This chapter describes (1) the role of demand management in a consumer-demand driven supply chain, (2) why a data framework for demand forecasting is essential to its success, (3) how to identify the essential components of a forecast decision support system, and (4) when and how automatic forecasting should be used.

**Demand Management for the Supply Chain**

Successful consumer-demand management organizations are those that have discovered how to apply effective data management practices and **agile forecasting** and planning processes to what is essentially a nontraditional supply chain discipline. In the demand forecasting discipline, we do not have the power to change future demand, so our role is to be agile by quickly and easily influencing the target or demand plan to better align it with actual future demand.

The manufacturing/distribution/retail pipeline starts with raw materials and purchased parts required by the manufacturing plant. At the manufacturing level, we can add the fabricated components, subassemblies, and assemblies used to produce the finished-goods inventory. At the distribution level, we generally have finished goods.

In a consumer-demand driven supply chain (which evolved over decades), information in the form of consumer demand also flows back in the opposite direction, so that all operations have complete visibility to the whole supply process (Figure 13.1). Instead of being driven or supplied by the manufacturer, consumers are the drivers of demand, demanding cheaper, faster and higher quality products. A firm’s success is a combination of an integrated supply chain, a sound infrastructure, and a focus on consumers.
EMBRACING CHANGE & CHANCE: Demand Forecasting Explained

Figure 13.1 A consumer-demand driven supply chain. (Source: L. Lapide, MIT, 2006)

Planning systems have a similar underlying logic, but different factors/parameters affect the inventory plan at each point in this pipeline (Figure 13.1):

- **Manufacturing resource planning** (MRP) plans the raw materials, purchased parts, and components.
- **Master production scheduling** (MPS) plans the finished goods.
- **Distribution resource planning** (DRP) plans the finished goods at the distribution centers.

| Material flow is from suppliers to the manufacturer through the distribution channel to the consumer. Information flow is in the reverse direction, from the consumer to the suppliers. |

Data-Driven Demand Management Initiatives

Although the analogy of a chain is useful in visualizing the “Sell What You Can Make” process (Figure 13.2a), it is far too simplistic to describe what really happens. Within the supplier/manufacturer, the supply chain includes the possibility of multiple sources of supply at every stage. In the distribution channel, multiple centers can supply multiple factories and provide service to multiple retail outlets. The supply chain model includes a number of highly integrated processes for sourcing/suppliers (production, scheduling, and supply sourcing), distribution (channel management, transportation, and warehouse operations), and customer interface/point-of-sale (demand management, order management, inventory management, and store operations).

<table>
<thead>
<tr>
<th>Sell What You Can Make</th>
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<tr>
<td>• Assume predictable, continuous demand</td>
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<td>• Efficient process</td>
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<td>• No external drivers of demand</td>
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<tr>
<th>Make What You Can Sell</th>
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<tr>
<td>• Assume unpredictable, discontinuous demand</td>
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<tr>
<td>• Adaptive process</td>
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<tr>
<td>• Both internal and external drivers of demand</td>
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Figure 13.2 Traditional vs consumer demand-driven supply chains: “Make What You Can Sell” versus “Sell What You Can Make.” (Source: Figure 1.3)
Material Flows

There are a number of initiatives in the supply used to describe material flow from suppliers to the manufacturer through the distribution channel to the consumer. Information flow is in the reverse direction, from the consumer to the suppliers. Quick Response (QR), Efficient Consumer Response (ECR), and Vendor Managed Inventory (VMI) are all terms used in the trade for strategies for making manufacturers responsible for keeping the retailer in stock. These acronyms represent industry initiatives to facilitate the flow of good information in a timely manner. By implementing these management strategies, companies have reduced costs, increased sales, gained competitive advantage, and taken market share away from laggards.

The material flowing through a supply chain can be viewed from any one of three perspectives: the product view (SKUs), the customer view, the distribution view, or the supplier/manufacturer sourcing view. The product view defines the individual SKU, its contents including documentation and accessories, and its packaging and labeling. The customer view defines how the end customer (e.g., retailers) uses product descriptions, product numbers (SKUs), and product options to uniquely identify a complete product configuration. A complete customer configuration may require a shipment of several different SKUs. The supplier manufacturer view, like an engineering parts list, tends to consider a product or assembly to be complete without regard for the packaging documentation, software, or accessories that will make it a SKU.

Figure 13.3 shows how a high-tech company looked at its business and realized how an overuse of demand hierarchies can add complexity to the demand forecasting process.

Figure 13.3 Product, customer, and sourcing views of the supply chain.

In Figure 13.4, the distinction between customer (light boxes) and consumer (dark boxes) is depicted as a comprehensive view of a supply chain for a packaged goods producer. The manufacturer produces a product for export, direct sales to consumers, the government, and the military; the product is sold to an extensive network of retailers. A grocery wholesaler or co-op retailer might distribute the product to supermarkets, grocery, and warehouse stores. Other distributors sell the product to chain drug stores, discount mass merchandisers, and variety stores.
Depending on the industry and business model, companies use forecasting systems in a variety of ways. For instance, distribution-oriented companies are likely to use systems to help organize the replenishment and flow of goods into distribution centers (Figure 13.5). These companies are also likely to send the output of forecasting systems to transportation management or other order-fulfillment systems.

A traditional supply chain is any sequential set of business operations leading from raw material through conversion processes, storage, distribution, and delivery to an end customer. In the integrated consumer-demand driven supply chain, demand management’s responsibility assures that information flows in the reverse direction as well.
Creating a Data Framework for Forecasting and Decision Support

Figure 13.5 Demand forecasting drives crucial links in the supply chain.

Information Flows
Manufacturing companies generally use forecasting systems to help synchronize production schedules and finished-goods inventory with actual customer/consumer sales. Therefore, they are more likely to feed forecast information to the Materials Resource Planning (MRP) module of an Enterprise Resource Planning (ERP) system or even to an Advanced Planning system (APS). In addition, demand forecast data are becoming part of the Sales and Operations Planning (S&OP) process, which brings people from different functional areas together to agree on a “final forecast” that drives the activities of the entire enterprise.

The sales and operations planning (S&OP) process brings people from different functional areas in the organization together to agree on a single forecast.

