sets.

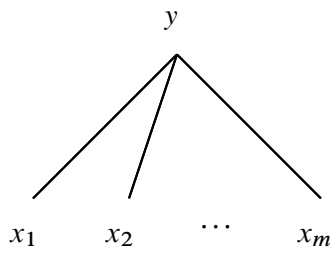
START=*option*
specifies a SAS date, datetime, or time value that represents the time ID value at which the reconciliation should begin. This option can be used to limit the reconciliation process only to forecasts that are outside the historical period. For example, START="&sysdate"D uses the automatic macro variable SYSDATE to start the reconciliation at the current date.

Details: HPFRECONCILE Procedure

Notation

Assume a two-level hierarchical structure as depicted in Figure 10.2.

Figure 10.2 Hierarchical Structure



Let y_t be the values of the parent series at time t, and let $\mathbf{x}_t = [x_{1,t}, x_{2,t}, \ldots, x_{m,t}]'$ be the vector child series at time t, $t = 1, \ldots, T$. As usual, indicate by $\hat{y}_t$ and $\hat{\mathbf{x}}_t$ the pre-reconciliation forecasts of y_t and $\mathbf{x}_t$, respectively, and denote by $\hat{\boldsymbol{\sigma}}_t = [\hat{\sigma}_{1,t}, \hat{\sigma}_{2,t}, \ldots, \hat{\sigma}_{m,t}]'$ the vector of prediction standard error for $\hat{\mathbf{x}}_t$. Denote by $\hat{\boldsymbol{\Sigma}}$ the diagonal matrix whose main diagonal is $\hat{\boldsymbol{\sigma}}_t^2$. Let the superscript tilde indicate the reconciled values, so that $\tilde{y}_t$ and $\tilde{\mathbf{x}}_t$ indicate the reconciled values of $\hat{y}_t$ and $\hat{\mathbf{x}}_t$, respectively. The number of child series m can vary with t; however, for simplicity, it is considered fixed in the following discussion.

At each time t, the values of the series $x_{i,t}$, $i = 1 \ldots, m$, and y_t are bound by an aggregation constraint. For example, if the x_i's are the sales at store level for a retail company, then y_t can be either the total sales at company level or the average sales per store. The aggregation constraint is $y_t = \sum_{i=1}^{m} x_{i,t}$, when you specify the AGGREGATE=TOTAL option of the PROC HPFRECONCILE statement. If instead you specify the AGGREGATE=AVERAGE option, the constraint is $y_t = \frac{1}{m} \sum_{i=1}^{m} x_{i,t}$.

If you need to have forecasts at both levels of the hierarchy, it is often more convenient to produce statistical forecasts separately for each series. However, the resulting forecasts do not abide by the aggregation constraint that binds the original series. The after-the-fact process through which the statistical forecasts are modified to enforce the aggregation constraint is called *reconciliation*.

By determining whether the upper-level forecasts or the lower-level forecasts are adjusted to meet the aggregation constraint, you can distinguish between bottom-up (BU) and top-down (TD) reconciliation.

PROC HPFRECONCILE enables you to impose constraints on the individual reconciled forecasts. For example, you can require that $\tilde{x}_1 = 10$ and $\tilde{x}_2 \geq 15$.

Top-Down Reconciliation

The goal of top-down (TD) reconciliation is to adjust the statistical forecasts $\hat{x}_{i,t}$ to obtain a new series $\{\tilde{x}_{i,t}\}$ of reconciled forecasts so that the sum of the reconciled forecasts at each fixed time t is equal to $\hat{y}_t$ and the sum satisfies the constraints that you specify in the CONSTRAINT= data set.

The problem can be restated as follows: minimize with respect to $\tilde{\mathbf{x}}$ a quadratic loss function

$$L(\tilde{\mathbf{x}}_t; \hat{\mathbf{x}}_t)$$

subject to the following constraints:

- the *top-down constraint*

$$\sum_{i=1}^{m} \tilde{x}_{i,t} = \hat{y}_t$$

- the equality constraints

$$\tilde{x}_{i,t} = e_{i,t} \qquad i \in E_t$$

- the lower bounds

$$\tilde{x}_{i,t} \geq l_{i,t} \qquad i \in L_t$$

- the upper bounds

$$\tilde{x}_{i,t} \leq u_{i,t} \qquad i \in U_t$$

where E_t, L_t, and U_t are subsets of $\{1, 2, \ldots, m\}$.

Equality constraints on the reconciled predicted values can be imposed with the EQUALITY variable of the CONSTRAINT= data set, or by using the WEIGHTED option with zero standard errors in the DISAGGDATA= data set. Bounds can be imposed either with the SIGN= option or with the LOWER and UPPER variables of the CONSTRAINT= data set.

PROC HPFRECONCILE employs an iterative interior point algorithm to solve the constrained quadratic optimization problem.

Choice of Loss Function

The loss function takes the following functional forms:

- When DISAGGREGATION=DIFFERENCE, the loss function is

$$L(\tilde{\mathbf{x}}_t; \hat{\mathbf{x}}_t) = (\tilde{\mathbf{x}}_t - \hat{\mathbf{x}}_t)' \mathbf{W}^{-1} (\tilde{\mathbf{x}}_t - \hat{\mathbf{x}}_t)$$

- When DISAGGREGATION=PROPORTIONS, the loss function is

$$L(\tilde{\mathbf{x}}_t; \hat{\mathbf{x}}_t) = (\tilde{\mathbf{x}}_t - \hat{\mathbf{x}}_t)' \hat{\mathbf{X}}^{-\frac{1}{2}} \mathbf{W}^{-1} \overline{\hat{\mathbf{X}}^{-\frac{1}{2}}} (\tilde{\mathbf{x}}_t - \hat{\mathbf{x}}_t)$$

where $\mathbf{W}$ is a positive semidefinite matrix of weights independent of $\tilde{\mathbf{x}}_t$, $\hat{\mathbf{X}}^{-\frac{1}{2}}$ is a diagonal matrix with the square root of $\hat{\mathbf{x}}_t$ on the main diagonal, and $\overline{\hat{\mathbf{X}}^{-\frac{1}{2}}}$ is its complex conjugate.

If the WEIGHTED option is not specified, $\mathbf{W}$ is the identity matrix $\mathbf{I}$. If the WEIGHTED option is specified, $\mathbf{W} = \hat{\mathbf{\Sigma}}$, the diagonal matrix with the estimated variances $\hat{\sigma}^2_{i,t}$ of $\hat{x}_{i,t}$ on the main diagonal. If an observation has zero prediction standard error, $\hat{\sigma}_{j,t} = 0$, it is equivalent to imposing a locked equality constraint equal to the original forecast, $\tilde{x}_{j,t} = \hat{x}_{j,t}$. However, if a locked equality constraint is specified in the CONSTRAINT= data set for that observation, the locked equality constraint has precedence over the zero weight.

When DISAGGREGATION=DIFFERENCE, the loss function is defined for any value of $\hat{\mathbf{x}}_t$.

When DISAGGREGATION=PROPORTIONS, the loss function is defined only when all $\hat{x}_{i,t}$ are different from zero. The solutions can be extended to the zero cases by letting $\tilde{x}_{i,t} := 0$ when $\hat{x}_{i,t} = 0$, if there is at least one $\hat{x}_{j,t}$ that is different from zero. The case where all $\hat{x}_{j,t}$ are zero is handled by setting $\tilde{x}_{i,t} := \frac{\hat{y}_t}{m}$ when AGGREGATE=TOTAL and $\tilde{x}_{i,t} := \hat{y}_t$ when AGGREGATE=AVERAGE.

Unconstrained Solutions

When the only constraint is the top-down constraint and $\mathbf{W} = \mathbf{I}$, the top-down problem admits intuitive solutions.

When DISAGGREGATION=DIFFERENCE, the loss function becomes

$$L(\tilde{\mathbf{x}}_t; \hat{\mathbf{x}}_t) = \sum_{i=1}^{m} (\hat{x}_{i,t} - \tilde{x}_{i,t})^2$$

This leads to the following solution

$$\tilde{x}_{i,t} = \hat{x}_{i,t} + \frac{\hat{r}_t}{m}$$

where $\hat{r}_t$ is the forecasting aggregate error—that is, when AGGREGATE=TOTAL,

$$\hat{r}_t := \hat{y}_t - \sum_{i=1}^{m} \hat{x}_{i,t}$$

and, when AGGREGATE=AVERAGE,

$$\hat{r}_t := m\hat{y}_t - \sum_{i=1}^{m} \hat{x}_{i,t}$$

Thus, when DISAGGREGATION=DIFFERENCE, the reconciled forecast $\tilde{x}_{i,t}$ is found by equally splitting the aggregation error $\hat{r}_t$ among the lower-level forecasts $\hat{x}_{i,t}$.

Notice that even if all statistical forecasts $\hat{x}_{i,t}$ are strictly positive, the reconciled forecasts $\tilde{x}_{i,t}$ need not be so if no bounds are specified via the SIGN= option. In particular, $\hat{x}_{i,t} = 0$ does not imply $\tilde{x}_{i,t} = 0$.

If DISAGGREGATION=PROPORTIONS, the loss function becomes

$$L(\tilde{\mathbf{x}}_t; \hat{\mathbf{x}}_t) = \sum_{i=1}^{m} \frac{\left(\hat{x}_{i,t} - \tilde{x}_{i,t}\right)^2}{|\hat{x}_{i,t}|}$$

This leads to the following solutions

$$\tilde{x}_{i,t} = \hat{x}_{i,t} + \frac{|\hat{x}_{i,t}|}{\sum_{j=1}^{m} |\hat{x}_{j,t}|} \hat{r}_t$$

When AGGREGATE=TOTAL and all the $\hat{x}_{j,t}$ have the same sign, the solution resolves to

$$\tilde{x}_{i,t} = \frac{\hat{x}_{i,t}}{\sum_{j=1}^{m} \hat{x}_{j,t}} \hat{y}_t$$

When AGGREGATE=AVERAGE and all the $\hat{x}_{j,t}$ have the same sign, the solution resolves to

$$\tilde{x}_{i,t} = \frac{\hat{x}_{i,t}}{\sum_{j=1}^{m} \hat{x}_{j,t}} m \hat{y}_t$$

Thus, the reconciled forecast $\tilde{x}_{i,t}$ is found by disaggregating the upper-level forecasts according to the proportion that $\hat{x}_{i,t}$ represents in the total sum of the lower-level forecasts.

Missing Values

Missing values of type `'.F'` in the input are interpreted as failed forecasts. If a type `'.F'` missing value is detected in any of the variables that are needed to compute the reconciled prediction, then the reconciled prediction too takes the value `'.F'`. If the IGNOREMISSF option of the HPFRECONCILE statement is specified, the `'.F'` missing values are treated as `'.'` missing values.

When some of the predicted values $\hat{x}_{i,t}$ are missing, with any type of missing values different from `'.F'`, the missing values are replaced by the actual values $x_{i,t}$, if these are present. This is done to prevent bias between the aggregated and reconciled forecasts, which results from models in which missing values in the predictions are generated because of the presence of lagged variables. If the actual value is also missing, the series is excluded from the reconciliation process.

When you use the WEIGHTED option and the standard error is missing, the weight is assumed to be the average of the nonmissing variances. If all standard errors are missing, the weights are assumed to be all equal to one, which is equivalent to not using the WEIGHTED option.

Standard Errors

When STDMETHOD=UNCHANGED, the reconciled standard error $\tilde{\sigma}_{i,t}$ of $\tilde{x}_{i,t}$ is equal to the original standard error $\hat{\sigma}_{i,t}$ of $\hat{x}_{i,t}$.

When STDMETHOD=DISAGG, the reconciled standard error is proportional to the original disaggregated standard error and is computed as follows:

$$\tilde{\sigma}_{i,t} = |w|\hat{\sigma}_{i,t}$$

where $w = \frac{\tilde{x}_{i,t}}{\hat{x}_{i,t}}$.

When STDMETHOD=AGG, the reconciled standard error of $\tilde{x}_{i,t}$ is proportional to the aggregated standard error,

$$\tilde{\sigma}_{i,t} = |\tilde{p}_{i,t}|\hat{\sigma}_t$$

where $\tilde{p}_{i,t} = \frac{\tilde{x}_{i,t}}{\tilde{y}_t}$ and $\hat{\sigma}_t$ is the standard deviation of $\hat{y}_t$.

If the selected method for the standard errors fails, PROC HPFRECONCILE tries to use a different method and displays a warning message in the log. For example, if STDMETHOD=DISAGG and the standard error is missing in the DISAGGDATA= data set, STDMETHOD=AGG is used instead, if possible. In such a case, the _RECONSTATUS_ variable identifies the observation that was not reconciled according to your preferences. You can also use the ERRORTRACE=ID option to display a message in the log that identifies the ID values for which the standard error was not reconciled according to your specification.

Care should be taken in interpreting standard errors when constraints are imposed on the reconciled forecasts. The presence of constraints renders the meaning of the reconciled standard errors ambiguous.

Confidence Limits

When CLMETHOD=SHIFT, the reconciled confidence limits are computed by re-centering the original confidence limits around the reconciled predicted values.

When CLMETHOD=GAUSS, the reconciled confidence limits are computed by assuming that the series is Gaussian with standard error equal to the reconciled standard error.

If the selected method for the confidence limits fails, PROC HPFRECONCILE tries to use a different method and displays a warning message in the log. For example, if CLMETHOD=SHIFT and the confidence limits are missing in the DISAGGDATA= data set, CLMETHOD=GAUSS is used instead. In such a case, the _RECONSTATUS_ variable identifies the observation that was not reconciled according to your preferences. You can also use the ERRORTRACE=ID option to display a message in the log that identifies the ID values for which the confidence limits were not reconciled according to your specification.

Care should be used in interpreting confidence limits when constraints are imposed on the reconciled forecasts. The presence of constraints renders the meaning of reconciled confidence limits ambiguous.

Bottom-Up Reconciliation

The goal of bottom-up (BU) reconciliation is to adjust $\hat{y}_t$ to obtain a new series $\{\tilde{y}_t\}$ of reconciled forecasts so that $\{\tilde{y}_t\}$ satisfies the aggregation constraint.

When AGGREGATE=TOTAL, this is done by setting

$$\tilde{y}_t = \sum_{i=1}^{m} \hat{x}_{i,t} \qquad t = 1, 2, \ldots$$

When AGGREGATE=AVERAGE, this is done by setting

$$\tilde{y}_t = \frac{1}{m} \sum_{i=1}^{m} \hat{x}_{i,t} \qquad t = 1, 2, \ldots$$

Because the bottom-up problem is exactly identified and admits a unique solution, additional constraints on $\tilde{y}_t$ specified in the CONSTRAINT= data set are either already satisfied by the solution or result in an infeasible problem that will be flagged by the _RECONSTATUS_ variable in the OUTFOR= data set.

Missing Predicted Values

Missing values of type `'.F'` in the input are interpreted as failed forecasts. If a type `'.F'` missing value is detected in any of the variables that are needed to compute the reconciled prediction, then the reconciled prediction also takes the value `'.F'`. If the IGNOREMISSF option of the HPFRECONCILE statement is specified, the `'.F'` missing values are treated as `'.'` missing values.

When some of the predicted values $\hat{x}_{i,t}$ are missing, with missing value different from `'.F'`, the missing values are replaced by the actual values $x_{i,t}$, if these are present. This is done to prevent bias between the aggregated and reconciled forecasts, which results from models in which missing values in the predictions are generated because of the presence of lagged variables. However, if all predicted values $\hat{x}_{i,t}$ are missing for a given time ID t, then the reconciliation process is considered failed for this t, even though the actual values $x_{i,t}$ are not missing.

Standard Errors

When STDMETHOD=UNCHANGED, the reconciled standard error $\tilde{\sigma}_t$ of $\tilde{y}_t$ is equal to the original standard error $\hat{\sigma}_t$ of $\hat{y}_t$.

When STDMETHOD=AGG, the reconciled standard error is proportional to the original aggregated standard error and is computed as follows:

$$\tilde{\sigma}_t = |w| \hat{\sigma}_t$$

where $w = \frac{\tilde{y}_t}{\hat{y}_t}$.

If STDMETHOD=DISAGG, the reconciled standard error $\tilde{\sigma}_t$ is

$$\tilde{\sigma}_t = \sqrt{\sum_{i=1}^{m} \hat{\sigma}_{i,t}^2}$$

when AGGREGATE=TOTAL, and

$$\tilde{\sigma}_t = \frac{1}{m}\sqrt{\sum_{i=1}^{m}\hat{\sigma}_{i,t}^2}$$

when AGGREGATE=AVERAGE.

If the selected method for the standard errors fails, PROC HPFRECONCILE tries to use a different method and displays a warning message in the log. For example, if STDMETHOD=AGG and the standard error is missing in the AGGDATA= data set, STDMETHOD=DISAGG is used instead, if possible. In such a case, the _RECONSTATUS_ variable identifies the observation that was not reconciled according to your preferences. You can also use the ERRORTRACE=ID option to display a message in the log that identifies the ID values for which the standard error was not reconciled according to your specification.

Confidence Limits

When CLMETHOD=SHIFT, the reconciled confidence limits are computed by re-centering the original confidence limits around the reconciled predicted values.

When CLMETHOD=GAUSS, the reconciled confidence limits are computed by assuming that the series is Gaussian with standard error equal to the reconciled standard error.

If the selected method for the confidence limits fails, PROC HPFRECONCILE tries to use a different method and displays a warning message in the log. For example, if CLMETHOD=SHIFT and the confidence limits are missing in the AGGDATA= data set, CLMETHOD=GAUSS is used instead, if possible. In such a case, the _RECONSTATUS_ variable identifies the observation that was not reconciled according to your preferences. You can also use the ERRORTRACE=ID option to display a message in the log that identifies the ID values for which the confidence limits were not reconciled according to your specification.

Data Set Input/Output

AGGDATA= Data Set

The AGGDATA= data set contains either a proper subset of or none of the variables specified in the BY statement, the time ID variable in the ID statement (when this statement is specified), and the following variables:

NAME	variable name
PREDICT	predicted values

The following variables can optionally be present in the AGGDATA= data set and are used when available. If not present, their value is assumed to be missing for computational purposes.

ACTUAL	actual values
LOWER	lower confidence limits
UPPER	upper confidence limits

ERROR	prediction errors
STD	prediction standard errors

Typically, the AGGDATA= data set is generated by the OUTFOR= option of the HPFENGINE procedure. See Chapter 5, "The HPFENGINE Procedure," for more details.

The AGGDATA= data set must be either sorted by the AGGBY variables and by the ID variable (when the latter is specified) or indexed on the AGGBY variables. Even when the data set is indexed, if the ID variable is specified, its values must be sorted in ascending order within each AGGBY group. See section "BY Statement" on page 327 for details about AGGBY variables and AGGBY groups.

You can specify custom names for the variables in the AGGDATA= data set by using the AGGDATA statement. See the section "AGGDATA Statement" on page 326 for more details.

DISAGGDATA= Data Set

The DISAGGDATA= data set contains the variables specified in the BY statement, the variable in the ID statement (when this statement is specified), and the following variables:

NAME	variable name
PREDICT	predicted values

The following variables can optionally be present in the DISAGGDATA= data set and are used when available. If not present, their value is assumed to be missing for computational purposes.

ACTUAL	actual values
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors
STD	prediction standard errors

Typically, the DISAGGDATA= data set is generated by the OUTFOR= option of the HPFENGINE procedure. See Chapter 5, "The HPFENGINE Procedure," for more details.

The DISAGGDATA= data set must be either sorted by the BY variables and by the ID variable when the latter is specified, or indexed on the BY variables. If the variable _NAME_ is present and has multiple values, then the index must be a composite index on BY variables and _NAME_, in that order. If _NAME_ is present and has only one value, then the index can contain only BY variables. Even when the data set is indexed, if the ID variable is specified, its values must be sorted in ascending order within each BY, or BY and _NAME_ group, as applicable. Indexing the DISAGGDATA= data set on the BY variables when it is already sorted by the BY variables leads to less efficient and less scalable operation if the available memory is not sufficient to hold the disaggregated data for the AGGBY group that is being processed. The amount of memory required depends on, among other things, the length of the series, the number of BY groups for each AGGBY group, and the number and format of the BY variables. For example, if there are four BY variables, each 16 characters long, 10,000 BY groups within each AGGBY group, and each series has length 100, then the minimum required memory for efficient processing is approximately 100 MB. If the memory is not sufficient, sorting the DISAGGDATA= data set, not indexing, is more efficient.

You can specify custom names for the variables in the DISAGGDATA= data set by using the DISAGGDATA statement. See the section "DISAGGDATA Statement" on page 327 for more details.

CONSTRAINT= Data Set

The CONSTRAINT= data set specifies the constraints to be applied to the reconciled forecasts. It contains the BY variables for the level at which reconciled forecasts are generated. That is, it contains the AGGBY variables when DIRECTION=BU, and the variables specified in the BY statement when DIRECTION=TD. If the _NAME_ variable is present in the AGGDATA= and DISAGGDATA= data set, it must also be present in the CONSTRAINT= data set. Additionally, the CONSTRAINT= data set contains the variable in the ID statement (when this statement is specified), and the following variables:

EQUALITY — an equality constraint for the predicted reconciled value

UNLOCK — a flag that specifies whether the equality constraint should be strictly enforced. Admissible values are as follows:

0	The equality constraint is locked.
1	The equality constraint is unlocked.

When EQUALITY is nonmissing and the UNLOCK flag is missing, the equality is treated as locked.

LOWERBD — lower bounds for the reconciled forecasts

UPPERBD — upper bounds for the reconciled forecasts

Locked equality constraints are treated as constraints, and therefore their value is honored. Unlocked equalities are instead treated as regular forecasts and, in general, are changed by the reconciliation process.

A constraint is said to be *active* when the reconciled prediction lies on the constraint. By definition, locked equalities are always active constraints.

If the NOTSORTED option is specified in the BY statement, then any BY group in the CONSTRAINT= data set that is out of order with respect to the BY groups in the AGGDATA= or DISAGGDATA= data set is ignored without any error or warning message. If the NOTSORTED option is not specified, then the BY groups in the CONSTRAINT= data set must be in the same sorted order as the AGGBY groups in the AGGDATA= data set when DIRECTION=BU, and in the same sorted order as the BY groups in the DISAGGDATA= data set when DIRECTION=TD; otherwise processing stops at the first such occurrence of a mismatch.

OUTFOR= Data Set

The OUTFOR= data set contains the following variables:

NAME	variable name
ACTUAL	actual values
PREDICT	predicted values
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors
STD	prediction standard errors
RECONSTATUS	reconciliation status

Additionally, it contains any other variable that was present in the input data set at the same level—that is, the DISAGGDATA= data set when DIRECTION=TD and the AGGDATA= data set when DIRECTION=BU.

When DIRECTION=BU and the AGGDATA= data set has not been specified, the OUTFOR= data set contains the variables in the previous list, the BY variables specified in the AGGBY statement, and the time ID variable in the ID statement.

If reconciliation fails with _RECONSTATUS_ between 1000 and 6000, PROC HPFRECONCILE copies the input values of the relevant variables to the OUTFOR= data set. If a variable is not present in the input data set, its value is set to missing in the OUTFOR= data set. The only exception to this rule is when the problem is infeasible and the FORCECONSTRAINT option is specified. See the section "The FORCECONSTRAINT Option" on page 339 for more details on the latter case.

The OUTFOR= data set is always sorted by the BY variables (and by the _NAME_ variable and time ID variable when these variables are present) even if input data sets are indexed and not sorted.

If the ID statement is specified, then the values of the ID variable in OUTFOR= data set are aligned based on the ALIGN= and INTERVAL= options specified on the ID statement. If ALIGN= option is not specified, then the values are aligned to the beginning of the interval.

If the RECDIFF option of the HPFRECONCILE statement has been specified, the OUTFOR= data sets also contains the following variable:

RECDIFF difference between the reconciled predicted value and the original predicted value

The _RECONSTATUS_ variable contains a code that specifies whether the reconciliation was successful or not. A corresponding message is also displayed in the log. You can use the ERRORTRACE= option to define how often the error and warning messages are displayed in the log. The _RECONSTATUS_ variable can take the following values:

0 Reconciliation was successful.

400 A unlocked equality constraint has been imposed.

500 A locked equality constraint has been imposed.

600 A lower bound is active.

700 An upper bound is active.

1000 The ID value is out of the range with respect to the START= and END= interval.

2000 There is insufficient data to reconcile.

3000 Reconciliation failed for the predicted value. This implies that it also failed for the confidence limits and standard error.

4000 Reconciliation failed for the standard error.

5000 Reconciliation failed for the confidence limits.

6000 The constrained optimization problem is infeasible.

7000 The option DISAGGREGATION=PROPORTION has been changed to DISAGGREGATION=DIFFERENCE for this observation because of a discordant sign in the input.

8000 The option STDMETHOD= provided by the user has been changed for this observation.

9000 The option CLMETHOD= provided by the user has been changed for this observation.

10000 The standard error hit the limits imposed by the STDDIFBD= option.

11000 Multiple warnings have been displayed in the log for this observation.

12000 The number of missing values in the STD variable in the DISAGGDATA= data set is different from the number of missing values in the union of the PREDICT and ACTUAL variables.

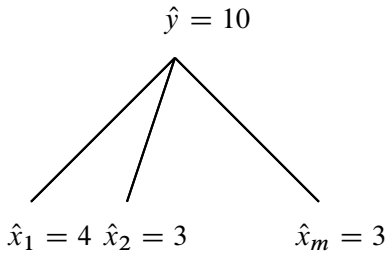
13000 The solution might be suboptimal. This means that the optimizer did not find an optimal solution, but the solution provided satisfies all constraints.

14000 A failed forecast ".F" has been detected in a relevant input variable.

The FORCECONSTRAINT Option

The FORCECONSTRAINT option applies when there are conflicts between the aggregation constraint and one or more constraints that you specify using the CONSTRAINT= data set, the SIGN= option, or the WEIGHTED option with zero weights. By default, when reconciliation is impossible, PROC HPFRECONCILE copies the input to the OUTFOR= data set without modification. However, if the reconciliation is infeasible because of a conflict between the constraints you specified and the aggregation constraint, you can ask PROC HPFRECONCILE to impose your constraints on the output even though that results in a violation of the aggregation constraint. For example, assume the input is described by the diagram in Figure 10.3 and assume you want to impose the following constraints on the reconciled forecasts: $\tilde{x}_1 = 7,\ \tilde{x}_2 \geq 5,\ \tilde{x}_3 \geq 0$.

Figure 10.3 FORCECONSTRAINT Option



The constraints are clearly in conflict the aggregation constraint $\sum \tilde{x}_i = \hat{y}$; therefore, PROC HPFRECONCILE will consider the problem infeasible. If you do not specify the FORCECONSTRAINT option, the predicted values in the OUTFOR= data set will equal the input predicted values (that is, $\tilde{x}_1 = 4,\ \tilde{x}_2 = 3,\ \tilde{x}_3 = 3$) and the _RECONSTATUS_ variable will take the value 6000. If you specify the FORCECONSTRAINT option, the OUTFOR= data set will contain the values $\tilde{x}_1 = 7,\ \tilde{x}_2 = 5,\ \tilde{x}_3 = 0$.

OUTINFEASIBLE= Data Set

The OUTINFEASIBLE= data set contains summary information about the nodes in the hierarchy for which reconciliation is infeasible because the aggregation constraint is incompatible with the constraints supplied by the user.

The OUTINFEASIBLE= data set is always produced at the level of the AGGDATA= data set.

The OUTINFEASIBLE= data set contains the AGGBY variables present in the AGGDATA= data set, the time ID variable, when it is specified, and the following variables:

NAME	variable name
ISRECONCILED	takes value 1 when the node is reconciled, and value 0 when it is not
FINALPREDICT	the predicted value for the parent node

AGGCHILDPREDICT	the aggregated prediction of the children nodes
LOWERBD	the lower bound implied by the constraints on FINALPREDICT
UPPERBD	the upper bound implied by the constraints on FINALPREDICT

If the ID statement is specified, then the values of the ID variable in OUTINFEASIBLE= data set are aligned based on the ALIGN= and INTERVAL= options specified in the ID statement. If ALIGN= option is not specified, then the values are aligned to the beginning of the interval.

OUTNODESUM= Data Set

The OUTNODESUM= data set contains the BY variables in the AGGDATA= data set (or in the AGGBY statement if the AGGDATA= data set is not specified), the time ID variable in the ID statement when this statement is specified, and the following variables:

NAME	variable name
NONMISSCHLD	number of nonmissing children of the current AGGBY group

OUTPROCINFO= Data Set

The OUTPROCINFO= data set contains the following variables:

SOURCE	source procedure that produces this data set
STAGE	stage of the procedure execution for which the summary variable is reported
NAME	name of the summary variable
LABEL	description of the summary variable
VALUE	value of the summary variable

For PROC HPFRECONCILE, the value of the _SOURCE_ variable is **HPFRECONCILE** and the value of the _STAGE_ variable is **ALL** for all observations. It contains observations that corresponds to each of the following values of the _NAME_.

NOBS_RECON	total number of observations subject to reconciliation
NOBS_SUCCESS	number of observations with successful reconciliation
NOBS_PREDICTFAIL	number of observations for which reconciliation failed for PREDICT. This number does not include failures to reconcile due to an infeasible problem or a failed (“.F”) forecast.
NOBS_PROBLEMSTATUS	number of observations for which some problem was encountered. This is the number of observations in the OUTFOR= data set that have a _RECONSTATUS_ value greater or equal to 1000.
NOBS_INFEASIBLE	number of observations for which reconciliation is infeasible due to incompatible constraints
NOBS_SUBOPTIMAL	number of observations for which the optimizer did not find an optimal solution
NOBS_LOCKEQ	number of observations subject to a locked equality constraint

NOBS_USER_LOCKEQ	number of observations for which a locked equality was specified in the CONSTRAINT= data set
NOBS_LOWERBD	number of observations for which a lower bound was imposed
NOBS_USER_LOWERBD	number of observations for which a lower bound was specified in the CONSTRAINT= data set
NOBS_UPPERBD	number of observations for which an upper bound was imposed
NOBS_USER_UPPERBD	number of observations for which an upper bound was specified in the CONSTRAINT= data set
NOBS_ACTIVE_LOWERBD	number of observations for which a lower bound is active
NOBS_ACTIVE_UPPERBD	number of observations for which an upper bound is active
NOBS_FAILED_FORECAST	number of observations for which a failed forecast (".F") was written
NPROB_TOTAL	total number of possible problems. One reconciliation problem is possible for each distinct value of time ID variable that appears in AGGDATA= or DISAGGDATA= data sets.
NPROB_CHANGED_LOSS	number of reconciliation problems for which DISAGGREGATION= option was changed internally because the supplied or default option was not feasible
NPROB_CHANGED_CLMETHOD	number of reconciliation problems for which CLMETHOD= option was changed internally because the supplied or default option was not feasible
NPROB_CHANGED_STDMETHOD	number of reconciliation problems for which STDMETHOD= option was changed internally because the supplied or default option was not feasible
NPROB_RECON	total number of problems subject to reconciliation
NPROB_INFEASIBLE	number of infeasible reconciliation problems due to incompatible constraints
NPROB_SUBOPTIMAL	number of reconciliation problems for which the optimizer did not find an optimal solution
NPROB_OPTIMIZER	number of reconciliation problems solved by using the optimizer
ID_MIN	minimum value of time ID for which reconciliation was attempted
ID_MAX	maximum value of time ID for which reconciliation was attempted
NAGGBY	total number of AGGBY groups processed
AVGDBY_PERABY	average number of BY groups per AGGBY group
NBY_IRREGULAR_ID	number of BY groups processed partially because of irregular ID values
NAGGBY_IRREGULAR_ID	number of AGGBY groups processed partially because of irregular ID values
AVGACTIVEDBY_PERID	average number of active BY groups per time ID for which reconciliation was attempted
NCONS_READ	total number of constraints read in the CONSTRAINT= data set

NCONS_IN_VALID_ID_RANGE	total number of constraints in the CONSTRAINT= data set with time ID values in the [START=,END=] range
NCONS_USED	number of constraints used
CONS_ISANYUNMATCHED	If any of the constraints in the CONSTRAINT= data set is left unmatched and unprocessed, then _VALUE_ for this observation is set to 1; otherwise, it is set to 0.
RC	return code of PROC HPFRECONCILE

Examples: HPFRECONCILE Procedure

Example 10.1: Reconciling a Hierarchical Tree

The HPFRECONCILE procedure reconciles forecasts between two levels of a hierarchy. It can also be used recursively for reconciling the whole hierarchy.

Consider the hierarchy structure for the SASHELP.PRICEDATA data set outlined in Figure 10.1. You can reconcile the hierarchy top down, starting from the top level 0 down to the bottom level 2. At each new iteration, the OUTFOR= data set of the previous reconciliation step becomes the AGGDATA= data set of the current step.

First, you need to compute the statistical forecasts for all levels. The statistical forecasts for level 1 and level 2 were already computed in the section "Getting Started: HPFRECONCILE Procedure" on page 318, so only the forecasts at the company levels are left to compute as shown in the following statements.

```
/* Forecast series at company level */

* Step 1: model selection;
proc hpfdiagnose data=sashelp.pricedata
                 outest=lvl0est
                 modelrepository=work.mymodels
                 prefilter=both
                 criterion=mape;
   id date interval=month notsorted;
   forecast sale / accumulate=total;
   input price / accumulate=average;
run;

* Step 2: estimation and forecasting;
proc hpfengine data=sashelp.pricedata
               inest=lvl0est
               out=_null_
               outest=lvl0fest
               modelrepository=mymodels
               outfor=lvl0for;
   id date interval=month notsorted;
   forecast sale / task=select accumulate=total;
   stochastic price /accumulate=average;
```

```
run;
```

First, you reconcile the top and region levels. The output data set lvl1recfor contains the reconciled forecasts at level 1. This data set becomes the AGGDATA= data set for the next step of TD reconciliation that involves level 1 and level 2. You can check that the reconciled forecasts at level 2 add up to the forecasts at level 0.

```
/* Reconcile forecasts top down from company to region */

proc hpfreconcile disaggdata=lvl1for
                  aggdata=lvl0for
                  direction=TD
                  outfor=lvl1recfor;
   id date interval=month;
   by region;
run;

/* Reconcile forecasts top down from region to region/product */

proc hpfreconcile disaggdata=lvl2for
                  aggdata=lvl1recfor
                  direction=TD
                  outfor=lvl2recfor;
   id date interval=month;
   by region product;
run;

/* Verify that level 2 forecasts add up to level 0 forecasts */

proc timeseries data=lvl2recfor out=toprec ;
   id date interval=month notsorted  accumulate=total;
   var predict;
run;

proc compare base=lvl0for compare=toprec criterion=0.00001;
   var predict;
run;
```

You can also reconcile the hierarchy from the bottom up. In such a case, the OUTFOR= data set of the previous step becomes the DISAGGDATA= data set of the current step.

Alternatively, you could choose to reconcile the hierarchy from the *middle out* from an intermediate level. In this case, you choose an intermediate level as a starting point, and reconcile all levels above from the bottom up, while reconciling all levels below from the top down. In the following SAS statements, the hierarchy of SASHELP.PRICEDATA is reconciled from the middle out, starting from level 1.

```
/* Reconcile forecasts bottom up from region to company */

proc hpfreconcile disaggdata=lvl1for
                  aggdata=lvl0for
                  direction=BU
                  outfor=lvl0recfor;
   id date interval=month;
   by region;
run;
```

```
/* Reconcile forecasts top down from region to region/product */

proc hpfreconcile disaggdata=lvl2for
                  aggdata=lvl1for
                  direction=TD
                  outfor=lvl2recfor;
   id date interval=month;
   by region product;
run;
```

You can use the external forecasts feature of the HPFENGINE procedure to generate summary statistics and statistics of fit for the reconciled forecasts, as shown in the following SAS statements for the company level.

First, an external model spec is generated using PROC HPFEXMSPEC. The characteristics of estimated models that determine the options for PROC HPFEXMSPEC can be found in the OUTEST= data set of the HPFENGINE call for the corresponding level. In this case, the lvl0fest data set shows that the estimated model has three parameters and that the dependent variable sales has not undergone any transformation.

```
/* Generate external model spec */

proc hpfexmspec modelrepository=mymodels
                specname=lvl0exm;
   exm transform=none nparms=3;
run;
```

Subsequently, a selection list that contains the external model is defined with PROC HPFSELECT as shown in the following statements.

```
/* Generate select list */

proc hpfselect modelrepository=mymodels
               selectname=lvl0selexm;
   spec lvl0exm/ exmmap(predict=predict lower=lower
                        upper=upper stderr=std);
run;
```

Finally, the EXTERNAL statement of the HPFENGINE procedure is used in conjunction with the FORECAST statement to generate the OUTSTAT= and OUTSUM= data sets that correspond to the reconciled forecasts input data set lvl0recfor and the model specifications contained in the external model lvl0exm as shown in the following statements.

```
/* Create OUTSTAT= and OUTSUM= data sets */
proc hpfengine data=lvl0recfor(rename=(actual=sales))
               out=_NULL_
               outstat=lvl0outstat
               outsum=lvl0outsum
               modelrepository=mymodels
               globalselection=lvl0selexm;
   id date interval=month notsorted;
   forecast sales;
   external predict lower
            upper std;
run;
```

Example 10.2: Aggregating Forecasts

If you do not provide the AGGDATA= input data set, but provide only the DISAGGDATA= data set, PROC HPFRECONCILE aggregates the forecasts according to the BY variable that you specify in the AGGBY option. If you use the options STDMETHOD=DISAGG and CLMETHOD=GAUSS, you can obtain standard errors and confidence interval as well.

In this example, the forecasts at level 2 of Figure 10.1 are aggregated to find forecasts at level 1 for the SASHELP.PRICEDATA data set.

```
/* Aggregate region/product forecasts to region level */

proc hpfreconcile disaggdata=lvl2for
                  direction=BU
                  outfor=lvl1aggfor
                  stdmethod=disagg
                  clmethod=gauss;
   id date interval=month;
   by region product;
   aggby region;
run;
```

Example 10.3: Disaggregating Forecasts

You can use the HPFRECONCILE procedure to disaggregate top-level forecasts according to proportions that you supply. This can be accomplished by creating a DISAGGDATA= data set that contains the proportions that you want to use in place of the PREDICT variable.

In this example, the level 1 forecasts of the variable sale in the SASHELP.PRICEDATA data set are disaggregated to level 2 according to the historical median proportions.

First, a combination of DATA steps and PROC UNIVARIATE is used to compute the median proportions and merge them with the level 2 OUTFOR= data set from PROC HPFENGINE as shown in the following statements.

```
/* Compute total sales per region */

proc timeseries data=sashelp.pricedata out=lvl1sales ;
   id date interval=month notsorted  accumulate=total;
   by region;
   var sale;
run;

/* Compute sale proportions */

proc sort data=sashelp.pricedata out=tmp;
   by region date;
run;

data lvl2prop;
   merge tmp lvl1sales(rename=(sale=totsale));
```

```
   by region date;
   prop = sale / totsale;
run;

/* Compute median sale proportions */

proc sort data=lvl2prop;
   by region product;
run;

proc univariate data=lvl2prop noprint;
   var prop;
   by region product;
   output out=lvl2medprop median=medprop;
run;

/* Merge median proportions with level2 OUTFOR */

data lvl2medfor;
   merge lvl2for lvl2medprop;
   by region product;
run;
```

Then PROC HPFRECONCILE is invoked, using the DISAGGDATA statement to specify that the variable medprop is to be used instead of the default PREDICT.

Note that the proportions do not need to sum to one. PROC HPFRECONCILE automatically rescales them to sum to one as shown in the following statements.

```
/* Disaggregate level1 forecasts according to median sale */

proc hpfreconcile disaggdata=lvl2medfor
                  aggdata=lvl1for
                  direction=TD
                  stdmethod=unchanged
                  clmethod=gauss
                  outfor=lvl2recmedfor;
   disaggdata predict=medprop;
   by region product;
run;
```

The variable medprop in the OUTFOR=lvl2recmedfor data set contains the disaggregated forecasts according to the proportions that you supplied.

In this case, the options STDMETHOD=UNCHANGED and CLMETHOD=GAUSS are used to obtain standard errors and confidence intervals. However, you need to be aware that they might not be reliable.

Alternatively, if you are interested in disaggregating the predicted values only, you can use the PREDICTONLY option as in the following statements.

```
/* Disaggregate level1 predict only */

proc hpfreconcile disaggdata=lvl2medfor
                  aggdata=lvl1for
                  direction=TD
                  predictonly
```

```
                  outfor=lvl2recmedfor;
   disaggdata predict=medprop;
   by region product;
run;
```

Example 10.4: Imposing Constraints

You can impose constraints on the reconciled forecasts by using the CONSTRAINT= option or the SIGN= option.

This example revisits Example 10.1 and imposes different types of constraints on the reconciled forecasts. Suppose you want all reconciled forecasts to be nonnegative, and for the month of April 2003 you want the following:

1. Product 1 at Region 1 to have a locked equality of 400
2. Product 2 at Region 1 to have an unlocked equality of 400
3. Product 4 at Region 2 to be less or equal to 300

First, you need to create a CONSTRAINT= data set that contains the constraints you want for the date of April 2003.

```
/* Create constraint data set */

data constraint;
   length _name_ $32;
   input region product _name_ $ date MONYY7. equality
         unlock lowerbd upperbd;
datalines;
   1 1 sale Apr2003 400 0 . .
   1 2 sale Apr2003 400 1 . .
   2 4 sale Apr2003 . .   . 300
   ;
```

Then, you reconcile the two levels by using the SIGN=NONNEGATIVE option to impose the nonnegativity constraint and by using the CONSTRAINT= option to impose your constraints on the reconciled forecasts in April 2003. The PREDICTONLY option of the HPFRECONCILE statement restricts the reconciliation to the PREDICT variable as shown in the following statements.

```
/* Reconcile forecasts with constraints */

proc hpfreconcile disaggdata=lvl2for
                  aggdata=lvl1for
                  direction=TD
                  sign=nonnegative
                  constraint=constraint
                  outfor=lvl2recfor
                  predictonly;
   id date interval=month;
   by region product;
```

```
run;
```

Chapter 11
The HPFSELECT Procedure

Contents

Overview: HPFSELECT Procedure **350**
Getting Started: HPFSELECT Procedure **351**
Syntax: HPFSELECT Procedure **352**
Functional Summary 352
PROC HPFSELECT Statement 354
COMBINE Statement 355
DELETE Statement 359
DIAGNOSE Statement 359
FORECASTOPTIONS Statement 360
SELECT Statement 360
SPECIFICATION Statement 361
Valid Statistic of Fit Names 364
Examples: HPFSELECT Procedure **366**
Example 11.1: The INPUTMAP Option 366
Example 11.2: The EVENTMAP Option 367
Example 11.3: The DIAGNOSE Statement 369
Example 11.4: External Models and User-Defined Subroutines 371
Example 11.5: Comparing Forecasts from Multiple External Sources 372
Example 11.6: Input to User-Defined Subroutines 374
Example 11.7: Changing an Existing Selection List 375
Example 11.8: Using a Combined Forecast 376

Overview: HPFSELECT Procedure

The HPFSELECT procedure enables you to control the forecasting process by defining lists of candidate models, or more generally candidate specifications, to be evaluated by PROC HPFENGINE. These lists are defined in terms of time series models, model selection lists, or model combination lists. Abstractly, each list created by the HPFSELECT procedure is a list of specifications. Using lists created by the HPFSELECT procedure, you can control which forecasting model or models SAS Forecast Server Procedures software uses to forecast particular time series.

The HPFSELECT procedure creates a list specification file for each invocation and stores it in a repository for later use by the HPFENGINE procedure. Each list specification has semantics defined by the type of list you create. These semantics determine the behavior of the list when it is executed in the HPFENGINE procedure. Each of these list files references specifications previously created and stored in a model repository by the HPFARIMASPEC, HPFESMSPEC, HPFEXMSPEC, HPFIDMSPEC, HPFUCMSPEC, or HPFSELECT procedures.

Abstractly, you should think of each specification in the list as producing a forecast when applied to a particular time series. The behavior of the list as defined by its type determines how those forecasts are used by the list and ultimately the forecast produced by the list itself.

The HPFSELECT procedure supports these types of lists:

Selection list
selects the best forecast of those produced by its list based on a specified statistic of fit criterion. Selection lists are also referred to as model selection lists. Selection lists are defined by the presence of the SELECT statement in the HPFSELECT procedure statement block. This is also the default list type when no other type-related statement is specified. You can also specify other options that control the forecasting model selection process such as the use of holdout samples to evaluate candidate forecast performance and various diagnostics applied to the target time series to characterize it for model selection.

Combination list
combines a subset of the forecasts produced by its list via a weighted average. Combination lists are specified via the presence of a COMBINE statement in the HPFSELECT procedure statement block. The COMBINE statement supports a variety of options to affect candidate forecast selection, to specify the method for determining the weights assigned to the forecasts in combination, and to control various other aspects of the final combined forecast results.

Further discussion of these concepts can be found in Chapter 17, "Forecast Model Selection Graph Details," for how they relate and interact in operation of the automated forecasting process in the context of the HPFENGINE procedure.

Getting Started: HPFSELECT Procedure

The following example shows how to create a model selection list file. Suppose the model repository MYLIB.MYMODELS contains three model specification files (A.XML, B.XML, C.XML) created by the following SAS statements.

```
proc hpfarimaspec repository=mymodels name=a;
   forecast symbol=y p=12 diflist=(1 12) noint;
   estimate method=ml;
run;

proc hpfesmspec repository=mymodels name=b;
   esm method=winters;
run;

proc hpfucmspec repository=mymodels name=c;
   forecast symbol=y;
   irregular;
   level;
   slope;
   season length=12;
run;
```

The following statements create a model selection list that will tell the HPFENGINE procedure to automatically select from the A, B, and C models based on the mean absolute percentage error (MAPE).

```
proc hpfselect repository=mymodels
               name=myselect;
   spec a b c;
   select criterion=mape;
run;
```

The options in the PROC HPFSELECT statement specify the name and location of the model selection file that is created. The REPOSITORY= option specifies that the output file be placed in the catalog MYLIB.MYMODELS, and the NAME= option specifies that the name of the file be "myselect.xml." The SPEC statement specifies the list of candidate models. The SELECT statement specifies options that control how the HPFENGINE procedure selects from the candidate models when applying the selection list MYSELECT to actual time series data.

The new selection list is available for use by the HPFENGINE procedure, shown in the following SAS statements. The GLOBALSELECTION= option refers to the selection list by name. Selection results are shown in Figure 11.1.

```
proc hpfengine data=sashelp.air
               repository=mymodels
               globalselection=myselect
               print=select
               out=_null_;
   id date interval=month;
   forecast air;
run;
```

Figure 11.1 Selection Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
A	3.1008419	No	ARIMA: Y ~ P = 12 D = (1,12) NOINT
B	3.0845016	Yes	Winters Method (Multiplicative)
C	4.3672770	No	UCM: Y = TREND + SEASON + ERROR

Syntax: HPFSELECT Procedure

The following statements are used with the HPFSELECT procedure:

PROC HPFSELECT *options* ;
  COMBINE *options* ;
  DELETE *specification-list* ;
  DIAGNOSE *options* ;
  FORECASTOPTIONS *options* ;
  SELECT *options* ;
  SPECIFICATION *specification-list* < / *options* > ;

Functional Summary

Table 11.1 summarizes statements and options that control the HPFSELECT procedure.

Table 11.1 PROC HPFSELECT Functional Summary

Description	Statement	Option
Statements		
Specifies the forecasting options	FORECASTOPTIONS	
Model Repository Options		
Specifies the model repository	PROC HPFSELECT	REPOSITORY=
Specifies the model specification name	PROC HPFSELECT	NAME=
Specifies the model specification label	PROC HPFSELECT	LABEL=
Forecasting Options		
Specifies the confidence limit width	FORECASTOPTIONS	ALPHA=
Forecast Combination Options		
Specifies the combination weight method	COMBINE	METHOD=
Specifies the encompassing test	COMBINE	ENCOMPASS=
Specifies the forecast combination criterion	COMBINE	CRITERION=

Table 11.1 *continued*

Description	Statement	Option
Specifies the percentage of missing forecast values	COMBINE	MISSPERCENT=
Specifies the percentage of missing horizon values	COMBINE	HORMISSPERCENT=
Specifies the combination of missing forecast values	COMBINE	MISSMODE=
Forecast Selection Options		
Specifies the forecast holdout sample size	SELECT	HOLDOUT=
Specifies the forecast holdout sample size as a percentage	SELECT	HOLDOUTPCT=
Specifies the model selection criterion	SELECT	CRITERION=
Model Specification Options		
Associates a symbol with data set variable	SPECIFICATION	INPUTMAP
Associates a symbol with an event	SPECIFICATION	EVENTAP
Associates external data with the specification	SPECIFICATION	EXMMAP
Associates an external subroutine with the specification	SPECIFICATION	EXMFUNC
Overrides specification labels	SPECIFICATION	LABEL
Validates model specifications	PROC HPFSELECT	VALIDATE
Model Selection List Options		
Removes specifications from the list	DELETE	
Specifies an input selection list	PROC HPFSELECT	INSELECTNAME=
Diagnostic Options		
Specifies the base value for an intermittent series	DIAGNOSE	IDMBASE=
Specifies the intermittency test threshold	DIAGNOSE	INTERMITTENT=
Specifies the seasonality test	DIAGNOSE	SEASONTEST=

PROC HPFSELECT Statement

PROC HPFSELECT *options* **;**

The following options can be used in the PROC HPFSELECT statement.

INSELECTNAME=*SAS-catalog-name*
provides a selection list as input to the HPFSELECT procedure. The input selection list is specified as a three-level name. The INSELECTNAME= option can be used to add models to existing lists, remove models from existing lists, change selection options, and so forth.

LABEL=*SAS-label*
specifies a descriptive label for the model selection to be stored in the SAS catalog or directory. The LABEL= option can also be specified as SELECTLABEL=.

NAME=*SAS-name*
names the model selection file to be stored in the SAS catalog or directory. The NAME= option can also be specified as SELECTNAME=.

REPOSITORY=*SAS-catalog-name* | *SAS-file-reference*
names the SAS catalog or directory to contain the model specification. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=.

VALIDATE
checks the validity of lists used by and generated by the HPFSELECT procedure invocation. VALIDATE covers both the list in the INSELECTNAME= option, if specified, and the list generated by the HPFSELECT procedure statement block. Validation ensures that all of the specifications in the respective forecast model selection graphs exist, that they are valid HPF XML model or list specifications, and that no cycles are created in the selection graph. A failure to validate the INSELECTNAME= results in the INSELECTNAME= being ignored. Undefined repository entries in the HPFSELECT procedure statement block SPECIFICATION statements are omitted from the generated list. A failure to validate the list generated from the HPFSELECT procedure statement block produces no new XML list specification entry in the model repository. Specifications required to satisfy the references in the INSELECTNAME= list are not automatically copied to the model repository identified by the REPOSITORY= option. This can be one common cause of validation problems. For more details about the forecast model selection graph, see Chapter 17, “Forecast Model Selection Graph Details.”

COMBINE Statement

COMBINE *comb-options* **;**

The COMBINE statement defines combination semantics for the list of specifications that are defined in the SPECIFICATION statements.

The following examples illustrate typical uses of the COMBINE statement:

```
proc hpfselect rep=work.rep
     name=combavg
     label="Avergage(T1,T2,T3)";

combine method=average;
spec t1 t2 t3;
run;

proc hpfselect rep=work.rep
     name=combrwgt
     label="RankWeight(T1,T2,T3)";

combine method=rankwgt(0.5,0.3,0.2);
spec t1 t2 t3 / inputmap(symbol=x data=temp);
run;
```

The following *comb-options* can be specified:

CRITERION=*option*

specifies the forecast combination criterion (statistic of fit) to be used when ranking forecast candidates in the context of the COMBINE statement. This option is often used in conjunction with the ENCOMPASS= and METHOD=RANKWGT options. If not specified, the default is determined by the HPFENGINE procedure. See the section "Valid Statistic of Fit Names" on page 364 for valid values.

ENCOMPASS=NONE

ENCOMPASS=*test-name***(***test-options***)**

specifies whether a forecast encompassing test be performed, and if so which type of test. The encompassing test attempts to eliminate forecasts from consideration that fail to add significant information to the final forecast. The default is ENCOMPASS=NONE, which specifies that no encompassing test be performed.

You can specify the following values for *test-name* and *test-options*:

OLS(ALPHA=*number*) uses an OLS-based regression test to estimate pairwise encompassing between candidate forecasts. Candidates are ranked from best to worst using the CRITERION= values. Iterating from best to worst, inferior candidates are tested with the best of the untested candidates for retention in the combined set. The significance level for the test is given by specifying ALPHA=*number* option. The default value is ALPHA=0.05 when the simple form ENCOMPASS=OLS is specified. The range is 0 to 1.

HLN(ALPHA=*number*) uses the Harvey-Leybourne-Newbold (HLN) test to estimate pairwise encompassing between candidate forecasts. Candidates are ranked from best to worst using the

CRITERION= values. Iterating from best to worst, inferior candidates are tested with the best of the untested candidates for retention in the combined set. The significance level for the test is given by specifying ALPHA=*number* option. The default value is ALPHA=0.05 when the simple form ENCOMPASS=HLN is specified. The range is 0 to 1.

HORMISSPERCENT=*number*

specifies a threshold for the percentage of missing forecast values in the combination horizon used to exclude a candidate forecast from consideration in the final combination. By default, no horizon missing percentage test is performed on candidate forecasts. If specified, the admissible range is 1 to 100. The forecast horizon is the region of time in which multistep forecasts are generated. This test and the MISSPERCENT test operate independent of each other. One or both can be specified.

METHOD=*weight-method***(***method-options***)**

specifies the method for determining the combination weights used in the weighted average of the candidate forecasts in the combination list. The default method is METHOD=AVERAGE. The simple form METHOD=*weight-method* can be used when no weight-specific options are desired.

The following values for *weight-method* and *method-options* can be specified:

AICC(*AICC-opts*) computes the combination weights based on corrected AIC weights. See Chapter 16, "Forecast Combination Computational Details," for the mathematical details of this process. Frequently there is considerable disparity between the weights due to the exponential weighting scheme, so options are allowed to affect the scaling and to cull low-scoring candidates from consideration for computational efficiency. By default, all AICC scored candidate forecasts are combined.

Possible values for *AICC-opts* include:

ABSWGT=*number* omits computed weights with values less than the specified value. The range is 0 to 1 inclusive. The remaining weights are normalized to sum to 1.

BESTPCT=*number* retains the best N of the candidates as a percentage of the total number weighted, where

$$N = \max\{\lfloor \frac{number \cdot M}{100} \rfloor, 1\} \tag{11.1}$$

and M denotes the number of candidate models in the combination after any specified forecast exclusion tests have been performed.

The N remaining weights are normalized to sum to 1.

BESTN=*N* retains the best N of the candidates as a percentage of the total number weighted. The N remaining weights are normalized to sum to 1.

LAMBDA=*number* specifies the scale factor used in the computation of the AICC weights. The default is LAMBDA=1.0, which results in the usual Akaike weights.

AVERAGE computes the simple average of the forecasts selected for combination. This is the default.

ERLS(*NLP-opts*) computes the combination weights based on a constrained least squares problem to minimize the ℓ_2 norm of the combined forecast residuals, subject to the constraint that the weights sum to 1.

LAD(*LAD-opts*) computes the weights based on a least absolute deviations measure of fit for the combined forecast. A linear program is formulated according to the *LAD-opts* to minimize an objective function expressed in terms of a absolute values of a loss series, subject to constraints that the weights sum to 1 and be nonnegative. Options permitted in *LAD-opts* include OBJTYPE and ERRTYPE.

The form of the objective can be specified by the OBJTYPE= option as:

OBJTYPE=L1 specifies that the objective is an ℓ_1 norm involving the loss series.

OBJTYPE=LINF specifies that the objective is an ℓ_∞ norm involving the loss series.

The form of the loss series in the objective can be specified as:

ERRTYPE=ABS specifies that the loss series terms are deviations.

ERRTYPE=APE specifies that the loss series terms are percentage deviations.

ERRTYPE=RAE specifies that the loss series terms are relative error deviations.

NERLS(*NLP-opts*) computes the combination weights based on a constrained least squares problem to minimize the ℓ_2 norm of the combined forecast residuals, subject to the constraints that the weights sum to 1 and be nonnegative.

NRLS(*NLP-opts*) computes the combination weights based on a constrained least squares problem to minimize the ℓ_2 norm of the combined forecast residuals, subject to the constraints that the weights be nonnegative.

OLS computes the combination weights that result from the ordinary least squares problem to minimize the ℓ_2 norm of the combined forecast residuals.

RANKWGT*(W1,...,Wn)* assigns weights using the rank of the candidate forecasts at the time the combination is performed as determined by the COMBINE statement CRITERION= values. These weights must sum to 1. If not, they are normalized and a warning is issued. The number of values specified must agree with the number of specification names declared in the SPECIFICATION statements in the PROC HPFSELECT statement block. The weights are assigned by ranking the candidate forecasts from best to worst. The best uses the first weight, W1, and so on. The set of weights used is normalized to account for candidates that fail to forecast or for candidates that are omitted from the final combination because of any of the COMBINE statement exclusion tests.

RMSEWGT computes the combination weights based on the RMSE statistic of fit for the forecast contributors. The weights are normalized to sum to 1. See Chapter 16, "Forecast Combination Computational Details," for details.

USERDEF*(W1,...,Wn)* assigns weights using the list of user-specified values. These weights must sum to 1. If not, they are normalized and a warning is issued. The number of values specified must agree with the number of specification names declared in the SPECIFICATION statements in the PROC HPFSELECT statement block. The weights correspond with the order of the names in the SPECIFICATION statements. The set of weights used is normalized to account for candidates that fail to forecast or for candidates that are omitted from the final combination because of any of the COMBINE statement exclusion tests.

MISSMODE=*miss-method*

specifies a method for treating missing values in the forecast combination. In a given time slice across the combination ensemble, one or more combination contributors can have a missing value. This setting determines the treatment of those in the final combination for such time indices.

The following *miss-method* values are available:

RESCALE rescales the combination weights for the nonmissing contributors at each time index to sum to 1.

MISSING generates a missing combined forecast at each time index with one or more missing contributors.

The default behavior is determined by the weight method selected as follows:

MISSMODE=RESCALE is the default for simple average, user-specified weights, ranked user weights, ranked weights, and RMSE weights.

