Oracle® Retail Demand Forecasting

User Guide

Release 13.0.4

July 2009

ORACLE

Oracle® Demand Forecasting User Guide, Release 13.0.4

Copyright © 2009, Oracle. All rights reserved.

Primary Author: Barrett Gaines

This software and related documentation are provided under a license agreement containing restrictions on use and disclosure and are protected by intellectual property laws. Except as expressly permitted in your license agreement or allowed by law, you may not use, copy, reproduce, translate, broadcast, modify, license, transmit, distribute, exhibit, perform, publish, or display any part, in any form, or by any means. Reverse engineering, disassembly, or decompilation of this software, unless required by law for interoperability, is prohibited.

The information contained herein is subject to change without notice and is not warranted to be error-free. If you find any errors, please report them to us in writing.

If this software or related documentation is delivered to the U.S. Government or anyone licensing it on behalf of the U.S. Government, the following notice is applicable:

U.S. GOVERNMENT RIGHTS Programs, software, databases, and related documentation and technical data delivered to U.S. Government customers are "commercial computer software" or "commercial technical data" pursuant to the applicable Federal Acquisition Regulation and agency-specific supplemental regulations. As such, the use, duplication, disclosure, modification, and adaptation shall be subject to the restrictions and license terms set forth in the applicable Government contract, and, to the extent applicable by the terms of the Government contract, the additional rights set forth in FAR 52.227-19, Commercial Computer Software License (December 2007). Oracle USA, Inc., 500 Oracle Parkway, Redwood City, CA 94065.

This software is developed for general use in a variety of information management applications. It is not developed or intended for use in any inherently dangerous applications, including applications which may create a risk of personal injury. If you use this software in dangerous applications, then you shall be responsible to take all appropriate fail-safe, backup, redundancy, and other measures to ensure the safe use of this software. Oracle Corporation and its affiliates disclaim any liability for any damages caused by use of this software in dangerous applications.

Oracle is a registered trademark of Oracle Corporation and/or its affiliates. Other names may be trademarks of their respective owners.

This software and documentation may provide access to or information on content, products, and services from third parties. Oracle Corporation and its affiliates are not responsible for and expressly disclaim all warranties of any kind with respect to third-party content, products, and services. Oracle Corporation and its affiliates will not be responsible for any loss, costs, or damages incurred due to your access to or use of third-party content, products, or services.

Licensing Note: This media pack includes a Restricted Use license for Oracle Retail Predictive Application Server (RPAS) - Enterprise Engine to support Oracle® Retail Demand Forecasting only.

Value-Added Reseller (VAR) Language

Oracle Retail VAR Applications

The following restrictions and provisions only apply to the programs referred to in this section and licensed to you. You acknowledge that the programs may contain third party software (VAR applications) licensed to Oracle. Depending upon your product and its version number, the VAR applications may include:

(i) the software component known as **ACUMATE** developed and licensed by Lucent Technologies Inc. of Murray Hill, New Jersey, to Oracle and imbedded in the Oracle Retail Predictive Application Server – Enterprise Engine, Oracle Retail Category Management, Oracle Retail Item Planning, Oracle Retail Merchandise Financial Planning, Oracle Retail Advanced Inventory Planning, Oracle Retail Demand Forecasting, Oracle Retail Regular Price Optimization, Oracle Retail Size Profile Optimization, Oracle Retail Replenishment Optimization applications.

(ii) the **MicroStrategy** Components developed and licensed by MicroStrategy Services Corporation (MicroStrategy) of McLean, Virginia to Oracle and imbedded in the MicroStrategy for Oracle Retail Data Warehouse and MicroStrategy for Oracle Retail Planning & Optimization applications.

(iii) the **SeeBeyond** component developed and licensed by Sun MicroSystems, Inc. (Sun) of Santa Clara, California, to Oracle and imbedded in the Oracle Retail Integration Bus application.

(iv) the **Wavelink** component developed and licensed by Wavelink Corporation (Wavelink) of Kirkland, Washington, to Oracle and imbedded in Oracle Retail Mobile Store Inventory Management.

(v) the software component known as **Crystal Enterprise Professional and/or Crystal Reports Professional** licensed by SAP and imbedded in Oracle Retail Store Inventory Management.

(vi) the software component known as **Access Via™** licensed by Access Via of Seattle, Washington, and imbedded in Oracle Retail Signs and Oracle Retail Labels and Tags.

(vii) the software component known as **Adobe Flex™** licensed by Adobe Systems Incorporated of San Jose, California, and imbedded in Oracle Retail Promotion Planning & Optimization application.

(viii) the software component known as **Style Report™** developed and licensed by InetSoft Technology Corp. of Piscataway, New Jersey, to Oracle and imbedded in the Oracle Retail Value Chain Collaboration application.

(ix) the software component known as **DataBeacon™** developed and licensed by Cognos Incorporated of Ottawa, Ontario, Canada, to Oracle and imbedded in the Oracle Retail Value Chain Collaboration application.

You acknowledge and confirm that Oracle grants you use of only the object code of the VAR Applications. Oracle will not deliver source code to the VAR Applications to you. Notwithstanding any other term or condition of the agreement and this ordering document, you shall not cause or permit alteration of any VAR Applications. For purposes of this section, "alteration" refers to all alterations, translations, upgrades, enhancements, customizations or modifications of all or any portion of the VAR Applications including all reconfigurations, reassembly or reverse assembly, re-engineering or reverse engineering and recompilations or reverse compilations of the VAR Applications or any derivatives of the VAR Applications. You acknowledge that it shall be a breach of the agreement to utilize the relationship, and/or confidential information of the VAR Applications for purposes of competitive discovery.

The VAR Applications contain trade secrets of Oracle and Oracle's licensors and Customer shall not attempt, cause, or permit the alteration, decompilation, reverse engineering, disassembly or other reduction of the VAR Applications to a human perceivable form. Oracle reserves the right to replace, with functional equivalent software, any of the VAR Applications in future releases of the applicable program.

Contents

Preface ..... **ix**
Audience ix
Related Documents ix
Customer Support ix
Review Patch Documentation ix
Oracle Retail Documentation on the Oracle Technology Network x
Conventions x
1 Introduction **1**
Overview 1
Forecasting Challenges and RDF Solutions 1
Selecting the Best Forecasting Method 2
Overcoming Data Sparsity through Source Level Forecasting 2
Forecasting Demand for New Products and Locations 3
Managing Forecasting Results through Automated Exception Reporting 3
Incorporating the Effects of Promotions and Other Event-Based Challenges on Demand 4
Oracle Retail Demand Forecasting Architecture 4
The Oracle Retail Predictive Application Server and RDF 4
Global Domain vs. Simple Domain Environnent 5
Oracle Retail Demand Forecasting Workbook Template Groups 6
Forecast 6
Promote (Promotional Forecasting) 6
Curve 7
RDF Solution and Business Process Overview 7
RDF and the Oracle Retail Enterprise 7
RDF Primary Workflow 7
2 Setting Forecast Parameters **9**
Overview 9
Forecast Administration Workbook Overview 9
Forecast Administration Workbook 12
Creating a Forecast Administration Workbook 12
Window Descriptions 12
Forecast Maintenance Workbook 28
Overview 28
Creating a Forecast Maintenance Workbook 28
Window Descriptions 29
Forecast Like-Item, Sister-Store Workbook 34
Overview 34
Creating a Forecast Like-Item, Sister-Store Workbook 34

Window Descriptions....35
Steps Required for Forecasting Using Each of the Like SKU / Sister Store Methods....39
Product/Location Cloning Administration Workbook....41
Overview....41
Window Descriptions....42
3 Generating and Approving a Forecast 47
Overview....47
Run a Batch Forecast....47
Overview....47
Procedures....48
Delete Forecasts....48
Overview....48
Permanently Removing a Forecast from the Oracle Retail Demand Forecasting System....48
Forecast Approval Workbook....49
Overview....49
Opening or Creating the Forecast Approval Workbook....50
Window Descriptions....52
Approving Forecasts through Alerts (Exception Management)....59
Overview....59
4 Forecast Analysis Tools 61
Overview....61
Interactive Forecasting Workbook....61
Overview....61
Opening the Interactive Forecasting Workbook....61
Window Descriptions....62
Forecast Scorecard Workbook....64
Overview....64
Opening or Creating a Forecast Scorecard Workbook....64
Window Descriptions....66
5 Promote (Promotional Forecasting) 69
Overview....69
What is Promotional Forecasting?....69
Comparison between Promotional and Statistical Forecasting....70
Developing Promotional Forecast Methods....70
Oracle Retail's Approach to Promotional Forecasting....71
Promotional Forecasting Terminology and Workflow....71
Promote Workbooks and Wizards....72
Promotion Planner Workbook Template....73
Overview....73
Opening or Creating a Promotion Planner Workbook....73

Window Descriptions....74
Promotion Maintenance Workbook Template....75
Overview....75
Opening the Promotion Maintenance Workbook Template....75
Window Descriptions....75
Promotion Effectiveness Workbook Template....78
Overview....78
Opening the Promotion Effectiveness Workbook Template....78
Window Descriptions....79
Promotion Management Workbook Template....83
Overview....83
Opening the Promotion Management Workbook Template....83
Window Descriptions....84
Setting Up the System to Run a Promotional Forecast....86
Viewing a Forecast that Includes Promotion Effects....86
Viewing and Editing Promotion System-Calculated Effects....87
Promotion Simulation ("what-if?") and Analysis....87
6 Oracle Retail Demand Forecasting Methods....89
Forecasting Techniques Used in RDF....89
Exponential Smoothing....89
Regression Analysis....89
Bayesian Analysis....89
Prediction Intervals....90
Automatic Method Selection....90
Source Level Forecasting....90
Promotional Forecasting....90
Time Series (Statistical) Forecasting Methods....91
Why Use Statistical Forecasting?....91
Exponential Smoothing (ES) Forecasting Methods....92
Average....92
Simple Exponential Smoothing....93
Croston's Method....93
Simple/Intermittent Exponential Smoothing....93
Holt Exponential Smoothing....94
Multiplicative Winters Exponential Smoothing....94
Additive Winters Exponential Smoothing....97
Seasonal Exponential Smoothing (SeasonalES)....97
Seasonal Regression....98
Bayesian Information Criterion (BIC)....99
Profile-Based Forecasting....103
Forecast Method....103
Profile-Based Method and New Items....104

Bayesian Forecasting 104
Sales Plans vs. Historic Data 105
Bayesian Algorithm 105
Causal (Promotional) Forecasting Method 106
The Causal Forecasting Algorithm 107
Causal Forecasting Process 107
Causal Forecasting with External Baseline 110
Causal Forecasting Using External Baseline Process 110
Causal Forecasting at the Daily Level 111
Final Considerations about Causal Forecasting 112
7 Preprocessing 113
Preprocessing Methods 114
Standard Median 114
Retail Median 115
Standard Exponential Smoothing 116
Lost Sales Standard Exponential Smoothing 117
Override 118
Increment 118
Forecast Sigma 119
Forecast Sigma Event 119
Clear 119
No Filtering 119
Preprocessing for Stock-outs 119
Preprocessing for Promotional Forecasting 119
Glossary 121

Preface

The *Oracle Retail Demand Forecasting User Guide* describes the application's user interface and how to navigate through it.

Audience

This document is intended for the users and administrators of Oracle Retail Demand Forecasting. This may include merchandisers, buyers, and business analysts.

Related Documents

For more information, see the following documents in the Oracle Retail Demand Forecasting Release 13.0.4 documentation set:

- *Oracle Retail Demand Forecasting Release Notes*
- *Oracle Retail Demand Forecasting Installation Guide*
- *Oracle Retail Demand Forecasting Administration Guide*
- *Oracle Retail Demand Forecasting Configuration Guide*
- Oracle Retail Predictive Application Server documentation

Customer Support

To contact Oracle Customer Support, access My Oracle Support at the following URL:

https://metalink.oracle.com

When contacting Customer Support, please provide the following:

- Product version and program/module name
- Functional and technical description of the problem (include business impact)
- Detailed step-by-step instructions to re-create
- Exact error message received
- Screen shots of each step you take

Review Patch Documentation

If you are installing the application for the first time, you install either a base release (for example, 13.0) or a later patch release (for example, 13.0.2). If you are installing a software version other than the base release, be sure to read the documentation for each patch release (since the base release) before you begin installation. Patch documentation can contain critical information related to the base release and code changes that have been made since the base release.

Oracle Retail Documentation on the Oracle Technology Network

In addition to being packaged with each product release (on the base or patch level), all Oracle Retail documentation is available on the following Web site (with the exception of the Data Model which is only available with the release packaged code):

http://www.oracle.com/technology/documentation/oracle_retail.html

Documentation should be available on this Web site within a month after a product release. Note that documentation is always available with the packaged code on the release date.

Conventions

Navigate: This is a navigate statement. It tells you how to get to the start of the procedure and ends with a screen shot of the starting point and the statement "the Window Name window opens."

> **Note:** This is a note. It is used to call out information that is important, but not necessarily part of the procedure.

```
This is a code sample
    It is used to display examples of code
```

A hyperlink appears like this.

1

Introduction

Overview

Oracle Retail Demand Forecasting is a Windows-based statistical and promotional forecasting solution. It uses state-of-the-art modeling techniques to produce high quality forecasts with minimal human intervention. Forecasts produced by the Demand Forecasting system enhance the retailer's supply-chain planning, allocation, and replenishment processes, enabling a profitable and customer-oriented approach to predicting and meeting product demand.

Today's progressive retail organizations know that store-level demand drives the supply chain. The ability to forecast consumer demand productively and accurately is vital to a retailer's success. The business requirements for consumer responsiveness mandate a forecasting system that more accurately forecasts at the point of sale, handles difficult demand patterns, forecasts promotions and other causal events, processes large numbers of forecasts, and minimizes the cost of human and computer resources.

Forecasting drives the business tasks of planning, replenishment, purchasing, and allocation. As forecasts become more accurate, businesses run more efficiently by buying the right inventory at the right time. This ultimately lowers inventory levels, improves safety stock requirements, improves customer service, and increases the company's profitability.

The competitive nature of business requires that retailers find ways to cut costs and improve profit margins. The accurate forecasting methodologies provided with Oracle Retail Demand Forecasting can provide tremendous benefits to businesses.

A connection from Oracle Retail Demand Forecasting to Oracle Retail's Advanced Retail Planning and Optimization (ARPO) solutions is built directly into the business process by way of the automatic approvals of forecasts, which may then fed directly to any ARPO solution. This process allows you to accept all or part of a generated sales forecast. Once that decision is made, the remaining business measures may be planned within an ARPO solution such as Merchandise Financial Planning, for example.

Forecasting Challenges and RDF Solutions

A number of challenges affect the ability of organizations to forecast product demand accurately. These challenges include selecting the best forecasting method to account for level, trending, seasonal, and spiky demand; generating forecasts for items with limited demand histories; forecasting demand for new products and locations; incorporating the effects of promotions and other event-based challenges on demand; and accommodating the need of operational systems to have sales predictions at more detailed levels than planning programs provide.

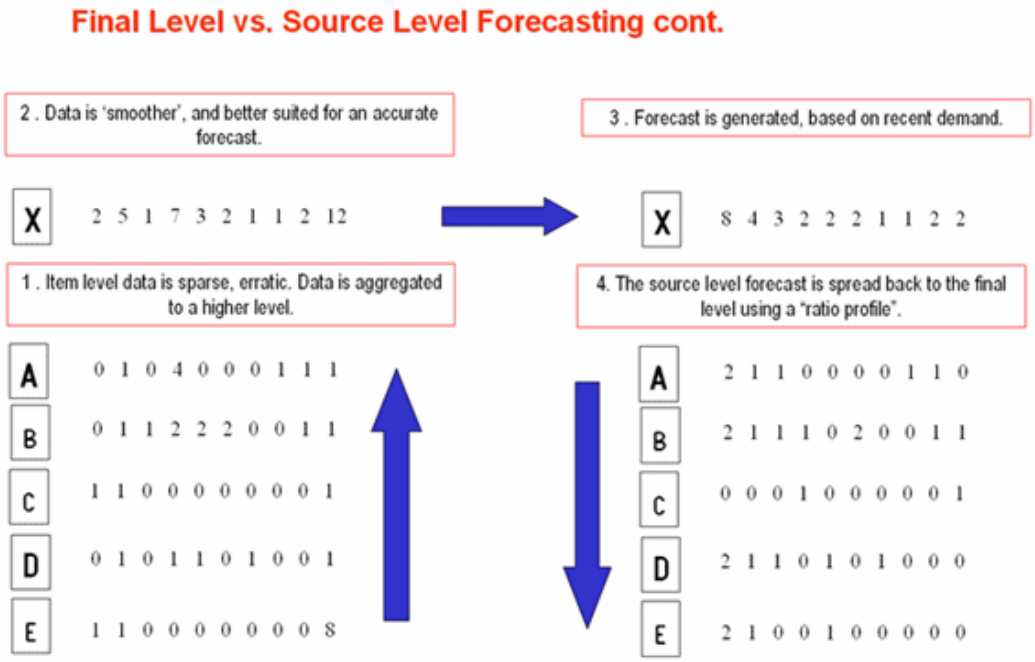
Selecting the Best Forecasting Method

One challenge to accurate forecasting is the selection of the best model to account for level, trending, seasonal, and spiky demand. Oracle Retail's AutoES (Automatic Exponential Smoothing) forecasting method eliminates this complexity.

The AutoES method evaluates multiple forecast models, such as Simple Exponential Smoothing, Holt Exponential Smoothing, Additive and Multiplicative Winters Exponential Smoothing, Croston's Intermittent Demand Model, and Seasonal Regression forecasting to determine the optimal forecast method to use for a given set of data. The accuracy of each forecast and the complexity of the forecast model are evaluated in order to determine the most accurate forecast method. You simply select the AutoES forecast generation method and the system finds the best model.

Overcoming Data Sparsity through Source Level Forecasting

It is a common misconception in forecasting that forecasts must be directly generated at the lowest levels (final levels) of execution. Problems can arise when historic sales data for these items is too sparse and noisy to identify clear selling patterns. In such cases, generating a reliable forecast requires aggregating sales data from a final level up to a higher level (source level) in the hierarchy in which demand patterns can be seen, and then generate a forecast at this source level. After a forecast is generated at the source level, the resulting data can be allocated (spread) back down to the lower level based on the lower level's (final level) relationship to the total. This relationship can then be determined through generating an additional forecast (interim forecast) at the final level. Curve is then used to dynamically generate a profile based on the interim forecasts. As well, a non-dynamic profile can be generated and approved to be used as this profile. It is this profile that determines how the source level forecast is spread down to the final level. For more information on Curve, see the *Curve User Guide*.



Some high-volume items may possess sufficient sales data for robust forecast calculations directly at the final forecast level. In these cases, forecast data generated at an aggregate level and then spread down to lower levels can be compared to the interim forecasts run directly at the final level. Comparing the two forecasts, each generated at a different hierarchy level, can be an invaluable forecast performance evaluation tool.

Your Oracle Retail Demand Forecasting system may include multiple final forecast levels. Forecast data must appear at a final level for the data to be approved and exported to another system for execution.

Forecasting Demand for New Products and Locations

Oracle Retail Demand Forecasting also forecasts demand for new products and locations for which no sales history exists. You can model a new product's demand behavior based on that of an existing similar product for which you do have a history. Forecasts can be generated for the new product based on the history and demand behavior of the existing one. Likewise, the sales histories of existing store locations can be used as the forecast foundation for new locations in the chain. For more details, see the Forecast Like-Item, Sister-Store Workbook section.

Managing Forecasting Results through Automated Exception Reporting

The RDF end user may be responsible for managing the forecast results for thousands of items, at hundreds of stores, across many weeks at a time. The Oracle Retail Predictive Application Server (RPAS) provides users with an automated exception reporting process (called Alert Management) that indicates to the user where a forecast value may lie above or below an established threshold, thereby reducing the level of interaction needed from the user.

Alert management is a feature that provides user-defined and user-maintained exception reporting. Through the process of alert management, you define measures that are checked daily to see if any values fall outside of an acceptable range or do not match a given value. When this happens, an alert is generated to let you know that a measure may need to be examined and possibly amended in a workbook.

The Alert Manager is a dialog box that is displayed automatically when you log on to the system. This dialog provides a list of all identified instances in which a given measure's values fall outside of the defined limits. You may pick an alert from this list and have the system automatically build a workbook containing that alert's measure. In the workbook, you can examine the actual measure values that triggered the alert and make decisions about what needs to be done next.

For more information on the Alert Manager, see the *RPAS User Guide*.

Incorporating the Effects of Promotions and Other Event-Based Challenges on Demand

Promotions, non-regular holidays, and other causal events create another significant challenge to accurate forecasting. Promotions such as advertised sales and free gifts with purchase might have a significant impact on a product's sales history, as can irregularly occurring holidays such as Easter.

Using Promotional Forecasting (an optional, add-on module to Oracle Retail Demand Forecasting), promotional models of forecasting can be developed to take these and other factors into account when forecasts are generated. Promotional Forecasting attempts to identify the causes of deviations from the established seasonal profile, quantify these effects, and use the results to predict future sales when conditions in the selling environment will be similar. This type of advanced forecasting identifies the behavioral relationship of the variable you want to forecast (sales) to both its own past and explanatory variables such as promotion and advertising.

Suppose that your company has a large promotional event during the Easter season each year. The exact date of the Easter holiday varies from year to year; as a result, the standard time-series forecasting model often has difficulty representing this effect in the seasonal profile. The Promotional Forecasting module allows you to identify the Easter season in all years of your sales history, and then define the upcoming Easter date. By doing so, you can causally forecast the Easter-related demand pattern shift.

Oracle Retail Demand Forecasting Architecture

The Oracle Retail Predictive Application Server and RDF

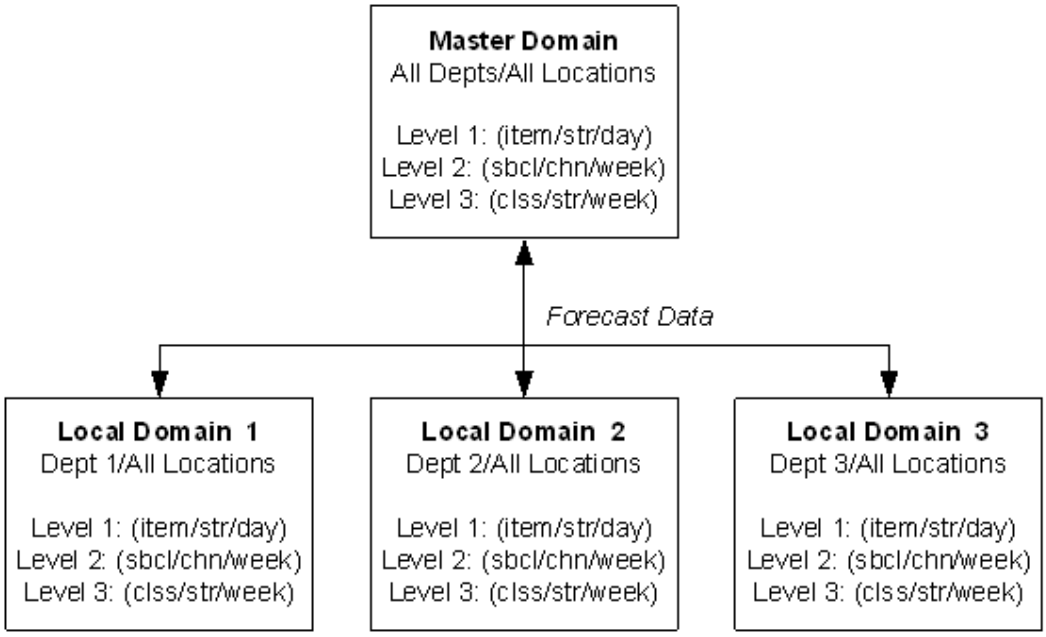
The Oracle Retail Demand Forecasting application is a member of the Advanced Retail Planning and Optimization Suite (ARPO), including other solutions such as Merchandise Financial Planning, Item Planning, Category Management, and Advance Inventory Planning. The ARPO solutions share a common platform called the Oracle Retail Predictive Application Server (RPAS). RDF leverages the versatility, power, and speed of the RPAS engine and user-interface. Features such as the following characterize RPAS:

- Multidimensional databases and database components (dimensions, positions, hierarchies)
- Product, location, and calendar hierarchies
- Aggregation and spreading of sales data
- Client-server architecture and master database
- Workbooks and worksheets for displaying and manipulating forecast data
- Wizards for creating and formatting workbooks and worksheets
- Menus, quick menus, and toolbars for working with sales and forecast data
- An automated alert system that provides user-defined and user-maintained exception reporting
- Charting and graphing capabilities

More details about the use of these features can be found in the *RPAS User Guide* and online help provided within your RDF solution.

Global Domain vs. Simple Domain Environnent

A Simple Domain environment supports isolated partitions of data. This type of environment does not allow for data to be aggregated across partitions into a single view. Whereas a Global Domain environment allows for data partitions to exist; however, certain data may be edited and viewed across partitions. Within this structure we refer to data within a partition as the Local domain (or sub-domain) and the view to data across multiple local domains as the Master domain. The following diagram represents a Global Domain environment:

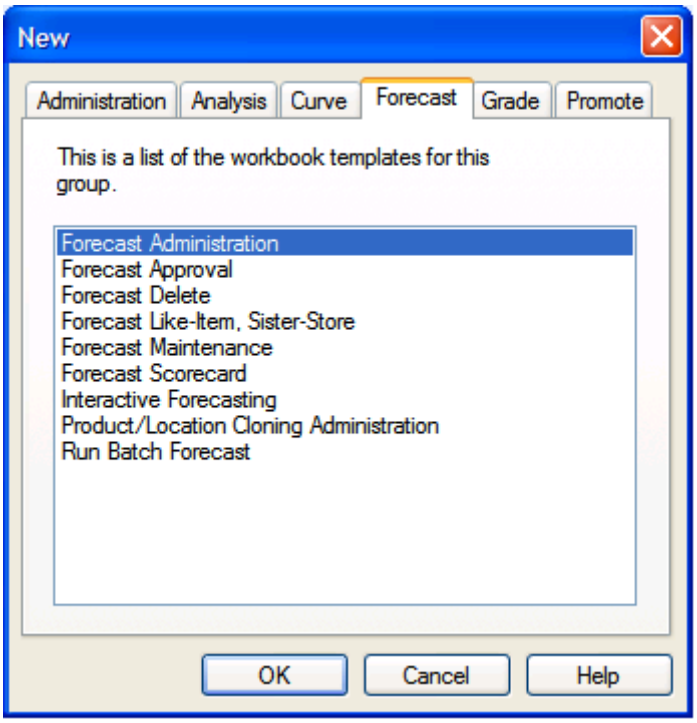


Within this structure, batch forecast results across all domains may be viewed within the Master Domain. This is achieved by passing measures with the same forecast birth date (date/time stamp) to each Local Domain when the batch forecast is generated. It is important to note that this cannot be achieved through the use of the **Run Batch Forecast** wizard. The *RDF Administration Guide* provides more information on execution of batch forecast processes to support a Global Domain environment.

The RDF solution in a Global Domain environment also supports centralized administration and maintenance of forecast parameters in the Master domain. Additional details on the availability and limitations of all of the workbook templates in the Master domain environment are provided in the following sections.

Oracle Retail Demand Forecasting Workbook Template Groups

In addition to the standard RPAS Administration and Analysis workbook template groups, there are several template groups that are associated with the Oracle Retail Demand Forecasting solution may include: Forecast, Promote, Curve or any ARPO solution (available modules are based upon licensing agreement).



New Dialog Box

Forecast

The Forecast module refers to the primary RDF functionality and consists of the workbook templates, measures, and forecasting algorithms that are needed to perform time-series forecasting. This includes the Forecast Administration, Forecast Maintenance, Forecast Like-Item, Sister-Store, Run Batch Forecast, Forecast Approval, Forecast Scorecard, Interactive Forecasting, and Delete Forecast workbook templates. The Forecast module also includes the batch forecasting routine and all of its component algorithms.

Promote (Promotional Forecasting)

The Promote module consists of the templates and algorithms required to perform promotional forecasting, which uses both past sales data and promotional information (for example, advertisements, holidays) to forecast future demand. This module includes the Promotion Maintenance, Promotion Planner and Promotion Effectiveness templates.

Curve

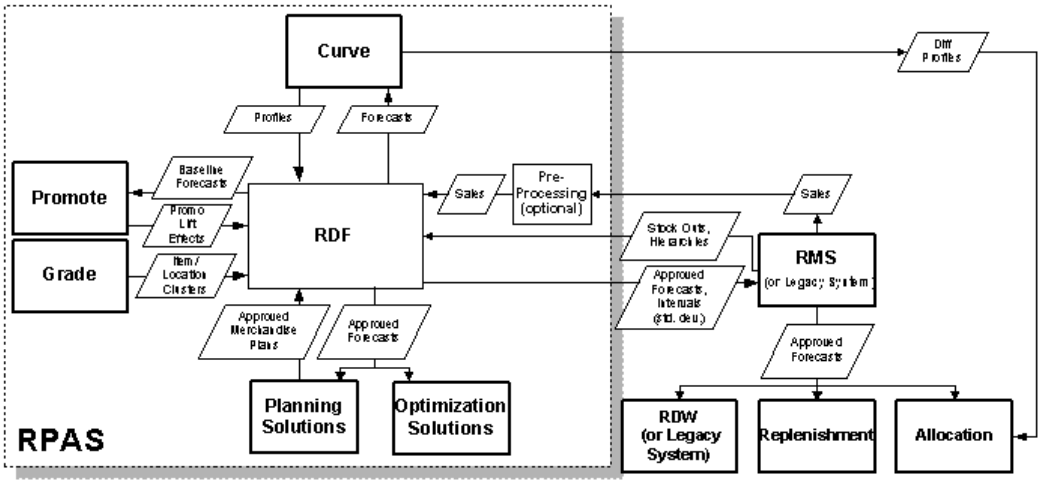
The Curve module consists of the workbook templates and batch algorithms that are necessary for the creation, approval, and application of profiles that may be used to spread source level forecasts down to final levels as well to generate profiles, which may be used in any RPAS solution. The types of profiles typically used to support forecasting are: Store Contribution, Product, and Daily profiles. These profiles may also be used to support Profile-Based Forecasting; however, Curve may be used to generate profiles that are used by other ARPO solutions for reasons other than forecasting. Profiles Types include: Daily Seasonal, Lifecycle, Size, Hourly, and User-Defined profiles. For more information on the Curve workbooks and worksheets, see the *Curve User Guide*.

RDF Solution and Business Process Overview

RDF and the Oracle Retail Enterprise

Oracle Retail has designed a forecasting solution separate from replenishment, allocation or planning. In order to provide a "single version of the truth," it is crucial to free up the user's time and supply the tools to focus on the analysis of forecast exceptions, historical data, and different modeling techniques. This empowers the user to make better decisions, thus improving overall accuracy and confidence in the forecast downstream.

Within the Oracle Retail Enterprise, Oracle Retail Merchandising System (RMS) supplies RDF with Point-of-Sale (POS) and hierarchy data that is used to create a forecast. Once the forecast is approved, it is exported to RMS in order to calculate a recommended order quantity. Forecasts can also be utilized (no export process required) in any RPAS solution to support merchandise, financial, collaborative, and price planning processes.



RDF Primary Workflow

There are a number of core super-user/end-user forecasting steps in the RDF workflow that are essential for producing accurate forecasts for the millions of item and location combinations that exist in a domain.

2

Setting Forecast Parameters

Overview

The Forecast workbook template group allows you to perform functions related to statistical time series forecasting. This chapter provides information on defining and maintaining the parameters that govern the generation of forecasts in RDF.

Forecast Administration Workbook Overview

Basic vs. Advanced Tabs

Forecast Administration is the first workbook used in setting up RDF to generate forecasts. It provides access to forecast settings and parameters that govern the whole domain (database). These settings and parameters are divided into two areas, accessed through the Basic and Advanced tabs beneath main tool bar.

The Basic tab is used to establish a final level forecast horizon, the commencement and frequency of forecast generation; and the specification of aggregation levels (Source Levels) and spreading (Profile) methods used to yield the final level forecast results.

The Advanced tab is used to set default values for parameters affecting the algorithm and other forecasting techniques used to yield final level and source level forecasts, thus eliminating the need to define these parameters individually for each product and location. If certain products or locations require parameter values other than the defaults, these fields can be amended on a case-by-case basis in the Forecast Maintenance workbook. The Forecast Maintenance workbook will be discussed in more detail later in this chapter.

Final vs. Source Level Forecasts

Often, forecast information is required for items at a very low level in the hierarchy. However, problems can arise in that data is often too sparse and noisy to identify clear patterns at these lower levels. For this reason, it sometimes becomes necessary to aggregate sales data from a low level to a higher level in the hierarchy in order to generate a reasonable forecast. Once this forecast is created at the higher or source level, the results can be allocated to the lower or final level dimension based on the lower level's relationship to the total.

In order to spread this forecasted information back down to the lower level, it is necessary to have some idea about the relationship between the final level and the source level dimensions. Often, an additional interim forecast is run at the low level in order to determine this relationship. Forecast data at this low level might be sufficient to generate reliable percentage-to-whole information, but the actual forecast numbers are more robust when generated at the aggregate level.

The Final Level worksheet represents forecast parameters for the lower (final) level, the level to which source forecast values are ultimately spread. Forecast data must appear at some final level in order for the data to be approved or exported to other systems. The Source Level worksheet represents the default values for forecast parameters at the more robust aggregate (source) level.

Forecasting Methods Available in Oracle Retail Demand Forecasting

A forecasting system's main goal is to produce accurate predictions of future demand. Oracle Retail's Demand Forecasting solution utilizes the most advanced forecasting algorithms to address many different data requirements across all retail verticals. Furthermore, the system can be configured to automatically select the best algorithm and forecasting level to yield the most accurate results.

The following section summarizes the use of the various forecasting methods employed in the system. This section is referenced throughout this document when the selection of a forecasting method is required in a workflow process. Some of these methods may not be visible in your solution based on configuration options set in the RPAS Configuration Tools. More detailed information on these forecasting algorithms is provided in Chapter 6: Oracle Retail Demand Forecasting Methods.