Each industry has its own production and distribution needs. Systems designed to manage the supply chain are focused on vertical markets in process manufacturing or discrete/repetitive/to-order manufacturing. Process manufacturers, which are predominantly batch-processing operations, include companies in the energy/petrochemical, chemical, and pharmaceutical industries. Electronics, fabricated metals, and automotive supplies are examples of discrete manufacturing markets.

In today’s global market place, companies must achieve both in-stock levels and high inventory turns. In addition to competitive pressures, many companies have found it necessary to share information and forecasts with their business partners. Retailers, in particular, frequently share forecasting information with their supply chain partners. Manufacturers have also recognized the importance of data-based demand forecasting and top-down planning along with joint collaborations in forecasting with suppliers and customers. Because of the high volume of items involved and the uncertain nature in variability (see Chapter 3), data-driven analytics (see Chapter 2) and statistical forecasting techniques (see Chapter 5) are increasingly being adopted by demand planners.

Creating Planning Hierarchies for Demand Forecasting
Demand planners frequently discuss dependent and independent demand forecasts. Independent (unconstrained, unbiased) demand, which must be forecasted, comes from the customer/consumer and includes the demand for finished goods as well as service parts. In contrast, dependent demand applies to raw materials and other components that are used in production. The dependent demand for items need not be forecasted; it is calculated from the schedules of the item required for production and distribution.
At its core, demand planners establish a set of processes that produce plans or sets of time-phased numbers (e.g., forecasted orders) representing the best estimate of what demand will be at a given time. For instance, a forecast for an item at a distribution center shows the estimated demand over time, by the week or by the month, going forward. An order needs to be placed with the manufacturer or supplier against these requirements so that the requested item can arrive at the distribution center in time for shipment to the retailer or consumer. The timing of these orders is a function of the lead times of the items and the safety stock that assures adequate supply.

**Demand planning is the process of managing all independent demands for a company’s product line and effectively communicating these demands to the master planner and top management production function.**

**What Are Planning Hierarchies?**

Most planning functions in an organization are performed in time hierarchies, with strategic and budget planning done once a year or less and tactical planning done quarterly, monthly, weekly, or daily. Each of these planning horizons requires forecasts at different levels of product and location/customer aggregation. Through the functional organization, we can view dimensions of demand in terms of marketing (brand-level forecasts by channel and sales currency and margins), sales (account- or regional-level forecasts by product category in sales currency), operations (distribution territory-level forecasts by SKU in cases or plant-level forecasts by SKU in units; incidentally, a SKU is the lowest level in which we might categorize a product, such as a bar code or product code that we might see on a box or the unit itself), and finance (regional-level forecasts by division in sales currency and margins).

Each functional user group sets its own requirements. For example, marketing personnel may want to review the demand forecast at a brand level in sales and margin rather than at the item level. Similarly, sales personnel prefer reviewing the demand forecast in currency by region or customer account. To support these related requirements, forecasting approaches may need to be developed for multiple levels and the multiple forecasts reconciled.

**The level of planning being supported by the demand forecasting process impacts the data and forecasting models needed.**

Moreover, some functions need to view the demand forecast at the lowest level in a hierarchy, whereas others need to see it at higher levels. However, not all of these functions can necessarily be placed in hierarchies. These different types of planning indicate the key concepts that underlie a forecasting database system—aggregation and allocation.

Because these requirements by the functional groups can occur at different levels, demand forecasters have a need for good data and efficient and effective forecasting methodologies to support such developments. All this is reflected in an operational demand plan, which assures that the right amount of the right product gets shipped to the right customer or location in the right time (and, of course, at the right price)—a bit of jargon, but nevertheless important to remember, because it provides the insight for the right data framework requirements.

The differing functional views of a demand forecast are important for reaching consensus. The sales and operations function must first review the demand forecasts and then approve or modify them based on their view of the business: integrating sales, marketing, operations, and financial plans into a single business plan; constantly balancing supply and demand; using company resources effectively throughout the enterprise; and making the results visible in inventory investment, product availability, and customer service.

**Operating Lead Times**

Lead time influences inventory at different levels—the time it takes to get raw material, to manufacture, to ship product, and to process data all influence cumulative inventory and lead times. Although reducing cycle
time is a major objective of Supply Chain Management (SCM), the variation in cycle times experienced by manufacturers and retailers can be quite substantial. Typical cycle-time variations for product development can be between 5 days and 15 weeks, for production 5 days to 6 weeks, for inbound transportation from supplier to distribution center 1 day to 1.5 weeks, and for outbound transportation from distribution center to final destination 2 days to 1.5 weeks. Accurate forecasts are essential to the success of SCM in order to yield shorter lead times and, hence, higher turns and lower costs.

The amount of time it takes for information and goods to flow through a supply chain pipeline is known as cycle time; it is also called lead time.

The safety stock for that same SKU is a plan for that component of inventory each week into the future. A replenishment plan for the same SKU shows the quantity of product arriving weekly at distribution center locations. A shipment plan for the same SKU shows the quantity of product that should be shipped to distribution center locations weekly.

Distribution Resource Planning—A Time-Phased Planned Order Forecast
Distribution managers face considerable complexities in managing inventory at various distribution points. Variables such as changing customer demand, transportation time, and shifting production schedules make it difficult to ensure correct inventory levels at the proper locations, at the proper time. DRP systems plan and manage the many variables that cause distribution problems.

A DRP system uses demand forecasts of independent demand—the demand of the consumer—instead of the dependent demand of the distribution center (DC) on the supplier/manufacturer. DRP starts with a forecast of consumer demand and calculates how long it will take to manufacture and move products through a distribution network to the consumer/customer.

DRP is part of the demand management function that creates long-term schedules designed to meet consumer/customer needs without holding excess inventory demand.

Figure 13.6 shows a simplified but typical DRP allocation for a single product, in which the requirements we need are tied to the order quantity in a one-for-one relationship (i.e., we need one, we get one). The forecasts are assumed to be 100 units per period (typically a month or a week). With an on-hand inventory of 100 units, the ending inventory in period 1 is 0, which is also the beginning inventory for period 2. In order to keep a one-period supply of safety stock, we need to order 200 units in period 1, which will be received in period 2 (because lead time = 1). This same logic is used for the future periods.

Figure 13.7 shows a DRP allocation with the added requirement that order quantity must be based on a minimum requirement (the lowest quantity that must be ordered). If the requirement is only one unit, the order must be 200 because the minimum is set to 200.

