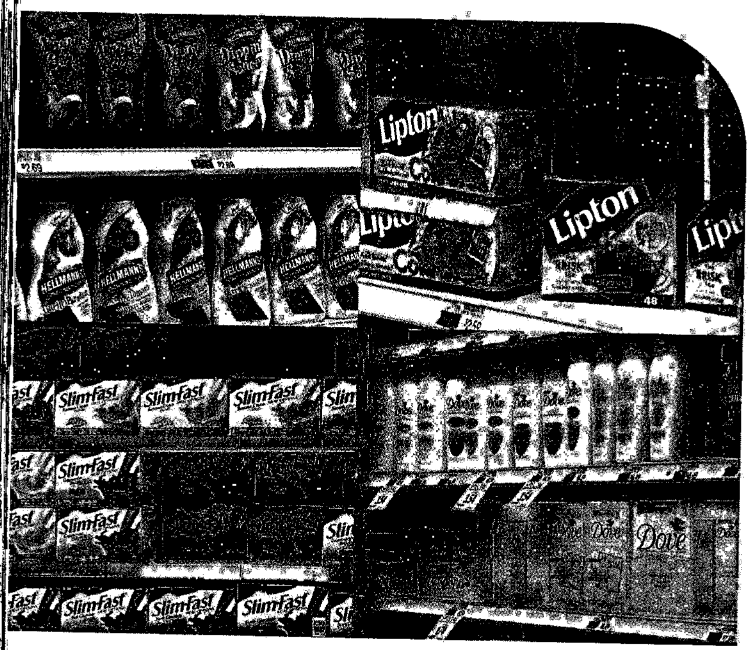
13 FORECASTING

LEARNING GOALS

After reading this chapter, you should be able to:

1. Identify the various forecasting methods available to customer demand planning systems.
2. Explain collaborative planning, forecasting, and replenishment (CPFR).
3. Use regression to make forecasts.
4. Make forecasts using the most common approaches for time-series analysis.
5. Identify the various measures of forecast errors.
6. Describe a typical forecasting process used by businesses.



Lipton tea is one of many Unilever products, and its demand around the world must be forecasted. For centuries, globalism's story traveled with merchants who shepherded spices along Eurasian trade routes. Now it travels over wires and radio waves, satellites, airplanes, and gigabytes.

UNILEVER

Unilever, the fast-moving consumer products supplier, has a state-of-the-art customer demand planning (CDP) system. CDP, first introduced in Chapter 10, "Supply Chain Integration," is a business-planning process that enables sales teams (and customers) to develop demand forecasts. Using software from Manugistics, the system blends historical shipment data with promotional data, allowing information sharing and collaboration with important customers. The system begins with shipment history and current order information. This baseline forecast depends solely on past and present information, so reliable data is a critical requirement. However, statistical information is not useful in forecasting the outcomes of certain events, promotions, rollouts, and special packages, which are common in the industry. To overcome this problem, planners at Unilever must adjust the statistical forecasts with planned promotion predictions conducted by special sales teams. For each promotion, the sales-planning system predicts the "lift," or projected increase in sales, and routes it to the demand-planning system, which applies it to appropriate stock-keeping units (SKUs) and distribution centers each week. In turn, these forecasts are reviewed and adjusted if needed.

Unilever also conducts external market research and internal sales projections that are analyzed, combined with the retail customer promotions, and fed into the demand-planning system. To further improve the accuracy of its forecasts and reduce inventory lead times, Unilever—the purveyor of Dove, Lipton, Hellmann's, and hundreds of other brands—compares point-of-sale (POS) data with its own forecasts. Most companies, including Unilever, only collect POS data from their largest customers. Ultimately, planners at Unilever negotiate the final numbers each week and feed these forecasts into the demand-planning system.

Overall, the current CDP system has been a success. Unilever has reduced its inventory and improved its customer service. However, if collaboration and the usage of POS data were to increase, Unilever would likely reap even larger benefits.