MISSMODE=MISSING is the default for AICC weights, OLS weights, restricted least squares weights, and LAD weights. For OLS and NRLS you cannot specify MISSMODE=RESCALE since the estimated weights are not constrained to sum to one.

MISSPERCENT=*number*

specifies a threshold for the percentage of missing forecast values in the combination estimation region that is used to exclude a candidate forecast from consideration in the final combination. By default, no missing percentage test is performed on candidate forecasts. If specified, the admissible range is 1 to 100. This test and the HORMISSPERCENT test operate independent of each other. One or both can be specified.

STDERR=*stderr-method*(*stderr-options*)

SEMODE=*stderr-method*(*stderr-options*)

specifies the method for computing the prediction error variance series. This series is used to compute the prediction standard error, which in turn is used to compute confidence bands on the combined forecast.

The simple form STDERR=*stderr-method* can be used when no method-specific options are desired.

The following values for *stderr-method* and *stderr-options* can be specified:

STDERR=DIAG computes the prediction error variance by assuming the forecast errors at time t are uncorrelated so that the simple diagonal form of Σ_t is used. This is the default method for computing prediction error variance.

STDERR=ESTCORR computes prediction error variance by using estimates of $\rho_{i,j,t}$, the sample cross-correlation between $e_{i,t}$ and $e_{j,t}$ over the time span $t = 1, \ldots, T$, where T denotes the last time index of the actual series y_t. This option implies, of course, that the error series $e_{i,t}$ and $e_{j,t}$ are assumed to be jointly stationary.

STDERR=ESTCORR(TAU=τ) is similar to STDERR=ESTCORR except that the cross-correlation estimates are localized to a time window of τ steps. The time span $t = 1, \ldots, T$ is quantized into segments of τ steps working from T backwards for in-sample cross-correlation estimates. The cross-correlation estimates from the interval $[T - \tau, T]$ are used for the period of multistep forecasts that extend beyond time T.

Computational details for combined forecasts can be found in Chapter 16, "Forecast Combination Computational Details."

DELETE Statement

DELETE *specification-list* **;**

The DELETE statement is used to remove model specifications from a selection list. There can be any number of model specifications listed in a DELETE statement and any number of DELETE statements.

DIAGNOSE Statement

DIAGNOSE *options* **;**

The DIAGNOSE statement is used to specify diagnostic options. DIAGNOSE options are used by the HPFENGINE procedure to subset a model selection list according to certain properties of a time series.

The following examples illustrate typical uses of the DIAGNOSE statement:

```
/* same as default options */
diagnose intermittent=2.0 seasontest=(siglevel=0.01);

/* no seasonality */
diagnose seasontest=(siglevel=0);
```

IDMBASE=AUTO | *number*

specifies the base value of the time series used to determine the demand series components for an intermittent demand model. The demand series components are determined based on the departures from this base value. If a base value is specified, this value is used to determine the demand series components. If IDMBASE=AUTO is specified, the time series properties are used to automatically adjust the time series. For the common definition of Croston's method use IDMBASE=0, which defines departures based on zero. The default is IDMBASE=AUTO.

Given a time series y_t and base value b the time series is adjusted by the base value to create the base-adjusted time series, $x_t = y_t - b$. Demands are assumed to occur when the base-adjusted series is nonzero (or when the time series y_t departs from the base value b).

When IDMBASE=AUTO, the base value is automatically determined by the time series median, minimum, and maximum values and the INTERMITTENT= option value.

INTERMITTENT=*number*

specifies a number greater than one that is used to determine whether or not a time series is intermittent. If the average demand interval is greater than this number, then the series is assumed to be intermittent. The default is INTERMITTENT=2.0.

LOGTEST=NO | YES
specifies whether or not to enable the dependent series log transform test, which determines whether to apply log transform to the dependent series. Based on the results of this test, candidate models can be removed during the model selection process. You can specify the following values:

NO No test

YES Enable the test

By default, LOGTEST=NO.

SEASONTEST=*option*
specifies the options that are related to the seasonality test.

You can specify the following *options*:

NONE No test

(SIGLEVEL=number) Significance probability value to use in testing whether seasonality is present in the time series. The value must be between 0 and 1.

A smaller value of the SIGLEVEL= option means that stronger evidence of a seasonal pattern in the data is required before the HPFENGINE procedure will use seasonal models to forecast the time series. The default is SEASONTEST=(SIGLEVEL=0.01).

FORECASTOPTIONS Statement

FORECASTOPTIONS *options* **;**

The FORECASTOPTIONS statement is used to specify forecasting options.

ALPHA=*number*
specifies the significance level to use in computing the confidence limits of the forecast. The value of ALPHA= must be between 0 and 1. The default is ALPHA=0.05, which produces 95% confidence intervals.

SELECT Statement

SELECT *options* **;**

The SELECT statement is used to specify forecast selection semantics for the list of specifications in the SPECIFICATION statements.

The following examples illustrate typical uses of the SELECT statement:

```
/* same as default options */
select criterion=rmse holdout=0 holdoutpct=0;

/* selection criterion mape with absolute holdout size 6 */
select criterion=mape holdout=6;
```

CHOOSE=*specification*
specifies the name of a model specification that will be chosen by the HPFENGINE procedure. By default, HPFENGINE will select the model with the best fit in terms of the statistic set by the CRITERION= option. The CHOOSE= option overrides this automatic selection and causes HPFENGINE to generate forecasts by using the model indicated in the option.

CRITERION=*option*
specifies the model selection criterion (statistic of fit) to be used to select from several candidate models. This option is often used in conjunction with the HOLDOUT= option. If not specified, the default is determined by the HPFENGINE procedure. See "Valid Statistic of Fit Names" on page 364 for the list of valid values for the CRITERION= option.

HOLDOUT=*n*
specifies the size of the holdout sample to be used for model selection. The holdout sample is a subset of actual time series that ends at the last nonmissing observation. The default is zero (no holdout sample).

HOLDOUTPCT=*number*
specifies the size of the holdout sample as a percentage of the length of the time series. If HOLDOUT=5 and HOLDOUTPCT=10, the size of the holdout sample is $min(5, 0.1T)$, where T is the length of the time series with beginning and ending missing values removed. The default is 100 (100%), which means no restriction on the holdout sample size based on the series length.

SPECIFICATION Statement

SPECIFICATION *specification-list* < / *options* > **;**

The SPECIFICATION statement is used to list model specifications. There can be any number of models specifications in the list and any number of SPECIFICATION statements. The SPECIFICATION statement can also be written as SPEC.

The following options can be used with the SPECIFICATION statement.

EVENTMAP (*symbol*= _NONE_ EVENT= *eventDef* < NODIFF >)

EVENTMAP (*symbol*= *string* EVENT= *eventDef*)
associates events with a model specification.

If SYMBOL=_NONE_ is used, the event specified in *eventDef* is added to the model as a simple regressor. By default, for an ARIMA model, any differencing applied to the dependent variable is applied in the same manner to the new event input. Specifying NODIFF indicates no differencing should be performed on the event.

If the SYMBOL string matches one of the symbols specified as input in either a UCM or ARIMA model, the event data will be used for the matching input. In this manner, events can enter models through complex transfer functions. The NODIFF option does not apply in this case, since differencing will be explicitly described in the input statement of the model.

If the event referenced by *eventDef* is a "predefined event" (see the HPFEVENT procedure), no INEVENT= option is required for the HPFENGINE procedure. Otherwise, the event named must be defined in an event data set by using the HPFEVENT procedure, and that data set must be given to the

HPFENGINE procedure with the INEVENT= option. An error will occur during the HPFENGINE procedure model selection if *eventDef* is not found in an event data set.

Only UCM and ARIMA models are valid when EVENTMAP is used. If another model type, such as exponential smoothing, has an EVENTMAP option, the option is simply ignored.

EXMMAP*(options)*
associates an external model specification with variable names in a DATA= data set, thus identifying the source of forecasts and optionally prediction standard errors, and the lower and upper confidence limits.

Available options are as follows:

PREDICT=var
identifies the variable to supply forecasts and is required.

STDERR=var
identifies the variable to supply the prediction standard error.

LOWER=var
identifies the variable to supply the lower confidence limit.

UPPER=var
identifies the variable to supply the upper confidence limit.

For example, if you want an external model "myexm" to use forecasts from the variable "yhat" in the DATA= data set passed to the HPFENGINE procedure, the appropriate statement would be as follows:

```
spec myexm / exmmap(predict=yhat);
```

If you also want to use prediction standard errors from the "std" variable in the same data set, use the following statement:

```
spec myexm / exmmap(predict=yhat stderr=std);
```

EXMFUNC*(string)*
associates an external model specification with a user-defined subroutine. The string parameter is the signature of the subroutine and has the following form:

subroutineName(*parameters*)

where parameters indicate the order, number, and type of arguments in the user-defined subroutine. The parameter _PREDICT_ is required, indicating the return of forecast values. Optional parameters for return of other data from the user-defined subroutine include the following:

STDERR	prediction standard error
LOWER	lower confidence limit
UPPER	upper confidence limit

The HPFENGINE procedure can also pass data into the user-defined subroutine by using the following options:

TIMEID	time ID
SEASON	seasonal index
ACTUAL	actual values

As an example, suppose the signature of a user-defined subroutine is defined in the FCMP procedure as follows:

```
subroutine userdef1(act[*], pred[*]);
```

Also suppose this subroutine is mapped to the external model "myexm" by using the following statement:

```
spec myexm / exmfunc('userdef1(_actual_ _predict_ )');
```

Then the HPFENGINE procedure will pass the array of actuals to the subroutine userdef1, and the function will compute the forecasts and return them to the HPFENGINE procedure.

Next, consider the case where a user-defined subroutine requires actuals, time ID values, and seasonal indices in order to compute and return forecasts and prediction standard errors. The subroutine might be defined as follows:

```
subroutine complexsub(act[*], timeid[*],
                      seasons[*], pred[*], stderr[*]);
```

It would be mapped to an external model named "myexm" by using the following statement:

```
spec myexm / exmfunc(
     'complexsub(_actual_ _timeid_ _season_ _predict_ _stderr_)'
                    );
```

This syntax is demonstrated further in Example 11.4.

INPUTMAP (SYMBOL= *string* **VAR=** *variable***)**

associates the symbols in a model specification with variable names in a DATA= data set.

The SYMBOL= option should match a symbol defined in a model specification. The VAR= option should match a variable name in a data set. When the model selection list is used in conjunction with the HPFENGINE procedure, the DATA= option specifies the input data set that contains the variable.

Mappings are needed because model specifications are generic. For example, suppose a model specification associates the symbol Y with the dependent variable. If you want to use this model to forecast the variable OZONE, you map Y to OZONE with INPUTMAP(SYMBOL=Y VAR=OZONE). If you later want to use the same specification to forecast SALES, you map Y to SALES with INPUTMAP(SYMBOL=Y VAR=SALES).

The INPUTMAP option is not required. By default, the HPFENGINE procedure attempts to locate variables in its DATA= data set that match the symbols in each specification listed in the selection list.

LABEL=*SAS-label*

overrides the label in the model specification and causes the new label to print in the model selection list in the HPFENGINE procedure. This option is useful if you have the same model specification listed more than once and want to distinguish between them in the HPFENGINE procedure output.

As an example, consider the following case of a single external model used twice in the selection list, with each occurrence mapped to a different external forecast:

```
spec myexm / exmmap(predict=yhatRALEIGH)
             label="External Model: Raleigh Forecasts";
spec myexm / exmmap(predict=yhatATLANTA)
             label="External Model: Atlanta Forecasts"
```

In the model selection list output from the HPFENGINE procedure, the new labels appear, rather than the label in “myexm” repeated twice.

Valid Statistic of Fit Names

Following is the list of valid values for specifying a desired statistic of fit:

SSE	sum of squares error
MSE	mean squared error
RMSE	root mean squared error
UMSE	unbiased mean squared error
URMSE	unbiased root mean squared error
MAXPE	maximum percent error
MINPE	minimum percent error
MPE	mean percent error
MAPE	mean absolute percent error
MDAPE	median absolute percent error
GMAPE	geometric mean absolute percent error
MINPPE	minimum predictive percent error
MAXPPE	maximum predictive percent error
MPPE	mean predictive percent error
MAPPE	symmetric mean absolute predictive percent error
MDAPPE	median absolute predictive percent error
GMAPPE	geometric mean absolute predictive percent error
MINSPE	minimum symmetric percent error
MAXSPE	maximum symmetric percent error
MSPE	mean symmetric percent error

SMAPE	symmetric mean absolute percent error
MDASPE	median absolute symmetric percent error
GMASPE	geometric mean absolute symmetric percent error
MINRE	minimum relative error
MAXRE	maximum relative error
MRE	mean relative error
MRAE	mean relative absolute error
MDRAE	median relative absolute error
GMRAE	geometric mean relative absolute error
MAXERR	maximum error
MINERR	minimum error
ME	mean error
MAE	mean absolute error
MASE	mean absolute scaled error
RSQUARE	R-square
ADJRSQ	adjusted R-square
AADJRSQ	Amemiya's adjusted R-square
RWRSQ	random walk R-square
AIC	Akaike information criterion
AICC	finite sample corrected AIC
SBC	Schwarz Bayesian information criterion
APC	Amemiya's prediction criterion
MAPES	mean absolute error percent of standard deviation
MDAPES	median absolute error percent of standard deviation
GMAPES	geometric mean absolute error percent of standard deviation

Examples: HPFSELECT Procedure

Example 11.1: The INPUTMAP Option

In this example, the HPFUCMSPEC procedure is used to define a UCM specification. The dependent variable is assigned the symbol Y, and an input is assigned the symbol X1. You ultimately want to forecast the series contained in the variable MASONRY with the input ELECTRIC. As demonstrated in the following SAS statements, the INPUTMAP option in the HPFSELECT procedure is used to tell the HPFENGINE procedure that MASONRY should replace Y and ELECTRIC should replace X1.

```
proc hpfucmspec repository=mymodels
                name=myucm
                label="My UCM spec";
   dependent symbol=Y;
   irregular;
   level;
   slope;
   season length=12;
   input symbol=X1;
run;

proc hpfselect repository=mymodels
               name=myselect;
   spec myucm /
   inputmap(symbol=Y var=MASONRY)
   inputmap(symbol=X1 var=ELECTRIC);
run;
```

The following call to the HPFENGINE procedure creates forecasts by using the UCM model with correct variable mappings. The model selection table that is created is shown in Output 11.1.1.

```
proc hpfengine data=sashelp.workers
               out=_null_
               repository=mymodels
               globalselection=myselect
               print=select;
   id date interval=month;
   forecast masonry;
   stochastic electric;
run;
```

Output 11.1.1 Selection Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
MYUCM	2.0744810	Yes	My UCM spec

As shown in the following SAS statements, the same result could be achieved by making the symbol in the

model specification match the variables in the HPFENGINE procedure's DATA= data set. No INPUTMAP option is required.

```
proc hpfucmspec repository=mymodels
                name=myucm
                label="My UCM spec";
   dependent symbol=MASONRY;
   irregular;
   level;
   slope;
   season length=12;
   input symbol=ELECTRIC;
run;

proc hpfselect repository=mymodels
               name=myselect
               label="My Selection List";
   spec myucm;
run;
```

The disadvantage here is that the model specification and data set are tightly linked.

Example 11.2: The EVENTMAP Option

Events are dynamically added as simple regressors to UCM and ARIMA models by using the EVENTMAP option in the SPECIFICATIONS statement.

In this example, you first create an ARIMA model and then create a selection list that directs the HPFENGINE procedure to choose between this model without an event and this model with the event. The following SAS statements illustrate this process. The results are shown in Output 11.2.1.

```
proc hpfevents data=sashelp.air;
   eventdef summer = (june july august);
   eventdata out=eventDB;
run;

proc hpfarimaspec repository=sasuser.repository name=arima;
   forecast symbol=air q=(1 12) transform=log;
run;

proc hpfselect repository=sasuser.repository name=select;
   spec arima;
   spec arima / eventmap(symbol=_none_ event=summer);
run;

proc hpfengine data=sashelp.air
               repository=sasuser.repository
               outest=outest1
               globalselection=select
               print=(select estimates)
               inevent=eventDB;
   id date interval=month;
```

```
   forecast air;
run;
```

Output 11.2.1 Selection and Estimation Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
ARIMA	20.048903	No	ARIMA: Log(AIR) ~ Q = (1,12)
ARIMA	19.654381	Yes	ARIMA: Log(AIR) ~ Q = (1,12)

Parameter Estimates for ARIMA Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**CONSTANT**	5.47071	0.04202	130.21	<.0001
AIR	**MA1_1**	-0.80089	0.02337	-34.27	<.0001
AIR	**MA1_12**	-0.27008	0.02374	-11.37	<.0001
SUMMER	**SCALE**	0.15504	0.05859	2.65	0.0091

In the following statements, you calculate the same results but this time explicitly create a model that includes the input in its specification. Then the event is added to the data set.

```
data air(keep=date air summer);
   set sashelp.air;
   summer = 0;
   if month(date) eq 6 or
      month(date) eq 7 or
      month(date) eq 8 then summer = 1;
run;

proc hpfarimaspec repository=sasuser.repository name=arimasummer;
   forecast symbol=air q=(1 12) transform=log;
   input symbol=summer;
run;

proc hpfselect repository=sasuser.repository name=select;
   spec arima arimasummer;
run;
```

Note that the results from the following PROC HPFENGINE run, shown in Output 11.2.2, are the same as the results of the simpler usage with the EVENTMAP option.

```
proc hpfengine data=air
               repository=sasuser.repository
               outest=outest2
               globalselection=select
               print=(select estimates);
   id date interval=month;
   forecast air;
   input summer;
run;
```

Output 11.2.2 Selection and Estimation Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
ARIMA	20.048903	No	ARIMA: Log(AIR) ~ Q = (1,12)
ARIMASUMMER	19.654381	Yes	ARIMA: Log(AIR) ~ Q = (1,12) + INPUT: SUMMER

Parameter Estimates for ARIMASUMMER Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**CONSTANT**	5.47071	0.04202	130.21	<.0001
AIR	**MA1_1**	-0.80089	0.02337	-34.27	<.0001
AIR	**MA1_12**	-0.27008	0.02374	-11.37	<.0001
summer	**SCALE**	0.15504	0.05859	2.65	0.0091

Example 11.3: The DIAGNOSE Statement

The DIAGNOSE statement enables control of the diagnostics used by the HPFENGINE procedure to subset the model selection list. Two ESM model specifications are created in this example: one seasonal and one nonseasonal. They are placed together in a selection list, with the seasonality test value allowed to remain at its default in this first case. The diagnostics in the HPFENGINE procedure judge the dependent series as seasonal and therefore exclude the nonseasonal model from consideration. The following statements illustrate the behavior with the explicit use of the DIAGNOSE statement. The results are shown in Output 11.3.1.

```
proc hpfesmspec repository=sasuser.repository name=logdouble;
   esm method=double transform=log;
run;

proc hpfesmspec repository=sasuser.repository name=logwinters;
   esm method=winters transform=log;
run;

proc hpfselect repository=sasuser.repository name=select;
   spec logdouble logwinters;
run;

proc hpfengine data=sashelp.air
               repository=sasuser.repository
               outest=outest1
               globalselection=select
               print=all;
   id date interval=month;
   forecast air;
run;
```

Output 11.3.1 Seasonality Test at Significance Level of 0.01

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
LOGDOUBLE	.	Removed	Log Double Exponential Smoothing
LOGWINTERS	2.7138783	Yes	Log Winters Method (Multiplicative)

In the following statements, the same two exponential smoothing models are used in a selection list again, but this time the seasonality test is disabled. Both models are fit to the series as a result. The results are shown in Output 11.3.2.

```
proc hpfselect repository=sasuser.repository name=select;
   spec logdouble logwinters;
   diagnose seasontest=none;
run;

proc hpfengine data=sashelp.air
               repository=sasuser.repository
               outest=outest1
               globalselection=select print=select;
   id date interval=month;
   forecast air;
run;
```

Output 11.3.2 No Seasonality Test Performed

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
LOGDOUBLE	10.167638	No	Log Double Exponential Smoothing
LOGWINTERS	2.713878	Yes	Log Winters Method (Multiplicative)

Finally, in the following statements, the seasonality test significance level is set to zero so that the series will not be judged as seasonal. In Output 11.3.3, note that the nonseasonal model is fit to the series, but the seasonal model is removed.

```
proc hpfselect repository=sasuser.repository name=select;
   spec logdouble logwinters;
   diagnose seasontest=(siglevel=0);
run;

proc hpfengine data=sashelp.air
               repository=sasuser.repository
               outest=outest1
               globalselection=select
               print=select;
   id date interval=month;
   forecast air;
run;
```

Output 11.3.3 All Series Treated as Nonseasonal

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
LOGDOUBLE	10.167638	Yes	Log Double Exponential Smoothing
LOGWINTERS	.	Removed	Log Winters Method (Multiplicative)

Example 11.4: External Models and User-Defined Subroutines

The EXMFUNC option enables you to associate an external model specification with a user-defined subroutine. In this example, you define a user subroutine and store it in a catalog. The following statements create a simple three-point moving average.

```
proc fcmp outlib=work.hpfengine.funcs;
   subroutine move_avg3(act[*], pred[*]);
      outargs pred;
      actlen = DIM(act);
      predlen = DIM(pred);
      pred[1] = 0;
      pred[2] = act[1]/3.0;
      pred[3] = (act[1] + act[2])/3.0;
      do i=4 to actlen+1;
         pred[i] = (act[i-1] + act[i-2] + act[i-3])/3.0;
      end;
      do i=actlen+2 to predlen;
         pred[i] = (pred[i-1] + pred[i-2] + pred[i-3])/3.0;
      end;
   endsub;
run;

options cmplib=work.hpfengine;
```

Now, just for comparison, you use the HPFARIMASPEC procedure to make a model specification that will produce the same three-point moving average.

```
proc hpfarimaspec repository=sasuser.repository name=arima;
   forecast symbol=y noint p=3
            ar=(0.333333333 0.333333333 0.333333333);
   estimate noest;
run;
```

Next, you use the HPFEXMSPEC procedure to create an external model specification and the HPFSELECT procedure to make a selection list with the external model, referring to the user-defined subroutine, and the ARIMA model.

```
proc hpfexmspec repository=sasuser.repository name=myexm;
   exm;
run;

proc hpfselect repository=sasuser.repository name=select;
```

```
   diagnose seasontest=none;
   spec arima;
   spec myexm / exmfunc('move_avg3(_actual_ _predict_ )')
                label="External Model from move_avg3";
run;
```

Finally, you use the HPFENGINE procedure to forecast a series by using the selection list just created. As expected, both models produce the same forecast, as indicated by the same selection fit statistic.

```
proc hpfengine data=sashelp.air
               out=_null_
               repository=sasuser.repository
               globalselection=select
               print=select;
   id date interval=month;
   forecast air;
run;
```

The output is shown in Output 11.4.1.

Output 11.4.1 External Model with User-Defined Subroutine versus ARIMA Model

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
ARIMA	13.455362	No	ARIMA: Y ~ P = 3 NOINT
MYEXM	13.455362	Yes	External Model from move_avg3

Example 11.5: Comparing Forecasts from Multiple External Sources

The EXMMAP option enables you to associate an external model specification with variables in a data set. This example uses the EXPAND procedure and the ARIMA procedure to generate data for the external forecasts. In practice these external data might come from judgmental forecasts or other systems. The external forecasts must be in the same data set as the series you are modeling. The following statements generate external data.

```
data temp;
   set sashelp.air;
   drop i;
   * introduce some missing for EXPAND to fill in;
   if mod(_n_, 5) eq 0 then air = .;
   if mod(_n_+1, 5) eq 0 then air = .;
   if mod(_n_+2, 5) eq 0 then air = .;
   output;

   if date eq '01dec1960'd then do;
      do i=1 to 4;
         date = intnx('month', '01dec1960'd, i);
         air = .;
         output;
      end;
```

```
      end;
   run;

proc expand data=temp extrapolate
            out=expandout;
   id date;
   convert air=interp;
run;

data temp;
   set sashelp.air;
   logair = log(air);
run;

proc arima data=temp;
   identify var=logair(1,12) noprint;
   estimate q=(1)(12) noconstant method=ml noprint;
   forecast out=arimaout(rename=(forecast=airline))
            lead=4 id=date
            interval=month noprint;
run;

data arimaout;
   set arimaout;
   airline = exp(airline);
run;

data temp;
   keep date interp airline air;
   merge expandout arimaout sashelp.air;
   by date;
run;
```

Next, you create a smoothing model to add to the selection, demonstrating that you can compare multiple external forecasts not only with one another but also with other statistical models. After the models are defined, they are added to a selection list. Notice that the same external model can be associated with different external forecasts and that the LABEL= option can be used to help differentiate between the two. Finally, the HPFENGINE procedure is called, and you see that the forecast originally generated by the ARIMA procedure best fits the historical data.

```
proc hpfesmspec repository=sasuser.repository name=esm;
   esm method=seasonal transform=auto;
run;

proc hpfexmspec repository=sasuser.repository name=exm;
   exm;
run;

proc hpfselect repository=sasuser.repository name=select;
   spec esm;
   spec exm / exmmap(predict=interp)
              label="Interpolation from PROC EXPAND";
   spec exm / exmmap(predict=airline)
              label="Forecasts from PROC ARIMA";
```

```
run;

proc hpfengine data=temp
               out=_null_
               repository=sasuser.repository
               globalselection=select
               lead=4
               print=select;
   id date interval=month;
   forecast air;
   external interp airline;
run;
```

The output is shown in Output 11.5.1.

Output 11.5.1 Two External Forecasts and a Smoothing Model

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
ESM	3.1909590	No	Log Seasonal Exponential Smoothing
EXM	5.5023045	No	Interpolation from PROC EXPAND
EXM	2.9239173	Yes	Forecasts from PROC ARIMA

Example 11.6: Input to User-Defined Subroutines

This example illustrates the different types of data that the HPFENGINE procedure can pass to a user-defined subroutine. Consider the following subroutine definition.

```
proc fcmp outlib=work.hpfengine.funcs;
   subroutine testsub(timeid[*], act[*], seasons[*],  pred[*]);
      outargs pred;
      actlen = DIM(act);
      predlen = DIM(pred);
      format date monyy.;

      * print the input;
      do i=6 to 18;
         date = timeid[i]; actual=act[i]; season=seasons[i];
         put i= date= actual= season=;
      end;

      * just return mean;
      mean = 0.0;
      do i=1 to actlen;
         mean = mean + act[i];
      end;
      mean = mean / actlen;

      do i=1 to predlen;
         pred[i] = mean;
```

```
      end;

   endsub;
run;
```

Suppose you have an external model specification and invocation of the HPFSELECT procedure such as the following.

```
proc hpfexmspec repository=sasuser.repository name=myexm1;
   exm;
run;

proc hpfselect repository=sasuser.repository name=select;
   diagnose seasontest=none;
   spec myexm1 / exmfunc('testsub(_timeid_ _actual_ _season_ _predict_)');
run;
```

Then the following call to the HPFENGINE procedure invokes the user-defined subroutine named TESTSUB.

```
options cmplib = work.hpfengine;
proc hpfengine data=sashelp.air
               out=_null_
               outfor=outfor
               repository=sasuser.repository
               globalselection=select;
   id date interval=month;
   forecast air;
run;
```

A partial listing of the log output from the run of the HPFENGINE procedure follows. The seasonal cycle length is 12, and thus the zero-based seasonal index repeats 0 through 11. Though not used in this simple subroutine, all these data are available when you are computing forecasts.

Example 11.7: Changing an Existing Selection List

The following SAS statements delete three specifications from a copy of SASHELP.HPFDFLT.BEST and add a new user-defined specification. The resulting list is named is SASUSER.REPOSITORY.SELECT.

```
proc hpfarimaspec repository=sasuser.repository name=arima;
   forecast symbol=y q=(1 12) dif=(1 12) noint transform=log;
run;

proc hpfselect name=select repository=sasuser.repository
     inselectname=sashelp.hpfdflt.best;
   delete smsimp smdamp smwint;
   spec arima;
run;
```

The following CATNAME statement gives the HPFENGINE procedure access to the model specifications in both catalogs SASHELP.HPFDFLT and SASUSER.REPOSITORY. The HPFENGINE procedure produces the output shown in Output 11.7.1.

```
catname twocats (sashelp.hpfdflt sasuser.repository);

proc hpfengine data=sashelp.air repository=work.twocats
     globalselection=select print=select out=_null_;
   id date interval=month;
   forecast air;
run;
```

Output 11.7.1 Modified Selection List

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
ARIMA	2.9672282	Yes	ARIMA: Log(Y) ~ D = (1,12) Q = (1,12) NOINT
SMLIN	.	Removed	Linear Exponential Smoothing
SMADWN	3.5343216	No	Winters Method (Additive)
SMSEAS	3.5196140	No	Seasonal Exponential Smoothing

Example 11.8: Using a Combined Forecast

In this example, the goal is to select between the forecasts from the classic ARIMA AIRLINE model and a combination of the forecasts from the AIRLINE model and the best seasonal exponential smoothing model (ESM). The following statements demonstrate the use of the COMBINE statement to define a model combination list, COMB2, and then use COMB2 in the context of a root selection list, SELECTCOMB, that is used to generate a forecast. SELECTCOMB is defined to select between the AIRLINE and COMB2 specifications by using forecast performance over a holdout sample of the last 6 months.

The COMBINE statement explicitly defines the method for determining the combination weights via the METHOD=AVERAGE option. In this case, omitting METHOD=AVERAGE produces the same result since that is the default weight method.

```
proc hpfarimaspec rep=work.rep specname=airline;
  forecast symbol=y dif=(1,s) q=(1)(1)s noint;
  estimate method=ml converge=.0001 delta=.0001 maxiter=150;
run;

proc hpfesmspec rep=work.rep name=bests;
  esm method=bests;
run;

proc hpfselect rep=work.rep name=comb2 label="AVG(AIRLINE,BESTS)";
  combine method=average;
  spec airline bests;
run;

proc hpfselect rep=work.rep name=selectcomb;
  select holdout=6;
  spec airline comb2;
run;
```

Run the selection list SELECTCOMB to choose between the better of the combined forecast and the AIRLINE model reference forecast:

```
proc hpfengine data=sashelp.air
    rep=work.rep globalselection=selectcomb
    out=out8 outfor=for8
    outmodelinfo=minfo8
    outstatselect=statsel8
    outstat=stat8
    outsum=sum8
    outcomponent=comp8
    lead=12 print=(all) plot=(components);
  id date interval=month;
  forecast air;
run;
```

From the model selection results in Output 11.8.1, the combination of the AIRLINE model forecast with the ESM forecast produces a better selection statistic of fit than the AIRLINE model alone.

Output 11.8.1 Model Selection Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
AIRLINE	3.8095583	No	ARIMA: Y ~ D = (1,s) Q = ((1)(1)s) NOINT
COMB2	2.3574267	Yes	AVG(AIRLINE,BESTS)

Output 11.8.2 through Output 11.8.4 show the parameter estimates for all of the models that contribute to the combination in addition to those for the combined forecast proper.

Output 11.8.2 Parameter Estimates for AIRLINE Model

Parameter Estimates for AIRLINE Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**MA1_1**	0.30868	0.08433	3.66	0.0003
AIR	**MA2_12**	0.10744	0.10190	1.05	0.2917

Output 11.8.3 Parameter Estimates for BESTS Model

Parameter Estimates for BESTS Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**Level Weight**	0.30728	0.03153	9.74	<.0001
AIR	**Trend Weight**	0.0010000	0.0030237	0.33	0.7413
AIR	**Seasonal Weight**	0.87493	0.07769	11.26	<.0001

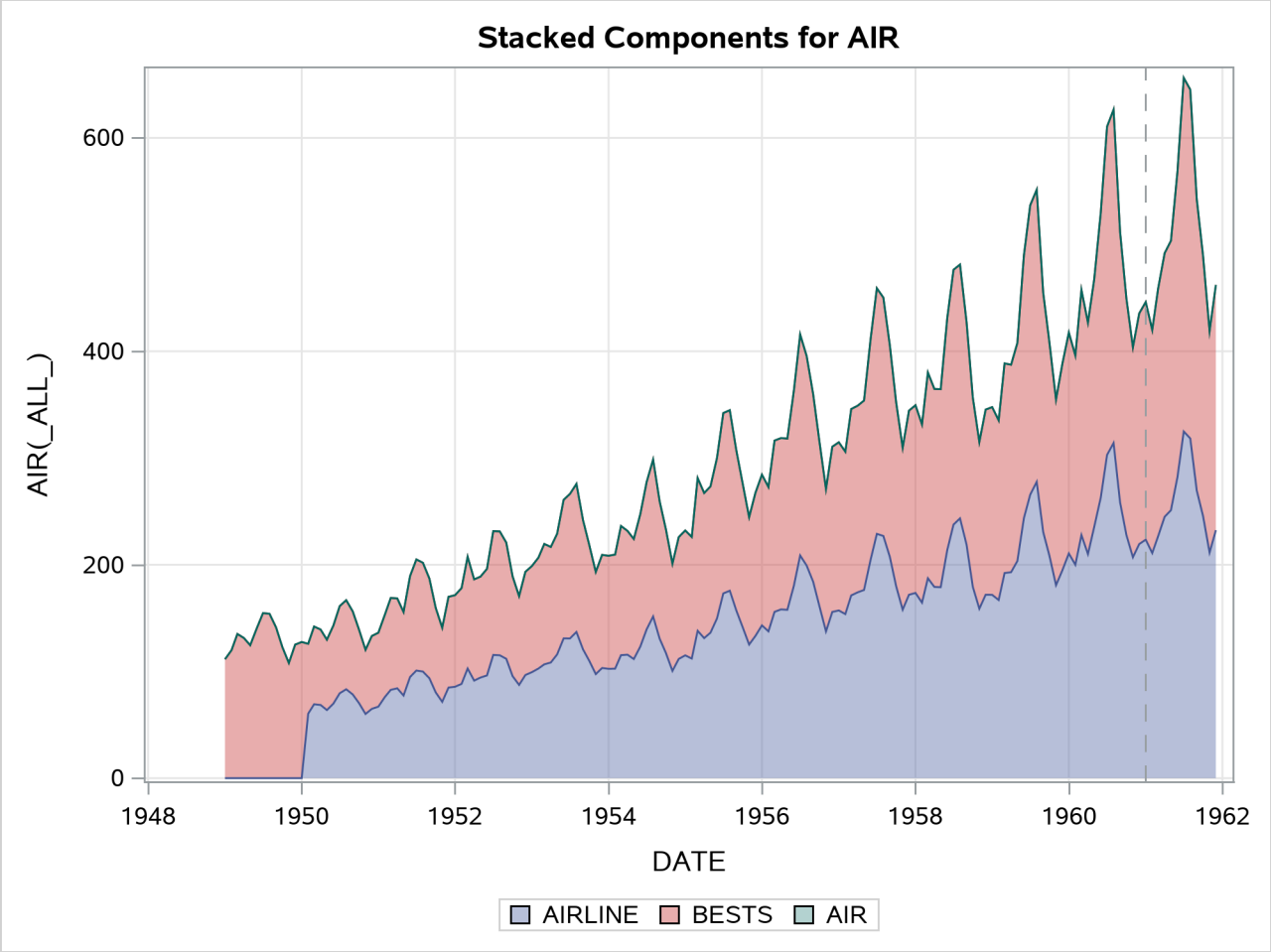
Output 11.8.4 Parameter Estimates for COMB2 Model

Parameter Estimates for COMB2 Model

Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
AIRLINE	WEIGHT	0.50000	.	.	.
BESTS	WEIGHT	0.50000	.	.	.

The weighted forecast components that contribute to the final combined forecast are plotted in a stack on the same set of axes. The weighted forecast components are plotted from bottom to top in the order of their combination to yield the final combined forecast.

Output 11.8.5 Combined Forecast Components



Chapter 12
The HPFTEMPRECON Procedure

Contents

Overview: HPFTEMPRECON Procedure **380**
Comparing the HPFTEMPRECON and HPFRECONCILE Procedures 380
Getting Started: HPFTEMPRECON Procedure **381**
Syntax: HPFTEMPRECON Procedure **381**
Functional Summary 382
PROC HPFTEMPRECON Statement 383
BY Statement 386
BENCHID Statement 386
ID Statement 388
RECONCILE Statement 390
Details: HPFTEMPRECON Procedure **391**
Mathematical Foundation 391
Input and Output Data Sets 393
Threading Details 397
Examples: HPFTEMPRECON Procedure **398**
Example 12.1: Reconciling Monthly Forecasts to Quarterly Forecasts 398
Example 12.2: Reconciling Multiple Variables 403
Example 12.3: Using Threads 406
References **408**

Overview: HPFTEMPRECON Procedure

Forecasters often need to produce forecasts for a certain time series at more than one frequency. For example, a company that provides warranty repairs for appliances needs to forecast the number of daily calls for staffing and operational planning. The company also needs to forecast service calls at the monthly frequency to plan long-term expansion and financial planning such as the purchase of more vehicles or the hiring of new staff.

A common practice is to generate the forecasts at the two time intervals independently so as to choose the best model for each frequency. That can result in forecasts that do not agree, in the sense that the accumulation over time of the high-frequency forecasts does not equal the forecasts generated by the model for the low-frequency data.

The HPFTEMPRECON procedure reconciles the high-frequency forecasts to the low-frequency forecasts in such a way that the accumulation of the reconciled high-frequency forecasts is equal to the low-frequency forecasts.

Typically, the forecasts for the two frequencies that are input to the HPFTEMPRECON procedure are generated using the two runs of the HPFENGINE procedure with different values for the INTERVAL= options in the ID statement.

Comparing the HPFTEMPRECON and HPFRECONCILE Procedures

The HPFTEMPRECON and the HPFRECONCILE procedures are related to each other in that both deal with reconciling two sets of forecasts that are generated independently. That is, they restore additivity under some form of aggregation in a hierarchy of forecasts. However, the hierarchies they deal with span different dimensions. The HPFRECONCILE procedure reconciles heterogeneous series to the aggregated parent in a hierarchy of forecasts for a given time interval that is equal for both the parent and the children series. For example, the parent node of the hierarchy is the given by the forecasts for the series of all electronic products, while the children nodes are the forecasts for the series of each element that compose the class of electronic products, such as TVs, DVD players, microwave ovens, and so on. For the HPFRECONCILE procedure the children and the parent forecasts need to be at the same frequency. The HPFTEMPRECON procedure, instead, reconciles forecasts for the same item at two different time frequencies whose intervals are nested in one another. In other words, it deals with a hierarchy of forecasts in the time dimension. For example, it reconciles monthly forecasts for the airline passenger data to the quarterly forecasts for the same series. For this reason, the HPFTEMPRECON procedure not only requires two input data sets, but also it requires that the two frequencies of the forecasts be specified in two separate statements: the ID statement for the high-frequency data, and the BENCHID statement for the low-frequency data.

Aggregation in the time dimension in which HPFTEMPRECON operates is henceforth referred to as *accumulation* to distinguish it from the aggregation across items in a hierarchy in which HPFRECONCILE operates.

Getting Started: HPFTEMPRECON Procedure

In the following example, the monthly forecasts contained in the outformon data set are adjusted to match, when accumulated, the quarterly forecasts in the outforqtr data set. The monthly reconciled forecasts are saved in the recfor data set. The relative statistics of fit are saved in the recstat data set.

Procedures User's Guide,

```
proc hpftemprecon
     data=outformon
     benchdata=outforqtr
     outfor=recfor
     outstat=recstat;
   id date interval=month;
   benchid date interval=qtr;
run;
```

Note that the HPFTEMPRECON procedure requires two input data sets because it reconciles forecasts at two different frequencies. The DATA= option in the PROC HPFTEMPRECON statement specifies the data set whose PREDICT variable contains the forecasts for the high-frequency data. The BENCHDATA= option specifies the data set whose PREDICT variable contains the forecasts for the low-frequency data. Likewise, there are two statements for specifying the time characteristics of the series. The ID statement specifies the variable in the DATA= data set that contains the time stamps and the interval frequency for the high-frequency data. The BENCHID statement specifies the variable in the BENCHDATA= data set that contains the time stamps and the interval frequency for the low-frequency data.

The PREDICT in the OUTFOR= data set contains the reconciled forecasts for the high-frequency data. The frequency of the reconciled forecasts is the same as that of the high-frequency data, as specified by the INTERVAL= option in the ID statement. When accumulated to the low frequency specified by the INTERVAL= option in the BENCHID statement, the reconciled forecasts are equal to the values of the PREDICT variable in the BENCHDATA= data set.

Syntax: HPFTEMPRECON Procedure

The HPFTEMPRECON procedure is controlled by the following statements:

PROC HPFTEMPRECON < *options* > **;**
BY *variables* < / *options* > **;**
BENCHID *variable* **INTERVAL**=*interval* < / *options* > **;**
ID *variable* **INTERVAL**=*interval* < / *options* > **;**
RECONCILE *indicator* < =*benchmark* >< / *options* > **;**

Functional Summary

Table 12.1 summarizes the statements and options used with the HPFTEMPRECON procedure.

Table 12.1 PROC HPFTEMPRECON Functional Summary

Description	Statement	Option
Statements		
Specifies the BY variables	BY	
Specifies the time ID variable of the high-frequency series	ID	
Specifies the time ID variable of the low-frequency series	BENCHID	
Specifies custom variables names	RECONCILE	
Time ID Options		
Specifies the alignment of time ID values	ID	ALIGN=
Specifies the ending time ID value	ID	END=
Specifies the date format	ID	FORMAT=
Specifies the frequency	ID	INTERVAL=
Specifies the starting time ID value	ID	START=
Specifies the missing value interpretation	ID	SETMISSING=
Specifies the zero value interpretation	ID	ZEROMISS=
Specifies the trim missing values	ID	TRIMMISS=
Benchmark Time BENCHID Options		
Specifies the alignment of time BENCHID values	BENCHID	ALIGN=
Specifies the ending time BENCHID value	BENCHID	END=
Specifies the date format	BENCHID	FORMAT=
Specifies the frequency	BENCHID	INTERVAL=
Specifies the starting time BENCHID value	BENCHID	START=
Specifies the missing value interpretation	BENCHID	SETMISSING=
Specifies the zero value interpretation	BENCHID	ZEROMISS=
Specifies the trim missing values	BENCHID	TRIMMISS=
Data Set Options		
Specifies the accumulation options for individual dependent variables	PROC HPFTEMPRECON	ACCDATA=
Specifies the input data set of the low-frequency forecasts (benchmarks)	PROC HPFTEMPRECON	BENCHDATA=
Specifies that the OUTFOR= data set contains the BENCHDIFF variable	PROC HPFTEMPRECON	BENCHDIFF
Specifies the input data set of the high-frequency forecasts	PROC HPFTEMPRECON	DATA=
Specifies the output data set to contain the reconciled forecasts	PROC HPFTEMPRECON	OUTFOR=

Table 12.1 *continued*

Description	Statement	Option
Specifies the output data set to contain summary information	PROC HPFTEMPRECON	OUTPROCINFO=
Specifies the output data set to contain statistics of fit.	PROC HPFTEMPRECON	OUTSTAT=
Analysis Options		
Specifies the type of relationship between the low-frequency and high-frequency data	PROC HPFTEMPRECON	BENCHACCUMULATION=
Specifies whether the portion of the data in the DATA= data set that are not covered by benchmarks in the BENCHDATA= data set should be used in the reconciliation process	PROC HPFTEMPRECON	BENCHCONS=
Specifies the bias correction	PROC HPFTEMPRECON	BIASCORRECTION=
Specifies the maximum number of iterations of the quadratic solver	PROC HPFTEMPRECON	MAXITER
Specifies that only the PREDICT variable be modified	PROC HPFTEMPRECON	PREDICTONLY
Specifies the exponent of the scale factor	PROC HPFTEMPRECON	SCALEEXP=
Specifies the value of the smoothing parameter	PROC HPFTEMPRECON	SMOOTH=
Specifies the sign bound on the benchmarked series	PROC HPFTEMPRECON	SIGN=

PROC HPFTEMPRECON Statement

PROC HPFTEMPRECON *options* **;**

The following *options* can be used in the PROC HPFTEMPRECON statement.

Options Related to the Input Data Sets

ACCDATA=*SAS-data-set*

specifies the name of the SAS data set that contains the BENCHACCUMULATION= option for each dependent variable listed in the _NAME_ variable. This option is useful when multiple FORECAST statements with different values of the ACCUMULATE= option are used in the HPFENGINE procedure.

See the section "ACCDATA= Data Set" on page 393 for more details about the ACCDATA= data set.

BENCHDATA=*SAS-data-set*
specifies the name of the SAS data set that contains the low-frequency series (benchmarks).

See the section "BENCHDATA= Data Set" on page 393 for more details about the BENCHDATA= data set.

DATA=*SAS-data-set*
specifies the name of the SAS data set that contains the high-frequency series.

See the section "DATA= Data Set" on page 394 for more details about the DATA= data set.

Options Related to the Output Data Sets

BENCHDIFF
specifies that the OUTFOR= data sets contain a variable named BENCHDIFF which is the difference between the reconciled predicted value and the input predicted value.

OUTFOR=*SAS-data-set*
names the output SAS data set to contain the reconciled values.

See the section "OUTFOR= Data Set" on page 395 for more details about the OUTFOR= data set.

OUTPROCINFO=*SAS-data-set*
names the output data set to contain the summary information of the processing done by PROC HPFTEMPRECON. When you write a program to assess the status of the procedure's execution, it is easier to parse a data set than it is to look at or parse the SAS log.

See the section "OUTPROCINFO= Data Set" on page 396 for more details about the OUTPROCINFO= data set.

OUTSTAT=*SAS-data-set*
names the output data set to contain the statistics of fit (or goodness-of-fit statistics). The OUTSTAT= data set is useful for evaluating how well the model fits the series. The statistics of fit are based on the entire range of the time series. See the section "OUTSTAT= Data Set" on page 397 for more details about the OUTSTAT= data set.

Options Related to Analysis

BENCHACCUMULATION=*option*
specifies how the data of the high-frequency series is accumulated within each BENCHID time period of the low-frequency series.

The following *options* determine how the high-frequency time series observations are accumulated within each time period based on the BENCHID variable and the frequency specified by the BENCHINTERVAL= option:

TOTAL	Observations are accumulated based on the total sum of their values.
AVERAGE | AVG	Observations are accumulated based on the average of their values.

See also the ACCDATA= option for an alternative way of specifying the BENCHACCUMULATION= option for individual dependent variables identified by the _NAME_ variable.

BIASCORRECTION=NONE | ADDITIVE | MULTIPLICATIVE

BIAS=NONE | ADDITIVE | MULTIPLICATIVE

specifies the type of bias correction to apply to the indicator series. The default is no bias correction (that is, BIASCORRECTION=NONE).

See the section "Mathematical Foundation" on page 391 for more details about the BIASCORRECTION= option.

BENCHCONS=STRICT | NOSTRICT

specifies whether the full range of the data in the DATA= data set or only the range covered by the data in BENCHDATA= should be used in the reconciliation process. The default is BENCHCONS=NOSTRICT, which corresponds to all data being used.

MAXITER=*k*

specifies the maximum number of iterations performed by the quadratic solver. The value *k* is an integer between 1 and the largest four-byte, signed integer, $2^{31} - 1$. The default value is MAXITER=100.

PREDICTONLY

specifies that only the predicted value be modified. If the PREDICTONLY option is not specified, the confidence limits are centered around the new forecasts again.

SCALEEXP=*n*

EXP=*n*

specifies the value of the exponent of the scaling factor. *n* is a number between 0 and 1. The default is SCALEEXP=0.

See the section "Mathematical Foundation" on page 391 for more details about the SCALEEXP= option.

SIGN=*option*

specifies the sign constraint on the reconciled series.

Valid values are as follows:

MIXED	if the output series can have any sign. This is the default.
NONNEGATIVE | POSITIVE	if the output series need to be nonnegative.
NONPOSITIVE | NEGATIVE	if the output series need to be nonpositive.

SMOOTH=*n*

specifies the value of the autoregressive smoothing parameter. *n* is a number between 0 and 1. The default is SMOOTH=0.9.

See the section "Mathematical Foundation" on page 391 for more details about the SMOOTH= option.

BY Statement

BY *variables* **;**

A BY statement can be used with PROC HPFTEMPRECON to obtain separate analyses for groups of observations defined by the BY variables.

When a BY statement appears, the procedure expects the input data set to be sorted in order of the BY variables.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data using the SORT procedure with a similar BY statement.
- Specify the BY statement option NOTSORTED or DESCENDING in the BY statement for the HPFTEMPRECON procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged in groups (according to values of the BY variables) and that these groups are not necessarily in alphabetical or increasing numeric order.
- Create an index on the BY variables using the DATASETS procedure.

For more information about the BY statement, see *SAS Programmers Guide: Essentials*. For more information about the DATASETS procedure, see the discussion in the *Base SAS Procedures Guide.*

BENCHID Statement

BENCHID *variable* < *options* > **;**

The BENCHID statement names a numeric variable that identifies observations in the BENCHDATA= data set. The BENCHID variable's values are assumed to be SAS date, time, or datetime values. The BENCHID statement specifies the frequency associated with the low-frequency time series. The BENCHID statement *options* also specify how the BENCHID values are aligned to form the low-frequency time series. The INTERVAL= option must also be specified in the BENCHID statement. The time interval specified in the BENCHID option must be coarser than the time interval specified in the ID option.

The following *options* can be used with the BENCHID statement:

ALIGN=*option*
controls the alignment of SAS dates used to identify output observations. The ALIGN= option accepts the following values: BEGINNING | BEG | B, MIDDLE | MID | M, and ENDING | END | E. The default is BEGINNING.

END=*option*
specifies a SAS date, datetime, or time value that represents the end of the data. If the last time BENCHID variable value is less than the END= value, the series is extended with missing values. If the last time BENCHID variable value is greater than the END= value, the series is truncated. For example, END="&sysdate"D uses the automatic macro variable SYSDATE to extend or truncate the series to the current date.

FORMAT=*option*

specifies a SAS format used for the DATE variable in the output data sets. The default format is the same as that of the DATE variable in the DATA= data set.

INTERVAL=*interval*

specifies the frequency of the low-frequency time series. For example, if the BENCHDATA= data set consists of quarterly observations, then INTERVAL=QTR should be used. Only one observation per time interval is allowed.

The frequency specified by the INTERVAL= option in the BENCHID statement must be lower than the frequency specified by the INTERVAL option in the ID statement. Additionally, the time ID intervals must be fully nested in the time BENCHID intervals. For example, the ID statement can have INTERVAL=QTR and the BENCHID statement can have INTERVAL=YEAR, but INTERVAL=WEEK and INTERVAL=MONTH are not allowed because weekly intervals are not fully nested in monthly intervals, since a week can span over two months.

See Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*), for the intervals that can be specified.

SETMISSING=*option* | *number*

specifies how missing values are assigned in the time series of low-frequency forecasts. If a number is specified, missing values are set to that number. If a missing value indicates an unknown value, this option should not be used. If a missing value indicates no value, a SETMISSING=0 should be used. You typically use SETMISSING=0 for transactional data because the absence of recorded data usually implies no activity. The following *options* can also be used to determine how missing values are assigned:

MISSING	Missing values are set to missing. This is the default option.
AVERAGE | AVG	Missing values are set to the average value.
MINIMUM | MIN	Missing values are set to the minimum value.
MEDIAN | MED	Missing values are set to the median value.
MAXIMUM | MAX	Missing values are set to the maximum value.
FIRST	Missing values are set to the first nonmissing value.
LAST	Missing values are set to the last nonmissing value.
PREVIOUS | PREV	Missing values are set to the previous nonmissing value. Missing values at the beginning of the series remain missing.
NEXT	Missing values are set to the next nonmissing value. Missing values at the end of the series remain missing.

START=*option*

specifies a SAS date, datetime, or time value that represents the beginning of the data. If the first time BENCHID variable value is greater than the START= value, missing values are added at the beginning of the series. If the first BENCHID variable value is less than the END= value, the series is truncated. This option and the END= option can be used to ensure that data associated with each BY group contain the same number of observations.

TRIMMISS=*option*

specifies how missing values are trimmed from the time series of low-frequency forecasts. The following *options* are available:

NONE	No missing values are trimmed.
LEFT	Beginning missing values are trimmed.
RIGHT	Ending missing values are trimmed.
BOTH	Both beginning and ending missing values are trimmed. This is the default.

ZEROMISS=*option*

specifies how beginning and ending zero values are interpreted in the time series of low-frequency forecasts. The following *options* can also be used to determine how beginning and ending zero values are assigned:

NONE	Beginning and ending zeros are unchanged. This is the default.
LEFT	Beginning zeros are set to missing.
RIGHT	Ending zeros are set to missing.
BOTH	Both beginning and ending zeros are set to missing.

If all of the series values are missing or zero, the series is not changed.

ID Statement

ID *variable* < *options* > **;**

The ID statement names a numeric variable that identifies observations in the input and output data sets for the high-frequency series in the DATA= data set and the reconciled series in the OUTFOR= data set. The ID variable's values are assumed to be SAS date, time, or datetime values. The ID statement also specifies the frequency associated with the actual time series. The ID statement *options* specify how the ID values are aligned to form the actual time series. The INTERVAL= option must be specified in the ID statement. There can be only one observation in the DATA= data set associated with each time ID interval.

The following *options* can be used with the ID statement:

ALIGN=*option*

controls the alignment of SAS dates used to identify output observations. The ALIGN= option accepts the following values: BEGINNING | BEG | B, MIDDLE | MID | M, and ENDING | END | E. The default is BEGINNING.

END=*option*

specifies a SAS date, datetime, or time value that represents the end of the data. If the last time ID variable value is less than the END= value, the series is extended with missing values. If the last time ID variable value is greater than the END= value, the series is truncated. For example, END="&sysdate"D uses the automatic macro variable SYSDATE to extend or truncate the series to the current date.

FORMAT=*option*

specifies a SAS format used for the DATE variable in the output data sets. The default format is the same as that of the DATE variable in the DATA= data set.

INTERVAL=*interval*

specifies the frequency of the indicator time series. For example, if the input data set consists of quarterly observations, then INTERVAL=QTR should be used.

The frequency specified by the INTERVAL= option of the ID statement must be higher than the frequency specified by the BENCHINTERVAL option in the BENCHID statement. Additionally, the time ID intervals must be fully nested in the time BENCHID intervals. For example, the ID statement can have INTERVAL=QTR and the BENCHID statement can have INTERVAL=YEAR, but INTERVAL=WEEK and INTERVAL=MONTH are not allowed because weekly intervals are not fully nested in monthly intervals since one week can span over two months.

See Chapter 4, "Date Intervals, Formats, and Functions" (*SAS/ETS User's Guide*), for the intervals that can be specified.

SETMISSING=*option* | *number*

specifies how missing values are assigned in the time series of high-frequency forecasts. If a *number* is specified, missing values are set to that number. If a missing value indicates an unknown value, this option should not be used. If a missing value indicates no value, a SETMISSING=0 should be used. You typically use SETMISSING=0 for transactional data because the absence of recorded data usually implies no activity. The following *options* can also be used to determine how missing values are assigned:

MISSING	Missing values are set to missing. This is the default option.
AVERAGE | AVG	Missing values are set to the average value.
MINIMUM | MIN	Missing values are set to the minimum value.
MEDIAN | MED	Missing values are set to the median value.
MAXIMUM | MAX	Missing values are set to the maximum value.
FIRST	Missing values are set to the first nonmissing value.
LAST	Missing values are set to the last nonmissing value.
PREVIOUS | PREV	Missing values are set to the previous nonmissing value. Missing values at the beginning of the series remain missing.
NEXT	Missing values are set to the next nonmissing value. Missing values at the end of the series remain missing.

START=*option*

specifies a SAS date, datetime, or time value that represents the beginning of the data. If the first time ID variable value is greater than the START= value, missing values are added at the beginning of the series. If the first time ID variable value is less than the END= value, the series is truncated. This option and the END= option can be used to ensure that data associated with each BY group contain the same number of observations.

TRIMMISS=*option*

specifies how missing values are trimmed from the time series of high-frequency forecasts. The following options are provided:

NONE	No missing values trimmed.
LEFT	Beginning missing values are trimmed.
RIGHT	Ending missing values are trimmed.
BOTH	Both beginning and ending missing values are trimmed. This is the default.

ZEROMISS=*option*

specifies how beginning and ending zero values are interpreted in the time series of high-frequency forecasts. The following *options* can also be used to determine how beginning and ending zero values are assigned:

NONE	Beginning and ending zeros are unchanged. This is the default.
LEFT	Beginning zeros are set to missing.
RIGHT	Ending zeros are set to missing.
BOTH	Both beginning and ending zeros are set to missing.

If all of the values in the accumulated series are missing or zero, the series is not changed.

RECONCILE Statement

RECONCILE *indicator< =benchmark> </options>* **;**

The RECONCILE statement enables you to specify custom names for a group of variables to be reconciled and identify the role each of those variables plays in the reconciliation process. Multiple reconcile statements can be specified. Each RECONCILE statement specifies one variable in the DATA= data set to be reconciled, and, optionally, the corresponding variable in the BENCHDATA= data set that should be used for reconciling that particular variable. The *indicator* argument is required in the RECONCILE statement. It specifies the name of the variable in the DATA= data set that contains the high-frequency predicted values to be reconciled. The optional *=benchmark* argument specifies the name of the variable in the BENCHDATA= data set that contains the low-frequency predicted values used as benchmarks in the reconciliation process.

You can also specify in the RECONCILE statement the variables in the DATA= data set that should be associated with the variable to be reconciled. You identify the roles of these variables and the corresponding data set variable name through the *role=variable options*.

ACTUAL=*variable-name*

specifies the name of the variable in the DATA= data set that contains the actual values.

LOWER=*variable-name*
specifies the name of the variable in the DATA= data set that contains the lower confidence limit values.

UPPER=*variable-name*
specifies the name of the variable in the DATA= data set that contains the upper confidence limit values.

STD=*variable-name*
specifies the name of the variable in the DATA= data set that contains the standard error values.

When the RECONCILE statement is not specified, the default names are PREDICT for the indicator variable, PREDICT for the benchmark variable in the BENCHDATA= data set, ACTUAL for the actual values, LOWER for the lower confidence limit, UPPER for the upper confidence limit, and STD for the standard error.

See Example 12.2 for an example of how to use the RECONCILE statement when you want to reconcile multiple indicator variables in the same DATA= data set.

When you use PROC HPFTEMPRECON to reconcile forecasts with the OUTFOR= data set results from various SAS Forecast Server procedures, it is not necessary, or even desirable, to use the RECONCILE statement. You only need to identify the DATA= and BENCHDATA= data sets and the corresponding time ID information for those data sets via ID and BENCHID statements, respectively. You can optionally specify a BY-clause in the PROC HPFTEMPRECON invocation if BY-group qualification was used when the original forecasts were produced.