Average

Oracle Retail Demand Forecasting uses a simple average model to generate forecasts.

Moving Average

Oracle Retail Demand Forecasting uses a simple moving average model to generate forecasts. Users can specify a Moving Average Window length.

AutoES

Oracle Retail Demand Forecasting fits the sales data to a variety of exponential smoothing models of forecasting, and the best model is chosen for the final forecast. The candidate methods considered by AutoES are:

- Simple ES
- Intermittent ES
- Trend ES
- Multiplicative Seasonal
- Additive Seasonal
- Seasonal ES

The final selection between the models is made according to a performance criterion (Bayesian Information Criterion) that involves a tradeoff between the model's fit over the historic data and its complexity.

Simple ES

Oracle Retail Demand Forecasting uses a simple exponential smoothing model to generate forecasts. Simple ES ignores seasonality and trend features in the demand data and is the simplest model of the exponential smoothing family. This method can be used when less than one year of historic demand data is available.

Intermittent ES

Oracle Retail Demand Forecasting fits the data to the Croston's model of exponential smoothing. This method should be used when the input series contains a large number of zero data points (that is, intermittent demand data). The original time series is split into a Magnitude and Frequency series, and then the Simple ES model is applied to determine level of both series. The ratio of the magnitude estimate over the frequency estimate is the forecast level reported for the original series.

Simple/IntermittentES

A combination of the Simple ES and Intermittent ES methods. This method applies the Simple ES model unless a large number of zero data points are present, in which case the Croston's model is applied.

TrendES

Oracle Retail Demand Forecasting fits the data to the Holt model of exponential smoothing. The Holt model is useful when data exhibits a definite trend. This method separates base demand from trend, and then provides forecast point estimates by combining an estimated trend and the smoothed level at the end of the series. For instance, where the forecast engine cannot produce a forecast using the Trend ES method, the Simple/Intermittent ES method is used to evaluate the time series.

Multiplicative Seasonal

Also referred to as Multiplicative Winters Model, this model extracts seasonal indices that are assumed to have multiplicative effects on the un-seasonalized series.

Additive Seasonal

Also referred to as Additive Winters Model, this model is similar to the Multiplicative Winters model, but is used when zeros are present in the data. This model adjusts the un-seasonalized values by adding the seasonal index (for the forecast horizon).

Seasonal ES

This method, a combination of several Seasonal methods, is generally used for known seasonal items or forecasting for long horizons. This method applies the Multiplicative Seasonal model unless zeros are present in the data, in which case the Additive Winters model of exponential smoothing is used. If less than two years of data is available, a Seasonal Regression model is used. If there is too little data to create a seasonal forecast (in general, less than 52 weeks), the system will select from the Simple ES, Trend ES, and Intermittent ES methods.

Seasonal Regression

Seasonal Regression cannot be selected as a forecasting method, but is a candidate model that is used only when the Seasonal ES method is selected. This model requires a minimum of 52 weeks of history to determine seasonality. Simple Linear Regression is used to estimate the future values of the series based on a past series. The independent variable is the series history one-year or one cycle length prior to the desired forecast period, and the dependent variable is the forecast. This model assumes that the future is a linear combination of itself one period before plus a scalar constant.

Causal

Causal is used for promotional forecasting and can only be selected if Promote is implemented. Causal uses a Stepwise Regression sub-routine to determine the promotional variables that are relevant to the time series and their lift effect on the series. AutoES utilizes the time series data and the future promotional calendar to generate future baseline forecasts. By combining the future baseline forecast and each promotion's effect on sales (lift), a final promotional forecast is computed. For instances where the forecasting engine cannot produce a forecast using the Causal method, the system will evaluate the time series using the Seasonal ES method.

No Forecast

No forecast will be generated for the product/location combination.

Bayesian

Useful for short lifecycle forecasting and for new products with little or no historic sales data, the Bayesian method requires a product's known sales plan (created externally to RDF) and considers a plan's shape (the selling profile or lifecycle) and scale (magnitude of sales based on Actuals). The initial forecast is equal to the sales plan, but as sales information comes in, the model generates a forecast by merging the sales plan with the sales data. The forecast is adjusted so that the sales magnitude is a weighted average between the original plan's scale and the scale reflected by known history. A Data Plan must be specified when using the Bayesian method. For instances where the Data Plan equals zero (0), the system will evaluate the time series using the Seasonal ES method.

Profile-based

Oracle Retail Demand Forecasting generates a forecast based on a seasonal profile that can be created in RPAS or legacy system. Profiles can also be copied from another profile and adjusted. Using historic data and the profile, the data is de-seasonalized and then fed to the Simple ES method. The Simple forecast is then re-seasonalized using the profiles. A Seasonal Profile must be specified when using the Profile-Based method. For instances where the Seasonal Profile equals zero (0), the system will evaluate the time series using the Seasonal ES method.

Forecast Administration Workbook

Creating a Forecast Administration Workbook

1. Within the Master or Local Domain, select **New** from the File menu.
2. Select the Forecast tab to display a list of workbook templates for statistical forecasting.
3. Select **Forecast Administration**.
4. Click **OK**.
5. The Forecast Administration wizard opens and prompts you to select the level of the final forecast. The final forecast level is a level at which approvals and data exports can be performed. Depending on your organization's setup, you may be offered a choice of several final forecast levels. Make the appropriate selection.
6. Click **Finish** to open the workbook.

Window Descriptions

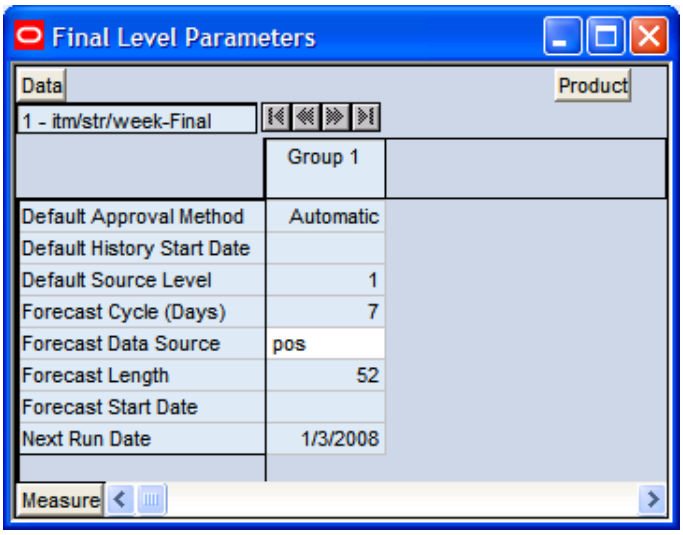
Basic Settings Workflow Tab

The Basic Settings workflow tab contains forecast administration settings. On the Basic Settings workflow tab, there are two worksheets:

- Final Level Parameters worksheet
- Final and Source Level Parameters worksheet

Final Level Worksheet – Basic Settings

The Final Level worksheet allows you to set the forecast horizon information, frequency of review, and all default parameters for the lower or final level forecast (the level to which aggregate forecast data will ultimately be spread). Forecast approvals and data exports can only be performed on forecasts at a final level. The following image provides an example of a view of the Final Level Parameters worksheet in a Master Domain with three partitions/local domains, partitioned based on group.



Final Level Parameters Worksheet

Field Descriptions

The following is a description of the Basic Settings contained in the Final Level Parameters worksheet:

Default Approval Method

This field is a drop-down list from which you select the default automatic approval policy for forecast items. Valid values are:

- Manual – The system-generated forecast will not be automatically approved. Forecast values must be manually approved by accessing and amending the Forecast Approval workbook.
- Automatic – The system-generated quantity will be automatically approved as-is.
- By Alert – This list of values may also include any **Forecast Approval** alerts that have been configured for use in the forecast approval process. Alerts are configured during the implementation. See the *RPAS Configuration Tools User Guide* for more information on the Alert Manager.

Default History Start Date

This field indicates to the system the point in the historical sales data at which to use in the forecast generation process. If no date is indicated, the system will default to the first date in your calendar. It is also important to note that the system ignores leading zeros that begin at the history start date. For example, if your history start date is January 1, 1999 and an item/location does not have sales history until February 1, 1999, the system will consider the starting point in that item/location's history to be the first data point where there is a non-zero sales value.

Default Source Level

The pick list of values displayed in this field allows the user to change the forecast level that will be used as the primary level to generate the source forecast. The source levels are set up in the RPAS Configuration Tool. A value from the pick list is required in this field at the time of forecast generation.

Forecast Cycle

The Forecast Cycle is the amount of time (measured in days) that the system waits between each forecast generation. Once a scheduled forecast has been generated, this field is used to automatically update the Next Run Date field. A non-zero value is required in this field at the time of forecast generation.

Forecast Data Source

This is a read-only value that displays the sales measure (the measure name) that will be the data used for the generation of forecasts (for example, pos). The measure that will be displayed here is determined at configuration time in the RPAS Configuration Tools.

Forecast Start Date

This is the starting date of the forecast. If no value is specified at the time of forecast generation, the system will use the data/time at which the batch is executed as the default value. If a value is specified in this field and it is used to successfully generate the batch forecast, this value will be cleared.

Forecast Length

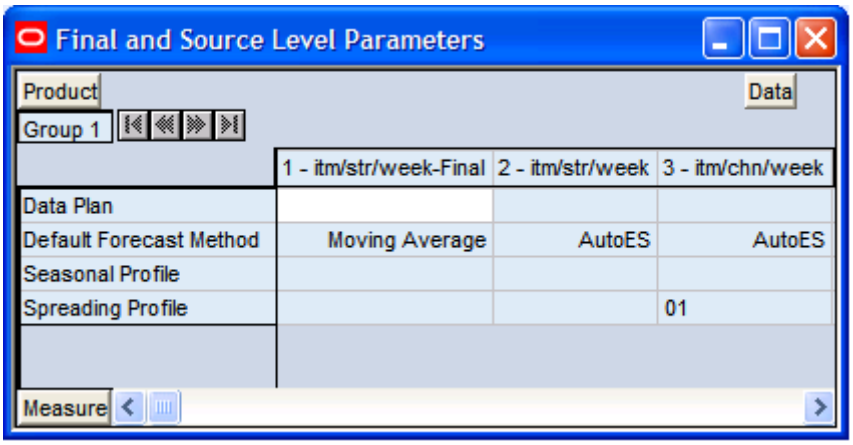
The Forecast Length is used with the Forecast Start Date to determine forecast horizon. The forecast length is based on the calendar dimension of the final level. For example, if the forecast length is to be 10 weeks, the setting for a final level at day is 70 (10 x 7 days).

Next Run Date

The Next Run Date is the date on which the next batch forecast generation process will automatically be run. Oracle Retail Demand Forecasting automatically triggers a set of batch processes to be run at a pre-determined time period. When a scheduled batch is run successfully, the Next Run Date automatically updates based on the Start Date value and the Forecast Cycle. No value is required in this field when the **Run Batch Forecast** wizard is used to generate the forecast or if the batch forecast is run from the backend of the domain(s) using the "override true" option. See the *RDF Administration Guide* for more information on forecast generation.

Final and Source Level Parameters Worksheet – Basic Settings

The Final and Source Level worksheet allows you to set the default parameters that are common to both the final and source level forecasts.



Final and Source Level Parameters Worksheet

Field Descriptions

The following is a description of the Basic Settings parameters contained in the Source Level worksheet:

Data Plan

Used in conjunction with the Bayesian forecast method, Data Plan is used to input the measure name of a sales plan that should be associated with the final level forecast. Sales plans, when available, provide details of the anticipated shape and scale of an item's selling pattern. If the Data Plan is required, this field should include the measure name associated with the Data Plan.

Default Forecast Method

The Default Forecast Method is a drop-down list from which you can select the primary forecast method that will be used to generate the forecast. Valid method options depend on your system setup. A summary of methods is provided earlier in this chapter and the last chapter in this guide covers each method in greater detail. It is important to note that **Causal** should not be selected unless the forecast level was set as a Causal level during the configuration. See the *RDF Configuration Guide* for more information on configurations using the Causal forecast method.

Seasonal Profile

Used in conjunction with the Profile-Based forecasting method, this is the measure name of the seasonal profile that will be used to generate the forecast at either the source or final level. Seasonal profiles, when available, provide details of the anticipated seasonality (shape) of an item's selling pattern. The seasonal profile can be generated or loaded, depending on your configuration. The original value of this measure is set during the configuration of the RDF solution.

Spreading Profile

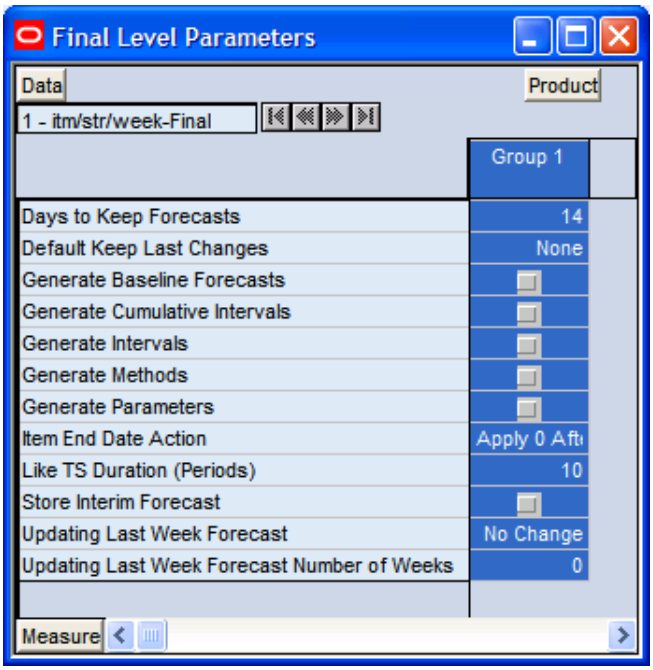
Used for Source Level Forecasting, the value of this measure indicates the profile level that will be used to determine how the source level forecast is spread down to the final level. No value is needed to be entered at the final level. For dynamically generated profiles, this value is the number associated with the final profile level (for example 01)—note that profiles 1 through 9 have a zero (0) preceding them in Curve—this is different than the forecasting level numbers. For profiles that must be approved, this is the measure associated with the final profile level. This measure is defined as "apvp"+level (for example: apvp01 for the approved profile for level 01 in Curve).

Advanced Settings Workflow Tab

The Forecast Administration Advanced Settings workflow tab is used to set parameters related to either the data that is stored in the system or the forecasting methods that will be used at the final or source levels. The parameters on this workflow tab are not as likely to be changed on a regular basis as the ones on the Basic Settings workflow tab.

Final Level Parameters Worksheet – Advanced Settings

The Final Level worksheet allows you to set the advanced parameters for the final level forecasts. The following image provides an example of a view of this worksheet in a Master Domain with three partitions/Local Domains, partitioned based on group.



Final Level Parameters Worksheet

Field Descriptions

The Final Level worksheet – Advanced Settings contains the following parameters:

Days to Keep Forecasts

This field is used to set the number of days that the system will store forecasts based on the date/time the forecast is generated. The date/time of forecast generation is also referred to as "birth date" of the forecast. A forecast is deleted from the system if the birth date plus the number of days since the birth date is greater than the value set in the "Days to Keep Forecast" parameter. This process occurs when either the **Run Batch Forecast** wizard is used to generate the forecast or when "PreGenerateForecast" is executed. See the *RDF Administration Guide* for more information on PreGenerateForecast.

Default Keep Last Changes

This field is a drop-down list from which you select the default change policy for forecast items. Valid values are:

- Keep Last Changes (None) – There are no changes that are introduced into the adjusted forecast.
- Keep Last Changes (Total) – Considers only the Last Approved Forecast in determining change policy. For each forecasted item/week-combination, Oracle Retail Demand Forecasting automatically introduces the same quantity that was approved in the Last Approved Forecast into the change only if that quantity differed from that in the Last System Forecast. If the quantities are the same, Oracle Retail Demand Forecasting will introduce the current system-generated forecast into the adjusted forecast.
- Keep Last Changes (Diff) – Considers both the Last System Forecast and the Last Approved Forecast in determining approval policy. For each forecasted item/week-combination, Oracle Retail Demand Forecasting determines the difference between the Last System Forecast and the Last Approved Forecast. This difference (positive or negative) is then added to the current system forecast and calculated as the adjusted forecast.
- Keep Last Changes (Ratio) – Considers both the Last System Forecast and the Last Approved Forecast in determining change. For each forecasted item/week-combination, Oracle Retail Demand Forecasting determines the difference between the Last System Forecast and the Last Approved Forecast. This difference is expressed as a percentage. This same percentage is used to calculate the adjusted forecast.

Generate Baseline Forecasts

A check should be indicated in this field (set to true) if the baseline forecast is to be generated to be viewed in any workbook. This parameter should be set if the level is to be used for Causal forecasting and the baseline will be needed for analysis purposes.

Generate Cumulative Interval

A check in this field (set to true) specifies whether you want Oracle Retail Demand Forecasting to generate cumulative intervals (this is similar to cumulative standard deviations) during the forecast generation process. Cumulative Intervals are a running total of Intervals and are typically required when RDF is integrated with the Oracle Retail Merchandising System. If you do not need cumulative intervals, you can eliminate

excess processing time and save disk space by clearing the check box. The calculated cumulative intervals can be viewed within the Forecast Approval workbook.

Generate Intervals

A check in this field (set to true) indicates that intervals (similar to Standard Deviations) should be stored as part of the batch forecast process. Intervals can be displayed in the Forecast Approval workbook. If you do not need intervals, excess processing time and disk space may be eliminated by clearing the check box. For many forecasting methods, intervals are calculated as standard deviation but for Simple, Holt, and Winters the calculation is more complex. Intervals are not exported.

Generate Methods

A check in this field (set to true) indicates that when an ES forecast method is used, the chosen forecast method for each fitted time series should be stored. The chosen method can be displayed in the Forecast Approval workbook.

Generate Parameters

A check in this field (set to true) indicates that the alpha, level, and trend parameters for each fitted time series should be stored. These parameters can be displayed in the Forecast Approval workbook.

Item End Date Action

This parameter allows the option for items with end dates within the horizon to have zero demand applied to time series before or after the interim forecast is calculated. The two options are:

- **Apply 0 After Spreading** — This is the default value. Spreading ratios are calculated for time series with no consideration made to the end date of an item. It is after the source forecast is spread to the final level when zero is applied to the System Forecast.
- **Apply 0 to Interim** — For items that have an end date within the forecast horizon, zero is applied to the Interim Forecast before the spreading ratios are calculated. This ensures that no units are allocated to the final level for time series that have ended.

Like TS Duration (Periods)

The Like TS Duration is the number of periods of history required, after which RDF stops using the substitution method and starts using the system forecast generated by the forecast engine. A value must be entered in this field if using like item/Sister-Store functionality. When the difference between the forecast start date and the history start date is greater than the Like TS Duration, RDF starts using the system forecast for the item.

Store Interim Forecast

A check should be placed in this field (set to true) if the interim forecast will be stored. The Interim Forecast is the forecast generated at the Final Level. This forecast is used as the Source Data within Curve to generate the profile (spreading ratios) for spreading the source level forecast to the final level. The interim forecast should only be stored if it is necessary for any analysis purposes.

Updating Last Week Forecast

This field is a drop-down list from which you can select the method for updating the Approved Forecast for the last specified number of week(s) of the forecast horizon. This option is valid only if the Approval Method Override (set in the Forecast Maintenance workbook) is set to Manual or Approve by alert, and the alert was rejected. This parameter is used with the **Updating Last Week Forecast Number of Weeks**.

- **No Change –** When using this method, the last week(s) in the forecast horizon will not have an Approved Forecast value. The number of weeks is determined by the value set in the **Updating Last Week Forecast Number of Weeks** parameter.
- **Replicate –** When using this method the last week(s) in the forecast horizon will be forecasted using the Approved Forecast for the week prior to this time period. To determine the appropriate forecast time period the value set in **Updating Last Week Forecast Number of Weeks** is subtracted from the Forecast Length. For example, if your Forecast Length is set to 52 weeks and **Updating Last Week Forecast Number of Weeks** is set to 20, week 32's Approved Forecast will be copied into the Approved Forecast for the next 20 weeks.
- **Use Forecast –** When using this method, the System Forecast for the last week(s) in the forecast horizon is approved.

Updating Last Week Forecast Number of Weeks

The Approved Forecast for the last week(s) in the forecast horizon is updated using the method specified from the **Updating Last Week Forecast** list.

Final and Source Level Worksheet – Advanced Settings

The Source Level worksheet allows you to set the advanced parameters for the source level forecasts.

Final and Source Level Parameters

Product | Data

Group 1

	1 - itm/str/week-Final	2 - itm/str/week	3 - itm/chn/week
Bayesian Alpha	1.00	1.00	1.00
Bayesian Cap Ratio	1.50	1.50	1.50
Crostons Min Gaps	5	5	5
DD Duration (Periods)	0	0	0
Default Moving Average Window Length	0	0	0
Default Winters Mode	Oracle Winters	Oracle Winters	Oracle Winters
Fall Back Method	Default	Default	Default
Holt Min Hist (Periods)	13	13	13
Max Alpha (Profile)	1.00	1.00	1.00
Max Alpha (Simple Holt)	1.00	1.00	1.00
Max Alpha (Winters)	1.00	1.00	1.00
Seasonal Smooth Index	0.80	0.80	0.80
Trend Damping Factor	0.50	0.50	0.50
Winters Min Hist (Periods)	104	104	104

Measure

Final and Source Level Parameters Worksheet

Field Descriptions

The Source Level worksheet – Advanced Settings contains the following parameters:

Bayesian Alpha (range (0, infinity))

When using the Bayesian forecasting method, historic data is combined with a known sales plan in creating the forecast. As POS data comes in, a Bayesian forecast is adjusted so that the sales magnitude is a weighted average between the original plan's scale and the scale reflected by known history. This parameter displays the value of alpha (the weighted combination parameter). An alpha value closer to one (or infinity) weights the sales plan more in creating the forecast, whereas alpha closer to zero weights the known history more. The default is 1.

Bayesian Cap Ratio

The Bayesian Cap ratio is used to cap the resulting Bayesian forecast if it deviates significantly from the sale plan. The Bayesian Cap ratio is used as follows:

$$\text{If } forecast_I > \text{ Bayesian Cap ratio * Max value of Past Sales AND}$$
$$forecast_I > \text{ Bayesian Cap ratio * Max value of Past Plan AND}$$
$$forecast_I > \text{ Bayesian Cap ratio * } Plan_I$$
$$\text{then}$$
$$forecast_I = Plan_I$$

It defaults to a value of 1.5

Croston Min Gaps

The Croston Min Gaps is the default minimum number of gaps between intermittent sales for the batch forecast to consider Croston's (Simple/IntermittentES) as a potential AutoES forecasting method for a time series. If there are not enough gaps between sales in a given product's sales history, the Croston's model is not considered a valid candidate model. The system default is five minimum gaps between intermittent sales. The value must be set based on the calendar dimension of the level. For example, if the value is to be 5 weeks, the setting for a final level at day is 35 (5x7days) and a source level at week will be 5.

DD Duration (weeks)

Used with Profile Based forecast method, the DD Duration is the number of weeks of history required after which the system stops using the DD (De-seasonalized Demand) approach and defaults to the "normal" Profile-Based method. The value must be set based on the calendar dimension of the level. For example, if the value is to be 10 weeks, the setting for a final level at day is 70 (10x7days) and a source level at week will be 10.

Default Moving Average Window Length

Used with Moving Average forecast method, this is the Default number of data points in history used in the calculation of Moving Average. This parameter can be overwritten at Item/Loc from the Forecast Maintenance workbook.

Fallback Method

Set this parameter **ONLY IF** the "Fallback Method" is to vary from the default Fallback Methods used by the selected forecasting algorithm. If the method selected as the **Default Forecast Method** or **Forecast Method Override** does not succeed for a time series, this method will be used to calculate the forecast and the default Fallback Methods in the forecasting process will be skipped entirely. The default Fallback Methods are as follows:

- If either the **Causal, Bayesian**, or **Profile-Based** are selected as the **Default Forecast Method** or **Forecast Method Override** and the method does not fit the data:

  Step 1: RDF will attempt to fit SeasonalES

  Step 2: RDF will attempt to fit TrendES

  Step 3: RDF will attempt to fit Simple/IntermittentES
- If the **SeasonalES** is selected as the **Default Forecast Method** or **Forecast Method Override** and neither **Multiplicative Seasonal** or **Additive Seasonal** fits the data:

  Step 1: RDF will attempt to fit TrendES

  Step 2: RDF will attempt to fit Simple/IntermittentES
- If either the **Multiplicative Seasonal** or **Additive Seasonal** are selected as the **Default Forecast Method** or **Forecast Method Override** and the method does not fit the data:

  Step 1: RDF will attempt to fit TrendES

  Step 2: RDF will attempt to fit Simple/IntermittentES
- If the **TrendES** is selected as the **Default Forecast Method** or **Forecast Method Override** and the method does not fit the data:

  Step 1: RDF will attempt to fit Simple/IntermittentES

Holt Min Hist (Periods)

Used with the AutoES forecast method, Holt Min Hist is the minimum number of periods of historical data necessary for the system to consider Holt (TrendES) as a potential forecasting method. Oracle Retail Demand Forecasting fits the given data to a variety of AutoES candidate models in an attempt to determine the best method; if not enough periods of data are available for a given item, Holt will not be considered as a valid option. The system default is 13 periods. The value must be set based on the calendar dimension of the level. For example, if the value is to be 13 weeks, the setting for a final level at day is 91 (13x7days) and a source level at week will be 13.

Max Alpha (Profile) (range (0,1])

In the Profile-based model fitting procedure, alpha, which is a model parameter capturing the level, is determined by optimizing the fit over the de-seasonalized time series. The time series is de-seasonalized based on a seasonal profile. This field displays the maximum value (that is, cap value) of alpha allowed in the model fitting process. An alpha cap value closer to 1 allows more reactive models (alpha = 1, repeats the last data point), whereas alpha cap closer to 0 only allows less reactive models. The default is 1.

Max Alpha (Simple, Holt) (range (0,1])

In the Simple or Holt (TrendES) model fitting procedure, alpha (a model parameter capturing the level) is determined by optimizing the fit over the time series. This field displays the maximum value (cap value) of alpha allowed in the model fitting process. An alpha cap value closer to 1 allows more reactive models (alpha = 1, repeats the last data point), whereas alpha cap closer to 0 only allows less reactive models. The default is 1.

Max Alpha (Winters) (range (0,1])

In the Winters (SeasonalES) model fitting procedure, alpha (a model parameter capturing the level) is determined by optimizing the fit over the time series. This field displays the maximum value (cap value) of alpha allowed in the model fitting process. An alpha cap value closer to 1 allows more reactive models (alpha = 1, repeats the last data point), whereas alpha cap closer to 0 only allows less reactive models. The default is 1.

Seasonal Smooth Index

This parameter is used in the calculation of seasonal index. The current default value used within forecasting is .80. Changes to this parameter will impact the value of seasonal index directly and impact the level indirectly. When seasonal smooth index is set to 1, seasonal index will be closer to the seasonal index of last year sales. When seasonal smooth index is set to 0, seasonal index will be set to the initial seasonal indexes calculated from history. This parameter is used when the Winters Mode is set to Oracle Winters. If the Winters Mode is Winters Standard, Winters Responsive, or Oracle winters Decomposition, this parameter is optimized and the user input value is ignored.

Trend Damping Factor (range (0,1])

This parameter determines how reactive the forecast is to trending data. A value close to 0 is a high damping, while a value if 1 implies no damping. The default is 0.5.

Winters Min Hist (Periods)

Used with the AutoES forecast method, the value in this field is the minimum number of periods of historical data necessary for Winters to be considered as a potential forecast method. If not enough years of data are available for a given time series, Winters will not be used. The system default is two years of required history. The value must be set based on the calendar dimension of the level. For example, if the value is to be 104 weeks/2 years, the setting for a final level at day is 728 (104 weeks x 7 days) and a source level at week will be 104.

Winters Mode

When any forecast method calls multiplicative or additive Winters, the system will execute the Winters forecasting approach indicated by the Winters Mode.

The Winters forecasting approaches are:

- Oracle Winters (default approach)

  Current or default seasonal forecasting approach, which uses a combination of Winters approach and decomposition. Decomposition allows level and trend to be optimized independently while maintaining a seasonal curve.

- Oracle Winters Decomposition

  Like Oracle Winters seasonal forecasting approach, Oracle Winters Decomposition uses a combination of Winters approach and decomposition. Key differences between Oracle Winters and Oracle Winters Decomposition include:
  - Seasonal smoothing factor is optimized.
  - The optimization places more importance on recent sales than historical sales.
  - Seasonal indices are recalculated based on optimization.
- Winters Standard

  The Standard Winters uses a standard Winters model, with no additional calculations. All three smoothing parameters are optimized.
- Winters Responsive

  Responsive Winters, like Standard Winters does not use decomposition and all three smoothing parameters are optimized. This approach is recommended for forecasting items with significant trends in the more recent historic sales.
  The difference between Winters Responsive and Winters Standard is:
  - Winters Responsive optimization places more importance on recent sales than historical sales.

The following table illustrates the key differences between the models.

Forecasting Approach	Optimized to Recent Sales	Decomposition	Seasonal Smoothing Parameter Optimized
Oracle Winters	No	Yes	No
Oracle Winters Decomposition	Yes	Yes	Yes
Winters Standard	No	No	Yes
Winters Responsive	Yes	No	Yes

Winters Mode Impact on AutoES and Causal

The Winters Mode measure determines which Forecasting Approach to use within AutoES and Causal. Also, the errors that are used to calculate the BIC may be different for different Forecasting Approaches and could impact the choice of Forecast Method within AutoES and Causal.

It is recommended that you choose a Forecasting Approach that best suits the nature of your business. The default forecasting approach is Oracle Winters. For additional information on the four forecasting approaches, please refer to the Forecasting Methods Available in Oracle Retail Demand Forecasting section.

> **Note:** If patching this change into a domain, in order to view this measure in the Forecast Administration workbook, it must be added to the **Final and Source Level Parameters** worksheet by selecting it from the Show/Hide dialog within the RPAS Client.

Causal Parameters Worksheet – Advanced Settings

The Causal Parameters worksheet allows you to set the parameters that support promotional forecasting. This worksheet only includes the causal forecast levels for the final level selected during the wizard process. This worksheet will not be visible if Promote/Promotional Forecasting is not implemented in your RDF environment.

Causal Parameters

Product: INDOOR FURNITURE 0032 | Data

	04 - Related Group/Climate Winter/Week - Source	05 - Related Group/Corporate Maintained Grouping 1/Week - Source	06 - Related Group/Back to School/Week - Source	07 - Related Group/Store/Week - Source
Causal - Disable Seasonal Regression				
Causal - Lift Estimate	Multiplicative	Hybrid	Multiplicative	Multiplicative
Causal - Seasonal Baseline Selection Criteria	Avg Criteria	Avg Criteria	Avg Criteria	Avg Criteria
Causal - Smoothing Method	MovingAverage	IndicatorBased	MovingAverage	MovingAverage
Causal Aggregation Profile	apvp37	apvp37	apvp37	apvp37
Causal Baseline Minimum Winters History Length	0	0	0	0
Causal Beta Scale	50.00	50.00	50.00	50.00
Causal Calculation Intersection				
Causal Calculation Intersection Periodicity	0	0	0	0
Causal Capping Number				
Causal Capping Ratio				
Causal Data Source				
Causal Higher Intersection				
Causal Short Season Threshold	52	52	52	52
Causal Spread Profile				
Disable Causal				
Minimum Causal Capping History (Periods)	0	0	0	0
Use Causal Capping				

Measure

Causal Parameters Worksheet

Causal – Disable Seasonal Regression

This parameter gives the user the option to remove Seasonal Regression from choice of Forecast Methods for baseline calculation within Causal Forecasting Method. It defaults to false, which means Seasonal regression is included in the choice of methods for baseline calculation within causal.

If set to true, Seasonal regression will be excluded from the choice of methods for baseline calculation within Causal.

> **Note:** This parameter does not impact the choice of forecast methods within SeasonalES.

Causal – Lift Estimate

The parameter gives the user the option to use either the multiplicative or hybrid models to decausalize the sales history.

- Multiplicative: this model extracts promotional lifts that are assumed to have multiplicative effects in order to decasualize the history.
- Hybrid: this model extracts the promotional lifts as additive effects in the decasualize phase to decausalize the history. Then later in the forecast phase, it applies the promotional lifts as multiplicative effect to the forecasted baseline. This is the system default value.

Causal – Seasonal Baseline Selection Criteria

This parameter allows the user to choose whether to use minimum or average baseline criteria to determine baseline stability within Causal Forecasting Method.

- Average baseline criteria: If system calculated average baseline forecast < 4, use Beta zero as System baseline forecast.
- Minimum baseline criteria: If system calculated minimum baseline forecast < 1, then use Beta zero as System baseline forecast.

This parameter defaults to Average Baseline Criteria.

Causal – Smoothing Method

This parameter gives the user the option to use either Indicator Based or Moving Average methods to smooth the sales history.

- Indicator Based: smoothes the periods that have active promotions (indicators) by using the sales of non-promoted periods in the time frame. This is the system default value.
- Moving Average: for each period *t*, the moving average method takes the average of the periods from *t*-2 to *t*+2 as the smoothed baseline.

Causal Aggregation Profile

Used only for Daily Causal Forecasting, the Causal Aggregation Profile is measure name of the profile used to aggregate promotions defined at "day" up to the "week." The value entered in this field is the measure name of profile. If this profile is generated within Curve, the format of the measure name will be "apvp"+level (for example: apvp01). Note that the only aggregation of promotion variables being performed here is along the Calendar hierarchy. RDF does not support aggregation of promotion variables along other hierarchies such as product and location hierarchies.

Causal Beta Scale

As part of the causal forecasting process, the average sales of non-promo periods in history are divided by the Beta Scale. If the betazero is above the **Causal Beta Scale** value, the causal forecasting method succeeds. If not, the causal forecasting method fails and the Fallback Method is used to generate the forecast for the time series.