Sources: Robert L. Mitchell, "Case Study: Unilever Crosses the Data Streams," *Computerworld* (December 17, 2001); Robert L. Mitchell, "Tech Check: Getting Demand Planning Right," *Computerworld* (December 17, 2001); www.unilever.com, July 6, 2008.

myomlab and the Companion Website at **www.pearsonhighered.com** contain many tools, activities, and resources designed for this chapter.

forecast

A prediction of future events used for planning purposes.

USING OPERATIONS TO COMPETE

Competing with Operations
Project Management

MANAGING PROCESSES

Process Strategy
Process Analysis
Quality and Performance
Capacity Planning
Constraint Management
Lean Systems

MANAGING SUPPLY CHAINS

Supply Chain Design
Supply Chain Integration
Location
Inventory Management
Forecasting
Operations Planning and Scheduling
Resource Planning

Balancing supply and demand begins with making accurate forecasts. A **forecast** is a prediction of future events used for planning purposes. Planning, on the other hand, is the process of making management decisions on how to deploy resources to best respond to the demand forecasts. Forecasting methods may be based on mathematical models that use available historical data or on qualitative methods that draw on managerial experience and judgments, or they may be based on a combination of both. Unilever's CDP system illustrates the value of merging forecasts from multiple sources.

In this chapter, our focus is on demand forecasts. We begin with different types of demand patterns and designing the forecasting system. We examine forecasting methods in three basic categories: judgment, causal, and time-series methods. Forecast errors are defined, providing important clues for making better forecasts. We conclude with multiple techniques, which bring together insights from several sources, and an overall process for making forecasts.

Forecasts are useful for both managing processes and managing supply chains. At the supply chain level, a firm needs forecasts to coordinate with its customers and suppliers. At the process level, output forecasts are needed to design the various processes throughout the organization, including identifying and dealing with in-house bottlenecks. For example, Hewlett-Packard produces network cards that turn dedicated HP printers into network-shared printers. Changing its forecasting process reduced its inventory levels by 20 to 30 percent reduction while maintaining high levels of product availability. Recognizing the important role of the forecasting process resulted in better overall performance of the supply chain.

FORECASTING ACROSS THE ORGANIZATION

As the Hewlett-Packard example shows, the organization-wide forecasting process cuts across functional areas. Forecasting overall demand typically originates with marketing, but internal customers throughout the organization depend on forecasts to formulate and execute their plans as well. Forecasts are critical inputs to business plans, annual plans, and budgets. Finance needs forecasts to project cash flows and capital requirements. Human resources needs forecasts to anticipate hiring and training needs. Marketing is an important source for sales forecast information because it is closest to external customers. Operations and supply chain managers need forecasts to plan output levels, purchases of services and materials, workforce and output schedules, inventories, and long-term capacities.

Managers throughout the organization make forecasts on many variables other than future demand, such as competitor strategies, regulatory changes, technological changes, processing times, supplier lead times, and quality losses. Tools for making these forecasts are basically the same tools covered here for demand: judgment, opinions of knowledgeable people, averages of experience, regression, and time-series techniques. Using these tools, forecasting can be improved. Still, forecasts are rarely perfect. As Samuel Clemens (Mark Twain) said in *Following the Equator*, "Prophesy is a good line of business, but it is full of risks." Smart managers recognize this reality and find ways to update their plans when the inevitable forecast error or unexpected event occurs.

DEMAND PATTERNS

Forecasting customer demand is a difficult task because the demand for services and goods can vary greatly. For example, demand for lawn fertilizer predictably increases in the spring and summer months; however, the particular weekends when demand is heaviest may depend on uncontrollable factors such as the weather. Sometimes patterns are more predictable. Thus, the peak hours of the day for a large bank's call center are from 9:00 A.M. to 12:00 P.M., and the peak day of the week is Monday. For its statement-rendering processes, the peak months are January, April, July, and October, which is when the quarterly statements are sent out. Forecasting demand in such situations requires uncovering the underlying patterns from available information. In this section, we discuss the basic patterns of demand.

time series

The repeated observations of demand for a service or product in their order of occurrence.

The repeated observations of demand for a service or product in their order of occurrence form a pattern known as a **time series**. There are five basic patterns of most demand time series:

1. *Horizontal.* The fluctuation of data around a constant mean.
2. *Trend.* The systematic increase or decrease in the mean of the series over time.
3. *Seasonal.* A repeatable pattern of increases or decreases in demand, depending on the time of day, week, month, or season.