In this context, it is important to remember that neither BENCHID nor ID support accumulation over duplicate time ID's in a given series. Thus for proper operation, it becomes important to specify the same BY-variable qualification in the PROC HPFTEMPRECON run as was used to construct the original low-frequency and high-frequency forecast data sets. This ensures seamless operation of PROC HPFTEMPRECON with the other SAS Forecast Server procedures with a minimum of SAS code. For more information about accumulation, see the HPFTEMPRECON BENCHACCUMULATION option.

Details: HPFTEMPRECON Procedure

Mathematical Foundation

Forecasters often deal with data that are accumulated at different time intervals. For example, long-term forecasts are determined using yearly data, while short-term forecasts are determined using weekly data. If the forecasts at the two time intervals are generated independently one from the other, the sum of the higher-frequency forecasts within each time interval of the lower-frequency series do not necessarily add up to the lower-frequency forecasts. The HPFTEMPRECON procedure reconciles the high-frequency forecasts to the low-frequency forecasts in such a way that the accumulation of the reconciled high-frequency forecasts is equal to the low-frequency forecasts.

The process of adjusting more frequent data to match less frequent but more reliable data is known in the statistical literature as *benchmarking*. Denton (1971) provided the first general framework for benchmarking based on the minimization of a quadratic loss function. A recent and comprehensive review of the topic can be found in Dagum and Cholette (2006). PROC HPFTEMPRECON follow an approach similar to the one

outlined in Quenneville et al. (2006). The lower-frequency forecasts are also referred to as the *benchmark forecasts*. The higher-frequency forecasts are also referred to as the *indicator forecasts*. The benchmarking procedure can be applied more generally to any two series that are measured at different time intervals. Therefore, this chapter more generally refers to the *benchmark series* and *indicator series* to indicate the forecasts involved in the benchmarking.

Denote the indicator series by x_t with $t = 1, \ldots, T$, where t is associated with a date that corresponds to the time ID variable of the indicator series. Denote the benchmark series by a_m, $m = 1 \ldots, M$. The benchmarks have a starting date $t_{1,m}$ and ending date $t_{2,m}$ such that $1 \leq t_{1,m} \leq t_{2,m} \leq T$.

The bias is defined as the expected discrepancy between the benchmark and the indicator series. You can decide whether to adjust the original indicator series to account for the bias using the BIASCORRECTION= option. Denote by s_t the bias-adjusted indicator series. When no adjustment for bias is performed, $s_t := x_t$.

The (*additive bias*) correction is given by:

$$b = \frac{\sum_{m=1}^{M} a_m - \sum_{m=1}^{M} \sum_{t=t_{1,m}}^{t_{2,m}} x_t}{\sum_{m=1}^{M} \sum_{t=t_{1,m}}^{t_{2,m}} 1}$$

In this case, the bias-adjusted indicator series is $s_t := b + x_t$.

The (*multiplicative bias*) correction is given by:

$$b = \frac{\sum_{m=1}^{M} a_m}{\sum_{m=1}^{M} \sum_{t=t_{1,m}}^{t_{2,m}} x_t}$$

In this case, the bias-adjusted indicator series is $s_t := b \cdot x_t$.

Note that the multiplicative bias is not defined when the denominator is zero. When such an event occurs and BIASCORRECTION=MULTIPLICATIVE, the required bias correction is not applied. Observations for which the bias correction cannot be applied are identified by the corresponding code in the _RECFLAGS_ variable in the OUTFOR= data set.

Let $\boldsymbol{s} := [s_1, s_2, \ldots, s_T]'$ be the vector of the bias-corrected indicator series, and let $\boldsymbol{\theta} := [\theta_1, \theta_2, \ldots, \theta_T]'$ be the vector of its reconciled values. Let D be the $T \times T$ diagonal matrix whose main-diagonal elements are $d_{t,t} = |s_t|^{\lambda}$, $t = 1, \ldots, T$. Indicate by V the tridiagonal symmetric matrix whose main-diagonal elements are $v_{1,1} = v_{T,T} = 1$ and $v_{t,t} = 1 + \rho^2$, $t = 2, \ldots, T-1$, and whose sub- and super-diagonal elements are $v_{t,t+1} = v_{t+1,t} = -\rho$, $t = 1, \ldots, T-1$. Define $Q := D^{+}VD^{+}$ and $\boldsymbol{c} := -Q\boldsymbol{s}$, where D^{+} indicates the Moore-Penrose pseudo-inverse of D.

The benchmarked (or reconciled) series is given by the values θ_t, $t = 1, \ldots, T$ that minimize the quadratic function

$$f(\boldsymbol{\theta}; \lambda, \rho) = \frac{1}{2}\boldsymbol{\theta}' Q \boldsymbol{\theta} + \boldsymbol{c}'\boldsymbol{\theta}$$

under the constraints

$$\sum_{t=t_{1,m}}^{t_{2,m}} \theta_t = a_m, \qquad m = 1, \ldots, M$$

where $0 \leq \rho \leq 1$ and $\lambda \in \Re$ are parameters that you define with the SMOOTH= and SCALEXP= options, respectively, in the PROC HPFTEMPRECON statement. When $\boldsymbol{s}$ does not contain zeros, the preceding target

function is equivalent to the one proposed by Quenneville et al. (2006). The parameter ρ is a smoothing parameter that controls movement preservation. The closer ρ is to one, the more the original series movement is preserved. The parameter λ typically takes values 0, 0.5, or 1 and controls the *proportionality* of the target function. For $\lambda = 0$, you have an additive benchmarking model. Note that when $\lambda = 0$ and $s_t = 0$, zero to the power zero is assumed to be one to guarantee that the target function be defined. For $\lambda = 0.5$ and $\rho = 0$, you have a pro-rating benchmarking model. The two first-difference versions of the penalty functions proposed by Denton (1971), as modified by Cholette (1984), can be retrieved as special cases by setting $\rho = 1$ and $\lambda = 0$, or $\lambda = 1$.

When $0 \leq \rho < 1$, the preceding minimization problem is equivalent to a constrained regression problem where the error between the bias-adjusted indicator and the benchmarked series follows an AR(1) process with autoregressive parameter proportional to ρ. See Quenneville et al. (2006) for more details.

Input and Output Data Sets

ACCDATA= Data Set

The ACCDATA= data set contains the BENCHACCUMULATION= option values for each dependent variable listed in the _NAME_ variable. The ACCDATA= data set is useful when the input data sets are generated by the HPFENGINE procedure with multiple FORECAST statements that do not have equal values of the ACCUMULATE= option.

The ACCDATA= data set must contain the following variables:

NAME the variable name

ACCUMULATE the value of the BENCHACCUMULATION= option to be used for the specified _NAME_ value

If not all possible values of _NAME_ are listed in the ACCDATA= data set, the BENCHACCUMULATION= option is determined by the value specified by the BENCHACCUMULATION= option in the HPFTEMPRECON statement.

BENCHDATA= Data Set

The BENCHDATA= data set contains the low-frequency data. The frequency at which the low-frequency series is measured must be lower than the frequency at which the high-frequency series in the DATA= data set is observed. Additionally, the intervals at which the high-frequency data is measured must be fully nested in one interval of the low-frequency data. That is, one interval of the high-frequency data cannot span over two intervals of the low-frequency data. For example, days are nested in weeks, but weeks are not nested in months because one week can span over two months. At most one observation is allowed for each time interval in the BENCHDATA= data set. If there are two or more observations for the same time interval, only the first one is used for the reconciliation process.

See the sections "BENCHID Statement" on page 386 and "ID Statement" on page 388 for more details about the time intervals.

Typically, the data set (which is specified in the BENCHDATA= option in the PROC HPFTEMPRECON statement) is generated by the OUTFOR= option in a previous run of PROC HPFENGINE that produces the forecasts for the low-frequency data. The INTERVAL= option in the BENCHID statement in the current

PROC HPFTEMPRECON run is also equal to the INTERVAL= option in the ID statement in the previous PROC HPFENGINE run. See Example 12.1 for an example of a typical run of HPFTEMPRECON which follows two runs of PROC HPFENGINE. See also Chapter 5, "The HPFENGINE Procedure," for more details about the HPFENGINE procedure.

The BENCHDATA= data set must contain the BY variables, the BENCHID variable, and the following variables:

NAME	variable name
PREDICT	predicted values

The following variables can optionally be present in the BENCHDATA= data set and are used when available. If they are not present, their value is assumed to be missing for computational purposes.

ACTUAL	actual values
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors
STD	prediction standard errors

The BENCHDATA= data set must be either sorted by the BY variables and by the BENCHID variable, or indexed on the same variables.

You can specify custom names for the variables in the BENCHDATA= data set by using the SAS RENAME= data set option or by using the RECONCILE statement.

DATA= Data Set

The DATA= data set contains the high-frequency data. The frequency at which the high-frequency series are measured must be higher than the frequency at which the low-frequency series in the BENCHDATA= data set are observed. Additionally, the intervals at which the high-frequency data are specified must not span over more than one interval of the low-frequency data. Only one observation is allowed for each time interval. If there are two or more observations in the same time interval, only the first one is used for the reconciliation process, and the observations that are not reconciled are identified by a type 'D' missing value for the PREDICT variable in the OUTFOR= data set, where the type 'D' missing value indicates a duplicate in the time ID sequence.

See the sections "BENCHID Statement" on page 386 and "ID Statement" on page 388 for more details about the time intervals.

Typically, the data set (which is specified in the DATA= option in the PROC HPFTEMPRECON statement) is generated by the OUTFOR= option in a previous run of PROC HPFENGINE that produces the forecasts for the high-frequency data. The INTERVAL= option in the ID statement in the current PROC HPFTEMPRECON run is also equal to the INTERVAL= option in the ID statement in the previous PROC HPFENGINE run. See Example 12.1 for an example of a typical run of HPFTEMPRECON which follows two runs of PROC HPFENGINE. See also Chapter 5, "The HPFENGINE Procedure," for more details about the HPFENGINE procedure.

The DATA= data set must contain the BY variables, the ID variable, and the following variables:

NAME	variable name
PREDICT	predicted values

The following variables can optionally be present in the DATA= data set and are used when available. If they are not present, their value is assumed to be missing for computational purposes.

ACTUAL	actual values
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors
STD	prediction standard errors

The DATA= data set must be either sorted by the BY variables and by the ID variable, or indexed on the same variables.

You can specify custom names for the variables in the DATA= data set by using the SAS RENAME data set option or by using the RECONCILE statement.

OUTFOR= Data Set

The OUTFOR= data set contains the BY variables, the time ID variable, and the following variables:

NAME	variable name
ACTUAL	actual values
PREDICT	predicted values
LOWER	lower confidence limits
UPPER	upper confidence limits
ERROR	prediction errors
STD	prediction standard errors
RECFLAGS	benchmarking status flags. This variable contains 32-bit flags in hexadecimal format that identify various characteristics of the corresponding value in the PREDICT column. These characteristics can be informational, or they represent errors encountered during the formulation and solution of the optimization problem used to generate the reconciled forecast, or sometimes both. The notation 0x*n* is used to indicate that *n* is to be interpreted as a hexadecimal digit. These bit-flags can occur in various combinations depending on need. A value of 0x0 in _RECFLAGS_ indicates that the corresponding PREDICT value was successfully reconciled without qualification. There are two categories of _RECFLAGS_ bits: some represent failures and some represent informational conditions. When a failure occurs, the benchmarked series in the OUTFOR data set is the original indicator series. The following list defines the flag values associated with failure conditions:

0x00000001 A generic error condition occurred.

0x00000002 Insufficient memory was available.

0x00000004 Input data inconsistency prohibited formulation of the optimization problem.

0x00000008 A quadratic solver error occurred.

0x00000010 A computational error occurred when the optimization problem was being solved.

0x00000020 A matching BY group was not found in the BENCHDATA= data set.

0x00000030 Not enough data to formulate the problem.

Informational flags are defined as follows:

0x00010000 A missing predicted value in DATA= data set was replaced by actual value.

0x00020000 An observation has no BENCHDATA= parent observation.

0x00030000 Bias correction was not applied.

If you want to interpret these flag values in SAS code, it might be helpful to consult the *SAS Functions and CALL Routines: Reference* for the DATA step functions such as BOR, BAND, and BRSHIFT.

BENCHDIFF difference between the reconciled series and the input series predicted value. This variable is generated only when the BENCHDIFF option is specified in the HPFTEMPRECON statement.

The OUTFOR= data set is always sorted by the BY variables, the _NAME_ variable, and the time ID variable, even if input data sets are indexed and not sorted.

The values of the ID variable in the OUTFOR= data set are aligned based on the ALIGN= and INTERVAL= options specified in the ID statement. If the ALIGN= option is not specified, then the values are aligned to the beginning of the interval.

When more than one observation is present in one time interval in the input DATA= data set, only the first observation is used in the reconciliation process and the observations that are not reconciled are identified by a type 'D' missing value for the PREDICT variable in the OUTFOR= data set, where the type 'D' missing value indicates a duplicate in the time ID sequence.

OUTPROCINFO= Data Set

The OUTPROCINFO= data set contains information about the run of the HPFTEMPRECON procedure. The following variables are present:

SOURCE the name of the procedure, in this case HPFTEMPRECON.

NAME name of an item being reported; can be the number of errors, notes, or warnings, number of benchmarks requested, and so on. Table 12.2 summarizes the values and meanings of the _NAME_ variable in PROC HPFTEMPRECON. When threads are used, the value of the row that corresponds to _STAGE_='THREAD' defines the number of threads used for solving reconciliation solver instances. Subsequent rows groups (which correspond to _STAGE_='THREAD'_*n*) record per-thread buffer statistics, where *n*=1, . . ., NCPUCOUNTS.

Table 12.2 Values of the _NAME_ Variable

NAME	_STAGE_	Meaning
SERIES	ALL	Number of series processed
REQUESTED	ALL	Number of reconciliations requested
FAILED	ALL	Number of reconciliations that failed
MODE	ALL	Thread mode used
NBUFIN	ALL	Number of input buffers serviced
NBUFOUT	ALL	Number of output buffers serviced
MINBUFIN	ALL	Minimum input buffer size processed
MINBUFOUT	ALL	Minimum output buffer size processed
MAXBUFIN	ALL	Maximum input buffer size processed
MAXBUFOUT	ALL	Maximum output buffer size processed
NTHREADS	THREAD	Number of threads used
NBUFIN	THREAD_*n*	Number of input buffers serviced
NBUFOUT	THREAD_*n*	Number of output buffers serviced
MINBUFIN	THREAD_*n*	Minimum input buffer size processed
MINBUFOUT	THREAD_*n*	Minimum output buffer size processed
MAXBUFIN	THREAD_*n*	Maximum input buffer size processed
MAXBUFOUT	THREAD_*n*	Maximum output buffer size processed

LABEL descriptive label for the item in _NAME_.

STAGE current stage of the procedure. For execution statistics gained from the procedure as a whole, this is set to `'ALL'`. For execution statistics related to a particular thread, it is set to `'THREAD'`_*n*, where *n* is the ordered number of the thread in question.

VALUE value of the item specified in _NAME_.

OUTSTAT= Data Set

See the section "OUTSTAT= Data Set" on page 205 in Chapter 5, "The HPFENGINE Procedure," for details about the OUTSTAT= data set.

Threading Details

PROC HPFTEMPRECON can multithread to reduce the elapsed time required to reconcile forecasts. For each indicator/benchmark series pairing in the reconciliation run, PROC HPFTEMPRECON must formulate and solve an instance of a mathematical program (MP) to generate reconciled forecasts (see the section "Mathematical Foundation" on page 391). Given a reconciliation run with a large number of BY groups or a run with several RECONCILE statements, or both in combination, substantial leverage can be gained by the use of multiprocessing to generate and solve the sequence of optimization problems. This can result in substantially reduced solution time with adequate CPU and memory resources on the system that runs PROC HPFTEMPRECON.

You can use SAS system options to control threading in PROC HPFTEMPRECON.You enable threading with the THREADS option, or disable it with the NOTHREAD option. The system option CPUCOUNT=

sets the maximum number of threads allowed. CPUCOUNT=1 is equivalent to no threading. If the BY statement is not specified, threading is disabled regardless of the value of these options, since the cost of using threads would outweigh the benefits when there is only one optimization program to solve. Other settings of CPUCOUNT in the presence of a BY statement choose the most appropriate threading strategy to use the available CPU resources.

See *SAS System Options: Reference* for more information about the THREADS | NOTHREADS and CPUCOUNT= system options. See also Example 12.3 for an example of using threads with PROC HPFTEMPRECON.

Examples: HPFTEMPRECON Procedure

Example 12.1: Reconciling Monthly Forecasts to Quarterly Forecasts

In this example, monthly forecasts for the data set Sashelp.Air are reconciled to the quarterly forecasts of the same series.

First, PROC HPFESMSPEC generates an exponential smoothing model specification which was selected by the HPFSELECT procedure. See Chapter 6 and Chapter 11 for more details about the HPFESMSPEC and HPFSELECT procedures, respectively.

```
proc hpfesmspec
      rep=work.repo
      specname=myesm;
   esm;
run;

proc hpfselect
      rep=work.repo
      name=myselect;
   spec myesm;
run;
```

Then, forecasts are generated with PROC HPFENGINE at the monthly and the quarterly frequencies using the selected model specification.

```
proc hpfengine
      data=sashelp.air
      rep=work.repo
      globalselection=myselect
      out=outmon
      outfor=outformon
      outmodelinfo=outmodmon;
   id date interval=month;
   forecast air;
run;

proc hpfengine
      data=sashelp.air
```

```
      rep=work.repo
      globalselection=myselect
      out=outqtr
      outfor=outforqtr
      outmodelinfo=outmodqrt;
   id date interval=qtr accumulate=total;
   forecast air;
run;
```

Finally, the monthly forecasts are reconciled to the quarterly forecasts using PROC HPFTEMPRECON with default values for the smoothing and scale exponent parameters.

```
proc hpftemprecon
      data=outformon
      benchdata=outforqtr
      outfor=benfor1
      outstat=benstat1;
   id date interval=month;
   benchid date interval=qtr;
run;
```

Output 12.1.1 displays the first 20 rows of the output data set BENFOR1, which contains the reconciled forecasts.

```
title 'BENFOR1';
proc print data=benfor1(obs=20); run;
```

Output 12.1.1 Reconciled Forecasts, Default Parameters

BENFOR1

Obs	_NAME_	DATE	ACTUAL	PREDICT	LOWER	UPPER	ERROR	STD	_RECFLAGS_
1	AIR	JAN1949	112	109.596	88.642	130.550	2.4038	10.6910	00000000
2	AIR	FEB1949	118	118.292	97.338	139.246	-0.2920	10.6910	00000000
3	AIR	MAR1949	132	134.101	113.147	155.055	-2.1010	10.6910	00000000
4	AIR	APR1949	129	131.261	110.307	152.215	-2.2608	10.6910	00000000
5	AIR	MAY1949	121	125.618	104.664	146.572	-4.6184	10.6910	00000000
6	AIR	JUN1949	135	142.663	121.709	163.617	-7.6630	10.6910	00000000
7	AIR	JUL1949	148	158.532	137.578	179.486	-10.5322	10.6910	00000000
8	AIR	AUG1949	148	158.191	137.237	179.145	-10.1907	10.6910	00000000
9	AIR	SEP1949	136	144.719	123.765	165.673	-8.7193	10.6910	00000000
10	AIR	OCT1949	119	124.365	103.411	145.319	-5.3648	10.6910	00000000
11	AIR	NOV1949	104	109.137	88.183	130.091	-5.1366	10.6910	00000000
12	AIR	DEC1949	118	127.854	106.900	148.808	-9.8543	10.6910	00000000
13	AIR	JAN1950	115	133.405	112.451	154.359	-18.4047	10.6910	00000000
14	AIR	FEB1950	126	138.363	117.408	159.317	-12.3625	10.6910	00000000
15	AIR	MAR1950	141	153.119	132.165	174.073	-12.1191	10.6910	00000000
16	AIR	APR1950	135	147.403	126.449	168.357	-12.4029	10.6910	00000000
17	AIR	MAY1950	125	136.212	115.258	157.166	-11.2116	10.6910	00000000
18	AIR	JUN1950	149	148.854	127.900	169.808	0.1464	10.6910	00000000
19	AIR	JUL1950	170	163.688	142.734	184.642	6.3119	10.6910	00000000
20	AIR	AUG1950	170	166.391	145.436	187.345	3.6095	10.6910	00000000

Output 12.1.2 displays the BENSTAT1 data set, which contains the statistics of fit for the reconciled forecasts.

```
title 'BENSTAT1';
proc print data=benstat1 noobs; run;
```

Output 12.1.2 Reconciled Forecasts Statistics of Fit

BENSTAT1

NAME	_REGION_	DFE	NMISSA	NOBS	N	NPARMS	NMISSP	TSS	SST	SSE	MSE
AIR	FORECAST	144	12	156	156	0	0	13371737	2058044.16	22969.94	159.513

RMSE	UMSE	URMSE	MAPE	MAE	RSQUARE	ADJRSQ	AADJRSQ	RWRSQ	AIC	AICC	SBC
12.6299	159.513	12.6299	3.92521	9.95548	0.98884	0.98892	0.98884	0.85901	730.386	730.386	730.386

APC	MAXERR	MINERR	MAXPE	MINPE	ME	MPE	MDAPE	GMAPE	MINPPE	MAXPPE	MPPE
159.513	33.0807	-35.4894	10.7302	-18.3817	0.035721	-0.74054	3.24930	2.57881	-15.5275	12.0200	-0.49959

MAPPE	MDAPPE	GMAPPE	MINSPE	MAXSPE	MSPE	SMAPE	MDASPE	GMASPE	MINRE	MAXRE	MRE
3.84944	3.31582	2.56290	-16.8345	11.3386	-0.61790	3.88241	3.30298	2.57007	-25.2160	11.9697	-0.17253

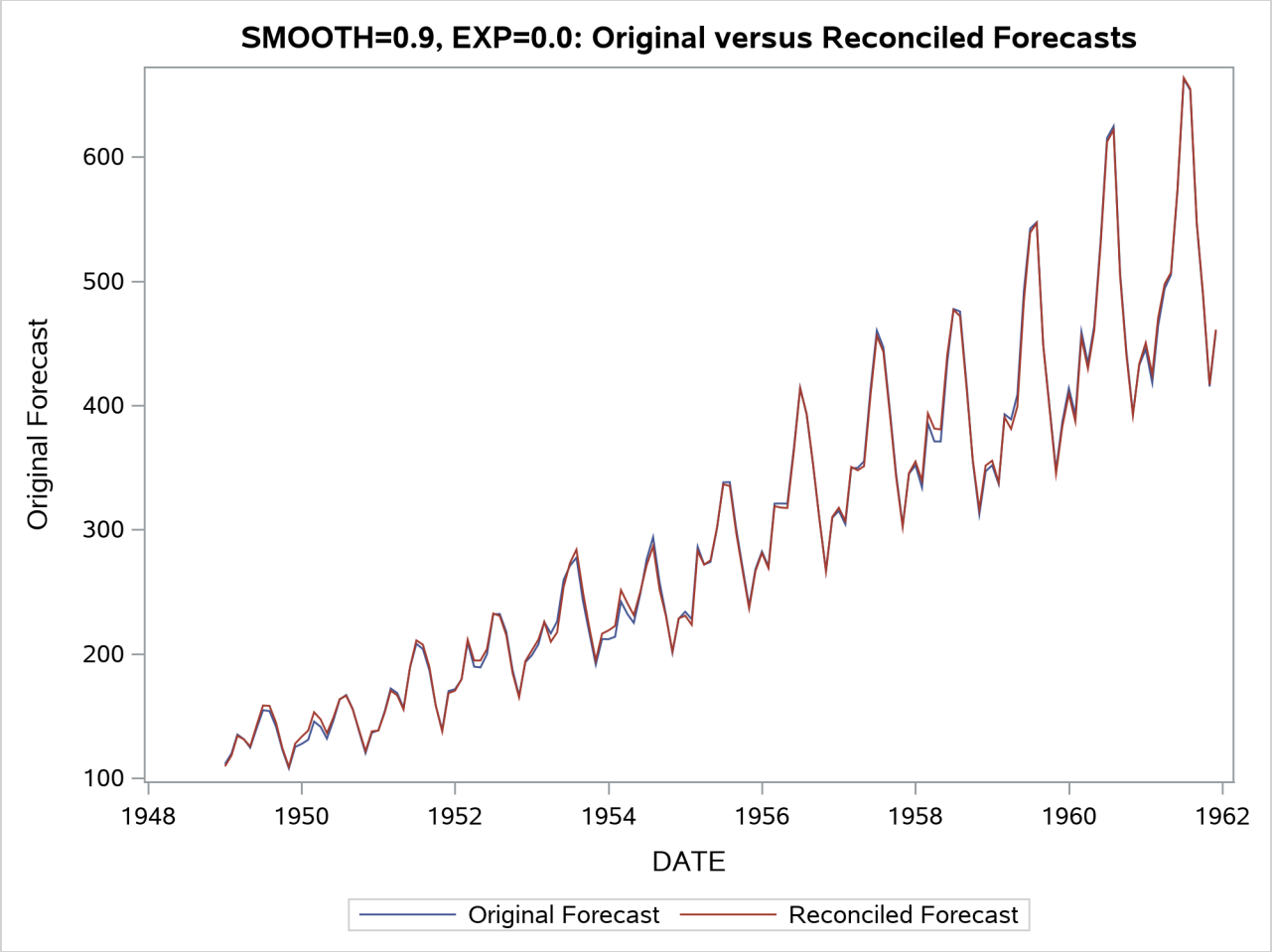
MRAE	MDRAE	GMRAE	MASE	MINAPES	MAXAPES	MAPES	MDAPES	GMAPES
0.99869	0.40464	0.36093	0.38497	0.12206	29.5828	8.29856	7.42818	5.48651

You can vary the reconciled forecasts by selecting the values of the SMOOTH= and EXP= options. Figure 12.1.3, Figure 12.1.4, and Figure 12.1.5 show the original forecasts versus the reconciled forecasts for different combinations of the two parameters. See the section "Mathematical Foundation" on page 391 for more details about the SMOOTH= and EXP= options.

```
data combined1;
   label opredict="Original Forecast";
   label bpredict="Reconciled Forecast";
   merge outformon(rename=(predict=opredict))
      benfor1(rename=(predict=bpredict));
   by _name_ date;
run;

title "SMOOTH=0.9, EXP=0.0: Original versus Reconciled Forecasts";
proc sgplot data=combined1;
   series x=date y=opredict;
   series x=date y=bpredict;
run;
```

Output 12.1.3 Original versus Reconciled Forecasts, SMOOTH=0.9, EXP=0

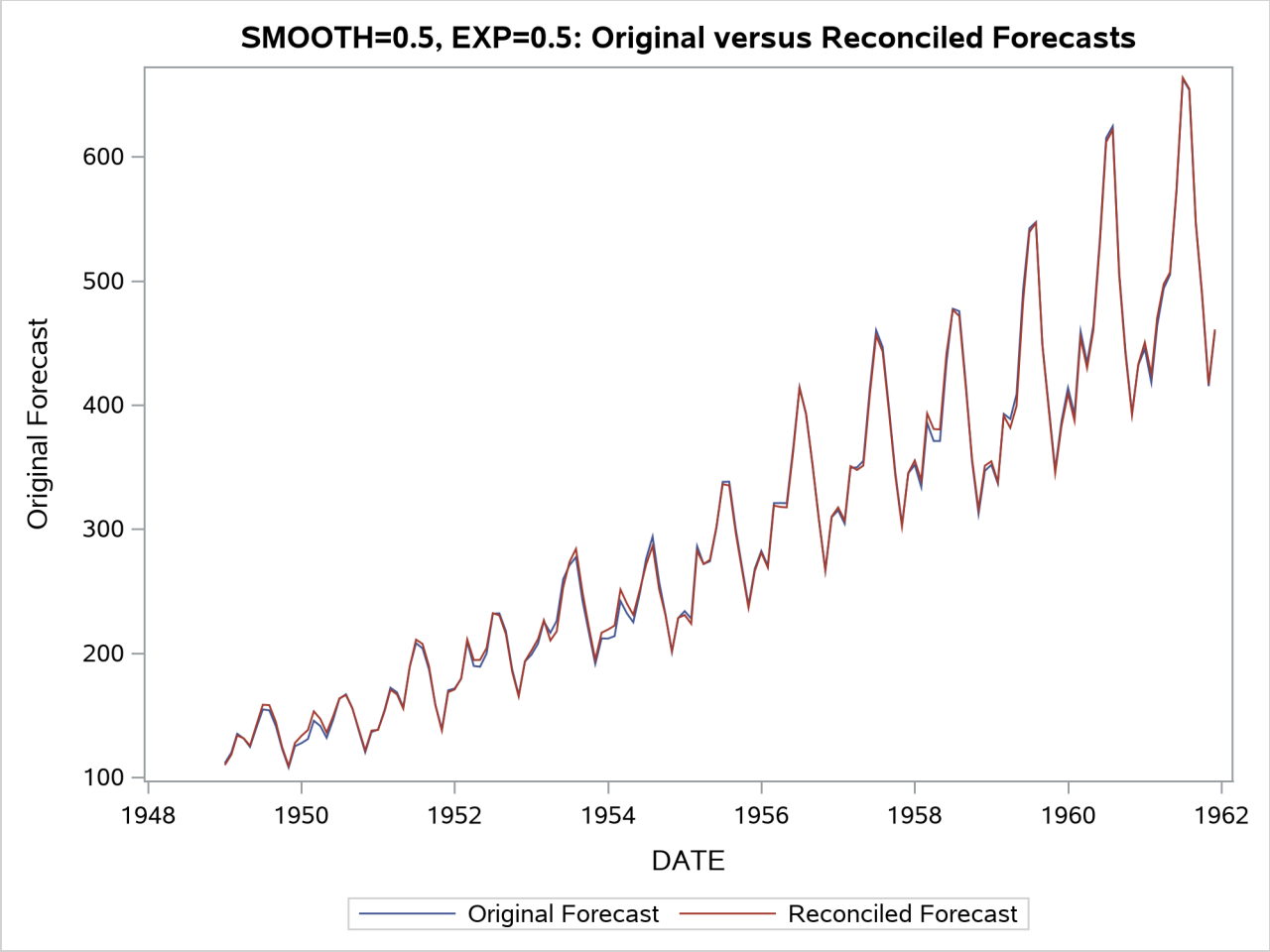



```
proc hpftemprecon
      data=outformon
      benchdata=outforqtr
      outfor=benfor2
      outstat=benstat2
      exp=0.5
      smooth=0.5;
   id date interval=month;
   benchid date interval=qtr;
run;

title "SMOOTH=0.5, EXP=0.5: Original versus Reconciled Forecasts";
data combined2;
   label opredict="Original Forecast";
   label bpredict="Reconciled Forecast";
   merge outformon(rename=(predict=opredict))
      benfor2(rename=(predict=bpredict));
   by _name_ date;
run;
proc sgplot data=combined2;
   series x=date y=opredict;
```

```
   series x=date y=bpredict;
run;
```

Output 12.1.4 Original versus Reconciled Forecasts, SMOOTH=0.5, EXP=0.5

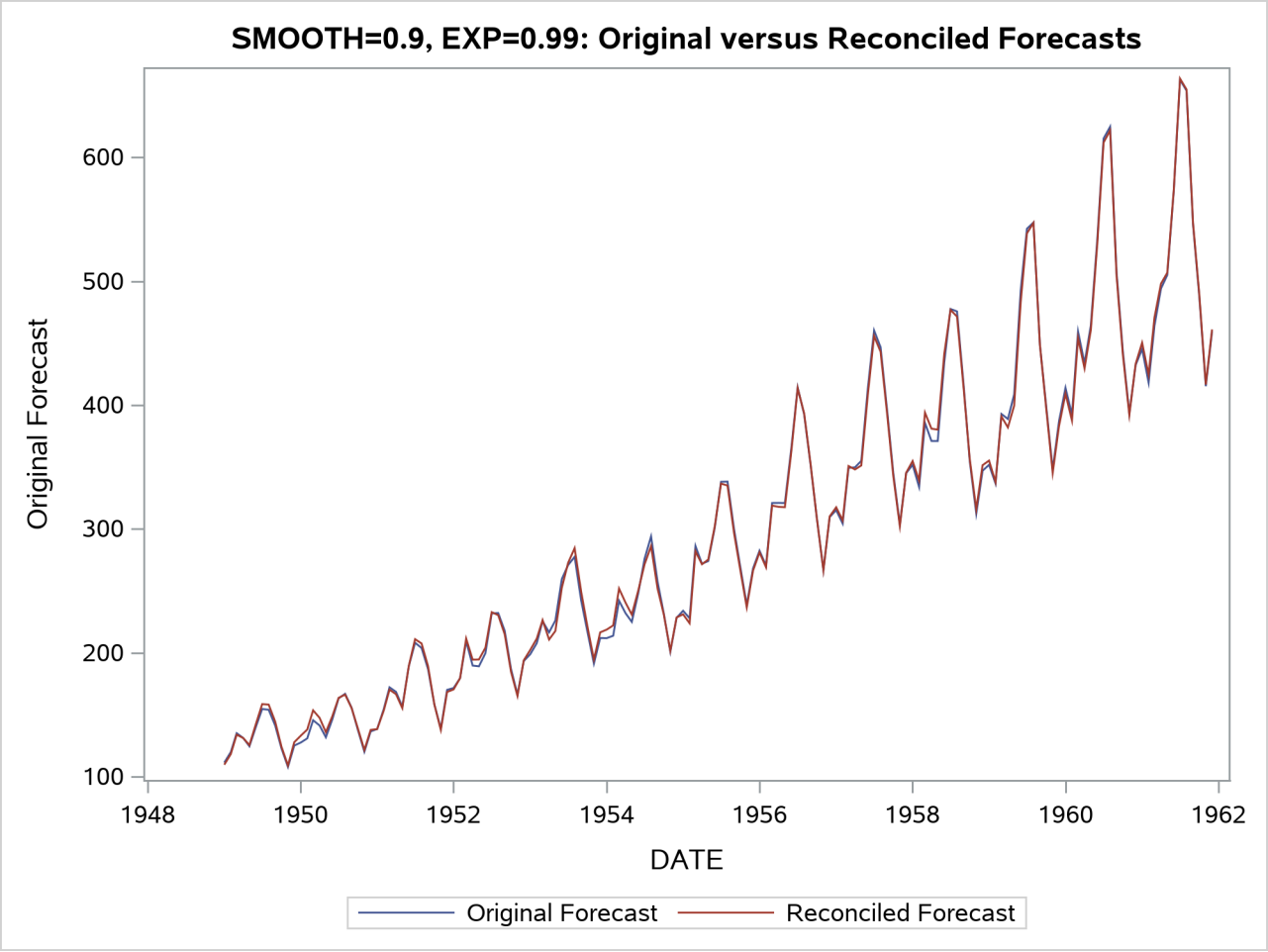



```
proc hpftemprecon
   data=outformon
      benchdata=outforqtr
      outfor=benfor3
      outstat=benstat3
      exp=0.99
      smooth=0.9;
   id date interval=month;
   benchid date interval=qtr;
run;

title "SMOOTH=0.9, EXP=0.99: Original versus Reconciled Forecasts";
data combined3;
   label opredict="Original Forecast";
   label bpredict="Reconciled Forecast";
   merge outformon(rename=(predict=opredict))
      benfor3(rename=(predict=bpredict)); by _name_ date;
run;
```

```
proc sgplot data=combined3;
   series x=date y=opredict;
   series x=date y=bpredict;
run;
```

Output 12.1.5 Original versus Reconciled Forecasts, SMOOTH=0.9, EXP=0.99



Example 12.2: Reconciling Multiple Variables

This example shows how you can use two RECONCILE statement to reconcile two variables in the DATA= data set to the same benchmark PREDICT variable in the BENCHDATA data set.

Suppose you collected from an expert judgmental forecasts in the forecasting horizon for the airline data set. You entered the forecasts in the judpred in the data set judgmental as follows:

```
data judgmental;
  attrib DATE length=8 format=MONYY7.;
  attrib judpred length=8;

  infile datalines dsd;
```

```
  input DATE @;
  input judpred @;
datalines4;
366,456
397,409
425,452
456,489
486,498
517,548
547,660
578,666
609,534
639,495
670,416
700,472
;;;;
```

You want to see how the reconciled statistical forecasts you derived in Example 12.1 compare to the reconciled judgmental forecasts when the quarterly statistical forecasts are used as benchmark. You can accomplish that by merging the two data predicted values in one data set and using two RECONCILE statements in PROC HPFTEMPRECON.

```
data judgmental;
   merge judgmental outformon(where=(date>"01dec1960"d));
   by date;
   keep date predict judpred;
run;


proc hpftemprecon
      data=judgmental
      benchdata=outforqtr
      outfor=benfor4
      outstat=benstat4
      exp=0.99
      smooth=0.9;
   id date interval=month;
   benchid date interval=qtr;
   reconcile predict=predict;
   reconcile judpred=predict;
run;
```

The first RECONCILE statement instructs PROC HPFTEMPRECON to reconcile the statistical forecasts PREDICT, and the second one reconciles the judgmental forecasts. The variable PREDICT on the right-hand side of the equality in both RECONCILE statements indicates that both statistical and judgmental monthly forecasts are to be reconciled against the quarterly statistical forecasts contained in the variable PREDICT in the data set outforqtr.

The OUTFOR= data set benfor4 contains the reconciled forecasts for both variables, stacked according to the order in which the RECONCILE statements appear. Similar to forecasts produced by different FORECAST statements of HPFENGINE, the _NAME_ variable is used to discriminate among variables.

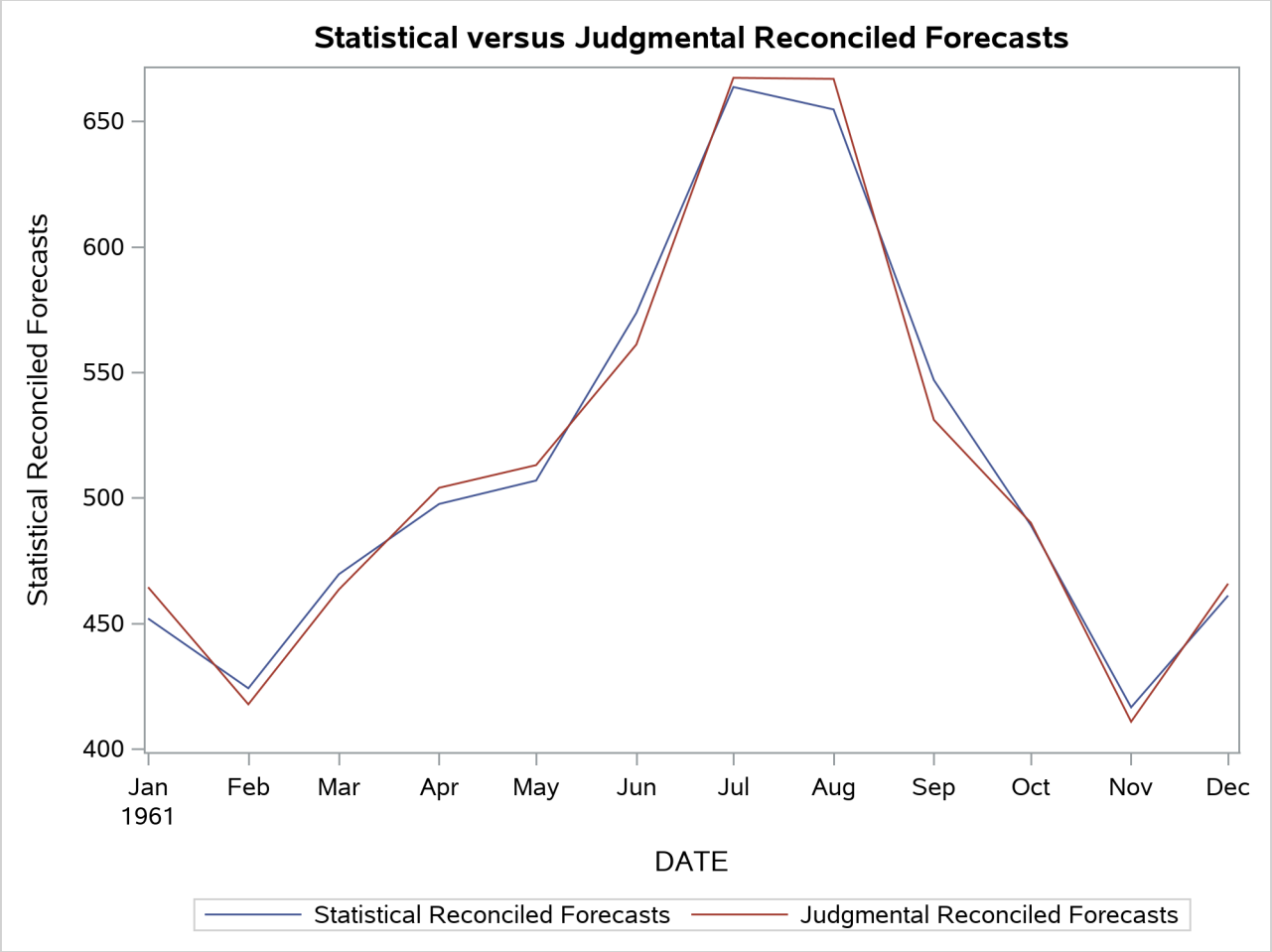
```
proc print data=benfor4; run;
```

Output 12.2.1 Reconciled Statistical and Judgmental Forecasts

Obs	_NAME_	DATE	ACTUAL	PREDICT	LOWER	UPPER	ERROR	STD	_RECFLAGS_
1	PREDICT	JAN1961	.	451.954	.	.	.	.	00000000
2	PREDICT	FEB1961	.	424.164	.	.	.	.	00000000
3	PREDICT	MAR1961	.	469.612	.	.	.	.	00000000
4	PREDICT	APR1961	.	497.599	.	.	.	.	00000000
5	PREDICT	MAY1961	.	506.940	.	.	.	.	00000000
6	PREDICT	JUN1961	.	573.717	.	.	.	.	00000000
7	PREDICT	JUL1961	.	663.692	.	.	.	.	00000000
8	PREDICT	AUG1961	.	654.747	.	.	.	.	00000000
9	PREDICT	SEP1961	.	546.957	.	.	.	.	00000000
10	PREDICT	OCT1961	.	489.079	.	.	.	.	00000000
11	PREDICT	NOV1961	.	416.598	.	.	.	.	00000000
12	PREDICT	DEC1961	.	461.118	.	.	.	.	00000000
13	judpred	JAN1961	.	464.419	.	.	.	.	00000000
14	judpred	FEB1961	.	417.781	.	.	.	.	00000000
15	judpred	MAR1961	.	463.530	.	.	.	.	00000000
16	judpred	APR1961	.	504.038	.	.	.	.	00000000
17	judpred	MAY1961	.	513.083	.	.	.	.	00000000
18	judpred	JUN1961	.	561.135	.	.	.	.	00000000
19	judpred	JUL1961	.	667.356	.	.	.	.	00000000
20	judpred	AUG1961	.	666.931	.	.	.	.	00000000
21	judpred	SEP1961	.	531.109	.	.	.	.	00000000
22	judpred	OCT1961	.	490.083	.	.	.	.	00000000
23	judpred	NOV1961	.	410.858	.	.	.	.	00000000
24	judpred	DEC1961	.	465.855	.	.	.	.	00000000

Figure 12.2.2 displays how the statistical reconciled forecasts compare to the judgmental reconciled forecasts.

Output 12.2.2 Statistical and Judgmental Reconciled Forecasts



Example 12.3: Using Threads

As discussed in section "Threading Details" on page 397, if you have a BY statement or multiple RECONCILE statements, it can be beneficial to enable multithreading so that independent parallel threads can handle simultaneous optimization problems. This example illustrates the uses of multithreading to reconcile monthly forecasts to quarterly forecasts for the variable sale in Sashelp.Pricedata.

First, select a model and generate forecasts at the two time intervals of interest for each combination of values of the variables Region, Line, and product.

```
/* MONTHLY FORECASTS */
*Step 1: model selection;
proc hpfdiagnose data=sashelp.pricedata
   outest=monthest
   modelrepository=work.mycat
   prefilter=both
   criterion=mape;
   id date interval=month;
```

```
   by region line product;
   forecast sale;
   input price;
run;

*Step 2: estimation and forecasting ;
proc hpfengine data=sashelp.pricedata inest=monthest
   out=_null_ outest=monthfest
   modelrepository=work.mycat outfor=monthfor;
   id date interval=month;
   by region line product;
   forecast sale / task=select ;
   stochastic price;
run;


/*  QUARTERLY FORECASTS */
*Step 1: model selection;
proc hpfdiagnose data=sashelp.pricedata
   outest=qtrest
   modelrepository=work.mycat
   prefilter=both
   criterion=mape;
   id date interval=qtr accumulate = total;
   by region line product;
   forecast sale;
   input price;
run;

*Step 2: estimation and forecasting ;
proc hpfengine data=sashelp.pricedata inest=qtrest
   out=_null_ outest=qtrfest
   modelrepository=work.mycat outfor=qtrfor;
   id date interval=qtr accumulate = total;
   by region line product;
   forecast sale / task=select ;
   stochastic price;
run;
```

Suppose your computer has eight cores and you want to enable multithreading but you want to limit the number of threads of PROC HPFTEMPRECON to four in order to reserve system resources for other tasks you want to run. You enable multithreading with the THREADS system options and set the maximum number of threads with the CPUCOUNT= option.

```
options threads cpucount=4;
```

Finally, proceed to reconcile the forecasts with PROC HPFTEMPRECON as you normally would. PROC HPFTEMPRECON internal logic decides the best multithreading strategy for each situation.

```
 proc hpftemprecon
  data=monthfor
  benchdata=qtrfor
  outfor=benchfor
  outstat=benchstat
```

```
  outprocinfo=outprocinfo;
id date interval=month;
by region line product;
benchid date interval=qtr;
run;
```

The OUTPROCINFO= data set contains statistics about the procedure run. When the variable _STAGE_ is set to `'ALL'`, the statistics refers to the procedure run as a whole. When _STAGE_ is set to `'THREAD'`_*n* the relative statistics refers to the *n*th thread only.

```
proc print data=outprocinfo;
run;
```

Output 12.3.1 PROC HPFTEMPRECON Run Information

Obs	_SOURCE_	_NAME_	_LABEL_	_STAGE_	_VALUE_
1	HPFTEMPRECON	SERIES	Number of series processed	ALL	17
2	HPFTEMPRECON	REQUESTED	Number of reconciliations requested	ALL	17
3	HPFTEMPRECON	FAILED	Number of reconciliations failed	ALL	0
4	HPFTEMPRECON	MODE	Thread mode used	ALL	2
5	HPFTEMPRECON	NBUFIN	Number of input buffers serviced	ALL	17
6	HPFTEMPRECON	NBUFOUT	Number of output buffers generated	ALL	17
7	HPFTEMPRECON	MINBUFIN	Minimum input buffer size processed	ALL	5896
8	HPFTEMPRECON	MINBUFOUT	Minimum output buffer size generated	ALL	5896
9	HPFTEMPRECON	MAXBUFIN	Maximum input buffer size processed	ALL	5896
10	HPFTEMPRECON	MAXBUFOUT	Maximum output buffer size generated	ALL	5896
11	HPFTEMPRECON	NTHREADS	Number of threads used	THREAD	3
12	HPFTEMPRECON	NBUFIN	Number of input buffers serviced	THREAD_1	6
13	HPFTEMPRECON	NBUFOUT	Number of output buffers generated	THREAD_1	6
14	HPFTEMPRECON	MINBUFIN	Minimum input buffer size processed	THREAD_1	5896
15	HPFTEMPRECON	MINBUFOUT	Minimum output buffer size generated	THREAD_1	5896
16	HPFTEMPRECON	MAXBUFIN	Maximum input buffer size processed	THREAD_1	5896
17	HPFTEMPRECON	MAXBUFOUT	Maximum output buffer size generated	THREAD_1	5896
18	HPFTEMPRECON	NBUFIN	Number of input buffers serviced	THREAD_2	5
19	HPFTEMPRECON	NBUFOUT	Number of output buffers generated	THREAD_2	5
20	HPFTEMPRECON	MINBUFIN	Minimum input buffer size processed	THREAD_2	5896
21	HPFTEMPRECON	MINBUFOUT	Minimum output buffer size generated	THREAD_2	5896
22	HPFTEMPRECON	MAXBUFIN	Maximum input buffer size processed	THREAD_2	5896
23	HPFTEMPRECON	MAXBUFOUT	Maximum output buffer size generated	THREAD_2	5896
24	HPFTEMPRECON	NBUFIN	Number of input buffers serviced	THREAD_3	6
25	HPFTEMPRECON	NBUFOUT	Number of output buffers generated	THREAD_3	6
26	HPFTEMPRECON	MINBUFIN	Minimum input buffer size processed	THREAD_3	5896
27	HPFTEMPRECON	MINBUFOUT	Minimum output buffer size generated	THREAD_3	5896
28	HPFTEMPRECON	MAXBUFIN	Maximum input buffer size processed	THREAD_3	5896
29	HPFTEMPRECON	MAXBUFOUT	Maximum output buffer size generated	THREAD_3	5896

References

Cholette, P. A. (1984). "Adjusting Sub-annual Series to Yearly Benchmarks." *Survey Methodology* 10:35–49.

Dagum, E. B., and Cholette, P. A. (2006). *Benchmarking, Temporal Distribution, and Reconciliation Methods for Time Series.* Vol. 186 of Lecture Notes in Statistics. New York: Springer.

Denton, F. T. (1971). "Adjustment of Monthly or Quarterly Series to Annual Totals: An Approach Based on Quadratic Minimization." *Journal of the American Statistical Association* 82:99–102.

Quenneville, B., Fortier, S., Chen, Z.-G., and Latendresse, E. (2006). "Recent Developments in Benchmarking to Annual Totals in X-12-ARIMA and at Statistics Canada." In *Proceedings of the Eurostat Conference on Seasonality, Seasonal Adjustment, and Their Implications for Short-Term Analysis and Forecasting*. Luxembourg: Eurostat.

Chapter 13
The HPFUCMSPEC Procedure

Contents

Overview: HPFUCMSPEC Procedure **412**
Getting Started: HPFUCMSPEC Procedure **412**
Syntax: HPFUCMSPEC Procedure **413**
Functional Summary 413
PROC HPFUCMSPEC Statement 415
AUTOREG Statement 416
BLOCKSEASON Statement 416
CYCLE Statement 418
DEPLAG Statement 419
FORECAST Statement 420
INPUT Statement 420
IRREGULAR Statement 422
LEVEL Statement 422
SEASON Statement 423
SLOPE Statement 424
Examples: HPFUCMSPEC Procedure **425**
Example 13.1: Some HPFUCMSPEC Syntax Illustrations 425
Example 13.2: How to Include a UCM in a Model Selection List 427
Example 13.3: How to Create a Generic Seasonal Model Specification 429
References **430**

Overview: HPFUCMSPEC Procedure

The HPFUCMSPEC procedure is used to create an unobserved component model (UCM) specification file. The output of this procedure is an XML file that stores the intended UCM specification. This XML specification file can be used for different purposes—for example, it can be used to populate the model repository used by the HPFENGINE procedure (see Chapter 5, "The HPFENGINE Procedure"). You can specify any UCM that can be analyzed by using the UCM procedure; see Chapter 41, "UCM Procedure" (*SAS/ETS User's Guide*). Moreover, the model specification can include series transformations such as log or Box-Cox transformations. Apart from minor modifications to accommodate series transformations, the model specification syntax of the HPFUCMSPEC procedure is similar to that of the UCM procedure.

Getting Started: HPFUCMSPEC Procedure

The following example shows how to create a UCM specification file. In this example the specification for a basic structural model (BSM) with one input is created.

```
proc hpfucmspec repository=mymodels
                name=BSM1
                label="Basic structural model with one input";
   forecast symbol=Y transform=log;
   input symbol=X;
   irregular;
   level;
   slope variance=0 noest;
   season length=12 type=trig;
run;
```

The options in the PROC HPFUCMSPEC statement are used to specify the location of the specification file that will be output. Here the REPOSITORY= option specifies that the output file be placed in a catalog MYMODELS, the NAME= option specifies that the name of the file be BSM1.xml, and the LABEL= option specifies a label for this catalog member. The other statements in the procedure specify the UCM.

The model specification begins with the FORECAST statement that specifies a transformation, such as a log or Box-Cox, for the variable that is to be forecast. In some cases, the forecast variable is also called the *dependent* variable or the *response* variable. Here, the FORECAST statement specifies a log transformation for the series being forecast. The SYMBOL= option in the FORECAST statement can be used to provide a convenient name for the forecast variable. This name is only a placeholder, and a proper data variable will be associated with this name when this model specification is used in actual data analysis. Next, the INPUT statement specifies transformations, such as log or Box-Cox, as well as lagging and differencing that are associated with the input variable. In this case the input variable enters the model as a simple regressor. Here again the SYMBOL= option can be used to supply a convenient name for the input variable. If a model contains multiple input variables, then each input variable has to be specified with a separate INPUT statement.

After the forecast and input series transformations are described, the components in the model are specified using different component statements. In the above example the model contains three components: an

irregular component, a *local linear trend* with fixed *slope*, and a *trigonometric seasonal* with season length 12.

Syntax: HPFUCMSPEC Procedure

The HPFUCMSPEC procedure uses the following statements.

PROC HPFUCMSPEC *options* ;
AUTOREG *options* ;
BLOCKSEASON *options* ;
CYCLE *options* ;
DEPLAG *options* ;
FORECAST *options* ;
INPUT *options* ;
IRREGULAR *options* ;
LEVEL *options* ;
SEASON *options* ;
SLOPE *options* ;

Functional Summary

Table 13.1 the statements and options that control the HPFUCMSPEC procedure.

Table 13.1 PROC HPFUCMSPEC Functional Summary

Description	Statement	Option
Model Repository Options		
Specifies the model repository	PROC HPFUCMSPEC	REPOSITORY=
Specifies the model specification name	PROC HPFUCMSPEC	NAME=
Specifies the model specification label	PROC HPFUCMSPEC	LABEL=
Options for Specifying Symbolic Series Names		
Specifies a symbolic name for the response series	FORECAST	SYMBOL=
Specifies a symbolic name for the input series	INPUT	SYMBOL=
Options for Specifying the Model		
Specifies the response series transformation	FORECAST	TRANSFORM=
Specifies the input series transformation	INPUT	TRANSFORM=
Specifies the input series differencing orders	INPUT	DIF=
Specifies the input series lagging order	INPUT	DELAY=
Specifies the initial value for the disturbance variance of the irregular component	IRREGULAR	VARIANCE=

Description	Statement	Option
Fixes the value of the disturbance variance of the irregular component to the specified initial value	IRREGULAR	NOEST
Specifies the initial value for the disturbance variance of the level component	LEVEL	VARIANCE=
Fixes the value of the disturbance variance of the level component to the specified initial value	LEVEL	NOEST
Specifies the initial value for the disturbance variance of the slope component	SLOPE	VARIANCE=
Fixes the value of the disturbance variance of the slope component to the specified initial value	SLOPE	NOEST
Specifies the season length of a seasonal component	SEASON	LENGTH=
Specifies the type of a seasonal component	SEASON	TYPE=
Specifies the initial value for the disturbance variance of a seasonal component	SEASON	VARIANCE=
Fixes the value of the disturbance variance of the seasonal component to the specified initial value	SEASON	NOEST
Specifies the block size of a block seasonal component	BLOCKSEASON	BLOCKSIZE=
Specifies the number of blocks of a block seasonal component	BLOCKSEASON	NBLOCKS=
Specifies the relative position of the first observation within the block of a block seasonal component	BLOCKSEASON	OFFSET=
Specifies the initial value for the disturbance variance of a block seasonal component	BLOCKSEASON	VARIANCE=
Fixes the value of the disturbance variance of the block seasonal component to the specified initial value	BLOCKSEASON	NOEST
Specifies the initial value for the period of a cycle component	CYCLE	PERIOD=
Specifies the initial value for the damping factor of a cycle component	CYCLE	RHO=
Specifies the initial value for the disturbance variance of the cycle component	CYCLE	VARIANCE=

Description	Statement	Option
Fixes the values of the parameters of the cycle component to the specified initial values	CYCLE	NOEST=
Specifies the initial value for the damping factor of the autoregressive component	AUTOREG	RHO=
Specifies the initial value for the disturbance variance of the autoregressive component	AUTOREG	VARIANCE=
Fixes the values of the parameters of the autoregressive component to the specified initial values	AUTOREG	NOEST=
Specifies the lags of the response series to be included in the model	DEPLAG	LAGS=
Specifies the initial values for the lag coefficients for the response lags	DEPLAG	PHI=
Fixes the values of lag coefficients to the specified initial values	DEPLAG	NOEST

PROC HPFUCMSPEC Statement

PROC HPFUCMSPEC *options* **;**

The following options can be used in the PROC HPFUCMSPEC statement.

LABEL=*SAS-label*
specifies a descriptive label for the model specification to be stored in the SAS catalog or external file reference. The LABEL= option can also be specified as SPECLABEL=.

NAME=*SAS-name*
names the model specification to be stored in the SAS catalog or external file reference. The NAME= option can also be specified as SPECNAME=.

REPOSITORY=*SAS-catalog-name*

REPOSITORY=*SAS-file-reference*
names the SAS catalog or external file reference to contain the model specification. The REPOSITORY= option can also be specified as MODELREPOSITORY=, MODELREP=, or REP=.

AUTOREG Statement

AUTOREG < *options* > **;**

The AUTOREG statement specifies an *autoregressive* component of the model. An autoregressive component is a special case of cycle that corresponds to the frequency of zero or π. It is modeled separately for easier interpretation. A stochastic equation for an autoregressive component r_t can be written as follows:

$$r_t = \rho r_{t-1} + \nu_t, \quad \nu_t \sim i.i.d.\ N(0, \sigma_\nu^2)$$

The damping factor ρ can take any value in the interval (–1, 1), including –1 but excluding 1. If $\rho = 1$, the autoregressive component cannot be distinguished from the random walk level component. If $\rho = -1$, the autoregressive component corresponds to a seasonal component with season length 2 or a nonstationary cycle with period 2. If $|\rho| < 1$, then the autoregressive component is stationary. The following examples illustrate the AUTOREG statement:

```
autoreg;
```

This statement includes an autoregressive component in the model. The damping factor ρ and the disturbance variance σ_ν^2 are estimated from the data.