Causal Calculation Intersection

Used only for Daily Causal Forecasting, the Causal Calculation Intersection is the intersection at which the causal forecast is run. The format needs to match the hierarchy dimension names set in the RPAS Configuration Tools (such as "itemstr_week"). Each dimension must have only four characters. The order of the dimension does not matter. There is no validation of correct format of this intersection.

Causal Calculation Intersection Periodicity

Used only for Daily Causal Forecasting, the Causal Calculation Intersection Periodicity must be set to the periodicity of Causal Calculation Intersection. Periodicity is the number of periods within one year that correspond to the calendar dimension (for example, 52 if the Causal Calculation Intersection is defined with the week dimension).

Causal Capping Number

The value of this parameter is a measure based on the same product and location intersection as the forecast level. This measure contains the maximum value to use for calculating the causal forecast for time series that meet the Causal Capping conditions. If **Use Causal Capping** is set to true, the history for the time series is greater than or equal to the **Minimum Causal Capping History**, and the preliminary forecast is greater than or equal to the value in the **Causal Capping Number** measure, then the forecast will be recalculated to be the value in the **Causal Capping Number** measure multiplied by the value in the **Causal Capping Ratio** measure.

Causal Capping Ratio

The value of this parameter is a measure based on the same product and location intersection as the forecast level. This measure contains the ratio to be used to calculate the forecasts for time series that meet the Causal Capping conditions. If **Use Causal Capping** is set to true, the history for the time series is greater than or equal to the value in the **Minimum Causal Capping History** measure, and the preliminary forecast is greater than or equal to the value in the **Causal Capping Number** measure, then the forecast will be recalculated to be the **Causal Capping Number** multiplied by the value in the **Causal Capping Ratio** measure.

Causal Data Source

Used only for Daily Causal Forecasting, the Causal Data Source is an optional setting that contains the measure name of the sales data to be used if the data for causal forecasting is different than the Data Source specified at the Final level. If needed, this field should contain the measure name of the source data measure (for example: dpos).

Causal Higher Intersection

An optional setting for Causal Forecasting, this intersection is the aggregate level to model promotions if the causal intersection cannot produce a meaningful causal effect. This intersection will apply to promotions that have a Promotion Type is set to **Override From Higher Level** (set in the Promotion Maintenance workbook). The format of this intersection needs to match the hierarchy dimension names set in the RPAS Configuration Tools—such as “sclsrgn_” (Subclass\Region), and it must not contain the calendar dimension. Each dimension must have only four characters. The order of the dimension does not matter. There is no validation of correct format of this intersection.

Causal Short Seasonal Threshold

Used only in Causal forecasting, this parameter is the minimum number of historical time periods that are required for SeasonalES to be used to produce the Causal forecast. Otherwise, the baseline from Causal regression will be used. The algorithm currently uses 52 weeks of history as the default for this parameter, but it may be set from 13 to 56 weeks. For an item with history less than the value in the Causal Short Seasonal Threshold and greater than 12 weeks, the BetaZero will be used only if Causal found the initial effects to be significant. Otherwise, the item will be forecasted using the Fallback Method.

Causal Spread Profile

Used only for Daily Causal Forecasting, the Causal Spread Profile is the measure name of the profile used to spread the causal baseline forecast from the Causal Calculation

Intersection to the Final Level. If this profile is generated in Curve, this measure value will be "apvp"+level (for example: apvp01).

Minimum Causal Capping History (Periods)

If **Use Causal Capping** is set to true, this parameter is used to set minimum number of historical time periods required before the system will consider a time series for causal capping.

Disable Causal

Place a check in this parameter (set to true) if causal forecasting is to be disabled for the forecast level. This parameter serves as a global override. This parameter can also help with performance, when not running Causal forecast method.

Use Causal Capping

Place a check in this parameter (set to true) if capping is to be applied to the causal forecast. Also required for causal capping are the following parameters:

- Causal Capping Number
- Causal Capping Ratio
- Minimum Causal Capping History

> **Note:** More detailed information on the Causal forecasting algorithm is provided in "Forecasting Methods Available in Oracle Retail Demand Forecasting."

Forecast Maintenance Workbook

Overview

The Forecast Maintenance workbook allows you to select and modify forecasting parameters for product/location combinations when the values of these parameters differ from the default values that are assigned in the Forecast Administration workbook.

Suppose, for example, that the default forecast method of all the products in the database was set in the Forecast Administration workbook to be AutoES. For a particular product, however, you know that a SeasonalES model is a better predictor of sales performance. To make this change, you must access the Forecast Maintenance workbook, select the product / location intersection to be reviewed, and make the appropriate change to the forecast method.

The Forecast Maintenance workbook is split into two workflow tabs:

- Basic Settings – Includes all Final Level worksheets and their respective Source Level worksheets.
- Advanced Settings – This tab includes the Forecast Start Date, End Date, and History Start Date measures for the selected Final Level.

Creating a Forecast Maintenance Workbook

1. Within the Master or Local Domain, select New from the File menu.
2. Select the Forecast tab to display a list of workbook templates for statistical forecasting. Highlight Forecast Maintenance.
3. Click **OK**. The Forecast Maintenance wizard opens and prompts you to select the level of the final forecast. Depending on your organization's setup, you may be offered a choice of several final forecast levels.
4. Select the final forecast level to be viewed in the workbook.
5. Click **Next**.
6. Select the locations to include in the workbook.
7. Click **Next**.
8. Select the products to include in the workbook.
9. Click **Next**.
10. Select any additional measures (that is, measures not standard in the Forecast Maintenance workbook) that you would like included. The measure options available in this screen are set in the RPAS Security Administration workbook / workbook Template Measure Rights worksheet.
11. Click **Finish** to display the workbook.

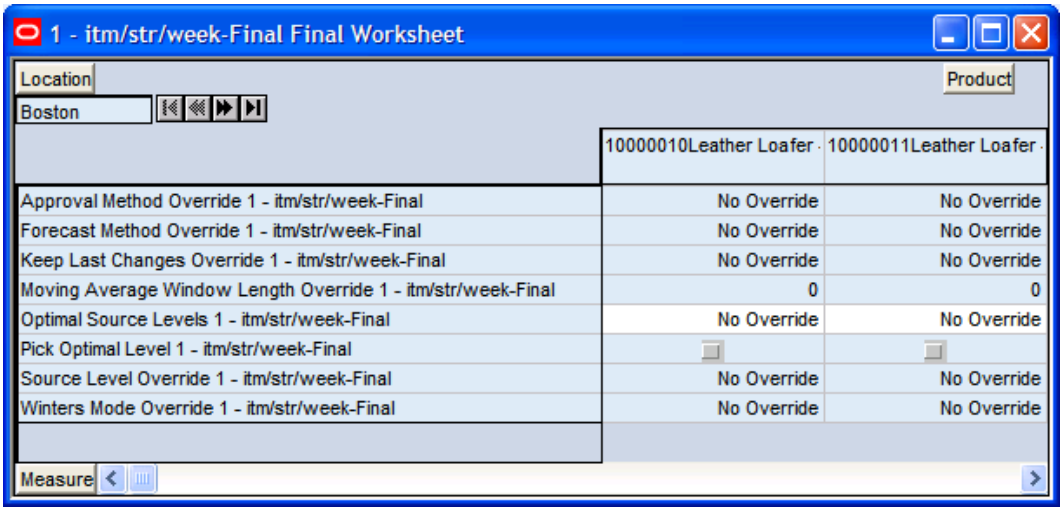
Window Descriptions

Basic Settings Workflow Tab

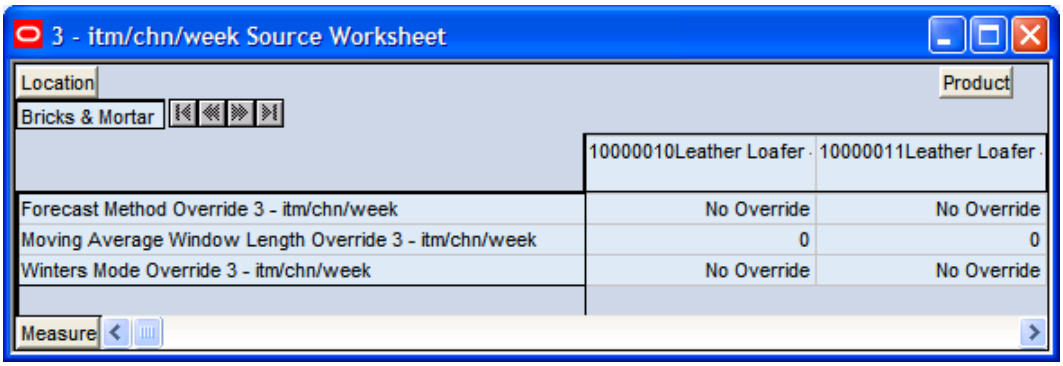
The Basic Settings workflow tab of Forecast Maintenance includes Final Level worksheets and their respective Source Level worksheets.

Final Level Worksheet and Source Level Worksheet – Basic Settings

The Final Level worksheet and Source Level worksheets allow for certain parameters set at a global level (in Forecast Administration) to vary at different item/locations. The following is an example view of both the Final Level and Source Level worksheets:



Final Level Worksheet – Basic Settings



Source Level Worksheet – Basic Settings

Field Descriptions

The Final Level worksheet and Source Level worksheet – Basic Settings contains the following parameters:

Approval Method Override

Set only at the final level, the Approval Method Override is a drop-down list from which you select the approval policy for individual product/location combinations. No value will be in this field if the system default set in the Forecast Administration workbook is to be used. Valid values are:

- **Manual –** The System Forecast and Adjusted Forecast are not automatically approved. Forecast values must be manually approved by accessing and amending the Forecast Approval workbook.
- **Automatic –** The Adjusted Forecast is automatically approved as-is.
- **By alert "name of the alert" –** This list of values may also include any Forecast Approval alerts that have been configured for use in the forecast approval process. Alerts are configured during the implementation. See the *RPAS Configuration Tools User Guide* for more information on the Alert Manager, and the *RDF Configuration Guide* for more information on configuring Forecast Approval Alerts.

> **Note:** If you select a specific alert as your approval method and later on you delete the alert, the approval will work as manual. The same will happen if the alert is on a wrong intersection.

Forecast Method Override

Set at both final and source levels, the Forecast Method Override is a drop-down list from which you can select a different forecast method than the Default Forecast Method set in the Forecast Administration workbook. **No Override** appears in this field if the system default set in the Forecast Administration workbook is to be used. Valid options depend on your system setup.

Winters Mode Override

Used only by Forecasting Methods calling Additive or Multiplicative Winters. This parameter allows the user to override the Winters Mode setting assigned in the Forecast Administration workbook. The default setting for this parameter is No Override.

Keep Last Changes Override

Set only at final levels, Keep Last Changes Override field may be used to override the default setting at a product/location intersection. **None** appears in this field if there is no override applied to the intersection.

Optimal Source Levels

Displayed only at final levels, a value will be populated in this field if **AutoSource** has been run on the final level. The AutoSource executable evaluates all levels associated to a final level and returns the source level that yields the optimal forecast results. For more information on AutoSource, see the *RDF Administration Guide*.

> **Note**: For item/stores that are new or highly seasonal, AutoSource may not return the best recommendation since new items may not have an adequate sales history length and highly seasonal items may only sell for a short period during the year. For these items, you should not set the AutoSource recommendation as default at the final level. Only use AutoSource recommendations for item/stores that have an adequate sales history.

Pick Optimal Level

Set only at final levels, a check in this field (set to true) indicates that the batch forecast should use the Optimal Source Level selected by AutoSource. For more information on AutoSource, see the *RDF Administration Guide*.

Source Level Override

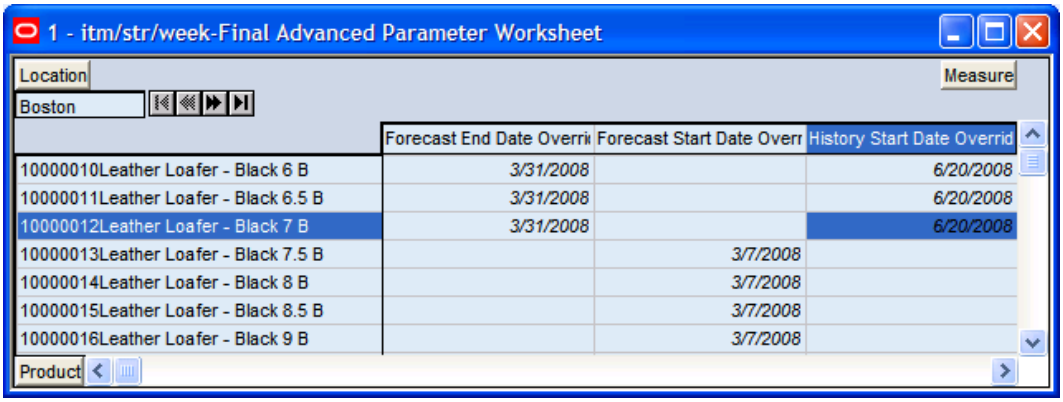
Set only at final levels, the Source Level Override is the level at which the aggregate, more robust forecast is run. Forecast data from this level is spread down to the lowest level based on the relationship between the two levels in the hierarchy. **No Override** appears in this field if the system default set in the Forecast Administration workbook is to be used.

Moving Average Window Length Override

Used with Moving Average forecast method, this is the number of data points in history used in the calculation of Moving Average. This parameter, when set to a non-zero value, overrides the value in the Forecast Administrator workbook.

Advanced Settings Workflow Tab

The Advanced Settings workflow tab is used to override the dates that are used in the forecast generation process as well as historical start dates for any intersection at the final level that varies from the default settings in the Forecast Administration workbook.



Final Advanced Parameter Worksheet

Field Descriptions

Forecast Start Date Override

This parameter represents the date to start forecasting at a particular intersection. If this date is set to the past, it is ignored in favor of the Forecast Start Date from the Forecast Administration workbook. This means that you do not need to change the Forecast Start Date once it is no longer in the future. It is important to understand how Forecast Start Date should be used in conjunction with Forecast End Date (see below). No value will be in this measure if the system default set in the Forecast Administration workbook is to be used.

> **Note:** This measure can also be set in the Forecast Like-Item, Sister-Store workbook. Changes to this measure can be seen in the Forecast Maintenance workbook and the Forecast Like-Item, Sister-Store workbook. The most recent commit (between either workbook) will be the value used by the system.

Forecast End Date Override

This parameter represents the last point in time for which the forecasting engine will forecast for a particular intersection. Should this parameter be set to a date less than the Forecast Start Date plus the Forecast Length (in Forecast Administration), the engine will forecast 0 past this date. If Forecast End Date is more than Forecasting Start Date plus Forecasting Length, you do NOT get a forecast outside Forecasting Start Date plus Forecasting Length. In other words, both Forecast Start Date and Forecasting End Date are relevant for time periods within the forecast horizon set at the global level. No value will be in this measure if the system default set in the Forecast Administration workbook is to be used.

> **Note:** This measure can also be set in the Forecast Like-Item, Sister-Store workbook. Changes to this measure can be seen in the Forecast Maintenance workbook and the Forecast Like-Item, Sister-Store workbook. The most recent commit (in either workbook) will be the value used by the system.

History Start Date Override

This parameter represents the first point in time from which the Forecasting Engine will begin training and modeling (that is, if there are two years of history, but you only want to use one year, you will set the start date to a year ago). This parameter will override the History Start Date set in the Forecast Administration workbook to the desired item/location intersection. For example, if you have a large spike in the first three weeks of sales for an item was on sale, you can set the Historical Start Date to one week past that period, and those first few weeks will not be used when generating the forecast.

It is also important to note that the system ignores leading zeros that begin at the history start date. For example, if your history start date is January 1, 2003 and an item/location does not have sales history until February 1, 2003, the system will consider the starting point in that item/location's history to be the first data point where there is a non-zero sales value.

If this parameter is set into the future, there would be no forecast as the history training window is read as zero.

Note: This measure can also be set in the Forecast Like-Item, Sister-Store workbook. Changes to this measure can be seen in the Forecast Maintenance workbook and the Forecast Like-Item, Sister-Store workbook. The most recent commit (between either workbook) will be the value used by the system.

Forecast Like-Item, Sister-Store Workbook

Overview

The Forecast Like-Item, Sister-Store workbook provides the ability to model a new product's demand after an existing product. Forecasts can thus be generated for the new product based on the selected history or the forecast of the existing product plus an Adjustment Ratio. Likewise, the sales history or the forecast of existing store locations can be used as the forecast foundation for new locations. This workbook includes the following worksheets:

- The Like-Item worksheet
- The Sister-Store worksheet
- The Advanced Parameter worksheet

Note: This workbook is only valid at final levels. Therefore, this workbook may include hierarchy dimensions that are at higher positions that item or store (for example: subclass or region).

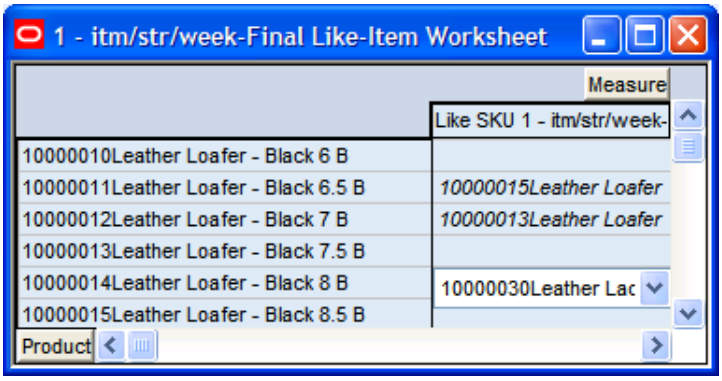
Creating a Forecast Like-Item, Sister-Store Workbook

1. Within the Simple or Local Domain, select **New** from the **File** menu.
2. Select the **Forecast** tab to display a list of workbook templates for statistical forecasting. Highlight **Forecast Like-Item, Sister-Store**.
3. Click **OK**. The wizard opens and prompts you to select the level of the final forecast. Depending on your organization's setup, you may be offered a choice of several final forecast levels.
4. Select the final forecast level to be viewed in the workbook.
5. Click **Next**.
6. Select the locations to include in the workbook.
7. Click **Next**.
8. Select the products to include in the workbook.
9. Click **Next**.
10. Select any additional measures (that is, measures not standard in the Forecast Like-Item, Sister-Store workbook) to be included. The measure options available in this screen are set in the RPAS Security Administration workbook / workbook Template Measure Rights worksheet.
11. Click **Finish** to display the workbook.

Window Descriptions

Like-Item Worksheet

The Like-Item worksheet is used to forecast a new item by modeling it after an existing item.



Final Like-Item Worksheet

Field Descriptions

The Like-Item worksheet contains the following parameters:

Like SKU

The Like SKU field displays the items selected during the wizard process. In the example shown in the above worksheet, the Like Item (existing item) is selected on the right from a pick-list across from the new item. The Like Item's forecast or sales will be used for the new item based on the parameters selecting in the Advance Parameter worksheet. In the example above, Leather Loafer – Black 8 B is a new item and Leather Lace-up Boat Shoes 8 B is being selected as the existing item that will be used to Leather Loafer – Black 8 B model's forecast.

> **Note:** When working with both the Like SKU and Sister Store worksheets, making a selection in one of the worksheets requires Calculate to be run before the pick-list options are available in the other worksheet.

Sister-Store Worksheet

The Sister-Store worksheet is used to forecast demand for a new store by modeling it after an existing store.

Final Sister-Store Worksheet

Field Descriptions

The Sister-Store worksheet contains the following parameter:

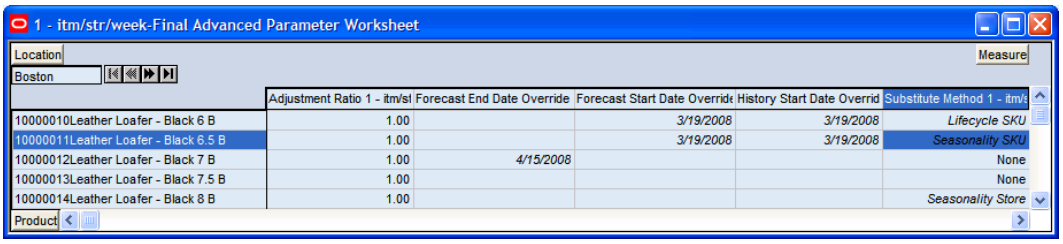
Sister Store

Displays the locations selected during the wizard process. In the example shown in the above worksheet, the Sister Store (existing Store) is selected on the right from a pick-list across from the new Store. The Sister Store's forecast or sales will be used for the new Store based on the parameters selecting in the Advance Parameter worksheet. In the screen shot above, the Boston is the new store and San Francisco is being selected as the store to be used for modeling Boston's forecast.

> **Note:** When working with both the Like SKU and Sister Store worksheets, if a selection is made in one of the worksheets, Calculate must be run before the pick-list options are available in the other worksheet.

Advance Parameter Worksheet

The Advance Parameter worksheet is used to manage item/locations in which the Forecast Start Date, Forecast End Date, or History Start Date varies from the default settings in the Forecast Administration workbook and to set the Adjustment Ratio for the new item or location being forecasted.



	Adjustment Ratio 1 - itm/sl	Forecast End Date Override	Forecast Start Date Overrid	History Start Date Overrid	Substitute Method 1 - itm/s
10000010Leather Loafer - Black 6 B	1.00		3/19/2008	3/19/2008	Lifecycle SKU
10000011Leather Loafer - Black 6.5 B	1.00		3/19/2008	3/19/2008	Seasonality SKU
10000012Leather Loafer - Black 7 B	1.00	4/15/2008			None
10000013Leather Loafer - Black 7.5 B	1.00				None
10000014Leather Loafer - Black 8 B	1.00				Seasonality Store

Final Advanced Parameter Worksheet

Field Descriptions

The Advanced Parameter worksheet contains the following parameters:

Adjustment Ratio

The user may enter an Adjustment Ratio to apply to the forecast for the new product / location combination displayed. This is a real number between $[0, \infty)$. The default (NA) value is 1.00, (in other words 100%) which translates to no adjustment.

> **Example:** If demand for a new item is expected to be 30% greater than its like item, the Adjustment Ratio would be set to 1.30. If demand for a new item is expected to be 30% less than its Like Item, the Adjustment % would set to .70.

Forecast Start Date Override

This parameter represents the date to start forecasting for an item/location combination. This parameter can be set in the future if using Like Item or Sister Store functionality and upon reaching that time, the forecast will be generated. If this date is set to the past, it is ignored in favor of the Forecast Start Date from the Forecast Administration workbook. This means that the Forecast Start Date for this intersection needs to be edited once it is no longer in the future. For Like item or Sister Store, the Forecast Start Date and the History Start Date should be set to the same date. It is important to understand how Forecast Start Date should be used in conjunction with Forecast End Date (See below). No value will be in this measure if the system default set in the Forecast Administration workbook is to be used.

> **Note:** This measure can also be set in the Forecast Maintenance workbook. Changes to this measure can be seen in the Forecast Maintenance workbook and the Forecast Like-Item, Sister-Store workbook. The most recent commit (between either of the workbooks) will be the value used by the system.

Forecast End Date Override

This parameter represents the last point in time for which the Forecasting Engine will forecast for an item/location combination. Should this parameter be set to a date less than the Forecast Start Date plus the Forecast Length (in Forecast Administration), the engine will forecast 0 past this date. If Forecast End Date is more than Forecasting Start Date plus Forecasting Length, NO forecast will be generated outside Forecasting Start Date plus Forecasting Length window. In other words, both Forecast Start Date and Forecasting End Date are relevant for time periods within the forecast horizon set at the global level. No value will be in this measure if the system default set in the Forecast Administration workbook is to be used.

Forecast End Date can be used for new item or location forecasting if the item or location needs to be forecasted for a period shorter than the Like TS Duration (set globally in Forecast Administration).

> **Note:** This measure can also be set in the Forecast Maintenance workbook. Changes to this measure can be seen in the Forecast Maintenance workbook and the Forecast Like-Item, Sister-Store workbook. The most recent commit (between either of the workbooks) will be the value used by the system.

History Start Date Override

This parameter represents the first point in time from which the Forecasting Engine will begin training and modeling (that is, if there are two years of history, but only one year is required, set the start date to a year ago). This parameter overrides at the item/store level from the global settings in the Forecast Administration workbook. This can be used to level out past sales. For example, if there is a large spike in the first three weeks of sales for an item was on sale, set the Historical Start Date to one week past that period, and those first few weeks will not be used when generating the forecast.

It is also important to note that the system ignores leading zeros that begin at the history start date. For example, if your history start date is January 1, 1999 and an item/location does not have sales history until February 1, 1999, the system will consider the starting point in that item/location's history to be the first data point where there is a non-zero sales value.

The History Start Date for the new item or new store should be set with the same date as the Forecast Start Date.

Note: When using any of the Lifecycle Methods (see Substitute Methods below), the History Start Date for the substitute item or location must be set to the point in the sales history that the new item or location will begin using as its sales.

Note: This measure can also be set in the Forecast Maintenance workbook. Changes to this measure can be seen in the Forecast Maintenance workbook and the Forecast Like-Item, Sister-Store workbook. The most recent commit (between either of the workbooks) will be the value used by the system.

Substitute Method

Displays a drop-down list from which the user can select the substitute method. When a Substitute Method is used to forecast, the method set for an intersection will be cleared once the Default Forecast Start Date is greater than the Forecast Start Date Override plus the Like TS Duration for the intersection. Valid options are:

- **None –** There is no substitution for this product/location combination. This is the default value.
- **Seasonality/New Item –** The user provides a Like Item that has a similar seasonality pattern that sells at the same store. The new product's forecast will be the like item's demand forecast with the applied adjustment. The forecast will be set to 0 for all dates before the new product's start date.
- **Seasonality/New Store –** The user provides a Sister Store that has a similar seasonality pattern that sells the same product. The product's forecast at the new store will be the demand forecast of the same product at the Sister Store with the applied adjustment. The forecast will be set to 0 for all dates before the new store's open date.
- **Seasonality/New Item /New Store –** The user provides a Like Item that sells at a Sister Store that has a similar seasonality pattern. The new product's forecast at the new store will be the demand forecast of the Like Item at the Sister Store with the applied adjustment. The forecast will be set to 0 for all dates before the new product's start date after the new store opens.
- **Lifecycle/New Item –** The user provides a Like Item that had a similar lifecycle pattern that sells at the same store. The new product's forecast will be the like items actual sales with the applied adjustment shifted such that the like item's first sales matches the new product's start date.
- **Lifecycle/New Store –** The user provides a Sister Store that had a similar lifecycle pattern that sells the same product. The product's forecast at the new store will be the products actual sales at the Sister Store with the applied adjustment shifted such that the Sister Store's first sales matches the new store's open date.

- **Lifecycle/New Item/New Store –** The user provides a like item that sells at a sister store that has a similar lifecycle pattern. The new product's forecast at the new store will be like item's actual sales at a sister store with the applied adjustment shifted such that the like item's first sales at the sister store matches the new product's start date after the new store opens.

Steps Required for Forecasting Using Each of the Like SKU / Sister Store Methods

The following outlines the steps required for using each of the above Substitution Methods:

To support Like SKU / Sister Store functionality, the Like TS Duration must be set in the Forecast Administration workbook – Advance tab. This parameter sets the number of weeks of history required after which Oracle Retail Demand Forecasting stops using the substitution method and starts using the system forecast generated by the forecast engine.

Procedures

Seasonality/SKU: Introduction of a new item at an existing store (like item with a similar forecast)

1. **Like-Item worksheet —** Select a like item from the drop-down list across from the new item.
2. **Advanced Parameter worksheet —** Set the Forecast Start Date for the new item at an existing store.
3. **Advanced Parameter worksheet —** Set the History Start Date for the new item at the existing store to the same date as the Forecast Start Date.
4. **Advance Parameter worksheet —** Set the Adjustment % (optional) for the new item at the existing store.

Seasonality/STR: Introduction of an existing item at a new store (sister store with similar forecast)

1. **Sister-Store worksheet —** Select a Sister Store from the drop-down list, across from the new store.
2. **Advanced Parameter worksheet —** Set the Forecast Start Date for the existing item at the new store.
3. **Advanced Parameter worksheet —** Set the History Start Date for the existing item at the new store to the same date as the Forecast Start Date.
4. **Advance Parameter worksheet —** Set the Adjustment % (optional) for the existing item at the new store.

Seasonality/SKU_STR: Introduction of a new item at a new store (like item and sister store with a similar forecast)

1. **Like-Item worksheet —** Select a like item from the drop-down list across from the new item.
2. **Sister-Store worksheet —** Select a Sister Store from the drop-down list across from the new store.
3. **Advanced Parameter worksheet —** Set the Forecast Start Date at the intersection of the new item and the new store.

4. **Advanced Parameter worksheet** — Set the History Start at the intersection of the new item and new store.
5. **Advance Parameter worksheet** — Set the Adjustment % (optional) at the intersection of the new item and new store.

Lifecycle/SKU - Introduction of a new item at an existing store (Like item's sales history to be used as the forecast for the new item)

1. **Like-Item worksheet** — Select a like item from the drop-down list across from the new item.
2. **Advanced Parameter worksheet** — Set the Forecast Start Date for the new item at the existing store.
3. **Advanced Parameter worksheet** — Set the History Start Date for the new item at the existing store to the same date as the Forecast Start Date.
4. **Advanced Parameter worksheet** — Set the History Start Date for the Like item at the existing store to the point in its sales history that will map to the new item's forecast.
5. **Advance Parameter worksheet** — Set the Adjustment % (optional) for the new item at the existing store.

Lifecycle/STR: Introduction of an existing item at new store (Sister Store's sales history to be used as the forecast for the new store)

1. **Sister-Store worksheet** — Select a Sister Store from the drop-down list across from the new Store.
2. **Advanced Parameter worksheet** — Set the Forecast Start Date for the existing item at the new store.
3. **Advanced Parameter worksheet** — Set the History Start Date for the existing item at the new store to the same date as the Forecast Start Date.
4. **Advanced Parameter worksheet** — Set the History Start Date at the intersection of the Sister Store and existing item to the date in its sales history that will map to the new store's forecast.
5. **Advance Parameter worksheet** — Set the Adjustment % (optional) for the existing item at the new store.

Lifecycle/SKU_STR: Introduction of a new item at a new store (Like item's and Sister Store's sales history to be used as the forecast for a new item at a new store)

1. **Like-Item worksheet** — Select a like item from the drop-down list across from the new item.
2. **Sister-Store worksheet** — Select a Sister Store from the drop-down list across from the new store.
3. **Advanced Parameter worksheet** — Set the Forecast Start Date at the intersection of the new item and new store.
4. **Advanced Parameter worksheet** — Set the History Start Date at the intersection of the new item and new store to the same date as the Forecast Start Date.
5. **Advanced Parameter worksheet** — Set the History Start Date at the intersection of the Like item and Sister Store to the date in its sales history that will map to the new item and new store's forecast.
6. **Advance Parameter worksheet** — Set the Adjustment % (optional) at the intersection of the new item and new store

Product/Location Cloning Administration Workbook

Overview

The Product/Location Cloning Administration workbook allows users to specify parameters to clone or copy history for new Items or Locations from existing Items and Locations. Since RDF needs history for forecasting, this functionality allows users to specify clone items and clone Stores for these new Product/Locations.

Cloning is different from Like Item/Sister Store functionality. Like item/Sister store functionality copies forecasts or history of the like item or sister store as the forecasts for the new SKU/Store. However, in cases where the two items have different promotion calendars, it is necessary to forecast based on history data and promotion calendar. Item/Loc Cloning functionality facilitates this process.

Also, by copying history from the parent product, users can start forecasting almost immediately after the launch of the new product.

Product/Location Cloning Administration can be performed from the Master or Local domain. The actual cloning or copying of history can be performed as part of batch run.

> **Note:** Clone is available as a special expression that can be configured to be called as a batch run to perform the actual copying of history.
>
> **Note:** When the Cloning administration workbook is built in the Master domain, if clone assignments are made such that a product is assigned a clone that belongs to a different local domain, then at the time of batch run RDF will not clone that specific product and continue processing after logging a message.

This workbook includes the following worksheets:

- Product Cloning worksheet
- Location Cloning worksheet
- Clone Mask worksheet

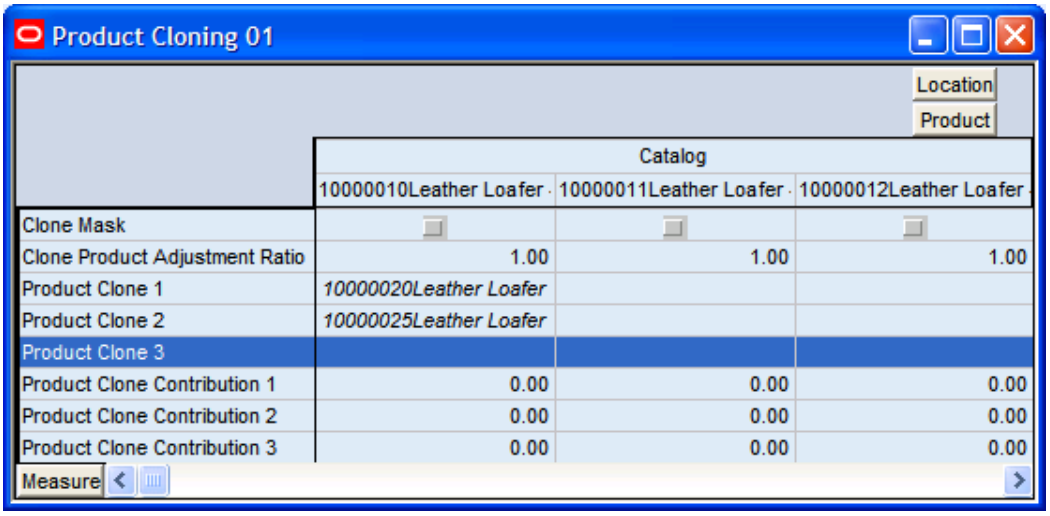
> **Note:** This workbook is only valid at final levels. Therefore, this workbook may include hierarchy dimensions that are at higher positions than item or store (for example: subclass or region).