4. *Cyclical.* The less predictable gradual increases or decreases in demand over longer periods of time (years or decades).
5. *Random.* The unforecastable variation in demand.

Cyclical patterns arise from two influences. The first is the business cycle, which includes factors that cause the economy to go from recession to expansion over a number of years. The other influence is the service or product life cycle, which reflects the stages of demand from development through decline. Business cycle demand is difficult to predict because it is affected by national or international events.

Four of the patterns of demand—horizontal, trend, seasonal, and cyclical—combine in varying degrees to define the underlying time pattern of demand for a service or product. The fifth pattern, random variation, results from chance causes and thus cannot be predicted. Random variation is an aspect of demand that makes every forecast ultimately wrong. Figure 13.1 shows the first four patterns of a demand time series, all of which contain random variations.

KEY DECISIONS ON MAKING FORECASTS

Before using forecasting techniques, a manager must make three decisions: (1) what to forecast, (2) what forecasting system to use, and (3) what type of forecasting technique to select for different items.

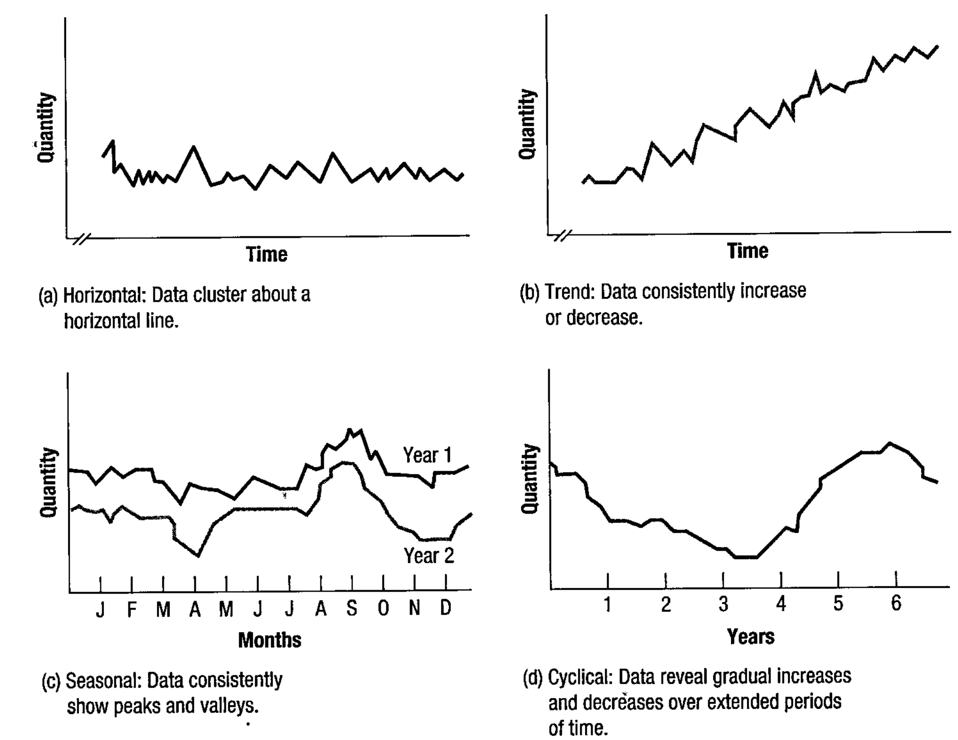
Deciding What to Forecast

Although some sort of demand estimate is needed for the individual services or goods produced by a company, forecasting total demand for groups or clusters and then deriving individual service or product forecasts may be easiest. Also, selecting the correct unit of measurement (e.g., service or product units or machine-hours) for forecasting may be as important as choosing the best method.

aggregation

The act of clustering several similar services or products so that forecasts and plans can be made for whole families.