NOEST=RHO

NOEST=VARIANCE

NOEST=(RHO VARIANCE)
fixes the values of ρ and σ_ν^2 to those specified in RHO= and VARIANCE= options.

RHO=*value*
supplies an initial value for the damping factor ρ during the parameter estimation process. The value of ρ must be in the interval (–1, 1), including –1 but excluding 1.

VARIANCE=*value*
supplies an initial value for the disturbance variance σ_ν^2 during the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

BLOCKSEASON Statement

BLOCKSEASON *NBLOCKS= integer BLOCKSIZE= integer* < *options* > **;**

The BLOCKSEASON or BLOCKSEASONAL statement is used to specify a seasonal γ_t that has a special block structure. The seasonal γ_t is called a *block seasonal* of block size m and number of blocks k if its season length s can be factored as $s = m * k$ and its seasonal effects have a block form—that is, the first m seasonal effects are all equal to some number τ_1, the next m effects are all equal to some number τ_2, and so on. This type of seasonal structure can be appropriate in some cases. For example, consider a series that is recorded on an hourly basis. Further assume that, in this particular case, the hour-of-the-day effect and the day-of-the-week effect are additive. In this situation the hour-of-the-week seasonality, having a season length of 168, can be modeled as a sum of two components. The hour-of-the-day effect is modeled using a simple seasonal of season length 24, while the day-of-the-week effect is modeled as a block seasonal that has the days of the week as blocks. This day-of-the-week block seasonal will have seven blocks, each of size 24.

A block seasonal specification requires, at the minimum, the block size m and the number of blocks in the seasonal k. These are specified using the BLOCKSIZE= and NBLOCKS= options, respectively. In addition, you might need to specify the position of the first observation of the series by using the OFFSET= option, if it is not at the beginning of one of the blocks. In the example just considered, this will correspond to a situation where the first series measurement is not at the start of the day. Suppose that the first measurement of the series corresponds to the hour between 6:00 and 7:00 a.m., which is the seventh hour within that day or at the seventh position within that block. This is specified as OFFSET=7.

The other options of this statement are very similar to the options in the SEASONAL statement. For example, a block seasonal can also be of one of the two types, DUMMY or TRIGONOMETRIC. There can be more than one block seasonal component in the model, each specified using a separate BLOCKSEASON statement. No two block seasonals in the model can have the same NBLOCKS= and BLOCKSIZE= specifications. The following example illustrates the use of the BLOCKSEASON statement to specify the additive, hour-of-the-week seasonal model:

```
season length=24 type=trig;
blockseason nblocks=7 blocksize=24;
```

The following options can be specified in the BLOCKSEASON statement.

BLOCKSIZE=*integer*
: specifies the block size, m . This is a required option in this statement. The block size can be any integer larger than or equal to two. Typical examples of block sizes are 24 (which corresponds to the hours of the day when a day is being used as a block in hourly data) or 60 (which corresponds to the minutes in an hour when an hour is being used as a block in data recorded by minutes), and so on.

NBLOCKS=*integer*
: specifies the number of blocks, k. This is a required option in this statement. The number of blocks can be any integer larger than or equal to two.

NOEST
: fixes the value of the disturbance variance parameter to the value specified in the VARIANCE= option.

OFFSET=*integer*
: specifies the position of the first measurement within the block, if the first measurement is not at the start of a block. The OFFSET= value must be between one and the block size. The default value is one. The *first measurement* refers to the start of the series.

TYPE=DUMMY | TRIG
: specifies the type of the seasonal component. The default type is DUMMY.

VARIANCE=*value*
: supplies an initial value for the disturbance variance σ_ω^2 in the γ_t equation, at the start of the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

CYCLE Statement

CYCLE < *options* > **;**

The CYCLE statement is used to specify a *cycle* component ψ_t in the model. The stochastic equation that governs a cycle component of period p and damping factor ρ is as follows:

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} \nu_t \\ \nu_t^* \end{bmatrix}$$

where ν_t and ν_t^* are independent, zero-mean Gaussian disturbances with variance σ_ν^2 and $\lambda = 2 * \pi / p$ is the angular frequency of the cycle. Any p strictly larger than 2 is an admissible value for the period, and the damping factor ρ can be any value in the interval (0, 1), including 1 but excluding 0. The cycles with the frequency zero and π, which correspond to the periods equal to infinity and two respectively, can be specified using the AUTOREG statement. The values of ρ smaller than 1 give rise to a stationary cycle, while $\rho = 1$ gives rise to a nonstationary cycle. As a default, values of ρ, p, and σ_ν^2 are estimated from the data. However, if necessary, you can fix the values of some, or all, of these parameters.

There can be multiple cycles in a model, each specified using a separate CYCLE statement. Currently, you can specify up to 50 cycles in a model.

The following examples illustrate the use of the CYCLE statement:

```
cycle;
cycle;
```

These statements request that two cycles be included in the model. The parameters of each of these cycles is estimated from the data.

```
cycle rho=1 noest=rho;
```

This statement requests inclusion of a nonstationary cycle in the model. The cycle period p and the disturbance variance σ_ν^2 are estimated from the data. In the following statement a nonstationary cycle with fixed period of 12 is specified. Moreover, a starting value is supplied for σ_ν^2.

```
cycle period=12 rho=1 variance=4 noest=(rho period);
```

The following options can be specified in the CYCLE statement.

NOEST=PERIOD

NOEST=RHO

NOEST=VARIANCE

NOEST= (< RHO > < PERIOD > < VARIANCE >)

fixes the values of the component parameters to those specified in the RHO=, PERIOD=, and VARIANCE= options. This option enables you to fix any combination of parameter values.

PERIOD=*value*

supplies an initial value for the cycle period during the parameter estimation process. Period value must be strictly larger than 2.

RHO=*value*

supplies an initial value for the damping factor in this component during the parameter estimation process. Any value in the interval (0, 1), including one but excluding zero, is an acceptable initial value for the damping factor.

VARIANCE=*value*

supplies an initial value for the disturbance variance parameter σ_v^2 to be used during the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

DEPLAG Statement

DEPLAG *LAGS = order* < *PHI* > *= value . . .* < *NOEST* > **;**

The DEPLAG statement is used to specify the lags of the forecast variable to be included as predictors in the model. The following example illustrates the use of DEPLAG statement:

```
deplag lags=2;
```

If the forecast series is denoted by y_t, this statement specifies the inclusion of $\phi_1 y_{t-1} + \phi_2 y_{t-2}$ in the model. The parameters ϕ_1 and ϕ_2 are estimated from the data. The following statement requests including $\phi_1 y_{t-1} + \phi_2 y_{t-4} - \phi_1\phi_2 y_{t-5}$ in the model. The values of ϕ_1 and ϕ_2 are fixed at 0.8 and –1.2.

```
deplag lags=(1)(4) phi=0.8 -1.2 noest;
```

The dependent lag parameters are not constrained to lie in any particular region. In particular, this implies that a UCM that contains only an *irregular* component and dependent lags, resulting in a traditional autoregressive model, is not constrained to be a stationary model. In the DEPLAG statement if an initial value is supplied for any one of the parameters, the initial values must be supplied for all other parameters also.

LAGS=*order*

LAGS=(*lag, . . . , lag* **) . . . (***lag, . . . , lag* **)**

LAGS=(*lag, . . . , lag* **)<** s_1 **> . . . (***lag, . . . , lag* **)<** s_k **>**

defines a model with specified lags. This is a required option in this statement. LAGS=($l_1, l_2, \ldots, l_k$) defines a model with specified lags of the forecast variable included as predictors. LAGS= *order* is equivalent to LAGS=(1, 2, . . . , *order*).

A concatenation of parenthesized lists specifies a factored model. For example, LAGS=(1)(12) specifies that the lag values, 1, 12, and 13, corresponding to the following polynomial in the backward shift operator, be included in the model:

$$(1 - \phi_{1,1}B)(1 - \phi_{2,1}B^{12})$$

Note that, in this case, the coefficient of the thirteenth lag is constrained to be the product of the coefficients of the first and twelfth lags.

You can also specify a multiplier after a parenthesized list. For example, LAGS=(1)(1)12 is equivalent to LAGS=(1)(12), and LAGS=(1,2)4(1)12(1,2)24 is equivalent to LAGS=(4,8)(12)(24,48).

NOEST
fixes the values of the parameters to those specified in PHI= options.

PHI=*value* **...**
lists starting values for the coefficients of the lagged forecast variable.

FORECAST Statement

FORECAST *options* **;**

The FORECAST statement specifies the symbolic name that represents the series to be forecast and also specifies an optional transformation to be applied to the series. The symbolic name is used in later steps to associate actual time series variables with the model specification when the specification is applied to data.

The following options can be specified in the FORECAST statement.

(SYMBOL|VAR)=*variable*
specifies a symbolic name for the forecast series. This symbol specification is optional. If the SYMBOL= option is not specified, *Y* is used as a default symbol.

TRANSFORM=*option*
specifies the transformation to be applied to the time series. The following transformations are provided:

NONE	no transformation
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5

When the TRANSFORM= option is specified, the time series must be strictly positive.

INPUT Statement

INPUT *options* **;**

The INPUT statements specify the inputs in the model. A separate INPUT statement is needed for each of the inputs. In this statement you can specify the delay order, the differencing orders, and the Box-Cox type transformations associated with the input variable under consideration.

The following options can be specified in the INPUT statement.

DELAY=*order*
specifies the delay (or lag) order for the input series.

DIF=*order*

DIF= *(order1, order2, . . .)*
specifies the differencing orders for the input series.

PREDEFINED=*option*
associates a predefined trend or a set of seasonal dummy variables with this transfer function. The SYMBOL= and PREDEFINED= options are mutually exclusive.

In the following list of options, let t represent the observation count from the start of the period of fit for the model, and let X_t be the value of the time trend variable at observation t.

LINEAR	a linear trend, with $X_t = t - c$
QUADRATIC	a quadratic trend, with $X_t = (t - c)^2$
CUBIC	a cubic trend, with $X_t = (t - c)^3$
INVERSE	an inverse trend, with $X_t = 1/t$
SEASONALDUMMIES	seasonal dummy variables. For a seasonal cycle of length s, the seasonal dummy regressors include $X_{i,t} : 1 \le i \le (s-1), 1 \le t \le n$ for models that include a level component, and $X_{i,t} : 1 \le i \le (s), 1 \le t \le n$ for models that do not include a level component. Each element of a seasonal dummy regressor is either zero or one, based on the following rule:

$$X_{i,t} = \begin{cases} 1 & \text{when } i = t \\ 0 & \text{otherwise} \end{cases}$$

(SYMBOL|VAR)=*variable*
specifies a symbolic name for the input series. This symbol specification is optional. If the SYMBOL= option is not specified, then *X* is used as a default symbol. If there are multiple INPUT statements, then an attempt is made to generate a unique set of input symbols.

TRANSFORM=*option*
specifies the transformation to be applied to the time series. The following transformations are provided:

NONE	no transformation
LOG	logarithmic transformation
SQRT	square-root transformation
LOGISTIC	logistic transformation
BOXCOX(*n*)	Box-Cox transformation with parameter number where number is between –5 and 5

When the TRANSFORM= option is specified, the time series must be strictly positive.

IRREGULAR Statement

IRREGULAR < *options* > **;**

The IRREGULAR statement is used to include an irregular component in the model. There can be at most one IRREGULAR statement in the model specification. The irregular component corresponds to the overall random error ϵ_t in the model; it is modeled as a sequence of independent, zero-mean Gaussian random variables with variance σ_ϵ^2. The options in this statement enable you to specify the value of σ_ϵ^2 and to output the forecasts of ϵ_t. As a default, σ_ϵ^2 is estimated using the data and the component forecasts are not saved or displayed. A few examples of the IRREGULAR statement are given next. In the first example the statement is in its simplest form, resulting in the inclusion of an irregular component with unknown variance.

```
irregular;
```

The following statement provides a starting value for σ_ϵ^2, to be used in the nonlinear parameter estimation process.

```
irregular variance=4;
```

The following options can be specified in the IRREGULAR statement.

NOEST
fixes the value of σ_ϵ^2 to the value specified in the VARIANCE= option.

VARIANCE=*value*
supplies an initial value for σ_ϵ^2 during the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

LEVEL Statement

LEVEL < *options* > **;**

The LEVEL statement is used to include a level component in the model. The level component, either by itself or together with a slope component, forms the trend component μ_t of the model. If the slope component is absent, the resulting trend is a random walk (RW) specified by the following equations:

$$\mu_t = \mu_{t-1} + \eta_t, \quad \eta_t \sim i.i.d.\ N(0, \sigma_\eta^2)$$

If the slope component is present, signified by the presence of a SLOPE statement (see "SLOPE Statement" on page 424), a locally linear trend (LLT) is obtained. The equations of LLT are as follows:

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t, \quad \eta_t \sim i.i.d.\ N(0, \sigma_\eta^2) \\ \beta_t &= \beta_{t-1} + \xi_t, \qquad \xi_t \sim i.i.d.\ N(0, \sigma_\xi^2) \end{aligned}$$

In either case, the options in the LEVEL statement are used to specify the value of σ_η^2 and to request forecasts of μ_t. The SLOPE statement is used for similar purposes in the case of slope β_t. The following examples illustrate the use of LEVEL statement. Assuming that a SLOPE statement is not added subsequently, a simple random walk trend is specified by the following statement:

```
level;
```

The following statements specify a locally linear trend with value of σ_η^2 fixed at 4. The value of σ_ξ^2, the disturbance variance in the slope equation, will be estimated from the data.

```
level variance=4 noest;
slope;
```

The following options can be specified in the LEVEL statement.

NOEST
fixes the value of σ_η^2 to the value specified in the VARIANCE= option.

VARIANCE=*value*
supplies an initial value for σ_η^2, the disturbance variance in the μ_t equation, at the start of the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

SEASON Statement

SEASON < *options* > **;**

The SEASON or the SEASONAL statement is used to specify a seasonal component γ_t in the model. A seasonal component can be one of the two types, DUMMY or TRIGONOMETRIC. A DUMMY type seasonal with season length s satisfies the following stochastic equation:

$$\sum_{i=0}^{s-1} \gamma_{t-i} = \omega_t, \qquad \omega_t \sim i.i.d.\ N(0, \sigma_\omega^2)$$

The equations for a TRIGONOMETRIC type seasonal are as follows:

$$\gamma_t = \sum_{j=1}^{[s/2]} \gamma_{j,t}$$

where $[s/2]$ equals $s/2$ if s is even and equals $(s-1)/2$ if it is odd. The sinusoids $\gamma_{j,t}$ have frequencies $\lambda_j = 2\pi j/s$ and are specified by the matrix equation

$$\begin{bmatrix} \gamma_{j,t} \\ \gamma^*_{j,t} \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma^*_{j,t-1} \end{bmatrix} + \begin{bmatrix} \omega_{j,t} \\ \omega^*_{j,t} \end{bmatrix}$$

where the disturbances $\omega_{j,t}$ and $\omega^*_{j,t}$ are assumed to be independent and, for fixed j, $\omega_{j,t}$ and $\omega^*_{j,t} \sim N(0, \sigma_\omega^2)$. If s is even, then the equation for $\gamma^*_{s/2,t}$ is not needed and $\gamma_{s/2,t}$ is given by

$$\gamma_{s/2,t} = -\gamma_{s/2,t-1} + \omega_{s/2,t}$$

Note that, whether the seasonal type is DUMMY or TRIGONOMETRIC, there is only one parameter, the disturbance variance σ_ω^2, in the seasonal model.

There can be more than one seasonal component in the model, necessarily with different season lengths. Each seasonal component is specified using a separate SEASON statement. A model with multiple seasonal components can easily become quite complex and can need large amounts of data and computing resources for its estimation and forecasting. Currently, at most three seasonals can be included in a model. The following examples illustrate the use of SEASON statement:

```
season length=4;
```

This statement specifies a DUMMY type (default) seasonal component with season length 4, corresponding to the quarterly seasonality. The disturbance variance σ_ω^2 is estimated from the data. The following statement specifies a trigonometric seasonal with monthly seasonality. It also provides a starting value for σ_ω^2.

```
season length=12 type=trig variance=4;
```

The following options can be specified in the SEASON statement.

LENGTH=*integer*

This option is used to specify the season length s. The season length can be any integer larger than or equal to 2, or it can be "s," indicating a placeholder that will be substituted later with an appropriate value. The specification of season length is optional; the default is LENGTH=s. The use of specifications with a placeholder for season lengths is further explained in Example 13.3. Typical examples of season lengths are 12, corresponding to the monthly seasonality, or 4, corresponding to the quarterly seasonality.

NOEST

fixes the value of the disturbance variance parameter to the value specified in the VARIANCE= option.

TYPE=DUMMY | TRIG

specifies the type of the seasonal component. The default type is DUMMY.

VARIANCE=*value*

supplies an initial value for the disturbance variance σ_ω^2 in the γ_t equation, at the start of the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

SLOPE Statement

SLOPE < *options* > **;**

The SLOPE statement is used to include a slope component in the model. The slope component cannot be used without the level component. The level and slope specifications jointly define the trend component of the model. A SLOPE statement without the accompanying LEVEL statement is ignored. The equations of the trend, defined jointly by the level μ_t and slope β_t, are as follows:

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t, \quad \eta_t \sim i.i.d.\ N(0, \sigma_\eta^2) \\ \beta_t &= \beta_{t-1} + \xi_t, \qquad\quad \xi_t \sim i.i.d.\ N(0, \sigma_\xi^2) \end{aligned}$$

The SLOPE statement is used to specify the value of the disturbance variance σ_ξ^2 in the slope equation and to request forecasts of β_t. The following statements request that a locally linear trend be used in the model. The disturbance variances σ_η^2 and σ_ξ^2 are estimated from the data.

```
level;
slope;
```

You can request a locally linear trend with fixed slope using the following statements:

```
level;
slope variance=0 noest;
```

The following options can be specified in the SLOPE statement.

NOEST
fixes the value of the disturbance variance σ_ξ^2 to the value specified in the VARIANCE= option.

VARIANCE=*value*
supplies an initial value for the disturbance variance σ_ξ^2 in the β_t equation, at the start of the parameter estimation process. Any nonnegative value, including zero, is an acceptable starting value.

Examples: HPFUCMSPEC Procedure

Example 13.1: Some HPFUCMSPEC Syntax Illustrations

The following statements illustrate the HPFUCMSPEC syntax for some of the commonly needed modeling activities. Suppose that a variety of UCMs are to be fitted to a data set that contains a sales series as the forecast variable and several promotional events as predictor series. In all these cases the model repository work.mymodels is kept the same, and the models are named as *model1, model2,* and so on to ensure uniqueness. Note that in a given repository, the models must have unique names. The symbols for the forecast and input variables are *sales* and *promo1, promo2,* and so on, respectively.

```
/* BSM with two inputs */
proc hpfucmspec repository=mymodels
                name=model1;
   forecast symbol=sales transform=log;
   input symbol=promo1 delay=3;
   input symbol=promo2 dif=1;
   irregular;
   level;
   slope variance=0 noest; /* non-varying slope */
   season length=12 type=trig;
run;

/* Model with one cycle and Box-Cox transform */
proc hpfucmspec repository=mymodels
                name=model2;
   forecast symbol=sales transform=BoxCox(0.8);
   irregular;
   level;
   slope;
   cycle rho=1 noest=(rho); /* fixed damping factor */
```

```
run;

/* Unsaturated monthly seasonal */
proc hpfucmspec repository=mymodels
                name=model3;
   forecast symbol=sales transform=log;
   irregular;
   level;
   slope;
   cycle period=12 rho=1 noest=(period rho);
   cycle period=6  rho=1 noest=(period rho);
   cycle period=4  rho=1 noest=(period rho);
run;

/* Supply starting values for the parameters */
proc hpfucmspec repository=mymodels
                name=model4;
   forecast symbol=sales transform=log;
   irregular;
   level;
   slope variance=10;
   cycle period=12 rho=0.9 noest=(period);
   cycle period=6 noest=(period);
run;

title "Models Added to MYMODELS Repository";
proc catalog catalog=mymodels;
   contents;
run;
```

Output 13.1.1 Listing of Models in MYMODELS Repository

Models Added to MYMODELS Repository

Contents of Catalog WORK.MYMODELS

#	Name	Type	Create Date	Modified Date	Description
1	BSM1	XML	08/06/2020 03:18:09	08/06/2020 03:18:09	Basic structural model with one input
2	MODEL1	XML	08/06/2020 03:18:09	08/06/2020 03:18:09	
3	MODEL2	XML	08/06/2020 03:18:10	08/06/2020 03:18:10	
4	MODEL3	XML	08/06/2020 03:18:10	08/06/2020 03:18:10	
5	MODEL4	XML	08/06/2020 03:18:10	08/06/2020 03:18:10	

Example 13.2: How to Include a UCM in a Model Selection List

One of the primary uses of the HPFUCMSPEC procedure is to add candidate UCMs to a model selection list that can be used by the HPFENGINE procedure (see Chapter 5, "The HPFENGINE Procedure"). The HPFUCMSPEC procedure is used to create the UCM specifications and the HPFSELECT procedure is used to add the specifications to a model selection list (see Chapter 11, "The HPFSELECT Procedure"). This example illustrates this scenario.

Here a series that consists of the yearly river flow readings of the Nile, recorded at Aswan (Cobb 1978), is studied. The data consists of readings from the years 1871 to 1970. This series is known to have had a shift in the level starting at the year 1899, and the years 1877 and 1913 are suspected to be outlying points.

The following DATA step statements read the data in a SAS data set and create dummy inputs for the shift in 1899 and the unusual years 1877 and 1913.

```
data nile;
   input riverFlow @@;
   year = intnx( 'year', '1jan1871'd, _n_-1 );
   format year year4.;
   if year >= '1jan1899'd then Shift1899 = 1.0;
   else Shift1899 = 0;
   if year = '1jan1913'd then Event1913 = 1.0;
   else Event1913 = 0;
   if year = '1jan1877'd then Event1877 = 1.0;
   else Event1877 = 0;
datalines;
   1120  1160  963  1210  1160  1160  813  1230   1370  1140
   995   935   1110 994   1020  960   1180 799    958   1140

... more lines ...
```

Three candidate models are specified, *m1, m2*, and *m3*. Out of these three models, *m1* is the simplest, which ignores the background information. Out of the other two models, *m2* uses only the shift in 1899, while *m3* uses all the three inputs. The following syntax shows how to specify these models and how to create a selection list that combines them with the HPFSELECT procedure. In the HPFSELECT procedure note the use of INPUTMAP option in the SPEC statement. It ties the symbolic variable names used in the HPFARIMASPEC procedure with the actual variable names in the data set. If the symbolic names were appropriate to start with, then the INPUTMAP option is not necessary.

```
proc hpfucmspec repository=mymodels
                name=m1;
   forecast symbol=y;
   irregular;
   level;
run;

proc hpfucmspec repository=mymodels
                name=m2;
   forecast symbol=y;
   irregular;
   level;
```

```
   input symbol=x1;
run;

proc hpfucmspec repository=mymodels
                name=m3;
   forecast symbol=y;
   irregular;
   level;
   input symbol=x1;
   input symbol=x2;
   input symbol=x3;
run;
```

The follow statements create a selection list that includes model specifications m1, m2 and m3.

```
proc hpfselect repository=mymodels
               name=myselect;

   spec m1 / inputmap(symbol=y var=riverFlow);

   spec m2 / inputmap(symbol=y var=riverFlow)
             inputmap(symbol=x1 var=Shift1899);

   spec m3 / inputmap(symbol=y var=riverFlow)
             inputmap(symbol=x1 var=Shift1899)
             inputmap(symbol=x2 var=Event1877)
             inputmap(symbol=x3 var=Event1913);
run;
```

This selection list can now be used in the HPFENGINE procedure for various types of analyses. The following syntax shows how to compare these models based on the default comparison criterion, mean absolute percentage error (MAPE). As expected, the model *m3* turns out to be the best of the three compared (see Figure 13.2.1).

```
proc hpfengine data=nile
               repository=mymodels
               globalselection=myselect
               lead=0
               print=(select);
   forecast riverFlow;
   input    Shift1899;
   input    Event1877;
   input    Event1913;
run;
```

Output 13.2.1 Model Selection Based on the MAPE Criterion

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
M1	13.096557	No	UCM: Y = LEVEL + ERROR
M2	11.978730	No	UCM: Y = LEVEL + X1 + ERROR
M3	10.532464	Yes	UCM: Y = LEVEL + X1 + ...+ X3 + ERROR

Example 13.3: How to Create a Generic Seasonal Model Specification

In the case of many seasonal model specifications, it is possible to describe a generic specification that is applicable in a variety of situations just by changing the season length specifications at appropriate places. As an example consider the basic structural model, which is very useful for modeling seasonal data. The basic structural model for a monthly series can be specified using the following statements.

```
proc hpfucmspec repository=mymodels
                name=MonthlyBSM
                label=
      "Basic Structural Model For A Series With Season Length 12";
   forecast symbol=Y transform=log;
   irregular;
   level;
   slope;
   season type=trig length=12;
run;
```

It is easy to see that the same syntax is applicable to a quarterly series if the length in the SEASON specification is changed from 12 to 4. A generic specification that allows for late binding of season lengths can be generated by the following syntax:

```
proc hpfucmspec repository=mymodels
                name=GenericBSM
                label="Generic Basic Structural Model";
   forecast symbol=Y transform= log;
   irregular;
   level;
   slope;
   season type=trig length=s;
run;
```

In this syntax the length in the SEASON specification is changed from 12 to "s." This syntax creates a template for the basic structural model that is applicable to different season lengths. When the HPFENGINE procedure (which actually uses such model specifications to estimate the model and produce the forecasts) encounters such a "generic" specification, it automatically creates a proper specification by replacing the season length placeholder with the value implied by the ID variable or its SEASONALITY= option. The following example illustrates the use of this generic specification. It shows how the same specification can be used for monthly and quarterly series. The parameter estimates for monthly and quarterly series are given in Figure 13.3.1 and Figure 13.3.2, respectively.

```
   /* Create a selection list that contains
      the Generic Airline Model */
proc hpfselect repository=mymodels
               name=genselect;
   spec GenericBSM;
run;

proc hpfengine data=sashelp.air
               repository=mymodels
               globalselection=genselect
               print=(estimates);
```

```
   id date interval=month;
   forecast air;
run;
```

Output 13.3.1 Parameter Estimates for the Monthly Series

The HPFENGINE Procedure

Parameter Estimates for GENERICBSM Model

Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
IRREGULAR	ERROR VARIANCE	0.0002344	0.0001079	2.17	0.0298
LEVEL	ERROR VARIANCE	0.0002983	0.0001057	2.82	0.0048
SLOPE	ERROR VARIANCE	8.4793E-13	6.2271E-10	0.00	0.9989
SEASON	ERROR VARIANCE	3.55769E-6	1.32347E-6	2.69	0.0072

```
   /* Create a quarterly series illustrating accumulating
      the monthly Airline series to quarterly */
proc timeseries data=sashelp.air out=Qair;
   id date interval=quarter;
   var air / accumulate=total;
run;

proc hpfengine data=Qair
               repository=mymodels
               globalselection=genselect
               print=(estimates);
   id date interval=quarter;
   forecast air;
run;
```

Output 13.3.2 Parameter Estimates for the Quarterly Series

The HPFENGINE Procedure

Parameter Estimates for GENERICBSM Model

Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
IRREGULAR	ERROR VARIANCE	7.82894E-8	1.72258E-7	0.45	0.6495
LEVEL	ERROR VARIANCE	0.0006272	0.0001764	3.56	0.0004
SLOPE	ERROR VARIANCE	4.35726E-9	.	.	.
SEASON	ERROR VARIANCE	0.00002010	9.68292E-6	2.08	0.0379

References

Cobb, G. W. (1978). "The Problem of the Nile: Conditional Solution to a Change Point Problem." *Biometrika* 65:243–251.

Part III

Forecasting Details

Chapter 14
Forecasting Process Summary

Contents

Background **434**
Transactional Data 434
Time Series Data 435
Forecasting Models 435
Forecasts 439
Forecast Function (Scoring) 440
Statistics of Fit 441
Automatic Forecasting Process **442**
Accumulation Step 442
Interpretation Step 442
Adjustment Step 443
Diagnostic Step 444
Model Selection Step 444
Parameter Estimation Step 445
Forecasting Step 445
Evaluation Step 445
Performance Step 445
Forecast Function (Score File) Generation Step 446
Automatic Forecasting Data **446**
Automatic Forecasting Data Flow 447
Forecast Scoring Data Flow 447
Automatic Forecasting Information **448**
Model Specification 448
Model Selection List 450
Selected Model Specification 451
Fitted Model 451
Forecast Function (Score File) 451
Automatic Forecasting Information Flow 452
Forecast Scoring Information Flow 453
Automatic Forecasting Repositories **453**
Event Repository 454
Model Specification Repository 454
Fitted Model Repository 456
Forecast Results Repository 457
Score Repository 457

Automatic Forecasting System Flow 457
Forecast Scoring System Flow 458
Automatic Forecasting Archives **460**
References **460**

Background

This chapter provides a brief theoretical background description of automatic forecasting. An introductory discussion of automatic forecasting topics can be found in Makridakis, Wheelwright, and Hyndman (1997); Brockwell and Davis (1996); Chatfield (2000). A more detailed discussion of time series analysis and forecasting can be found in Box, Jenkins, and Reinsel (1994); Hamilton (1994); Fuller (1995); Harvey (1994).

This chapter also provides a summary of the SAS Forecast Server Procedures forecasting process. Forecasting steps, data and information flows, and information repositories are explained in this chapter.

Transactional Data

Transactional data are time-stamped data that are collected over time at no particular frequency. Some examples of transactional data are:

- Internet data
- point-of-sale (POS) data
- inventory data
- call center data
- trading data

Businesses often want to analyze transactional data for trends and seasonal variation. To analyze transactional data for trends and seasonality, statistics must be computed for each time period and season of concern. The frequency and the season might vary with the business problem. Various statistics can be computed for each time period and season. For example:

- web visits by hour and by hour of day
- sales per month and by month of year
- inventory draws per week and by week of month
- calls per day and by day of week
- trades per weekday and by weekday of week

Time Series Data

Time series data are time-stamped data that are collected over time at a particular frequency. Some examples of time series data are:

- web visits per hour
- sales per month
- inventory draws per week
- calls per day
- trades per weekday

As you can see, the frequency that is associated with the time series varies with the problem at hand. The frequency or *time interval* can be hourly, daily, weekly, monthly, quarterly, yearly, or many other variants of the basic time intervals. The choice of frequency is an important modeling decision. This decision is especially true for automatic forecasting. For example, if you want to forecast the next four weeks, it is best to use weekly data rather than daily data. The forecast horizon in the former case is 4, while in the latter case it is 28.

Associated with each time series is a seasonal cycle or *seasonality*. For example, the length of seasonality for a monthly time series is usually assumed to be 12 because there are 12 months in a year. Likewise, the seasonality of a daily time series is usually assumed to be 7. The usual seasonality assumption might not always hold. For example, if a particular business' seasonal cycle is 14 days long, the seasonality is 14, not 7.

Time series that consist of mostly zero values (or a single value) are called interrupted or *intermittent time series*. These time series are mainly constant-valued except for relatively few occasions. Intermittent time series must be forecast differently from non-intermittent time series.

Forecasting Models

A skilled analyst can choose from a number of forecasting models. For automatic forecasting of large numbers of time series, only the most robust models should be used. The goal is not to have the analyst manually choose the very best model for forecasting each time series. The goal is to provide a list of *candidate models* that will forecast the large majority of the time series well. In general, when analysts have a large number of time series to forecast, they should use automatic forecasting for the low-valued forecasts; then they can spend a larger portion of their time dealing with high-valued forecasts or with low-valued forecasts that are problematic.

The candidate models that are used here are considered the most robust in the forecasting literature, and these models have proven their effectiveness over time. These models consider the local level, local trend, and local seasonal components of the time series. The term *local* describes the fact that these components evolve with time. For example, the local trend component might not be a straight line, but a trend line whose slope changes with time. In each of these models, there is an error or random component that models the uncertainty.

The components that are associated with these models are useful not only for forecasting but also for describing how the time series evolves over time. The forecasting model decomposes the series into its various components. For example, the local trend component describes the trend (up or down) at each point in time, and the final trend component describes the expected future trend. These forecasting models can also indicate departures from previous behavior or can be used to cluster time series.

The parameter estimates (*weights* or *component variances*) describe how fast the component is changing with time. Weights or component variances near 0 indicate a relative constant component; weights near 1 or large component variances indicate a relatively variable component. For example, a seasonal weight near 0 or a component variance near 0 represents a stable seasonal component, and a seasonal weight near 1 or a large component variance represents an unstable seasonal component. Parameter estimates should be optimized for each time series for best results.

Local Level Models

The local level models forecast time series whose level (or mean) component varies with time. These models predict the local level for future periods. Conceptually, this can be expressed as

(series) = (local level) + (error)

Examples of local level models are simple exponential smoothing and local level unobserved component model. This model has one parameter (level), which describes how the local level evolves. The forecasts for the future periods are simply the final local level which is a constant.

Local Trend Models

The local trend models forecast time series whose level or trend (slope) components vary with time. These models predict the local level and trend for future periods. Conceptually, this can be expressed as

(series) = (local level) + (local trend) + (error)

Examples of local trend models are double (Brown), linear (Holt), damped-trend exponential smoothing, and local trend unobserved component model. The double model has one parameter (defining both level and trend weights), the linear model has two parameters (level and trend weights), and the damped-trend model has three parameters (level, trend, and damping weights). The damping weight parameter dampens the trend over time. The forecasts for the future periods are a combination of the final local level and the final local trend.

Local Seasonal Models

The local seasonal models forecast time series whose level or seasonal components vary with time. These models predict the local level and season for future periods. Conceptually, this can be expressed as

(series) = (local level) + (local season) + (error)

Examples of local seasonal models are seasonal exponential smoothing and the local seasonal unobserved component model. The seasonal model has two parameters (level and seasonal). The forecasts for the future periods are a combination of the final local level and the final local season.

Local Models

The local models forecast time series whose level, trend, or seasonal components vary with time. These models predict the local level, trend, and seasonal component for future periods. Conceptually, this can be expressed in either an additive form,

(series) = (local level) + (local trend) + (local season) + (error)

or in a multiplicative form,

(series) = ((local level) + (local trend)) x (local season) + (error)

Examples of local models are the Winters method (additive or multiplicative) and the basic structural model. These models have three parameters (level, trend, and seasonal). The forecasts for the future periods are a combination of the final local level, the final local trend, and final local season.

ARIMA Models

The autoregressive integrated moving average (ARIMA) models forecast time series whose level, trend, or seasonal properties vary with time. These models predict the future values of the time series by applying nonseasonal or seasonal polynomial filters to the disturbances. Using different types of polynomial filters permits the modeling of various properties of the time series. Conceptually, these models can be expressed as

(series) = disturbance filter (error)

Examples of ARIMA models are the exponentially weighted moving average (EWMA), moving average (MA) processes, integrated moving average (IMA) processes, autoregressive (AR) processes, integrated autoregressive (IAR) processes, and autoregressive moving average (ARMA) processes.

Causal Models

Causal time series models forecast time series data that are influenced by causal factors. Input variables (regressor or predictor variables) and calendar events (indicator, dummy, or intervention variables) are examples of causal factors. These independent (exogenous) time series causally influence the dependent (response, endogenous) time series and therefore can aid the forecasting of the dependent time series.

Examples of causal time series models are autoregressive integrated moving average with exogenous inputs (ARIMAX), which are also known as transfer function models or dynamic regression models, and unobserved component models (UCM), which are also known as state-space models and structural time series models. Conceptually, an ARIMAX model of this form can be expressed as

(series) = transfer function filter (causal factors) + disturbance filter (error)

while a UCM model of this form can be expressed as

(series) = (local level) + (local trend) + (local season) + (causal factors) + (error)

These regression models are *dynamic* because they take into account the autocorrelation between observations that are recorded at different times. Dynamic regression includes and extends multiple linear regression (static regression).

Input variables are usually continuous-valued time series. They represent causal factors that influence the dependent time series throughout the time range. Examples of input variables are prices, temperatures, and other economic or natural factors. Input variables are contained in the time series data set.

Calendar events can be represented by indicator variables that are usually discrete-valued. They indicate when the causal factor influences the dependent time series. Zero values usually indicate the absence of the event, and nonzero values usually indicate the presence of the event. These dummy regressors can consist of pulses (points), steps (shifts), ramps, and temporary changes and combinations of these primitive shapes. The values of the indicator variable depend on the time interval. For example, if the calendar event is New Year's Day and the time interval is monthly, a pulse indicator variable is nonzero for each January and zero otherwise.

In addition to the causal factors, the causal model can contain components that are described in preceding sections: local level, local trend, and local seasonal. Causal models decompose the time series into causal factors and the local components. This decomposition is useful for demand analysis (promotional analysis and intervention analysis).

Transformed Models

Except for the Winters method multiplicative model, the preceding forecasting models are linear; that is, the components must be added together to re-create the series. Because time series are not always linear with respect to these components, automatic forecasting must consider transformed versions of the preceding forecasting models. Some useful time series transformations are the following:

- logarithmic
- square-root
- logistic
- Box-Cox

For example, suppose the underlying process that generated the series has one of the following nonlinear forms:

Form	Description
(series) = exp ((local level) + (local trend) + (error))	exponential growth model
(series) = (local level) x (local season) x (error)	multiplicative error model

Transforming the preceding nonlinear forms permits the use of a linear forecasting model:

Model	Description
log(series) = (local level) + (local trend) + (error)	log local trend model
log(series) = log(local level) + log(local seasonal) + log(error)	log local seasonal model

The preceding transformations can be applied only to positive-valued time series.

Intermittent Demand Models

Intermittent demand models or interrupted time series models forecast intermittent time series data. Because intermittent series are mostly constant valued (usually 0) except on relatively few occasions, it is often easier to predict when the series departs and how much the series departs from this constant value rather than to predict the next value. An example of an intermittent demand model is Croston's method.

Intermittent demand models decompose the time series into two parts: the interval series and the size series. The interval series measures the number of time periods between departures. The size series measures the

magnitude of the departures. After this decomposition, each part is modeled and forecast independently. The interval forecast predicts when the next departure will occur. The size forecast predicts the magnitude of the next departure. After the interval and size predictions are computed, they are combined (predicted magnitude divided by predicted number of periods for the next departure) to produce a forecast for the average departure from the constant value for the next time period.

External and User-Defined Models

In addition to the previously described general classes of exponential smoothing models, unobserved component models, autoregressive integrated moving average models, and intermittent demand models, SAS Forecast Server Procedures software allows for external models and user-defined models.

External models are used for forecasts that are provided external to the system. These external forecasts might have originated from an external statistical model from another software package, might have been provided by an outside organization (for example, marketing organization or government agency), or might be based on judgment. External models allow for the evaluation of external forecasts and for tests for unbiasedness.

User-defined models are external models that you implement by using the SAS programming language or the C programming language. For these models, you create your own computational algorithm to generate the forecasts. These models are considered external because they are not implemented in SAS Forecast Server Procedures software.

Forecasts

Forecasts are time series predictions made for future periods. They are random variables and therefore have an associated probability distribution. For example, assuming a normal distribution, the forecasts for the next three months can be viewed as three "bell curves" that are progressively flatter (or wider). The mean or median of each forecast is called the *prediction*. The variance of each forecast is called the *prediction error variance*, and the square root of the variance is called the *prediction standard error*. The variance is computed from the forecast model parameter estimates and the model residual variance.

The forecast for the next future period is called the *one-step-ahead forecast*. The forecast for h periods in the future is called the *h-step-ahead forecast*. The *forecast horizon* or *forecast lead* is the number of periods into the future for which predictions are made (one-step, two-step, . . . , h-step). The larger the forecast horizon, the larger the prediction error variance at the end of the horizon. For example, forecasting daily data four weeks into the future implies a forecast horizon of 28, whereas forecasting weekly data four weeks into the future implies a forecast horizon of only 4. The prediction standard error at the end of the horizon in the former case might be larger than the prediction standard error in the latter case.

The *confidence limits* are based on the prediction standard errors and a chosen confidence limit size. A confidence limit size of 0.05 results in 95% confidence limits. The confidence limits are often computed assuming a normal distribution, but other distributions could be used. As with the prediction standard errors, the width of the confidence limits increases with the forecast horizon. Once again, the forecast horizon of 28 will have wide confidence limits at the end of the horizon, representing greater uncertainty.

The *prediction error* is the difference between the actual value and the predicted value when the actual value is known. The prediction errors are used to calculate the statistics of fit that are described later. For transformed models, it is important to understand the difference between the model errors (residuals) and the prediction errors. The residuals measure the departure from the model in the transformed metric (log,

square root, and so on). The prediction errors measure the departure from the original series. You should not directly compare the model residuals of a transformed model and an untransformed model when evaluating the model fit. You can compare the prediction errors between any two models because prediction errors are computed on the same metric.

Taken together, the predictions, prediction standard errors, and confidence limits at each period in the forecast horizon are the *forecasts*. Although many people use the term "forecast" to imply only prediction, a forecast is not one number for each future time period.

Using a transformed forecasting model requires the following steps:

1. The time series data are transformed.
2. The transformed time series data are fit using the forecasting model.
3. The forecasts are computed using the parameter estimates and the transformed time series data.
4. The forecasts (predictions, prediction standard errors, and confidence limits) are inverse transformed.

The naive inverse transformation results in *median forecasts*. Obtaining *mean forecasts* requires that the prediction and the prediction error variance both be adjusted based on the transformation. In addition, the model residuals will be different from the prediction errors because of this inverse transformation. If no transformation is used, the model residual and the prediction error will be the same, and likewise the mean and median forecast will be the same (assuming a symmetric disturbance distribution).

For causal models, the future values of the causal factors must be provided in order to forecast the time series. A causal factor is *deterministic* if its future values are known with certainty. A causal factor is *controllable* if its future values are under the control of the organization that produces the forecasts. A causal factor is *stochastic* if its future values are not known with certainty. If the causal factor is *stochastic*, it must also be forecast, and the uncertainty of its forecast (prediction standard errors) must be incorporated into the uncertainty of the time series forecast.

Forecast Function (Scoring)

For causal models that include controllable causal factors, the predictions can be influenced by the future decisions made by the organization that produces the forecasts. Changing the future values of the controllable causal factors changes the forecasts. Organizations want to make decisions that benefit themselves. To help organizations make better decisions, the future values of the controllable causal factors can be varied to their benefit. The future values of the causal factors can be varied for scenario analysis (what-if analysis), stochastic optimization, or goal-seeking to aid proper decision-making.

In scenario analysis, the organization sets the future values of the causal factors to specific values and then evaluates the effect on the forecasts. In stochastic optimization, the organization algorithmically varies the future values of the causal factors to find the optimum of an objective function (profit, revenue, or cost function) based on the forecasts. In goal seeking, the organization algorithmically varies the future values of the causal factors in order to determine the values that achieve a certain goal (profit, revenue, or cost goal) based on the forecasts.

For example, suppose the following:

- An organization desires to predict the demand for a product or service.
- The demand is influenced by its sales price and by its advertising expenditures.
- These data are recorded over time.

The following types of analysis can be used to answer questions about the time series data:

- Scenario analysis can help answer the question "What happens to demand if the organization increases the sales price and decreases the advertising expenditures?"
- Stochastic optimization can help answer the question "What is the optimal sales price and advertising expenditure combination that maximizes profit?"
- Goal-seeking can help answer the question "What are the combinations of sales price and advertising expenditures that achieve a specified sales target?"

The sales price and advertising expenditures for a given time period can influence demand in future time periods. Static regression ignores these dynamic effects, which often leads to poor predictions, which in turn leads to poor decisions. Dynamic regression captures these dynamic effects and provides better predictions, which in turn facilitates better decisions.

Forecast score files (or forecast functions) summarize the time series model's parameter estimates and the final states (historical time series information). These files can be used to quickly generate the forecasts required for the iterative nature of scenario analysis, stochastic optimization, and goal-seeking computations. Since most of the computational effort associated with automatic forecasting is time series analysis, diagnostics, model selection, and parameter estimation, forecast scoring is relatively effortless. Therefore, forecast scoring makes the iterative nature of large scale decision-making more tractable.

The results of forecast scoring include the predictions, prediction standard errors, and the confidence limits. All of these results can be used in decision-making.

Statistics of Fit

The *statistics of fit* evaluate how well a forecasting model performs by comparing the actual data to the predictions. For a given forecast model that has been fitted to the time series data, the model should be checked or evaluated to see how well it fits or forecasts the data. Commonly used statistics of fit are root mean square error (RMSE), mean absolute percentage error (MAPE), Akaike information criteria (AIC), and many others. The statistics of fit can be computed from the model residuals or the prediction errors.

When the full range of data is used to both fit and also evaluate the model, this is referred to as *in-sample evaluation*. When the most recent data are excluded for parameter estimation (holdout) and this *holdout sample* is used for evaluation, this is referred to as *holdout sample evaluation*. Holdout sample analysis is similar to *training* and *testing* of neural networks. A portion of the data is withheld from training (fit) and the withheld data (holdout) are used to test performance.

When a particular statistic of fit is used for forecast model selection, it is referred to as the *model selection criterion*. For example, if the MAPE (an often recommended choice) is used as a model selection criterion,

the forecast model with smallest MAPE in the evaluation region (in-sample or holdout-sample) is chosen as the *best model*.

When a particular statistic of fit is used to judge how well the forecasting process is predicting the future, it is referred to as the *performance statistic*.

Automatic Forecasting Process

Automatic forecasting is usually defined as forecasting without the aid of an analyst skilled in time series analysis techniques or as forecasting when the number of forecasts is too numerous for an analyst to investigate. Automatic forecasting is usually performed on each time series independently. For each time series and for each candidate model, the parameter estimates are optimized for best results. This means that several optimizations might be required for each time series.

Accumulation Step

The *accumulation* of time-stamped data into time series data is based on a particular frequency. For example, time-stamped data can be accumulated to form hourly, daily, weekly, monthly, or yearly time series. Additionally, the method for accumulating the transactions within each time period is based on a particular statistic. For example, the sum, mean, median, minimum, maximum, standard deviation, and other statistics can be used to accumulate the transactions within a particular time period.

For automatic forecasting, accumulation is the most important decision because the software makes most of the remaining decisions. If weekly forecasts of the average of the transactions are needed, then the accumulation frequency should be weekly and the accumulation statistic should be the average.

Accumulating the transactional data on a relatively small time interval can require a long forecast horizon. For example, if the data are accumulated on an hourly basis and if it is desired to forecast one month into the future, the forecast horizon is very long and the width of the confidence limits will be very wide toward the end of the horizon. In this situation, the forecast content or usefulness of the forecast will be low.

Interpretation Step

Once the time-stamped data has been accumulated, there might be no data recorded for certain time periods (resulting in missing values in the accumulated time series). These missing values can represent unknown values (and so they should remain missing) or they can represent no activity (in which case they should be set to zero or some other appropriate value). Some transactional databases set missing data at the beginning or end of the time series to zero values. These zero values should be set to missing values. Missing values and zero values need to be interpreted before analyzing the time series.

Adjustment Step

Once the time-stamped data has been accumulated and interpreted, the time series to forecast might require adjustment prior to analysis or *pre-forecast adjustment*. By adjusting the time series for known systematic variations or deterministic components, the underlying stochastic (unknown) time series process can be more readily identified and modeled.

Examples of systematic adjustments are currency-unit conversions, exchange rates, trading days, and other known systematic variations. Examples of deterministic adjustments are advanced bookings and reservations, contractual agreements, and other known contributions or deterministic components.

After analysis, the statistical forecast of the adjusted time series might require *post-forecast adjustment* to return forecasts in the original metric.

Typically the pre-forecast and post-forecast adjustments are operations that are inverses of each other. For example, to adjust a time series for exchange rates, it is often desirable to perform the following steps, in which division and multiplication are inverse operations of each other:

1. *Divide* the time series by the exchange rate.
2. Analyze and forecast the adjusted time series without regard to exchange rates.
3. Adjust the forecasts, *multiplying* by the exchange rate.

For another example, to adjust a time series for advanced bookings, it is often desirable to perform the following steps, in which subtraction and addition are inverse operations of each other:

1. *Subtract* the advanced bookings from the time series.
2. Analyze and forecast the adjusted time series without regard to advanced booking.
3. Adjust the forecasts, *adding* the advanced bookings.

Systematic variations or deterministic components are included in the time series data. Adjustments are data whose effect is *excluded* prior to statistical analysis. Causal factors are data whose effect is *included* with the statistical analysis.

Diagnostic Step

Given the time series data, the time series diagnostics subset the potential list of candidate models to those that are judged appropriate to a particular time series. Time series that have trends (deterministic or stochastic) should be forecast with models that have a trend component. Time series with seasonal trends (deterministic or stochastic) should be forecast with models that have a seasonal component. Time series that are nonlinear should be transformed for use with linear models. Time series that are intermittent should be forecast with intermittent models.

The importance of the diagnostics should not be underestimated. Applying a seasonal model to a nonseasonal time series, particularly one with a short history, can lead to over-parameterization or false seasonality. Applying a linear model to a nonlinear time series can lead to underestimation of the growth (or decline). Applying a non-intermittent model to an intermittent series will result in predictions biased toward zero.

If it is known, *a priori*, that a time series has a particular characteristic, then the diagnostics should be overridden and the appropriate model should be used. For example, if the time series is known to be seasonal, the diagnostics should be overridden to always choose a seasonal model.

There can be several causal factors that might or might not influence the dependent time series. The multivariate time series diagnostics determine which of the causal factors *significantly* influence the dependent time series. These diagnostics include cross-correlation analysis and transfer function analysis.

Once again, if it is known, *a priori*, that a particular causal factor is known to influence the dependent time series, then the diagnostics should be overridden and the appropriate model should be used.

Model Selection Step

After the candidate models have been subset by the diagnostics, each model is fit to the data (with the holdout sample excluded). After model fitting, the one-step-ahead forecasts are made in the fit region (in-sample) or the multistep-ahead forecasts are made in the holdout sample region (out-of-sample). The model selection criterion is used to select the best performing model from the appropriate subset of the candidate models. As described previously, the model selection criteria are statistics of fit.

If the length of the time series is short, holdout sample analysis might not be possible due to a lack of data. In this situation, the full range of the data should be used for fitting and evaluation; otherwise, holdout sample analysis is recommended.

Parameter Estimation Step

After the best forecasting model is selected from the candidate models, the selected model is fit to the full range of the data to obtain the most accurate model parameter estimates. If you excluded the holdout sample in this step, you would be ignoring the most recent and influential observations. Most univariate forecasting models are weighted averages of the past data, with the most recent having the greatest weight. After the model is selected, excluding the holdout sample can result in poor forecasts. Holdout sample analysis is used only for forecast model selection, not for forecasting.

Forecasting Step

After the model parameters are estimated, forecasts (predictions, prediction standard errors, prediction errors, and confidence limits) are made using the model parameter estimates, the model residual variance, and the full range of data. If a model transformation was used, the forecasts are inverse transformed on a mean or median basis.

When it comes to decision-making based on the forecasts, the analyst must decide whether to base the decision on the predictions, lower confidence limits, upper confidence limits, or the distribution (predictions and prediction standard errors). If there is a greater penalty for over-predicting, the lower confidence limit should be used. If there is a greater penalty for under-predicting, the upper confidence limit should be used. Often for inventory control decisions, the distribution (mean and variance) is important.

Evaluation Step

After the forecasts are made, the in-sample statistics of fit are computed based on the one-step-ahead forecasts and the actual data. These statistics can be used to identify poorly fitting models prior to making business decisions based on these forecasts. If forecasts do not predict the actual data well, they can be flagged to signal the need for more detailed investigation by the analyst.

In addition to the statistics of fit, distribution and correlation analysis of the prediction errors can help evaluate the adequacy of the forecasting model.

Performance Step

The previous steps are used to forecast the future. This ex-post forecast evaluation judges the performance of the forecasting model. After forecasting future periods, the actual data becomes available as time passes. For example, suppose that monthly forecasts are computed for the next three months into the future. After three months pass, the actual data are available. The forecasts made three months ago can now be compared to the actual data of the last three months.

The availability of the new data begs the following questions:

- How well are you forecasting?
- Why are you forecasting poorly?

- If you were forecasting well before, what went wrong?

Some useful measures of forecast performance are the statistics of fit described in the section "Statistics of Fit" on page 441. When the statistics of fit are used for performance measures, the statistics are computed from the previous predictions and the newly available actual data in the forecast horizon. For example, the MAPE can be computed from the previous predictions and the newly available actual data in the three-month forecast horizon.

Another useful measure of forecast performance is determining whether the newly available data fall within the previous forecasts' confidence limits. For example, performance could be measured by whether or not the newly available actual data fall outside the previous forecasts' confidence limits in the three-month forecast horizon.

If the forecasts were judged to be accurate in the past, a poor performance measure (such as actual data outside the confidence limits) could also be indicative of a change in the underlying process. A change in behavior, an unusual event, or other departure from past patterns might have occurred since the forecasts were made.

Such departures from past trends might be normal and indicate the need to update the forecasting model selection for this variable, or they can be a warning of special circumstances that warrant further investigation.

Large departures from forecast can sometimes reflect data errors, changes in policies or data definitions (for example, what exactly is counted as sales), fraud, or a structural change in the market environment.

Forecast Function (Score File) Generation Step

After the selected model is fit to the full range of the data, a summary of model parameter estimates and the final states (historical time series information) are stored in a forecast score file. Subsequent decision-making processes can the use the forecast score file for scenario (what-if) analysis, stochastic optimization, or goal-seeking.

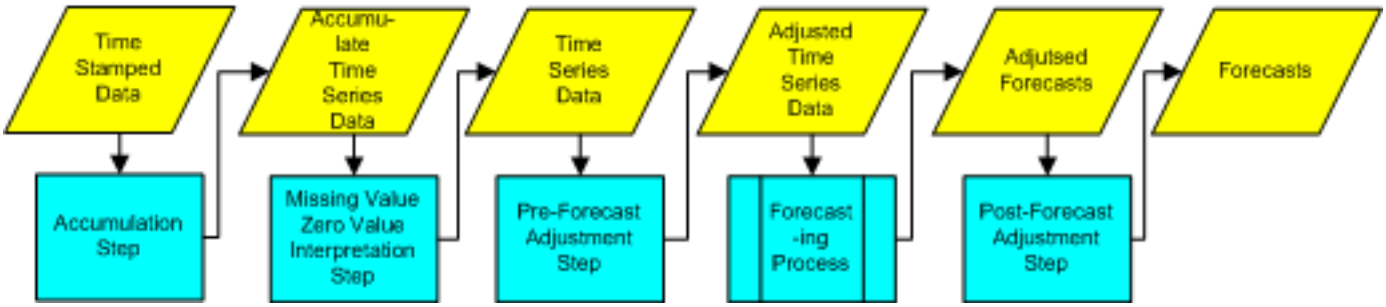
Automatic Forecasting Data

For forecast scoring, you must specify the future values of the controllable causal factors (scenario analysis); otherwise, the future values must be iteratively generated by the decision process (stochastic optimization or goal-seeking).

Automatic Forecasting Data Flow

The input and output of the automatic forecasting process are the time-stamped data set and the forecasts, respectively. Figure 14.1 depicts the automatic forecasting data flow.

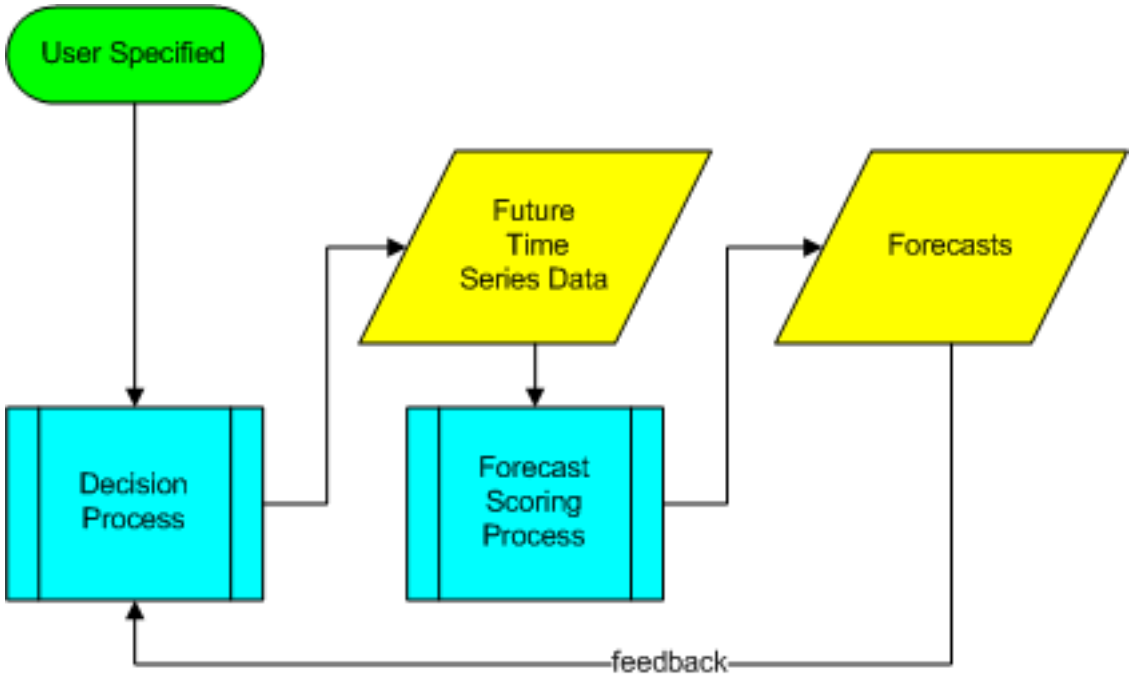
Figure 14.1 Automatic Forecasting Data Flow



Forecast Scoring Data Flow

The input and output of the forecast scoring process are the future values of the controllable causal factors and the forecasts, respectively. Figure 14.2 illustrates the forecast scoring data flow.

Figure 14.2 Forecast Scoring Data Flow



Automatic Forecasting Information

To automatically forecast a single time series, the time series must be diagnosed, selected, or specified to obtain a selected model used for forecasting. These abstract statistical concepts must be made concrete and persistent in a computer's storage. In addition to the time series data, the information described in the section "Model Specification" on page 448 is needed.

Model Specification

A *model specification* indicates that a specific type of forecasting model be fit to the historical data and used to produce forecasts. Given a time series and a model specification, a forecast for the time series is generated by applying the abstract statistical concepts associated with model specification. A model specification is not dependent on any specific time series data; a given specification can be used for many different series.