Figure 13.8 shows a DRP allocation in which the requirements are tied to the order quantity based on a minimum requirement and multiple (quantities above and beyond the minimum amount). For example, if the total need is 22, the minimum is 20, and the multiple is 5, then the total order should be 25.
A manufacturing and distribution schedule, usually covering several weeks or months, is created to meet that order forecast. For example, a manufacturer of service parts may ship parts to several DCs that service dealers worldwide. If each DC tracks its own inventory and places orders independently, it will create a demand on the supplier/manufacturer that varies unpredictably. By using DRP, the supplier/manufacturer obtains a greater visibility of upcoming orders. With accurate information about demand and inventory in each area, the DRP system can calculate a long-term plan for when each part should be produced and in what quantity, thus ensuring that each DC has the product it needs.

Benefits from a DRP system include reduced transportation costs; higher customer-service levels; fewer stock outs; improved communication among sales, distribution, and production; and having the right product at the right place at the right time.
Spreadsheet Example: How to Create a Time-Phased Replenishment Plan

The basic function of DRP is to create a recommended order that is sent to manufacturing plants in order to plan production. Figure 13.9 shows the spreadsheet calculations involved in forecasting the Planned Orders and Months Supply. Here a number of inventory factors must be taken into account, such as on-hand, on-order, and backordered quantities.

**Basic Distribution Resource Planning.** The basic DRP calculation starts with a demand forecast. The demand forecast (labeled “Total Forecast” in Figure 13.9) is the total forecast of independent demand, namely the (unbiased) statistical baseline forecast plus judgmental overrides made by the planners and management. Other forecasts may need to be included, such as a forecast from a division or region that is not part of the main forecasting system. Also, samples, not for sale, are included here. These are handled in the lines below the final forecast. In this spreadsheet, the Gross Requirements are the sum of the forecast lines. The gross requirements are determined for any practical number of periods into the future, with 12 to 18 months being typical. Next, we determine Planned Receipts. At time \( T = 2 \) (June 01, in this case), the gross requirements over a lead-time of one period are 1689 and the ending Projected Inventory at \( T = 1 \) (May 01) is 380. The gross requirements over safety time (months coverage) starting at lead-time-period ahead are 4168 units (= 1958 + 2210). The Planned Receipts are calculated as follows:

\[
\text{Planned receipts} = \text{Gross requirements summed over lead times} - \text{Projected inventory} + \text{Gross requirements summed over safety times starting at lead-time-period ahead}
\]

For example, the planned receipts for period \( T = 2 \) are \((1689 - 380) + (1958 + 2210) = 5477\). Next, the Planned Orders are offset one month back, determined by the lead time, so that the orders can be received as planned. Scheduled Receipts already committed. The firm Planned Orders are the overridable receipts. The projected (ending) inventory for this period is determined thus:

\[
\text{Projected inventory} = \text{Previous period ending inventory} + \text{Planned receipts} - \text{Gross requirements}
\]

The projected inventory at the end of period \( T = 2 \) (Jun 01) is 4168 (= 380 + 5477 – 1689). Once the projected inventory has been determined, a calculation of Months Supply can be made as a measure of safety stock.

At the next period, the process repeats itself. Now, for \( T = 3 \) (Jun 01), the planned receipts are \((1958 - 4168) + (2210 + 3314) = 3214\). These are the planned orders offset to \( T = 2 \). The ending inventory is 5424 (= 4168 + 3214 – 1958).

For the very first period, things are a little different. The initial projected inventory is 380 (= 2000 + 1400 – 3020):  

\[
\text{Projected inventory (initial period)} = \text{On-hand} + \text{On-order} - \text{Gross requirements}
\]

**Minimum and Multiples.** When we take minimum quantities and multiples into account, the DRP calculation needs to be augmented. In this example (Figure 13.8), a minimum order is 2000 and additional orders are placed in multiples of 50. At \( T = 2 \) (Jun 01), the planned receipts previously calculated (= 5477) become 5500 because of the minimum and multiple conditions. The projected inventory now includes 23 additional units and becomes 4191 (= 4168 + 23). The remaining calculations remain the same, taking the minimum order quantity and multiples in consideration.
EMBRACING CHANGE & CHANCE: Demand Forecasting Explained

To fully balance the supply chain, an increased awareness and exchange of information must be established between the demand creation side of sales and marketing and the supply side of manufacturing and distribution. This should include both short-term communications about promotional programs that will affect demand and long-term communication for capacity planning. It is essential to keep the goal of balancing supply with demand in mind and to communicate it across all functional groups at the outset of each new sales initiative.

A Framework for Agility in Forecast Decision Support

One of the biggest paybacks of an effective demand management process is the creation of a centralized demand forecasting and decision support system (FDSS), in which sales, marketing, operations, and financial planners can then cooperatively view their own forecasts on their own terms with the knowledge that these forecasts will be centrally reconciled and distributed to collaborating partner organizations. This sharing of “one number” forecasts with other organizations, and more possibly, in the future, with business partners, results in a streamlined, agile demand forecasting process, allowing for reduced costs and increased sales and profits for the business.

Typically, in many firms across most industries there is a lack of integrated business planning (IBP) at the operational planning and business execution levels. Such systems have difficulty meeting the requirements of demand forecasting, because the discipline requires a rather unique software architecture. Unexpected demands, which must be met at any location, wreak havoc on operations. At the higher levels of planning, such as strategic planning levels, demand forecasters have more options and more time to effect change. At the operational levels, however, forecasters are more strapped for quality data, modeling options, and effective software systems.

ERP systems support transaction-based processes for human resources, budgeting, and operations. A demand forecasting system is better served by data-driven decision support, or a software environment that requires internal and external forecast data, can run complex analytical algorithms, and can quickly and easily analyze unstructured decisions so that managers can make business decisions more easily.

The single forecast of customer demand, at the item-location level, provides the unifying perspective from which to integrate all forecasting activities in the supply chain.

Achieving the benefits of a one-number forecast requires the integration of clean data, information, and predictive analytics across the whole business enterprise. The analytical database systems to support these activities are called Forecast Decision Support Systems (FDSS). Demand forecasters need to build flexibility into their operations, and the implementation of planning systems integrates the different levels of planning across the enterprise. FDSS is a flexible information and business intelligence processing application in contrast to the operational data processing applications used in the conventional ERP context.
An agile forecast decision support system (FDSS) is a cloud-based software environment that supports the demand forecasting process. It allows the practitioner to readily clean and analyze data, execute automatic modeling algorithms, evaluate multiple models and simulate forecast performance, and reconcile a variety of forecast-related information and results for the purpose of driving a company’s objectives for the future. It should also have the functionality to incorporate informed judgment and track forecast accuracy on an ongoing basis.