Window Descriptions

Product Cloning Worksheet

The Product Cloning worksheet allows users to make Clone Product assignments for new Products. From this worksheet, users can specify up to three parent Products for a given Product that is being cloned. Also, it allows users to specify different parent Products for different Locations. For example, CS Spring Water 1 sells like Diet Soda single in North America, but sells like Regular Soda in Asia. The Product Cloning worksheet thus is at Product and Location intersection.

Users have the ability to specify associated contributions for each of the Clone Products, and have the ability to specify an overall Adjustment Ratio.



Product Cloning 01

Location
Product

	Catalog		
	10000010Leather Loafer	10000011Leather Loafer	10000012Leather Loafer
Clone Mask			
Clone Product Adjustment Ratio	1.00	1.00	1.00
Product Clone 1	*10000020Leather Loafer*		
Product Clone 2	*10000025Leather Loafer*		
Product Clone 3			
Product Clone Contribution 1	0.00	0.00	0.00
Product Clone Contribution 2	0.00	0.00	0.00
Product Clone Contribution 3	0.00	0.00	0.00

Measure

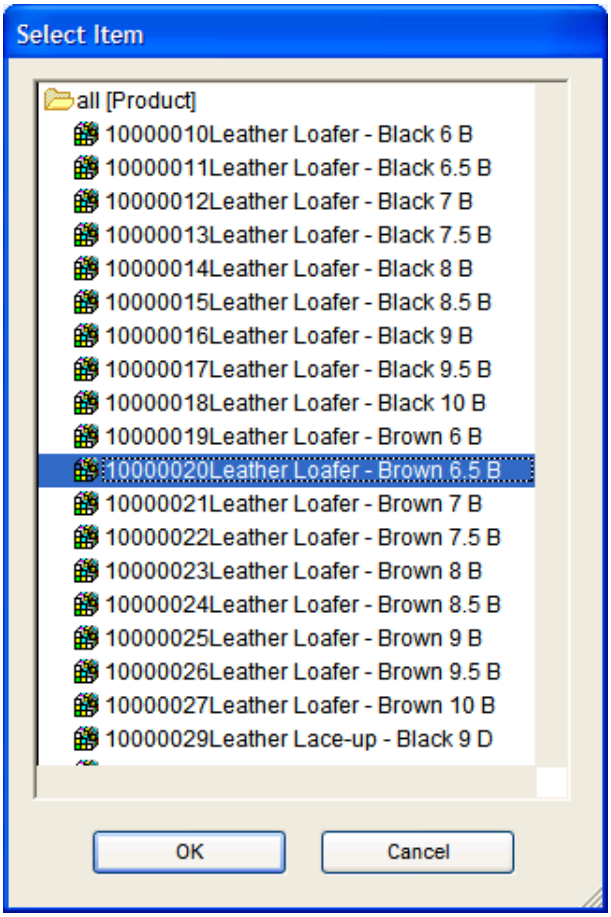
Product Cloning Worksheet

Field Descriptions

The Product Cloning worksheet contains the following measures:

Product Clone1, Product Clone 3, Product Clone 3

Parent Products for the new Product being cloned. It is optional to specify more than one Product Clone. The selection or assignment of Product Clone is made by clicking on this measure and a Single Hier Select Wizard pops up. Assignments are made by selecting a Product and clicking OK. Please see the *RPAS User Guide* for more details on the Single Hier Select Wizard.



Product Clone Contribution1, Product Clone Contribution2, Product Clone Contribution3

Relative contributions of all clone Products. If user does not specify contributions, but makes selections for Product Clones and commits the changes, at the time of commit the contributions are calculated to have equal weights for all specified Product Clones. If user specifies Product clone contributions, they get normalized such that they add up to one at the time of commit. Product Clone contributions with no associated Product Clone values get set to zero at the time of commit.

Clone Product Adjustment Ratio

The user may enter an Adjustment Ratio to apply to the cloned history of the new product. This is a real number between [0, ∞) . The default (NA) value is 1.00, (in other words 100%) which translates to no adjustment.

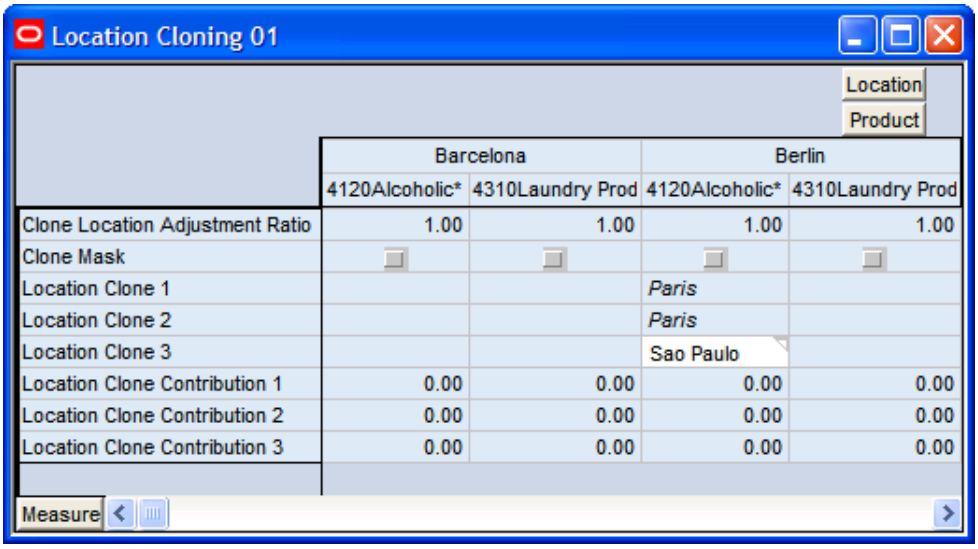
Example:

If demand for a new item is expected to be 30% greater than its clone item, the Adjustment Ratio would be set to 1.30. If demand for a new item is expected to be 30% less than its clone item, the Adjustment % would set to .70.

Location Cloning Worksheet

Location Cloning worksheet allows users to make clone Location assignments for new Locations. Location Cloning worksheet allows users to specify up to three Clone Locations for a given Location that is being cloned. Also, it allows users to specify different parent Locations for different Products. For example, the Beverly Hills store sells like the Miami store for swim wear and sells like the New York store for electronics. The Location Cloning worksheet thus is at Location and Product intersection.

Users have the ability to specify associated contributions for each of the Parent Locations, and have the ability to specify an overall Adjustment Ratio.



Location Cloning 01

Location
Product

	Barcelona		Berlin	
	4120Alcoholic*	4310Laundry Prod	4120Alcoholic*	4310Laundry Prod
Clone Location Adjustment Ratio	1.00	1.00	1.00	1.00
Clone Mask				
Location Clone 1			*Paris*	
Location Clone 2			*Paris*	
Location Clone 3			Sao Paulo	
Location Clone Contribution 1	0.00	0.00	0.00	0.00
Location Clone Contribution 2	0.00	0.00	0.00	0.00
Location Clone Contribution 3	0.00	0.00	0.00	0.00

Measure

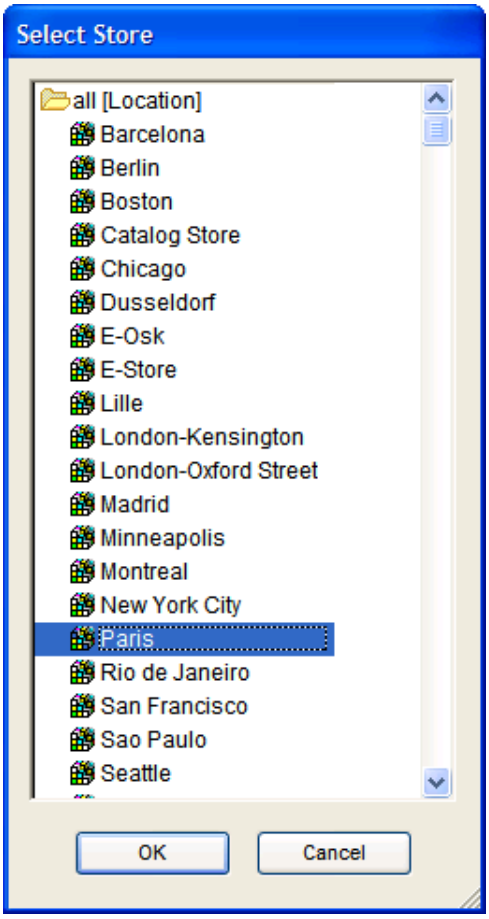
Location Cloning Worksheet

Field Descriptions

The Location Cloning worksheet contains the following measures:

Location Clone1, Location Clone 3, Location Clone 3

Parent Locations for the new Location being cloned. It is optional to specify more than one parent clones. The selection or assignment of Location Clone is made by clicking on this measure and a Single Hier Select Wizard pops up. Assignments are made by selecting a Location and clicking OK. Please see the *RPAS User Guide* for more details on the Single Hier Select Wizard.



Location Clone Contribution1, Location Clone Contribution2, Location Clone Contribution3

Relative contributions of all Clone Locations. If user does not specify contributions, but makes selections for Location Clones and commits the changes, at the time of commit the contributions are calculated to have equal weights for all specified Location Clones. If user specifies contributions, at the time of commit, Location clone contributions get normalized so that they add up to 1. Location Clone contributions with no associated Location Clone values get set to zero at the time of commit.

Clone Location Adjustment Ratio

The user may enter an Adjustment Ratio to apply to the cloned history of the new location. This is a real number between [0, ∞) . The default (NA) value is 1.00, (in other words 100%) which translates to no adjustment.

Example:

If demand for a new store is expected to be 30% greater than its clone store, the Adjustment Ratio would be set to 1.30. If demand for a new store is expected to be 30% less than its clone store, the Adjustment % would set to .70.

> **Note:** Adjustment Ratios and Clone Contributions specified in the Product Cloning and Location Cloning worksheets are used together while evaluating the result for a given Item/Store.

Example:

SKU1

SKU2	SKU3
20%	80%

Adjustment Ratio = 1

STR1:

STR2	STR3
50%	50%

Adjustment Ratio = 0.5

The contributions are calculated as:

SKU2/STR2 at 5% (=20% x 0.5x50%); SKU2/STR3 at 5%;SKU3/STR2 at 20%(=80%x0.5x50%);SKU3/STR3 at 20%

Clone Mask Worksheet

This worksheet allows users to enable cloning for Product/Locations by setting the Clone Mask measure to true.

> **Note:** Clone Mask measure can also be brought in using the Show/Hide option in the Product Cloning and Location worksheets. The clone mask can also be set based on business rules by configuring RPAS rules.

3

Generating and Approving a Forecast

Overview

Once a user has completed setting all global and individual forecast parameters a forecast must be generated and approved. The Forecast workbook template group provides the workbooks necessary to support these tasks.

Run a Batch Forecast

Overview

The forecast generation process creates demand forecasts for all product/location combinations that are set to forecast within the forecast horizon window. Forecasts are typically run automatically as scheduled batch jobs. Oracle Retail Demand Forecasting regularly triggers a set of processes to be run at a pre-determined time when system use is at a minimum, such as overnight.

Scheduling of the automatic batch forecasting process is supported in part through the Forecast Administration workbook where a default value is set for the forecast cycle (number of days between forecast runs). The Forecast Cycle measure and Next Run Date field in the Forecast Administration workbook support the automatic scheduling of batch forecasting jobs in the Oracle Retail Demand Forecasting solution. Refer to the Forecast Administration workbook description for further information.

The Run Batch Forecast wizard allows the user to manually execute the forecast generation process at a time other than the regularly scheduled batch job. If a Global Domain environment is implemented, forecasts generated in the Local domain can be viewed in the Master domain, however this forecast is isolated to the data in the Local domain. The execution of "PreGenerateForecast" at the Master domain, then passing the output of the process to "Generate" from the backend of each Local domain allows for the Local domains to share a birth date, thus supporting a view to forecast data across Local domains in the Master domain. See the *RDF Administration Guide* for more information on "PreGenerateForecast" and "Generate."

Prior to using the Run Batch Forecast wizard, at minimum the following tasks must be performed:

1. Create or access a Forecast Administration workbook.
2. In the Forecast Start Date measure, enter the starting date of the forecast horizon; otherwise the system will default to the system date (today).
3. Set a Default Forecasting Method for the Final and Source Level.
4. Set a Default Source Level for the Final Level.
5. Set the Forecast Length if there is no value already in this measure.
6. Set the Spreading Profile if the Source Level(s) are at aggregate dimensions above the Final Level.
7. Commit any changes by selecting **File – Commit Now**.
8. Close the workbook.

Procedures

Run a Batch Forecast Manually

1. Within the Local or Simple domain, select **New** from the File menu.
2. Select the Forecast tab to display a list of workbook templates for statistical forecasting. Highlight Run Batch Forecast and click **OK**.
3. The Run Batch Forecast Wizard opens and prompts the user to select the Final Level(s) to forecast. Select **Next** or **Finish**.

The Run Batch wizard automatically executes "PreGenerateForecast" and "Generate" within the Simple or Local Domain. If **Next** is selected from the last wizard screen, the wizard will not advance to the completion message until the forecast has been generated. Depending on the amount of product/locations to be forecasted and the forecast horizon, it may take a several minutes before the system advances to the final screen. When the forecast generation is completed, the wizard will display a screen that notifies the user of the forecast generation ID.

After a forecast is generated, the Forecast Start Date field is cleared. This ensures that the same forecast will not be generated again on the same date. The Next Run Date field is also updated based on the birth date of the forecast plus the Forecast Cycle. Both fields can be viewed in the Forecast Administration workbook.

Delete Forecasts

Overview

The **Days to Keep Forecasts** parameter (set in the Forecast Administration workbook) supports the automatic deletion of old forecasts when the Run Batch wizard or "PreGenerateForecast" is executed. Occasionally, a user may need to manually delete a forecast. Some reasons might include:

- A forecast was run with the wrong source levels selected.
- The forecast horizon was not properly set.
- Old forecasts need to be deleted to save space on the server.

The Delete Forecasts Wizard guides you through the process of deleting unwanted forecasts from the system. Deletions of forecasts are permanent.

Permanently Removing a Forecast from the Oracle Retail Demand Forecasting System

If the Delete Forecast wizard is used in a Global Domain environment, deleting a forecast in the Master domain deletes the selected birth date within all domains. Deleting a forecast in the Local domain deletes the selected birth date only within the Local domain.

1. From the Simple domain, Master domain, or Local domain; select **New** from the File menu.
2. Select the Forecast tab to display a list of workbook templates for demand forecasting.
3. Select **Delete Forecasts**
4. Click **OK**.
5. Select the forecast generation date(s) of the forecast to delete.
6. Click **Next**.

7. Select **Yes** to verify forecast deletion, or **No** to cancel deletion and exit the Forecast Deletion Wizard.

> **Note:** The deletion of forecasts from Oracle Retail Demand Forecasting is permanent.

8. Click **Finish** to process the request. If **Yes** was selected on the final wizard screen, the forecast is deleted.

Forecast Approval Workbook

Overview

After the forecast is generated, the next steps in the forecasting process are analysis and approval. Approval of forecasts is required before the forecasted data can be exported to other processes, such as replenishment programs. The Forecast Approval workbook allows you to view, analyze, adjust, and approve forecast results.

Some system forecasts may be set to be automatically approved by the system. The default approval method for items in a forecast is set in the Forecast Administration workbook, and these policies can be amended for individual product/location combinations in the Forecast Maintenance workbook. Any forecasts not set to Automatic Approval may require evaluation, adjustments, and ultimately approval before subsequent processes are executed.

You can view and analyze forecast data at multiple forecast levels (source level and final level) simultaneously. Revisions to and approvals of final level forecast values are made on the appropriate worksheets in the Forecast Approval workbook. The Forecast Approval workbook can contain up to five types of worksheets:

- **Final Forecast worksheet –** This worksheet allows you to review final level system-forecasted quantities and make revisions to them if needed
- **Source Level worksheet –** This worksheet displays the system-generated source level forecast, and allows you to compare this data with final level forecast values.
- **Approval worksheet –** This worksheet allows you to specify the manual approval policy of forecasts by product and location.
- **Final System Parameters worksheet –** This option is only available if "Generate System Parameters" or "Generate Methods" is turned on in the Forecast Administration workbook.
- **Source System Parameters worksheet(s) –** This option is only available if "Generate System Parameters" or "Generate Methods" is turned on in the Forecast Administration workbook, and a Source Level was designated in Forecast Administration.
- **Valid Forecast Run worksheet –** This worksheet allows you to review the partition dimensions in which the generated forecast was run.

When the Forecast Approval workbook is displayed, you may review the system-generated forecast and measures for any levels included in the workbook and make adjustments to forecast values at the final level. Forecast values are overwritten in the Adjusted Forecast measure on the Final Forecast worksheet. Approvals are made for each product/location combination in the Approval Method measure of the Forecast Approval worksheet.

After you complete your work, you can save the workbook using the Save function on the File menu. To update the master database with the approved forecast values, you must commit the workbook using the Commit Now or Commit Later option on the File menu. Once the workbook is committed, the forecast values are stored in the master database and can be used by other processes.

Opening or Creating the Forecast Approval Workbook

Select **Open** from the **File** menu to bypass the Forecast Approval Wizard and open an existing Forecast Approval workbook. Or perform the following:

1. Within the Master domain, Simple domain, or Local Domain; select **New** from the **File** menu.
2. Select the **Forecast** tab to display a list of workbook templates for statistical forecasting.
3. Select **Forecast Approval**. Click **OK**.
4. The Forecast Approval wizard opens and prompts you to select the final level at which to approve forecast values. Make your selection Click **Next**.
5. Select the forecast level(s) to include in the Forecast Approval workbook. Select as many forecast levels as necessary for comparison. Click **Next**.
6. Select the birth date of the forecast you wish to approve.
   - Select **Use the most recently generated forecast** to build a workbook containing the most recent forecast values.

     Note: Use the most recently generated forecast must be selected if the workbook supports an AutoWorkbook build.
   - Click **Select from a list of forecast** to select from a list of previously generated forecasts stored in the system. Note that if this option is selected, the system will automatically highlight the first forecast in the list, and if no further selections are made by the user, this first forecast will be used.
   - If no selection is made by the user, the birth date defaults to the latest generated generation ID.

   Click **Next**.
7. Select the specific locations you want to view. It is important to include all locations that are members of the location dimensions in the forecast levels to be analyzed. For example, if you select to view a forecast level that is defined at item/chain/week, you should include all locations that are members of the particular chain to be analyzed. It is recommended that “Position Query” functionality or selection from aggregate levels in the Location hierarchy is employed if the workbook is generated using AutoWorkbook build. Click **Next**.
8. Select the merchandise you want to view. It is important to include all products that are members of the Merchandise dimensions in the forecast levels to be analyzed. For example, if you select to view a forecast level that is defined at subclass/store/week, you must include all items that are members of the particular subclass to be analyzed. It is recommended that “Position Query” functionality or selection from aggregate levels in the Merchandise hierarchy is employed if the workbook is generated using AutoWorkbook build. Click **Next**.

9. Select the first date of history to include in the workbook. You may choose to either set the "Forecast Start Date minus the number of periods" or select the first date of history from the displayed list. It is recommended that the "Forecast Start Date minus the number of periods" is set if the workbook is generated using AutoWorkbook build.

   Note: If you make no selection, the system will use the forecast start date.

   Click **Next**.

10. Select the last date in the forecast horizon to include in the workbook. You may either choose to "Include the following number of time periods of the forecast horizon" or select the last date to include of the horizon from the displayed list. It is recommended that "Include the following number of time periods of the forecast horizon" is set if the workbook is generated using AutoWorkbook build. The value entered must be within the forecast horizon. Click **Next**.

11. Select the last date in the calendar to include in the workbook. You may choose to either set the "Forecast end date plus the following number of time periods" or select the last date to include of the post-horizon calendar from the displayed list. It is recommended that "Forecast end date plus the following number of time periods" is set if the workbook is generated using AutoWorkbook build.

    Note: If you make no selection, the system will use the "last date in the forecast horizon" chosen by the user in the previous wizard screen.

    Click **Next**.

12. Place checkmarks next to any additional registered measures you would like to view in your workbook. The valid values of these measures may only be viewed if **Generate Intervals**, **Generate Cumulative Intervals**, **Generate Methods**, **Generate Parameters**, **Generate Baselines**, or **Store Interim Forecasts** were selected in the Forecast Administration workbook.

    Note: If any of these parameters are included in the Forecast Approval workbook using AutoWorkbook build and are later de-selected for generation in the Forecast Administration workbook, AutoWorkbook must be set again.

    Click **Next**.

13. From the list provided, select any additional measures beyond the default measures in the workbook that you would like to view. Click **Finish** to build and open the workbook.

Window Descriptions

Final Forecast Worksheet

The Final Forecast worksheet allows you to review the forecasted quantities and make adjustments to forecasts if needed. The primary objective in the Forecast Approval workbook is to review and edit forecast values using the Adjusted Forecast field on the Final Level worksheet and, ultimately approve forecasts that have been user-adjusted or require manual approval.

1 - itm/str/week-Final Final Level Worksheet

Product | Location | Calendar

10000010Leather Loafer - Black 6 B | Boston

	1/4/2008	1/11/2008	1/18/2008
Adjusted Cumulative Interval 1 - itm/str/week-Final	1.02	1.75	2.45
Adjusted Forecast 1 - itm/str/week-Final	3.50	1.50	5.00
Approved Cumulative Interval 1 - itm/str/week-Final	1.50	3.00	4.50
Approved Forecast 1 - itm/str/week-Final	5.00	5.00	5.00
Approved System Forecast 1 - itm/str/week-Final	3.40	3.36	3.29
Forecast Cumulative Interval 1 - itm/str/week-Final	1.02	1.75	2.45
Forecast Interval 1 - itm/str/week-Final	4.00	4.00	3.00
History Data 1 - itm/str/week-Final	3.13	3.13	3.13
Interim Forecast 1 - itm/str/week-Final	3.28	3.24	3.18
Last Approved System Forecast 1 - itm/str/week-Final	3.16	3.26	3.36
System Baseline 1 - itm/str/week-Final	3.40	3.36	3.29
System Forecast 1 - itm/str/week-Final	3.40	3.36	3.29

Measure

Final Level Worksheet

Field Descriptions

The following is a description of the standard measures that are contained in the Final Level worksheet:

Adjusted Cumulative Interval

When changes are made to the Adjusted Forecast, the value of the Forecast Cumulative Interval is recalculated in this measure. The values in this measure are read-only. To view and store this measure:

- Generate Cumulative Intervals must be selected in the Forecast Administration workbook.
- Cumulative Intervals must be selected to be viewed in the Forecast Approval wizard.

Adjusted Forecast

The value in this field initially defaults to the System Forecast if the forecast is automatically approved by the system or via a Forecast Approval Alert. Otherwise, the value in the Adjusted Forecast will be different than the System Forecast if:

1. Adjusted Forecast has been updated by the user
2. Keep Last Changes is set to **Total**, **Difference** or **Ratio**
3. Update Last Week(s) Forecast is set to **Replicate**

Changes to the Adjusted Forecast will be automatically approved. The Approval worksheet will update with the date of the adjustment the name of the user to make the adjustment.

> **Note:** Changes to the Adjusted Forecast for periods outside of the forecast horizon will not be committed.
>
> **Note:** Edits to any non-committed values in the Forecast Approval workbook are overwritten when data is 'Refreshed.'

Approved Cumulative Interval

The Approved Cumulative Interval is the cumulative interval that was approved at the time of the workbook build. The values contained in this measure are read-only. If changes are made to the Adjusted Forecast, the Approved Cumulative Interval will reflect the recalculated values when the workbook is committed and data is refreshed.

Approved Forecast

The Approved Forecast is the forecast quantity that was approved at the time of the workbook build. The values contained in this measure are read-only. If changes are made to the Adjusted Forecast, the Approved Forecast will update with the new values when the workbook is committed and data is refreshed.

Approved System Forecast

The Approved System Forecast is populated with the last System Forecast approved for a time series:

1. Approval Method set to **Automatic Approval**
2. Approval Method set to a **Forecast Approval Alert** and the alert is not triggered
3. Update Last Week(s) Forecast is set to **Use Forecast**

The values in this measure are read-only.

Forecast Cumulative Interval

Cumulative Intervals are used in safety stock calculation within allocation and replenishment systems. This value is similar to a running total of the Forecast Interval and is read-only. To see this measure:

- **Generate Cumulative Intervals** must be selected in the Forecast Administration workbook.
- **Cumulative Intervals** must be selected to be viewed in the Forecast Approval wizard.

Forecast Interval

The Forecast Interval is calculated on the particular forecast region as capped standard deviation for some methods. It takes into consideration the system forecast for capping as well.

The forecast interval for any given week *i* is capped to a minimum of

$$0.3 * Forecast_i * \sqrt{i}$$

and a maximum of

$$Forecast_i * \sqrt{i}$$

where *i* is the *i*th week in forecast horizon. For example, *i* can equal 1, 2, 3, etc.

When forecasts are approved, the corresponding Intervals and Cumulative Interval measures are approved. To see this measure:

- **Generate Intervals** must be selected in the Forecast Administration workbook.
- **Intervals** must be selected to be viewed in the Forecast Approval wizard.

History Data

History Data (a read-only measure) is the sales data used to generate the forecast. This allows you to compare Actuals to forecasted values. When the workbook is created, the Data Source measure is copied into History Data.

Interim Forecast

The Interim Forecast is the forecast generated at the final level that is used as the Data Source in Curve to produce the Spreading Profile. This profile determines how the Source Forecast will be spread down to the Final Forecast level. The values in this measure are read-only. To see this measure:

- **Generate Interim Forecast** must be selected in the Forecast Administration workbook.
- **Interim Forecast** must be selected to be viewed in the Forecast Approval wizard.

Last Approved Forecast

The Last Approved Forecast is the approved system forecast value when an approval occurred on a previous batch forecast for the time series. The values contained in this measure are read-only.

System Baseline

The System Baseline is a forecast generated on past sales data that contains no promotions (that is, normal demand given no causal effects). To see a generated Baseline Forecast:

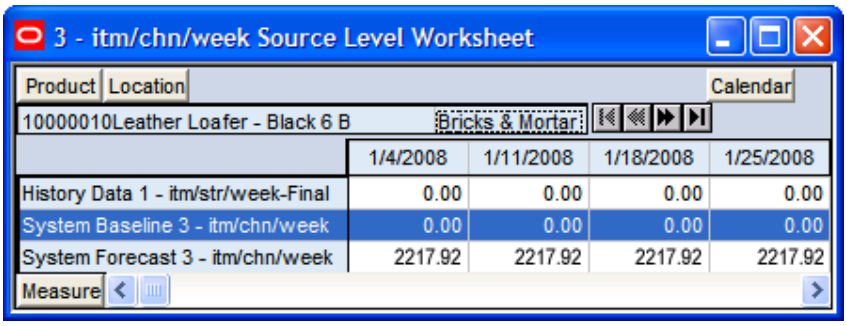
- Promotional Forecasting must be implemented.
- **Generate Baseline** must be selected in the Forecast Administration workbook.
- The **System Baseline** must be selected to be viewed in the Forecast Approval wizard.

System Forecast

The System Forecast displays the system generated forecast for the time series. The values contained in this field are read-only.

Source Level Worksheet

The Source Level worksheet displays the system-generated source level forecast. Final level forecast values in the Final Level worksheet can be viewed alongside and compared with their corresponding source level forecasts.



Source Level Worksheet

Field Descriptions

The following is a description of the standard measures that are contained in the Source Level worksheet:

History Data

History Data (a read-only measure) is the sales data used to generate the forecast. This allows you to compare Actuals to forecasted values. When the workbook is created, the Data Source measure is copied into History Data.

System Baseline

The System Baseline is a forecast generated on past sales data that contains no promotions (that is, normal demand given no causal effects). To see a generated Baseline Forecast:

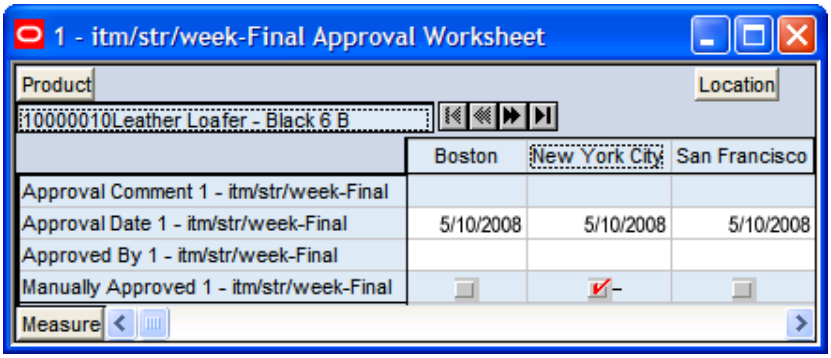
- Promote must be implemented.
- **Generate Baseline** must be selected in the Forecast Administration workbook.
- The **System Baseline** must be selected to be viewed in the Forecast Approval wizard.

System Forecast

The System Forecast displays the system generated forecast for the time series. The values contained in this field are read-only.

Approval Worksheet

The Forecast Approval worksheet allows for non-adjusted System Forecast to be approved. This worksheet can also be used to view the approval date of forecast values, and also display the name of the user that manually approved forecast values for a given product/location combination. The default Approval Method is set in Forecast Administration workbook and for product/location combinations that vary from the default, the Forecast Maintenance workbook can be used.



Approval Worksheet

Field Descriptions

The Approval worksheet(s) contain the following standard measures:

Approval Comment

Approval Comment is a field in which notes may be entered regarding the forecast values or any pertinent information for specified product/location combinations.

Approval Date

Approval Date is a read-only field that displays the date that the forecasted quantity was approved either automatically during the batch forecast process or when changes are made to the Adjusted Forecast. This information is necessary for Demand Forecasting to carry out any subsequent processes, such as replenishment procedures.

Approved By

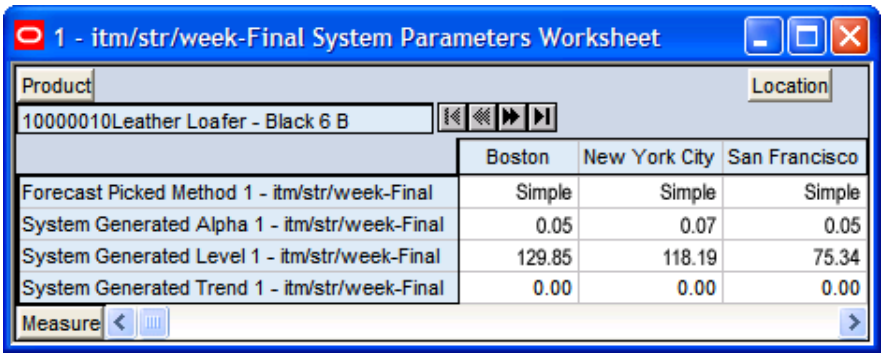
Approved By is a read-only field that displays the name of the user to approve forecasts for an item/location. This field may be populated with 'Sys' if the system was set to automatically approve forecasts during the batch forecast process.

Manually Approved

Manually Approved is a Boolean flag. This field may be checked if you want to accept the System Forecast quantity for a time series that has yet to be approved. The flag is also activated when a change is made to the Adjusted Forecast and 'Calculate' occurs. When this flag is activated, the time series for an item/location are approved and both the Approval Date and Approved By fields are updated.

Final or Source System Parameters Worksheet

The Final or Source Parameters worksheets allow you to view the alpha, level, and trend parameters for each fitted time series. These parameters are only available to be viewed if **Generate Parameters** or **Generate Methods** are activated in the Advanced tab of the Forecast Administration workbook.



	Boston	New York City	San Francisco
Forecast Picked Method 1 - itm/str/week-Final	Simple	Simple	Simple
System Generated Alpha 1 - itm/str/week-Final	0.05	0.07	0.05
System Generated Level 1 - itm/str/week-Final	129.85	118.19	75.34
System Generated Trend 1 - itm/str/week-Final	0.00	0.00	0.00

System Parameters Worksheet

Field Descriptions

The Final and Source Parameters worksheet(s) contain the following standard measures:

Forecast Method Picked

This field includes the forecast method that was used to generate the forecast for the given product/location combination. This field is useful when combined methods are requested. Then this field displays the actual method the system picked from the combined methods. In case stand-alone methods are chosen, generally this field is the same as the method chosen in forecast administration or forecast maintenance. However, if the requested method is unable to produce a good fit, the system will default to a "simpler method" and that method is displayed here. To see this measure:

- **Generate Methods** must be selected in the Forecast Administration workbook.
- **System Generated Methods** must be selected to be viewed in the Forecast Approval wizard.

System Generated Alpha

This is the system-calculated alpha value (which is an internal optimization parameter that corresponds to the rate of decay of the weighting on the historical values) for the corresponding product/location combination if the chosen method is one of the following methods: Simple, Holt, Additive Winters, Multiplicative Winters, and Profile Based. To see this measure:

- **Generate Parameters** must be selected in the Forecast Administration workbook.
- **System Generated Parameters** must be selected to be viewed in the Forecast Approval wizard.

System Generated Level

This is the system-calculated level (which is the constant baseline forecast) if the chosen method is one of the following methods: Simple, Holt, Additive Winters, Multiplicative Winters, and Seasonal Regression. To see this measure:

- **Generate Parameters** must be selected in the Forecast Administration workbook.

- **System Generated Parameters** must be selected to be viewed in the Forecast Approval wizard.

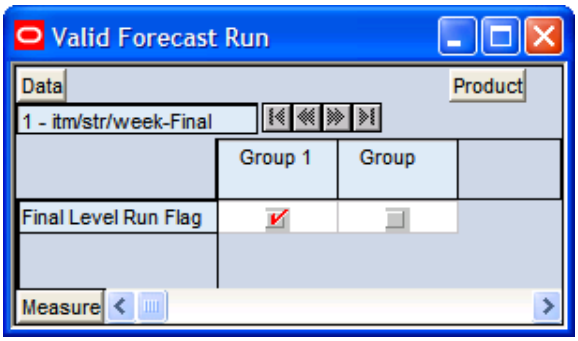
System Generated Trend

This is the system-calculated trend (which is the rate of change of the baseline forecast with time) if the chosen method is one of the following methods: Holt, Additive Winters, Multiplicative Winters, and Seasonal Regression. To see this measure:

- **Generate Parameters** must be selected in the Forecast Administration workbook.
- **System Generated Parameters** must be selected to be viewed in the Forecast Approval wizard.