Associated with a model specification is a list of symbols that represent the time series to which the specification applies. These symbols must be mapped to actual time series variables in the input data set, or to event specifications, before the model specification can be used to create a fitted model for forecasting.

The following theoretical time series models are supported: ESM, IDM, ARIMAX, UCM, EXTERNAL, USER-DEFINED.

Except for the external and user-defined models, all of the models are implemented to allow nonlinear transformations (log, square root, logistic, Box-Cox) of the dependent and independent time series.

Exponential Smoothing Models (the HPFESMSPEC Procedure)

Exponential smoothing models are extrapolation methods that predict future values based on exponentially weighted past values of the time series.

The following exponential smoothing models are supported:

- simple exponential smoothing (SIMPLE)
- double exponential smoothing (DOUBLE)
- linear exponential smoothing (LINEAR)
- damped-trend exponential smoothing (DAMPTREND)
- seasonal exponential smoothing (SEASONAL)
- multiplicative Winters method (WINTERS)
- additive Winters method (ADDWINTERS)

Intermittent Demand Models (the HPFIDMSPEC Procedure)

Intermittent demand models are extrapolation methods that predict future values based on exponentially weighted past values of intermittent (interrupted) time series components. These methods use nonseasonal exponential smoothing models to forecast the intermittent time series components (interval, size, average demand) independently.

The following intermittent demand models are supported:

- Croston's method (CROSTON)
- average demand (AVERAGE)

Autoregressive Moving Average with Exogenous Inputs (the HPFARIMASPEC Procedure)

ARIMAX models implement Box-Jenkins models with or without transfer function inputs.

The following ARIMA models are supported:

- simple and seasonal ARIMA
- factored and subset ARIMA
- preceding models with simple and seasonal transfer function inputs
- preceding models with factored and subset transfer function inputs

Unobserved Component Models with Exogenous Inputs (the HPFUCMSPEC Procedure)

Unobserved component models (UCMs) implement structural time series models with or without input variables.

The following UCMs are supported:

- local level
- local slope (or trend)
- local seasons (up to three seasons)
- local cycles (no limit to the number of cycles)
- exogenous inputs
- combinations of the preceding components

External Models (the HPFEXMSPEC Procedure)

External models are forecasts provided by methods external to the system. These methods might be judgmental inputs or forecasts provided by an external system such as another forecasting system. These forecasts must be recorded in the input time series data set.

When only the future predictions are provided, prediction standard errors and confidence limits are computed using the past prediction errors, if available. These additional forecasting components can be computed assuming nonlinear transformations (log, square root, logistic, Box-Cox) and autocorrelation (white noise, prediction error autocorrelation, series autocorrelation).

Because the system has no knowledge of how the forecasts were computed, there are no parameter estimates. However, the forecast bias can be computed, and a test for unbiasedness can be made.

User-Defined Models

User-defined models are forecasting methods provided by the user of the system. These methods are implemented in the SAS language or the C language. Since the system has no knowledge of how the forecasts were computed, the forecasts are treated as if they were external forecasts.

There is usually more than one model specification associated with a model repository. A model specification does not depend on a particular time series, and a particular model specification can be assigned to different time series. However, a unique model specification must be assigned or selected for each time series in order to forecast the time series.

A model specification can also be referred to in one or more model selection lists.

The model specification is stored in an XML format, and this format follows the spirit of the predictive model markup language (PMML) specification. It is stored as a SAS catalog entry or as an external file.

See Chapter 19, "Using User-Defined Models," for more information.

Model Selection List

A model selection list specifies a list of candidate model specifications and how to choose which model specification is best suited to forecast a particular time series. Given a time series and an appropriate model selection list, a forecasting model can be automatically selected for the time series. Since the model selection process is applied to each series individually, the process might select a different model for different series and might select a different model for a given time series, with the passage of time as more data are collected. A model selection list is not dependent on any specific time series data.

A model selection list consists of the following:

List of candidate model specifications	specifies the list of model specifications to consider when choosing the model for forecasting.
Selection diagnostics	specifies how to subset the list of model specifications models to those that are judged appropriate to a particular time series.
Holdout sample size	specifies the size of the holdout sample region. A holdout sample size of zero indicates that the full range of data is used to both fit and also evaluate the forecast. The holdout sample size can be

	an absolute size or a percentage of the length of the time series data.
Model selection criterion	specifies the statistic of fit to be used to select the best performing model from the subset list of the candidate models returned by the selection diagnostics.
Confidence limit size	specifies the confidence limit size for computing lower and upper confidence limits.

There might be more than one model selection list associated with a model repository. A model selection list does not depend on a particular time series, and a particular model selection list can be assigned to different time series. However, a unique model selection list must be assigned to each time series. If desired, each time series to be forecast can have its own model selection list; typically, for time series with similar characteristics, the same model selection list is assigned.

The model selection list is stored in an XML format and this format follows the spirit of the PMML specification. It is stored as a SAS catalog entry or as an external file.

See Chapter 11, "The HPFSELECT Procedure," for more information.

Selected Model Specification

A selected model specification is a model specification that is the result of the diagnostic or model selection processes for a particular time series. The selected model specification is used to forecast this time series.

The file reference of the selected model specification is stored in a SAS data set.

Fitted Model

A fitted model results from applying a model specification to specific time series data. Given a time series and a model specification (diagnosed, selected, or specified), the model parameter estimates can be optimized to fit the time series data. The fitted model is used to forecast this time series.

The parameter estimates associated with fitted models are stored in a SAS data set.

Forecast Function (Score File)

A forecast model score file encodes the information that is needed to compute forecasts for a time series given the future values of the causal factors. Given a time series and a model specification (diagnosed, selected, or specified), a fitted time series model is estimated. Given a fitted model and a time series, a forecast model score file can be generated that efficiently encapsulates all information needed to forecast the series when future inputs are provided.

The forecast model score file is stored in an XML format that follows the spirit of the PMML score file. It is stored as a SAS catalog entry or as an external file.

Forecast model score files can be used for scenario analysis, goal seeking, or stochastic optimization. SAS functions are provided that can refer to the forecast model score files to calculate forecasts from the fitted

model given alternative inputs. These functions can be used in user-written SAS data set programs or in SAS analytical procedures such as the MODEL procedure or the NLP procedure.

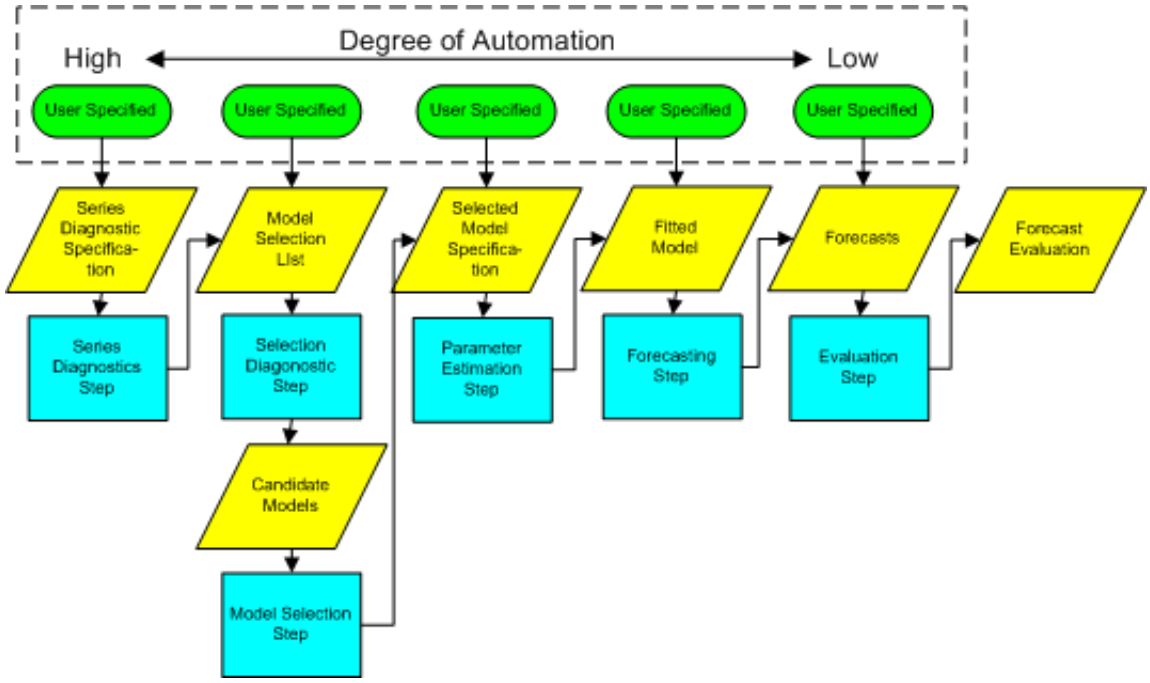
For examples and additional information, see Chapter 18, "Using Forecasting Model Score Files and DATA Step Functions."

Automatic Forecasting Information Flow

SAS Forecast Server Procedures software is designed to support fully automated forecasting. SAS Forecast Server Procedures software also provides you a great deal of control over the forecasting process when you want to override steps in the automatic process. You can control any or all of the forecasting steps, or you can allow the system to control all steps.

The degree of automation depends on how much information you specify. For each time series, the information flow of the automatic forecasting technique is described in Figure 14.3.

Figure 14.3 Automatic Forecasting Information Flow



The more information you provide, the less automation is needed. If you specify the forecasts (external forecasts), nothing is required. If you specify the fitted model, only forecasting is required. If you specify the selected model specification, then parameter estimation and forecasting are required. If you specify a model selection list, then model selection, parameter estimation, and forecasting are required. If the diagnostic specification is specified, then diagnostics, model selection, parameter estimation, and forecasting are required. If you specify nothing, the default diagnostics or model selection list is used.

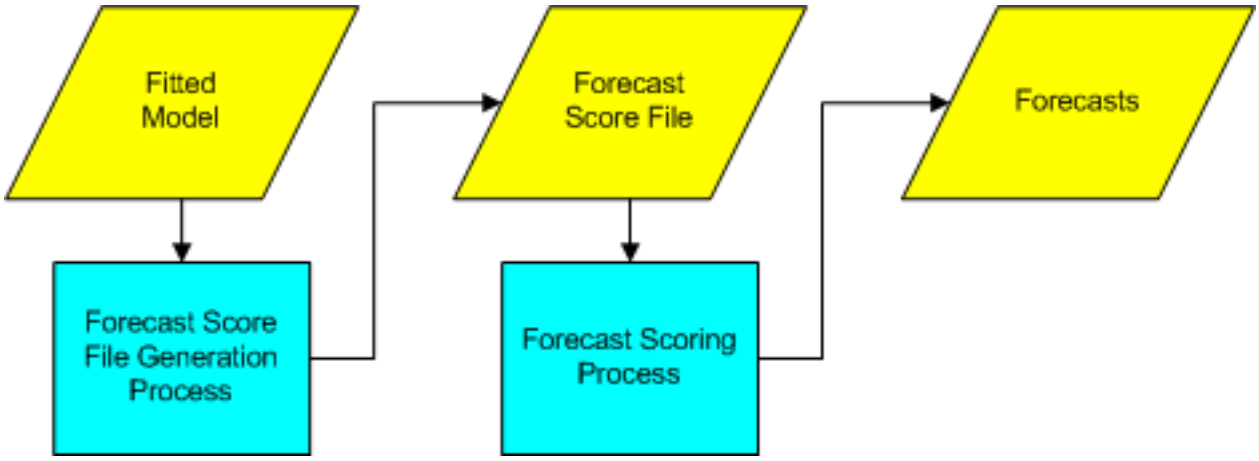
The more information you provide, the less computational effort is needed. Series diagnostics are the most expensive, followed by model selection, parameter estimation, and forecasting. Because the information persists in the computer's storage, differing degrees of automation can be used over time. For instance, it might be desirable to use the diagnostic step every six months, the model selection step every three months,

the parameter estimation step every month, and the forecasting step every week. This staggering of the degree of automation reduces the processing time by allowing the most up-to-date information about the time series data to influence the automatic forecasting process over time.

Forecast Scoring Information Flow

For each time series, the information flow of the forecast scoring technique presented here is described in Figure 14.4.

Figure 14.4 Forecast Scoring Information Flow



A fitted model generates a forecast score file. Using the forecast score file and given the future values of the controllable causal factors, the forecast scoring process generates the forecasts.

Automatic Forecasting Repositories

Since there are many time series to forecast, large-scale automatic forecasting requires the efficient management of large amounts of information about each time series. In addition to the time series data, the following information repositories are needed.

Event Repository

An event repository stores information about calendar events with a brief description of each event. Calendar events can be represented by indicator variables that could be stored in the time series data. However, because the influential calendar events can vary from series to series, there might be too many to store efficiently and many calendar events will be redundant, making updates difficult. Therefore, it is better to store a brief description of the calendar event, to reproduce the indicator variable in the computer's memory when needed, and to store the calendar events independently of the time series data, to allow the reuse and update of the calendar events. Additionally, the event repository can be used by more than one time-stamped data set.

See Chapter 7, "The HPFEVENTS Procedure," for more information about creating event definitions and storing them in an event repository.

Model Specification Repository

A *model specification repository* stores information about time series models (model specification) and how to select an appropriate time series model (model selection list) when given a particular time series. A model specification can be assigned to each time series. However, because the model specification can vary from series to series, there might be too many to store efficiently and many model specifications will be redundant, making updates difficult. Therefore, it is better to store model specifications independently of the time series data to allow the reuse and update of the model specification. Additionally, the model specification repository can be used by more than one time-stamped data set.

The model specification repository contains the following information:

model specification file	SAS catalog entry or external file that *specifies a time series model to use* for forecasting
model selection list file	SAS catalog entry or external file that specifies *how to select a model specification* to use for a particular time series

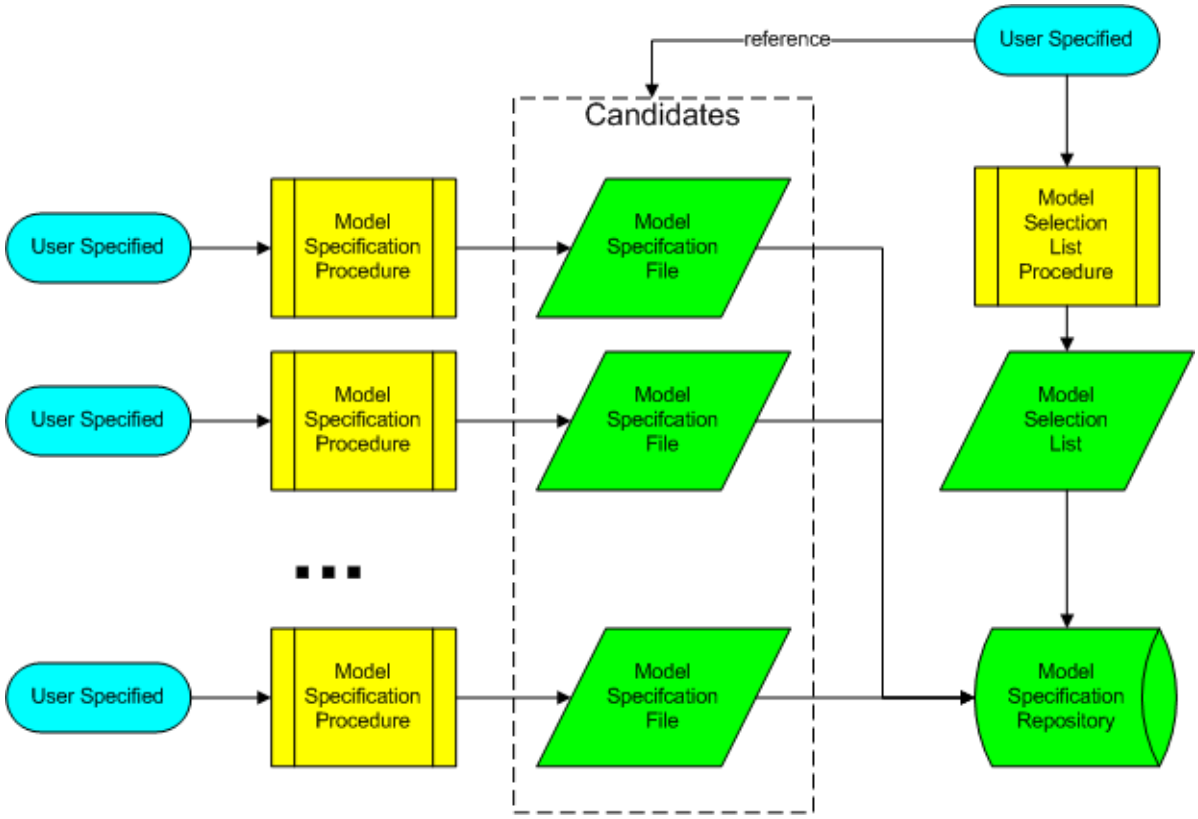
The repository consists of SAS catalogs or external directories (or folders). More than one catalog can be combined using the SAS Libname Engine.

Creating a Model Specification Repository

You can create model specification files and populate the model specification repository by using the HPFESMSPEC, HPFIDMSPEC, HPFARIMASPEC, HPFUCMSPEC, and HPFEXMSPEC procedures. After creating the model specification files, you can create model selection list files by using the HPFSELECT procedure.

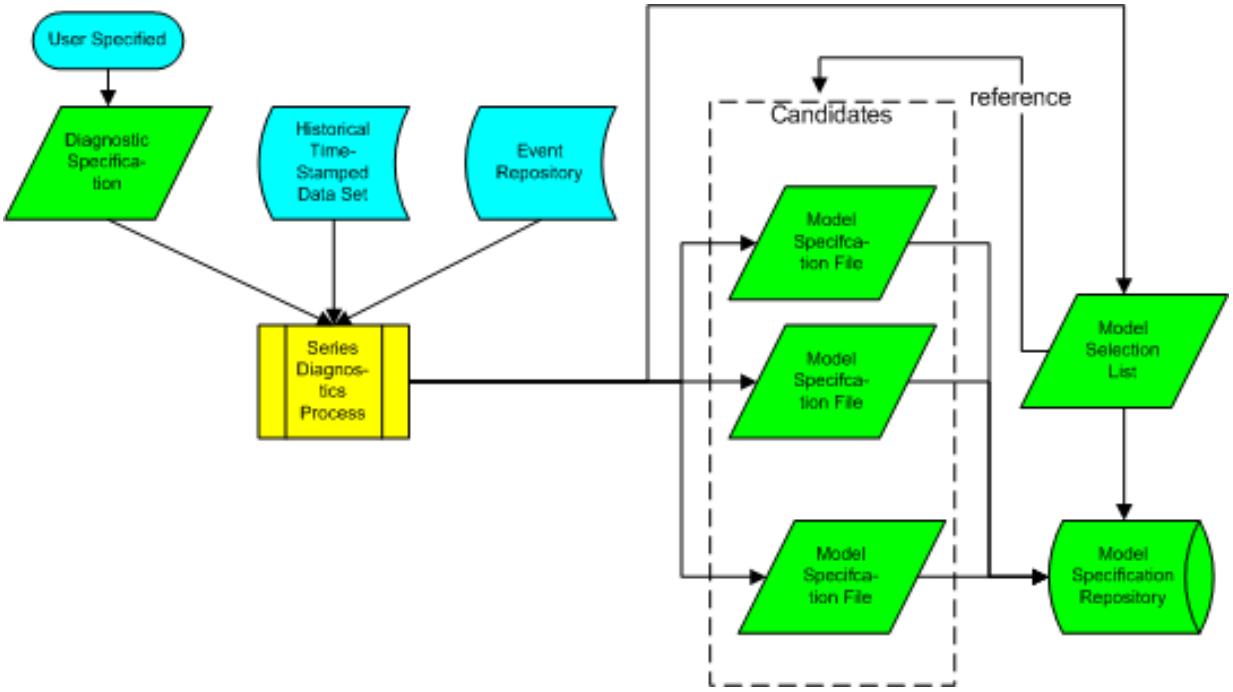
Figure 14.5 illustrates the process of adding user-created model specification files and model selection list files.

Figure 14.5 Creating a Model Specification Repository



You can also create the model specification files and model selection files by using the HPFDIAGNOSE procedure. Given the historical time series data and the calendar events, the HPFDIAGNOSE procedure automatically creates model specification files and model selection files. Figure 14.6 illustrates the series diagnostic process of automatically creating model specification files and model selection list files.

Figure 14.6 Series Diagnostic Process



Fitted Model Repository

A fitted model repository stores information about the selected model specification and its parameter estimates for each time series. Because each time series has different parameter estimates, the fitted model repository will often be large. There is one fitted model repository for each time-stamped data set.

The repository consists of a single SAS data set and associated SAS catalogs or external files that are referenced in the rows of the data set. The forecasting model repository is generated using the series diagnostics or default model selection lists.

For each time series, the fitted model repository specifies the following:

model selection list name (reference)	SAS catalog entry name or external file name for the model selection list used to select this model. These lists are contained in a model specification repository.
model specification name (reference)	SAS catalog entry name or external file name that specifies the current model being used for forecasting. These specifications are contained in the model specification repository.
variable mapping	data set rows that map the time series data specification variables and events to model specification symbols
forecasting model parameter estimates	data set rows that contain the model parameter estimates associated with the current model
forecast score name (reference)	SAS catalog entry name or external file name that specifies the forecast scores associated with the current model. These scores are stored in the forecast score repository.

Forecast Results Repository

A forecast results repository stores information about the forecasts, forecast evaluations, and forecast performance for each time series. The forecast results repository consists of several data sets. Because each time series has forecasts and statistics of fit associated with these forecasts, the forecast results repository will often be large. There is one forecast results repository for each time-stamped data set.

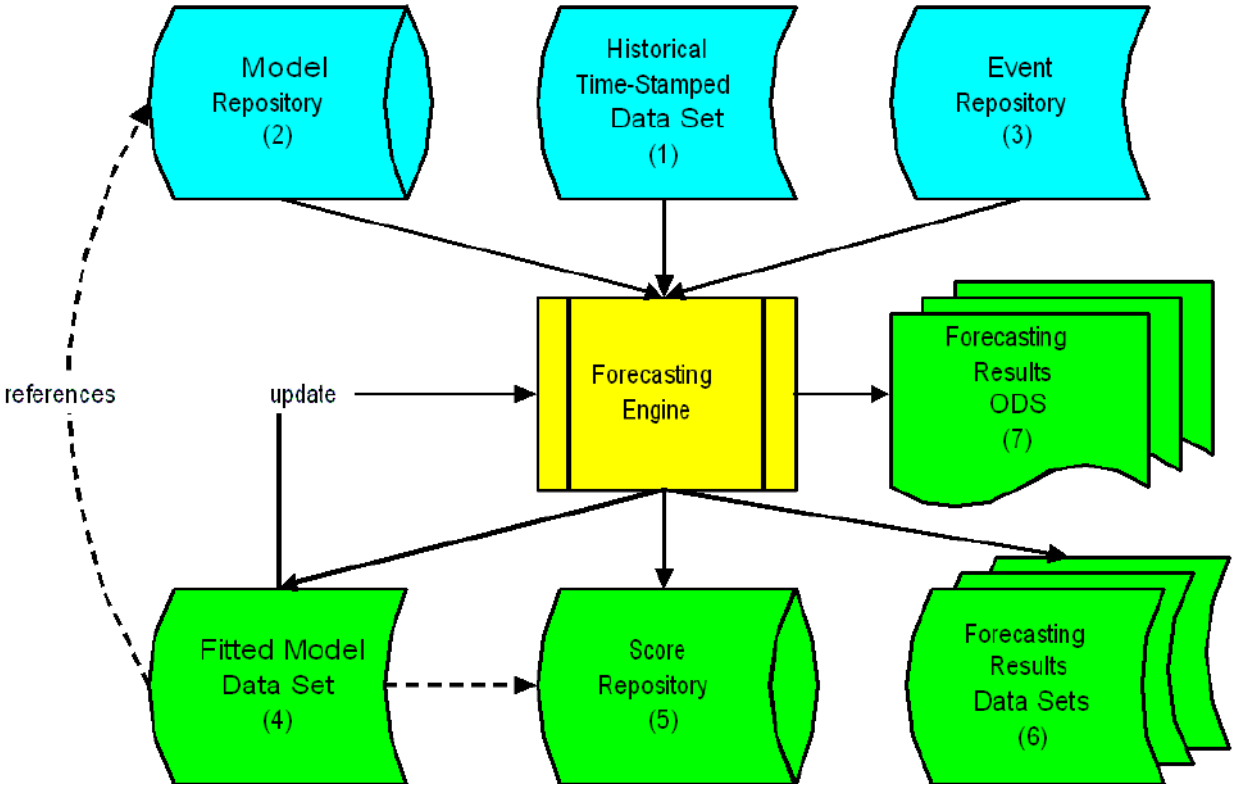
Score Repository

A score repository stores information about how to score each time series. Because each time series has a different score, the score repository will often be large because it summarizes information contained in the model specification repository, fitted model repository, and the final states (historical time series data). There is one score repository for each time-stamped data set.

Automatic Forecasting System Flow

Along with the time series data, the preceding information repositories are needed for large-scale automatic forecasting. Figure 14.7 shows the system flow for the automatic forecasting technique when there are many time series.

Figure 14.7 Automatic Forecasting System Flow



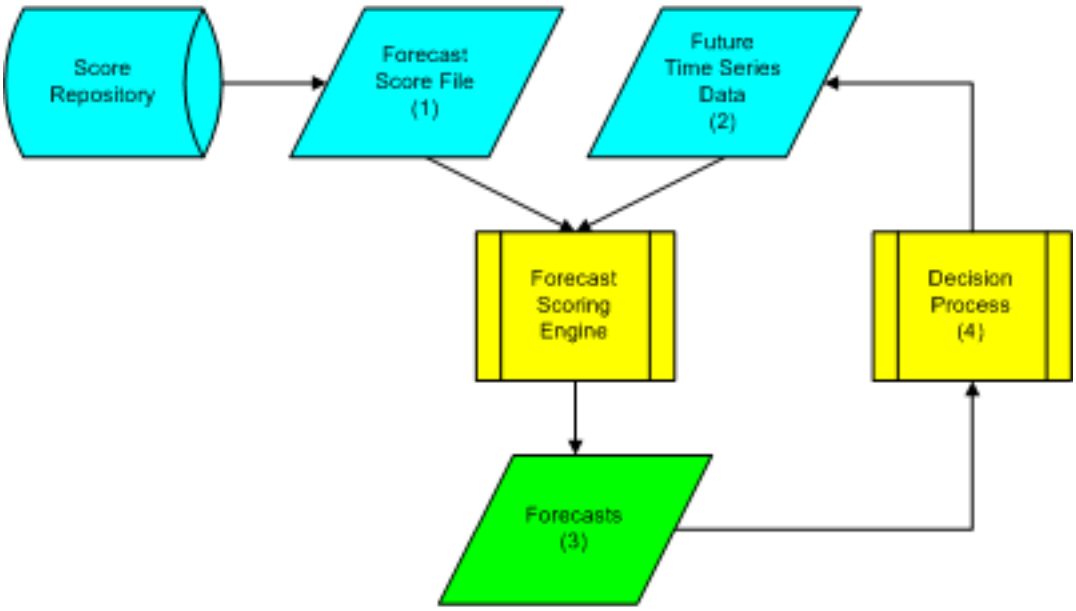
For each historical time series to forecast, the automatic forecasting system works as follows:

1. The time-stamped data are read from the time-stamped data set and accumulated, interpreted, and adjusted to form the time series to forecast.
2. The modeling information (model specifications and model selection list) associated with the time series is read from the model repository.
3. The calendar events associated with each model specification are read from the event repository.
4. Using the time series, modeling information, and calendar events, the forecasting engine creates or uses (updates) the fitted model.
5. From the fitted model, forecast score files are generated and stored in the score repository.
6. From the fitted model, forecast results data sets are created and stored.
7. From the fitted model, forecasting results ODS (printed tables and graphs) are created and rendered.

Forecast Scoring System Flow

For each time series, the automatic forecasting system generates a forecast score file that can be used in subsequent decision-making processes. Figure 14.8 shows the system flow for each file that uses the forecast scoring technique.

Figure 14.8 Forecast Scoring System Flow



For each time series to score, the forecast scoring process works as follows:

1. The forecast score file is read from the score repository.
2. The future values of the controllable causal factors are provided by the decision-making process.
3. Using the forecast score file and the future values, the forecast scoring process generates forecast results.
4. Steps 2 and 3 are repeated as needed by the decision-making process.

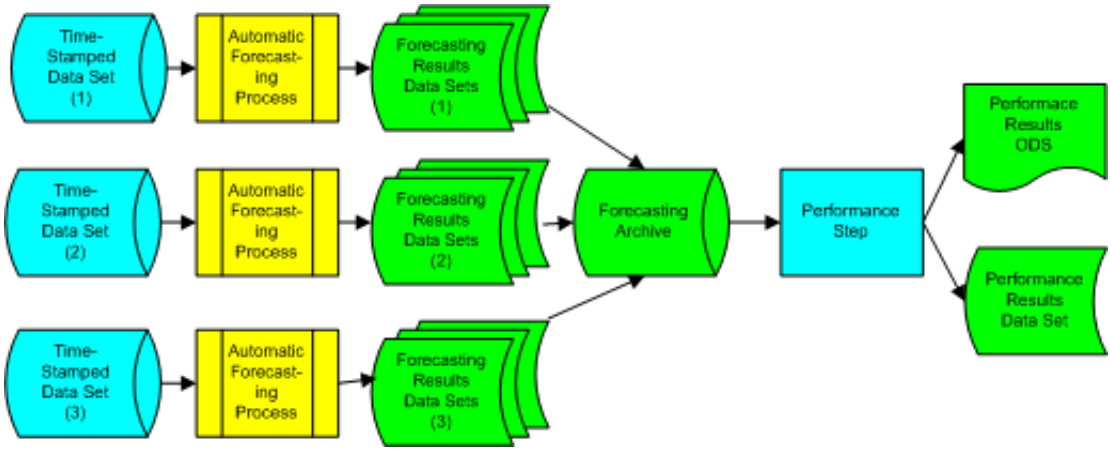
The automatic forecasting process that creates the forecast scoring file is significantly more computationally expensive than the forecast scoring process. The forecast score file needs to be created only once, whereas the iterative nature of decision-making processes might require many scores.

Automatic Forecasting Archives

Since automatic forecasting is used to forecast over time, the automatic forecasting process must be monitored for accuracy (quality control) or *forecast performance*. Therefore, the forecasts, generated over time, must be archived to measure forecast performance. Likewise, the forecast performance must be archived over time.

The automatic forecasting archives are shown in Figure 14.9.

Figure 14.9 Automatic Forecasting Archives



At each forecast origin (or time the forecast is created), forecasts are created from the time-stamped data observed up to the forecast origin. The forecasts from the forecast origin through the forecast horizon are recorded in the *forecasting archive*. The forecast archive contains the historical forecasts as well as their forecast origins. The forecast archive can be evaluated to measure the historical performance.

References

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control*. 3rd ed. Englewood Cliffs, NJ: Prentice-Hall.

Brockwell, P. J., and Davis, R. A. (1996). *Introduction to Time Series and Forecasting*. New York: Springer-Verlag.

Chatfield, C. (2000). *Time-Series Forecasting*. Boca Raton, FL: Chapman & Hall/CRC.

Fuller, W. A. (1995). *Introduction to Statistical Time Series*. New York: John Wiley & Sons.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton, NJ: Princeton University Press.

Harvey, A. C. (1994). *Time Series Models*. Cambridge, MA: MIT Press.

Makridakis, S. G., Wheelwright, S. C., and Hyndman, R. J. (1997). *Forecasting: Methods and Applications*. New York: John Wiley & Sons.

Chapter 15
Forecasting Process Details

Contents

Forecasting Process Summary **462**
- Parameter Estimation 462
- Model Evaluation 462
- Forecasting 462

Smoothing Models **463**
- Smoothing Model Calculations 463
- Smoothing State and Smoothing Equations 463
- Smoothing State Initialization 464
- Missing Values 464
- Predictions and Prediction Errors 464
- Smoothing Weights 465
- Specifying the Smoothing Weights 465
- Optimizing the Smoothing Weights 466
- Equations for the Smoothing Models 466

ARIMA Models **478**
- ARIMA Model Based Series Decomposition 478

Unobserved Component Models **480**

Intermittent Models **480**
- Intermittent Time Series 480
- Intermittent Series Decomposition and Analysis 480
- Croston's Method 481
- Average Demand Method 482
- Time-Indexed versus Demand-Indexed Holdout Samples 483
- Automatic Intermittent Demand Model Selection 483

External Models **484**
- External Forecasts 484
- External Forecast Prediction Errors 484
- External Forecast Prediction Bias 485
- External Forecast Prediction Standard Errors 485
- External Forecast Confidence Limits 487

Series Transformations **487**
- Predictions for Transformed Models 488

Series Diagnostic Tests **489**

Statistics of Fit **489**

References **493**

This chapter provides computational details on several aspects of the SAS Forecast Server Procedures software.

Forecasting Process Summary

This section summarizes the forecasting process. You can use a variety of forecasting models to forecast a series with the SAS Forecast Server Procedures software. The final choice of model depends on the type of analysis needed and whether any predictor variables will be used in the forecasting. The available model types are ARIMA models, unobserved component models (UCMs), smoothing models, and intermittent models. The ARIMA model and UCM can use the predictor variables, whereas the smoothing and intermittent models do not involve predictor variables.

Parameter Estimation

Computational details for the smoothing and intermittent models are provided in the sections "Smoothing Models" on page 463 and "Intermittent Models" on page 480. For more information about ARIMA modeling and UCM modeling, see Chapter 7, "ARIMA Procedure" (*SAS/ETS User's Guide*), and Chapter 41, "UCM Procedure" (*SAS/ETS User's Guide*), respectively. The results of the parameter estimation process are printed in the "Parameter Estimates" table or stored in the OUTEST= data set.

Model Evaluation

Model evaluation is based on the one-step-ahead prediction errors for observations within the period of evaluation. The one-step-ahead predictions are generated from the model specification and parameter estimates. The predictions are inverse transformed (median or mean) and adjustments are removed. The prediction errors (the difference of the dependent series and the predictions) are used to compute the statistics of fit, which are described in section "Statistics of Fit" on page 489. The results generated by the evaluation process are printed in the "Statistics of Fit" table or stored in the OUTSTAT= data set.

Forecasting

The forecasting process is similar to the model evaluation process described in the preceding section, except that k-step-ahead predictions are made from the end of the data through the specified forecast horizon and prediction standard errors and confidence limits are calculated. The forecasting process treats the future/forecast values of stochastic inputs (for all types of models ARIMA and UCM) as constants. The forecasts and confidence limits are printed in the "Forecast" table or stored in the OUTFOR= data set.

Smoothing Models

This section details the computations performed for the exponential smoothing and Winters method forecasting models.

Smoothing Model Calculations

For the descriptions and properties of various smoothing methods see: Gardner (1985); Chatfield (1978); Bowerman and O'Connell (1979). This section summarizes the smoothing model computations.

Given a time series $\{Y_t : 1 \leq t \leq n\}$, the underlying model assumed by the smoothing models has the following (additive seasonal) form:

$$Y_t = \mu_t + \beta_t t + s_p(t) + \epsilon_t$$

where

μ_t	represents the time-varying mean term.
β_t	represents the time-varying slope.
$s_p(t)$	represents the time-varying seasonal contribution for one of the p seasons.
ϵ_t	are disturbances.

For smoothing models without trend terms, $\beta_t = 0$; and for smoothing models without seasonal terms, $s_p(t) = 0$. Each smoothing model is described in the following sections.

At each time t, the smoothing models estimate the time-varying components described above with the *smoothing state*. After initialization, the smoothing state is updated for each observation by using the *smoothing equations*. The smoothing state at the last nonmissing observation is used for predictions.

Smoothing State and Smoothing Equations

Depending on the smoothing model, the *smoothing state* at time t consists of the following:

L_t is a smoothed level that estimates μ_t.

T_t is a smoothed trend that estimates β_t.

S_{t-j}, $j = 0, \ldots, p-1$, are seasonal factors that estimate $s_p(t)$.

The smoothing process starts with an initial estimate of the smoothing state, which is subsequently updated for each observation by using the *smoothing equations*.

The smoothing equations determine how the smoothing state changes as time progresses. Knowledge of the smoothing state at time $t-1$ and that of the time-series value at time t uniquely determine the smoothing

state at time t. The *smoothing weights* determine the contribution of the previous smoothing state to the current smoothing state. The smoothing equations for each smoothing model are listed in section "Equations for the Smoothing Models" on page 466.

Smoothing State Initialization

Given a time series $\{Y_t : 1 \leq t \leq n\}$, the smoothing process first computes the smoothing state for time $t = 1$. However, this computation requires an initial estimate of the smoothing state at time $t = 0$, even though no data exists at or before time $t = 0$.

An appropriate choice for the initial smoothing state is made by backcasting from time $t = n$ to $t = 1$ to obtain a prediction at $t = 0$. The initialization for the backcast is obtained by regression with constant and linear terms and seasonal dummy variables (additive or multiplicative) as appropriate for the smoothing model. For models with linear or seasonal terms, the estimates obtained by the regression are used for initial smoothed trend and seasonal factors; however, the initial smoothed level for backcasting is always set to the last observation, Y_n.

The smoothing state at time $t = 0$ obtained from the backcast is used to initialize the smoothing process from time $t = 1$ to $t = n$ (Chatfield and Yar 1988).

For models with seasonal terms, the smoothing state is normalized so that the seasonal factors S_{t-j} for $j = 0, \ldots, p-1$ sum to zero for models that assume additive seasonality and average to one for models (such as Winters method) that assume multiplicative seasonality.

Missing Values

When a missing value is encountered at time t, the smoothed values are updated using the *error-correction form* of the smoothing equations with the one-step-ahead prediction error e_t set to zero. The missing value is estimated using the one-step-ahead prediction at time $t-1$, that is $\hat{Y}_{t-1}(1)$ (Aldrin and Damsleth 1989). The error-correction forms of each of the smoothing models are listed in the sections "ARIMA Models" on page 478, "Unobserved Component Models" on page 480, "Intermittent Models" on page 480, "External Models" on page 484, "Series Transformations" on page 487, "Series Diagnostic Tests" on page 489, and "Statistics of Fit" on page 489.

Predictions and Prediction Errors

Predictions are made based on the last known smoothing state. Predictions made at time t for k steps ahead are denoted $\hat{Y}_t(k)$, and the associated prediction errors are denoted $e_t(k) = Y_{t+k} - \hat{Y}_t(k)$. The *prediction equation* for each smoothing model is listed in the sections "ARIMA Models" on page 478, "Unobserved Component Models" on page 480, "Intermittent Models" on page 480, "External Models" on page 484, "Series Transformations" on page 487, "Series Diagnostic Tests" on page 489, and "Statistics of Fit" on page 489.

The *one-step-ahead predictions* refer to predictions made at time $t-1$ for one time unit into the future—that is, $\hat{Y}_{t-1}(1)$—and the *one-step-ahead prediction errors* are more simply denoted $e_t = e_{t-1}(1) = Y_t - \hat{Y}_{t-1}(1)$. The one-step-ahead prediction errors are also the model residuals, and

the sum of squares of the one-step-ahead prediction errors is the objective function used in smoothing weight optimization.

The *variance of the prediction errors* are used to calculate the confidence limits (Sweet 1985; McKenzie 1986; Yar and Chatfield 1990; Chatfield and Yar 1991). The equations for the variance of the prediction errors for each smoothing model are listed in the sections "ARIMA Models" on page 478, "Unobserved Component Models" on page 480, "Intermittent Models" on page 480, "External Models" on page 484, "Series Transformations" on page 487, "Series Diagnostic Tests" on page 489, and "Statistics of Fit" on page 489.

Note: $var(\epsilon_t)$ is estimated by the mean square of the one-step-ahead prediction errors.

Smoothing Weights

Depending on the smoothing model, the smoothing weights consist of the following:

α	is a level smoothing weight.
γ	is a trend smoothing weight.
δ	is a seasonal smoothing weight.
ϕ	is a trend damping weight.

Larger smoothing weights (less damping) permit the more recent data to have a greater influence on the predictions. Smaller smoothing weights (more damping) give less weight to recent data.

Specifying the Smoothing Weights

Typically the smoothing weights are chosen to be from zero to one. (This is intuitive because the weights associated with the past smoothing state and the value of current observation would normally sum to one.) However, each smoothing model (except Winters method—multiplicative version) has an ARIMA equivalent. Weights chosen to be within the ARIMA additive-invertible region guarantee stable predictions (Archibald 1990; Gardner 1985). The ARIMA equivalent and the additive-invertible region for each smoothing model are listed in the sections "ARIMA Models" on page 478, "Unobserved Component Models" on page 480, "Intermittent Models" on page 480, "External Models" on page 484, "Series Transformations" on page 487, "Series Diagnostic Tests" on page 489, and "Statistics of Fit" on page 489.

Optimizing the Smoothing Weights

Smoothing weights are determined so as to minimize the sum of squared one-step-ahead prediction errors. The optimization is initialized by choosing from a predetermined grid the initial smoothing weights that result in the smallest sum of squared, one-step-ahead prediction errors. The optimization process is highly dependent on this initialization. It is possible that the optimization process will fail due to the inability to obtain stable initial values for the smoothing weights (Greene 1993), and it is possible for the optimization to result in a local minima.

The optimization process can result in weights being chosen outside both the zero-to-one range and the ARIMA additive-invertible region. By restricting weight optimization to additive-invertible region, you can obtain a local minimum with stable predictions. Likewise, weight optimization can be restricted to the zero-to-one range or other ranges.

Standard Errors

The standard errors associated with the smoothing weights are calculated from the Hessian matrix of the sum of squared, one-step-ahead prediction errors with respect to the smoothing weights used in the optimization process.

Weights near Zero or One

Sometimes the optimization process results in weights near zero or one.

For simple or double (Brown) exponential smoothing, a level weight near zero implies that simple differencing of the time series might be appropriate.

For linear (Holt) exponential smoothing, a level weight near zero implies that the smoothed trend is constant and that an ARIMA model with deterministic trend might be a more appropriate model.

For damped-trend linear exponential smoothing, a damping weight near one implies that linear (Holt) exponential smoothing might be a more appropriate model.

For Winters method and seasonal exponential smoothing, a seasonal weight near one implies that a nonseasonal model might be more appropriate and a seasonal weight near zero implies that deterministic seasonal factors might be present.

Equations for the Smoothing Models

Simple Exponential Smoothing

The model equation for simple exponential smoothing is

$$Y_t = \mu_t + \epsilon_t$$

The smoothing equation is

$$L_t = \alpha Y_t + (1 - \alpha) L_{t-1}$$

The error-correction form of the smoothing equation is

$$L_t = L_{t-1} + \alpha e_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t$$

The ARIMA model equivalency to simple exponential smoothing is the ARIMA(0,1,1) model

$$(1 - B)Y_t = (1 - \theta B)\epsilon_t$$

$$\theta = 1 - \alpha$$

The moving-average form of the equation is

$$Y_t = \epsilon_t + \sum_{j=1}^{\infty} \alpha \epsilon_{t-j}$$

For simple exponential smoothing, the additive-invertible region is

$$\{0 < \alpha < 2\}$$

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t) \left[1 + \sum_{j=1}^{k-1} \alpha^2 \right] = var(\epsilon_t)(1 + (k-1)\alpha^2)$$

Double (Brown) Exponential Smoothing

The model equation for double exponential smoothing is

$$Y_t = \mu_t + \beta_t t + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha Y_t + (1-\alpha)L_{t-1}$$

$$T_t = \alpha(L_t - L_{t-1}) + (1-\alpha)T_{t-1}$$

This method can be described equivalently in terms of two successive applications of simple exponential smoothing:

$$S_t^{[1]} = \alpha Y_t + (1-\alpha)S_{t-1}^{[1]}$$

$$S_t^{[2]} = \alpha S_t^{[1]} + (1-\alpha)S_{t-1}^{[2]}$$

where $S_t^{[1]}$ are the smoothed values of Y_t and $S_t^{[2]}$ are the smoothed values of $S_t^{[1]}$. The prediction equation then takes the form:

$$\hat{Y}_t(k) = (2 + \alpha k/(1-\alpha))S_t^{[1]} - (1 + \alpha k/(1-\alpha))S_t^{[2]}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + T_{t-1} + \alpha e_t$$

$$T_t = T_{t-1} + \alpha^2 e_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t + ((k-1) + 1/\alpha)T_t$$

The ARIMA model equivalency to double exponential smoothing is the ARIMA(0,2,2) model

$$(1 - B)^2 Y_t = (1 - \theta B)^2 \epsilon_t$$

$$\theta = 1 - \alpha$$

The moving-average form of the equation is

$$Y_t = \epsilon_t + \sum_{j=1}^{\infty} (2\alpha + (j-1)\alpha^2)\epsilon_{t-j}$$

For double exponential smoothing, the additive-invertible region is

$$\{0 < \alpha < 2\}$$

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t) \left[1 + \sum_{j=1}^{k-1} (2\alpha + (j-1)\alpha^2)^2 \right]$$

Linear (Holt) Exponential Smoothing

The model equation for linear exponential smoothing is

$$Y_t = \mu_t + \beta_t t + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \gamma(L_t - L_{t-1}) + (1 - \gamma)T_{t-1}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + T_{t-1} + \alpha e_t$$

$$T_t = T_{t-1} + \alpha\gamma e_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t + kT_t$$

The ARIMA model equivalency to linear exponential smoothing is the ARIMA(0,2,2) model

$$(1 - B)^2 Y_t = (1 - \theta_1 B - \theta_2 B^2)\epsilon_t$$

$$\theta_1 = 2 - \alpha - \alpha\gamma$$

$$\theta_2 = \alpha - 1$$

The moving-average form of the equation is

$$Y_t = \epsilon_t + \sum_{j=1}^{\infty} (\alpha + j\alpha\gamma)\epsilon_{t-j}$$

For linear exponential smoothing, the additive-invertible region is

$$\{0 < \alpha < 2\}$$

$$\{0 < \gamma < 4/\alpha - 2\}$$

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t)\left[1 + \sum_{j=1}^{k-1} (\alpha + j\alpha\gamma)^2\right]$$

Damped-Trend Linear Exponential Smoothing

The model equation for damped-trend linear exponential smoothing is

$$Y_t = \mu_t + \beta_t t + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + \phi T_{t-1})$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)\phi T_{t-1}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + \phi T_{t-1} + \alpha e_t$$

$$T_t = \phi T_{t-1} + \alpha\gamma e_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t + \sum_{i=1}^{k} \phi^i T_t$$

The ARIMA model equivalency to damped-trend linear exponential smoothing is the ARIMA(1,1,2) model

$$(1-\phi B)(1-B)Y_t = (1-\theta_1 B - \theta_2 B^2)\epsilon_t$$

$$\theta_1 = 1 + \phi - \alpha - \alpha\gamma\phi$$

$$\theta_2 = (\alpha - 1)\phi$$

The moving-average form of the equation (assuming $|\phi| < 1$) is

$$Y_t = \epsilon_t + \sum_{j=1}^{\infty} (\alpha + \alpha\gamma\phi(\phi^j - 1)/(\phi - 1))\epsilon_{t-j}$$

For damped-trend linear exponential smoothing, the additive-invertible region is

$$\{0 < \alpha < 2\}$$

$$\{0 < \phi\gamma < 4/\alpha - 2\}$$

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t)\left[1 + \sum_{j=1}^{k-1} (\alpha + \alpha\gamma\phi(\phi^j - 1)/(\phi - 1))^2\right]$$

Seasonal Exponential Smoothing

The model equation for seasonal exponential smoothing is

$$Y_t = \mu_t + s_p(t) + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha(Y_t - S_{t-p}) + (1 - \alpha)L_{t-1}$$

$$S_t = \delta(Y_t - L_t) + (1 - \delta)S_{t-p}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + \alpha e_t$$

$$S_t = S_{t-p} + \delta(1 - \alpha)e_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t + S_{t-p+k}$$

The ARIMA model equivalency to seasonal exponential smoothing is the ARIMA(0,1,p+1)(0,1,0)$_p$ model

$$(1-B)(1-B^p)Y_t = (1-\theta_1 B - \theta_2 B^p - \theta_3 B^{p+1})\epsilon_t$$

$$\theta_1 = 1-\alpha$$

$$\theta_2 = 1-\delta(1-\alpha)$$

$$\theta_3 = (1-\alpha)(\delta-1)$$

The moving-average form of the equation is

$$Y_t = \epsilon_t + \sum_{j=1}^{\infty} \psi_j \epsilon_{t-j}$$

$$\psi_j = \begin{cases} \alpha & \text{for } j \mod p \neq 0 \\ \alpha + \delta(1-\alpha) & \text{for } j \mod p = 0 \end{cases}$$

For seasonal exponential smoothing, the additive-invertible region is

$$\{\max(-p\alpha, 0) < \delta(1-\alpha) < (2-\alpha)\}$$

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t)\left[1 + \sum_{j=1}^{k-1} \psi_j^2\right]$$

Multiplicative Seasonal Smoothing

In order to use the multiplicative version of seasonal smoothing, the time series and all predictions must be strictly positive.

The model equation for the multiplicative version of seasonal smoothing is

$$Y_t = \mu_t s_p(t) + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha(Y_t / S_{t-p}) + (1-\alpha)L_{t-1}$$

$$S_t = \delta(Y_t / L_t) + (1-\delta)S_{t-p}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + \alpha e_t / S_{t-p}$$

$$S_t = S_{t-p} + \delta(1-\alpha)e_t / L_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t S_{t-p+k}$$

The multiplicative version of seasonal smoothing does not have an ARIMA equivalent; however, when the seasonal variation is small, the ARIMA additive-invertible region of the additive version of seasonal described in the preceding section can approximate the stability region of the multiplicative version.

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t)\left[\sum_{i=0}^{\infty}\sum_{j=0}^{p-1}(\psi_{j+ip}S_{t+k}/S_{t+k-j})^2\right]$$

where ψ_j are as described for the additive version of seasonal method and $\psi_j = 0$ for $j \geq k$.

Winters Method—Additive Version

The model equation for the additive version of Winters method is

$$Y_t = \mu_t + \beta_t t + s_p(t) + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha(Y_t - S_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

$$S_t = \delta(Y_t - L_t) + (1-\delta)S_{t-p}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + T_{t-1} + \alpha e_t$$

$$T_t = T_{t-1} + \alpha\gamma e_t$$

$$S_t = S_{t-p} + \delta(1-\alpha)e_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = L_t + kT_t + S_{t-p+k}$$

The ARIMA model equivalency to the additive version of Winters method is the ARIMA(0,1,p+1)$(0,1,0)_p$ model

$$(1-B)(1-B^p)Y_t = \left[1 - \sum_{i=1}^{p+1} \theta_i B^i\right]\epsilon_t$$

$$\theta_j = \begin{cases} 1-\alpha-\alpha\gamma & j = 1 \\ -\alpha\gamma & 2 \le j \le p-1 \\ 1-\alpha\gamma-\delta(1-\alpha) & j = p \\ (1-\alpha)(\delta-1) & j = p+1 \end{cases}$$

The moving-average form of the equation is

$$Y_t = \epsilon_t + \sum_{j=1}^{\infty} \psi_j \epsilon_{t-j}$$

$$\psi_j = \begin{cases} \alpha + j\alpha\gamma & \text{for} j \mod p \neq 0 \\ \alpha + j\alpha\gamma + \delta(1-\alpha), & \text{for} j \mod p = 0 \end{cases}$$

For the additive version of Winters method (Archibald 1990), the additive-invertible region is

$$\{\max(-p\alpha, 0) < \delta(1-\alpha) < (2-\alpha)\}$$

$$\{0 < \alpha\gamma < 2-\alpha-\delta(1-\alpha)(1-cos(\vartheta)\}$$

where ϑ is the smallest nonnegative solution to the equations listed in Archibald (1990).

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t)\left[1 + \sum_{j=1}^{k-1} \psi_j^2\right]$$

Winters Method—Multiplicative Version

In order to use the multiplicative version of Winters method, the time series and all predictions must be strictly positive.

The model equation for the multiplicative version of Winters method is

$$Y_t = (\mu_t + \beta_t t)s_p(t) + \epsilon_t$$

The smoothing equations are

$$L_t = \alpha(Y_t / S_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

$$S_t = \delta(Y_t/L_t) + (1-\delta)S_{t-p}$$

The error-correction form of the smoothing equations is

$$L_t = L_{t-1} + T_{t-1} + \alpha e_t/S_{t-p}$$

$$T_t = T_{t-1} + \alpha\gamma e_t/S_{t-p}$$

$$S_t = S_{t-p} + \delta(1-\alpha)e_t/L_t$$

NOTE: For missing values, $e_t = 0$.

The k-step prediction equation is

$$\hat{Y}_t(k) = (L_t + kT_t)S_{t-p+k}$$

The multiplicative version of Winters method does not have an ARIMA equivalent; however, when the seasonal variation is small, the ARIMA additive-invertible region of the additive version of Winters method described in the preceding section can approximate the stability region of the multiplicative version.

The variance of the prediction errors is estimated as

$$var(e_t(k)) = var(\epsilon_t)\left[\sum_{i=0}^{\infty}\sum_{j=0}^{p-1}(\psi_{j+ip}S_{t+k}/S_{t+k-j})^2\right]$$

where ψ_j are as described for the additive version of Winters method and $\psi_j = 0$ for $j \geq k$.

ARIMA Models

The SAS Forecast Server Procedures software uses the same statistical model technology to identify, fit and forecast ARIMA models as does SAS/ETS Software. For information about the methods SAS Forecast Server Procedures software uses for ARIMA models, see Chapter 7, "ARIMA Procedure" (*SAS/ETS User's Guide*). All the SAS/ETS ARIMA output (such as the parameter estimates, forecasts, diagnostic measures, and so on) is available in SAS Forecast Server Procedures software. Moreover, you can obtain additional output in SAS Forecast Server Procedures software. This additional output includes a wider variety of fit statistics and a model-based decomposition of the response series forecasts into subcomponents such as transfer functions effects and the estimated stationary noise component. These subcomponents can be useful for interpreting the model being used.

ARIMA Model Based Series Decomposition

Consider a general ARIMA model that can be fit to a response series Y_t:

$$D(B)Y_t = \mu + \sum_i \frac{\omega_i(B)}{\delta_i(B)} B^{k_i} X_{i,t} + \frac{\theta(B)}{\phi(B)} a_t$$

where

t	indexes time.
B	is the backshift operator; that is, $BX_t = X_{t-1}$.
$D(B)$	is the difference operator operating on the response series Y_t.
μ	is the constant term.
$\phi(B)$	is the autoregressive operator, represented as a polynomial in the backshift operator: $\phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$.
$\theta(B)$	is the moving-average operator, represented as a polynomial in the back shift operator: $\theta(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$.
a_t	is the independent disturbance, also called the random error.
$X_{i,t}$	is the ith input time series or a difference of the ith input series at time t.
k_i	is the pure time delay for the effect of the ith input series.
$\omega_i(B)$	is the numerator polynomial of the transfer function for the ith input series.
$\delta_i(B)$	is the denominator polynomial of the transfer function for the ith input series.

The model expresses the response series, possibly differenced, as a sum of a constant term, various transfer function effects, and the effect of a stationary ARMA disturbance term. Of course, in a given situation many of these effects might be absent. Denoting the individual transfer function effects by γ_i and the ARMA disturbance term by n, you can decompose the response series in a few different ways. Consider two alternate decompositions here. In the first case Y_t is decomposed as

$$Y_t = L_t + \mu + \sum_i \gamma_{it} + n_t$$

where the L_t term includes the contribution from the lagged response values that correspond to the differencing operator $D(B)$. For example, if $D(B) = 1 - B$, corresponding to the differencing of order 1, then $L_t = Y_{t-1}$. An alternate decomposition of Y_t can be as follows:

$$Y_t = \frac{\mu}{D(B)} + \sum_i \frac{\gamma_{it}}{D(B)} + \frac{n_t}{D(B)}$$

Note that if the differencing operator $D(B)$ is identity, then the L_t term is zero and these two alternate decompositions are identical. Otherwise the terms in the second decomposition are the "integrated," with respect to $D(B)$, versions of the corresponding terms in the first decomposition. In practice many terms in these decompositions are not observed but are estimated from the data, which results in similar decompositions of $\hat{Y}_t$, the *forecasts* of Y_t. In the HPFENGINE procedure you can obtain these decompositions of $\hat{Y}_t$ by choosing various options in the PROC HPFENGINE statement: you can output them as a data set by using the OUTCOMPONENT= data set option, print them by using the PRINT=COMPONENT option, or plot them by using the PLOT=COMPONENTS option. The type of decomposition is controlled by the COMPONENTS= option in the HPFENGINE statement. If COMPONENTS=INTEGRATE is specified, then the calculated decomposition is of the second type, and the default decomposition is of the first type. Consider the following points about these decompositions:

- If the response series being modeled is actually log transformed, then the resulting decompositions are *multiplicative* rather than *additive*. In this case, similar to the series forecasts, the decomposition terms are also inverse transformed. If the response series is transformed using a transformation other than log (such as Box-Cox or square root), then these decompositions are difficult to interpret and they do not have such additive or multiplicative properties.
- In the first type of decomposition the components in the decomposition always add up, or multiply in the log transformation case, to the series forecasts. In the integrated version of the decomposition this additive property might not always hold because there are no natural choices of starting values that can be used during the integration of these components that guarantee the additivity of the resulting decomposition.

Unobserved Component Models

The SAS Forecast Server Procedures software uses the same statistical model technology to identify, fit and forecast unobserved component models (UCMs) as does SAS/ETS software. For information about the methods the SAS Forecast Server Procedures software uses for UCMs, see Chapter 41, "UCM Procedure" (*SAS/ETS User's Guide*).

Intermittent Models

This section details the computations performed for intermittent forecasting models.

Intermittent Time Series

Intermittent time series have a large number of values that are zero. These types of series commonly occur in Internet, inventory, sales, and other data where the demand for a particular item is intermittent. Typically, when the value of the series associated with a particular time period is nonzero, *demand* occurs; and when the value is zero (or missing), *no demand* occurs. Since it is entirely possible that the number of time periods for which *no demand* occurs is large, many of the series values are zero. Typical time series models (for example, smoothing models) are inadequate in the case of intermittent time series because many of the series values are zero. Since these models are based on weighted-summations of past values, they bias forecasts away from zero. Unlike the smoothing models that provide forecasts for future time periods, intermittent forecasting models provide recommended *stocking levels* or *estimated demand per period* that are used to satisfy future demand.