A Data-Driven Forecast Decision Support Architecture

In an integrated demand management system, projected demand plans are visible in a common database accessed by those along the supply chain. The source of the corporate (internal) data is a legacy database residing on a secure corporate server that can be accessed by its users via the Cloud or through a network server. This enables the firm to guarantee the integrity and accuracy of the essential input information. To collaborate with forecast users outside the firm, the forecasting system needs to be able to communicate with vendors’ planning systems through an extranet or internet connection. In addition, when external information on economic, demographic, regulatory and competitive factors is required, demand forecasters can access many of these data sources through a dashboard.

The demand forecasting system needed to support a supply chain has a number of components for linking to data sources.

![Figure 13.10 A dashboard display for the data preparation phase.](image)

Once quality data sources are in place, a demand forecaster can interact with the data through a presentation component (interface) of the forecasting system (Figure 13.10). The client-centric part of the system allows for flexible data input, data conversions, data cleaning and adjustment, prices, graphs, note pad, scheduled receipts, and on-hand inventory, data displays (year-to-date, percentages of annual totals), and communication.

To adequately perform the planning function, the forecaster needs to have ready access to multiple modeling algorithms and approaches. The modeling component of the system should allow for quantitative assessments (promotion analysis, statistical techniques, and data analysis), qualitative assessments (event management, field sales, and new product introductions), batch forecasting engine, best-performance evaluation criteria, analyst re-studies on models, outlier detection and correction, exception handling, integrated forecasting, and planning and user feedback.

Information needs to be distributed to forecast users through a data-reporting component. This provides output in terms of standard reports, flexible user-defined reports, special studies, data export to SCM and ERP systems, and electronic linkages with customers and suppliers.
Dimensions of Demand
Effective demand planning requires that demand forecasters incorporate data into their forecasts, whatever their aggregation, to adequately support their clients and the sales, marketing, and financial and operations planners in the firm. Hence demand forecasting is done at different levels of detail, involving:

- **period** *(time) granularity* (annually, quarterly, monthly, weekly, daily, shifts, or hours)
- **product** *(SKU) hierarchy* (business operating units, category, brand, product flavors, sizes, or special packs)
- **place** *(geographical/customer/location) segments* (global, national, market zone, channel, sales regions, warehouses, plants, zip codes, stores, and customers)

Demand forecasting is performed at different levels of detail incorporating dimensions of period, product, and customer/location.

The forecast dimensions of period, product, and place can be represented by a triangle (Figure 13.11), in which each dimension depicts a relational database forecasting hierarchy (Figure 13.12).
Period Granularity. Depending on the forecasting environment, a forecasting system needs to be able to support a calendar. For typical SCM applications, the weekly and monthly time buckets (period granularity) are most frequently used for forecasting. Because weeks do not roll up neatly into months, there are different weekly patterns in use. For example, a 4-4-5 pattern means that the first month of a quarter is made up 4 weeks, the next month is 4 weeks, and the last month is 5 weeks. There are also firms that operate on a 13-period year. Quarterly and yearly figures do not need to be stored because they accumulate naturally from months and can be readily rolled up in a database. In the energy utility industry, for example, a calendar is disaggregated even further into days, hours, and 30-minute time buckets.

In terms of period granularities,

- the forecast cycle describes how often we should forecast. For many companies this is a monthly process, but with the higher service levels required to satisfy customers these days, it is not unusual to see a forecast cycle every week.
- the forecast horizon tells how far out we should forecast. Many companies use a 12 to 18 month rolling forecast horizon. Today, with e-business, companies are shortening the horizon to 1 to 3 months to ensure that their businesses can respond to the increased volatility driven by new market dynamics.
- the forecast granularity tells how detailed we should make the forecast. Commonly used quarterly granularity often does not provide the level of detail needed to address customer-service level requirements, efficient supply planning, or the need of marketing to respond to critical issues. Thus, demand and supply forecasting may need to implement a weekly forecast granularity for forecasts within critical manufacturing lead times.

Product Hierarchy. To support a demand forecasting function, the demand planning system needs to maintain a variety of product-specific detail. The lowest level item identification is typically the Stock Keeping Unit (SKU). For each SKU, the system needs to maintain fields on unit price, unit costs (labor, material, etc., so as to be able to calculate margins), unit shipments (carton and pallet quantity, unit weight, and unit cube), lead time, and other attributes (description, promotion cut-in and cut-out dates, and summary category identifiers).

Place Segmentation. Location/customer-specific information starts with a designation of a lowest level location code. Typically, this is a customer account code that other segments can be mapped into. Additional fields might include description, discount rates, codes to map customer/locations into regions, channels, warehouses, and field sales accounts. In addition, there may be conversions of the units of demand to sales revenue, profit margin, costs, pallets, cases, shift hours, and so on.

The demand forecasting system needed to support a demand management function has a number of components for linking to data sources.

Specifying Product Hierarchies and Customer/Location Segments

Using a cosmetic product manufacturer/distributor as an illustrative example, we can display the summary levels for customer/locations as columns and the associated labels as rows in a design spreadsheet for a relational database (Figure 13.13). For example, two sales type summaries are shown: R (Revenue) and NR (Nonrevenue). The other columns can have as many rows as there are summaries needed to specify the business operation. In practice, it is advisable to make sure the summary categories (columns) cover all the forecast reporting needs of the end user.
Likewise, in the initial specification of the relational database, demand forecasters need to obtain the user requirements for product summary categories (columns) and categories labels (rows), as depicted in Figure 13.14. For this illustrative cosmetics FDSS, seven product summary categories are needed to satisfy the end user requirements. Each summary category can have as many label rows as needed. Here, All Product represents the Summary category for ALL SKUs by location category or Sales Plan totals by location category. In this specification 43 Brand names and 34 Family names are available in the FDSS.

Figure 13.13 Illustrative customer-location segmentation organized by division, sales type, and customer type.