Valid Forecast Run Worksheet

In a Global Domain environment, the Valid Forecast Run worksheet allows you to identify which Local domains share the forecast birth date selected in the wizard when viewed in the Master domain. If in a Local domain, only the single position of the partition dimension will be displayed.



Valid Forecast Run Worksheet

Field Descriptions

The measure displayed on this worksheet is viewed at final level / partition intersection. The Valid Forecast Run worksheet includes the following standard measure:

Final Level Run Flag

The Final Level Run Flag is a read-only Boolean measure. A check (set to true) displayed in this field indicates which positions from the partition dimension had a successful forecast run for the birth date selected in the Forecast Approval wizard.

> **Note:** Edits to the Adjusted Forecast can only be committed for partitions that have an activated Final Level Run Flag.

Approving Forecasts through Alerts (Exception Management)

Overview

Oracle Retail Demand Forecasting provides you with ability to manually approve every single product/location forecast value. However, due to the extremely large volume of product/location forecast values that will be generated for each forecast cycle, RPAS provides additional functionality that enhances your ability to evaluate and approve a forecast.

When configuring an RDF solution, specific Forecast Approval Alerts and alert parameters may be defined and applied during the batch process, and they may also be inserted into the Forecast Approval workbook. Alerts report product/location forecast values that exceed expected thresholds. If a specific product/location forecast value exceeds a threshold, the alert measure is flagged as "on" and visible to the user as a check mark in the appropriate product/location intersection.

- The complexities of retail operations can result in the need to define many alerts; each designed to watch for a specific scenario that would require a user's evaluation of a forecast value.

For more information on how alert measures and rules are defined and registered, refer to the R*PAS Configuration Tools User Guide* and *RDF Administration Guide*.

4

Forecast Analysis Tools

Overview

Oracle Retail Demand Forecasting provides you with a number of tools that may be used for additional forecast analysis. The Forecast workbook template group provides the workbooks necessary to complete these tasks.

Interactive Forecasting Workbook

Overview

The Interactive Forecasting workbook is a forecast simulation tool that allows you to make changes to forecast parameters and see the results without having to wait for the batch run. In this workbook, you can edit various forecast parameters including sales history and forecast method. A new forecast is produced based on the changed parameters. In addition to forecasts, the Interactive Forecasting workbook can also generate fit in historical region and the system picked model if an ES forecast method is used.

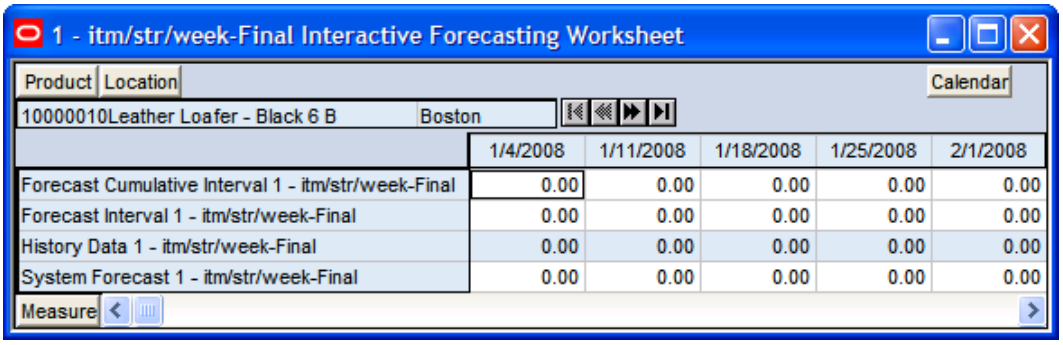
Opening the Interactive Forecasting Workbook

1. Within the Local or Simple domain, select **New** from the File menu.
2. Select the **Forecast** tab to display a list of workbook templates.
3. Select **Interactive Forecasting**. Click **OK**.
4. Select the forecast level. Click **Next**.
5. Select the forecast starting date. Click **Next**.
6. Select the first date in the historical data to use for generating the forecast. Click **Next**.
7. Select the end date for the forecast horizon. Click **Next**.
8. Perform one of the following options:
   - Specify future time periods beyond the forecast horizon to include in your workbook.
   - Select **Do not include dates** after the horizon if no future dates are to be included in the workbook.

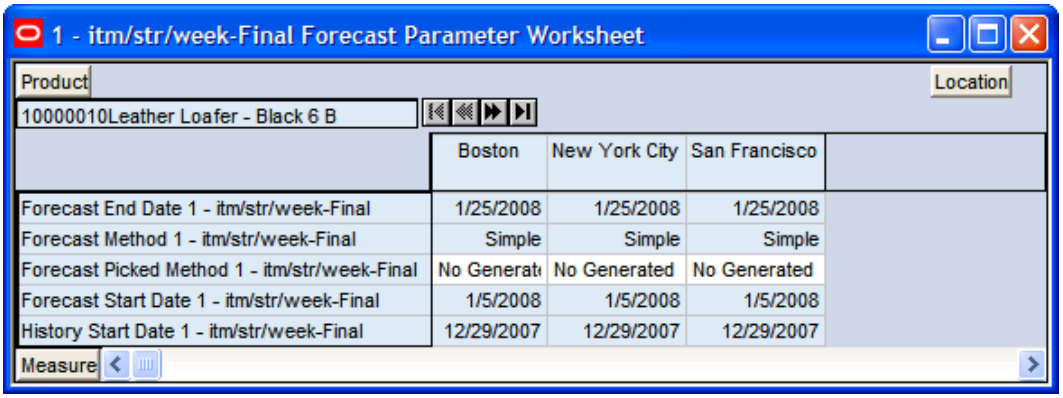
   Click **Next**.
9. Select the products to be included in the workbook. Click **Next**.
10. Select the locations to be included in the workbook. Click **Next**.
11. Select extra measures (if needed) to be included in the forecasting workbook. Click **Finish**.

Once the wizard is completed, the forecast is generated based on the user selections in the wizard and the Default Forecast Method set for the specified forecast level in the Forecast Administration workbook.

After the forecast generation is complete, the Interactive Forecasting workbook is displayed.



Interactive Forecasting Worksheet



Forecast Parameter Worksheet

The workbook contains two worksheets:

- Forecasting Parameter worksheet
- Interactive Forecasting worksheet

Window Descriptions

Forecasting Parameter Worksheet

The Forecasting Parameter worksheet is based on the intersection of the Product and Location dimensions for the select forecast level.

The Forecasting Parameter worksheet contains the following measures. Of these measures, all but System picked model are editable. Changes can be made to the editable parameters, that is, History Start Date, Forecast Method, Forecast Start Date, and Forecast End Date to re-generate a forecast of the time series.

Field Descriptions

Forecast Method

A drop-down list from which you can select the method used to generate the forecast. The workbook defaults to the method selected in the Forecast Administration Workbook for the specified level.

Forecast Picked Method

This is the method that was used to generate the forecast for the given product/location combination. This field is useful when combined methods are requested (for example ES methods). Then this field displays the actual method the system picked from the combined methods. In case stand-alone methods are chosen, generally this field is the same as the method chosen in Forecast Administration or Forecast Maintenance. However, if the requested method is unable to produce a good fit, the system will default to a "simpler method" and that method is displayed here.

History Start Date

This is the starting date for historical sales data. For example, if your system start date is January 1, 2003, but you only want to use historical sales data from the beginning of 1999, you need to set your History Start Date to January 1, 1999. Only history after this date is used for generating the forecast. The default is the system start date unless otherwise specified. If sales data is collected weekly or monthly, Oracle Retail Demand Forecasting generates forecasts only using data from sales periods after the one containing the history start date.

It is also important to note that the system ignores leading zeros that begin at the history start date. For example, if your history start date is January 1, 1999 and an item/location does not have sales history until February 1, 1999, the system will consider the starting point in that item/location's history to be the first data point where there is a non-zero sales value.

Forecast Start Date

This is first date of the forecast horizon. The default is the start date selected in the wizard.

Forecast End Date

This is the last date of the forecast horizon. The default is the end date selected in the wizard.

Interactive Forecasting Worksheet

The Interactive Forecasting worksheet is based on the intersection of the Product, Location, and Calendar dimensions for the forecast level selected in the wizard process. The Interactive Forecasting worksheet contains the History Data and the System Forecast. Of these measures, only History Data is editable.

Field Descriptions

History Data

This is the historical sales data set in the Forecast Administration workbook. This field is editable so you can change out-of-character sales if needed. For example, if your battery sales went up during a major power outage, you can lower the sales data back to a more normal level so the unusually high sales will adversely affect your forecast. However these changes are for simulation purposes only and cannot be committed.

System Forecast

The quantity that the system predicts will be required for the product, location, and calendar combination displayed. Changes to History Data, History Start Date, Forecast Start Date, Forecast End Date, and Forecast Method will cause the System Forecast to re-calculate when 'Calculate' is selected from the tool bar.

Forecast Scorecard Workbook

Overview

This section describes the purpose and content of the Forecast Scorecard and the steps required in order to create and access this workbook. This section also discusses the two types of worksheets contained in the Forecast Scorecard workbook, as well as the definitions of parameters that exist in each. Evaluating forecast accuracy through the use of error statistics is discussed, as is the process of comparing historical forecasts to actual sales data.

The purpose of the Forecast Scorecard is to monitor the accuracy of both system-generated forecasts and approved final forecasts. Once a forecast has been generated and actual point-of-sale data is received for the forecasted period, statistical information can be reviewed to help you analyze the accuracy of forecasting models and methods.

The Forecast Scorecard template consists of a wizard and two worksheets.

Based on your selections in the wizard, the Forecast Scorecard provides statistical information and comparison data that allow you to monitor the accuracy of system-generated forecasts and final approved forecasts.

- The Final Error Measure worksheet displays statistical information, such as mean error and root mean squared error, that reflects the accuracy of the forecast.
- The Final Actuals vs. Forecasts worksheet displays forecast results and actual point-of-sale values for specified product/location/calendar combinations.

Opening or Creating a Forecast Scorecard Workbook

Select **Open** from the File menu to bypass the Forecast Scorecard Wizard. Or, perform the following:

1. Within the Master, Local or Simple domain, select **New** from the File menu.
2. Select the **Forecast** tab to display a list of workbook templates.
3. Select **Forecast Scorecard**. Click **OK**. The Forecast Scorecard wizard opens.
4. You are prompted to select the forecast level that you want to evaluate. Make a selection. Click **Next**.
5. Select the generation date of the forecast you wish to review.
   - Click **Use the most recent generated forecast** to build a workbook containing the most recent forecast values.
   - Click **Select from a list of forecast** to select from a list of previously generated forecasts stored in the system.

   Click **Next**.
6. Select the measures associated with the forecast results to be evaluated. Click **Next**.
7. Check the boxes corresponding to the error statistics that you want calculated for the forecast data. Click **Next**.

8. Select the specific locations that you want to view. It is important to include all locations that are members of the location dimensions in the forecast levels to be analyzed. For example, if you select to view a forecast level that is defined at item/chain/week, you should include all locations that are members of the particular chain to be analyzed. It is recommended that "Position Query" functionality or selection from aggregate levels in the Location hierarchy is employed if the workbook supports an AutoWorkbook build. Make your selection. Click **Next**.
9. Select the merchandise you want to view. It is important to include all products that are members of the Merchandise dimensions in the forecast levels to be analyzed. For example, if you select to view a forecast level that is defined at subclass/store/week, you must include all items that are members of the particular subclass to be analyzed. It is recommended that "Position Query" functionality or selection from aggregate levels in the Merchandise hierarchy is employed if the workbook supports an AutoWorkbook build. Make your selection. Click **Next**.
10. Select the first date of history to include in the workbook. You may either choose to set the **Forecast Start Date minus the number of periods** or select the first date of history from the displayed list. It is recommended that the **Forecast Start Date minus the number of periods** is set if the workbook supports an AutoWorkbook build. Make your selection. Click **Next**.
11. Select the last date in the forecast horizon to include in the workbook.
    - Choose **Include the following number of time periods of the forecast horizon**.

      Note: It is recommended that "Include the following number of time periods of the forecast horizon" is set if the workbook supports an AutoWorkbook build.

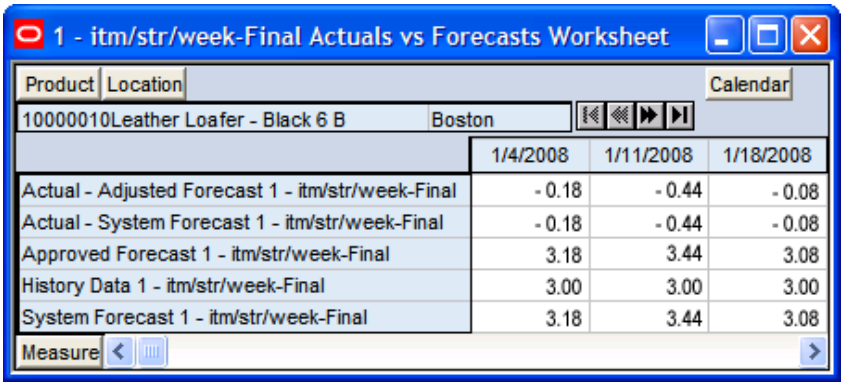
    - Select the last date to include of the horizon from the displayed list. Click **Next**.
12. Select the last date in the calendar to include in the workbook.
    - Set the **Forecast end date plus the following number of time periods**.

      Note: It is recommended that **Forecast end date plus the following number of time periods** is set if the workbook supports an AutoWorkbook build.

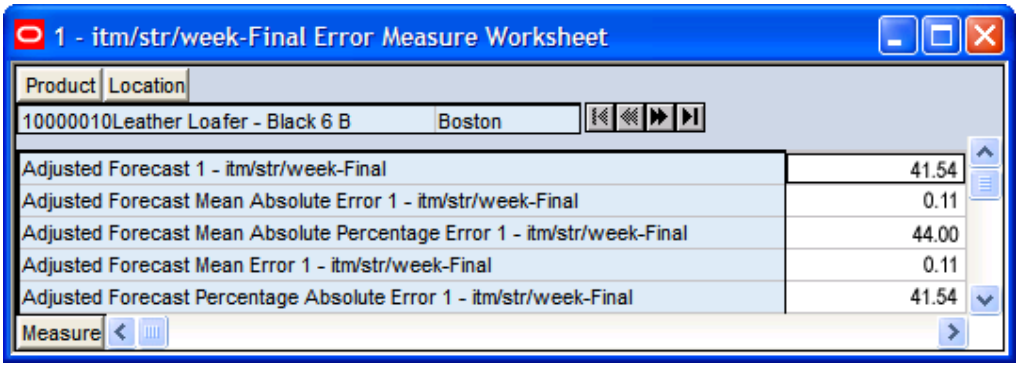
    - Select the last date to include of the post-horizon calendar from the displayed list.

    Click **Next**.
13. Select any additional measures to be included in the workbook. Click **Finish**.

After the wizard process is completed, the Forecasting workbook is displayed.



Actuals vs Forecast Worksheet



Error Measure Worksheet

Window Descriptions

Error Measure Worksheet

The Final Error Measure worksheet displays statistical information that reflects the accuracy of the forecast measures selected in the wizard process. You may need to evaluate a variety of such statistics to verify and compare forecast accuracy.

Given the situation, different levels of forecast accuracy can be useful. For example, in a situation with noisy data and no forecast previously available, a 200% error can be considered excellent and useful. In another situation with smooth data, if an old method of forecasting provided forecasts with a 10% error, a new method of forecasting with a 20% error would not be considered useful.

Different levels of forecasting accuracy are obtained at different levels of product aggregation. Item level forecasts with a 200% error can roll up into division-level forecasts with a 10% error. Therefore, the error measures are most useful when comparing different methods of forecasting or when looking at a particular model's accuracy over time. Accurate forecasts should lead to a reduction in inventory holding costs, or to an increase in customer service levels; forecast errors should be converted into dollars saved.

> **Note:** All error statistics are calculated over the first period in the forecast to the last period in the forecast for which forecast data is available.

Field Descriptions

The following is a description of the measures that can be included in the Final Error Measure worksheet: The error statistics will be shown for each forecast that you chose to include in the workbook (such as System Forecast, Final Forecast, and so on).

History Data for Forecast Window

The sum of all actual sales from the first period in the forecast to the last period in the forecast for which point-of-sale data is available.

System Forecast, Adjusted Forecast, Approved Forecast, Approved System Forecast, Interim Forecast

Your workbook may include one or all of the above forecast measures. These measures are selected in the wizard process. This is the average value of these measures over the forecast horizon select in the wizard process.

Mean Error

The error of a forecast observation is the difference between the forecasted value and the actual POS value. The Mean Error statistic is a measure of the average error over time. This is calculated by summing the errors for all observations, and then by dividing by the number of observations to obtain the average. It measures forecast accuracy by calculating the error in units. Because a positive error in one period can cancel out a negative error in another period, this measure is useful when you are interested in how well the forecast predicts over the forecast horizon rather than on a period-to-period basis. Mean error is useful as a measure of forecast bias. A negative mean error suggests that overall the forecasting model overstates the forecast while a positive mean error indicates forecasts that are generally too low.

Mean Absolute Error

The absolute error of a forecast observation is the absolute value of the difference between the forecasted value and the actual POS value. The Mean Absolute Error statistic is a measure of the average absolute error. This is calculated by summing the absolute errors for all observations, and then by dividing by the number of observations to obtain the average. Mean Absolute Error gives you a better indication of how the forecast performed period by period, because the absolute value function ensures that negative errors in one period are not canceled out by positive errors in another. Mean Absolute Error is most useful for comparing two forecast methods for the same series.

Root Mean Squared Error

This is the square root of the Mean Squared Error. The Root Mean Squared Error is one of the most commonly used measures of forecast accuracy because of its similarity to the basic statistical concept of a standard deviation. It evaluates the magnitude of errors in a forecast on a period-by-period basis, and it is best used to compare alternative forecasting models for a given series.

Mean Absolute Percentage Error

The percentage error of a forecast observation is the difference between the actual POS value and the forecasted value, divided by the actual POS value. The result of this calculation expresses the forecast error as a percentage of the actual value. The Mean Absolute Percentage Error statistic measures forecast accuracy by taking the average of the sum of the absolute values of the percentage error calculations across all observations. This method is useful when comparing the accuracy of forecasts for different volume products (it normalizes error by volume).

Percentage Absolute Error

The absolute error of a forecast observation is the absolute value of the difference between the forecasted value and the actual POS value. The Percentage Absolute Error statistic measures forecast accuracy by calculating the total absolute error as a percentage of the total actual POS. It is calculated by summing the absolute errors for all observations, dividing this value by the absolute value of the sum of all Actuals, and dividing the result by the number of observations in the series. Finally, multiply the total by 100 to obtain a percentage result.

Actuals vs. Forecasts Worksheet

This worksheet displays forecast results and actual point-of-sale values for each product, location, and time period specified in the Forecast Scorecard Wizard. This worksheet allows you to compare the results of both system-generated forecasts and final approved forecasts to actual sales quantities.

The Actuals vs. Forecasts worksheet may contain the following measures:

Actuals – (minus) System Forecast, Adjusted Forecast, Approved Forecast, Approved System Forecast, Interim Forecast

This displays the difference between the actual sales quantities and the committed forecast values for the forecast measures selected during the wizard process. Negative values indicate that the final forecast exceeded actual sales.

History Data

History Data displays the actual point-of-sale quantities for the product, location, and calendar combinations displayed.

System Forecast, Adjusted Forecast, Approved Forecast, Approved System Forecast, Interim Forecast

Your workbook may include one or all of the above forecast measures. These measures are selected in the wizard process. These measures display the forecasted quantity for the product, location, and calendar combinations included in the workbook.

5

Promote (Promotional Forecasting)

Overview

Promote is an optional add-on automated predictive solution that allows you to incorporate the effects of promotional and causal events (such as, radio advertisements and holiday occurrences) into your time-series forecasts. The promotional forecasting process uses both past sales data and promotional information to forecast future demand.

This chapter provides an introduction to promotional forecasting and explains how it differs from the traditional statistical forecasting methodology. It discusses the advantages and limitations of both statistical and promotional forecasting models, and it outlines the use of Oracle Retail's Causal method of forecasting demand. It describes terminology used in the context of promotional forecasting, and it concludes with detailed descriptions of the workbook templates contained in the Promote workbook Template Group.

What is Promotional Forecasting?

Traditional statistical forecasting methods provide significant benefits to the process of forecasting consumer demand, because they are good at predicting level, trend, and seasonality based on sales history. The limitation of traditional statistical methods is that they forecast with less accuracy when there are special events that cause significant deviations in selling patterns.

For example, the Easter holiday, for which companies often run promotions, occurs on a different date each year. Traditional statistical forecast methods can identify seasonality in sales history, but this seasonality is based on periodic similarities in the sales pattern. Since Easter occurs on different dates from year to year (that is, its period of recurrence is not regular), manual intervention is required to predict change in demand using the traditional statistical forecasting method. Events like this are called promotion events. Promotion events, such as advertisements, irregularly occurring holidays, competitor information, free gift with purchase offers, and so on are events that drive businesses from the normal selling cycle. The goal of a promotional forecasting system is to improve time series forecasting by:

- Providing the forecasting system with visibility as to when certain promotion events were active in the past (for example, identifying which weeks of a given year were affected by an Easter promotion).
- Automatically determining the statistical effect, if any, of these events.
- Incorporating significant effects into the future forecasts for time periods also associated with the observed promotion event.

The Promote module combines the automation of statistical time series forecasting with the improved accuracy found in customized causal forecasting. Promote uses both past sales data and promotional information (for example, advertisements, holidays) to forecast future demand. In order to understand the underlying rationale for the promotional forecasting process, it is important to understand the advantages and limitations of its underlying components.

Comparison between Promotional and Statistical Forecasting

Statistical time series forecasting uses past demand to predict future demand. The most basic component of the time series forecast is the level of sales. This is usually determined by looking at demand in the recent past. There often exists an underlying trend that can be detected within sales history. This is usually determined by looking at the change in demand in the recent past. A third factor influencing retail demand is seasonality. A forecasting algorithm trying to determine the effects of seasonality can only look for periodic similarities in the sales pattern. For example, December sales from previous years can be used to adjust the forecast for December only because December occurs regularly every 12 months. At every step, the time series approach is limited to using historical demand to predict future demand without regard to the underlying causes that are driving demand in the first place.

Promotional events; however, can create problems in estimating level, trend, and seasonality. Certain events, such as irregularly occurring holidays, newspaper/radio advertisements, free gift with purchase offers, and special discounts can cause significant deviations from the selling pattern.

Promotional forecasting unlike statistical forecasting attempts to predict future demand by identifying the factors that influence spikes and dips of past demand. Once these factors are known, the magnitude and direction of their effect can be evaluated. Their presence can then be incorporated into forecasting models for use during times when the causal factors are again expected to be present.

Developing Promotional Forecast Methods

This section describes how custom promotional forecast models have been developed in the past, leading to the discovery of several consistent findings. These findings have been incorporated into Oracle Retail's development of the Promote forecasting module.

Promotional forecasting uses promotional factors to predict future demand. The first step is to determine all of the pertinent information affecting sales and transform this information into variables that the system understands. Seasonality, for instance, can be represented by a single seasonal continuous variable, such as the number of daylight hours or average daily temperature.

Alternatively, it can be represented by 12 different indicator variables representing each of the months. An indicator variable consists only of 0's and 1's (1 indicates that the event is "on"). For example, a monthly indicator variable for January would consist of a 1 during the first month of the year and 0's for the remaining months.

Once a list of variables is determined, the model needs to represent the promotion events in terms of their influence on overall demand. For example, if a set of promotional variables has a multiplicative promotional effect on demand, a log transformation may be needed to improve the model. After a suitable model is developed, it must be implemented using multivariate linear regression or neural network architecture with custom code handling the data loading and variable transformations. The final custom model may be quite accurate over the data set on which it was developed. However, this model may not be general enough to be used universally across all data sets, thus requiring the development of multiple custom models to cover a client's entire domain. This has been found to be very time consuming and costly.

The process of developing custom promotional models has; however, brought to light a number of consistent patterns:

- Level, trend, and seasonality are universal components of almost any forecast.
- Including a time-series forecast as an input variable often improves promotional models.
- Indicator variables are robust in that they can represent both additive and multiplicative effects.

These findings have led Oracle Retail to develop a novel approach to promotional forecasting that combines the automation and generalization of time series forecasting with the improved (albeit data set specific) accuracy met through customized causal forecasting.

Oracle Retail's Approach to Promotional Forecasting

Oracle Retail combines time series forecast methods with causal forecast methods, resulting in a new forecast method supported by the promotional forecasting module. Promote uses the AutoES method of forecast generation to determine a baseline time series forecast, and then uses indicator variables to represent promotional events of interest. By giving the forecasting routine visibility as to when certain events occurred in the past, the system can correlate changes in the sales demand with these events and determine each promotional event's effect on sales. Then whenever these events occur in the future, the promotional effects can be incorporated into the forecast.

The Promotional Forecasting module has been developed to produce generalized promotional models automatically with little human intervention. Combined with the system's ability to allow you to develop your own data loading routines, Promotional Forecasting provides a cost-effective means for producing forecasts using promotional information.

Promotional Forecasting Terminology and Workflow

Promotional Forecasting is designed to produce sales forecasts using both past sales history and event on/off information, both of which you provide. Using the sales data, the system first determines a seasonal time series model to describe the purchasing behavior of consumers. Differences between the seasonal model and the actual sales are then correlated with known events. Events that are found to have a statistically significant impact on sales are then included in a promotional forecast model as promotion events. For each promotion event, its promotion effect on sales is determined. The final promotional model consists of the seasonal model, promotion event on/off information, and each promotion event's resulting effect on sales. By combining these three, a final promotional forecast is computed.

Note: More detailed information on the Causal forecasting algorithm is provided in the Forecasting Methods Available in Oracle Retail Demand Forecasting section.

Examples of Promotion Events

The following are examples of promotional variables that could be created and the manner in which their associated on/off event status is specified:

Example 1: Christmas Day applies to all products/locations. The Christmas promotional variable will therefore have only one dimension – Day. Because Christmas Day falls on the 359th day of each non-leap year, the Day359 variable will be set to TRUE for every such year (all other days will be set to FALSE).

Example 2: A television advertisement is run locally in the New York/New Jersey area for the four weeks at the beginning of the spring fashion season. The TVAD promotional variable will have two associated dimensions – State and Week. Week13, Week14, Week15, and Week16 will be set to TRUE only for states NY and NJ (all other states/weeks will be set to FALSE). Since no product dimension exists, the TV ad is assumed to have an effect on all products.

Example 3: A holiday promotion is run involving all sporting goods items for the two weeks prior to Father's Day. The Father's Day promotional variable has two associated dimensions – item and Week. For this year, Week23 and Week24 will be set to TRUE only for individual items related to sporting goods items (all other weeks and all other items will be set to FALSE). Since no location dimension exists, the Father's Day promotion is assumed to apply to all stores.

After promotional variables have been loaded into Oracle Retail Demand Forecasting, you can use the Promotion Planner workbook to view, edit, and update associated values without having to reload new data.

Promote Workbooks and Wizards

The Promote workbooks and wizards allow you to manage the promotion events used in the system's promotional forecasting processes, and view/edit the system's analysis of the effects of these events on demand. The Promote workbook templates include:

- **Promotion Planner –** Allows you to specify when certain promotional events were active in the past, and when they will be active in the future.
- **Promotion Maintenance –** Allows you to review the system-calculated promotional lift effects, edit these effects, and determine how changes will be factored into the promotional model.
- **Promotion Effectiveness –** Our promotional what-ifing workbook. This allows you to analyze the performance of previous promotions and simulate future promotions by editing when promotional events will be active for an item/location and by modifying the promotion lift effects.
- **Promotion Management –** Allows you to enable and disable promotions for causal forecast levels and to specify whether promotions can have a negative effect.
- **Forecast Administration –** External to Promote, the Forecast Administration workbook includes several parameters that may be used as additional configuration options for promotional forecasting.

Promotion Planner Workbook Template

Overview

In order to correlate deviations from the seasonal forecast with the occurrence of historic promotion events, the system needs visibility as to when these events were active. The system must also be informed of dates on which the status of upcoming promotion events will again be "on," so the anticipated promotion effects can be built into the forecasting model.

The Promotion Planner workbook allows you to indicate to the system when certain events were active in the past and when they will be active in the future. All promotional events should be represented as accurately as possible so the modeling routine can more precisely detect correlations between event occurrences and changes in sales values.

The Promotion Planner workbook consists of as many worksheets as are necessary to represent all unique dimensional intersections associated with the promotion events contained in the workbook. A separate worksheet is constructed for each of the required intersections. For example, promotion events such as Advertisement and Gift with Purchase may be loaded at the [Item/Store/Week] intersection, while an event such as Christmas is loaded at the [Day] level.

In this setup, the Advertisement and Gift with Purchase promotions would appear on one worksheet, and Christmas would appear on another. Whenever a hierarchy is not included in the base intersection (as in the case of the Christmas promotional event) the event is assumed to apply to all positions in the undefined hierarchy. Thus, Christmas is assumed to apply to all products and all locations, but only to the Day-level calendar position(s) specified in the Promotion Planner worksheet.

Opening or Creating a Promotion Planner Workbook

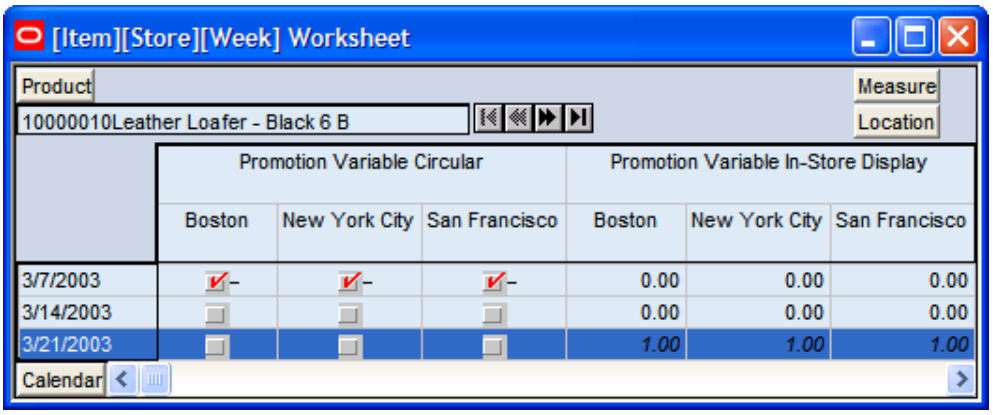
The Promotion Planner wizard steps you through the process of creating a new Promotion Planner workbook from a template. To access the Promotion Planner, select Open from the File menu to bypass the wizard and open an existing Promotion Planner workbook, or perform the following steps:

1. Within the Local or Simple domain, select **New** from the File menu.
2. On the Promote tab, select **Promotion Planner**. Click **OK**.
3. The Promotion Planner wizard opens and prompts you to select the promotion events to edit or review. Click **Next**.
4. Select the locations that need to have promotions planned. Click **Next**.
5. Select the products that need to have promotions planned. Click **Next**.
6. Select the dates that need to have promotions planned. Click **Next**.
7. Click **Finish** to build the workbook.

Window Descriptions

Promotion Planner Workbook and Worksheet

The Promotion Planner workbook allows you to view and edit the on/off information associated with each configured promotional event. This workbook provides an interface in which you can specify the time periods (and possibly products and/or locations) for which certain promotional variables are active.



Promotion Planner Worksheet

Promotion Variables

Promotion Variables are defined as either Boolean (by default) or Real types during the configuration process in the Promote Plug-In. See the *RDF Configuration Guide* for additional details on configuring the Promote solution.

For Promotion Variables defined as Boolean types, a check in a given cell indicates that the associated promotion event's status is "on" (or 100% of the lift effect applies) for that intersection. If no check is indicated, the event's status is "off."

For Promotion Variables defined as Real types, a value of '1.00' in a given cell indicates that the associated promotion event's status is "on" (or 100% of the lift effect applies) for that intersection. A value of "0.00" indicates that the event's status is "off."

Among the ways Causal variables can be implemented include: price or discount %. Your Oracle Retail Consultant can best determine the most accurate set up of promotion variables based upon your promotional forecasting requirements.

Promotion Maintenance Workbook Template

Overview

The Promotion Maintenance workbook provides a view to the system-calculated and adjusted lift effects. You can edit effects at any product/location intersection and determine how these changes will be factored into the promotional models. The Promotion Maintenance workbook contains one worksheet. There may be multiple versions of this worksheet, defined at various causal levels.

Opening the Promotion Maintenance Workbook Template

The Promotion Maintenance wizard steps you through the process of creating a new Promotion Maintenance workbook from a template.

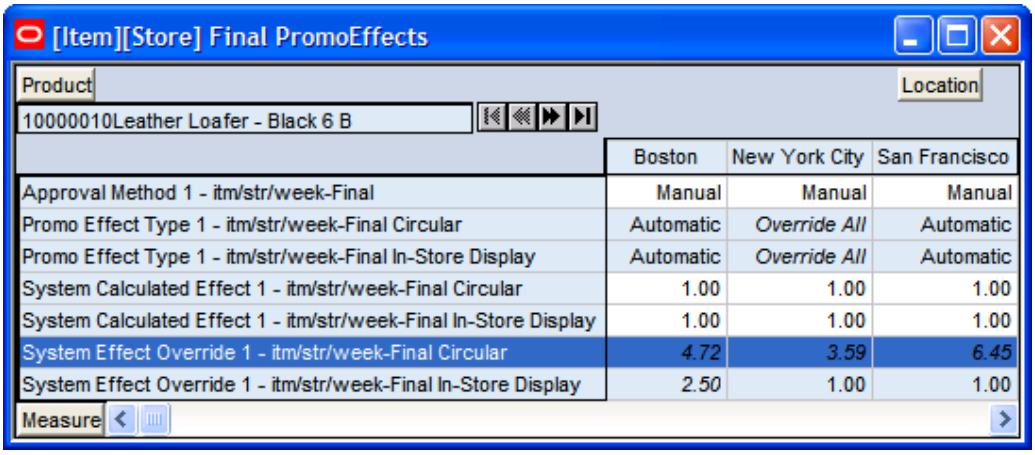
1. Within the Local or Simple domain, select **New** from the File menu.
2. On the Promote tab, select **Promotion Maintenance**. Click **OK**.
3. Select the promotion events to analyze. Click **Next**.
4. Select the causal forecast level for analysis. Click **Next**.
5. Select the locations to analyze. Click **Next**.
6. Select the products to analyze. Click **Next**.
7. Select additional measures to view in the workbook (if necessary). Click **Finish**.