Intermittent Series Decomposition and Analysis

An intermittent time series (demand series) can be decomposed into two components: a demand interval series and a demand size series. Both of these component series are indexed based on when a *demand* occurred (demand index) rather than each time period (time index). The demand interval series is constructed based on the number of time periods between *demands*. The demand size series is constructed based on the size (or value) of the *demands* excluding zero (or base) demand values. Using these two component series, the average demand series is computed by dividing the size component values by the interval component values.

When a *demand* occurs typically depends on a *base* value. Typically, the base value is zero (default), but it can be any constant value and can be automatically determined based on the characteristics of the demand series.

Given a time series y_t, for $t = 1$ to T, where t is the time index, suppose that there are N nonzero demands occurring at times $t = t_i$, where $t_{i-1} < t_i$, for $i = 1$ to N. The time series is dissected into the demand interval series and the demand size series as follows:

(demand interval series)	$q_i = t_i - t_{i-1}$	for $i = 2$ to N
(demand size series)	$d_i = y_{t_i} - base$	for $i = 1$ to N
(average demand series)	$a_i = d_i / q_i$	for $i = 2$ to N

For the beginning of the demand series, q_1 is assigned to t_1, which assumes that a demand just occurred prior to the first recorded observation. For the end of the demand series, q_{N+1} is assigned to $(T + 1 - t_N)$, which assumes that demand will occur just after the last recorded observation. The next future demand size, d_{N+1}, is always set to missing.

After decomposition, descriptive (summary) statistics can be computed to gain a greater understanding of the demand series including those statistics based on the season index.

For statistical analysis and model fitting, q_i and a_i for $i = 2$ to N and d_i for $i = 1$ to N are used. For forecasting, q_i for $i = 1$ to $N + 1$, a_i for $i = 1$ to N, and d_i for $i = 1$ to N are used.

Croston's Method

Croston's method models and forecasts each component independently, then combines the two forecasts. The following provides a description of how Croston's method is used in SAS Forecast Server Procedures software. For more detailed information about this method see: Croston (1972); Willemain, Smart, and Shocker (1994). The following description of Croston's method is based on the perspective of a person familiar with typical time series modeling techniques such as smoothing models.

By treating each component of the demand series as a time series based on the demand index, optimal smoothing parameters can be estimated and predictions for each component can be computed using nonseasonal exponential smoothing methods (simple, double, linear, and damped-trend) as well as their transformed versions (log, square-root, logistic, and Box-Cox).

For example, the following simple smoothing equations are used to generate predictions for demand size and interval components:

(smoothed demand interval series)	$L_i^q = L_{i-1}^q + \alpha_q (q_{i-1} - L_{i-1}^q)$
(smoothed demand size series)	$L_i^d = L_{i-1}^d + \alpha_d (d_{i-1} - L_{i-1}^d)$

The demand interval parameter α_q and demand size parameter α_d and the starting, intermediate, and final smoothing level states, L_i^q and L_i^d, are estimated from the data using simple exponential smoothing parameter estimation. For the starting state at $i = 1$, $L_1^q = \max(q_1, L_0^q)$ where L_0^q is the final backcast level state. For $i > 1$, the one-step-ahead prediction for demand interval q_i is $\hat{q}_i = L_{i-1}^q$. For $i > 0$, the one-step-ahead prediction for demand size d_i is $\hat{d}_i = L_{i-1}^d$.

Other (transformed) nonseasonal exponential smoothing methods can be used in a similar fashion. For linear smoothing, $L_1^q = \max(q_1 - T_0^q, L_0^q)$ where T_0^q is the final backcast trend state. For damp-trend smoothing, $L_1^q = \max(q_1 - \phi_q T_0^q, L_0^q)$ where ϕ_q is the damping parameter and T_0^q is the final backcast trend state. For double smoothing, $L_1^q = \max(q_1 - T_0^q / \alpha_q, L_0^q)$ where α_q is the weight parameter and T_0^q is the final backcast trend state.

Using these predictions based on the demand index, predictions of the average demand per period can be estimated. Predicted demand per period is also known as "stocking level," assuming that disturbances affecting q_i are independent of d_i. (This assumption is quite significant.)

(estimated demand per period) $y_i^* = \hat{d}_i / \hat{q}_i$

$\mathrm{E}[y_i^*] = E[d_i]/E[q_i] = E[z_{i-1}]/E[p_{i-1}] = \mu_d/\mu_q$

(variance) $Var(y_i^*) = (\hat{d}_i/\hat{q}_i)^2(Var(d_i)/\hat{d}_i^2 + Var(q_i)/\hat{q}_i^2)$

where μ_d, $\bar{d}$, and s_d are the mean, sample average, and standard deviation, respectively, of the nonzero demands, and μ_q, $\bar{q}$, and s_q are the mean, sample average, and standard deviation, respectively, of the number of time periods between demands.

For the beginning of the series, the denominator of y_1^* is assigned q_i or the starting smoothing state p_0, whichever is greater. For the end of the series, the denominator of y_{N+1}^* is assigned $q_{N+1} = (T + 1 - t_N)$ or the final smoothing state p_N, whichever is greater.

After the average demand per period has been estimated, a stocking level can be recommended:

(recommended stocking level) $\hat{y}_t = y_i^*$ when $t_i =< t < t_{i+1}$

(variance) $Var(\hat{y}_t) = Var(y_i^*)$ when $t_i =< t < t_{i+1}$

Since the predicted demand per period is different than typical time series forecasts, the usual way of computing statistics of fit should also be different. The statistics of fit are based on the difference between the recommended stocking levels between demands and the demands:

(accumulated recommended stocks) $s_t = \sum_{i=0}^{t}(\hat{y}_t - y_i^*)$

(estimate—demand) $e_{t_i} = \hat{d}_i q_i - d_i$ when time t_{i+1} has demand

Croston's method produces the same forecasts as simple exponential smoothing when demand occurs in every time period, $q_i = 1$ for all i, but different (lower) prediction error variances. Croston's method is recommended for intermittent time series only.

Average Demand Method

Similar to Croston's method, the average demand method is used to forecast intermittent time series; however, the average demand method forecasts the average demand series directly, whereas Croston's method forecasts average demand series indirectly using the inverse decomposition of the demand interval and size series forecasts.

By treating the average demand series as a time series based on the demand index, optimal smoothing parameters can be estimated and predictions for average demand can be computed using nonseasonal exponential smoothing methods (simple, double, linear, and damped-trend) as well as their transformed versions (log, square-root, logistic, and Box-Cox).

For example, the following simple smoothing equations are used to generate predictions for the average demand series:

(smoothed average demand series) $L_i^a = L_{i-1}^a + \alpha_a(a_{i-1} - L_{i-1}^a)$

The average demand level smoothing parameter α_a and the starting, intermediate, and final smoothing level states L_i^a are estimated from the data by using simple exponential smoothing parameter estimation. For the starting state at $i = 1$, $L_1^a = \max(a_1, L_0^a)$ where L_0^a is the final backcast level state. For $i > 1$, the one-step-ahead prediction for a_i is $\hat{a}_i = L_{i-1}^a$.

Other nonseasonal exponential smoothing methods can be used in a similar fashion. For linear smoothing, $L_1^a = \max(a_1 - T_0^a, L_0^a)$ where T_0^a is the final backcast trend state. For damp-trend smoothing, $L_1^a = \max(a_1 - \phi_a T_0^a, L_0^a)$ where ϕ_a is the damping parameter and T_0^a is the final backcast trend state. For double

smoothing, $L_1^a = \max(a_1 - T_0^a/\alpha_a, L_0^a)$ where α_a is the weight parameter and T_0^a is the final backcast trend state.

Using these predictions based on the demand index, predictions of the average demand per period are provided directly, unlike Croston's method where the average demand is predicted using a ratio of predictions of the demand interval and size components.

(estimated demand per period)	$y_i^* = \hat{a}_i + base$
	$\mathrm{E}[y_i^*] = E[a_i]$
(variance)	see the exponential smoothing models

For the beginning of the series, $\hat{a}_1$ is derived from the starting level smoothing state and starting trend smoothing state (if applicable).

After the average demand per period has been estimated, a stocking level can be recommended similar to Croston's method.

The average demand method produces the same forecasts as exponential smoothing when demand occurs in every time period, $q_i = 1$ for all i, but different (lower) prediction error variances. The average demand method is recommended for intermittent time series only.

Time-Indexed versus Demand-Indexed Holdout Samples

Holdout samples are typically specified based on the time index. But for intermittent demand model selection, demand-indexed-based holdouts are used for model selection.

For example, consider "holdout the last six months data." For a demand series, the demand indexed holdout refers to the "demands that have occurred in the last six months." If there are four demands in the last six months, the demand indexed holdout is four for a time-indexed holdout of six. If there are no demands in the time-indexed holdout, the demand-indexed holdout is zero and in-sample analysis is used.

Automatic Intermittent Demand Model Selection

The exponential smoothing method to be used to forecast the intermittent demand series can be specified, or it can be selected automatically using a model selection criterion and either in-sample or holdout sample analysis. The exponential smoothing method for each demand series component (interval, size, and average) and the choice between Croston's method and the average demand method can be automatically selected.

For Croston's method, the exponential smoothing methods used to forecast the demand interval and size components are automatically selected independently. For the average demand method, the exponential smoothing methods used to forecast the average demand component are automatically selected, again independently. Based on the model selection criterion, the selection is based on how well the method fits (in sample) or predicts (holdout sample) the demand series component by treating the demand index as a time index. The following equations describe the component prediction errors associated with each of the demand series components that are used in component model selection:

(demand interval series)	$e_i^q = q_i - \hat{q}_i$	for $i = 2$ to N
(demand size series)	$e_i^d = d_i - \hat{d}_i$	for $i = 1$ to N
(average demand series)	$e_i^a = a_i - \hat{a}_i$	for $i = 2$ to N

After the exponential smoothing methods are selected for each demand series component, the predictions for either Croston's method ($\hat{d}_i/\hat{q}_i$), the average demand method $\hat{a}_i$, or both are computed based on the selected method for each component.

When choosing between Croston's method and the average demand method, the model is selected by considering how well the model predicts average demand with respect to the time. The following equations describe the average prediction errors associated with the predicted average demand that are used in model selection:

(Croston's method)	$e_i^c = (d_i/q_i) - (\hat{d}_i/\hat{q}_i)$	for $i = 2$ to N
(average demand method)	$e_i^a = a_i - \hat{a}_i$	for $i = 2$ to N

External Models

External forecasts are forecasts provided by an *external source*. External forecasts might originate from a statistical model, from another software package, might have been provided by an outside organization (for example, marketing organization or government agency), or might be given based solely judgment.

External Forecasts

Given a time series, $\{y_t\}_{t=1}^{T}$, where $t = 1, \ldots, T$ is the time index and T is the length of the time series, the external model data source must provide predictions for the future time periods, $\{\hat{y}_t\}_{t=T+1}^{T+H}$, where H represents the forecast horizon. The external data source might or might not provide in-sample predictions for past time periods, $\{\hat{y}_t\}_{t=1}^{T}$. Additionally, the external source might or might not provide the prediction standard errors $\{Std(\hat{y}_t)\}_{t=1}^{T+H}$, lower confidence limits $\{Lower(\hat{y}_t)\}_{t=1}^{T+H}$, and the upper confidence limits $\{Upper(\hat{y}_t\}_{t=1}^{T+H}$ for the past or future time periods.

External Forecast Prediction Errors

If the external forecast predictions are provided for past time periods, the external forecast prediction errors $\{\hat{e}_t\}_{t=1}^{T}$ can be computed, $\hat{e}_t = y_t - \hat{y}_t$. If any of these predictions are not provided by the external source, the prediction errors are set to missing.

For judgmental forecast with no historical judgments, all prediction errors are missing. For this situation, a judgment about the prediction standards errors should also be provided.

External Forecast Prediction Bias

You often want forecasts to be unbiased. If available, the external forecast prediction errors are used to compute prediction bias from the external source.

When the external forecast predictions are provided for past time periods, SAS Forecast Server Procedures software uses the in-sample prediction errors $\{\hat{e}_t\}_{t=1}^{T}$ to estimate the bias of the forecasts that are provided by the external source as follows:

$$Bias = \sum_{t=1}^{T} (y_t - \hat{y}_t)/T = \sum_{t=1}^{T} \hat{e}_t/T$$

The prediction mean square error can be used to help judge the significance of this bias.

$$Variance = \sum_{t=1}^{T} (\hat{e}_t - Bias)^2/(T-1)$$

Missing values are ignored in the above computations, and the denominator term is reduced for each missing value.

External Forecast Prediction Standard Errors

The external model data might include estimates of the prediction standard errors and confidence limits. If these estimates are not supplied along with the data for the external model (which is usually the case for judgmental forecasts), the SAS Forecast Server Procedures software can approximate the prediction standard errors and the confidence limits by using the in-sample prediction errors.

When the external forecasts do not contain the prediction standard errors, they are approximated using the external forecast prediction errors. In order to approximate the external forecast prediction standard errors, the external model residuals, variance, and autocorrelations must be approximated. (If the prediction standard errors are provided by the external source, approximation is not required.)

In order to approximate the external model residuals $\{\hat{\epsilon}_t\}_{t=1}^{T}$, the transformation used to generate the external forecast must be provided as part of the external model specification. Let $z_t = f(y_t)$ be the specified transformation; if there is no specified functional transformation, $z_t = y_t$. The transformation can be used to approximate the external model residuals, $\hat{\epsilon}_t = f(y_t) - f(\hat{y}_t) = z_t - \hat{z}_t$.

After they are approximated, the external model residuals can be used to approximate the external model variance $\hat{\sigma}_\epsilon^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{\epsilon}_t^2$ and the external model residual autocorrelation.

The external model residual autocorrelations can be approximated given assumptions about the autocorrelation structure $\rho(j)$ where $j \geq 0$ represents the time lags.

The following autocorrelation structures can be specified using the METHOD= option. These options are listed in order of increasing assumed autocorrelation. (In the following formulas $0 < v < 1$ represents the value of the NLAGPCT= option.)

no autocorrelation (METHOD=NONE)

$$\rho(j) = 1 \qquad \text{for} \qquad j = 0$$
$$\rho(j) = 0 \qquad \text{for} \qquad j > 0$$

This option generates constant prediction error variances.

white noise autocorrelation (METHOD=WN)

This option generates white noise prediction error variances.

error autocorrelation (METHOD=ERRORACF)

$$\rho(j) = 1 \qquad \text{for} \qquad j = 0$$
$$\hat{\rho}(j) = \frac{1}{T} \sum_{t=j+1}^{T} \hat{\epsilon}_t \hat{\epsilon}_{t-j} / \hat{\sigma}_\epsilon^2 \qquad \text{for} \qquad 0 < j < vT$$
$$\rho(j) = 0 \qquad \text{for} \qquad j > vT$$

series autocorrelation (METHOD=ACF)

$$\rho(j) = 1 \qquad \text{for} \qquad j = 0$$
$$\hat{\rho}(j) = \frac{1}{T} \sum_{t=j+1}^{T} z_t z_{t-j} / \hat{\sigma}_z^2 \qquad \text{for} \qquad 0 < j < vT$$
$$\rho(j) = 0 \qquad \text{for} \qquad j > vT$$

where $\hat{\sigma}_z^2 = \frac{1}{T} \sum_{t=1}^{T} (z_t - \bar{z})^2$ and $0 < v < 1$.

This option typically generates linear prediction error variances larger than ERRORACF.

perfect autocorrelation (METHOD=PERFECT)

$$\rho(j) = 1 \qquad \text{for} \qquad j \geq 0$$

This option generates linear prediction error variances.

The external model residual variance and the autocorrelations can approximate the external (transformed) prediction standard errors $\{Std(\hat{z}_t)\}_{t=1}^{T+H}$ where $Std(\hat{z}_t) = \sigma_\epsilon$ for $t = 1, \ldots, T$ are the one-step-ahead prediction standards errors and $Std(\hat{z}_{T+h}) = \sqrt{\sigma_\epsilon^2 \sum_{j=0}^{h-1} \hat{\rho}(j)^2}$ for $h = 1, \ldots, H$ are the multistep-ahead prediction standard errors.

If there was no transformation used to generate the external forecasts, $Std(\hat{y}_t) = Std(\hat{z}_t)$. Otherwise, the external transformed predictions $\{\hat{z}\}_{t=1}^{T}$ and the approximate external transformed prediction standard errors $\{Std(\hat{z}_t)\}_{t=1}^{T+H}$ are used to approximate the external prediction standard errors $\{Std(\hat{y}_t)\}_{t=1}^{T+H}$ by computing the conditional expectation of the inverse transformation (mean) or computing the inverse transformation (median).

To summarize, the external forecast prediction standard errors $\{Std(\hat{y}_t)\}_{t=1}^{T+H}$ can be approximated from the external forecast prediction errors $\{\hat{e}_t\}_{t=1}^{T}$, given the following assumptions about the external forecasts provided by the external source:

functional transformation	(TRANSFORM= option)	$z_t = f(y_t)$
autocorrelation structure	(METHOD= option)	$\rho(j)$
autocorrelation cutoff	(NLAGPCT= option)	v

External Forecast Confidence Limits

Because the external forecasts might not contain confidence limits, they must be approximated using the forecast prediction standard errors (which might be provided by the external model data source or approximated from the in-sample prediction errors) as follows:

$$Lower(\hat{y}_t) = \hat{y}_t - Std(\hat{y}_t)Z_{\frac{\alpha}{2}}$$

$$Upper(\hat{y}_t) = \hat{y}_t + Std(\hat{y}_t)Z_{\frac{\alpha}{2}}$$

where α is the confidence limit width, $(1-\alpha)$ is the confidence level, and $Z_{\frac{\alpha}{2}}$ is the $\frac{\alpha}{2}$ quantile of the standard normal distribution.

To summarize, the external forecast confidence limits can be approximated given only the actual time series $\{y_t\}_{t=1}^{T}$ and the external forecast predictions $\{\hat{y}_t\}_{t=T+1}^{T+H}$. More information provided about the external forecast prediction standard errors $\{Std(y_t)\}_{t=1}^{T+H}$, such as the functional transform $f()$ and the autocorrelation structure $\rho(j)$ and v improves the accuracy of these approximations.

Series Transformations

For forecasting models, transforming the time series can aid in improving forecasting accuracy.

There are four transformations available, for strictly positive series only. Let $y_t > 0$ be the original time series, and let w_t be the transformed series. The transformations are defined as follows:

log — is the logarithmic transformation

$$w_t = \ln(y_t)$$

logistic — is the logistic transformation

$$w_t = \ln(cy_t/(1-cy_t))$$

where the scaling factor c is

$$c = (1-e^{-6})10^{-\text{ceil}(\log_{10}(max(y_t)))}$$

and $\text{ceil}(x)$ is the smallest integer greater than or equal to x .

square root — is the square root transformation

$$w_t = \sqrt{y_t}$$

Box Cox — is the Box-Cox transformation

$$w_t = \begin{cases} \frac{y_t^{\lambda}-1}{\lambda}, & \lambda \neq 0 \\ \ln(y_t), & \lambda = 0 \end{cases}$$

Parameter estimation is performed using the transformed series. The transformed model predictions and confidence limits are then obtained from the transformed time-series and these parameter estimates.

The transformed model predictions $\hat{w}_t$ are used to obtain either the minimum mean absolute error (MMAE) or minimum mean squared error (MMSE) predictions $\hat{y}_t$, depending on the setting of the forecast options. The model is then evaluated based on the residuals of the original time series and these predictions. The transformed model confidence limits are inverse-transformed to obtain the forecast confidence limits.

Predictions for Transformed Models

Since the transformations described in the previous section are monotonic, applying the inverse-transformation to the transformed model predictions results in the *median* of the conditional probability density function at each point in time. This is the minimum mean absolute error (MMAE) prediction.

If $w_t = \mathrm{F}(y_t)$ is the transform with inverse-transform $y_t = \mathrm{F}^{-1}(w_t)$, then

$$\mathrm{median}(\hat{y}_t) = \mathrm{F}^{-1}(E\,[w_t]) = \mathrm{F}^{-1}(\hat{w}_t)$$

The minimum mean squared error (MMSE) predictions are the *mean* of the conditional probability density function at each point in time. Assuming that the prediction errors are normally distributed with variance σ_t^2, the MMSE predictions for each of the transformations are as follows:

log — is the conditional expectation of inverse-logarithmic transformation

$$\hat{y}_t = E\left[e^{w_t}\right] = \exp\left(\hat{w}_t + \sigma_t^2/2\right)$$

logistic — is the conditional expectation of inverse-logistic transformation

$$\hat{y}_t = E\left[\frac{1}{c(1 + exp(-w_t))}\right]$$

where the scaling factor $c = (1 - 10^{-6})10^{-\mathrm{ceil}(\log_{10}(\max(y_t)))}$.

square root — is the conditional expectation of the inverse-square root transformation

$$\hat{y}_t = E\left[w_t^2\right] = \hat{w}_t^2 + \sigma_t^2$$

Box Cox — is the conditional expectation of the inverse Box-Cox transformation

$$\hat{y}_t = \begin{cases} E\left[(\lambda w_t + 1)^{1/\lambda}\right], & \lambda \neq 0 \\ E\left[e^{w_t}\right] = \exp(\hat{w}_t + \frac{1}{2}\sigma_t^2), & \lambda = 0 \end{cases}$$

The expectations of the inverse logistic and Box-Cox ($\lambda \neq 0$) transformations do not generally have explicit solutions and are computed using numerical integration.

Series Diagnostic Tests

This section describes the diagnostic tests that are used to determine the kinds of forecasting models appropriate for a series.

The series diagnostics are a set of heuristics that provide recommendations about whether or not the forecasting model should contain a log transform, trend terms, and seasonal terms or whether or not the time series is intermittent. These recommendations are used by the automatic model selection process to restrict the model search to a subset of the model selection list.

The tests that are used by the series diagnostics do not always produce the correct classification of the series. They are intended to accelerate the process of searching for a good forecasting model for the series, but you should not rely on them if finding the very best model is important to you.

The series diagnostics tests are intended as a heuristic tool only, and no statistical validity is claimed for them. These tests might be modified and enhanced in future releases of the SAS Forecast Server Procedures software. The testing strategy is as follows:

1. **Intermittent test.** Compute the average time interval between demands. If the average time interval is greater than a preset limit, an intermittent forecasting model is used.
2. **Seasonality test.** The resultant series is tested for seasonality. A seasonal dummy model with AR(1) errors is fit, and the joint significance of the seasonal dummy estimates is tested. If the seasonal dummies are significant, the AIC statistic for this model is compared to the AIC for and AR(1) model without seasonal dummies.

Statistics of Fit

This section explains the goodness-of-fit statistics reported to measure how well different models fit the data. The statistics of fit for the various forecasting models can be printed or stored in a data set.

The various statistics of fit reported are as follows. In these formulae below, the following conventions apply:

1. n is the number of nonmissing observations,
2. k is the number of fitted parameters in the model,
3. Unless otherwise noted, the errors are set to zero in the statistical computations when $|y_t - \hat{y}_t| < \epsilon$ where ϵ is the largest double precision number satisfying $1 = 1 + \epsilon$. This happens without regard to whether the denominator is zero.
4. Unless otherwise noted, the errors are ignored in the statistical computations when the denominator is zero.

$APE = |100 * (y_t - \hat{y}_t)/y_t|$ is the absolute percent error.

$ASPE = |100 * (y_t - \hat{y}_t)/0.5(y_t + \hat{y}_t)|$ is the absolute symmetric percent error.

$APPE = |100 * (y_t - \hat{y}_t)/\hat{y}_t|$ is the absolute predictive percent error.

$RAE = |(y_t - \hat{y}_t)/(y_t - y_{t-1})|$ is the relative absolute error.

$APES = 100 * |y_t - \hat{y}_t| / \sqrt{\sum_{t=1}^{n}(y_t - \bar{y})^2/(n-1)}$ is the absolute error as a percentage of the standard deviation.

$ASE = |y_t - \hat{y}_t| / \frac{1}{n-1} \sum_{t=2}^{n} |y_t - y_{t-1}|$ is the absolute scaled error.

Number of nonmissing observations.
The number of nonmissing observations used to fit the model.

Number of observations.
The total number of observations used to fit the model, including both missing and nonmissing observations.

Number of missing actuals.
The number of missing actual values.

Number of missing predicted values.
The number of missing predicted values.

Number of model parameters.
The number of parameters fit to the data. For combined forecast, this is the number of forecast components.

Total sum of squares (uncorrected).
The total sum of squares for the series, SST, uncorrected for the mean: $\sum_{t=1}^{n} y_t^2$.

Total sum of squares (corrected).
The total sum of squares for the series, SST, corrected for the mean: $\sum_{t=1}^{n} (y_t - \overline{y})^2$, where $\overline{y}$ is the series mean.

Sum of square errors.
The sum of the squared prediction errors, SSE. $SSE = \sum_{t=1}^{n} (y_t - \hat{y}_t)^2$, where $\hat{y}_t$ is the one-step predicted value.

Mean square error.
The mean squared prediction error, MSE, calculated from the one-step-ahead forecasts. $MSE = \frac{1}{n} SSE$. This formula enables you to evaluate small holdout samples.

Root mean square error.
The root mean square error (RMSE), $\sqrt{MSE}$.

Mean absolute error.
The mean absolute prediction error, $\frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t|$.

Minimum absolute percent error.
The minimum of the absolute percent errors (MINAPE).

Maximum absolute percent error.
The maximum of the absolute percent errors (MAXAPE).

Mean absolute percent error.
The mean of the absolute percent errors (MAPE).

Median absolute percent error.
The median of the absolute percent errors (MdAPE).

Geometric mean absolute percent error.
The geometric mean of the absolute percent errors (GMAPE).

Minimum absolute error as percentage of SD.
The minimum of the absolute error as a percentage of the standard deviation (MINAPES).

Maximum absolute error as percentage of SD.
The maximum of the absolute error as a percentage of the standard deviation (MAXAPES).

Mean absolute error as percentage of SD.
The mean of the absolute error as a percentage of the standard deviation (MAPES).

Median absolute error as percentage of SD.
The median of the absolute error as a percentage of the standard deviation (MdAPES).

Geometric mean error as percentage of SD.
The geometric mean of the absolute error as a percentage of the standard deviation (GMAPES).

Minimum absolute symmetric percent error.
The minimum of the absolute symmetric percent errors (MINASPE).

Maximum absolute symmetric percent error.
The maximum of the absolute symmetric percent errors (MAXASPE).

Mean absolute symmetric percent error.
The mean of the absolute symmetric percent errors (SMAPE).

Median absolute symmetric percent error.
The median of absolute symmetric percent errors (MdASPE).

Geometric mean symmetric percent error.
The geometric mean of the absolute symmetric percent errors (GMASPE).

Minimum absolute predictive percent error.
The minimum of the absolute predictive percent errors (MINAPPE).

Maximum absolute predictive percent error.
The maximum of the absolute predictive percent errors (MAXAPPE).

Mean absolute predictive percent error.
The mean of the absolute predictive percent errors (MAPPE).

Median absolute predictive percent error.
The median absolute predictive percent prediction error (MdAPPE).

Geometric mean absolute predictive percent error.
The geometric mean absolute predictive percent prediction error (GMAPPE).

Minimum relative absolute error.
The minimum of the relative absolute errors (MINRAE).

Maximum relative absolute error.
The maximum of the relative absolute errors (MAXRAE).

Mean relative absolute error.
The mean of the relative absolute errors (MRAE).

Median relative absolute error.
The median of the relative absolute errors (MdRAE).

Geometric relative absolute error.
The geometric mean of the relative absolute errors (GMRAE).

Mean absolute scaled error.
The mean of the absolute scaled errors (MASE).

R-square.
The R^2 statistic, $R^2 = 1 - SSE/SST$. If the model fits the series badly, the model error sum of squares, *SSE* , might be larger than *SST* and the R^2 statistic will be negative.

Adjusted R-square.
The adjusted R^2 statistic, $1 - (\frac{n-1}{n-k})(1 - R^2)$.

Amemiya's adjusted R-square.
Amemiya's adjusted R^2, $1 - (\frac{n+k}{n-k})(1 - R^2)$.

Random walk R-square.
The random walk R^2 statistic (Harvey's R^2 statistic using the random walk model for comparison), $1 - (\frac{n-1}{n})SSE/RWSSE$, where $RWSSE = \sum_{t=2}^{n} (y_t - y_{t-1} - \mu)^2$ and $\mu = \frac{1}{n-1} \sum_{t=2}^{n} (y_t - y_{t-1})$.

Akaike's information criterion.
Akaike's information criterion (AIC), $n \ln(SSE/n) + 2k$.

Akaike's information criterion, finite sample size corrected.
Akaike's information criterion with an empirical correction for small sample sizes (AICC), $AIC + \frac{2k(k+1)}{n-k-1}$.

Schwarz Bayesian information criterion.
Schwarz Bayesian information criterion (SBC or BIC),
$n \ln(SSE/n) + k \ln(n)$.

Amemiya's prediction criterion.
Amemiya's prediction criterion, $\frac{1}{n} SST (\frac{n+k}{n-k})(1 - R^2) = (\frac{n+k}{n-k}) \frac{1}{n} SSE$.

Maximum error.
The largest prediction error.

Minimum error.
The smallest prediction error.

Maximum percent error.
The largest percent prediction error, $100 \max((y_t - \hat{y}_t)/y_t)$. The summation ignores observations where $y_t = 0$.

Minimum percent error.
The smallest percent prediction error, $100 \min((y_t - \hat{y}_t)/y_t)$. The summation ignores observations where $y_t = 0$.

Mean error.
The mean prediction error, $\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)$.

Mean percent error.
The mean percent prediction error, $\frac{100}{n} \sum_{t=1}^{n} \frac{(y_t - \hat{y}_t)}{y_t}$. The summation ignores observations where $y_t = 0$.

References

Aldrin, M., and Damsleth, E. (1989). "Forecasting Non-seasonal Time Series with Missing Observations." *Journal of Forecasting* 8:97–116.

Anderson, T. W. (1971). *The Statistical Analysis of Time Series*. New York: John Wiley & Sons.

Archibald, B. C. (1990). "Parameter Space of the Holt-Winters' Model." *International Journal of Forecasting* 6:199–209.

Bartolomei, S. M., and Sweet, A. L. (1989). "A Note on the Comparison of Exponential Smoothing Methods for Forecasting Seasonal Series." *International Journal of Forecasting* 5:111–116.

Bowerman, B. L., and O'Connell, R. T. (1979). *Time Series and Forecasting: An Applied Approach*. North Scituate, MA: Duxbury Press.

Box, G. E. P., and Cox, D. R. (1964). "An Analysis of Transformations." *Journal of the Royal Statistical Society, Series B* 26:211–234.

Box, G. E. P., and Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control*. Rev. ed. San Francisco: Holden-Day.

Brocklebank, J. C., and Dickey, D. A. (1986). *SAS System for Forecasting Time Series*. 1986 ed. Cary, NC: SAS Institute Inc.

Brown, R. G. (1962). *Smoothing, Forecasting, and Prediction of Discrete Time Series*. New York: Prentice-Hall.

Brown, R. G., and Meyer, R. F. (1961). "The Fundamental Theorem of Exponential Smoothing." *Operations Research* 9:673–685.

Chatfield, C. (1978). "The Holt-Winters Forecasting Procedure." *Journal of the Royal Statistical Society, Series C* 27:264–279.

Chatfield, C., and Yar, M. (1988). "Holt-Winters Forecasting: Some Practical Issues." *The Statistician* 37:129–140.

Chatfield, C., and Yar, M. (1991). "Prediction Intervals for Multiplicative Holt-Winters." *International Journal of Forecasting* 7:31–37.

Cogger, K. O. (1974). "The Optimality of General-Order Exponential Smoothing." *Operations Research* 22:858–867.

Cox, D. R. (1961). "Prediction by Exponentially Weighted Moving Averages and Related Methods." *Journal of the Royal Statistical Society, Series B* 23:414–422.

Croston, J. D. (1972). "Forecasting and Stock Control for Intermittent Demands." *Operational Research Quarterly* 23:289–303.

Davidson, J. E. H. (1981). "Problems with the Estimation of Moving Average Processes." *Journal of Econometrics* 16:295–310.

Fair, R. C. (1986). "Evaluating the Predictive Accuracy of Models." In *Handbook of Econometrics*, vol. 3, edited by Z. Griliches and M. D. Intriligator, 1979–1995. New York: North-Holland.

Fildes, R. (1979). "Quantitative Forecasting—the State of the Art: Extrapolative Models." *Journal of the Operational Research Society* 30:691–710.

Fuller, W. A. (1976). *Introduction to Statistical Time Series*. New York: John Wiley & Sons.

Gardner, E. S., Jr. (1984). "The Strange Case of the Lagging Forecasts." *Interfaces* 14:47–50.

Gardner, E. S., Jr. (1985). "Exponential Smoothing: The State of the Art." *Journal of Forecasting* 4:1–38.

Granger, C. W. J., and Newbold, P. (1977). *Forecasting Economic Time Series*. New York: Academic Press.

Greene, W. H. (1993). *Econometric Analysis*. 2nd ed. New York: Macmillan.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton, NJ: Princeton University Press.

Harvey, A. C. (1981). *Time Series Models*. New York: John Wiley & Sons.

Harvey, A. C. (1984). "A Unified View of Statistical Forecasting Procedures." *Journal of Forecasting* 3:245–275.

Hopewood, W. S., McKeown, J. C., and Newbold, P. (1984). "Time Series Forecasting Models Involving Power Transformations." *Journal of Forecasting* 3:57–61.

Hyndman, R. J. (2006). "Another Look at Forecast-Accuracy Metrics for Intermittent Demand." *Foresight* (June): 43–46.

Ledolter, J., and Abraham, B. (1984). "Some Comments on the Initialization of Exponential Smoothing." *Journal of Forecasting* 3:79–84.

Ljung, G. M., and Box, G. E. P. (1978). "On a Measure of Lack of Fit in Time Series Models." *Biometrika* 65:297–303.

Makridakis, S. G., Wheelwright, S. C., and McGee, V. E. (1983). *Forecasting: Methods and Applications*. 2nd ed. New York: John Wiley & Sons.

McKenzie, E. (1984). "General Exponential Smoothing and the Equivalent ARMA Process." *Journal of Forecasting* 3:333–344.

McKenzie, E. (1986). "Error Analysis for Winters' Additive Seasonal Forecasting System." *International Journal of Forecasting* 2:373–382.

Montgomery, D. C., and Johnson, L. A. (1976). *Forecasting and Time Series Analysis*. New York: McGraw-Hill.

Morf, M., Sidhu, G. S., and Kailath, T. (1974). "Some New Algorithms for Recursive Estimation on Constant Linear Discrete Time Systems." *IEEE Transactions on Automatic Control* 19:315–323.

Nelson, C. R. (1973). *Applied Time Series for Managerial Forecasting*. San Francisco: Holden-Day.

Newbold, P. (1981). "Some Recent Developments in Time Series Analysis." *International Statistical Review* 49:53–66.

Pankratz, A., and Dudley, U. (1987). "Forecast of Power-Transformed Series." *Journal of Forecasting* 6:239–248.

Priestley, M. B. (1981). *Spectral Analysis and Time Series*. London: Academic Press.

Roberts, S. A. (1982). "A General Class of Holt-Winters Type Forecasting Models." *Management Science* 28:808–820.

Sweet, A. L. (1985). "Computing the Variance of the Forecast Error for the Holt-Winters Seasonal Models." *Journal of Forecasting* 4:235–243.

Willemain, T. R., Smart, C. N., and Shocker, J. H. (1994). "Forecasting Intermittent Demand in Manufacturing: Comparative Evaluation of Croston's Method." *International Journal of Forecasting* 10:529–538.

Winters, P. R. (1960). "Forecasting Sales by Exponentially Weighted Moving Averages." *Management Science* 6:324–342.

Yar, M., and Chatfield, C. (1990). "Prediction Intervals for the Holt-Winters Forecasting Procedure." *International Journal of Forecasting* 6:127–137.

Chapter 16
Forecast Combination Computational Details

Contents

Forecast Combination Model **497**
Forecast Combination Process **499**
Encompassing Tests **501**
OLS and HLN Encompassing Tests 502
Methods for Determining Forecast Combination Weights **504**
Simple Average 504
User-Specified Weights 505
Rank Weights 505
Ranked User Weights 505
RMSE Weights 506
AICC Weights 506
Ordinary Least Squares (OLS) Weights 507
Restricted Least Squares Weights 507
Least Absolute Deviation (LAD) Weights 508
Weighted Combination of Selected Forecasts **510**
Combined Forecast Error Variance Estimation **511**
References **511**

Forecast Combination Model

Given a time series Y_t and set of M forecasting models denoted by $F_i(), i = 1, \ldots, M$ with possible inputs (not shown), the following relationship is presumed for each

$$y_t = F_i(Y_{t-1}) + \epsilon_{i,t}$$

where Y_{t-1} denotes a vector of time series observations up to time $t-1$ and $\epsilon_{i,t}$ are IID disturbances with respect to t assumed $E[\epsilon_{i,t}] = 0$. Forecasting results from the set of models $F_i()$ are presumed to be available at the outset of the combination processing. They are generated on demand from running the models and consuming their results to generate the forecast combination.

Independently, each model $F_i()$ is fit to produce a fitted forecast model that is denoted $\hat{F}_i()$. Define the following notation for the results of $\hat{F}_i()$:

$\hat{y}_{i,t}$ denotes the prediction for fitted model $\hat{F}_i()$ at time t.

$e_{i,t} = y_t - \hat{y}_{i,t}$ denotes the prediction error for fitted model $\hat{F}_i()$ at time t.

$\hat{\sigma}^2_{i,t} = \mathrm{Var}(e_{i,t})$ denotes the prediction error variance for fitted model $\hat{F}_i()$ at time t.

$\hat{\sigma}_{i,t} = \sqrt{\mathrm{Var}(e_{i,t})}$ denotes the prediction standard error for fitted model $\hat{F}_i()$ at time t.

The combined forecast, denoted y_c, uses combination weights, w_i, to combine the fitted model forecasts as a weighted average of the predicted values with possible restrictions on the combination weights. More precisely,

$\hat{y}_{c,t} = \sum_{i=1}^{M} w_i \hat{y}_{i,t}$ denotes the combined forecast at time t.

The combination weights can correspond to a simple average, they can be user-specified, or they can be estimated using a variety of methods from the fitted forecast results. For the present discussion, the estimated weights are denoted $\hat{w}_i$ regardless of how they are obtained. This leads to the following expressions for the combined forecast and its prediction error:

$\hat{y}_{c,t} = \sum_{i=1}^{M} \hat{w}_i \hat{y}_{i,t}$ denotes the combined forecast prediction at time t.

$e_{c,t} = y_t - \hat{y}_{c,t}$ denotes the combined forecast prediction error at time t.

The prediction error variances are most generally defined by:

$$\begin{aligned}
\mathrm{Var}(e_{c,t}) &= \mathrm{Var}(y_t - \hat{y}_{c,t}) \\
&= \mathrm{Var}(y_t - \sum_{i=1}^{M} \hat{w}_i \hat{y}_{i,t}) \\
&= \mathrm{Var}(y_t - \sum_{i=1}^{M} \hat{w}_i (y_t - e_{i,t}) \\
&= \mathrm{Var}(y_t (1 - \sum_{i=1}^{M} \hat{w}_i) + \sum_{i=1}^{M} \hat{w}_i e_{i,t})
\end{aligned}$$

When you assume or impose the constraint $\sum_{i=1}^{M} \hat{w}_i = 1$, simplification results in

$$\begin{aligned}
\mathrm{Var}(e_{c,t}) &= \mathrm{Var}(\sum_{i=1}^{M} \hat{w}_i e_{i,t}) \\
&= \hat{W}_t^T \Sigma_t \hat{W}_t
\end{aligned}$$

where $\hat{W}_t$ denotes the fitted weight vector $M \times 1$ and $\Sigma_t = \mathrm{Var}(E_t)$ with $E_t = (e_{1,t}, e_{2,t}, \ldots, e_{M,t})^T$ denotes the ensemble prediction error vector at time t.

Alternatively, this can be expressed as:

$$\begin{aligned}\mathrm{Var}(e_{c,t}) &= \sum_{i=1}^{M} \hat{w}_i^2 \mathrm{Var}(e_{i,t}) + 2\sum_{j<i} \hat{w}_i \hat{w}_j \mathrm{Cov}(e_{i,t}, e_{j,t}) \\ &= \sum_{i=1}^{M} \hat{w}_i^2 \sigma_{i,t}^2 + 2\sum_{j<i} \hat{w}_i \hat{w}_j \rho_{i,j,t} \sigma_{i,t} \sigma_{j,t}\end{aligned}$$

If the prediction errors for the individual forecasts are not correlated at time t, then

$$\Sigma_t = \mathrm{diag}(\sigma_{i,t}^2)$$

and the combined forecast prediction error variance and standard error series are simply

$$\begin{aligned}\mathrm{Var}(e_{c,t}) &= \textstyle\sum_{i=1}^{M} \hat{w}_i^2 \sigma_{i,t}^2 \\ \hat{\sigma}_t &= \sqrt{\textstyle\sum_{i=1}^{M} \hat{w}_i^2 \sigma_{i,t}^2}\end{aligned}$$

Otherwise, computation of prediction error variance estimates is more complicated. See the section "Combined Forecast Error Variance Estimation" on page 511 for more discussion about this topic.

Forecast Combination Process

As described in the previous section, forecast combination operates in the context of a set of forecast models, $\{F_i()\}_{i=1}^{M}$, and uses results of the set of the corresponding fitted models $\{\hat{F}_i()\}_{i=1}^{M}$. That discussion of the mathematical details of forecast combination presumes all of the forecasts in the set $F_i()$ are used in the combination. The set of candidate forecasts considered during a forecast combination can in fact be a superset of the active set of forecasts that are finally combined. Denote the candidate set of forecasts for consideration as $\mathcal{F}(0)$. Elements of this set are some collection of forecasts $F_i(), i = 1, \ldots, M$. This set of candidate forecasts is defined through the XML that is generated from the HPFSELECT procedure when you create a combined model list.

A concept used in the remainder of this chapter is that of a time interval for weight estimation. Denote the time index set for an estimation interval region by

$$\mathcal{T}_W = \{t_b^W, \ldots, t_e^W\}$$

where t_b^W and t_e^W denote the begin and end time indices for the weight estimation region.

The forecast combination process follows a sequence of steps that operates on and within a set of forecasts. In the abstract, step i in this process takes a set $\mathcal{F}(i-1)$ as input and produces a set $\mathcal{F}(i)$ as output to the next step. As discussed, some steps function to potentially reduce the candidate set $\mathcal{F}(i-1)$ by the application of some form of test. The following sequence reduces the initial candidate set, $\mathcal{F}(0)$, to a final set of forecasts that are combined in the final step of the process:

1. Forecast candidate tests:
   Tests for seasonality and intermittency can be specified in the combined model list. As for the model selection list, these tests are determined by diagnostics on the actual time series y_t. The tests have the same behavior as those specified in model selection list context. As a result of these tests, a possibly reduced set of candidate forecasts $\mathcal{F}(1)$ is generated. If $\mathcal{F}(1)$ is empty, no further processing is performed and the combined forecast produces no result.

2. Forecast missing value tests:
   For each $F_i() \in \mathcal{F}(1)$, two forms of missing value tests can be performed on its predicted series $\hat{y}_{i,t}, t = 1, \ldots, T$. In the following, define

$$\text{MISSING}(x) = \begin{cases} 1 & \text{if } x \text{ is a missing value} \\ 0 & \text{otherwise} \end{cases}$$

   Forecast fit region percentage missing: A test for missing forecast values over the fit region of the $\hat{y}_{i,t}$ series can be specified as a threshold, P_{miss}. The percentage missing from $\hat{y}_{i,t}$ is defined by

$$p_i = 100[\frac{\sum_{t=1}^{T} \text{MISSING}(\hat{y}_{i,t})}{|\mathcal{T}_W|}]$$

   where $|\mathcal{T}_W|$ denotes the number of time indices in the estimation region. If $p_i \geq P_{miss}$, then the forecast for candidate $F_i()$ is omitted from $\mathcal{F}(1)$.

   Forecast horizon percentage missing: A forecast horizon missing test can be specified as a threshold, H_{miss}. The forecast horizon is the range of time indices that correspond to multistep forecasts denoted by $[t_b^H, t_e^H]$ with span $H = t_e^H - t_b^H$. The percentage of missing values from the predicted series $\hat{y}_{i,t}$ is then defined by

$$p_i = 100[\frac{\sum_{t=t_b^H}^{t_e^H} \text{MISSING}(\hat{y}_{i,t})}{H}]$$

   If $p_i \geq H_{miss}$, then the forecast for candidate $F_i()$ is omitted from $\mathcal{F}(2)$.

   The end result of this step is the set of candidates $\mathcal{F}(2) \subseteq \mathcal{F}(1)$.

3. Encompassing tests:
   For the set $\mathcal{F}(2)$, a test can be performed to determine which of the forecasts $F_i() \in \mathcal{F}(1)$ adds information to the final combined forecast. By default, no encompassing tests are performed on the combination candidates. The goal of this step is to produce a new set of candidates $\mathcal{F}(3)$ in which each forecast contributes information to the final combination. If $\mathcal{F}(2)$ contains only one element, no test is performed. The details of encompassing tests are further discussed the section "Encompassing Tests" on page 501.

4. Weight estimation:
   This step assigns weights to the forecasts that are present in the set $\mathcal{F}(3)$ as directed by the combined model list. A detailed discussion of weight methods is provided in the section "Methods for Determining Forecast Combination Weights" on page 504. Provision is made for weight assignment to reduce

the set of forecasts based on method-specific criteria. For some estimation methods, a weight might be non-estimable, for example, and the corresponding forecast is eliminated from use in the combined forecast. For others, a user-defined criterion allows for exclusion of weights that fall below a given threshold; hence the corresponding forecasts are eliminated from use in the combined forecast. The result is that a set of weights for the forecasts in $\mathcal{F}(4)$ is produced by this step.

5. Forecast combination:
   This step performs the weighted combination of the forecasts in the set $\mathcal{F}(4)$. For each $t, t = 1, \ldots, T$, forecast combination produces a value for $\hat{y}_{c,t}$ according to the expression

$$\hat{y}_{c,t} = \sum_{i=1}^{M} \hat{w}_{i,t}\hat{y}_{i,t}$$

   where $\hat{y}_{i,t}$ denotes the prediction for fitted model $\hat{F}_i()$ at time t and $\hat{w}_{i,t}$ denotes the weight assigned to fitted model $\hat{F}_i()$ at time t.

   This expression provides for the possibility that the weight estimates assigned in the previous step can be adjusted for each time slice t in the panel of forecasts being combined. This permits treatment of missing values in one or more of the $\hat{y}_{i,t}$ series at a given time index t. The combined model list specifies a treatment mode for missing forecast values in the combination step. The default treatment mode is dependent on the weight estimation method. For more details about treatment modes, see "Weighted Combination of Selected Forecasts" on page 510.

Encompassing Tests

Methods for testing forecast encompassing are somewhat varied in the literature, ranging from relatively simple pairwise comparisons to more complicated schemes based on causal inference and D-separation which model the causal relationships in a directed acyclic graph (DAG). The current set of methods supported includes the following:

- Ordinary least squares (OLS) test
- Harvey, Leybourne, and Newbold (HLN) test

Both OLS and HLN tests are very similar in their elimination process and are discussed together in the next section.

OLS and HLN Encompassing Tests

The elimination process begins by ranking all of the forecasts in $\mathcal{F}(2)$ by a designated statistic-of-fit criterion value from the best to worst performing over the range of time indices $\mathcal{T}_W$. Option settings in effect during the PROC HPFENGINE run and the actual time series y_t determine $\mathcal{T}_W$.

The elimination process is iterative. Each pass begins with the best-ranked forecast of those not previously certified and compares it to each of the lower-ranked ones in the rank sequence. Suppose $F_i()$ from $\mathcal{F}(2)$ is the best-ranked of those not already certified. At this point, $F_i()$ becomes certified for inclusion. What remains then is to determine whether any lower-ranked uncertified forecast $F_j()$ is encompassed by $F_i()$. Define that forecast $F_i()$ encompasses forecast $F_j()$ if the encompassing test on the pair $(F_i(), F_j())$ fails to reject the null hypothesis of the encompassing test. Both OLS and HLN encompassing tests produce a statistic that has a t distribution. The OLS test uses a one-sided alternative in the right tail, while the HLN test uses a two-tailed test. The details of the t statistic computation and its associated degrees of freedom are provided later, but are not needed to define the process. The prediction error values $\hat{e}_{i,t}$ and $\hat{e}_{j,t}$ are used to compute this t statistic for both of these tests. Call it $T_{i,j}$ and denote its associated degrees of freedom as $\nu_{i,j}$. Note that $T_{i,j}$ estimates the degree of orthogonality between $F_i()$ and $F_j()$. The null is then

$$H_0: T_{i,j} = 0$$

When H_0 is rejected, encompassing is not conclusive and the forecast $F_j()$ remains in $\mathcal{F}(2)$. When H_0 is not rejected, encompassing is concluded at the specified confidence level and the forecast $F_j()$ is removed from $\mathcal{F}(2)$. This pairwise comparison process proceeds through all of the models ranked lower than $F_i()$. At the end of the pass on $F_i()$, one of two conditions exists: there are no lower-ranked elements that remain in $\mathcal{F}(2)$ or else there are more. If no more lower-ranked forecasts remain, then the set of certified forecast candidates in $\mathcal{F}(2)$ are passed along to the next step. If there are more, another pass is started with the best of those forecasts that remain in $\mathcal{F}(2)$ and are not already certified (that is, tested against those of lower rank than itself). This process terminates with some collection of certified forecasts to be combined being those left in the set $\mathcal{F}(2)$.

OLS Test Statistic

This test regresses a convex combination of two prediction error series to test the hypothesis that the combination error is best explained by the use of both forecasts in combination. The mathematical details of this regression are summarized here. Take two forecasts, $F_{1,t}$ and $F_{2,t}$ over time $t = 1, \ldots T$, and postulate the model:

$$F_{c,t} = (1-\lambda)F_{1,t} + \lambda F_{2,t} + \epsilon_t, \text{ where } 0 \leq \lambda \leq 1$$

Define $e_{i,t} = y_t - F_{i,t}, i = 1, 2$, as the respective prediction errors with ϵ_t as the prediction error of the combined forecast. Then observe that the proposed regression is equivalent to:

$$e_{1,t} = \lambda(e_{1,t} - e_{2,t}) + \epsilon_t$$

The combined forecast has a smaller expected error variance than $F_{1,t}$ unless the covariance between $e_{1,t}$ and $(e_{1,t} - e_{2,t})$ is 0. Rejecting the hypothesis $\lambda = 0$ means there is statistical evidence to conclude that this

covariance is not 0. Failure to reject means that λ is not significantly different from 0. Respectively, these amount to rejecting the hypothesis that $F_{1,t}$ encompasses $F_{2,t}$, or in failing to do so, that $F_{1,t}$ encompasses $F_{2,t}$ and that $F_{2,t}$ should not be included in the combined forecast. A great deal has been written about the use of OLS to estimate the parameter λ in this setting and the Type I errors that result from tests that use such estimates. Harvey, Leybourne, and Newbold (1998) discuss this at some length and argue for more robust encompassing tests including their HLN test.

HLN Test Statistic

The HLN test statistic proposed and studied by Harvey, Leybourne, and Newbold (1998) is a modified form of the Diebold-Mariano (DM) test. The mathematical details of the HLN test are summarized here. Diebold and Mariano (1995) proposed a test statistic for the equality of prediction mean squared errors that can be adapted to test for forecast encompassing. Given two forecast error series $e_{i,t}$, define a loss differential sequence d_t by

$$d_t = (e_{1,t} - e_{2,t})e_{1,t}, t = 1, \ldots, T$$

To test the null hypothesis that $E[d_t] = 0$, the DM test statistic is defined as the ratio

$$\mathrm{DM} = \frac{\overline{d}}{\sqrt{\mathrm{Var}(\overline{d})}}$$

Assuming k-step ahead forecasts and that k-step ahead forecasts exhibit dependence up to lag $k-1$, a consistent estimator of variance in the DM statistic is

$$\hat{\mathrm{Var}}(\overline{d}) = \frac{1}{T}[\gamma_{\overline{d}}(0) + 2\sum_{h=1}^{k-1}\gamma_{\overline{d}}(h)]$$

where $\gamma_{\overline{d}}(h)$ is the autocovariance of $\overline{d}$ at lag h. $\gamma_{\overline{d}}(h)$ is estimated in the usual way via

$$\hat{\gamma}_{\overline{d}}(h) = \frac{1}{T}\sum_{t=h+1}^{T}(d_t - \overline{d})(d_{t-h} - \overline{d})$$

Harvey, Leybourne, and Newbold (1998) further refine this by creating a modified DM test statistic denoted MDM:

$$\mathrm{MDM} = T^{-1/2}[T + 1 - 2k + T^{-1}k(k-1)]^{1/2}\mathrm{DM}$$

They compare the resulting statistic against critical values from a t_{T-1} distribution. These two modifications to the DM test result in the HLN test for forecast encompassing. The test for encompassing then tests the null:

$$H_0: MDM = 0$$

Rejecting H_0 is inconclusive for $F_i()$ encompassing $F_j()$, and $F_j()$ remains in the forecast set. Failure to reject H_0 concludes that $F_i()$ encompasses $F_j()$ at the specified confidence level, and $F_j()$ is removed from the forecast set.

Methods for Determining Forecast Combination Weights

Forecast combination weights $\hat{w}_i, i = 1, \ldots, M$, are determined via one of the following methods:

- simple average
- user-defined weights
- rank weights
- ranked user weights
- root mean squared error (RMSE) weights
- corrected Akaike's information criterion (AICC) weights
- ordinary least squares (OLS) weights
- restricted least squares weights,
- least absolute deviation (LAD) weights

In all of these methods, the original set of candidate forecasts, previously called $\mathcal{F}(0)$, can be reduced through steps that lead to the estimation of combination weights. For purposes of the following discussion, denote the possibly reduced set of forecasts as $\mathcal{F}$ and denote its index set by

$$\mathcal{I}(\mathcal{F}) = \{i : F_i() \in \mathcal{F}\}$$

Subsequent sections describe each of these methods.

Simple Average

The combination weights are determined solely by the cardinality of the set $\mathcal{F}$. Define the combination weight estimates for the forecasts in $\mathcal{F}$ by

$$\hat{w}_i = \frac{1}{M}, \forall i \in \mathcal{I}(\mathcal{F})$$

where $M = |\mathcal{F}|$

User-Specified Weights

The combined model list from PROC HPFSELECT that specifies this method includes a set of user-defined weights, $w_i, i = 1, \ldots, M$, which correspond to the forecasts $F_i(), i = 1, \ldots, M$ specified in the combined model list.

Define the combination weight estimates for the forecasts in $\mathcal{F}$ by

$$\hat{w}_i = \frac{w_i}{W}, \forall i \in \mathcal{I}(\mathcal{F})$$

where $W = \sum_{i \in \mathcal{I}(\mathcal{F})} w_i$.

Rank Weights

This method uses a user-designated statistic-of-fit criterion to rank the performance of the forecasts that comprise the set $\mathcal{F}$ over a fit region $\mathcal{T}_W$. Define $\mathcal{R}$ to be the ordered set of ranked forecasts $F_i()$ in $\mathcal{F}$, omitting any forecast with a noncomputable value, and let

$$R_i = \mathrm{RANK}(F_i), \forall i \in \mathcal{I}(\mathcal{F})$$

where $\mathrm{RANK}(F_i)$ denotes the position of F_i in the ordered set $\mathcal{R}$.

Define the combination weight estimates for the forecasts in $\mathcal{F}$ by

$$\hat{w}_i = \frac{1/R_i}{W}, \forall i \in \mathcal{I}(\mathcal{F})$$

where $W = \sum_{i \in \mathcal{I}(\mathcal{F})} 1/R_i$.

For discussion of the use of this method, see Kişinbay (2007); Aiolfi and Timmerman (2006).

Ranked User Weights

This weight estimation method is a combination of the preceding rank weights and user-defined weights methods. Given the set of forecasts $\mathcal{F}$, the forecasts are ranked by a designated statistic-of-fit criterion over the estimation region $\mathcal{T}_W$. Then the first user-defined weight is associated with the best forecast, the second user-defined weight is associated with the second best forecast, and so on. The resulting weight assignments are then normalized by the same procedure as for user-defined weights.

RMSE Weights

This weight estimation method uses root mean squared error (RMSE) values computed from the prediction error series associated with each forecast $F_i() \in \mathcal{F}$. RMSE values are computed over a fit region $\mathcal{T}_W$. This method can result in a reduction of the set $\mathcal{F}$ if the computation of the RMSE value for the prediction error series fails for a given forecast.

Define

$$\mathrm{RMSE}_i = \mathrm{RMSE}(\hat{\mathbf{e}}_i), \forall i \in \mathcal{I}(\mathcal{F})$$

where $\hat{\mathbf{e}}_i$ is the prediction error series vector for $F_i() \in \mathcal{F}$.

Remove any $F_i()$ with a noncomputable RMSE from $\mathcal{F}$ and its corresponding index i from $\mathcal{I}(\mathcal{F})$.

Define the combination weight estimates for the forecasts in $\mathcal{F}$ by

$$\hat{w}_i = \frac{1/\mathrm{RMSE}_i}{W}, \forall i \in \mathcal{I}(\mathcal{F})$$

where $W = \sum_{i \in \mathcal{I}(\mathcal{F})} 1/\mathrm{RMSE}_i$.

A reference that discusses the use of this method is Kişinbay (2007).

AICC Weights

This weight estimation method uses corrected Akaike's information criterion (AICC) values computed from the prediction error series that are associated with each forecast $F_i() \in \mathcal{F}$. This method can result in a reduction of the set $\mathcal{F}$ if the computation of the AICC value fails for the prediction error series for a given forecast. Let P_i denote the number of parameters in the forecast model $F_i \in \mathcal{F}$ and define

$$\mathrm{AICC}_i = \mathrm{AICC}(\hat{\mathbf{e}}_i, P_i), \forall i \in \mathcal{I}(\mathcal{F})$$

where $\hat{\mathbf{e}}_i$ is the prediction error series vector for $F_i() \in \mathcal{F}$.