Figure 13.14 An illustrative product hierarchy organized by All Product, Group, Brand, Brand Type, Super Category, Family, and Product Type.
Dealing with Cross-Functional Forecasting Data Requirements

The multilevel forecasting database requires that demand be \textit{collected, stored, and cleaned} at the lowest level of product and location so that accurate summaries can be obtained for product lines and families by customer locations and segments. For example, if a giant retailer has 5,000 stores and 100,000 items, and if a typical store carries a full line of items, the demand forecaster can potentially expect 500,000,000 lowest level records. In contrast, an online store carrying 35,000 items in one of six distribution centers can expect 210,000 lowest level records to manage and forecast.

Typically, demand is collected so that baseline forecasts can be reviewed and adjusted by sales account, channel, or region (Figure 13.16). For example, a coupon program for a consumer product may be planned regionally; therefore, the impact on a product’s forecast needs to be assessed from a regional perspective. If, for instance, a competitor plans a promotional event, a defensive change to a similar brand’s forecast needs to be created. These are generally made as judgmental overrides to a baseline forecast by field forecast managers and consolidated into a consensus forecast.

Most companies go through a process to project their sales and operations plans for the next 1 to 3 years, which they use to create the budget. The assumptions and analyses are done at the macro level. Because annual sales levels are used to drive financial planning, demand forecasts are usually expressed in monetary terms, and the time granularity is typically expressed in months and quarters. The entities being forecast are often product categories or other product organizational groupings.
As the year progresses, the business also needs sales projections to plan financials as well as operations. During the monthly planning cycle, marketing may be responsible for a sales forecast—financial or unit volumes—by brand or product family. At the same time, the operations departments need to know demand at the SKU level for the next several weeks as inventories are produced, distributed, and delivered to customers.

![Figure 13.17 Demand forecasting and the cross-functional business process.](image)

Each functional group in the company has its own forecast data requirements (Figure 13.17), but not necessarily at the lowest product and customer-location level. For example, marketing personnel may want to review the demand forecast at the brand level in sales and margin currency rather than in SKUs and unit volume level. Sales personnel may find it more useful to see a demand forecast in currency by region or customer account. In support of these related requirements, forecasting approaches may need to be developed for multiple levels to support the reconciliation of these different forecasts. To work effectively, the demand forecasting process must generate views in terms that are familiar to each of the functions (Figure 13.18). These views need to be at different aggregation levels or dimensions as well as in different versions of the measure of demand. Some functions need to view the forecast in currency and some in units.

![Figure 13.18 A dashboard display for reconciling multiple forecast scenarios.](image)
A “best practice” demand forecasting process, striving to obtain the “single best number demand forecast” to drive the business, involves obtaining consensus among different functional planning organizations for centralized FDSS database requirements.

After a baseline (unbiased, unconstrained) demand forecast has been produced, other organizations in the company, as well as its trading partners, contribute to refining the forecast through a collaborative process known as Collaborative Planning, Forecasting and Replenishment (CPFR). The APICS society dictionary defines CPFR as (1) a collaboration process whereby supply chain trading partners can jointly plan key materials to production and delivery of final products to end customers, where collaboration encompasses business planning, sales forecasting, and all operations required to replenish raw materials and finished goods; (2) a process philosophy for facilitating endorsed by Voluntary Interindustry Commerce Standards (VICS). In the CPFR model, retailers and manufacturers extend collaboration from operational planning through execution. (APICS is the leading provider of supply chain, operations, and logistics management research, publications, and education and certification programs; www.apics.org.)

The result of a collaborative forecasting process is a “one-number forecast” that becomes the basis for replenishment and production plans to meet customer needs in a timely and cost-effective way.

Agile Demand Forecasting

The Internet is the perfect means for transforming conventional industry models because it constitutes an infrastructure that transcends traditional boundaries. In place of conventional planning systems based on sequential relationships, in which orders are placed with a supplier, inventory is consumed, and another order is placed, Web-enabled planning systems can now provide a near-instantaneous communications link among trading partners. The new ways to take account of customer and consumer preferences promote new views of point-of-sale replenishment solutions, so today we can communicate changing needs with greater agility to more entities.

Consumer orders may be placed directly with the supplier online, a new aspect of demand that must be taken into account when developing agile demand forecasting solutions. Suppliers can now reside in the center of a web of customers—all communicating needs and information via the Internet.

Automated Statistical Models for Baseline Demand Forecasting

Nowadays, forecasting systems frequently incorporate options for automatic forecast model selection. The particular implementation of an automated procedure may vary greatly among the software programs; even within an individual program, it can take on a number of different forms. In this section, we describe an approach for the univariate time series model selection used for baseline forecasting described in Chapter 8.

In most forecasting software systems, model choices for exponential smoothing can be made manually or through several levels of automation. In a manual mode, the user makes all choices, including model selections, estimates of smoothing parameters, and initializations. More typically, the forecaster’s responsibility is to select a model, and the software will use an optimization procedure to find the best parameter values for the model fit. The type of exponential smoothing forecast profile (Holt, Winters, or damped trend) depicted in a Pegels diagram (see Chapter 8) depends directly on the types of trend and seasonal patterns found in the historical data and the forecast profile expected in the forecast horizon (Figure 13.19).

A Pegels classification of exponential smoothing techniques in a state-space modeling framework gives rise to 30 trend-seasonal forecast profiles with prediction limits for trend and seasonal patterns.
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Figure 13.19 Classification of exponential smoothing models for state-space forecasting. (Source: Hyndman et al., Forecasting with Exponential Smoothing—The State Space Approach. (2008).

The values given by the smoothing weights determine the relative emphasis given to the immediate and distant past in the historical data. Initial values for level, trend, and seasonal indexes are usually required to start the updating process inherent in most smoothing algorithms.

For the high-volume forecasting needed for demand, inventory and production planning, a software system capable to run in automatic mode is essential to perform a “best” model selection.

Most commonly, automatic model selections involve some kind of a contest or tournament among a set of forecasting techniques (Figure 13.20). Each of the included models is used to forecast a particular time series, and the one that does so most accurately (according to preset criteria) is declared the preferred (“best”). Typically, each of several model profiles is fit to the entire time series, and the procedure that results in the best value of a performance statistic (e.g., MSE or MAD) is declared the best.