Window Descriptions

Promotion Maintenance Workbook and Worksheets

Final PromoEffects Worksheet

The Final PromoEffects worksheet allows you to view and modify the system-calculated effects of a given promotion.



	Boston	New York City	San Francisco
Approval Method 1 - itm/str/week-Final	Manual	Manual	Manual
Promo Effect Type 1 - itm/str/week-Final Circular	Automatic	*Override All*	Automatic
Promo Effect Type 1 - itm/str/week-Final In-Store Display	Automatic	*Override All*	Automatic
System Calculated Effect 1 - itm/str/week-Final Circular	1.00	1.00	1.00
System Calculated Effect 1 - itm/str/week-Final In-Store Display	1.00	1.00	1.00
System Effect Override 1 - itm/str/week-Final Circular	*4.72*	*3.59*	*6.45*
System Effect Override 1 - itm/str/week-Final In-Store Display	*2.50*	1.00	1.00

Final PromoEffects Worksheet

Field Descriptions

System Calculated Effect

The System Calculated Effect is a read-only measure indicating the lift effect generated by the system.

System Effect Override

The user-specified lift effect. This user-entered effect is active if used in conjunction with the "Override All" and "Override Future Only" Promotion Effect Types. Otherwise, it equals 1.00.

Promo Effect Type

Causal variable types define how causal variables are treated in the causal model fitting process (which includes a call to the lower level regression engine) and the forecast generation process where the model is used to extend the forecast over the forecast horizon. Following are the drop-down list options:

- **Automatic –** The inclusion of the causal variable is decided by regression. If the causal variable is found to be significant on the training set, it is included in the model. Otherwise, it is rejected. Automatic is the system default Promotion Effect Type.
- **Forced In –** The causal variable is forced in to the model, thus regression is not given a choice to reject even if the effect is considered insignificant by regression. As a result, we will always return an effect even if it has a negative impact to the demand forecast.
- **Disabled –** The variable is excluded from the model, hence no effect will be returned either.
- **Override All –** This type allows you to specify a causal effect that will be used during the fitting and forecasting process. This is a directive that is recognized only by the causal engine and not by the lower level regression engine. For causal variables specified as "Override All," you also specify the corresponding causal effect in the Promotion Effect Override. The causal engine then de-causalizes the training data using the user-specified effect. The variable is then internally set to "Disabled" to calculate the fit. During forecast generation, the user-specified effect is used to determine the causal forecast. Therefore, you must change the Promotion Effect Type when this user-specified effect is no longer to be used.
- **Override Future Only –** This type allows you to specify a causal effect that will be used only during forecasting process and not during the fitting process. This is also a directive that is recognized only by the causal engine and not by the lower level regression engine. For causal variables specified as "Override Future," you also specify the corresponding causal effect in the Promotion Effect Override. The causal engine then internally sets the causal variable to "Automatic" to calculate the fit. The calculated effect is not written back to the effects array (so as to not overwrite the user specified effect). During forecast generation the calculated effect is ignored, and instead, the user-specified effect is used to produce a causal forecast. Therefore, you must change the Promotion Effect Type when this user-specified effect is no longer to be used.

- **Override from Higher Level –** Used in conjunction with the Causal Higher Intersection set in the Forecast Administration workbook, this promotion type allows the system to use the geometric mean of causal effects computed from product/location combination in the same group (the intersection level specified in the Causal Higher Intersection during system setup) for product/location combinations for which from sales history alone a causal effect is unable to be computed for that causal variable. The way the system handles this is by having the effects array filled in with higher-level effects for those variable specified as "Override Higher Level" and which did not have an effect returned in the previous run. The effect array is passed to the causal engine. If the engine succeeds in computing a significant effect, it writes back the system computed effect and uses it for generating a forecast. Otherwise, it uses the effect passed in (which as mentioned is the average effect among product stores belonging to the same group) for generating the forecast. Note that if no significant effects are found for any of the product/locations in the Causal Higher intersection group, then the system uses the geometric mean of causal effects calculated from all Product/Locations as the override effect being passed in.
- **Automatic Boolean –** If the promotion variable will always be set to 0.00 or 1.00 (meaning inactive or active respectively), this type will produce the same results as the Automatic type described above; however, Automatic Boolean will improve the performance (speed) of the forecasting engine during the batch run of the forecast.

> **Note:** Changes that are committed in the Promotion Maintenance workbook will not be incorporated into the forecast until another forecast is generated in RDF batch forecast process.

Promotion Effectiveness Workbook Template

Overview

The Promotion Effectiveness workbook Template is a historical and future view to the effects of a planned promotion.

This workbook has two worksheets:

- View of promotion effects
- Visibility to Actuals, forecasts, baselines, and promotion variable/event information

In this workbook, you view the promotional forecast. There is also the ability to analyze the effects on the forecast if a promotion does or does not occur. This analysis is performed by turning a promotional event or attribute on or off for dates in the future plans, and/or by modifying the Simulated Effect. This workbook is intended for simulation and analysis purposes only. There is no Commit functionality.

> **Note:** Changes to the Promotion Effects workbook cannot be committed back to the master database; however, this workbook is useful for reporting on the performance of past promotions and simulating the effects of future promotions to support more accurate promotional modeling.

Opening the Promotion Effectiveness Workbook Template

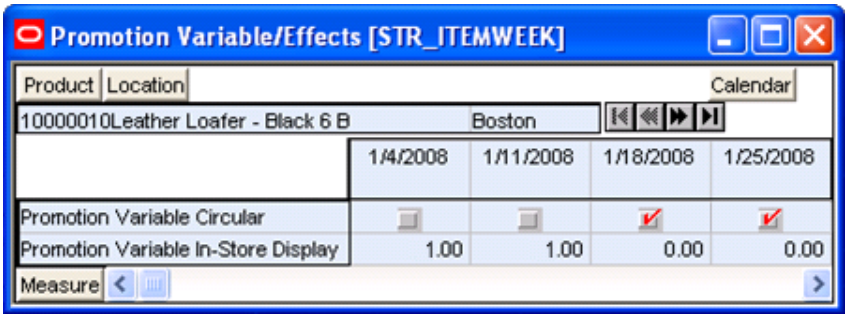
The Promotion Effectiveness wizard steps you through the process of creating a new Promotion Effectiveness workbook from a template.

1. Within the Local or Simple domain, select **New** from the File menu.
2. On the Promote tab, select **Promotion Effectiveness**. Click **OK**.
3. Select the causal level. Click **Next**.
4. Select the forecast level for analysis. Click **Next**.
5. Select the dates to analyze. Click **Next**.
6. Select the locations to analyze. Click **Next**.
7. Select the products to analyze. Click **Next**.
8. Select any additional measures that need to be included in the workbook (if necessary). Click **Finish**.

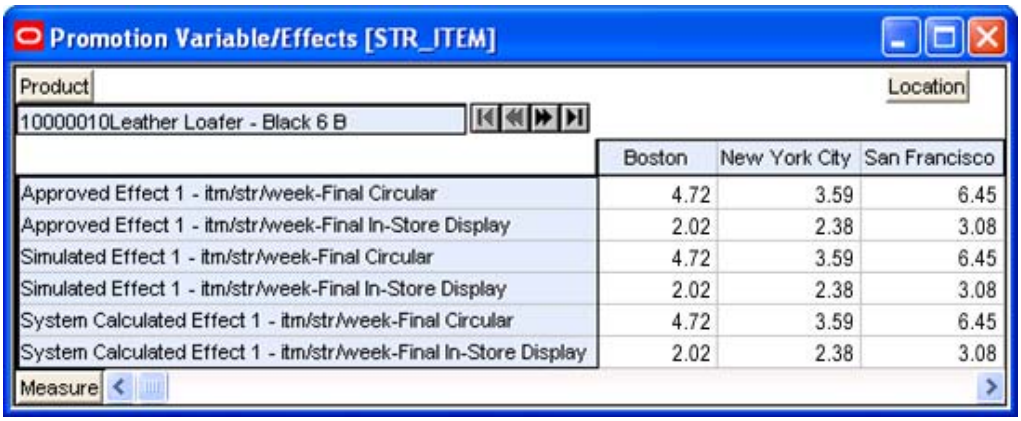
Window Descriptions

Promotion Variable/Effects Worksheets

The Promotion Variable/Effects worksheets allow you to simulate the activation and de-activation of promotions, and it allows for promotion lift effects to be adjusted. The Promotion Variable/Effects worksheets are built at the hierarchy intersections of the promotion variables configured in the system, and at the product and location intersection of the causal forecast level selected during the wizard process. For example, if all of the variables are defined at the item/store/week level, only one worksheet would be built. However, if variables have been defined at different intersections, multiple worksheets will be created based on each of the unique intersections. As well, if the causal forecast level selected for the workbook is the item/store/week level, an additional Promotion Variable/Effects worksheet will be created at the item/store level in order to display the lift effect measures.



Promotion Variable/Effects [STR_ITEMWEEK] Worksheet



Promotion Variable/Effects [STR_ITEM] Worksheet

Field Descriptions

The Promotion Variable/Effects worksheets contain the following measures:

Promotion Variables

Promotion Variables are defined as either Boolean (by default) or Real types during the configuration process in the Promote Plug-In. See the *RDF Configuration Guide* for additional details on configuring the Promote solution.

For Promotion Variables defined as Boolean types, a check in a given cell indicates that the associated promotion event's status is "on" (or 100% of the lift effect applies) for that intersection. If no check is indicated, the event's status is "off."

For Promotion Variables defined as Real types, a value of '1.00' in a given cell indicates that the associated promotion event's status is "on" (or 100% of the lift effect applies) for that intersection. A value of '0.00' indicates that the event's status is "off."

Among the ways causal variables can be implemented includes: price, % contribution of the lift effect, or discount %. Your Oracle Retail Consultant can best determine the most accurate set up of promotion variables based upon your promotional forecasting requirements.

Approved Effect

This is a read-only measure. This is the approved promotion lift effect used in the generation of the current System Forecast in RDF.

Simulated Effect

This is a read/write measure. The Simulated Effect will default to the Approved Effect. Changes to this measure will have an impact to the Historical Forecast and the Future Forecast.

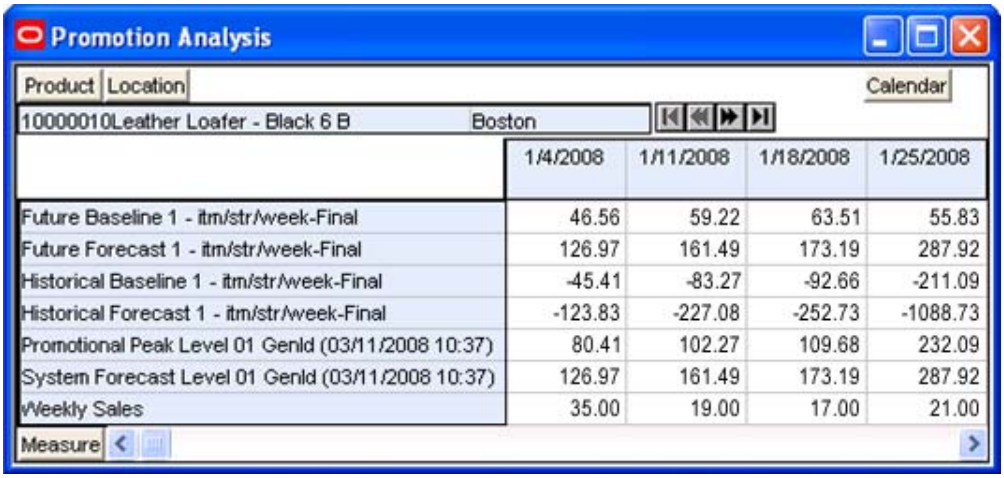
System Calculated Effect

The System Calculated Effect is a read-only measure. This is the promotion lift effect originally calculated by the system during the forecast generation process. This value can be different from the Approved Effect if you edited the System Effect Override in the Promotion Maintenance workbook, and then another batch forecast was run.

> **Note:** The Approved Effect, Simulated Effect, and System Calculated Effect are only visible on the worksheet that is at the same product and location intersection as the causal forecast level selected during the wizard process.

Promotion Analysis Worksheet

The Promotion Analysis worksheet is created at the same base intersection as the causal forecast level selected during the wizard process. Changes made to the Promotion Variables and Simulated Promo Effect on the Promotion Effectiveness worksheet will be reflected in the recalculation of the Historical Forecast and Future Forecast.



	1/4/2008	1/11/2008	1/18/2008	1/25/2008
Future Baseline 1 - itm/str/week-Final	46.56	59.22	63.51	55.83
Future Forecast 1 - itm/str/week-Final	126.97	161.49	173.19	287.92
Historical Baseline 1 - itm/str/week-Final	-45.41	-83.27	-92.66	-211.09
Historical Forecast 1 - itm/str/week-Final	-123.83	-227.08	-252.73	-1088.73
Promotional Peak Level 01 GenId (03/11/2008 10:37)	80.41	102.27	109.68	232.09
System Forecast Level 01 GenId (03/11/2008 10:37)	126.97	161.49	173.19	287.92
Weekly Sales	35.00	19.00	17.00	21.00

Promotion Analysis Worksheet

Field Descriptions

The Promotion Analysis worksheet contains the following measures:

History Data (the measure that represents Sales/Actuals)

This is a read-only measure. History Data is the sales data used to generate the forecast. This allows the user to compare Actuals to forecasted values. When the workbook is created, the Data Source specified in the Forecast Administration workbook is included in the Promotion Analysis.

System Forecast

This is a read-only measure. This is the latest forecast quantity approved for the product/location combination.

> **Note:** Changes that are committed in the Promotion Maintenance workbook are used to determine values for the System Calculated Effect and the Approved Effect. However, if a forecast has not been generated in RDF since the changes were made in the Promotion Maintenance workbook, the System Forecast will not include these changes.

Promotional Peak

This is a read-only measure. The Promotional Peak is the unit-lift over the Baseline Forecast calculated during the forecast generation process.

Future Baseline

This is a read-only measure. Calculated as the System Forecast minus (–) the Promotional Peaks. User-changes to the editable measures in the Promotion Variable/Effects worksheets do not affect this value.

Future Forecast

This is a read-only measure. The Future Forecast equals the Future Baseline multiplied by the Simulated Effect if the promotion variable is greater than 0 (zero). If there are more than one promotion variables, the sum of the Simulated Effects for the variables is multiplied by the Future Baseline.

If there is no active promotion variable, the Future Forecast equals the Future Baseline.

Historical Baseline

This is a read-only measure. Calculated in one of two ways based on the value of the System Forecast:

1. Historical Baseline equals Sales minus the Promotion Peak if the System Forecast is greater than 0 (zero).
2. Historical Baseline equals Sales with the Moving Average applied if the System Forecast equals 0 (zero). If Sales are also 0 (zero), the Historical Baseline will also equal 0 (zero).

Historical Forecast

This is a read-only measure. The Historical Forecast equals the Historical Baseline multiplied by the Simulated Effect if the promotion variable is greater than 0 (zero). If there are more than one promotion variables, the sum of the Simulated Effects for the variables is multiplied by the Historical Baseline.

If there is no active promotion variable, the Historical Forecast equals the Historical Baseline.

Promotion Management Workbook Template

Overview

The Promotion Management workbook template allows the user to enable and disable promotions for causal forecast levels and to specify whether promotions can have a negative effect.

This workbook has two worksheets:

- Promotion Enable
- Accept Negative Lift

Opening the Promotion Management Workbook Template

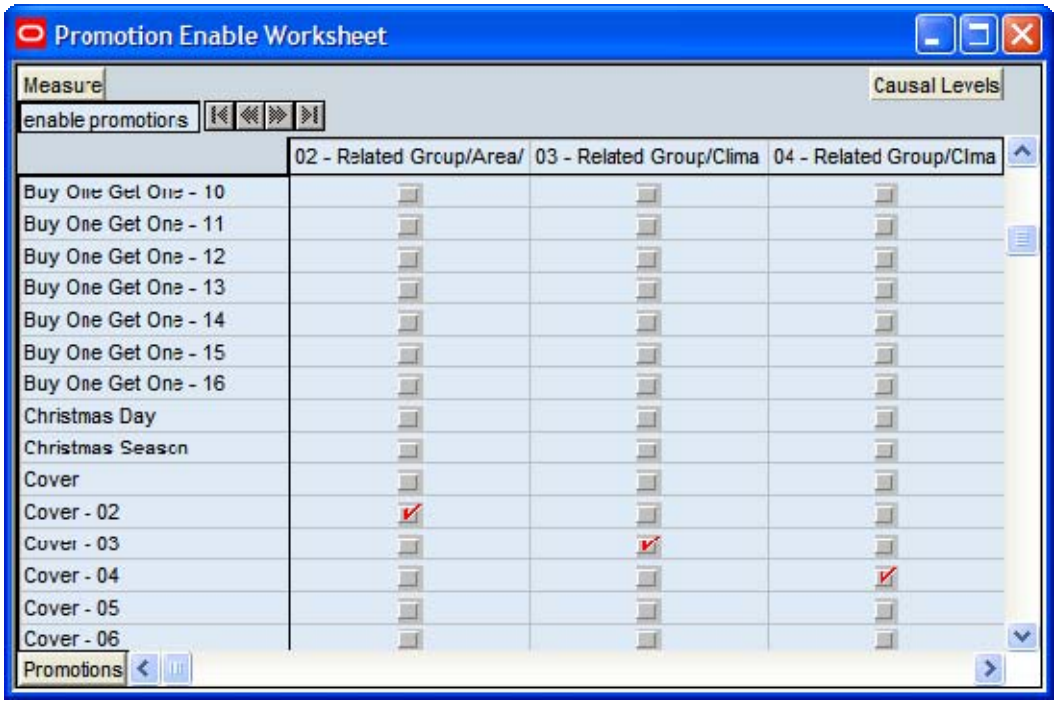
The Promotion Management wizard helps you create a new Promotion Management workbook from a template.

1. Within the Local or Simple domain, select **New** from the **File** menu.
2. On the Promote tab, select **Promotion Management**. Click **OK**.
3. Select the causal level. Click **Next**.
4. Select the promotions. Click **Finish**.

Window Descriptions

Promotion Enable Worksheet

The Promotion Enable worksheet allows the user to enable or disable a promotion for the causal forecast levels. The Promotion Enable worksheet is built at the hierarchy intersections of the promotion variables and the causal levels selected during the wizard process.



Promotion Enable Worksheet

Field Descriptions

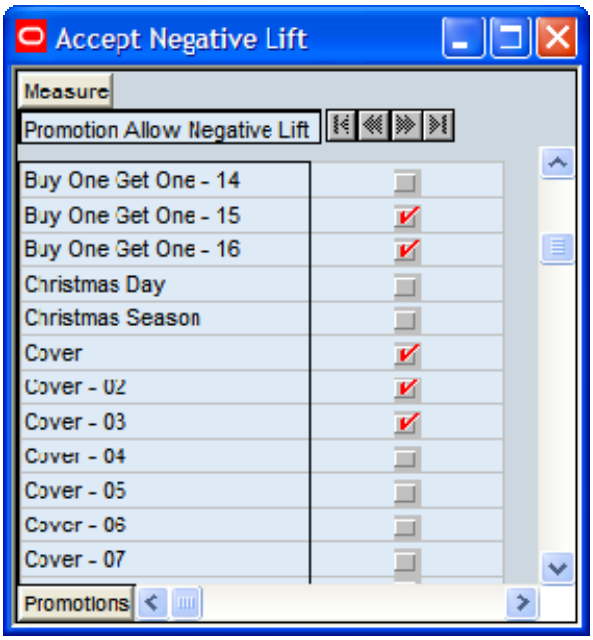
The Promotion Enable worksheet contains the following measure:

Enable Promotions

This is a read/write Boolean measure. The Enable Promotions measure allows the user to enable a subset of promotions for a certain causal forecast level. It defaults to True for all causal forecast levels.

Accept Negative Lift Worksheet

The Accept Negative Lift worksheet allows the user to specify whether a promotion is allowed to have negative effect. The Promotion Enable worksheet is built at the hierarchy intersections of the promotion variables selected during the wizard process.



Field Descriptions

The Accept Negative Lift worksheet contains the following measure:

Promotion Allow Negative Lift

This is a read/write Boolean measure. The Promotion Allow Negative Lift measure allows the user to specify whether a promotion is allowed to have negative effect. When this measure is set to False for a promotion, the forecast engine does not allow that promotion to have any negative lift (Effect < 1). It defaults to True for all promotions.

Procedures in Promotional Forecasting

The following outlines the standard procedures performed in order to set up the system to run a promotional forecast (more detailed steps follow in the next section):

- Set up the system to run a promotional forecast
- Set forecast parameters in the Forecast Administration workbook
- Set forecast parameters in the Forecast Maintenance workbook
- Set promotions to be active in the Promotion Planner workbook
- Run the batch forecast
- View and Edit Causal Forecast results
- Analyze forecasts in the Forecast Approval workbook
- Analyze and edit causal effects in the Promotion Maintenance workbook
- Promotion Simulation (what-ifing) and Analysis

Setting Up the System to Run a Promotional Forecast

1. On the Forecast tab, select and build a Forecast Administration workbook.
   a. In the Forecast Administration workbook: Advance Parameter worksheet, select **Generate Baseline**.
   b. Optional: **Set the Default Forecast Method** to **Causal** for the desired level if the level is to be use only for Promotional Forecasting.
   c. Optional: **Set the Causal Higher Intersection** for the desired level if the Override from Higher Level promotion type will be used.
   d. Optional for use with Daily Causal Forecasting: Set the values for the following parameters:
      – **Causal Aggregation Profile**
      – **Causal Calculation Intersection**
      – **Causal Calculation Intersection Periodicity**
   e. Commit your changes to the master database by selecting **Commit Now** from the File menu.
2. On the Forecast tab, select and build a Forecast Maintenance workbook.
   a. Set the **Forecast Method Override** to **Causal** for any items/locations at the desired levels that will use Promotional Forecasting.
   b. Commit your changes to the master database by selecting **Commit Now** from the File menu.
3. On the Forecast tab, select and build a Promotion Planner workbook.
   a. Set causal variables for items and locations historically in that the selected promotions are active.
   b. Commit your changes to the master database by selecting **Commit Now** from the File menu.
4. On the Forecast tab, select **Run Batch**.
   - Generate a Forecast.

Viewing a Forecast that Includes Promotion Effects

1. On the Forecast tab, select and build a Forecast Approval workbook and include System Baseline in your workbook.
2. In the Final Level worksheet, review the System Baseline and the System Forecast. The System Baseline is predicted demand given no causal effects. The System Forecast is the sum of the System Baseline and the Promotional Peak calculated during the forecast generation process based on the causal data and settings.

Viewing and Editing Promotion System-Calculated Effects

1. On the Promote tab, select and build a Promotion Maintenance workbook.
   a. In the PromoEffects worksheet, review the System-Calculated Effect.
   b. If the System Calculated Effect is to be modeled using a method other than Automatic, edit the **Promotion Effect Type**.
   c. If you choose to adjust the system-calculated effect, adjustments can be made to the System Effect Override. You must also set the **Promotion Effect Type** to **Override All** or **Override Future Only**.
2. On the Forecast tab, select **Run Batch**.
   - Generate a Forecast.

Promotion Simulation ("what-if?") and Analysis

Follow this procedure to perform analysis on past promotions and simulate the effects of historic or future promotions:

1. On the Promote tab, select and build a Promotion Effectiveness workbook
2. In the Promotion Variable/Effects worksheet review the Promotion System-Calculated Effect and edit the Simulated Promo Effect, then select **Calculate** to recalculate the Future Forecast.

> **Note:** Changes to the Promotion Effects workbook cannot be committed; however, this workbook is useful for:
>
> - Reporting on the performance of past promotions.
> - Simulating the effects of future promotions to support more accurate promotional modeling.

6

Oracle Retail Demand Forecasting Methods

This chapter discusses the forecasting methods used in Oracle Retail Demand Forecasting in detail.

Forecasting Techniques Used in RDF

Oracle Retail Demand Forecasting uses a variety of predictive techniques to generate forecasts of demand. The technical methods used are driven by the goal to provide the most accurate forecasts possible in an automatic and efficient manner. These methods have been analyzed, optimized, and refined over years of research on retail specific data.

The primary techniques RDF uses include:

- Exponential smoothing
- Regression analysis
- Bayesian analysis
- Prediction intervals
- Automatic method selection
- Source level forecasting
- Promotional forecasting

Exponential Smoothing

Exponential smoothing models fit basic features of the demand pattern such as level, trend, and seasonality, and project these into the future. These models provide computational benefits and have been chosen for their ability to handle different types of time series, including short and/or noisy series that are characteristic of retail sales. They are "smoothing" models because they use weighted averages on historic data. They are "exponential smoothing" models because the weighting used decays at an exponential rate. That is, more recent data is weighted more heavily than the past.

Regression Analysis

Regression analysis is another standard technique used in prediction. Regression uses a least-squares estimator to fit a model of predictor variables to another set of target variables. Seasonal Regression is an Oracle Retail specific extension of this procedure for use in seasonal models with between one and two years of history. Causal Forecasting uses stepwise regression to determine which causal variables are significant.

Bayesian Analysis

Bayesian analysis considers a priori information as a starting point in development of a prediction. Bayesian forecasting, as developed by Oracle Retail, uses a sales plan as the starting point that is adjusted based on observed data. This method fills a gap in standard time series forecasting when new, short lifecycle or products with significant lifecycles are being forecast.

Prediction Intervals

Prediction from these various models gives the estimated mean outcome. By using standard statistical distributional assumptions, RDF develops measures of uncertainty associated with forecast point estimates from these models. While this is of key concern for various optimization solutions of the forecast, the technical details are beyond the scope of this document. For further details on prediction interval calculations, see Char&Yatfield, International Journal of Forecasting, March 1992.

Automatic Method Selection

Providing multiple forecasting methods is only valuable if the appropriate model can be selected in an accurate and efficient manner. In order to make this feasible in a retail environment, Oracle Retail has developed a number of different meta-methods that can automatically select the best method among a number of competing models. Automatic Exponential Smoothing (AutoES) is an example of one such method that clients can select. The final selection between the competing models is made according to a performance criterion that involves a tradeoff between the model's fit over the historic data and its complexity. A description of the competing models used within AutoES is described in section two of this document. In academia, this discipline is known as Information Theory and is used in the combination and selection of various competing models.

Source Level Forecasting

Sometimes it is difficult to capture seasonality, trend, or causal effects on the final level (item/store) due to scarcity of the data. Also, time series are often too noisy at that level. To overcome these issues, RDF utilizes source level forecasting. In source level forecasting, data is aggregated first to a higher level across the product or location hierarchy (or both). Then the forecast is generated and proportionally spread down to the final level. We have experimentally proven that source level forecasting technique often improves the accuracy on the final level.

Promotional Forecasting

In some instances, especially in retail, pure time series techniques are inadequate for forecasting demand. Instead of using only historic demand patterns to forecast future demand, additional causal or promotional factors are used to better explain past performance. With the help of a promotional calendar, an indication of when promotions will be run in the future, these promotional forecasting techniques can better predict demand in the future.

Time Series (Statistical) Forecasting Methods

This section describes those techniques within RDF that generate forecasts directly from only a single time series. Generally the time series provided is past sales history for a given item/Store that is used to predict what future demand might be. In actual practice these algorithms have been and can be used to forecast a myriad of different data streams at any product/location level (shipment data at item/warehouse, financial data at dept./chain, and so on).

The following topics present fundamentals of the Oracle Retail Demand Forecasting statistical forecasting processes. Included is a discussion of the importance of confidence intervals and confidence limits, the time series methods used to generate forecasts, and how the best forecasting method is selected from a list of candidate models.

A wide variety of statistical forecasting techniques are available, ranging from very simple to very sophisticated. All of these methods attempt to best capture the statistical probability distribution discussed above, and they do this by fitting quantitative models to statistical patterns from historical data. Put simply, the better the history of the variable being forecasted, the stronger these statistical patterns will be. Increased forecast accuracy depends on the strength of these patterns in relation to background irregularities.

Oracle Retail Demand Forecasting is able to use several time series methods to produce forecasts. Time series methods extrapolate features from the past (in this case, past sales data) to the future. The time series methods that the system offers include:

- Auto Exponential Smoothing Forecasting (AutoES)
- Seasonal Exponential Smoothing Forecasting (SeasonalES)
- Simple Moving Average
- Simple Exponential Smoothing
- Croston's Method
- Holt Exponential Smoothing
- Multiplicative Winters Exponential Smoothing
- Additive Winters Exponential Smoothing
- Seasonal Regression
- Bayesian Information Criterion

Why Use Statistical Forecasting?

The purpose of statistical forecasting is to make the process of predicting future events both objective and quantitative. Statistical forecasting utilizes information from the past (such as sales data) to predict what will happen in the future. Forecast accuracy depends on the degree to which a mathematical model can detect and extract statistical patterns from historic data. The most common statistical methodologies used are univariate. This means that they are based solely on the history of one variable, such as sales. Each forecast observation reflects a future value of the sole input variable. Statistical forecasting processes are relatively easy to implement, and the better the historical data, the better the resulting forecasts.

Businesses benefit greatly from the use of systematic statistical forecasting techniques that aim to accurately predict product demand, enabling these businesses to maintain sufficient product inventory levels. When inventory levels are optimized, lost sales due to product stock-outs are greatly reduced, as are the costs incurred by overstocking.

Exponential Smoothing (ES) Forecasting Methods

The primary process by which RDF automatically fits an exponential smoothing model to a time series is called Automatic Exponential Smoothing (AutoES). When AutoES forecasting is chosen in RDF, a collection of candidate models is initially considered. The models in the candidate list include:

- Simple (One Parameter) Exponential Smoothing
- Croston's Method (Intermittent ES)
- Holt (Two Parameter) Exponential Smoothing (Trend ES)
- Winters (Three Parameter) Exponential Smoothing (Seasonal ES)
- Seasonal Regression

These models include level information, level and trend information, and level, trend and seasonality information, respectively. The optimal smoothing parameters for each model form are determined automatically (that is, greater smoothing will be applied to noisier data). The final selection between the resulting models is made according to a performance criterion that involves a tradeoff between the model's fit over the historic data and its complexity.

The amount of available historic information can affect the complexity of the model that can be fit. For example, fitting a seasonal model would not be appropriate without a complete year of historic data. In fact, one prefers to see each "season" occur multiple times. For a particular series, even if the amount of available history allows one to fit a complex model (that is, one with seasonal components), the resulting model is not necessarily superior to a simpler model. If a simpler model (for example, a model with only a level component or level and trend components) fits "as well" as a seasonal model, the AutoES forecasting process will find the simpler model to be preferable. In such a case, the simpler model captures the basic features supported by the data without over fitting and therefore will generally project better forecasts.

Average

A simple moving average forecast involves taking the average of the past *n* time periods and using that average as the forecast for all future time periods (where *n* is the length of fitting period). Simple moving average forecasts are frequently used in the system because:

- They make few assumptions about the historical time series
- They can be generated with little historical data
- They are very fast to generate

Typically, moving average forecasts are generated at the final forecast level (for example, item/store) and their results used to spread more sophisticated higher-level forecasts (for example, those generated with exponential smoothing).

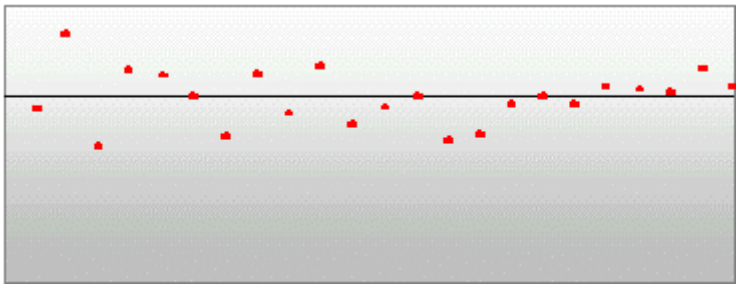
A Simple Moving Average model assumes that historical data is too short or noisy to consider seasonal effects or local trend, and is based on the level of the series. Since this model does not use a smoothing parameter to place added weight on more recent historic values, a Simple Moving Average model is not actually in the exponential smoothing family. However, it is an adequate model to use when low-level (final forecast) ratios are needed for RDF's spreading of high-level (aggregate) forecasts. That is, when aggregate forecasts can be calculated for long and less noisy aggregate time series, Simple Moving Average models provide an adequate (and computationally quick) forecast to determine the ratios needed for RDF spreading. User input in overriding the

automatic training horizon further enhances the simple robustness of this model for base-level data.

Simple Exponential Smoothing

Simple Exponential Smoothing does not consider seasonality or trend features in the demand data (if they exist). It is the simplest model of the exponential smoothing family, yet still adequate for many types of RDF demand data. Forecasts for short horizons can be estimated with Simple Exponential Smoothing when less than a year of historic demand data is available and acts-like associations are not assigned in RDF.

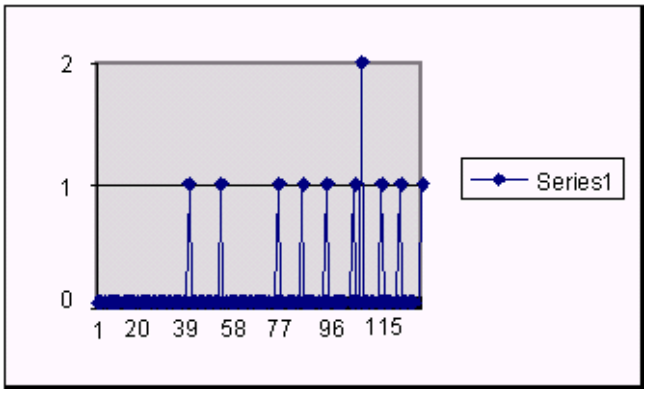
The following figure is an example of a forecast in which data seems to be un-trended and un-seasonal; note the flat appearance of the forecast.