Remove any $F_i()$ with a noncomputable AICC from $\mathcal{F}$ and its corresponding index from $\mathcal{I}(\mathcal{F})$. Denote the least AICC_i value computed as $\mathrm{AICC}_{\min}$ and define

$$\Delta_i = \mathrm{AICC}_i - \mathrm{AICC}_{\min}, \forall i \in \mathcal{I}(\mathcal{F})$$

Define the combination weight estimates for the forecasts in $\mathcal{F}$ by

$$\hat{w}_i = \frac{\exp(-\frac{1}{2}\lambda\Delta_i)}{W}$$

where $W = \sum_{i \in \mathcal{I}(\mathcal{F})} \exp(-\frac{1}{2}\lambda\Delta_i)$ and $0 \leq \lambda$. When $0 \leq \lambda \leq 1$, the resulting method is a compromise between simple forecast averaging (obtained when $\lambda = 0$) and the usual Akaike weights (obtained when $\lambda = 1$). When λ is set to large values, say $\lambda > 10$, the resulting method tends to select the best single model based on its AICC performance. Frequently, the tendency to effectively pick the best forecast based on its AICC value is observed even when $\lambda = 1$ unless the other candidate forecasts have AICC values that are reasonably close to the smallest.

Ordinary Least Squares (OLS) Weights

OLS weights are computed by solving an unconstrained least squares problem. As usual, the weights are computed via the normal equations to minimize

$$z = \sum_{t=1}^{T}(y_t - \sum_{i=1}^{M} w_i \hat{y}_{i,t})^2$$

The resulting weight estimates $\hat{w}_i$ are used to combine the forecasts in $\mathcal{F}$. This estimation does not impose a constraint that the weights to sum to one. Therefore, results in section "Forecast Combination Model" on page 497 related to that assumption do not hold for OLS weights.

Restricted Least Squares Weights

Three weight methods, NRLS, ERLS, and NERLS, fall into this category. All are formulated as a constrained least squares problem and solved through a nonlinear optimization solver. All forms minimize the objective function:

$$z = \sum_{t \in \mathcal{T}_W} (y_t - \sum_{i=1}^{M} w_i \hat{y}_{i,t})^2$$

Constraints imposed by methods cast into this form include:

- NRLS (nonnegative restricted least squares) imposes the constraints:

$$w_i \geq 0, i = 1, \ldots, M$$

- ERLS (equality restricted least squares) imposes the constraint:

$$\sum_{i=1}^{M} w_i = 1$$

- NERLS (nonnegative equality restricted least squares) imposes the constraints:

$$\sum_{i=1}^{M} w_i = 1,$$
$$w_i \geq 0, i = 1, \ldots, M$$

The resulting weight estimates $\hat{w}_i$ are used to combine the forecasts in $\mathcal{F}$.

Least Absolute Deviation (LAD) Weights

Many time series statistic-of-fit criteria measure some form of absolute deviation of the forecast series from the actual series, so it is natural to cast the combination weights problem into some form of least absolute deviations (LAD) setting. LAD weights are determined by formulating a linear program (LP) to minimize an objective function expressed in terms of absolute losses at each time index t.

A loss series, denoted u_t, is constructed for $t \in \mathcal{T}_W$, depending on the specification of the type of loss to minimize in the objective. Define u_t as follows for these different loss types:

- Simple error

  $$u_t = y_t - \sum_{i=1}^{M} w_i \hat{y}_{i,t}$$

  This corresponds to ERRTYPE=ABS in the COMBINE statement.

- Percentage error

  $$u_t = \frac{y_t - \sum_{i=1}^{M} w_i \hat{y}_{i,t}}{y_t}$$

  This corresponds to ERRTYPE=APE in the COMBINE statement.

- Relative error

  $$u_t = \frac{y_t - \sum_{i=1}^{M} w_i \hat{y}_{i,t}}{y_t - \eta_t}$$

  where η_t denotes the naive forecast of y_t. Under normal circumstances $\eta_t = y_{t-1}$ except when y_{t-1} is missing. In those cases η_t holds the last nonmissing y_{t-1} value until a nonmissing y_t is encountered to replace in lagged context. Evidently, u_t can be defined only when both y_t and η_t are contemporaneously nonmissing. This corresponds to ERRTYPE=RAE in the COMBINE statement.

The optimization problem (LAD) is posed in terms of this loss series. LAD weights can be determined to minimize one of these objectives:

- ℓ_1 norm of the loss series produces an objective in the form:

  $$\min z = \sum_{t \in \mathcal{T}_W} |u_t|$$

  This corresponds to OBJTYPE=L1 in the COMBINE statement.

- ℓ_∞ norm of the loss series produces an objective of the form:

  $$\min z = \max \{|u_t|\}_{t \in \mathcal{T}_W}$$

  This corresponds to OBJTYPE=LINF in the COMBINE statement.

For details about the COMBINE statement syntax, see the section "COMBINE Statement" on page 355.

So the problem (LAD) takes this abstract form:

$$\min z = f(\mathbf{y}, \hat{\mathbf{Y}}, \mathbf{w})$$
$$\text{subject to:}$$
$$\mathbf{1}^T\mathbf{w} = 1,$$
$$\mathbf{w} \geq 0$$

where $\mathbf{w}$ is the $M \times 1$ matrix of combination weights, $\mathbf{y}$ is the $T \times 1$ matrix of actual values, $\hat{\mathbf{Y}}$ is the $T \times M$ matrix of forecasts, and $\mathbf{1}$ is an $M \times 1$ matrix of ones.

The abstractly posed form of the LAD problem is inherently nonlinear due to the absolute values in the objective. It can be linearized by introducing a different set of artificial decision variables and expressing the objective in terms of those. Constraints that involve those artificial decision variables must be added to insure that the objective evaluates in terms of absolute values. See Chvátal (1983) for details.

The essence of this translation into an LP uses the fact that

$$\xi = |u| \Leftrightarrow \xi \geq u \text{ and } \xi \geq -u$$

Using this, each $|u_t|$ in the ℓ_1 objective is replaced by ξ_t

$$\min z = \sum_{t=1}^{T} \xi_t$$

and two constraints are added to the LP for each u_t:

$$\xi_t \geq u_t \text{ and } \xi_t \geq -u_t$$

For the ℓ_∞ objective, only one artificial variable ξ_0 is needed. The objective becomes

$$\min z = \xi_0$$

and two constraints are added to the LP for each u_t:

$$\xi_0 \geq u_t \text{ and } \xi_0 \geq -u_t$$

Three complications arise in the construction of the LP formulation:

- Missing values in forecasts:
  When $\hat{y}_{i,t}$ is missing, the row for time index t is omitted from the $\hat{\mathbf{Y}}$ matrix.
- Missing values in the actual series:
  When y_t is missing, the row that corresponds to t is omitted from the $\hat{\mathbf{Y}}$ matrix
- Zero values in actual series:
  When the loss series is expressed in terms of percentage deviation, the u_t value is undefined for any time index t where y_t is zero. For percentage deviation, when y_t is zero, the row for time index t is omitted from the $\hat{\mathbf{Y}}$ matrix.

In terms of the abstract LAD problem, all of these omissions affect the objective function. The same is true in the LP formulation, but the impact on the simplex of feasible solutions by the omission of some constraints becomes apparent. Omitting time indices from the formulation decreases the number of artificial decision variables added; hence fewer LP constraints incorporates less loss series information into the weight estimation.

Solving the LP for the LAD problem results in a set of weights $\hat{w}_i$ that optimize the selected objective function subject to the normalization and nonnegativity constraints on the weights.

Weighted Combination of Selected Forecasts

Denote the set of forecasts $F_i()$ to combine as $\mathcal{F}$. As noted previously, the combined forecast $\hat{y}_{c,t}$ is defined by

$$\hat{y}_{c,t} = \sum_{i \in \mathcal{F}} \hat{w}_{i,t} \hat{y}_{i,t}$$

where $\hat{y}_{i,t}$ denotes the prediction for fitted model $\hat{F}_i()$ at time t and $\hat{w}_{i,t}$ denotes the weight assigned to fitted model $\hat{F}_i()$ at time t.

The presence of missing values in the forecasts at a given time t affects the generation of the combined forecast $\hat{y}_{c,t}$. The resulting value is determined by the forecast combination missing value treatment mode. This behavior can be specified in the combined model list for the forecast combination and if specified there takes precedence over any default. The default value for missing value treatment mode is dependent on the weight method selected.

The following discussion presumes that at a given time t one or more of the $\hat{y}_{i,t}$ values is missing. Given that premise, the behaviors defined for missing value treatment are:

- Rescale (MISSMODE=RESCALE):
  $\hat{w}_i$ values associated with the nonmissing $\hat{y}_{i,t}$ values are dynamically normalized to satisfy the requirement for the sum of weights equal one. Define

  $$\mathcal{N}_t = \{i : \hat{y}_{i,t} \text{ is nonmissing}\}$$

  and define W as

  $$W = \sum_{i \in \mathcal{N}_t} \hat{w}_i$$

  Then the combined forecast $y_{c,t}$ is given by

  $$\hat{y}_{c,t} = \frac{1}{W} \sum_{i \in \mathcal{N}_t} \hat{w}_{i,t} \hat{y}_{i,t}$$

- Missing (MISSMODE=MISSING):
  The combined forecast $\hat{y}_{c,t}$ is set to missing.

The default missing value treatment is defined by weight method as follows:

- MISSMODE=RESCALE is the default for simple average, user-specified weights, ranked user weights, rank weights, and RMSE weights.
- MISSMODE=MISSING is the default for AICC weights, OLS weights, restricted least squares weights, and LAD weights. For OLS and NRLS, you are not permitted to specify MISSMODE=RESCALE since the estimated weights are not constrained to sum to one.

Combined Forecast Error Variance Estimation

The combination weight estimates are treated as if they are known parameters in all the prediction error variance expressions shown in the section "Forecast Combination Model" on page 497.

To control the method of estimating prediction error variance, you can specify an option in the combined model list that defines the forecast combination. In all cases, the estimated prediction error variance of the combined forecast makes use of the estimates of prediction error variance from the forecasts that are finally combined and the exact weights used in that combination at each time t. See the section "Weighted Combination of Selected Forecasts" on page 510 for details that impact weights over the combination time span.

Prediction error variance estimation modes available for the combined forecast include:

STDERR=DIAG specifies that the variance computation assumes the forecast errors at time t are uncorrelated so that the simple diagonal form of Σ_t is used.

STDERR=ESTCORR specifies that the variance computation estimates correlations $\rho_{i,j,t}$ via the sample cross-correlation between $e_{i,t}$ and $e_{j,t}$ over the time span $t = 1, \ldots, T$, where t denotes the last time index of the actual series y_t. Of course, using STDERR=ESTCORR implies that the error series $e_{i,t}$ and $e_{j,t}$ are assumed to be jointly stationary.

STDERR=ESTCORR(TAU=τ) is similar to STDERR=ESTCORR except that the cross-correlation estimates are localized to a time window of n steps. The time span $t = 1, \ldots, T$ is quantized into segments of τ steps working from t backwards for in-sample cross-correlation estimates. The cross-correlation estimates from the interval $[T - \tau, T]$ are used for the period of multistep forecasts that extend beyond time t.

References

Aiolfi, M., and Timmerman, A. (2006). "Persistence of Forecasting Performance and Combination Strategies." *Econometrics* 135:31–53.

Burnham, K. P., and Anderson, D. R. (1998). *Model Selection and Inference: A Practical Information-Theoretic Approach*. New York: Springer-Verlag.

Chvátal, V. (1983). *Linear Programming*. New York: W. H. Freeman.

Diebold, F. X., and Lopez, J. A. (1996). "Forecast Evaluation and Combination." In *Handbook of Statistics*, edited by G. S. Maddala and C. R. Rao, 241–268. Amsterdam: North-Holland.

Diebold, F. X., and Mariano, R. (1995). "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics* 13:253–265.

Harvey, D., Leybourne, S., and Newbold, P. (1998). "Tests for Forecast Encompassing." *Journal of Business and Economic Statistics* 16:254–259.

Kişinbay, T. (2007). *The Use of Encompassing Tests for Forecast Combination*. Working Paper WP/07/264, International Monetary Fund.

Little, M. (2009). "An Information Criterion-Based Method for Constructing Combining Weights for Multimodel Forecasting and Prediction." US Patent 20090319310.

Winkler, R. L., and Makridakis, S. G. (1983). "The Combination of Forecasts." *Journal of the Royal Statistical Society, Series A* 146:150–157.

Chapter 17
Forecast Model Selection Graph Details

Contents

Introduction **513**
Forecast Model Selection Graphs by Example **514**
Example 17.1: Selection between Model Forecasts and a Combined Forecast 514
Example 17.2: Combining Selected Forecasts 517
Forecast Model Selection Graph Operation **521**
OUTSTATSELECT Behavior 525
OUTEST Behavior 526
OUTSTAT Behavior 526
OUTMODELINFO Behavior 526
OUTSUM Behavior 526
OUTCOMPONENT Behavior 527
OUTFOR Behavior 527
OUT Behavior 527
ODS Print Behavior 527
ODS Plot Behavior 527

Introduction

This chapter provides details on several aspects of the forecast model selection graph used in the SAS Forecast Server Procedures software.

The forecast model selection graph is a directed acyclic graph (DAG) defined through the use of the HPFSELECT procedure and the various model specification procedures. Nodes in the forecast model selection graph are the XML specifications, and the arcs are defined by the references in list specifications that are created via PROC HPFSELECT.

The forecast model selection graph supports a wide range of model selection and forecasting options and is an evolution of previous mechanisms. Earlier versions of SAS Forecast Server Procedures software permitted a one-level structure known as a model selection list. It held a set of alternative time series models evaluated to pick the best model for each time series realization where it was applied. With the addition of combined forecasts, the extension of the model selection list concept to the forecast model selection graph is a natural one. You can easily see the motivation with these two scenarios:

- selecting between the best performing individual model forecast and a combined forecast
- combining the best performing forecast from a model selection list with other forecasts

Given these scenarios, the need for the forecast model selection graph generalization becomes apparent. Indeed, supporting these two scenarios basically provides the framework for the generality of the forecast model selection graph. Subsequent sections of this chapter demonstrate by example use of these concepts and provide insight into any rules on usage imposed by the software.

Forecast Model Selection Graphs by Example

Example 17.1: Selection between Model Forecasts and a Combined Forecast

This example demonstrates the use of the model selection list to select between a reference model for a time series forecast and a combined forecast. The candidate models that make up the combined model list are forecast, combined using the simple average of the forecasts, and the final forecast selected based on best performance between the reference model's forecast and the combined forecast.

Begin by defining an exponential smoothing model (ESM) as the reference to use as the gauge for better performance. The ESM generated is denoted by the name T0.

```
proc hpfesmspec rep=work.rep specname=t0;
   esm method=best;
run;
```

Define three forecast candidates to be considered for combination. Each of these models is forecast independently, and the results are used in a combined forecast definition.

```
proc hpfesmspec rep=work.rep specname=t1;
   esm method=bestn;
run;

proc hpfesmspec rep=work.rep specname=t2;
   esm method=bests;
run;

proc hpfarimaspec rep=work.rep specname=t3;
   forecast symbol=y dif=(1,s) q=(1)(1)s noint;
   estimate method=ml converge=.0001 delta=.0001 maxiter=150;
run;
```

The following statements define a combined model list. Note that the combined model list has a name, COMB3, and it specifies the three models, T1, T2, and T3, which are identified by their names in the SPEC statement. Recognizing this connection through XML specification names is the key to building forecast model selection graphs. In this example, the nonseasonal ESM BESTN defined in specification T1 is excluded from the combination because of the seasonality test performed by the combined model list.

```
proc hpfselect rep=work.rep name=comb3 label="Average(T1,T2,T3)";
   combine method=average;
   spec t1 t2 t3;
run;
```

The next group of statements defines the model selection list to select between the better of the reference ESM forecast and the combined forecast. Note again that this declaration relies on the names used in the SPEC statement in PROC HPFSELECT to define the set of candidates that comprise the list. The essential difference is the semantic intent for the model selection list, which is to choose the best forecast from the set of candidates as opposed to combining them as in the previous group of statements. The default behavior of the PROC HPFSELECT invocation is to define a model selection list; when you add the COMBINE statement to the PROC HPFSELECT statement block, you define a combined model list for the candidates identified via the SPEC statements. This is discussed in greater detail in section "Forecast Model Selection Graph Operation" on page 521.

```
proc hpfselect rep=work.rep name=select;
   spec comb3 t0;
run;
```

Run the model selection list to select between the better of the combined forecast and the reference ESM forecast.

```
proc hpfengine data=sashelp.air
               rep=work.rep
               globalselection=select
               out=out1
               lead=24
               print=(all)
               plot=(components);
   id date interval=month;
   forecast air;
run;
```

It can be seen in Output 17.1.1 that the combined forecast achieves the better performance between the two competing forecasts in the model selection list.

Output 17.1.1 Model Selection Results

The HPFENGINE Procedure

Model Selection Criterion = MAPE			
Model	**Statistic**	**Selected**	**Label**
COMB3	2.9607784	Yes	Average(T1,T2,T3)
T0	3.0845016	No	Best Smoothing Method

Output 17.1.2 and Output 17.1.3 show parameter estimates for the forecasts that contribute to the combination. Output 17.1.4 shows the parameter estimates for the combined forecast.

Output 17.1.2 Parameter Estimates for the T2 Model

Parameter Estimates for T2 Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**Level Weight**	0.30728	0.03153	9.74	<.0001
AIR	**Trend Weight**	0.0010000	0.0030237	0.33	0.7413
AIR	**Seasonal Weight**	0.87493	0.07769	11.26	<.0001

Output 17.1.3 Parameter Estimates for the T3 Model

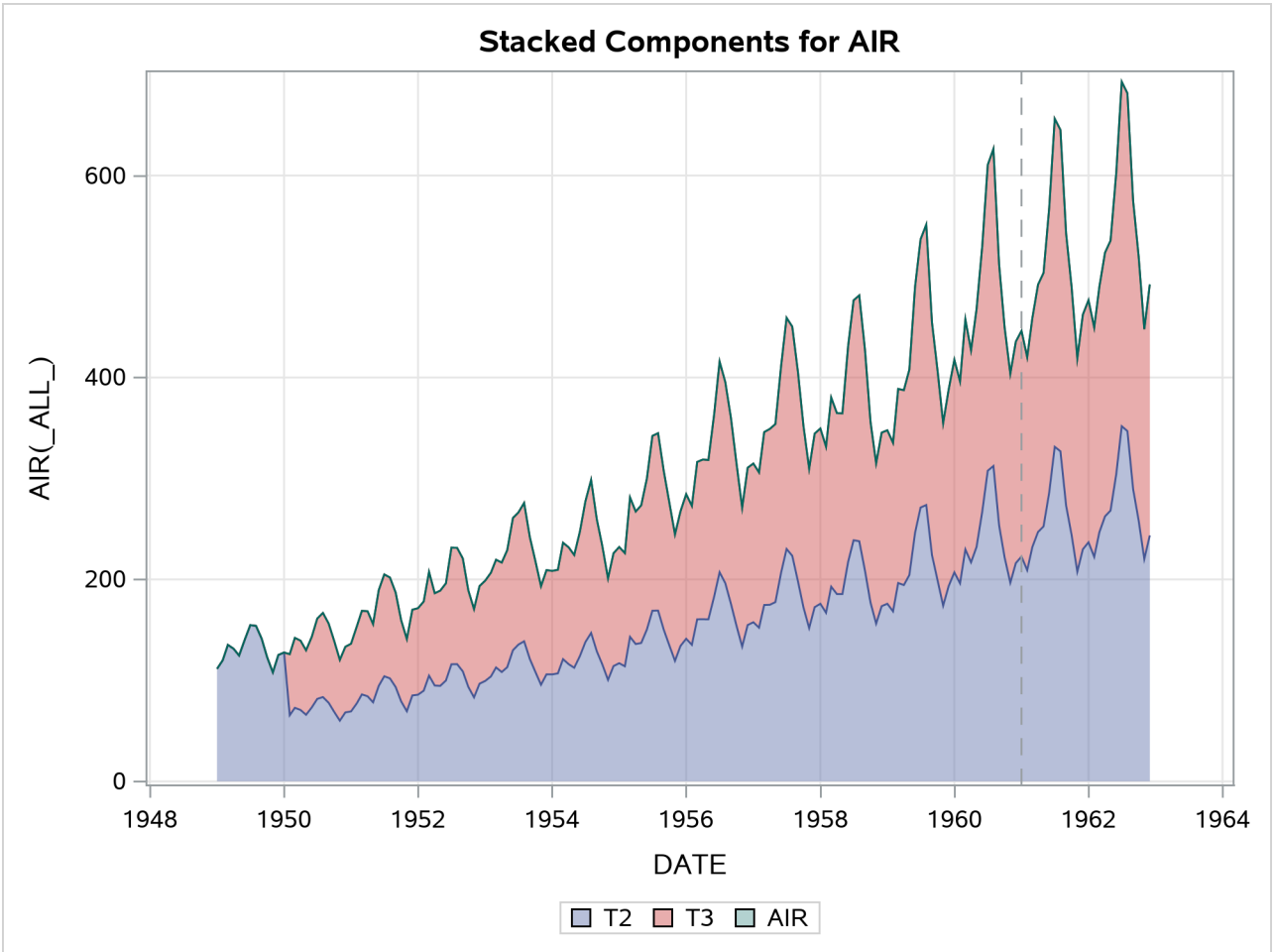
Parameter Estimates for T3 Model					
Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
AIR	MA1_1	0.30868	0.08433	3.66	0.0003
AIR	MA2_12	0.10744	0.10190	1.05	0.2917

Output 17.1.4 Parameter Estimates for COMB3 Combined Forecast

Parameter Estimates for COMB3 Model					
Component	Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
T2	WEIGHT	0.50000	.	.	.
T3	WEIGHT	0.50000	.	.	.

The weighted forecast components that contribute to the final combined forecast are plotted in a stack on the same set of axes. The weighted forecast components are plotted from the bottom to the top in the order of their combination, yielding the final combined forecast.

Output 17.1.5 Combined Forecast Components



Example 17.2: Combining Selected Forecasts

This example demonstrates combining the forecast from a time series model with the best forecast selected from a model selection list. The candidates in the model selection list, named TBEST, are forecast, and the best is selected. That forecast is combined with the forecast from the ARIMA model named AIRLINE. Combination weights for the final forecast are generated based on corrected Akaike's information criterion (AICC) weights.

The following statements define two forecast candidates, T1 and T2, to be considered for model selection. Each of these models is forecast independently, and the best forecast is selected by the model selection list named TBEST. TBEST inherits its holdout and criterion from the root model selection list, SELECT, which is defined in the next group of statements. See "Forecast Model Selection Graph Operation" on page 521 for the definition of the root model selection list.

```
proc hpfesmspec rep=work.rep specname=t1;
   esm method=bests;
run;

proc hpfucmspec rep=work.rep specname=t2;
   level;
   slope;
   irregular;
   season type=dummy length=s;
run;

proc hpfselect rep=work.rep name=tbest;
   spec t1 t2;
run;
```

The following statements define the ARIMA AIRLINE model to generate a forecast that is combined with the forecast selected by TBEST. AICC weights are used for this combination. You must define a model selection list as the basis for running the combination, as described in more detail in the section "Forecast Model Selection Graph Operation" on page 521. The model selection list, named SELECT, defines a holdout of six samples and root mean squared error (RMSE) as the selection criterion.

```
proc hpfarimaspec rep=work.rep specname=airline;
   forecast symbol=y dif=(1,s) q=(1)(1)s noint;
   estimate method=ml converge=.0001 delta=.0001 maxiter=150;
run;

proc hpfselect rep=work.rep name=comb2 label="AICC(TBEST,T3)";
   combine method=aicc;
   spec tbest airline;
run;

proc hpfselect rep=work.rep name=select;
   select holdout=6 criterion=rmse;
   spec comb2;
run;
```

```
proc hpfengine data=sashelp.air
               rep=work.rep
               globalselection=select
               out=out1
               lead=24
               print=(all)
               plot=(components);
   id date interval=month;
   forecast air;
run;
```

Output 17.2.1 Model Selection Results

The HPFENGINE Procedure

Model Selection Criterion = RMSE			
Model	**Statistic**	**Selected**	**Label**
COMB2	20.059523	Yes	AICC(TBEST,T3)

Output 17.2.2 and Output 17.2.3 show the parameter estimates the forecasts that contribute to the combination. Output 17.2.4 shows the parameter estimates for the combined forecast.

Output 17.2.2 Parameter Estimates for T1 Model

Parameter Estimates for T1 Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**Level Weight**	0.30728	0.03153	9.74	<.0001
AIR	**Trend Weight**	0.0010000	0.0030237	0.33	0.7413
AIR	**Seasonal Weight**	0.87493	0.07769	11.26	<.0001

Output 17.2.3 Parameter Estimates for AIRLINE Model

Parameter Estimates for AIRLINE Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
AIR	**MA1_1**	0.30868	0.08433	3.66	0.0003
AIR	**MA2_12**	0.10744	0.10190	1.05	0.2917

Output 17.2.4 Parameter Estimates for Combined Forecast

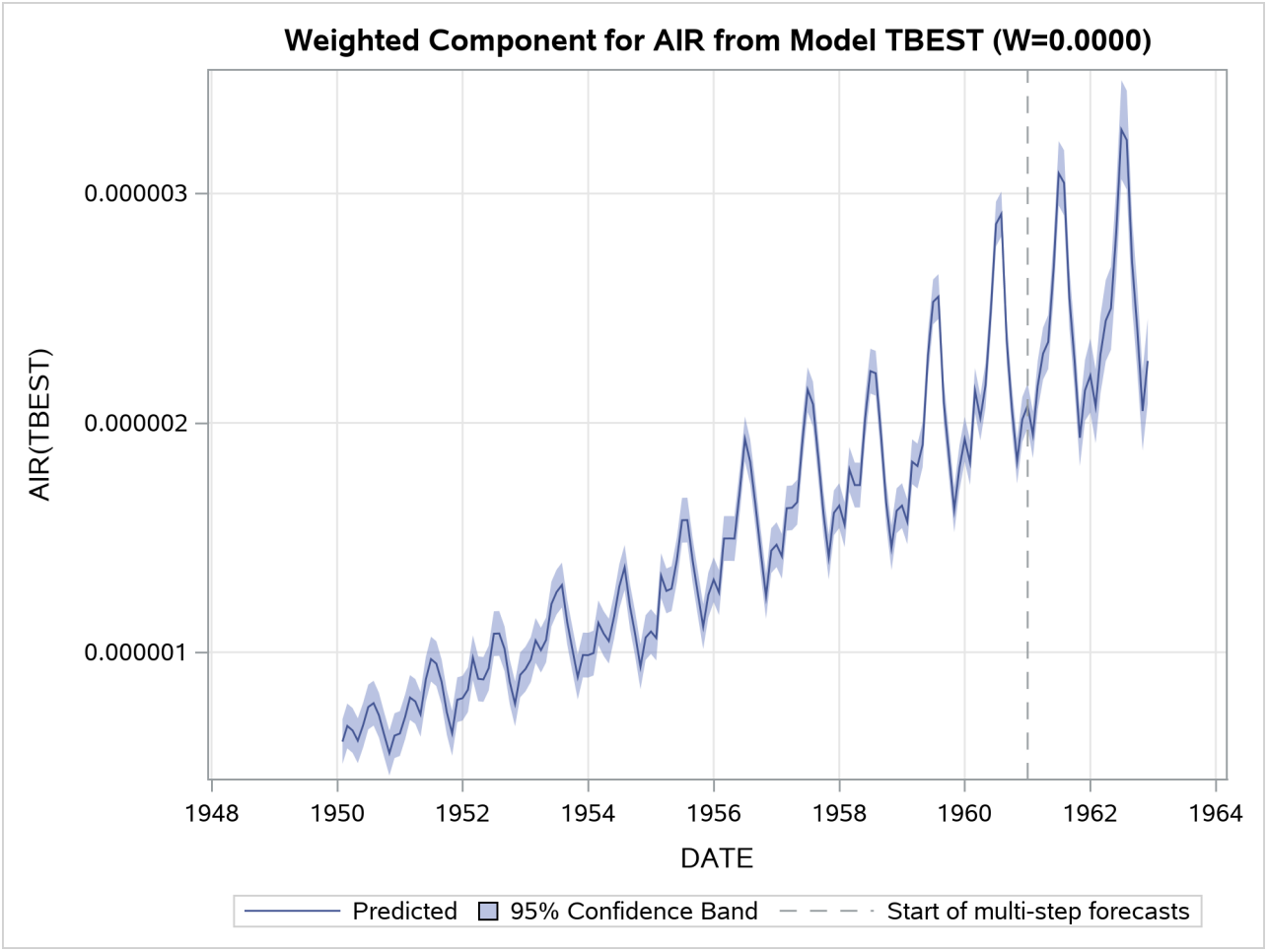
Parameter Estimates for COMB2 Model					
Component	**Parameter**	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**
TBEST	**WEIGHT**	4.65996E-9	.	.	.
AIRLINE	**WEIGHT**	1.00000	.	.	.

From the weights used in COMB2, it is obvious that the AICC weights are heavily slanted towards the ARIMA AIRLINE model. This is not surprising since the ARIMA AIRLINE model is well-tuned from its

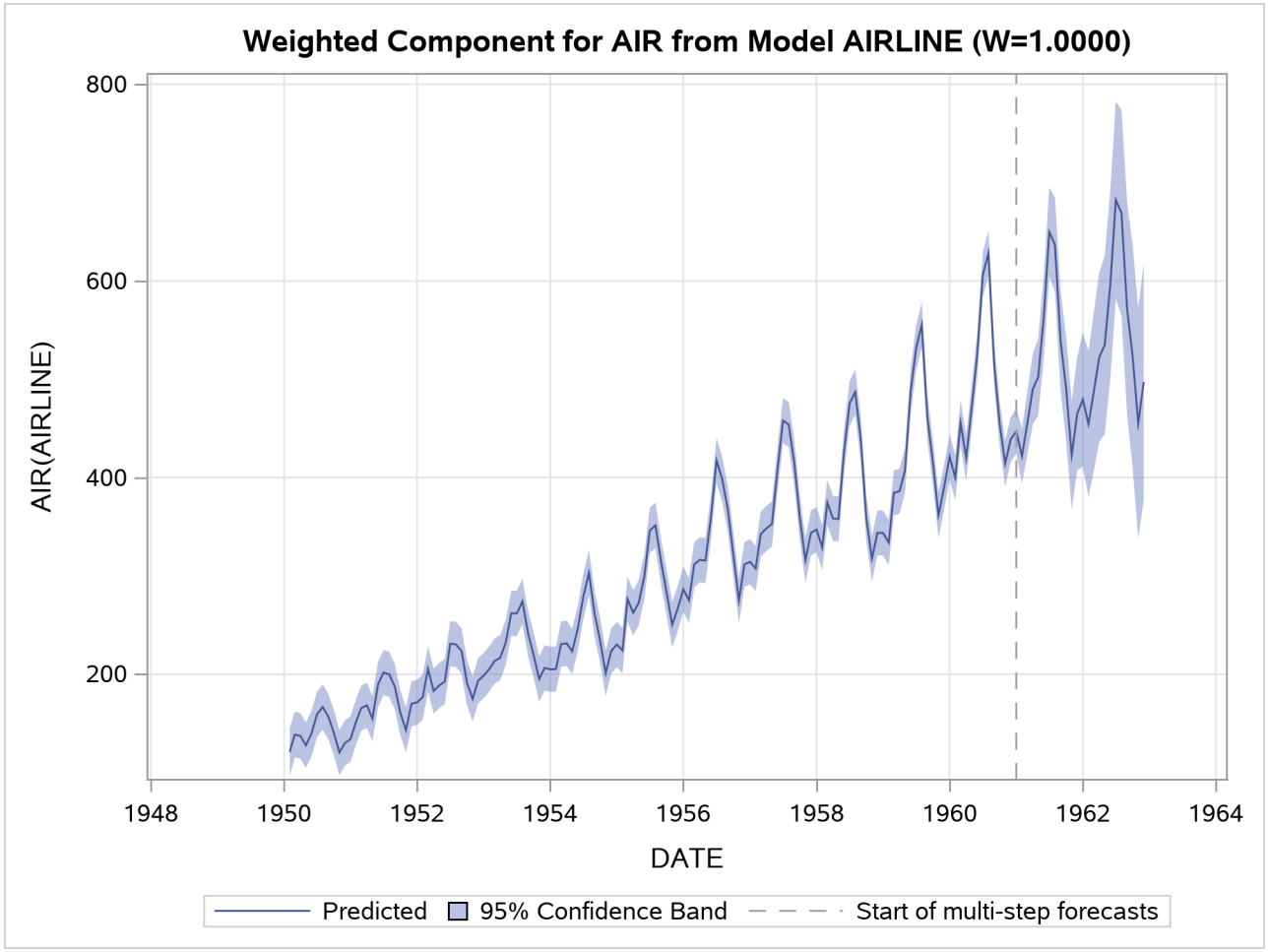
history to model this particular data set.

The weighted components are plotted separately followed by the stack of weighted forecast components as in the previous example. Pay careful attention to the Y-axis scale of the weighted component plot for the TBEST forecast in contrast to the Y-axis scale for the weighted component plot for the AIRLINE model forecast. The stacked component plot clearly reflects the dominance of the AIRLINE model forecast in the combined forecast.

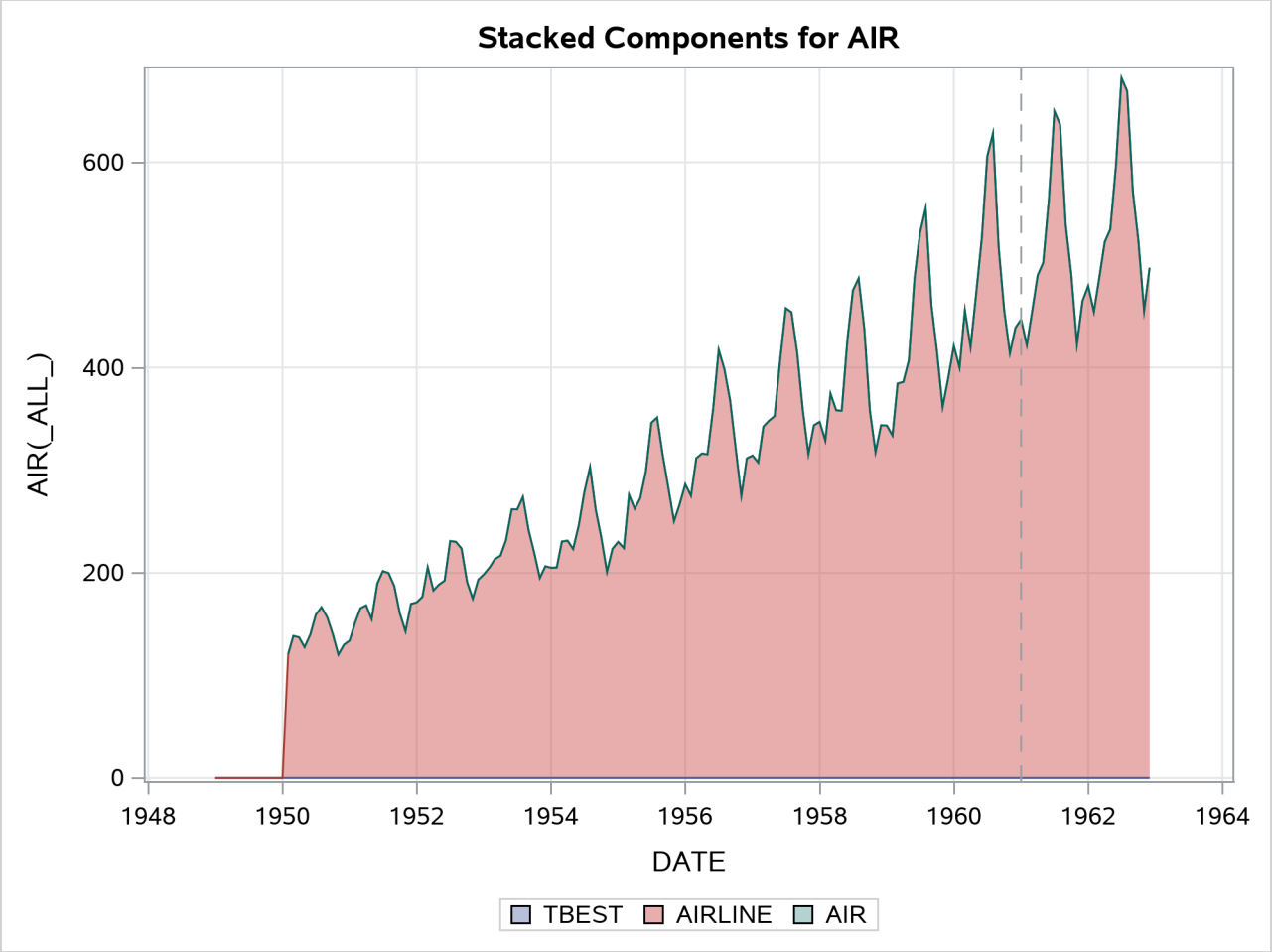
Output 17.2.5 Combined Forecast Components



Output 17.2.6 Combined Forecast Components



Output 17.2.7 Combined Forecast Components

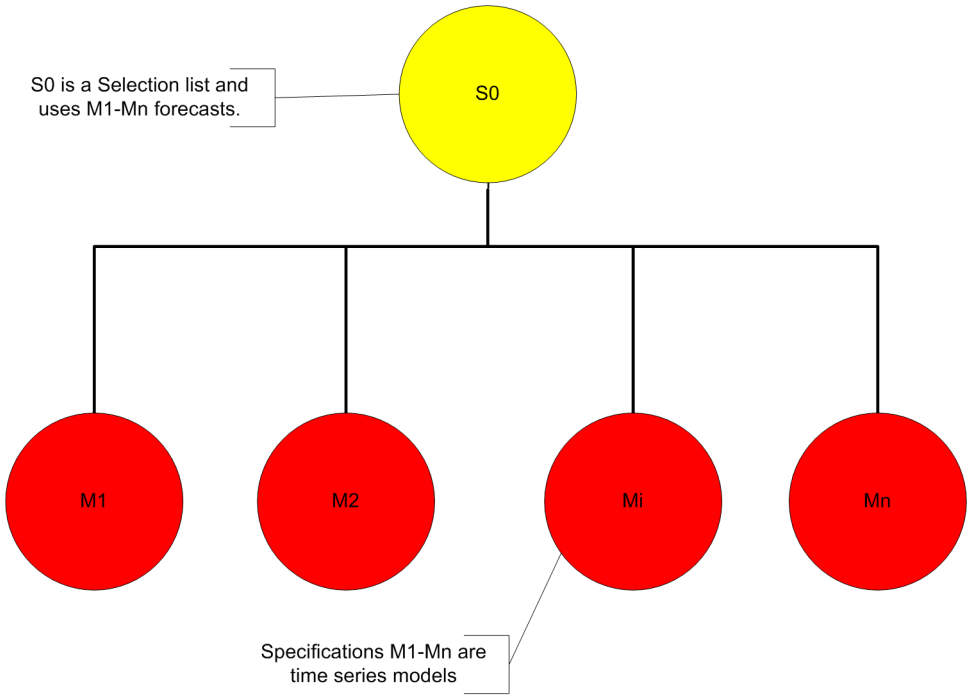


Forecast Model Selection Graph Operation

This section provides some insight into the operation of the forecast model selection graph as it works in the context of the HPFENGINE procedure. This insight can help you understand the behavior of forecast model selection graphs with respect to output data sets and ODS-related output.

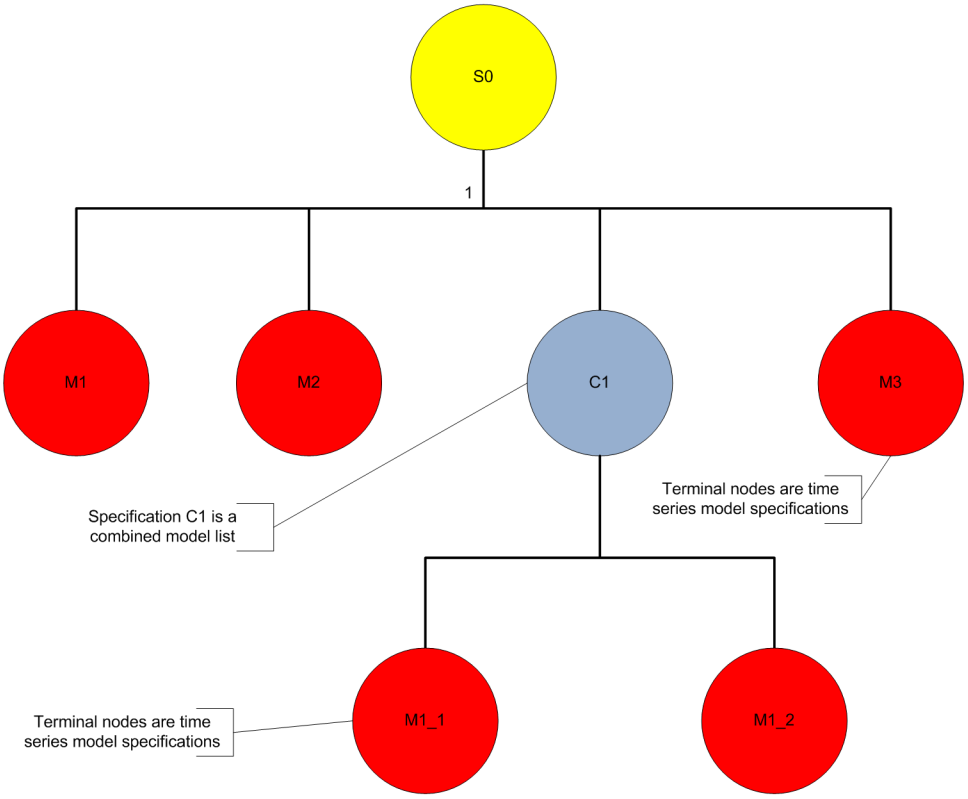
Every time series processed by PROC HPFENGINE during one of its runs uses some form of forecast model selection graph to produce its forecast. Previously these were limited to a one-level model selection list. The model selection list held the names of the time series models in its list. In the context of the forecast model selection graph, more complex forecasting scenarios are now possible. Figure 17.2.8 depicts the forecast model selection graph equivalent for the one-level model selection list.

Output 17.2.8 Simple Model Selection List



Every forecast model selection graph starts with a single root node which must be a model selection list node. The forecast model selection graph generated from the root model selection list must contain at least one time series forecasting model to use in forecasting the time series realization for which it is used. Forecast model selection graphs that have no time series model specifications can produce no forecast by themselves. Obviously, only the last-chance forecasts in PROC HPFENGINE can handle the failed forecast from any such forecast model selection graph; without any time series models in the forecast model selection graph, there is nothing to produce any forecast for any list to either combine or select. Figure 17.1 depicts the forecast model selection graph for a two-level forecasting process.

Figure 17.1 Simple Model Selection Graph



The root model selection list in the forecast model selection graph defines some properties that apply to all of the nodes in the forecast model selection graph. These properties include:

- SELECT statement HOLDOUT= option
- SELECT statement HOLDOUTPCT= option
- DIAGNOSE statement
- FORECASTOPTIONS statement

The stages of PROC HPFENGINE's execution, its so-called "tasks," perform as usual in the context of the more general forecast model selection graph with the natural extension from the one-level model selection list. When a TASK=SELECT invocation is used, the best forecast from the forecast model selection graph is selected. Then the best path through the forecast model selection graph is fitted and forecast to produce a final forecast for any time series realization where it is used. When a TASK=FIT, UPDATE, or FORECAST invocation is used, the saved model and parameter information from a previous OUTEST data set is used to restore the context needed to run the best path through the forecast model selection graph as directed by the specified TASK= option.

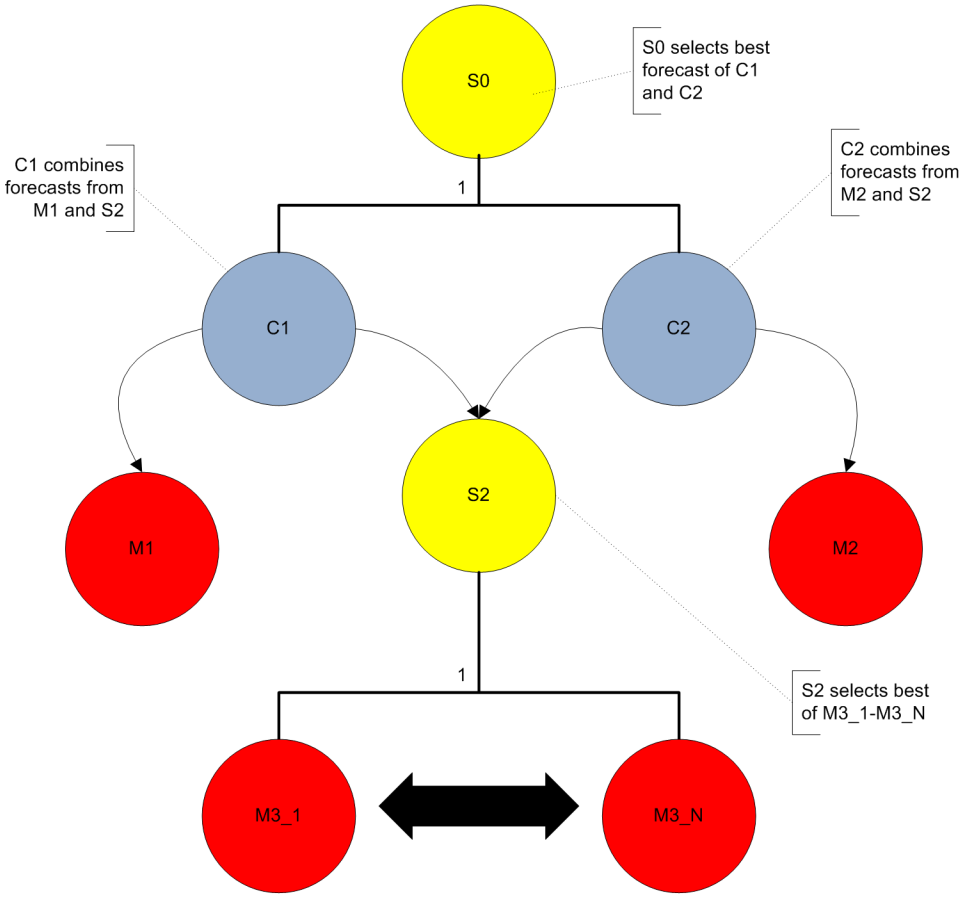
As noted from the examples, the specification name forms the basis for constructing the forecast model selection graph and connecting it together. Nodes in the forecast model selection graph generally fall into two distinct groups: lists and leaf nodes. Leaf nodes, as the name implies, are terminal in the forecast model selection graph. They represent instances of one of the time series model families: ESM, IDM, ARIMA, UCM, or EXM. List nodes, as the name implies, are lists of specifications, or more correctly, specification names. In general, the specification name that appears in a list can be the name of a leaf node or the name of another list. For obvious reasons, cycles are not permitted in the forecast model selection graph (the forecast model selection graph is a rooted-DAG).

Lists fall into two categories:

- the model selection list selects the best of its alternative forecasts according to a selection criterion that is evaluated over some specified region of the forecast. The model selection list's forecast is the forecast of the best of its list of contributors.
- the combined model list combines its contributing forecasts as a weighted average according to a specified method for generating the weights. The combined model list has its own forecast apart from its contributors.

Each node in the forecast model selection graph is viewed by any consumer of its results as the source of a time series forecast. Lists define context that is directly applied to the evaluation of time series models that belong to the list. Each list is uniquely identified in the context of the forecast model selection graph construction by its name, and the topology of the forecast model selection graph is determined by the arcs that connect a list to its specifications. The same time series model specifications can belong to different lists in the forecast model selection graph, and they are evaluated independently in the context of their respective lists. The results of a list can be consumed by many traversal paths through the forecast model selection graph, but the list's results are computed only once when first demanded and then consumed by all traversal paths that reference the list. Apart from the previous discussion of shared root node properties, a list node does not inherit properties accumulated along the traversal path that demands its results. So properties such as the maps are autonomously defined in the scope of each list to satisfy the needs of the time series models that are referenced from the list. Each list is endowed with those properties from its definition via PROC HPFSELECT and subjected overrides from the invocation of PROC HPFENGINE. The isolation of the computation of a list node's forecast from any traversal path context enables all consumers to share its forecast. Figure 17.2 depicts the forecast model selection graph of a forecasting process with multiple nodes that consume the results of a common list node.

Figure 17.2 Complex Model Selection Graph



OUTSTATSELECT Behavior

The OUTSTATSELECT data set receives a record for each forecast that is evaluated during a TASK=SELECT invocation of PROC HPFENGINE. As in the one-level model selection list case, this happens regardless of whether the forecast is used in the final forecast or not. Leaf nodes and combined model list's processed during the TASK=SELECT forecast model selection graph traversal add records to OUTSTATSELECT. Model selection list nodes in the forecast model selection graph traversal produce no records of their own. The following values are generated in the _SELECTED_ column of the OUTSTATSELECT records:

YES — to indicate that the _MODEL_ specification in the OUTSTATSELECT record is selected by the root model selection list in the forecast model selection graph

USED	to indicate that the _MODEL_ specification in the OUTSTATSELECT record is used to produce the selected forecast in the forecast model selection graph
NO	to indicate that the _MODEL_ specification in the OUTSTATSELECT record is neither selected nor used to produced the selected forecast in the forecast model selection graph

OUTEST Behavior

The OUTEST data set receives a set of records for each model that is used during the final forecast traversal path through the forecast model selection graph. Parameter estimate records are added from the lowest level contributor nodes in the traversal path up to the highest level. Each node in the traversal can produce one or more OUTEST data set records.

OUTSTAT Behavior

The OUTSTAT data set receives output for the selected forecast from the root model selection list in the forecast model selection graph. OUTSTAT always receives a record for the parameter estimation or fit region of the forecast. If a forecast performance region is specified via the BACK= option in the PROC HPFENGINE statement, a record is also generated for the selected forecast over the performance region.

OUTMODELINFO Behavior

The OUTMODELINFO data set receives output for the selected model from the root model selection list in the forecast model selection graph. When the selected model is a combined model, the information recorded in the OUTMODELINFO data set reflects characteristics of the models used in the combination. See the section “OUTMODELINFO= Data Set” on page 204 for more details.

OUTSUM Behavior

The OUTSUM data set receives output for the selected forecast from the root model selection list in the forecast model selection graph. When the selected model is a combined model, the forecasts contained in the OUTSUM data set are the combined forecasts.

OUTCOMPONENT Behavior

The OUTCOMPONENT data set receives output for the selected forecast from the root model selection list in the forecast model selection graph. When the selected model is a combined model, the components are the weighted forecasts used to generate the combined model's forecast.

OUTFOR Behavior

The OUTFOR data set receives the forecast that results from the final forecast traversal path through the forecast model selection graph. One collection of OUTFOR records is produced for the requested time span for the time series being forecast.

OUT Behavior

The OUT data set receives the forecast that results from the final forecast traversal path through the forecast model selection graph. One collection of OUTFOR records is produced for the time span for the time series being forecast.

ODS Print Behavior

Requested ODS tables are printed for the selected forecast from the root model selection list in the forecast model selection graph with the following exceptions:

- The ODS ModelSelection table displays information for each forecast considered in the root model selection list.
- The ODS Estimates table is repeated as needed to display parameter estimates for the models used during the final forecast traversal path through the forecast model selection graph. Tables are printed from the lowest level contributor nodes up to the highest level contributor nodes.

ODS Plot Behavior

Requested ODS plots are generated for the selected forecast from the root model selection list in the forecast model selection graph.

Chapter 18
Using Forecasting Model Score Files and DATA Step Functions

Contents

Overview **529**
HPFSCSIG Function **529**
Example 18.1: HPFSGSIG Use 530
HPFSCSUB Function **531**
Example 18.2: HPFSCSUB Use 532

Overview

The HPFENGINE procedure can generate forecast score files. The HPFSCSIG and HPFSCSUB functions are used in conjunction with these score files to produce forecasts.

HPFSCSIG Function

The HPFSCSIG function creates a text string that represents a template for the appropriate usage of the HPFSCSUB function given a forecast scoring file.

Syntax

HPFSCSIG *(scoreFile, horizon, outType)* **;**

scoreFile is a SAS file reference that contains the forecast scoring information.

horizon is the forecast horizon or lead. This must be a positive integer value.

outType is one of the following strings: PREDICT, STDERR, LOWER, or UPPER. *OutType* determines whether the score function computes and returns the forecast value, standard error, lower confidence limit, or upper confidence limit, respectively. By default a 95% confidence interval($\alpha = 0.05$) is assumed for computing critical values for upper and lower confidence limits. You can change this by specifying the alternate syntax Lxx for LOWER or Uxx for UPPER where xx is the confidence interval percentage desired($\alpha = (100 - xx)/100$). The legal range for xx is $0 < xx \leq 99$.

Details

The syntax of the forecast scoring function is variable and depends on the horizon and certain details found in the score file. HPFSCSIG aids the user in constructing subroutine calls with the correct syntax.

Example 18.1: HPFSGSIG Use

Consider the following case of an ARIMAX model with three inputs. Two of them are predefined trend curves, and the third is specified as controllable in the call to PROC HPFENGINE. A score file is produced, and HPFSCSIG called to provide a template for the call of HPFSCSUB.

```
   data air;
      set sashelp.air;
      controlinput = log(air);
   run;

proc hpfarimaspec modelrepository=work.repo
                  specname=ar;
   dependent symbol=Y q=1 dif=12;
   input predefined=LINEAR;
   input symbol=controlinput;
   input predefined=INVERSE;
run;

proc hpfselect modelrepository=work.repo
               selectname=select;
   spec ar;
run;

proc hpfengine data=air
               print=(select estimates)
               modelrepository=work.repo
               globalselection=select
               outest=engineoutest
               scorerepository=work.scores;
   id date interval=month;
   forecast air;
   controllable controlinput / extend=avg;
   score;
run;

filename score catalog "work.scores.scor0.xml";

data a;
   sig = hpfscsig( 'score', 3, 'predict' );
   put sig=;
run;

proc print data=a;
run;
```

The HPFSCSIG function call produces the result shown in Figure 18.1.1.

Output 18.1.1 Result of the HPFSCSIG Function Call

Obs	sig
1	HPFSCSUB('XML',3,'controlinput',?,?,?,'PREDICT',!,!,!)

Provide the pre-assigned SAS fileref in place of the XML, replace the question marks (?) with the desired inputs, and the output is written to variables placed where there are exclamation marks (!).

HPFSCSUB Function

The HPFSCSUB function returns the forecasts, standard errors, or confidence limits given a forecast scoring file and future values of all controllable inputs.

Syntax

HPFSCSUB *(scoreFile, horizon,* $X_1, X_{1,1}, \ldots, X_{1,horizon}, \ldots, X_j, X_{j,1}, \ldots, X_{j,horizon}, \ldots,$ *outType,* $O_1, \ldots, O_{horizon},$ *<,name-value-pair, ... >)* **;**

scoreFile is a SAS file reference that contains the forecast scoring information.

horizon is the forecast horizon or lead. This must be a positive integer value.

X_j specifies the name of a controllable variable needed to produce forecasts. The next *horizon* arguments are the future inputs for controllable variable X_j.

$X_{j,k}$ is the value for the controllable variable X_j at horizon k. For each X_j you must specify numeric arguments $X_{j,1}$ through $X_{j,horizon}$.

outType is one of the following strings: PREDICT, STDERR, LOWER, or UPPER. *outType* determines whether the score function computes and returns the forecast value, standard error, lower confidence limit, or upper confidence limit, respectively. By default a 95% confidence interval($\alpha = 0.05$) is assumed for computing critical values for upper and lower confidence limits. You can change this by specifying the alternate syntax Lxx for LOWER or Uxx for UPPER where xx is the confidence interval percentage desired($\alpha = (100 - xx)/100$). The legal range for xx is $0 < xx \leq 99$.

O_k is the subroutine output at horizon k. You must specify arguments O_1 through $O_{horizon}$ as numeric variables.

You can specify optional name-value pairs (*name-value-pair* arguments) the HPFSCSUB call. These optional arguments allow you to specify settings that alter the behavior of the HPFSCSUB call. These *name-value-pair* arguments must be specified in groups of two. The first argument in each pair must be a character string (literal or character variable) that identifies the name of a property you wish to set. Property names begin and end with a "." character. The type of the second argument depends on the on the property name that you specify, as do the values that are accepted for it.

You can specify the following property name values:

.HORIZONSTART. specifies the time stamp value that is used to determine the starting time index that corresponds to $X_{j,1}$ and O_1. The value argument must be numeric. It is interpreted as a SAS DATE or DATETIME value, and it must be consistent with the units for the time ID variable that was specified in the PROC HPFENGINE step that created the score file. The time stamp value that you specify must fall into a time period in the region of multi-step forecasts that are produced from the PROC HPFENGINE step that created the score file; otherwise, the HPFSCSUB call generates an error.

Details

The HPFSCSUB function returns the forecasts, standard errors, or confidence limits given a forecast scoring file and future values of all controllable inputs. Because the syntax is variable and depends on the input score file, HPFSCSIG is normally used to determine the layout of the subroutine call.

The score might have been computed using ARIMAX, UCM, or another model. HPFSCSUB automatically detects this and computes the requested return values appropriately.

Example 18.2: HPFSCSUB Use

This example demonstrates how to use the HPFSCSUB function for a simple case. It uses the score file from PROC HPFENGINE to compute a forecast. The score file is stored in the scor0 entry within the catalog work.score. Note that in the ARIMAX model specification there are two transfer functions with PREDEFINED= behavior and one based on the symbol Controlinput. Note that even though the model includes three inputs, it is only necessary to designate the variable Controlinput as controllable in the PROC HPFENGINE invocation. Therefore, only future values of the variable Controlinput are required to generate forecasts by using the score file. Future values of the other inputs are determined automatically by their respective predefined behavior in the model specification.