Figure 13.20 A dashboard display for automated model selection.
Selecting Models Visually

The first step in model selection is to visually display the salient features of the historical data. For well-behaved time series, the appropriate type of trend and/or seasonality pattern may be readily seen in a time plot of the data. In some cases, it will be difficult to judge even visually whether the series is seasonal or nonseasonal. This can happen when the product was affected by special events, such as promotions, which as noted can be confounded with a seasonal pattern in monthly data. Turning points also complicate model identification because they may make models result in poor forecasts because conventional time series models are not designed for it.

Seasonal Model Selection. If at least two to three seasonal cycles are available, seasonality can usually be identified visually. We can perform a preliminary ANOVA two-way decomposition (see Figure 5.25) and look for the percentage variation attributable to seasonality. We can check to see if the peaks (troughs) occur during the same quarter or month of every year in a tier chart (see Figure 5.17). Further, we can trace yearly peaks and yearly troughs visually (see Figure 5.19); if they are widening over time, this signals that seasonality is multiplicative, and if they are relatively constant, this suggests additive seasonality. Other visual displays include box plots by month (each box plot representing the values for a given month), which can point to a pattern of seasonality (Figure 13.21). The medians in the box plots are connected to indicate an average level of the seasonality. The height of the box plot indicates the variability of the seasonal period. On the other hand, box plots by year (each box representing one year’s values) can be helpful in distinguishing additive from multiplicative seasonality (Figure 13.22). The medians are connected in the box plots, which suggest little or no trend in the data. There is an unusual value in one of the years (1998). If the spread of the box plot increases with increasing years, this may indicate a multiplicative seasonality. In this example, we should choose for additive seasonality.

![Figure 13.21 Box plots by month for series N410 from IJF-M3 competition. (Fifty monthly values from the MICRO set; Source: www.maths.monash.edu.au/~hyndman/forecasting/)](image)

![Figure 13.22 Box plots by year for series N410 from IJF-M3 competition. (Fifty monthly values from the MICRO set; Source: www.maths.monash.edu.au/~hyndman/forecasting/)](image)
Keep the following rule in mind when deciding whether to use an additive or multiplicative seasonal model:

If the data are inventory demands, intermittent demands, or without trends, running and comparing multiple additive seasonal models is recommended; otherwise, multiplicative seasonal models will work quite well.

Sometimes, the appearance of intrayear fluctuations in a time plot may not indicate seasonality, in that the peaks (or troughs) do not recur at the same time each year. Selecting a seasonal model for such a series is not advisable because the underlying sources of the fluctuations, miscast as seasonal, go unmodeled. One visual aid to help with this is the tier chart (see Figure 5.17), in which the horizontal axis displays the seasons of the year (in quarters or months) and the values for the seasons of any one year are connected. In Figure 13.23a, the seasonality is vivid, whereas in Figure 13.23b the intrayear variation is too irregular to be modeled as a seasonal index.

Figure 13.23 Time plots of intrayear variation for (a) a seasonal time series and (b) a nonseasonal time series.

**Trend Model Selection.** Volatility in a time series makes it difficult not only to distinguish seasonality in a time series but to distinguish trend as well. Smoothing the seasonal fluctuations of a volatile series may be necessary to permit the identification of the underlying trend. The following visual rules have been recommended by Tashman and Kruk (from “The use of protocols to select exponential smoothing procedures: A reconsideration of forecasting competitions,” *International Journal of Forecasting* [1996]):

1. If the recent trend in the time series is unstable (defined as a change in direction from growth to decline or vice versa), use a constant level method.
2. If the recent trend is stable and appears flatter (slower) than the global trend, use a damped trend method.
3. If the recent trend is stable and appears as steep as or steeper than the global trend, use a linear or exponential trend method.

If the data are seasonal, these rules can be applied to the deseasonalized data. In Chapter 7, we discuss a spreadsheet approach for making the selection of turning points in trends visually.

When the main source of variation in a time series is due to seasonality, the time series can be smoothed by seasonal adjustment (see Chapter 6). This suggests that the demand forecaster should examine a plot of the deseasonalized data or the annualized data. Alternatively, the use of an appropriate moving average of the time series (a four-period moving average for quarterly data or a 12-period moving average for monthly data) may be useful.

**Outliers in Model Selection.** Finally, there are techniques for dealing with outliers and special events. An outlier may be due to a disruption of business (as a result of a catastrophic act of nature or a work stoppage), a windfall resulting perhaps from a legal ruling or business restructuring, a missed sale perhaps due to an out-of-stock inventory situation, or a simple data-entry error. If the outlying values are not identified and in some way reduced in influence, the underlying estimates of the level, trend, and seasonal components of a time series can be severely distorted. For example, an outlier toward the current end of the time series will change the current trend estimate and result in biased forecasts for the near future. It can also exaggerate the forecast errors and widen prediction intervals.

**Rolling Forecast Simulations.** The rolling forecast simulation is an evaluation procedure that involves a three-way split of the time series. First, a subset of the historical data is withheld from a time series to serve as a test period for evaluating forecasting accuracy. Next, the remaining period of fit is divided between the first $T_1$ observations and the remaining $T_2$ observations. We call the first $T_1$ observations the **within sample fit period** and the $T_2$ observations, from $T_1 + 1$ to $T_1 + T_2$, the **post-sample fit period**.

For each model under consideration, a pair of rolling forecast simulations are performed. The first rolling simulation is implemented using the post-sample fit period data to compute forecast error measures, which are used as error minimization criteria to optimize the smoothing weights and to select the best-performing model at each lead time (Figure 13.24). As a result, one model may be chosen to supply one-step-ahead forecasts while another is preferred for two-step-ahead forecasts. The second rolling simulation is performed on the test period data, traditionally for the purpose of evaluating the accuracy of the forecasts made by the model selected.

![Evaluate Forecast](image)

**Figure 13.24** A dashboard display of waterfall chart based on multiple rolling forecast simulations.

**A Unified Approach.** If a time series is trending, then removing trend through differencing will lead to a time series that is less variable—that is, it becomes a time series with a smaller variance. This observation can be used to create a procedure for choosing an appropriate type of trend for the data. As illustrated in
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Chapter 7, the procedure compares the variability of (1) the original series, (2) the first differences, and (3) the differences of order two of the series. In essence,

1. if the least volatile series is the original series, then the original series must be without trend and, hence, the most appropriate smoothing procedure is one without a trend. This could be simple exponential smoothing (N, N) or a constant level model with seasonality (N, A) or (N, M). See Figure 13.19.