Croston's Method

Croston's method is used when the input series contains a large number of zero data points (that is, intermittent demand data). The method involves splitting the original time series into two new series: (i) magnitude series and (ii) frequency series. The magnitude series contains all the non-zero data points, while the frequency series consists of the time intervals between consecutive non-zero data points. A Simple Exponential Smoothing model is then applied to each of these newly created series to forecast a magnitude level as well as a frequency level. The ratio of the magnitude estimate over the frequency estimate is the forecast level reported for the original series.

The following figure shows a sales history of data where the demand for a given period is often zero.



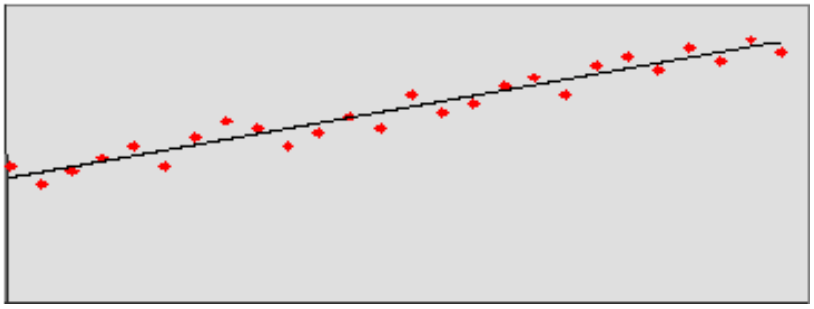
Simple/Intermittent Exponential Smoothing

This method is a combination of the Simple ES and Croston's (Intermittent ES) methods. The Simple ES model is applied to the time series unless a large number of zero data points are present. In this case, the Croston's model is applied.

Holt Exponential Smoothing

Holt exponential smoothing treats data as linearly trended but non-seasonal. The Holt model provides forecast point estimates by combining an estimated trend (for the forecast horizon - h) and the smoothed level at the end of the series. RDF uses a damped Holt model that decays the trend component so that it disappears over the first few weeks. This improves forecasts created using Holt over longer forecast horizons.

When this forecasting method is selected, the forecasts are seen as trending either up or down, as in the following example:



Multiplicative Winters Exponential Smoothing

RDF now offers a choice of four different forecasting approaches within the Multiplicative Seasonal Forecasting Method.

The Winter's forecasting approaches, including the current seasonal approach, are:

- Oracle Winters (current or default approach)
- Oracle Winters Decomposition
- Winters Standard
- Winters Responsive

All four approaches use the same calculation for arriving at forecasts.

Overall, a forecast point estimate is evaluated as:

$$\hat{Y}_t(h) = \left(L_t + \left[\sum_{i=1}^{h} \varphi^i \right] T_t \right) \hat{S}_t(h),$$

a function of level, trend, seasonality and trend dampening factor.

Winters Standard and Winters Responsive both use a basic Winter's method:

The Level at the end of the series (time t) is:

$$L_t = \alpha \frac{Y_t}{S_{t-p}} + (1-\alpha)(L_{t-1} + T_{t-1})$$

The Trend at the end of the series (time t) is:

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

The Seasonal Index for the time series (applied to the forecast horizon) is:

$$S_t = \delta \frac{Y_t}{L_t} + (1-\delta)S_{t-p}$$

The difference between the two approaches is how these values are optimized within the optimization routine.

Oracle Winters and Oracle Winters Decomposition use a Winters-based decomposition approach to update the level, trend and Seasonal Indexes. Each of these methods calculates initial seasonal indices from a baseline Holt forecast. Seasonal indices, level and trend are then updated in separate stages, using Winter's model as a basis for the updates. The difference between the two approaches is which parameters are optimized and in which stages seasonal indices are updated.

Oracle Winters

Oracle Winters is the current seasonal forecasting approach, which uses a combination of Winters approach and decomposition. Decomposition allows level and trend to be optimized independently while maintaining a seasonal curve.

From sufficient data, RDF extracts seasonal indexes that are assumed to have multiplicative effects on the de-seasonalized series. Note that the component describing the de-seasonalized values (which is multiplied by the seasonal index $\hat{S}_t(h)$) is the Holt model described above. In this case, three parameters are used to control smoothing of the components of level, trend, and seasonality.

Oracle Winters Decomposition

Like the Oracle Winters seasonal forecasting approach, Oracle Winters Decomposition uses a combination of Winters approach and decomposition.

From sufficient data, RDF extracts seasonal indexes that are assumed to have multiplicative effects on the de-seasonalized series. Note that the component describing the de-seasonalized values (which is multiplied by the seasonal index $\hat{S}_t(h)$) is the Holt model described above.

The key difference between Oracle Winters and Oracle Decomposition is that the Seasonal smoothing parameter is also optimized, and the calculation of Seasonal Indices and de-seasonalizing of data is done with in the optimization routine for Oracle Winters Decomposition.

Also the optimization routine with in Oracle Winters Decomposition, while minimizing forecast errors, tends to weigh more recent Forecast errors heavier.

As with Oracle Winters, three parameters are used to control smoothing of level, trend, and seasonality.

Key differences between Oracle Winters and Oracle Winters Decomposition include:

- Seasonal smoothing factor is optimized.
- The optimization places more importance on recent sales than historical sales.
- Seasonal indices are recalculated based on optimization.

When this forecasting approach is selected, the forecasts tend to be more responsive to recent changes in levels while maintaining a substantial seasonal component.

Winters Standard

The Winters Standard uses a standard Winters model, with no additional calculations. All three smoothing parameters are optimized here.

Initial Seasonal Indices are set to one. Initial level and trend are calculated from average selling levels over initial periods. The optimization routine chooses optimal level, trend and smoothing parameters that minimize Forecast Errors in the fit region. All forecast errors within the fit region are weighed equally.

Seasonal Indices, level and trend are calculated based on the optimal values of level, trend, and Seasonal Smoothing parameters: α, γ and δ.

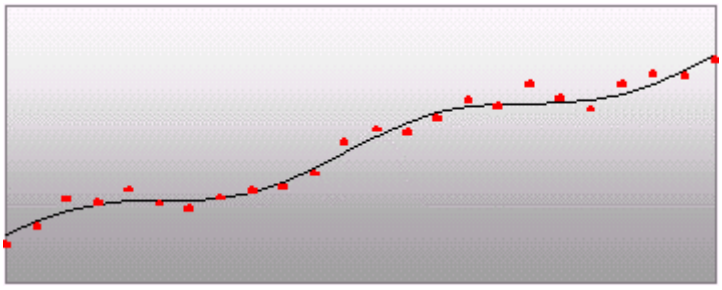
When this forecasting approach is selected, the forecasts tend to be responsive to changes in levels. In cases where there is no obvious correlation in seasonality from period to period or where there are significant changes in level, these forecasts may generate smoother, less seasonal forecasts.

Winters Responsive

Winters Responsive is similar to Winters Standard except the Optimization routine, while minimizing forecast errors, weighs more recent Forecast errors heavier. Winters Responsive, like Standard Winters, optimizes all three smoothing parameters.

When this forecasting approach is selected, the forecasts tend to be more responsive to recent changes in levels. In cases where there are significant shift in levels, resulting in high responsiveness to levels, these forecasts tend to be smoother, with less seasonality.

When the Multiplicative Seasonal forecasting method is selected, the forecasts tend to look "squiggly," as shown in the following figure.



Multiplicative Winters Exponential Smoothing

Additive Winters Exponential Smoothing

RDF now offers a choice of four different Forecasting approaches within the Additive Seasonal Forecasting Method:

The Winters forecasting approaches, including the current seasonal approach, are:

- Oracle Winters (current or default approach)
- Oracle Winters Decomposition
- Winters Standard
- Winters Responsive

All four approaches use the same calculation for arriving at forecasts:

Overall, a forecast point estimate is evaluated as:

$$\hat{Y}_t(h) = L_t + \left[\sum_{i=1}^{h} \varphi^i\right] T_t + \hat{S}_t(h)$$

a function of level, trend, seasonality and trend dampening factor.

Winters Standard and Winters Responsive both use a basic Winter's method:

The Level at the end of the series (time t) is:

$$L_t = \alpha(Y_t - S_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

and the Trend at the end of the series (time t) is:

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

and the Seasonal Index for the time series (applied to the forecast horizon) is:

$$S_t = \delta(Y_t - L_t) + (1-\delta)S_{t-p}$$

The difference between the two approaches is how these values are optimized within the optimization routine.

Oracle Winters and Oracle Winters Decomposition use a Winters-based decomposition approach to update the level, trend and Seasonal Indexes.

Please refer to Multiplicative Winters Exponential Smoothing in this document for a description of each of the Forecasting Approaches.

Seasonal Exponential Smoothing (SeasonalES)

In certain instances, it is known that seasonal models will generally outperform non-seasonal models in forecast accuracy. When this is true (generally used for known seasonal items or for forecasts with a long horizon), it is advantageous to prevent AutoES from selecting from the Simple/Holt/Croston's methods. Choosing SeasonalES does just this. In instances where there exists too little data to create a seasonal forecast (less than 52 weeks of history), the SeasonalES method will cascade to select between Simple/Holt/Croston. In all other instances, a seasonal model (Winter's or Seasonal Regression) will be chosen. See the following section for more information on Seasonal Regression.

Seasonal Regression

A common benchmark in seasonal forecasting methods is sales last year. A sales last year forecast is based entirely on sales from the same time period of last year. Forecasting using only sales last year involves simple calculations and often outperforms other more sophisticated seasonal forecasting models. This method performs best when dealing with highly seasonal sales data with a relatively short sales history.

The seasonal models used in earlier releases of Oracle Retail Demand Forecasting (Additive and Multiplicative Winters) were designed to determine seasonality. However, they were not designed to work with sales histories of shorter than two years. Because sales histories of longer than two years are often difficult to obtain, many retail environments need a seasonal forecast that can accommodate sales data histories of between one and two years. In addition, the Additive and Multiplicative Winters models search for short-term trends and have difficulties with trends occurring inside the seasonal indices themselves. The current Oracle Retail Demand Forecasting Seasonal Regression forecasting model is designed to address these needs.

The Seasonal Regression Model uses simple linear regression with last year's data as the predictor variable and this year's sales as the target variable. The system determines the multiplicative and additive weights that best fit the data on hand. When optimizing the Seasonal Regression Model, the sales last year forecast is inherently considered, and it will automatically be used if it is the model that best fits the data. If there have been significant shifts in the level of sales from one year to the next, the model will learn that shift and appropriately weight last year's data (keeping the same shape from last year, but adjusting its scale).

As with other seasonal models, you can forecast demand for products with insufficient sales histories using this method if:

- You paste in fake history as needed, providing a seasonal profile for the previous year.
- You also forecast for a source level (with the same seasonality profile as the forecasted item and with more than one year of history) using seasonal regression and spread these forecast results down to the member products.

The Seasonal Regression Model is included in the AutoES family of forecasting models, and is thus a candidate model that will be selected if it best fits the data.

This method captures the trend of a series through the slope of the regression line while the series shifted by a cycle provides its seasonal profile. Using this method, the resulting forecast for the original series is calculated. The regression method provides a much better forecast of the series than was possible with the other exponential smoothing algorithms.

Based on the assumptions of the model that this method is trying to describe, versus the noisy data it is likely to receive, several exceptions to this regression technique are caught and corrected. First, since it is logically impossible to receive a negative value for the slope (such a value suggesting an inverse seasonality), whenever a negative slope is detected, the regression is rerun with the intercept fixed to zero. This guarantees that a positive slope will be calculated and thus a more logical forecast will be given.

The second noise-driven concession is to check the slope to determine if it is either too slight or too great. If this is the case, the method rejects itself out of hand and allows one of the other competing methods to provide the forecast.

Bayesian Information Criterion (BIC)

Within AutoES, the model that minimizes the Bayesian Information Criterion (BIC) is selected as the final model. The BIC criterion attempts to balance model complexity with goodness-of-fit over the historical data. The BIC criterion rewards a model for goodness-of-fit and penalizes a model for its complexity. The complexity penalty is necessary to avoid over fitting.

There are various equivalent versions of the Bayesian Information Criterion, but RDF minimizes the following:

$$BIC = s \cdot n^{k/2n}$$

where n is the number of periods in the available data history, k is the number of parameters to be estimated in the model (a measure of model complexity), and s is the root mean squared error computed with one-step-ahead forecast errors resulting from the fitted model (a measure of goodness-of-fit). Note that since each member of the model candidate list is actually a family of models, an optimization routine to select optimal smoothing parameters is required to minimize s for each model form (that is, to select the best model).

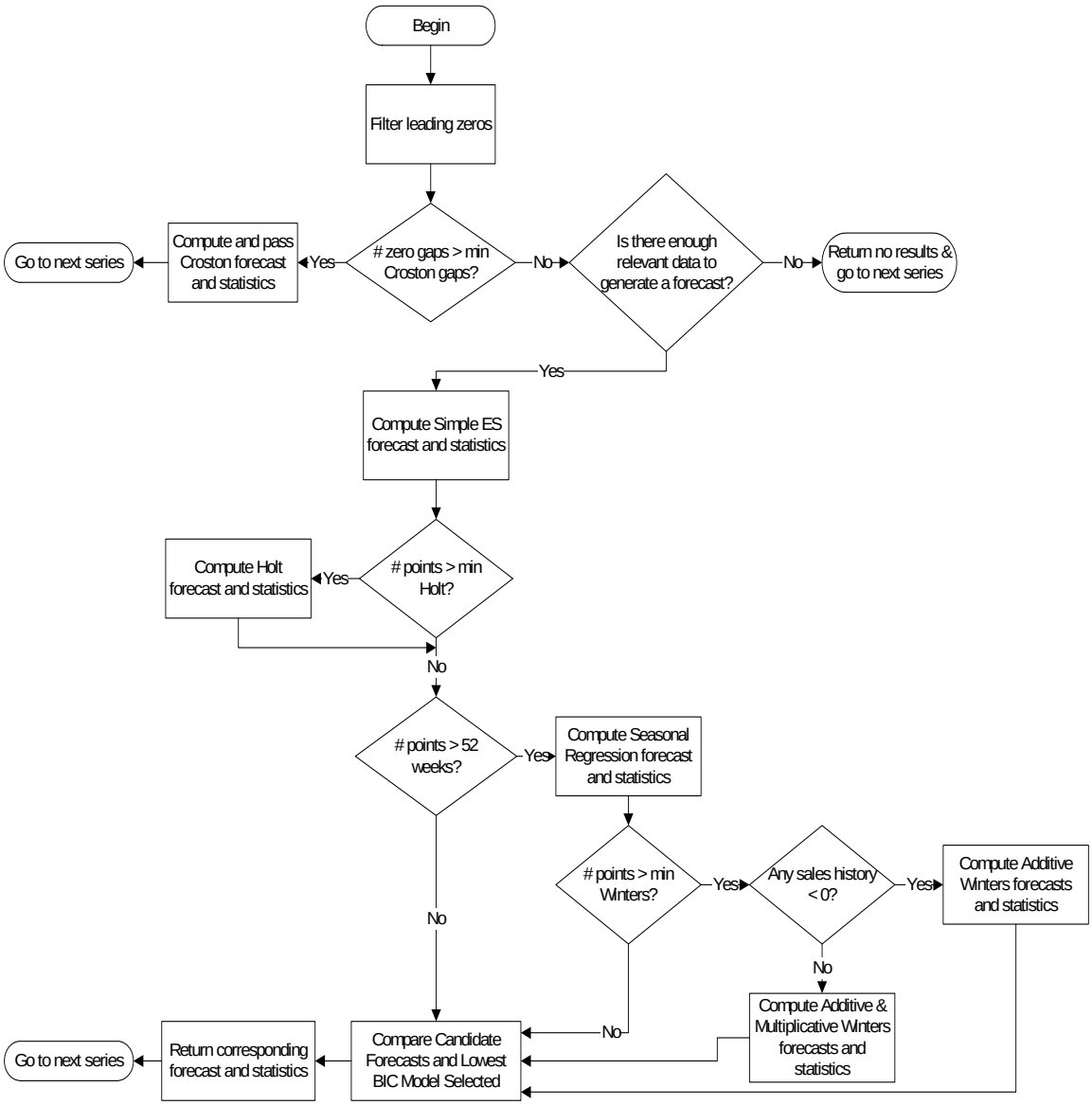
Within RDF, a few modifications to the standard selection criteria have been made. These include reducing the number of parameters the Winter's model is penalized by discounting seasonal indices that have little impact on the forecast (multiplicative indices close to 1, additive indices close to 0). These changes tend to favor the seasonal models to a slightly higher degree that improves the forecasts on retail data, especially for longer forecast horizons.

AutoES Flowchart

The following outlines the processing routine steps that the system runs through to evaluate each time series set to forecast using the AutoES method.

1. Filter all leading zeros in the input data that is within the training window. Go to
2. Does the time series contain the minimum data points to qualify to forecast using the Croston's method? If yes, generate the forecast and statistics using the Croston's method, and move on to the next time series. If no, move on to Step 3.
3. Does the time series contain enough relevant data to generate a forecast? If yes, generate a forecast and statistics using the Simple ES method and move on to Step 4. If no, do not forecast, and go to the next time series.
4. Does the time series contain the minimum data points to qualify to forecast using the Holt method? If yes, generate a forecast and statistics using the Holt method and move on to Step 5. If no, move on to Step 5.
5. Does the time series contain more than 52 weeks of input data? If yes, generate a forecast and statistics using the Seasonal Regression method and move on to Step 6. If no, move on to Step 9.
6. Does the time series contain the minimum data points to qualify to forecast using Winters methods? If yes, move on to Step 7. If no, move on to Step 9.
7. Does the time series contain any data point with sales equal qualify to forecast using Additive Winters method? If yes, generate the forecast and statistics using the Additive Winters method, and move on to Step 9. If no, move on to Step 8.
8. Does the time series qualify to forecast using the Multiplicative Winters method? If yes, generate the forecast and statistics using both the Additive Winters and Multiplicative Winters methods, and move on to Step 9.

9. Compare all candidate forecasts using BIC Criterion.
10. Return the corresponding forecast and statistics for the system-selected forecast method, and move on to the next time series.



Automatic Forecast Level Selection (AutoSource)

This section describes how the automatic forecast level selection (AutoSource) could help improve the accuracy of your forecasts.

In the system, one of the key elements to producing accurate forecasts is using the system's ability to aggregate and spread sales data and forecasts across the product and location hierarchies. Low selling or relatively new products can use aggregated data from similar products/locations at a higher level in the hierarchy, generate forecasts using this data, and then spread these higher level forecasts back down to provide more accurate forecasts. The difficulty comes in deciding which products/locations will benefit from this technique and from what level in the hierarchy these source level forecasts should be spread.

The Automatic Forecast Level Selection feature of the system automates the selection of best aggregation level (forecast source level) for each product/location combination. While providing invaluable information regarding the best aggregate level for source forecasts, the Automatic Forecast Level Selection process may be very CPU intensive. To solve this problem, the task of selecting best aggregation levels for product/location combinations is decomposed and processed piecemeal during times when the computer would normally be idle. Identifying the best aggregation levels for sets of products and locations can be divided into a number of sub-problems:

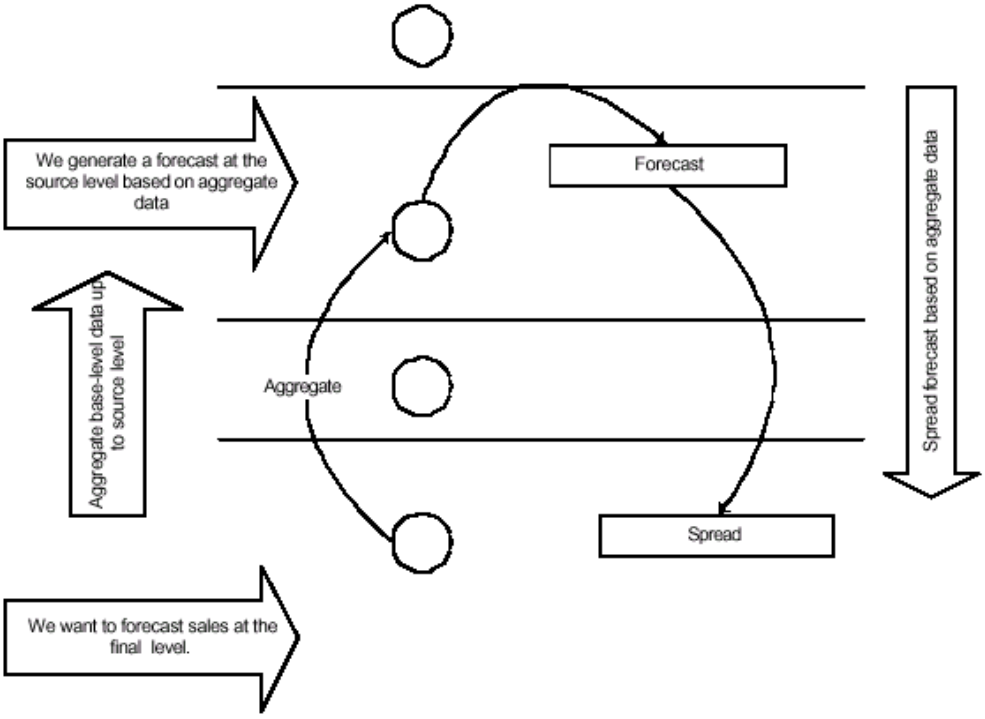
- Forecasting
- Determining the best source level forecast
- Status and scheduling

The Forecast Level Selection Process

The automatic source generation level selection subsystem selects the best source generation level for each product/location in a given final forecast level. In order to determine the best level, a final forecast is generated for each product/location using each candidate source generation level. As illustrated in the figure below, a final forecast is generated by:

1. Aggregating up from the base level to the source level
2. Generating a source level forecast
3. Spreading the source-level forecast down to the final level

For example, assume base-level sales data is at the ITEM/STORE level, the final forecast level is at the ITEM/STORE level, and the candidate source generation level is at the STYLE/STORE level. In this case, base-level sales data is aggregated from the ITEM/STORE level up to the STYLE/STORE level. A STYLE/STORE forecast is generated, and the forecast data is spread back down to the ITEM/STORE level. This forecast represents the final forecast.



Determining the Best Source Level Forecast

The selection of the best level is based on a train-test approach. In this process, historical data is used to generate a forecast for a test period for which actual sales data already exists. The forecast, generated over the train period, can be compared to the actual sales figures in the test period to calculate the percent absolute error (PAE) between the two.

A final-level forecast is generated for each product/location combination using each potential source generation level. Each time a source level forecast is generated, a PAE is calculated for that level. If that PAE is better than the current best PAE (corresponding to the current best source generation level), the source generation level that generated that better PAE becomes the new best level.

Status and Scheduling

Identifying the best aggregation level for a given set of products and locations may take a significant amount of time (that is, an amount of time that is greater than the duration of the computer's shortest idle period). This task, however, can be partitioned meaning that the problem of selecting the best aggregation levels can be decomposed into smaller sub problems to be solved piecemeal during times when the computer would normally be idle.

For each product/location combination at the final forecast level, the problem consists of:

1. Generating forecasts at each unique aggregation level
2. Using the train-test approach to evaluate the percent absolute error statistics for each

One or more of these subtasks will be performed during each period that the computer is idle. The best aggregation status keeps track of which sub problems have been performed and which sub problems remain. In this way, when the best aggregation procedure is run, the procedure knows what the next sub problem is.

Best aggregation level procedures are run during idle computer periods. The scheduling of the Automatic Forecast Level Selection process (AutoSource) must be integrated with the schedules of other machine processes. In general, you should select a schedule so that source generation level selection does not conflict with other activities. The following is an example of a typical schedule for the Automatic Forecast Level Selection process: Monday through Thursday, the selection process starts at midnight and runs for eight hours. On Friday and Saturday, the process is allowed to run for 20 hours. Sunday is reserved for generating forecasts.

Using the System-Selected Forecast Level

You have the option of accepting the system-generated source level selection or manually selecting a different source level to be used. The value for the source forecast level can be manipulated in the Final Level worksheet of the Forecast Maintenance workbook. For each product/location combination, the best source forecast level identified by Oracle Retail Demand Forecasting will appear in the Optimal Source Level measure on this worksheet. You can enable the use of this level by placing a checkmark in the Pick Optimal Level measure for that product/location. The absence of a checkmark in this measure causes the system to default to the Default Source Level or the Source Level Override value if this has been set by the user.

Profile-Based Forecasting

The Profile-based forecasting method generates a forecast based on a seasonal profile. The profile may be loaded, manually entered, or generated by Curve. It can also be copied from another profile and adjusted.

Forecast Method

The Profile-based forecasting method proceeds as follows:

1. The historical data and the profile are loaded.
2. The data are de-seasonalized using the profile and then fed to Simple method.
3. The alpha is capped by 0.5.
4. The Simple forecast is re-seasonalized using the profiles.

Profile-Based Method and New Items

The Profile-based forecasting method can be successfully used to forecast new items. In order to do that, we need to have a profile (which can be copied from an item that shares the same seasonality) and a number that specifies the de-seasonalized demand (DD value). The forecast is calculated using the DD value multiplied by the profile. The confidence interval is set to 1/3 of the DD value.

If the DD value is used to forecast, the history (if exists) of the product is ignored. Once we have enough history (number of data points exceed a global parameter), the forecast stops using the DD value and it defaults to the "normal" Profile Based method.

Bayesian Forecasting

The Bayesian Forecasting method is based on combining historic sales data with sales plan data. It is especially effective for new products with little or no historic sales data.

Your sales plan can incorporate expert knowledge in two ways — shape and scale.

- **Shape** is the selling profile or lifecycle that can be derived from a sales plan. For example, the shape for certain fashion items might show sales ramping up quickly for the first four weeks and then trailing off to nothing over the next eight weeks.
- **Scale**, or magnitude, of a sales plan is the total quantity expected to be sold over the plan's duration.

Bayesian Forecasting assumes that the shape that sales will take is known, but the scale is uncertain. In Bayesian Forecasting, when no sales history is available, the sales forecast figures are equal to the sales plan figures. At this point, there is no reason to mistrust the sales plan. As point of sale data becomes available, the forecast is adjusted and the scale becomes a weighted average between the initial plan's scale and the scale reflected by known sales history. Confidence in the sales plan is controlled by the amount of sales data on hand and a Bayesian sensitivity constant (Bayesian Alpha), which you can set between zero and infinity.

Unlike standard time series forecasting, which requires only sales history to produce a forecast, Bayesian Forecasting requires a sales plan and sales history (if available). Because of this difference, Bayesian Forecasting is not included in AutoES. You must select it manually as a forecasting method in Forecast Administration or Forecast Maintenance.

Obtaining accurate short life-cycle product forecasts is very difficult, and standard statistical time series forecasting models frequently do not offer an adequate solution for many retailers. The following are major problems in automatically developing these forecasts:

- The lack of substantial sales history for a product (which especially makes obtaining seasonal forecasts very difficult)
- The difficulty of automatically matching a new product to a previous product or profile
- The inability to include planners' intuition into a forecasting model. For example, the overall sales level of the product, how quickly the product will take off, how the product's sales will be affected by planned promotions.

Using a Bayesian approach, a short life-cycle forecasting algorithm was developed that begins with a product's seasonal sales plan (that is developed externally to the system by the planner). As sales information arrives during the first few days or weeks of the season, the model generates a forecast by merging the information contained in the sales

plan with the information contained in the initial sales data. These forecast updates can be critical to a company's success and can be used to increase or cancel vendor orders.

As forecasting consultants and software providers, Oracle Retail assists clients in obtaining "good" forecasts for future demands for their products based upon historical sales data and available causal information. Depending on the information available, Oracle Retail's software supports various forms of exponential smoothing and regression based forecasting. Frequently, clients already have some expectations of future demands in the form of sales plans. Depending on the quality of their plans, they can provide very useful information to a forecasting algorithm (especially when only limited historical sales data is available). A forecasting algorithm was developed that merges a customer's sales plans with any available historical sales in a Bayesian fashion (that is, it uses new information to update or revise an existing set of probabilities).

Sales Plans vs. Historic Data

In most retail situations, clients are interested in obtaining good product forecasts automatically with little or no human intervention. For stable products with years of historic sales data, our time series approaches (Simple, Holt, Winters, Regression based Causal, and so on) produce adequate results. The problem arises when attempting to forecast products with little or no history. In such instances, expert knowledge (generally in the form of sales plans) is required. Given that both sales plans and time series forecasts are available, an obvious question exists: When should the transition from sales plan to time series forecasting occur? In answering that question (in a particular scenario), suppose that we have determined that thirteen weeks of history is the transition point. Does that mean that at 12 weeks the time series results are irrelevant and that at 14 weeks the sales plan has no value? Our intuition tells us that instead of a hard-edge boundary existing; there is actually a steady continuum where the benefits from the sales plan decrease as we gather more historic sales data. This was the motivation for developing an approach that would combine the two forecasts in a reasonable manner.

Bayesian Algorithm

Bayesian forecasting is primarily designed for use with new product/location positions. The following guidelines should be followed:

1. No more than one plan should exist for a given product/location position. If multiple plans are to be set up for different time periods, the domain should be set up with different forecasting levels for each time period of interest.
2. Any time period with non-zero Actuals for a given product/location position should have a corresponding plan component. Otherwise, the system will assume a plan exists and equals zero and will act accordingly.
3. Any non-zero Actuals not within the time period of interest should be overridden to zero.

Causal (Promotional) Forecasting Method

Causal, or promotional, forecasting requires three input streams:

- Time Series Data
- Historical Promotional Calendar
- Future Promotional Calendar

Promote decomposes the problem of promotional forecasting into two sub-tasks:

- Estimating the effect that promotions have on demand
- Forecasting baseline (that is no promotions) demand

To accomplish the first task, a stepwise regression sub-routine is used. This routine will take a time series and a collection of promotional variables and determine which variables are most relevant and what effect those relevant variables have on the series. Thus, the output from the algorithm is a selection of promotional variables and the effects of those variables on the series. In the second step, the time series is de-causalized using the promo effects. Then, AutoES is used to calculate the baseline demand. Once we know the effects and we have the baseline demand, we can generate a promotional forecast by applying the effects wherever the promotion is active in the future.

It should be noted that just because promotional forecasting is selected, it does not necessarily imply that a "promotional" forecast will result. In some instances, no promotional variables will be found to be statistically significant. In these cases, the forecast ends up equivalent to a standard time series forecasts. If you want to force in certain promotional variables into the model, this can be managed through forecasting maintenance parameters.

Oracle Retail's experience in promotional forecasting has led us to believe that there are a few requirements that are necessary to successfully forecast retail promotions:

- Baseline forecasts need to consider seasonality; otherwise "normal" seasonal demand will be attributed to promotional effects.
- Promotional Effects need to be able to be analyzed at higher levels in the retail product and location hierarchies. This produces cleaner signals and alleviates issues involved in forecasting new items and new Stores and issues involving data sparsity.
- Users need to be aware that the forecasting models cannot tell the difference between causal effects and correlated effects. What this means is that users should be wary of promotional effects attributed to an event that occurs at the same time every year. The system cannot distinguish between the promotional effect and the normal seasonality of the product. The same can be said for any two events that always occur at the same time. The combined effect will most likely be attributed to one or the other event.

The Causal Forecasting Algorithm

For purposes of understanding the algorithm, a promotional variable is defined as a causal event that is only active for certain series at certain points in time. It is assumed that these events are entered into the system independently of the forecasting algorithm and that a vehicle exists for determining which promotional variable are relevant to a particular series.

The core of the causal forecasting algorithm uses a stepwise regression sub-routine. This routine takes a time series and a collection of promotional variables, and it determines which variables are most relevant and what effect those relevant variables have on the series. Thus, the output from the algorithm is a selection of promotional variables and the effects of those variables on the series.

Causal variable types define how causal variables are treated in the causal model fitting process (which includes a call to the lower level regression engine) and the forecast generation process where the model is used to extend the forecast over the forecast horizon. See the Promote/Promotional Forecasting chapter for information on each of the causal variable types:

- Automatic
- Force In The Model
- Disabled
- Override All
- Override Future
- Override Higher Level

Causal Forecasting Process

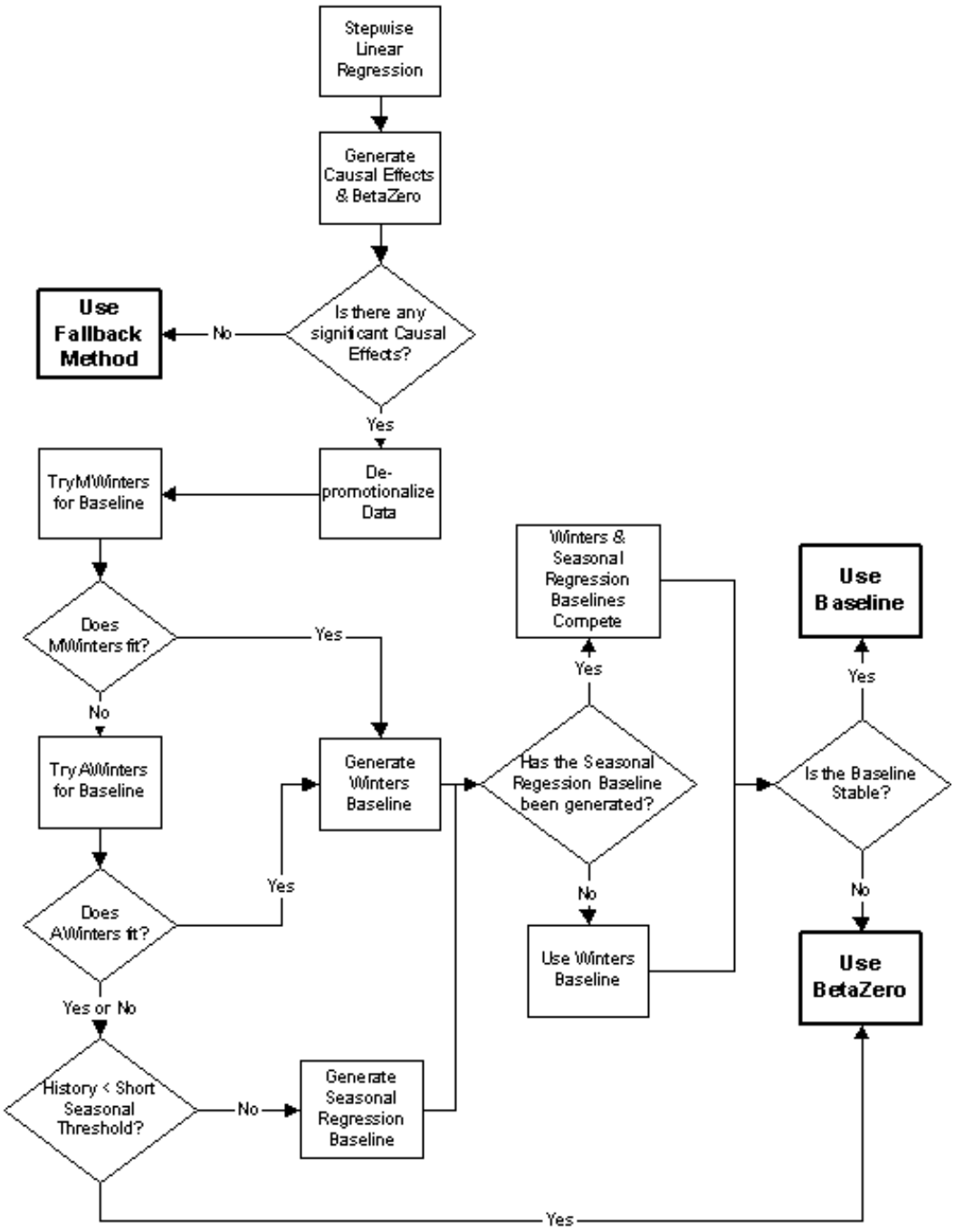
The causal forecasting algorithm itself lies in the AutoES binary code, and it executes in the following manner.