Level of Aggregation Few companies err by more than 5 percent when forecasting the annual total demand for all their services or products. However, errors in forecasts for individual items and shorter time periods may be much higher. Recognizing this reality, many companies use a two-tier forecasting system. They first cluster (or "roll up") several similar services or products in a process called **aggregation**, making forecasts for families of services or goods that have similar demand requirements and common processing, labor, and materials requirements. Next they derive forecasts for individual items, which are sometimes called stock-keeping units. A *stock-keeping unit (SKU)* is an individual item or product



(a) Horizontal: Data cluster about a horizontal line.

(b) Trend: Data consistently increase or decrease.

(c) Seasonal: Data consistently show peaks and valleys.

(d) Cyclical: Data reveal gradual increases and decreases over extended periods of time.

◀ FIGURE 13.1
Patterns of Demand

that has an identifying code and is held in inventory somewhere along the supply chain, such as in a distribution center.

Units of Measurement Rather than using dollars as the initial unit of measurement, forecasts often begin with service or product units, such as SKUs, express packages to deliver, or customers needing maintenance service or repairs for their cars. Forecasted units can then be translated to dollars by multiplying them by the unit price. If accurately forecasting demand units for a service or product is not possible, forecast the standard labor or machine-hours required of each of the critical resources.

Choosing a Forecasting System

Often companies must prepare forecasts for hundreds or even thousands of services or products repeatedly. For example, a large network of health care facilities must calculate demand forecasts for each of its services for every department. This undertaking involves voluminous data that must be manipulated frequently. However, software such as Unilever's CDP system can ease the burden of making these forecasts and coordinating the forecasts between retailers and suppliers. Many forecasting software packages are available, including Manugistics, Forecast Pro, and SAS. The forecasting routines in OM Explorer and POM for Windows give some hint of their capabilities.

Many firms, including Wal-Mart and Campbell Soup, use a specific CDP process called **collaborative planning, forecasting, and replenishment (CPFR)** for supply chain integration that allows a supplier and its customers to collaborate on making demand forecasts by using the Internet. Managerial Practice 13.1 describes Wal-Mart's experience with this approach.

collaborative planning, forecasting, and replenishment (CPFR)

A nine-step process for supply chain integration that allows a supplier and its customers to collaborate on making the forecast by using the Internet.

Choosing the Type of Forecasting Technique

CDP systems offer a variety of forecasting techniques, and no one of them is best for all items and situations. The forecaster's objective is to develop a useful forecast from the information at hand with the technique that is appropriate for the different patterns of demand. Two general types of forecasting techniques are used: judgment methods and quantitative methods. **Judgment methods** translate the opinions of managers, expert opinions, consumer surveys, and salesforce estimates into quantitative estimates. Quantitative methods include causal methods and time-series analysis. **Causal methods** use historical data on independent variables, such as promotional campaigns, economic conditions, and competitors' actions, to predict demand. **Time-series analysis** is a statistical approach that relies heavily on historical demand data to project the future size of demand and recognizes trends and seasonal patterns.

judgment methods

A forecasting method that translates the opinions of managers, expert opinions, consumer surveys, and salesforce estimates into quantitative estimates.

causal methods

A quantitative forecasting method that uses historical data on independent variables, such as promotional campaigns, economic conditions, and competitors' actions, to predict demand.

time-series analysis

A statistical approach that relies heavily on historical demand data to project the future size of demand and recognizes trends and seasonal patterns.

JUDGMENT METHODS

Forecasts from quantitative methods are possible only when there is adequate historical data, often called the *history file* by various commercial software packages. However, the history file may be nonexistent when a new product is introduced or when technology is expected to change. The history file might exist but be less useful when certain events (such as rollouts or special packages) are reflected in the past data, or when certain events are expected to occur in the future. In some cases, judgment methods are the only practical way to make a forecast. In other cases, judgment methods can also be used to modify forecasts that are generated by quantitative methods. Such adjustments are particularly important when the forecaster has important contextual knowledge. *Contextual knowledge* is knowledge that practitioners gain through experience, such as cause-and-effect relationships, environmental cues, and organizational information that may have an effect on the variable being forecast. Finally, judgment methods can be used to adjust the history file that will be analyzed with quantitative methods to discount the impact of special one-time events that occurred in the past. Four of the more successful judgment methods are as follows: (1) salesforce estimates, (2) executive opinion, (3) market research, and (4) the Delphi method.