2. if the first differences reduce the variability, the damped trend model (Ad, N) is most appropriate.

3. if the least volatile series is the difference of order two, strong trend, linear or exponential, is recommended (MAd, N).

The damped trend method includes a trend modification parameter (see Chapter 8). With $0 < \phi < 1$, an upward trend gradually decays. However, for the extreme case when $\phi = 1$, the trend is linear and for the other extreme, when $\phi = 0$, the trend is flat. Hence, the damped trend model can emulate a linear trend or constant level in the time series.

One limitation of this framework is that it does not include additive seasonality, an option that can be especially important when the seasonal time series takes on values close to zero. Also, the damped trend optimization algorithm is sensitive to outliers—there can be no guarantee that optimal value for $\phi$ will properly reflect the nature of the trend in the data. In the past, a consistently reliable performance with this procedure was achieved in a number of corporations across pharmaceutical, high-tech, CPG, chemical, and medical device manufacturers.

Ideally, the criterion for selecting a “best” model should be based on a forecasting evaluation rather than a measure of goodness of fit.

Some Caveats on Automatic Method Selection. The drawbacks of fully automated systems for forecasting with smoothing procedures can become problematic if the data are very irregular (e.g., intermittent demand) or unusual data characteristics, such as unstable seasonality and outliers, go undetected. Even a few outliers, especially near the start of the forecast horizon, can have a significant impact on the eventual pattern of a forecasts. Hence, a visual inspection and numerical exploration of data as a first step in model selection is recommended.

When dealing with exceptional products or aggregates that are of particular importance to the business operation, some degree of manual oversight, especially with regard to adjusting outliers and the selection of a particular model, is useful. Very little is gained by manually selecting parameter values for the components, because their setting has relatively little impact on the forecast profile generated by the smoothing algorithm. Experience teaches that determination of the best smoothing weights should be left to the optimization (search) algorithms embedded in the forecasting software.

Despite the more than adequate computer power available today, some heuristic methods are still being advocated in software solutions for demand forecasting and planning. These methods are mechanical and have no basis in statistical theory, so they lack completeness and the ability to characterize uncertainty correctly (change without chance component—an incomplete pie). Although little has been documented on its comparative accuracy with objective statistical techniques, a study of cookware demand in Focus forecasting reconsidered, by Gardner and Anderson, demonstrated that it produces less accurate results than the seasonal, damped trend exponential smoothing models (described in detail in Chapter 8). Nevertheless, heuristic procedures have an intuitive appeal that is often appreciated by practitioners.

Searching for Optimal Smoothing Procedures

Once a smoothing model has been selected, an algorithm is applied to find the optimal values of the smoothing weights. Once the weights are determined, the level, trend, and seasonal components of the forecasting equations are constructed to produce model extrapolations into the future.

The optimization algorithm itself requires some technical choices to be made, although many programs specify default values, often behind the scenes. The technical choices concern (1) which error-minimization criterion to use, (2) which search procedure to use, and (3) which starting values (also called initial values) to use for initiating the search procedure.
In the simplest case of simple exponential smoothing, the only component of the forecasting equation is the current level; it is an exponentially weighted average of the historical values, with the relative emphasis given to the more recent values versus the distant past. The simple exponential smoothing method (treated in Chapter 8) has a smoothing equation

\[ L_t = \alpha Y_t + (1 - \alpha) L_{t-1} \]

in which \( \alpha \) is the smoothing coefficient \((0 < \alpha < 1)\). The value of the level, \( L_t \), becomes the forecast of the next period’s data value \((Y_t(1) = L_t)\), so that the error in estimating or forecasting one period-ahead is

\[ e_t(1) = Y_{t+1} - Y_t(1) = Y_{t+1} - L_t \]

The typical smoothing algorithm seeks to calculate \( L_t \) to minimize these one-period-ahead forecast errors. This requires that we first specify an error-minimization criterion—typically, the MAD or MSE. Second, we must calculate the value of \( \alpha \) that satisfies this criterion; if it is close to zero, this implies more even weighting of the recent and distant past, and if it is close to unity, this implies that virtually all emphasis is placed on the recent past.

The implementation of smoothing algorithms is complicated by the need for starting values or assumptions about the value of the level/trend/seasonal indexes as of the initial time period in the series. Because of this, implementations of the same model in different systems may show some small numerical differences in coefficients and results. However, the forecast profiles should look the same for different implementations of the same model.

### Error-Minimization Criteria

The error-minimization criterion defines what is best or optimal in an optimization procedure. In principle, any error measure can serve as a basis for optimization. In practice, software programs rely most commonly on a squared error measure: MSE or RMSE, the square root of MSE. In this procedure, calculations are made to keep the squared one-period-ahead forecast errors to a minimum.

The choice of the error criterion, also interpretable as a loss function, could make a difference in practice. The most common alternative error-minimization measures are the Mean Absolute Deviation (MAD) and the Mean Absolute Percentage Error (MAPE). In this case, the optimization criteria seek to keep the absolute errors to a minimum.

### Searching for Optimal Smoothing Weights

Modern forecasting software can be expected to include at least one search procedure for optimizing the smoothing weights. The most common is the grid search. For example, by selecting a smoothing weight \( \alpha \) in simple exponential smoothing, we can implement a crude grid search by setting \( \alpha \) equal to designated values between 0 and 1, for example, the 100 values \((0.01, 0.02, 0.03, \ldots, 0.98, 0.99, 1.00)\). Then, for each \( \alpha \) value, an error measure of choice is calculated. Finally, the \( \alpha \) value, which keeps the defined measure to a minimum, can be found. Although this design might be adequate for a simple model, it proves to be unacceptably slow for procedures such as the Winters method, which involves simultaneously optimizing three smoothing weights—one each for the level, trend, and seasonal components. Using the crude grid search for this would require not just 100 comparisons but 1 million. Therefore, certain shortcuts are typically employed to cut down on the number of comparisons that must be considered.

A more refined grid search begins by comparing just a few values—for example, the two values 0.33 and 0.66 in simple exponential smoothing by determining which of these generates the smaller error. This is followed by finer and finer searches about this point. If 0.33 is the initial choice over 0.66, the next step is to compare the values 0.16, 0.33, and 0.49 in the hope of progressively homing in to the overall optimum value.