1. The binary reads the history of the time series.
2. The binary reads the type of each promotional variable into the system.
3. The binary reads in all the promotional variables that apply to the series.
4. The binary creates an internal promotional variable to allow the modeling of trend.
5. Promotional variables, internal promotional variables, promotional variable types, and the series itself are passed to the stepwise regression routine with the historic data serving as the dependent variables.
6. If the regression finds no significant promotional variables, the casual method is considered to have failed to fit. In this case, the standard time series methods are used to generate a forecast and we skip to step 14.
7. The fit at time t, fit(t), is defined in terms of β_0, the intercept of the regression, β_I, the effect corresponding to promotional variable *i*, and $p_i(t)$, is the value of promo variable I, in time t as:

   $fit(t) = \beta_0 + \Sigma\ \beta_i * p_i(t)$
8. The Time Series is de-causalized in the fit region of the history by removing the causal effects. That is, subtracting the additive causal effects for the product/location/time positions where the corresponding promo variables are “on.”

9. A seasonal model is fitted to the de-causalized series. The seasonal model is the winner of a competition between Seasonal ES, Additive Winters, and Multiplicative Winters. The RMSE is determined across the fit region on the de-causalized series and the winning model is the one that produces the least RMSE.
10. The winning seasonal model is then used to determine the seasonal forecast by applying the fit(t) function across the forecast horizon. This forecast is also exported as the baseline forecast (that is forecast without any causal influences).
11. The forecast is obtained by re-causalizing the seasonal forecast. This is done by adding back the additive causal effects for the product/location/time positions where the corresponding promo variables are "on" in the forecast region.
12. The binary writes the winning promotional variables effects back to the database.
13. The selected model is recorded in the database.
14. The binary records the forecast and the baseline in the database.

The following diagram summarizes this above process.



Causal Forecasting with External Baseline

Rather than use a sales history that may not have sufficient or accurate data, users can load an external baseline into the RDF Causal Engine instead. External baselines are often generated using data that is rolled up to a higher dimension than SKU/store, providing a greater depth of data and hence a less-noisy sales history. The sales data used to generate the external baseline can be corrected for out-of-stock, promotional, and other short-term event information using Preprocessing. These external baselines are then spread back to the SKU/store level and then loaded in the RDF Causal Engine. The Engine then uses this external baseline (rather than the causal baseline) along with the historic promotional data and future planned promotions data to create the system forecast, which is the external baseline with the lifts, which were calculated from the promotional data, applied on top.

Causal Forecasting Using External Baseline Process

When an external baseline is used, the AutoES binary code executes in the following manner:

1. The binary reads the history of the time series.
2. The binary reads the type of each promotional variable into the system.
3. The binary reads in all the promotional variables that apply to the series.
4. The binary creates an internal promotional variable to allow the modeling of trend.
5. Promotional variables, internal promotional variables, promotional variable types, and the series itself are passed to the stepwise regression routine with the historic data serving as the dependent variables.
6. If the regression finds no significant promotional variables, the casual method is considered to have failed to fit. In this case, the forecast equals the external baseline.
7. The fit at time t, fit(t), is defined in terms of β_0, the intercept of the regression, β_I, the effect corresponding to promotional variable *i*, and $p_i(t)$, is the value of promo variable I, in time t as:

   $fit(t) = \beta_0 + \Sigma\, \beta_i * p_i(t)$
8. The forecast is obtained by re-causalizing the external baseline. This is done by adding back the additive causal effects for the product/location/time positions where the corresponding promo variables are “on” in the forecast region.
9. The binary writes the winning promotional variables effects back to the database.
10. The selected model is recorded in the database.
11. The binary records the forecast and the baseline in the database.

Causal Forecasting at the Daily Level

The causal forecasting at the daily level is calculated by spreading the weekly causal forecast down to day. The spreading utilizes causal daily profiles, thus obtaining a causal forecast at the day granularity.

The daily casual forecast process executes in the following manner:

1. Preprocess the day level promotional variables by multiplication with daily profiles. Aggregate the preprocessed continuous day level promotional variables to the week level.
2. Calculate the causal forecast at the weekly level. Set promotional effects if desired. Use the RDF causal engine to generate the forecast.
3. Calculate the multiplicative promotional effects at the item/store level for every promo variable. The effects can be either:
   - Manually preset (See step 1).
   - Calculated. When calculating the causal forecast, the calculated causal effects are written back to the database. If the effects are calculated at higher level than item/store, the effects will be replicated down to item/store – reasonable assumption since the effects are multiplicative. If source level forecasting is used and causal method is used both at the source level and at the final level, the effects from the final level will be used.
4. Daily profiles are calculated using the Curve module. Since we use as much history as possible and we average it over seven days, we assume that these profiles are de-causalized. The de-causalized daily profiles capture the day of week effect and should be quite stable.
5. Causal effects are applied to the daily profiles. We multiply the profiles by the causal effects. We then have to renormalize the profiles.

Example:

For every item/store combination, calculate a normal week-to-day profile based on historic data. Note that this profile is already computed for spreading the weekly forecasts to the day level. Suppose for a certain product, the profile is as follows:

Mon	Tues	Wed	Thu	Fri	Sat	Sun	Week
10%	10%	10%	10%	20%	30%	10%	100%

Suppose that that in the past, the promotion was held on Wednesday, Thursday, and Friday of week w6:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
		P	P	P		

Then the continuous weekly indicator for this promotion in w6 should be set to 0.4, which is the sum of the weights of Wednesday, Thursday, and Friday.

Now assume that the same promotion will be held in a future week (w36), but only on Thursday:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
			P			

Then the continuous weekly indicator for w36 should be set to 0.1, which is the weight of Thursday only.

The approach to use the continuous promotion indicators to generate an accurate causal forecast at the day level is as follows:

- Calculate the weekly multiplicative effect for the promotion using the standard causal forecasting system with continuous indicators.
- Calculate the forecast for w36 using the standard causal forecasting system with continuous indicators.
- Update the week-to-day profile of w36 so that the weight of Thursday is doubled (the multiplicative factor is 2):

Mon	Tue	Wed	Thu	Fri	Sat	Sun	Week
10%	10%	10%	**20%**	20%	30%	10%	**110%**

- Normalize the profile for w36:

Mon	Tue	Wed	Thu	Fri	Sat	Sun	Week
9%	9%	9%	18%	18%	27%	9%	100%

Finally, spread the forecast of w36 using the normalized profile.

Final Considerations about Causal Forecasting

In Oracle Retail's approach to causal forecasting, the causal effects are obtained by fitting a stepwise linear regression model that determines which variables are most relevant and what effect those relevant variables have on the series. The data used to fit the regression is the fit history of each time series, so basically we fit a model per time series. A problem arises due to potential lack of significant data (that is, when a promotional variable is not represented in the history, but it is present in the forecast region). In that case, the effect for that variable would not be computed at all, thus affecting the accuracy of the forecast. There are a few solutions that make use of the effects from other similar time series. One solution would be to do source level causal forecasting and then spread down to the final level. This would be equivalent to using the effects at the source level for time series that have no causal variable instances in the history. This has a serious conceptual drawback—by aggregating the promotional variables at the source level, we would force the effects on the other time series in the same aggregation class that would otherwise not have the causal variables on at the same time. An alternate solution is whenever a causal effect cannot be computed because of lack of significant data, an averaged effect from another time-series in the same aggregation class is going to be used instead. See Override Higher Level type.

7

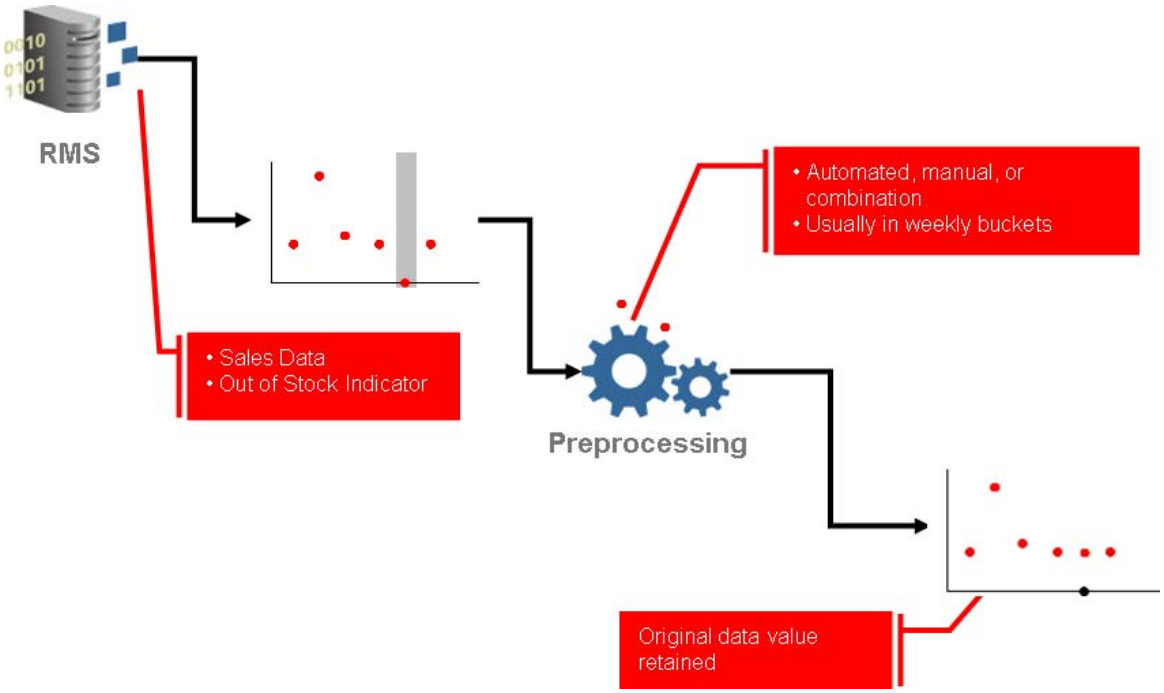
Preprocessing

Preprocessing is a filtering module that will automatically adjust historical data to correct data points that do not represent general demand pattern. Essentially, it smoothes out spikes and dips in historical sales data, replacing stock-out data and data from short term events, such as promotions and temporary price changes, with data points that more accurately represent typical sales for that period. By adjusting the historical sales, preprocessing can provide smarter data to the RDF Causal Engine, thus creating a smarter baseline forecast.

Common preprocessing corrections are:

- Out of stock – Interfaced from RMS, weekly or daily
- Outliers – Indicator not required, depends on method
- Short term events – promotions, temporary price changes

For example, the diagram below illustrates how preprocessing adjusts for stock-outs.



Preprocessing for Stock-outs

In this diagram, RMS sends historical sales data to the preprocessing module of RDF. In that sales data, RMS has flagged out-of-stock instances with indicators (the gray portion of the first data set). Preprocessing takes note of that out-of-stock indicator and adjusts the sales for that time period to reflect a more typical sales quantity, taking into account trending and seasonality. Note in the diagram that preprocessing has removed the dip in sales in the second data set and has replaced it with a new data point.

Preprocessing Methods

Preprocessing uses several methods to massage historical data. These methods are listed and discussed below.

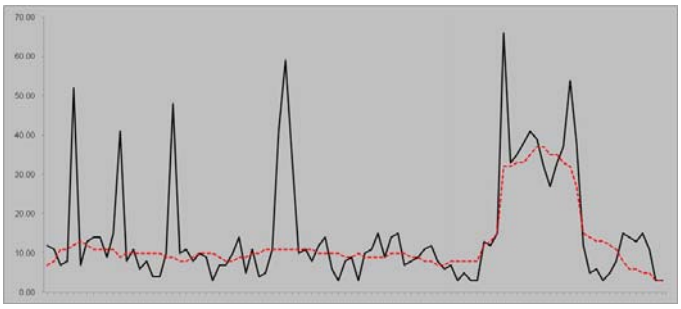
- Standard Median
- Retail Median
- Standard Exponential Smoothing
- Lost Sales Standard Exponential Smoothing
- Override
- Increment
- Forecast Sigma
- Forecast Sigma Event
- Clear
- No Filtering

Standard Median

Standard Median calculates baselines on long time ranges.

Input: none
Optional parameter: window length
Formula:

$$LSOVER(t) = median\ value\ over\left(t - \frac{window}{2},\ t + \frac{window}{2}\right)$$



Standard Median Example

When data points for the full window are not available, preprocessing will pad the beginning and end of the time series with the first and the last data points, respectively so that there are values for the full window.

Retail Median

Retail Median calculates baselines on long time ranges and improves side effects by making five standard median filter passes.

Input: none
Optional parameter: window length
Formula:

$$Median1 = StdMedian(Src)$$

$$Median2 = StdMedian(Median1)$$

$$Diff1(t) = Median2(t) – Median2(t\text{-}1)$$

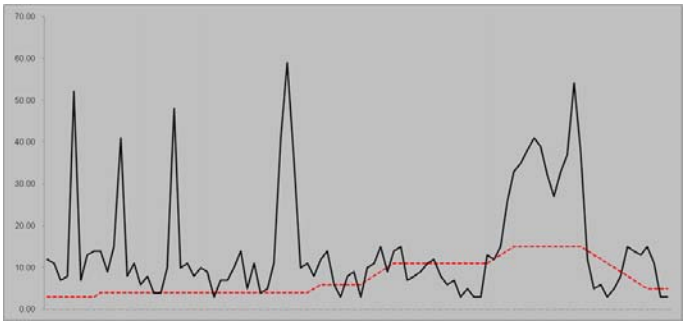
$$Median_Diff1 = StdMedian(Diff1)$$

$$Smooth1(t) = Smooth1(t\text{-}1) + Median_Diff1(t)$$

$$Diff2(t) = Smooth1(t) – Smooth1(t\text{-}1)$$

$$Avg_Diff2 = StdMedian(Diff2)$$

$$Smooth2(t) = Smooth2(t\text{-}1) + Avg_Diff2(t)$$



Retail Median Example

Standard Exponential Smoothing

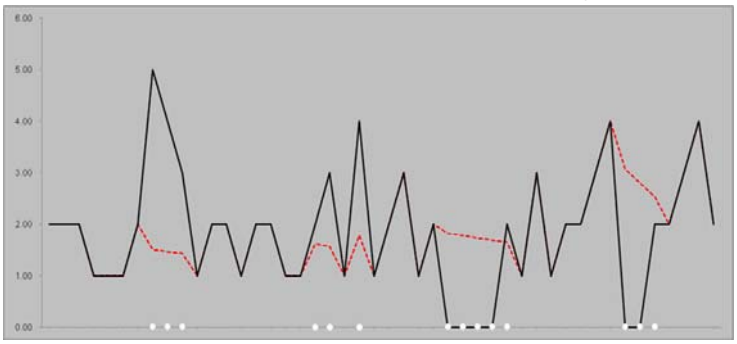
Standard Exponential Smoothing removes spikes (such as promotional promo, temporary price changes, etc.).

Input: event indicator
Optional parameters: ES (Exponential Smoothing) Parameter and a number of future and past periods used to calculate the future/past velocities.
Formula:

$$past\ velocity = \frac{\sum_{i=1}^{np} (1-\alpha)^{i-1} * src(t_f - i)}{\sum_{i=1}^{np} (1-\alpha)^{i-1}}$$

$$future\ velocity = \frac{\sum_{i=1}^{nf} (1-\alpha)^{i-1} * src(t_l - i)}{\sum_{i=1}^{nf} (1-\alpha)^{i-1}}$$

$$LSOVER(t) = past\ velocity + \frac{future\ velocity - past\ velocity}{t_l - t_f + 2} * (t - t_f + 1),\ where\ \ t \in [t_f, t_l]$$



Standard Exponential Smoothing Example

When event flags exist within the future and past velocity windows, rather than consider the entire window, preprocessing will only consider unflagged data points after the last event flag in the history window to compute the past velocity. It does a similar process for the future window by using the unflagged data points prior to the first event flag in the future window to compute the future velocity. Consecutive events are smoothed using the same velocities.

If future velocities cannot be calculated, then the past velocities, if they exist, will be used as future and past velocities, and vice versa. When neither of the velocities can be calculated, there is no adjustment.

If the velocity window contains all zero values, then the calculated velocity will be zero. A velocity of zero is a legitimate value if it occurs within the selling window. A velocity of zero is not acceptable if it calculated based on values outside of the selling window.

Lost Sales Standard Exponential Smoothing

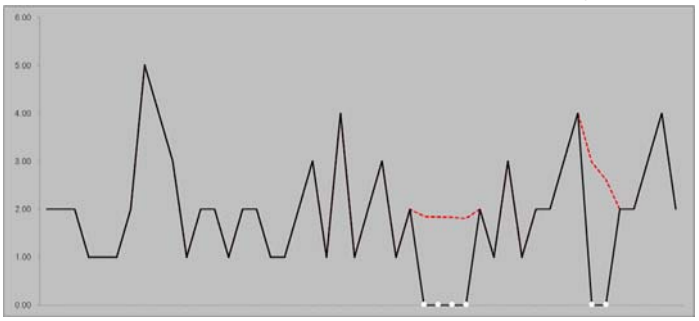
Lost Sales Standard Exponential Smoothing calculates baselines on long time ranges. It is like Standard Exponential Smoothing, but it allows only positive adjustments.

Input: out-of-stock indicator
Optional parameters: ES (Exponential Smoothing) parameter and a number of future and past periods used to calculate the future/past velocities.
Formula:

$$past\ velocity = \frac{\sum_{i=1}^{np} (1-\alpha)^{i-1} * src(t_f - i)}{\sum_{i=1}^{np} (1-\alpha)^{i-1}}$$

$$future\ velocity = \frac{\sum_{i=1}^{nf} (1-\alpha)^{i-1} * src(t_l - i)}{\sum_{i=1}^{nf} (1-\alpha)^{i-1}}$$

$$LSOVER(t) = past\ velocity + \frac{future\ velocity - past\ velocity}{t_l - t_f + 2} * (t - t_f + 1),\ where\ \ t \in [t_f, t_l]$$



Lost Sales Standard Exponential Smoothing Example

When event flags exist within the future and past velocity windows, rather than consider the entire window, preprocessing will only consider unflagged data points after the last event flag in the history window to compute the past velocity. It does a similar process for the future window by using the unflagged data points prior to the first event flag in the future window to compute the future velocity. Consecutive events are smoothed using the same velocities.

If future velocities cannot be calculated, then the past velocities, if they exist, will be used as future and past velocities, and vice versa. When neither of the velocities can be calculated, there is no adjustment.

If the velocity window contains all zero values, then the calculated velocity will be zero. A velocity of zero is a legitimate value if it occurs within the selling window. A velocity of zero is not acceptable if it calculated based on values outside of the selling window.

Override

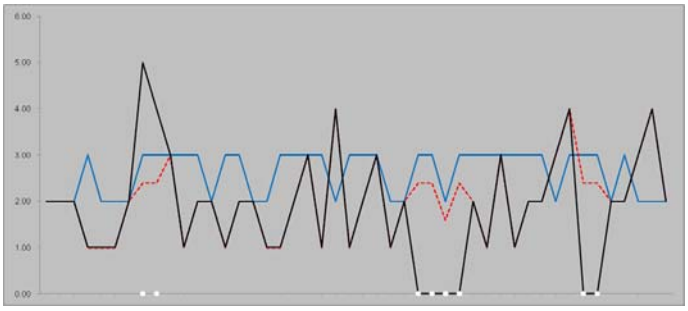
Override fills gaps in data when a reference measure exists.

Input: reference measure (R(t)) to copy data from
Optional parameter: outage/mask (M(i)), adjustment ratio (a)
Formula:

Overrides LSOVER with the Src adjusted by the adjustment ratio according to the mask:

$$LSOVER(t) = a*R(t) \qquad \text{if } M(i) \text{ is true}$$

$$LSOVER(t) = Src(t) \qquad \text{if } M(i) \text{ is false}$$



Override Example

Increment

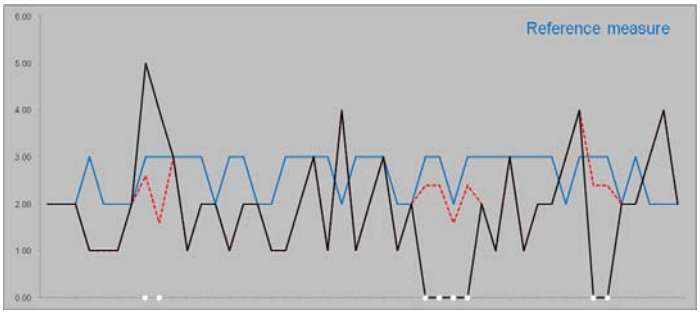
Increment updates gaps or outliers in data when a reference measure exists.

Input: reference measure (R(t)) to copy data from
Optional parameter: outage/mask (M(i)), adjustment ratio (a)
Formula:

Increments the Src with the reference adjusted by the adjustment ratio according to the mask:

$$LSOVER(t) = SRC(t) + a*R(t) \qquad \text{if } M(i) \text{ is true}$$

$$LSOVER(t) = Src(t) \qquad \text{if } M(i) \text{ is false}$$



Forecast Sigma

Forecast Sigma removes spikes in recent data when no indicators are available.

Inputs: forecast and confidence intervals
Optional parameters: number of stddev for upper bound
number of stddev for lower bound
forecast lower bound
min history required for filtering

Formula:

If the difference in the sales and forecast is larger than a threshold, the override value is brought within some bounds of the forecast.

Forecast Sigma Event

Like Forecast Sigma, Forecast Sigma Event removes spikes in recent data when no indicators are available but also takes outage as input.

Inputs: outage, forecast, confidence intervals
Optional parameters: number of stddev for upper bound
number of stddev for lower bound
forecast lower bound
min history required for filtering

Formula:

If outage is on:

$$LSOVER = forecast$$

Otherwise, if the difference in the sales and forecast is larger than a threshold, the override value is brought within some bounds of the forecast.

Clear

This preprocessing method clears the preprocessing adjustments from previous runs.

No Filtering

This preprocessing method does not filter the source data.

Preprocessing for Stock-outs

When using preprocessing to correct for stock-outs, the system expects out of stock indicators from a merchandising system like RMS. The system can be set up for automatic adjustment of sales history to correct for stock-outs as well as for manual user overrides under exception cases.

When set to automatically adjust sales history to correct stock-outs, Preprocessing takes into account into account trending and seasonality and adjusts the sales that were flagged by the out-of-stock indicator to reflect a more typical sales quantity.

Preprocessing for Promotional Forecasting

Preprocessing adjusts promotional data in a similar way that it does stock-outs. Typically, historical data shows a higher rate of sale during promotional periods. Were these spikes in sales to be left in historical sales data and loaded in the RDF Causal Engine, the baseline forecast created from this data would reflect similar spikes in future sales.

Glossary

Note: With a few exceptions, this glossary contains definitions of terms specific to Oracle Retail Demand Forecasting. For further definitions of terms and concepts relating to the RPAS user interface, see the *RPAS Online Help* or *RPAS User Guide*.

Additive Seasonal Method

Also referred to as Additive Winters Model, this model is similar to the Multiplicative Winters model, but is it used when zeros are present in the data. This model adjusts the un-seasonalized values by adding the seasonal index for the forecast horizon.

Alert

A notice displayed to system users that a forecasted value is above or below user-defined limits (an exception).

Alert Manager Window

A window that displays the alerts assigned to you. This dialog provides a list of all identified instances in which a monitored measure's values fall outside a set of defined limits. You may pick an alert from this list and have RCS automatically build a workbook containing the measure values that triggered the alert.

AutoES Method or Automatic Exponential Smoothing Method

Oracle Retail Demand Forecasting fits the sales data to a variety of exponential smoothing (time series) models of forecasting, and the best model is chosen for the final forecast. The candidate methods considered by AutoES are:

- Simple ES
- Intermittent ES
- Trend ES
- Multiplicative Seasonal
- Additive Seasonal and Seasonal ES

The final selection between the models is made according to a performance criterion (Bayesian Information Criterion) that involves a tradeoff between the model's fit over the historic data and its complexity.

Bayesian Method

Useful for short lifecycle forecasting and for new products with little or no historic sales data. The Bayesian method requires a product's known sales plan (created externally to RDF) and considers a plan's shape (the selling profile or lifecycle) and scale (magnitude of sales based on Actuals). The initial forecast is equal to the sales plan, but as sales information comes in, the model generates a forecast by merging the sales plan with the sales data. The forecast is adjusted so that the sales magnitude is a weighted average between the original plan's scale and the scale reflected by known history.

Causal Method

Causal is a forecasting method used for promotional forecasting and can only be selected if Promote is implemented. Typically, the Causal method is used at the Final Levels (that is, item/week/week). Causal uses a Stepwise Regression sub-routine to determine the promotional variables that are relevant to the time series and their lift effect on the series. AutoES utilizes the time series data and the future promotional calendar to generate future baseline forecasts. By combining the future baseline forecast and each promotion's effect on sales (lift), a final promotional forecast is computed.

Croston's Model of Exponential Smoothing

See Intermittent Exponential Smoothing.

Curve

An optional automated predictive solution that transforms organization-level assortment plans into base-level weekly sales forecasts.

Exception

A forecast value that is greater than or less than a user-defined limit.

Exponential Smoothing

A form of a weighted moving average. It weights decline in data exponentially. Most recent data weighted more heavily. Requires smoothing constant (α). Ranges from 0 to 1. Subjectively chosen.

Final Forecast Level

A low level in a hierarchy from which a forecast is generated, and at which approvals and data exports can be performed. Often, data from forecasts at a low level is insufficient to generate reliable forecasts without first aggregating the data to a higher level and then spreading the data back to the low level.

Forecast

In Oracle Retail Demand Forecasting (RDF), Forecast refers to RDF's statistical forecasting capabilities.

Forecast-Driven Planning

Planning that keys off of forecasts fed directly into a planning system. Connection to Oracle Retail Demand Forecasting (RDF) is built directly into the business process supported by Oracle Retail Predictive Planning through an automatic approval of a forecast that is fed directly in the planning system. This allows you to accept all or part of Sales Value forecast. Once that decision is made, the balance of business measures are planned within Oracle Retail Predictive Planning.

Holt's Model of Exponential Smoothing

See Trend Exponential Smoothing

Interactive Forecasting

A workbook in RDF that is used to simulate forecast by modifying parameters such as Forecast Method and History Start Date

IntermittentES or Intermittent Exponential Smoothing

Oracle Retail Demand Forecasting fits the data to the Croston's model of exponential smoothing. This method should be used when the input series contains a large number of zero data points (that is, intermittent demand data). The original time series is split into a Magnitude and Frequency series, and then the Simple ES model is applied to determine level of both series. The ratio of the magnitude estimate over the frequency estimate is the forecast level reported for the original series.

Like Item or Like SKU

An item that will be used as a model to forecast a new item introduction.

Lost Sales

Periods in sales data in which there was no inventory to meet consumer demand.

Measure

Any item of data that can be represented on a grid in worksheets.

Measure Description

The description of the measure that can be viewed in a workbook. This description may contain relationships and calculations.

Measure Function

Internal functions that can be used to simplify building calculations for a measure.

Measure Identifier

The combination of role, version, metric, and units that uniquely specifies a single measure.

Metric

A measure definition with the role, version, and units omitted.

Multiplicative Seasonal

Also referred to as Multiplicative Winters Model, this model extracts seasonal indices that are assumed to have multiplicative effects on the un-seasonalized series.

Preprocessing

In Oracle Retail Demand Forecasting (RDF), Preprocessing refers to a module that processes data before forecasts are generated to adjust for situations, such as lost sales and unusually high demand.

Profile

Spreading ratios that are used in the Curve process. Typical profiles can include store participation, size distribution, and time (phase-to-week) profiles, as well as other information. Profiles are generated using historical data and phase definitions, based on your system configuration.

Profile Based

Oracle Retail Demand Forecasting generates a forecast based on a seasonal profile that can be created in Curve or a legacy system. Profiles can also be copied from another profile and adjusted. Using historic data and the profile, the data is de-seasonalized and then fed to the Simple ES method. The Simple forecast is then re-seasonalized using the profiles.

Profile Spread

Used at the final level to utilize a profile (either generated externally or with Curve) to determine the spreading ratios from the Source level forecast down to the Final level.

Promote

Promote is an optional add-on automated predictive solution that allows you to incorporate the effects of promotional and causal events, such as radio advertisements and holiday occurrences, into your time series forecasts. The promotional forecasting process uses both past sales data and promotional information to forecast future demand.

Promotion Planning

A workbook template and simulation process used within the context of promotional forecasting. Promotion planning involves specifying whether the event status for a particular promotional variable is active (on) or inactive (off) for a specific product/location/calendar combination. When past promotional events are represented as accurately as possible, the modeling routine can more precisely detect correlation between event occurrences and changes in sales values.

Promotional Effectiveness

A workbook template used in the context of promotional forecasting. This workbook allows you to analyze the effects of promotions on items at both the micro and the macro level. "What if" analysis can also be performed on the results of promotional forecasts, as you can modify future and past promotional inputs, the system-estimated effects of promotions and the promotional forecasts themselves.

Promotional Forecasting

Promote's forecasting technique (also referred to as Causal forecasting) uses promotional factors and events to predict future demand. Promotion events are events; such as advertisements, holidays, competitor information, and other factors that affect the normal selling cycle for a business.

Promotion Group

A set of products or locations that are believed to exhibit similar effects during common causal events. Promotion groups should be established to maximize the number of time series for each group (so each promotional event can be evaluated from as many different observations as possible) while ensuring that each time series is affected by causal events to the same degree.

Seasonal ES Method

A combination of several Seasonal methods. This method is generally used for known seasonal items or forecasting for long horizons. This method applies the Multiplicative Seasonal model unless zeros are present in the data, in which case the Additive Winters model of exponential smoothing is used. If less than two years of data is available, a Seasonal Regression model is used. If there is too little data to create a seasonal forecast (in general, less than 52 weeks), the system will select from the Simple ES, Trend ES, and Intermittent ES methods.

Seasonal Regression

Seasonal Regression cannot be selected as a forecasting method, but it is a candidate model used when the Seasonal ES method is selected. This model requires a minimum of 52 weeks of history to determine seasonality. Simple Linear Regression is used to estimate the future values of the series based on a past series. The independent variable is the series history one-year or one cycle length prior to the desired forecast period, and the dependent variable is the forecast. This model assumes that the future is a linear combination of itself one period before plus a scalar constant.

Simple/Intermittent ES Method

A combination of the Simple ES and Intermittent ES methods. This method applies the Simple ES model unless a large number of zero data points are present. In this case, the Croston's model is applied.

SimpleES or Simple Exponential Smoothing Method

Oracle Retail Demand Forecasting uses a simple exponential smoothing model to generate forecasts. Simple ES ignores seasonality and trend features in the demand data, and it is the simplest model of the exponential smoothing family. This method can be used when less than one year of historic demand data is available.

Simple Moving Average

See Average Method.

Sister Store

A store that will be used as a model to forecast a new store.

Source Level Forecast

The level at which the aggregate, more robust forecast is run.

Time Series

Set of evenly spaced numerical data obtained by observing response variable at regular time periods. This data is used to forecast based only on past values. It assumes that factors influencing past and present will continue influence in future.

Training Window

The number of weeks of historical sales data to use in generating a forecast.

Trend Exponential Smoothing or TrendES

Also referred to as Holt's Model, Oracle Retail Demand Forecasting fits the data to the Holt model of exponential smoothing. The Holt model is useful when data exhibits a definite trend. This method separates out base demand from trend, and then provides forecast point estimates by combining an estimated trend and the smoothed level at the end of the series.

Wizard

A set of screens that guide you through the process of creating a new workbook or performing other actions in a solution by asking you various questions and having you select values.

Workbook

The framework used for displaying data and user functions. Workbooks are task-specific and may contain one or more worksheets. Users define the format of their workbooks. Also see workbook template, worksheet.

Workbook Template

The framework for creating a workbook. You build each new workbook from an existing workbook template, such as Pre-Season Financial Plan or Forecasting Administration. Several workbook templates are supplied with the Oracle Retail Predictive Solutions, and are available for selection when you choose **File – New** to create a new workbook.

Worksheet

A multidimensional spreadsheet used to display workbook-specific information. worksheet data can also be displayed in chart format.