Salesforce estimates are forecasts compiled from estimates made periodically by members of a company's salesforce. The salesforce is the group most likely to know which services or products customers will be buying in the near future and in what quantities. Forecasts of individual salesforce members can be combined easily to get regional or national sales estimates. However, individual biases of the salespeople may taint the forecast. For example, some people are naturally optimistic, whereas others are more cautious. Adjustments in forecasts may need to be made.

salesforce estimates

The forecasts that are compiled from estimates of future demands made periodically by members of a company's salesforce.

MANAGERIAL PRACTICE 13.1 — Wal-Mart Uses CPFR and the Internet to Improve Demand Planning Performance

Wal-Mart has long been known for its careful analysis of cash register receipts and for working with suppliers to reduce inventories. In the past, like many other retailers, Wal-Mart did not share its forecasts with its suppliers. The result was forecast errors as much as 60 percent of actual demand. Retailers ordered more than they needed, and suppliers produced more than they could sell.

To combat the ill effects of forecast errors on inventories, Benchmarking Partners, Inc., was funded in the mid-1990s by Wal-Mart, IBM, SAP, and Manugistics to develop a software package. A key benefit of the package was the capability of providing more reliable medium-term forecasts. The system allowed manufacturers and merchants to work together on forecasts by using the Internet rather than fax or phone, which would have been a heavy burden with the thousands of items stocked at each store requiring weekly forecasts.

Wal-Mart initiated this new approach with Listerine, a primary product of Warner-Lambert that in 2000 joined with Pfizer. Listerine is currently produced and distributed by Johnson & Johnson, which acquired Pfizer's consumer health care division in 2006. The system worked in the following way during this pilot period. Wal-Mart and Warner-Lambert independently calculated the demand they expected for Listerine six months into the future, taking into consideration factors such as past sales trends and promotion plans. They then exchanged their forecasts over the Internet. If the forecasts differed by more than a predetermined percentage, the retailer and the manufacturer used the Internet to exchange written comments and supporting data. The parties went through as many cycles as needed to converge on an acceptable forecast. After the pilot ended, the benefits to Wal-Mart included a reduction in stockouts from 15 percent to 2 percent as well as significant increases in sales and reductions in inventory costs. Likewise, Warner-Lambert benefited by having a smoother production plan and lower average costs. This system was later generalized and dubbed CPFR, which stands for collaborative planning, forecasting, and replenishment.

Following the pilot with Warner-Lambert, Wal-Mart had a CPFR pilot with Sara Lee in which the firms exchanged information such as forecasts and replenishment data. In return, Wal-Mart benefited by ensuring that it had the right item at the right time and at the right place, thus increasing customer satisfaction and profitability.

A customer examining a bottle of Listerine at a drug store. Listerine was the "test case" for a new forecasting standard called CPFR, which stands for "collaborative planning, forecast, and replenishment." Using the Internet, retailers such as Wal-Mart and manufacturers exchange their forecasts for products such as Listerine and are much better able to match supply with demand.

Sources: VICS (2002), "Collaborative Planning, Forecasting, and Replenishment," Version 2.0, www.cpfr.org; Jerold P. Cederlund, Rajiv Kohli, Susan A. Sherer, and Yuliang Yao, "How Motorola Put CPFR into Action," *Supply Chain Management Review* (October 2007), pp. 28–35.

Executive opinion is a forecasting method in which the opinions, experience, and technical knowledge of one or more managers or customers (as with CPFR) are summarized to arrive at a single forecast. As we discuss later, executive opinion can be used to modify an existing sales forecast to account for unusual circumstances, such as a new sales promotion or unexpected international events. Executive opinion can also be used for **technological forecasting**. The quick pace of technological change makes keeping abreast of the latest advances difficult.

executive opinion

A forecasting method in which the opinions, experience, and technical knowledge of one or more managers are summarized to arrive at a single forecast.

technological forecasting

An application of executive opinion to keep abreast of the latest advances in technology.