Much faster than the grid search is the simplex (or hill-climbing) method, which presets certain values for the weights and then seeks local (error) minimum points. However, the simplex method carries the risk that there could be more than one local minimum, in which case the smoothing weights that result depend on
the preset values. It is recommended that the simplex search be used only for relatively well-behaved (non-
erratic) time series.

Starting Values
In order to initiate the grid search or simplex algorithm, starting values must be assigned to the level, trend,
and seasonal components. A starting value is an estimate of that component’s value during the initial time
period in the historical series. The influence of the starting value gradually diminishes as the actual historical
data are entered, and if the series is long enough, the impact becomes negligible.

In many time series, especially seasonal series, starting values can make a difference in the smoothing
weights and forecasts generated. The usual choices for starting values distinguish the seasonal component
from the level and trend components. For the seasonal component, one can use the RMA classical
decomposition seasonal indexes as starting values (see Chapter 5). Because these indexes give the same
weight to periods in the recent and distant past, only the first three complete years of data should be used to
allow the seasonal patterns to evolve over time. An alternative to the classical decomposition is a linear
regression model with seasonal dummy variables (Chapter 10).

For the level and trend components, there are several options:

- *Early values* or the very first data point often serves as the starting value for the level component. The change from the first to the second data points (or average of a group of early changes) serves as the starting value for the trend component.
- *The (global) mean* of the time series can be used as the starting value for the level component. If the data are seasonal, the mean of the deseasonalized series can be used.
- *The slope and intercept of a linear regression* model can be used as the starting values for the trend and level components, respectively. This option cannot be applied to damped trends.
- *Backcasting* reverses the time order of the data, using the most recent data point as the start and updating in reverse until an estimate for the earliest time is reached. Unlike regression, backcasting can be applied to damped as well as linear trends.

What is the bottom line? Most forecasting practitioners do not find it practical to take time to adjust the
technical settings in their software’s computational algorithms to attempt to accommodate the particulars of
individual time series. The comforting news is that empirical research suggests that reliance on the program’s
default settings is unlikely to be very harmful and is certainly cost-beneficial. But just as the user of an
automatic camera might find it rewarding to go for manual overrides on specific occasions, so the demand
forecaster may find occasional rewards for the extra effort in attending to the details.

Computational Support for Management Overrides
When making overrides to a baseline forecast, the integrity of the baseline forecast is maintained at all times.
This means that it remains a statistically generated forecast stored at the lowest levels. A manual override
made at any product and or location summary gets prorated down to the lowest levels and stored as override
amounts. For instance, an override of 35 in April 2003 (04/03) and 45 in July 2003 (07/03) will not change
the statistical forecast but is allocated to the lowest level location codes for SKU 01540617 in direct
proportion that the 10 forecasted units are allocated in the database for those periods (Figure 13.25). When
aggregated, the sum of the statistical forecast and the override is labeled Stored Total Forecast.

Consolidating Multiple Overrides. It is useful to create rules of making multiple overrides, such as

1. **Tier method.** The Tier method of overrides work as follows:
   1. Override 3 dominates Override 2.
   2. Override 2 dominates Override 1.

For example, Marketing VP Tom makes adjustments in Override 3 line of the grid. This forecast would replace
a forecast in Override 2 made by Product Manager Karen. Likewise, the Product Manager’s forecast in
Override 2 would replace Override 1 made by a field sales forecaster Carl.

2. **Composite method.** In the Composite method, all overrides are given equal significance, and an
   unweighted average of the three forecasts for the period is taken.
(3) **Sum method.** In the **Sum** method, all overrides are added as the sum of the three overrides entered for the particular period.

**Selecting an Adjustment Method.** It can be helpful to adjust options for calculating changes to forecasts, such as Add, Replace, Subtract, or Percent Change. This will affect how the numbers in the override rows are adjusted. Operations should be based on the baseline forecast or the adjusted (Total) forecast, but the table with the baseline forecast numbers must not be updated with changes from this.

![Figure 13.25 A dashboard display for consolidating multiple forecast overrides.](image)

**Constraining Forecast Overrides.** Because overrides can be made at any level in the product and/or customer summaries, the FDSS needs to constrain an override to be applied to some but not all the location/customer codes making up the summary (Figure 13.26). The **Constrain** option that lets you select/deselect those customers not requiring the override (Constrained Items) can be shown in a dialog box, as shown. This example shows that certain 138 Canton customers will not have any overrides allocated when overrides are made for SKU codes 015452V7, 01546655, etc., shown under Constrained Items.
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Reviewing the Override Audit Log. The Override Audit Log allows the user to view the overrides that were done for a particular SKU, Category, Region, or any combination of Location and Products. This view allows the user to see what was done for one forecast and apply this to a new forecast. The audit log as well as a report should be viewable in the FDSS on-screen as well.

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<thead>
<tr>
<th>ID</th>
<th>Product</th>
<th>Override Date</th>
<th>Cust1</th>
<th>Cust2</th>
<th>Cust3</th>
<th>Prod1</th>
<th>Prod2</th>
<th>Prod3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Admin</td>
<td>2021-01-31</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>Admin</td>
<td>2021-02-01</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
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<td>Admin</td>
<td>2021-02-02</td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>4</td>
<td>Admin</td>
<td>2021-02-03</td>
<td>19</td>
<td>20</td>
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</tr>
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<td>32</td>
<td>33</td>
<td>34</td>
<td>35</td>
<td>36</td>
</tr>
</tbody>
</table>

Figure 13.26 A dialog box for a Constrain option.

Figure 13.27 Display of an override audit log.

Takeaways

Demand forecasters are in the business of making statements about future demand for products and services in the face of uncertainty. It is part of an ongoing process affecting sales, marketing, inventory, logistics, production, and all other aspects of the supply chain. A bottom-up demand forecast incorporates a logical and coherent series of steps that, if performed in an organized management-supported fashion, can improve forecasting effectiveness, agility, and accuracy throughout the supply chain.

This chapter has presented a process for the automated forecasting of large volumes of end items by customer/location in the supply chain. Key functions supported by a demand forecasting system include flexible modeling and statistical forecasting engine, database management, exploratory data analysis, decision support, performance analysis, exception handling, and reporting.

An effective, agile demand forecasting process will result in lower costs and improved customer satisfaction. Inclusion of demand forecasting as a vital element in the supply chain is a requisite step toward the goal of having the right quantity of the right product at the right place at the right time (and at the right price)!