In the call to PROC HPFENGINE, the controllable input was extended with the mean of the Controlinput series. Therefore the mean is used as input to the forecast score function so that a valid comparison can be made between the forecast results from PROC HPFENGINE and HPFSCSUB.

```
proc hpfarimaspec modelrepository=work.repo
                  specname=ar;
   dependent symbol=Y q=1 dif=12;
   input predefined=LINEAR;
   input symbol=controlinput;
   input predefined=INVERSE;
run;

proc hpfselect modelrepository=work.repo
               selectname=select;
   spec ar;
run;

* generate score;
proc hpfengine data=air
               modelrepository=work.repo
               out=engineout
               globalselection=select
```

```
                scorerepository=work.scores;
   id date interval=month;
   forecast air;
   controllable controlinput / extend=avg;
   score;
run;

filename score catalog "work.scores.scor0.xml";

proc means data=air mean noprint;
   var controlinput;
   output out=controlmean mean=mean;
run;

data _null_;
   set controlmean;
   call symput( "mean", mean );
run;


data forecasts;
   array p{3} p1-p3;
   keep date forecast;

   format date monyy.;
   date = '01jan1961'd;

   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'PREDICT', p1, p2, p3 );
   do i=1 to 3;
     forecast = p{i};
     output;
     date = intnx('month', date, 1);
   end;
run;

data compare;
   merge engineout forecasts;
   by date;
run;

proc print data=compare(where=(forecast ne .)) noobs;
run;
```

Figure 18.2.1 shows the output generated by the preceding statements.

Output 18.2.1 Output from Example

DATE	AIR	forecast
JAN1961	416.408	416.408
FEB1961	391.715	391.715
MAR1961	419.312	419.312

Continuing the previous example, you can also specify the confidence interval percentage points for HPFSC-

SUB as the following sample code demonstrates. Observe that you can specify different percentage points for the upper and lower critical values to obtain asymmetric limit bands.

You should note that even though you specify the 'Uxx' or 'Lxx' selectors independently of each other, the critical Z-value computed is that for a symmetric two-sided confidence interval. In order to affect a true 1-sided confidence limit, you can make the appropriate adjustment in the 2-sided percentage point you provide in the selector string or perform a custom calculation in DATA step code using the desired percentage point value in the PROBIT function in conjunction with the HPSCSUB function returns for 'PREDICT' and 'STDERR'. The following DATA step demonstrates using this technique to directly compute the corresponding upper and lower confidence interval limits as a comparison to the values returned from HPFSCSUB.

```
data myoutfor;
   array p{3} p1-p3;
   array se{3} se1-se3;
   array ucl{3} ucl1-ucl3;
   array lcl{3} lcl1-lcl3;
   keep date scucl sclcl myucl mylcl;

   format date monyy.;
   date = '01jan1961'd;

   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'PREDICT', p1, p2, p3 );
   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'STDERR', se1, se2, se3 );
   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'L99', lcl1, lcl2, lcl3 );
   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'U90', ucl1, ucl2, ucl3 );
   do i=1 to 3;
       scucl = ucl{i};
       sclcl = lcl{i};
       myucl=p{i} + probit(1-0.1/2) * se{i};
       mylcl=p{i} - probit(1-0.01/2) * se{i};
       output;
       date = intnx('month', date, 1);
   end;
run;

proc print data=myoutfor noobs;
run;
```

Figure 18.2.2 shows the output generated by the preceding statements.

Output 18.2.2 Output from Example

date	scucl	sclcl	myucl	mylcl
JAN61	435.744	386.128	435.744	386.128
FEB61	413.103	358.221	413.103	358.221
MAR61	440.700	385.817	440.700	385.817

The previous example can be extended to demonstrate the use of optional property-value pairs in the HPFSCSUB call. Suppose that you only want to control the forecast response for the last three periods of the 12 month horizon in the score file that was generated by the PROC HPFENGINE step. You can use the *.HORIZONSTART.* property to set the start of the forecast horizon to 01OCT1961 with a *horizon* argument of 3. HPFSCSUB then uses the values for the controllable variables prior to 01OCT1961 from the PROC HPFENGINE step so that you only specify future values for the periods 01OCT1961 through 01DEC1961.

```
data last3;
   array p{3} p1-p3;
   array se{3} se1-se3;
   array ucl{3} ucl1-ucl3;
   array lcl{3} lcl1-lcl3;
   keep date scucl sclcl myucl mylcl;

   format date monyy.;
   date = '01oct1961'd;

   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'PREDICT', p1, p2, p3, '.horizonstart.', date);
   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'STDERR', se1, se2, se3, '.horizonstart.', date);
   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'L99', lcl1, lcl2, lcl3, '.horizonstart.', date);
   call HPFSCSUB( 'score', 3, 'CONTROLINPUT', &mean, &mean, &mean,
                  'U90', ucl1, ucl2, ucl3, '.horizonstart.', date);
   do i=1 to 3;
       scucl = ucl{i};
       sclcl = lcl{i};
       myucl=p{i} + probit(1-0.1/2) * se{i};
       mylcl=p{i} - probit(1-0.01/2) * se{i};
       output;
       date = intnx('month', date, 1);
   end;
run;

proc print data=last3 noobs;
run;
```

Figure 18.2.3 shows the output generated by the preceding statements.

Output 18.2.3 Output from Example

date	scucl	sclcl	myucl	mylcl
OCT61	479.878	424.995	479.878	424.995
NOV61	408.475	353.592	408.475	353.592
DEC61	450.072	395.189	450.072	395.189

The use of the *.HORIZONSTART.* property is particularly useful in conjunction with the HORIZONSTART= option from the PROC HPFENGINE ID statement. The *.HORIZONSTART.* property allows you to set the time index where you expect to logically begin the specification of future values for the controllable variables without regard to the exact point in time where multi-step forecasting begins (multi-step forecasting can begin prior to the HORIZONSTART= time if the dependent series ends in missing values). You should refer

to the Examples section for PROC HPFENGINE for additional information about using HPFSCSUB. There you will find a more substantial example demonstrating the integration of optimization and forecasting.

Chapter 19
Using User-Defined Models

Contents

Introduction 537
Defining and Using a SAS Language Function or Subroutine 539
Defining and Using a C Language External Function 542
Input Time Series Keywords 546
Returned Forecast Component Keywords 546

Introduction

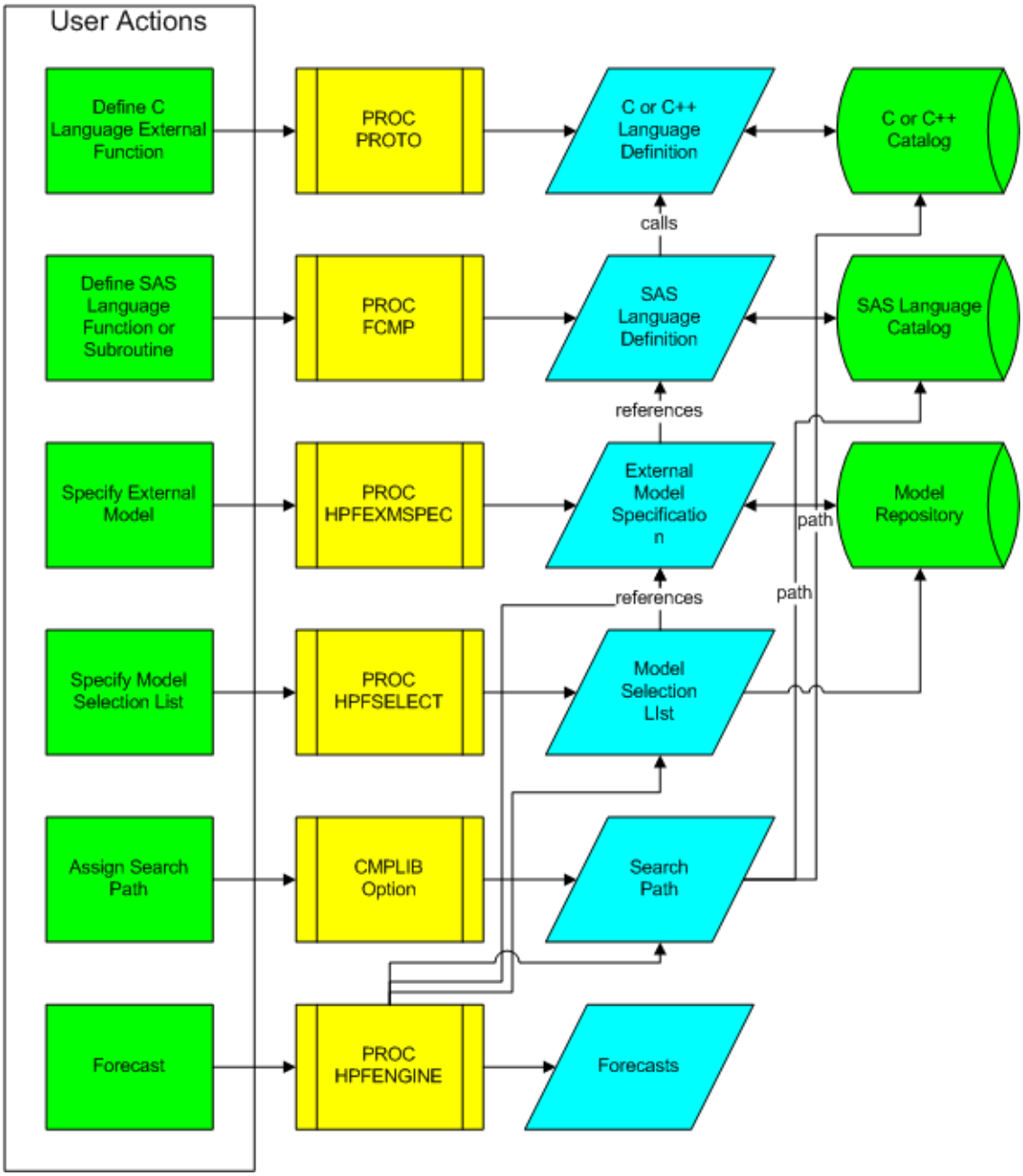
You can use user-defined forecasting models in the SAS Forecast Server Procedures software. The forecasts that are produced by these models are considered external forecasts because they are forecasts that originate from an external source.

A user-defined forecasting model can be written in the SAS language or in the C language by using the FCMP procedure or the PROTO procedure, respectively. The HPFENGINE procedure cannot use C language routines directly. The procedure can use only SAS language routines that might or might not call C language routines. Creating user-defined routines is more completely described in the FCMP procedure and the PROTO procedure documentation. For more information about the FCMP and PROTO procedures, see the *Base SAS Procedures Guide*.

The SAS language provides integrated memory management and exception handling such as operations on missing values. The C language provides flexibility and enables the integration of existing C language libraries. However, proper memory management and exception handling are solely the responsibility of the user. Additionally, the support for standard C libraries is restricted. If given a choice, it is highly recommended that user-defined functions and subroutines and functions be written in the SAS language using the FCMP procedure.

In order to use a SAS language function or routine, an external model specification must also be specified. In order to use a C or C++ language external function, it must be called by a SAS language function or subroutine, and an external model specification must also be specified. External model specifications are specified by the HPFEXMSPEC procedure. The following diagram describes an example of the ways user-defined forecasting models can be defined, specified, and used to forecast.

Figure 19.1 User-Defined Forecasting Models



The SAS language function or routine can call other SAS language functions or routines as long as the search path for these functions and routines are provided.

Defining and Using a SAS Language Function or Subroutine

The FCMP procedure provides a simple interface for compiling functions and subroutines for use by the SAS Forecast Server Procedures software. The FCMP procedure accepts a slight variant of the SAS DATA step language. Most features of the SAS programming language can be used in functions and subroutines processed by the FCMP procedure. For more information about the FCMP procedure, see the *Base SAS Procedures Guide*.

For example, the following SAS statement creates a user-defined forecasting model for a simple linear trend line called LINEARTREND that is written in the SAS language and stores this subroutine in the catalog WORK.HPFUSER. The user-defined forecasting model has the following subroutine signature:

```
subroutine <subroutine-name> ( <array-name>[*], <array-name>[*],
                               <array-name>[*], <array-name>[*],
                               <array-name>[*] );
```

where the first array, ACTUAL, contains the time series to be forecast, the second array, PREDICT, contains the returned predictions, the third array, STD, contains the returned prediction standard errors, the fourth array, LOWER, contains the returned lower confidence limits, and the fifth array, UPPER, contains the returned upper confidence limits.

```
proc fcmp outlib=work.hpfuser.funcs;
   subroutine lineartrend( actual[*], predict[*], std[*],
                           lower[*], upper[*] );
      outargs predict, std, lower, upper;
      nobs = dim(actual);
      n      = 0;
      sumx   = 0;
      sumx2  = 0;
      sumxy  = 0;
      sumy   = 0;
      sumy2  = 0;

      do t = 1 to nobs;
         value = actual[t];
         if nmiss(value) = 0 then do;
            n     = n     + 1;
            sumx  = sumx  + t;
            sumx2 = sumx2 + t*t;
            sumxy = sumxy + t*value;
            sumy  = sumy  + value;
            sumy2 = sumy2 + value*value;
         end;
      end;

      det = (n*sumx2 - sumx*sumx);
      constant = (sumx2 * sumy - sumx * sumxy) / det;
      slope    = (-sumx  * sumy + n    * sumxy) / det;
      length = DIM(predict);
      do t = 1 to length;
         predict[t] = constant + slope*t;
      end;
```

```
      sume2 = 0;
      do t = 1 to nobs;
         value = actual[t];
         if nmiss(value) = 0 then do;
            error = value - predict[t];
            sume2  = sume2 + error*error;
         end;
      end;

      stderr   = sqrt(sume2 / (n-2));
      zvalue   = probit(1-0.05/2);
      width    = zvalue*stderr;
      length = DIM(predict);
      do t = 1 to length;
         std[t]     = stderr;
         lower[t]   = predict[t] - width;
         upper[t]   = predict[t] + width;
      end;

   endsub;
quit;
```

In order to use a user-defined forecasting model, an external forecast model specification must be specified using the HPFEXMSPEC procedure. For example, the following SAS statements create an external model specification called LINEARTREND and store this model specification in the catalog WORK.MYREPOSITORY. Since the user-defined forecasting model uses two parameters, CONSTANT and SLOPE, the NPARMS=2 option is specified in the EXM statement. The number specified in this option is used for computing statistics of fit (for example, RMSE, AIC, and BIC).

```
proc hpfexmspec modelrepository=work.myrepository
                specname=lineartrend
                speclabel="User defined linear trend";
   exm nparms=2;
run;
```

The HPFSELECT procedure can be used to create a model selection list that contains an external model specification as a possible candidate model. For example, the following SAS statements create a model selection list called MYSELECT and store this model selection list in the catalog WORK.MYREPOSITORY.

```
proc hpfselect modelrepository=work.myrepository
               selectname=myselect
               selectlabel="My Select List";
   spec lineartrend /
      exmfunc(
      "lineartrend(_actual_ _predict_ _stderr_ _lower_ _upper_)"
      );
run;
```

To use the user-defined forecasting model defined by the FCMP procedure in the HPFENGINE procedure, the CMPLIB option must list the catalogs that contain the SAS language functions and routines. For more information about the FCMP procedure, see the *Base SAS Procedures Guide*.

For example, the following SAS statement specifies the SAS catalogs that are required to use the user-defined

forecasting model.

```
options cmplib= work.hpfuser;
```

At this point:

- A SAS language subroutine has been defined, LINEARTREND, and stored in the SAS catalog, WORK.HPFUSER.
- An external model specification, LINEARTREND, has been stored in the model repository, WORK.MYREPOSITORY.
- A model selection list, MYSELECT, has been stored in the model repository, WORK.MYREPOSITORY.
- The search path for the SAS language functions and subroutines has been set to WORK.HPFUSER.

The HPFENGINE procedure can now use the user-defined forecasting routine.

For example, the following SAS statements forecast the monthly time series contained in the SASHELP.AIR data set. This data set contains two variables DATE and AIR. The MODELREPOSITORY= WORK.MYREPOSITORY option of the PROC HPFENGINE statement specifies the model repository, and the GLOBALSELECTION=MYSELECT options specifies the model selection list.

```
proc hpfengine data=sashelp.air
               out=cmpout
               outfor=cmpfor
               outstat=cmpstat
               modelrepository=myrepository
               globalselection=myselect;
   id date interval=month;
   forecast air;
run;
```

The OUT= data set contains the original data extrapolated by the simple linear trend model (values returned in the _PREDICT_ array), and the OUTFOR= data set contains the forecasts (values returned in the _PREDICT_, _STDERR_, _LOWER_, and _UPPER_ array) and the prediction errors. The OUTSTAT= data set contains the statistics of fit based on the prediction errors and the NPARMS=2 option of the external model specification.

Defining and Using a C Language External Function

The PROTO procedure enables you to register, in batch, external functions written in the C or C++ programming languages for use in SAS. In order to use an external function, it must be called from a SAS language function or subroutine. For more information about the PROTO procedure, see the *Base SAS Procedures Guide*.

For example, the following SAS statements create a user-defined forecasting model for a simple linear trend line called LINEARTREND_C that is written in the C language and store this external function in the catalog WORK.CHPFUSER.

```
proc proto package=work.chpfuser.cfuncs;
   double lineartrend_c( double   zvalue,
                         double * actual,
                         int      actualLength,
                         double * predict,
                         double * std,
                         double * lower,
                         double * upper,
                         int      predictLength );
   externc lineartrend_c;
      double lineartrend_c( double   zvalue,
                            double * actual,
                            int      actualLength,
                            double * predict,
                            double * std,
                            double * lower,
                            double * upper,
                            int      predictLength ) {

      int      t, n;
      double   value, sumxy, sumx, sumx2, sumy, sumy2;
      double   det, constant, slope, stderr, width;
      double   error, sume2;
      n      = 0;
      sumx   = 0;
      sumx2  = 0.;
      sumxy  = 0.;
      sumy   = 0.;
      sumy2  = 0.;
      for ( t = 0; t < actualLength; t ++ ) {
         value = actual[t];
         n     = n     + 1;
         sumx  = sumx  + t;
         sumx2 = sumx2 + t*t;
         sumxy = sumxy + t*value;
         sumy  = sumy  + value;
         sumy2 = sumy2 + value*value;
      }

      det = (n*sumx2 - sumx*sumx);
      constant = (sumx2 * sumy - sumx * sumxy) / det;
```

```
      slope    = (-sumx  * sumy + n    * sumxy) / det;
      for ( t = 0; t < predictLength; t ++ ) {
         predict[t] = constant + slope*t;
      }

      sume2 = 0;
      for ( t = 0; t < actualLength; t ++ ) {
         value = actual[t];
         error = value - predict[t];
         sume2  = sume2 + error*error;
      }

      stderr   = sqrt(sume2 / (n-2.));
      width    = zvalue*stderr;
      for ( t = 0; t < predictLength; t ++ ) {
         std[t]     = stderr;
         lower[t]   = predict[t] - width;
         upper[t]   = predict[t] + width;
      }
   return(0);
   }
externcend;
run;
```

The following SAS statements create a user-defined forecasting model for a simple linear trend called LINEARTREND and store this subroutine in the catalog WORK.HPFUSER. The catalog WORK.CHPFUSER contains functions or subroutines that are used in LINEARTREND. The user-defined forecasting model has the following subroutine signature:

```
SUBROUTINE <SUBROUTINE-NAME> ( <ARRAY-NAME>[*], <ARRAY-NAME>[*],
                               <ARRAY-NAME>[*], <ARRAY-NAME>[*],
                               <ARRAY-NAME>[*] );
```

where the first array, ACTUAL, contains the time series to be forecast, the second array, PREDICT, contains the return predictions, the third array, STD, contains the returned prediction standard errors, the fourth array, LOWER, contains the return lower confidence limits, and the fifth array, UPPER, contains the return upper confidence limits. The LINEARTREND subroutine calls the external function LINEARTREND_C. The DIM function returns the length of the array. For example, the DIM(ACTUAL) function returns the length of the time series array; and the DIM(PREDICT) returns the length of the prediction array. DIM(PREDICT) DIM(ACTUAL) represents the forecast horizon or lead.

```
proc fcmp outlib=work.hpfuser.funcs
          inlib=work.chpfuser;
   subroutine lineartrend( actual[*], predict[*],
                           std[*], lower[*], upper[*] );
      outargs actual, predict, std, lower, upper;
      zvalue = probit(1-0.05/2);
      ret = lineartrend_c( zvalue, actual, DIM(actual),
                           predict, std, lower, upper, DIM(predict));
   endsub;
quit;
```

In order to use a user-defined forecasting model, an external forecast model specification must be specified using the HPFEXMSPEC procedure. For example, the following SAS statements create an external model spec-

ification called LINEARTREND and store this model specification in the catalog WORK.MYREPOSITORY. Since the user-defined forecasting model uses two parameters, CONSTANT and SLOPE, the NPARMS=2 option is specified in the EXM statement. The number specified in this option is used in computing statistics of fit.

```
proc hpfexmspec modelrepository=work.myrepository
                specname=lineartrend
                speclabel="User defined linear trend";
   exm nparms=2;
run;
```

The HPFSELECT procedure can be used to create a model selection list that contains an external model specification as a possible candidate model. For example, the following SAS statements create a model selection list called MYSELECT and store this model selection list in the catalog WORK.MYREPOSITORY. The keyword _PREDICT_ indicates the returned predictions, the keyword _STDERR_ indicates the returned prediction standard errors, the keyword _LOWER_ indicates the returned lower confidence limits, and the keyword _UPPER_ indicates the returned upper confidence limits.

```
proc hpfselect modelrepository=work.myrepository
               selectname=myselect
               selectlabel="My Select List";
   spec lineartrend /
      exmfunc(
      "lineartrend(_actual_ _predict_ _stderr_ _lower_ _upper_)"
      );
run;
```

To use the user-defined forecasting model defined by the FCMP procedure in the HPFENGINE procedure, the CMPLIB option must list the catalogs that contains the SAS language functions and routines and C language external functions. For more information about the FCMP procedure, see the *Base SAS Procedures Guide*.

For example, the following SAS statement specifies the SAS catalogs that are required to use a user-defined forecasting model.

```
options cmplib=( work.hpfuser work.chpfuser);
```

At this point:

- A C language external function has been defined, LINEARTREND_C, and stored in the SAS catalog, WORK.CHPFUSER.
- A SAS language subroutine has been defined, LINEARTREND, which calls the external function, LINEARTREND_C, and stored in the SAS catalog, WORK.HPFUSER.
- An external model specification, LINEARTREND, has been stored in the model repository, WORK.MYREPOSITORY.
- A model selection list, MYSELECT, has been stored in the model repository, WORK.MYREPOSITORY.
- The search path for the SAS language functions and subroutines has been set to WORK.HPFUSER and WORK.CHPFUSER.

The HPFENGINE procedure can now use the user-defined forecasting routine.

For example, the following SAS statements forecast the monthly time series contained in the SASHELP.AIR data set. This data set contains two variables DATE and AIR. The MODELREPOSITORY= WORK.MYREPOSITORY option of the PROC HPFENGINE statement specifies the model repository, and the GLOBALSELECTION=MYSELECT options specifies the model selection list.

```
proc hpfengine data=sashelp.air
               out=proout
               outfor=profor
               outstat=prostat
               modelrepository=myrepository
               globalselection=myselect;
   id date interval=month;
   forecast air;
run;
```

The OUT= data set contains the original data extrapolated by the simple linear trend model (values returned in the _PREDICT_ array), and the OUTFOR= data set contains the forecasts (values returned in the _PREDICT_, _STDERR_, _LOWER_, and _UPPER_ array) and the prediction errors. The OUTSTAT= data set contains the statistics of fit based on the prediction errors and the NPARMS=2 option of the external model specification.

Output 19.2 shows the results of a PROC COMPARE run that compares the forecasts from the OUTFOR= data sets from these two implementations of the same algorithm.

Figure 19.2 Comparison of OUTFOR Data Sets

```
                    Observation Summary

                Observation      Base  Compare

                First Obs           1        1
                Last  Obs         156      156

Number of Observations in Common: 156.
Total Number of Observations Read from WORK.CMPFOR: 156.
Total Number of Observations Read from WORK.PROFOR: 156.

Number of Observations with Some Compared Variables Unequal: 0.
Number of Observations with All Compared Variables Equal: 156.


                  Values Comparison Summary

Number of Variables Compared with All Observations Equal: 8.
Number of Variables Compared with Some Observations Unequal: 0.
Total Number of Values which Compare Unequal: 0.
Total Number of Values not EXACTLY Equal: 102.
Maximum Difference: 5.6843E-14.
```

Input Time Series Keywords

The user can specify keywords related to the input time series in the EXMFUNC option of the SPECIFICATION statement in the HPFSELECT procedure. The _TIMEID_ keyword specifies that the time ID values are passed as input arrays to the user-defined forecasting model. The _SEASON_ keyword specifies that the season index values are passed as input arrays to the user-defined forecasting model.

Returned Forecast Component Keywords

A user-defined forecasting function or subroutine must return the predictions, specified by the keyword _PREDICT_ in the signature description found in the EXMFUNC option of the SPECIFICATION statement in the HPFSELECT procedure. The prediction standard errors and the lower and upper confidence limits are optional and are specified by the keywords, _STDERR_, _LOWER_, and _UPPER_, respectively. The HPFENGINE procedure computes the forecast components that are not returned by the user-defined forecasting function based on the external model specification.

Chapter 20
Using External Forecasts

Contents

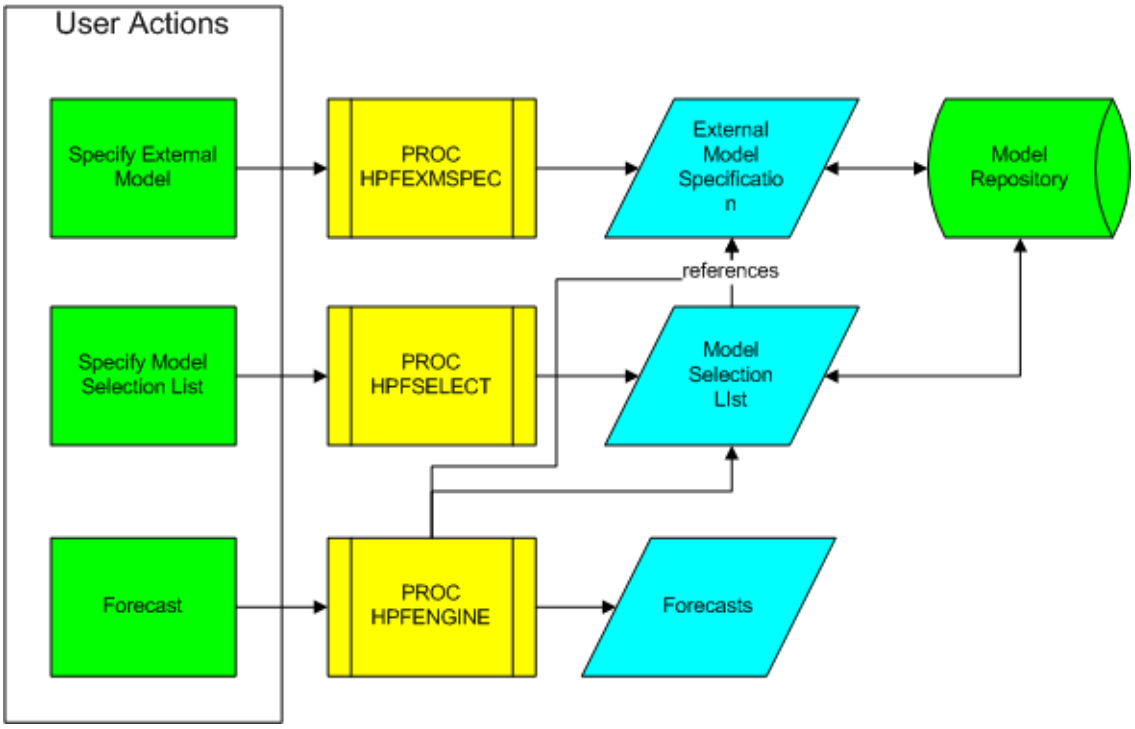
Introduction 547
Specifying and Using an External Model Specification 548

Introduction

External forecasts are forecasts provided by an external source. External forecasts can originate from a statistical model or from another software package, and can have been provided by an outside organization (for example, marketing organization or government agency), or might be given based solely on judgment.

To use an external forecast in SAS Forecast Server Procedures software, an external model specification must be specified using the HPFEXMSPEC procedure. The model specification describes statistical properties of how the forecast was derived. Figure 20.1 describes an example of the ways external forecasts can be specified and used to forecast.

Figure 20.1 Using External Forecasts



Specifying and Using an External Model Specification

The HPFEXMSPEC procedure specifies external models for use by the SAS Forecast Server Procedures software. The HPFEXMSPEC procedure enables the user to specify information about how the forecasts were derived. This information is used to compute forecast components that are not provided by the user.

For example, the data set Sashelp.Air contains a monthly time series represented by two variables: DATE and AIR. The following SAS statements create an external forecast in the log transformed metric and store the external forecasts in the data set Work.Externalforecast. In this example, the HPF procedure is used as the source of the forecasts; but one could imagine that the origin could be any external source.

```
proc timeseries data=sashelp.air
                out=logair(rename=air=logair);
   id date interval=month;
   var air / transform=log;
run;

proc hpf data=logair out=hpfout
         outfor=hpfforecast;
   id date interval=month;
   forecast logair / model=addwinters;
run;

data externalforecast;
   drop _NAME_ ACTUAL ERROR;
   merge sashelp.air hpfforecast; by date;
run;
```

The data set Work.Externalforecast contains six variables: DATA, AIR, PREDICT, STD, LOWER and UPPER.

The HPFEXMSPEC procedure can be used to create an external model specification. Continuing the example, the following SAS statements create an external model specification called MYEXTERNAL and store this model specification in the model repository Sasuser.Mymodels. The TRANSFORM=LOG option specifies that the external forecasts were generated in the log transformed metric and these forecasts need to be inverse-transformed back to the original metric. The NPARMS=3 option specifies the number of parameters used to generate the external forecasts.

```
proc hpfexmspec modelrepository=sasuser.myrepository
                specname=myexternal;
    exm transform=log nparms=3;
run;
```

The HPFSELECT procedure can be used to create a model selection list that contains an external model specification as a possible candidate model. Continuing the example, the following SAS statements create a model selection list called MYSELECT and store this model selection list in the catalog Sasuser.Myrepository. The EXMMAP option in the following SPEC statement provides the mapping for the external model's symbols to the data set variables. The PREDICT= option specifies the variable that contains the predictions, the STDERR= option specifies the variable that contains the prediction standard errors, the LOWER= option specifies the variable that contains the lower confidence limits, and the UPPER= option specifies the variable that contains the upper confidence limits.

```
proc hpfselect modelrepository=sasuser.myrepository
               selectname=myselect
               selectlabel="My Select List";
   spec myexternal /
        exmmap(predict=predict lower=lower upper=upper stderr=std);
run;
```

At this point:

- External forecasts are contained in the data set Work.Externalforecast.
- An external model specification, MYEXTERNAL, has been stored in the model repository, Sasuser.Myrepository.
- A model selection list, MYSELECT, has been stored in the model repository, Sasuser.Myrepository.

The HPFENGINE procedure can now use both the external model specification and the external forecasts.

Continuing the example, the following SAS statements forecast the monthly time series contained in the Work.Externalforecast data set. The MODELREPOSITORY option of the PROC HPFENGINE statement specifies the model repository as Sasuser.Myrepository, the GLOBALSELECTION=MYSELECT option specifies the model selection list, and the EXTERNAL statement specifies the data set variables required to satisfy the mappings defined in the SPEC statement's EXMMAP option for the external model, MYEXTERNAL.

```
proc hpfengine data=externalforecast
               out=engout
               outfor=engforecast
               outstat=outstat
               modelrepository=sasuser.myrepository
               globalselection=myselect;
   id date interval=month;
   forecast air;
   external predict lower upper std;
run;
```

The OUT=ENGOUT data set contains the original data extrapolated by the external forecasts and the OUTFOR=ENGFORECAST data set contains the forecasts (values contained in the PREDICT=, STDERR=, LOWER=, and UPPER= data set variables) and the prediction errors. The OUTSTAT=ENGSTAT data set contains the statistics of fit based on the prediction errors and the NPARMS=3 option of the external model specification.

Chapter 21
Using Auxiliary Data Sets

Contents

Auxiliary Data Summary **551**
AUXDATA Functionality **552**
AUXDATA Alignment across BY Groups 553
AUXDATA Alignment over the Time Dimension 553
AUXDATA Examples **555**
Example 21.1: Simple AUXDATA Demonstration 555
Example 21.2: AUXDATA with BY Groups 560

Auxiliary Data Summary

Auxiliary data set support enables the HPFENGINE and HPFDIAGNOSE procedures to use auxiliary data sets to contribute input variables to the run of the procedure step. This functionality creates a virtual data source that enables some of the input variables to physically reside in different data sets; in previous versions, all variables were required to be physically present in a single DATA= data set. For example, this functionality enables sharing of common explanatory time series data across multiple forecasting projects.

Furthermore, auxiliary data set support enables more than the simple separation of shared data. It also facilitates the elimination of redundancy in these auxiliary data sources by performing partial matching on BY-group qualification. Duplication of explanatory time series for the full BY-group hierarchy is no longer required for the auxiliary data sets.

Finally, this functionality permits more than one auxiliary data source to be used concurrently to materialize the virtual time series vectors across a given BY-group hierarchy. So explanatory variables that have naturally different levels of BY-group qualification can be isolated into separate data sets and supplied with separate AUXDATA= options to optimize data management and performance.

AUXDATA Functionality

Both the HPFDIAGNOSE and HPFENGINE procedures now support the AUXDATA=*DataSet* option. When used, this option declares the presence of an auxiliary data set to optionally provide input variables to satisfy various declaration statements in the respective procedure steps.

There are two classes of time series data set sources:

- a primary data set from the DATA=*DataSet* option
- auxiliary data sources from AUXDATA=*DataSet* options

You can specify zero or more AUXDATA= options in the PROC statement. Each AUXDATA= option establishes an auxiliary data set source to supply variables declared in subsequent statements that comprise the procedure step.

Variables referenced in the PROC invocation fall into two classes:

- those that must be physically present in the primary data set
- those that can reside in either the primary or an auxiliary data set

For those that can be resolved from an auxiliary data set, variable resolution proceeds in reverse order from the last AUXDATA= option in the PROC statement to the first. If the variable in question is not found in any of those, the variable must be present in the primary data set for the procedure step to be successful.

Currently, for the HPFENGINE and HPFDIAGNOSE procedures, dependent variables and the variable identified in the ID statement must be physically present in the primary data set. Dependent variables are those that are identified in FORECAST statements in the respective HPFENGINE or HPFDIAGNOSE procedure invocations. The ID variable, if specified, must also be present in each of the auxiliary data sets with the same variable name and units as in the primary data set.

For variables that are candidates for placement in auxiliary data sets, the procedure performs a lookup step. The lookup proceeds in reverse order across the auxiliary data sets specified in the PROC statement.

For PROC HPFDIAGNOSE, variables in the following statements are candidates for AUXDATA placement:

- ADJUST (right-hand-side variables)
- INPUT

For PROC HPFENGINE, variables in the following statements are candidates for AUXDATA placement:

- ADJUST (right-hand-side variables)
- CONTROL
- EXTERNAL
- INPUT
- STOCHASTIC

AUXDATA Alignment across BY Groups

All BY statement variables must be physically present in the primary data set. However, it is not necessary to have the BY variables present in any of the auxiliary data sets. All, some, or none of the BY variables can be present in any auxiliary data set, as your requirements dictate. Partial BY-group matching is performed between the primary data set and the auxiliary data sets based on the number of BY statement variables that are present in the respective auxiliary data sets.

For example, suppose you have a hierarchy of (REGION, PRODUCT) in the primary data set, which holds the time series variables for monthly sales metrics. Suppose you have an auxiliary data set with time series qualified by REGION for pertinent explanatory variables and another with time series for other explanatory variables to be applied across all (REGION, PRODUCT) groupings of the primary data set. In this scenario, each (REGION, PRODUCT) group in the primary data set seeks a match with a corresponding REGION from the first auxiliary data set to materialize the time series for its variables, but no matching is performed on the second auxiliary data set to materialize the time series for its variables. So if ('SOUTH','EDSEL') is a BY group from the primary data set, the 'SOUTH' BY group series from the first auxiliary data set are used, and the series from the second auxiliary data set are supplied without qualification. If the next primary BY group is ('SOUTH', 'HUDSON'), then the 'SOUTH' BY group is again used to supply the time series from the first auxiliary data set, and the unqualified series are supplied from the second auxiliary data set. So on it goes, each auxiliary data set performing a partial match on the BY variables it holds within the BY group from the primary data set.

AUXDATA Alignment over the Time Dimension

The series from each BY group of the primary data set defines a reference time span for the auxiliary data sets. Only the intersection of the time interval for each auxiliary series with the reference span is materialized. Head or tail missing values are inserted into the auxiliary series for start or stop times that lie inside the reference span. More generally, missing value semantics apply to the head and tail regions that require filling to materialize the full reference time span.

With time series materialized from a single primary data set, there is no latitude for different time ID ranges between the different variables because each observation read contains not only the time ID but also the associated values for all of the variables. With some series materialized from the primary data set and some materialized from auxiliary data sets, the possibility exists for the reference time span to have an arbitrary intersection with the time span of the corresponding series from the auxiliary sources. The intent is to materialize the portion of the auxiliary series time span that intersects with the reference time span and to handle head and tail shortages via missing value semantics as needed.

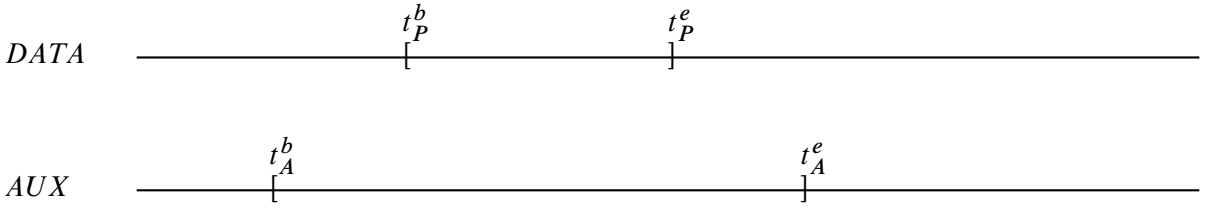
For the previous usage scenario with a primary data set and two auxiliary data sets, when data is read over a sequence of primary BY groups it might be necessary to materialize various spans of the auxiliary series with appropriate missing value semantics applied as needed to resolve head and tail shortages even though the actual time series contributed from the auxiliary data sets does not physically change. The following discussion breaks this down into several cases depending on intersection possibilities between the reference time span and the auxiliary time span.

Legend:

- t_P^b denotes the begin time ID of the primary (DATA=) series.

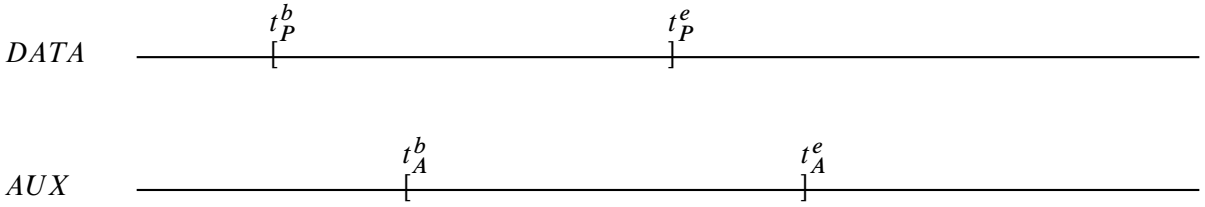
- t_P^e denotes the end time ID of the primary (DATA=) series.
- t_A^b denotes the begin time ID of the AUXDATA series.
- t_A^e denotes the end time ID of the AUXDATA series.
- $[t_P^b, t_P^e]$ denotes the time span for the primary (DATA=) series (also known as the reference time span).
- $[t_A^b, t_A^e]$ denotes the time span for the AUXDATA series.

Case 1:



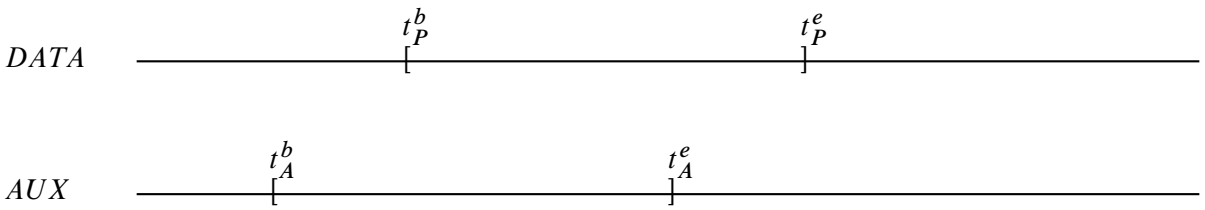
Here $[t_P^b, t_P^e] \subseteq [t_A^b, t_A^e]$. The auxiliary time span includes the reference span as a subset. Values in the AUXDATA series to the left of t_P^b and values to the right of t_P^e are truncated from the AUXDATA series that is materialized in connection with the primary series.

Case 2:



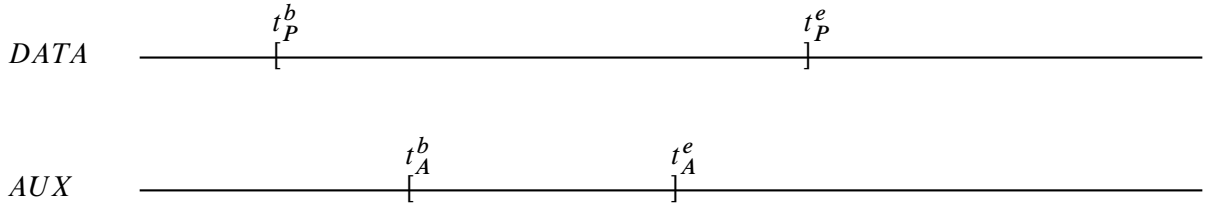
Here $[t_P^b, t_P^e] = [t_P^b, t_A^b) \cup [t_A^b, t_P^e]$. The reference time span leads the auxiliary time span with a non-empty intersection. AUXDATA series values in $[t_P^b, t_A^b)$ are materialized with missing value semantics. AUXDATA series values in $[t_A^b, t_P^e]$ are materialized as actual subject to missing value semantics.

Case 3:



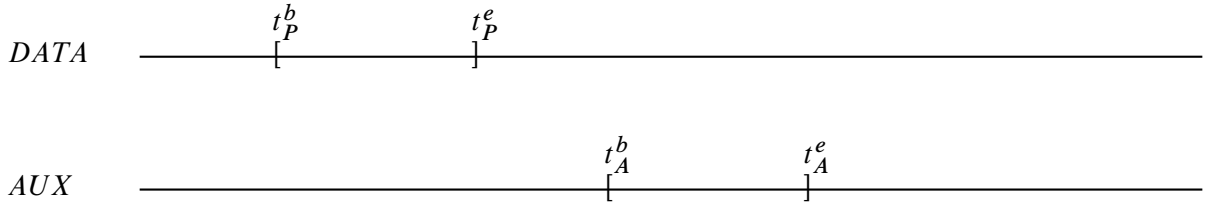
Here $[t_P^b, t_P^e] = [t_P^b, t_A^e] \cup (t_A^e, t_P^e]$. The reference time span lags the auxiliary time span with a non-empty intersection. AUXDATA series values in $[t_P^b, t_A^e]$ are materialized as actual subject to missing value semantics. AUXDATA series values in $(t_A^e, t_P^e]$ are materialized with missing value semantics.

Case 4:



Here $[t_A^b, t_A^e] \subset [t_P^b, t_P^e]$. The auxiliary time span is a subset of the reference time span. AUXDATA series values in $[t_P^b, t_A^b)$ and values in $(t_A^e, t_P^e]$ are materialized with missing value semantics. AUXDATA series values in $[t_A^b, t_A^e]$ are materialized as actual subject to missing value semantics.

Case 5:



Here $[t_P^b, t_P^e] \cap [t_A^b, t_A^e] = \oslash$. The auxiliary time span does not intersect the reference time span at all. In this case all AUXDATA series values are materialized with missing value semantics.

AUXDATA Examples

Example 21.1: Simple AUXDATA Demonstration

This is a simple demonstration of the use of AUXDATA in the context of PROC HPFDIAGNOSE and PROC HPFENGINE that shows the separation of explanatory variables from forecast variables.

The following statements create an unobserved components model (UCM) specification, MYUCM, with an input X1, and a model selection list, MYSELECT, to map the model's Y symbol to data set variable MASONRY and its X1 symbol to the data set variable ELECTRIC:

```
proc hpfucmspec repository=work.mymodels name=myucm;
   dependent symbol=Y;
   irregular;
```

```
   level;
   slope;
   season length=12;
   input symbol=X1;
run;

proc hpfselect repository=work.mymodels name=myselect;
   spec myucm / inputmap(symbol=Y var=MASONRY)
                inputmap(symbol=X1 var=ELECTRIC);
run;
```

The following statements run PROC HPFENGINE with a data set Workers as its single data source.

```
proc hpfengine data=workers
               repository=work.mymodels
               globalselection=myselect
               out=wout
               outcomponent=wcomp
               outest=west
               outfor=wfor
               outstat=wstat
               outmodelinfo=wmodel
               outindep=wind
               print=select;
   id date interval=month;
   forecast masonry;
   stochastic electric;
run;
```

The following statements show how you can use that Workers data set as both DATA= and AUXDATA= sources by judicious use of the KEEP= data set option. There is no practical advantage to this. It simply demonstrates the scoping of the AUXDATA feature to resolve variables from the proper data set and materialize the same result regardless of how PROC HPFENGINE acquires the time series it processes.

```
proc hpfengine data=workers(keep=date masonry)
               auxdata=workers
               repository=work.mymodels
               globalselection=myselect
               out=woutx
               outcomponent=wcompx
               outest=westx
               outfor=wforx
               outstat=wstatx
               outmodelinfo=wmodelx
               outindep=windx
               print=select;
   id date interval=month;
   forecast masonry;
   stochastic electric;
run;
```

But perhaps you are skeptical. Is this is really working? After all, Workers is the input data set and it does have all of the columns.

So split up Workers into Workdep and Workaux data sets as follows:

```
data workdep;
   set workers(keep=date masonry);
run;

data workaux;
   set workers(keep=date electric);
run;
```

Then run PROC HPFENGINE again on the separated data sets Workdep and Workaux:

```
proc hpfengine data=workdep
               auxdata=workaux
               repository=work.mymodels
               globalselection=myselect
               out=woutx2
               outcomponent=wcompx2
               outest=westx2
               outfor=wforx2
               outstat=wstatx2
               outmodelinfo=wmodelx2
               outindep=windx2
               print=select;
   id date interval=month;
   forecast masonry;
   stochastic electric;
run;
```

You can use the COMPARE procedure to compare the output data sets between this and either of the previous steps. You will see some differences in the data set labels for some of them; everything else should be the same.

```
proc compare data=wfor(label='x')
             compare=wforx2(label='x');
run;
```

Output 21.1.1 Compare AUXDATA OUTFOR Results

```
                        The COMPARE Procedure
                Comparison of WORK.WFOR with WORK.WFORX2
                             (Method=EXACT)

                          Data Set Summary

Dataset               Created          Modified  NVar    NObs  Label

WORK.WFOR     06AUG20:03:17:42  06AUG20:03:17:42     8      79  x
WORK.WFORX2   06AUG20:03:17:43  06AUG20:03:17:43     8      79  x


                          Variables Summary

                Number of Variables in Common: 8.


                         Observation Summary

                    Observation      Base  Compare

                    First Obs           1        1
                    Last  Obs          79       79

  Number of Observations in Common: 79.
  Total Number of Observations Read from WORK.WFOR: 79.
  Total Number of Observations Read from WORK.WFORX2: 79.

  Number of Observations with Some Compared Variables Unequal: 0.
  Number of Observations with All Compared Variables Equal: 79.

  NOTE: No unequal values were found. All values compared are exactly
        equal.
```

You can also run this example on a combination of the HPFDIAGNOSE and HPFENGINE procedures as follows. First, run PROC HPFDIAGNOSE and PROC HPFENGINE on the full Workers data set:

```
proc hpfdiagnose data=workers
                 repository=work.wdiagnose
                 outest=wdiagest;
   id date interval=month;
   forecast masonry;
   input electric;
   arimax identify=both;
   ucm component=(all);
run;

proc hpfengine data=workers
               repository=work.wdiagnose
               inest=wdiagest
               out=wout
```

```
                outcomponent=wcomp
                outest=west
                outfor=wfor
                outstat=wstat
                outmodelinfo=wmodel
                outindep=wind
                print=select;
   id date interval=month;
   forecast masonry;
   stochastic electric;
run;
```

Next, do the same thing using the Workdep and Workaux data sets from above:

```
proc hpfdiagnose data=workdep
                 auxdata=workaux
                 repository=work.wdiagnosex
                 outest=wdiagestx;
   id date interval=month;
   forecast masonry;
   input electric;
   arimax identify=both;
   ucm component=(all);
run;

proc hpfengine data=workdep
               auxdata=workaux
               repository=work.wdiagnosex
               inest=wdiagestx
               out=woutx
               outcomponent=wcompx
               outest=westx
               outfor=wforx
               outstat=wstatx
               outmodelinfo=wmodelx
               outindep=windx
               print=select;
   id date interval=month;
   forecast masonry;
   stochastic electric;
run;
```

To finish up this example, run PROC COMPARE on the OUTFOR data sets between the two runs:

```
proc compare data=wfor(label='x')
             compare=wforx(label='x');
run;
```

Output 21.1.2 Compare AUXDATA OUTFOR Results

```
                    The COMPARE Procedure
             Comparison of WORK.WFOR with WORK.WFORX
                        (Method=EXACT)

                        Data Set Summary

Dataset              Created          Modified  NVar    NObs  Label

WORK.WFOR    06AUG20:03:17:45  06AUG20:03:17:45     8      79  x
WORK.WFORX   06AUG20:03:17:45  06AUG20:03:17:45     8      79  x


                        Variables Summary

                  Number of Variables in Common: 8.


                       Observation Summary

                    Observation      Base  Compare

                    First Obs           1        1
                    Last  Obs          79       79

  Number of Observations in Common: 79.
  Total Number of Observations Read from WORK.WFOR: 79.
  Total Number of Observations Read from WORK.WFORX: 79.

  Number of Observations with Some Compared Variables Unequal: 0.
  Number of Observations with All Compared Variables Equal: 79.

  NOTE: No unequal values were found. All values compared are exactly
        equal.
```

Example 21.2: AUXDATA with BY Groups

This example is a more complicated case that demonstrates the use of partial BY-group matching between the primary source specified in the DATA= option and multiple AUXDATA= data sets. The example is contrived, but it demonstrates the utility of AUXDATA for consolidating explanatory data and eliminating redundancy. Suppose you have collection of time series that represent demand for a service qualified by the variables REGION and CLASS, which represent a region of the country and the service class. Suppose you want to include regional variables in the model as regressors and also some global (unqualified) variables as regressors. With the single-source DATA= mode of the HPFDIAGNOSE and HPFENGINE procedures, you would have to replicate each of those regional variables and each of those global variables in the SAS data set you provide as input to those respective procedures in order to perform time series diagnosis and subsequent model selection and forecasting. If there are hundreds of thousands (or more) distinct groups of REGION and CLASS, then the storage cost and I/O penalty for storing and moving all that redundant information can become significant, especially if that common data can be used across a variety of forecasting projects in the organization. So how would the SAS code look to use these kinds of data?

Some data are fabricated to fit this structure. The same series is replicated in each BY group regardless of BY-group level. The following details for the data sets constructed for this example are pertinent:

- REGION and CLASS each have two distinct values for a total of four primary BY groups.
- The Master data set contains the fully qualified, single-source version of the data that you would use as the data source if you did not have AUXDATA support. It has lots of redundant information for the explanatory variables included in it as a result.
- The Depdata data set contains the dependent variables to be forecast, the time ID, and the BY variables.
- The Regdata data set contains the regional independent variables, the time ID, and the REGION BY variable.
- The Natdata data set contains the global independent variables and time ID.

The following statements set up PROC HPFDIAGNOSE and PROC HPFENGINE runs to compare the results. First, the single-source run is just a matter of running PROC HPFDIAGNOSE over the Master data set and passing the generated model repository and OUTEST data set into PROC HPFENGINE to forecast the Master data set. This would have been the only option available to you for this analysis prior to AUXDATA support.

```
proc hpfdiagnose data=master
                 repository=work.diagrep
                 outest=diagest;
   by region class;
   id date interval=day;
   forecast y;
   input x z;
   arimax identify=both;
   ucm component=(all);
run;

proc hpfengine data=master
               repository=work.diagrep
               inest=diagest
               out=ex2out
               outcomponent=ex2comp
               outest=ex2est
               outfor=ex2for
               outstat=ex2stat
               outmodelinfo=ex2model
               outindep=ex2indep
               print=select;
   by region class;
   id date interval=day;
   forecast y;
   input x z;
run;
```

The following statements use the AUXDATA approach. The fully qualified dependent variables of interest to analyze and forecast are in the Depdata data set. The regional independent variables are in Regdata and the global (unqualified) independent variables are in Natdata. The following HPFDIAGNOSE and HPFENGINE procedure steps perform the same analysis, model selection, and forecast, but they use the normalized data sources as input instead of the single-source Master data set:

```
proc hpfdiagnose data=depdata
                 auxdata=natdata
                 auxdata=regdata
                 repository=work.diagrepx
                 outest=diagestx;
   by region class;
   id date interval=day;
   forecast y;
   input x z;
   arimax identify=both;
   ucm component=(all);
run;

proc hpfengine data=depdata
               auxdata=natdata
               auxdata=regdata
               repository=work.diagrepx
               inest=diagestx
               out=ex2outx
               outcomponent=ex2compx
               outest=ex2estx
               outfor=ex2forx
               outstat=ex2statx
               outmodelinfo=ex2modelx
               outindep=ex2indepx
               print=select;
   by region class;
   id date interval=day;
   forecast y;
   input x z;
run;
```

To finish up, the following statements compare the statistics of fit to see that indeed the same results are produced regardless of how the data are obtained. While the other output data sets are omitted here for brevity, they should also compare cleanly.

```
proc compare data=ex2stat(label='x')
             compare=ex2statx(label='x');
run;
```

Output 21.2.1 Compare AUXDATA Statistics of Fit Results

```
                    The COMPARE Procedure
          Comparison of WORK.EX2STAT with WORK.EX2STATX
                        (Method=EXACT)

                      Data Set Summary

Dataset                 Created          Modified  NVar    NObs  Label

WORK.EX2STAT   06AUG20:03:17:47  06AUG20:03:17:47    59       4  x
WORK.EX2STATX  06AUG20:03:17:48  06AUG20:03:17:48    59       4  x


                      Variables Summary

                Number of Variables in Common: 59.


                     Observation Summary

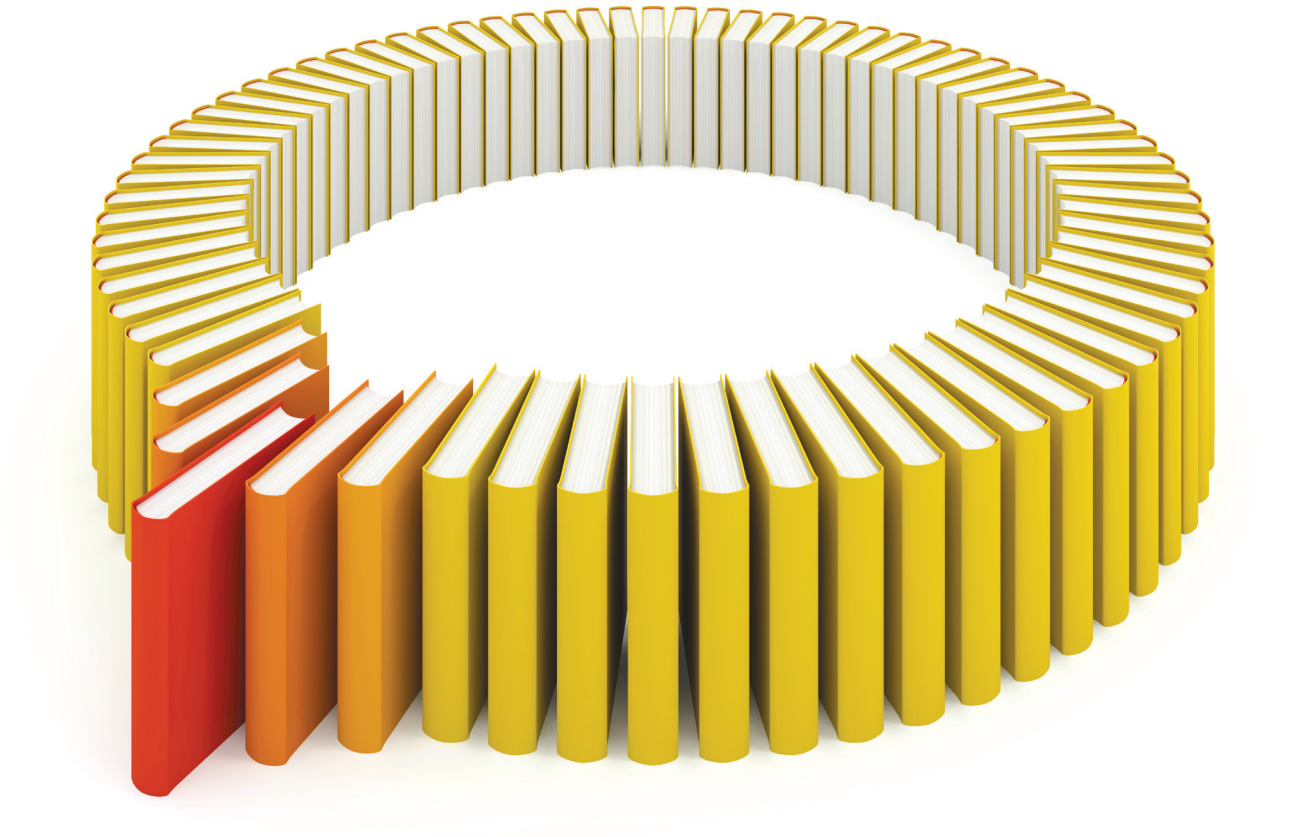
                  Observation      Base  Compare

                  First Obs           1        1
                  Last  Obs           4        4

   Number of Observations in Common: 4.
   Total Number of Observations Read from WORK.EX2STAT: 4.
   Total Number of Observations Read from WORK.EX2STATX: 4.

   Number of Observations with Some Compared Variables Unequal: 0.
   Number of Observations with All Compared Variables Equal: 4.

   NOTE: No unequal values were found. All values compared are exactly
         equal.
```



Gain Greater Insight into Your SAS® Software with SAS Books.

Discover all that you need on your journey to knowledge and empowerment.

support.sas.com/bookstore
for additional books and resources.

sas
THE POWER TO KNOW®

SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration. Other brand and product names are trademarks of their respective companies. © 2013 SAS Institute Inc. All rights reserved. S107969US.0613