Market research is a systematic approach to determine external consumer interest in a service or product by creating and testing hypotheses through data-gathering surveys. Conducting a market research study includes designing a questionnaire, deciding how to administer it, selecting a representative sample, and analyzing the information using judgment and statistical tools to interpret the responses. Although market research yields important information, it typically includes numerous qualifications and hedges in the findings.

market research

A systematic approach to determine external consumer interest in a service or product by creating and testing hypotheses through data-gathering surveys.

The **Delphi method** is a process of gaining consensus from a group of experts while maintaining their anonymity. This form of forecasting is useful when no historical data are available from which to develop statistical models and when managers inside the firm have no experience on which to base informed projections. A coordinator sends questions to each member of the group of outside experts, who may not even know who else is participating. The coordinator prepares a statistical summary of the responses along with a summary of arguments for particular

Delphi method

A process of gaining consensus from a group of experts while maintaining their anonymity.

responses. The report is sent to the same group for another round, and the participants may choose to modify their previous responses. These rounds continue until consensus is obtained.

In the remainder of this chapter, we turn to the commonly used quantitative forecasting approaches.

Causal Methods: Linear Regression

Causal methods are used when historical data are available and the relationship between the factor to be forecasted and other external or internal factors (e.g., government actions or advertising promotions) can be identified. These relationships are expressed in mathematical terms and can be complex. Causal methods are good for predicting turning points in demand and for preparing long-range forecasts. We focus on linear regression, one of the best known and most commonly used causal methods.

linear regression

A causal method in which one variable (the dependent variable) is related to one or more independent variables by a linear equation.

dependent variable

The variable that one wants to forecast.

independent variables

Variables that are assumed to affect the dependent variable and thereby "cause" the results observed in the past.

In **linear regression**, one variable, called a dependent variable, is related to one or more independent variables by a linear equation. The **dependent variable** (such as demand for doorknobs) is the one the manager wants to forecast. The **independent variables** (such as advertising expenditures and new housing starts) are assumed to affect the dependent variable and thereby "cause" the results observed in the past. Figure 13.2 shows how a linear regression line relates to the data. In technical terms, the regression line minimizes the squared deviations from the actual data.

In the simplest linear regression models, the dependent variable is a function of only one independent variable and, therefore, the theoretical relationship is a straight line:

$$Y = a + bX$$

where

Y = dependent variable

X = independent variable

a = Y-intercept of the line

b = slope of the line

The objective of linear regression analysis is to find values of a and b that minimize the sum of the squared deviations of the actual data points from the graphed line. Computer programs are used for this purpose. For any set of matched observations for Y and X, the program computes the values of a and b and provides measures of forecast accuracy. Three measures commonly reported are the sample correlation coefficient, the sample coefficient of determination, and the standard error of the estimate.

The *sample correlation coefficient, r*, measures the direction and strength of the relationship between the independent variable and the dependent variable. The value of r can range from -1.00 to $+1.00$. A correlation coefficient of $+1.00$ implies that period-by-period changes in direction (increases or decreases) of the independent variable are always accompanied by changes in the same direction by the dependent variable. An r of -1.00 means that decreases in the independent variable are always accompanied by increases in the dependent variable, and vice versa. A zero value of r means no linear relationship exists between the variables. The closer the value of r is to ± 1.00, the better the regression line fits the points.

The *sample coefficient of determination* measures the amount of variation in the dependent variable about its mean that is explained by the regression line. The coefficient of determination is the square of the correlation coefficient, or r^2. The value of r^2 ranges from 0.00 to 1.00. Regression equations with a value of r^2 close to 1.00 mean a close fit.

The *standard error of the estimate*, s_{yx}, measures how closely the data on the dependent variable cluster around the regression line. Although it is similar to the sample standard deviation, it measures the error from the dependent variable, Y, to the regression line, rather than to the mean. Thus, it is the standard deviation of the difference between the actual demand and the estimate provided by the regression equation. When determining which independent variable to include in the regression equation, you should choose the one with the smallest standard error of the estimate.

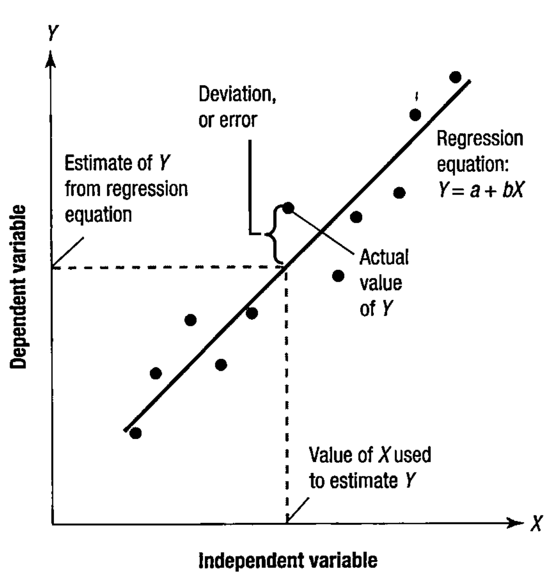


FIGURE 13.2 ▲
Linear Regression Line Relative to Actual Data

EXAMPLE 13.1 Using Linear Regression to Forecast Product Demand

The supply chain manager seeks a better way to forecast the demand for door hinges and believes that the demand is related to advertising expenditures. The following are sales and advertising data for the past 5 months:

Month	Sales (thousands of units)	Advertising (thousands of $)
1	264	2.5
2	116	1.3
3	165	1.4
4	101	1.0
5	209	2.0

The company will spend $1,750 next month on advertising for the product. Use linear regression to develop an equation and a forecast for this product.

PEARSON myomlab

Active Model 13.1 in **myomlab** provides insight on varying the intercept and slope of the model.

SOLUTION

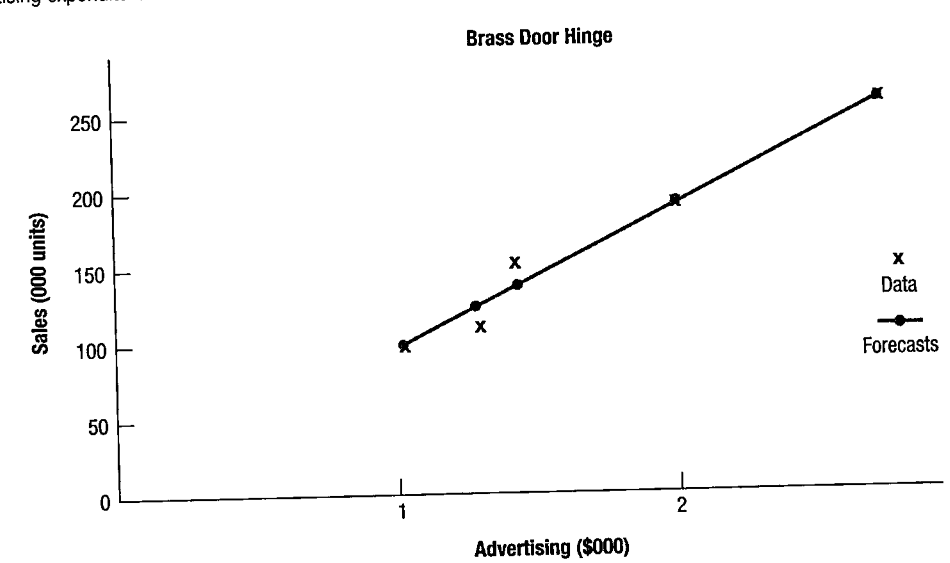
We used POM for Windows to determine the best values of a, b, the correlation coefficient, the coefficient of determination, and the standard error of the estimate.

$$a = -8.135$$
$$b = 109.229X$$
$$r = 0.980$$
$$r^2 = 0.960$$
$$s_{yx} = 15.603$$

The regression equation is

$$Y = -8.135 + 109.229X$$

and the regression line is shown in Figure 13.3. The sample correlation coefficient, r, is 0.98, which is close to 1.00 and suggests an unusually strong positive relationship exists between sales and advertising expenditures. The sample coefficient of determination, r^2, implies that 96 percent of the variation in sales is explained by advertising expenditures.



◀ FIGURE 13.3
Linear Regression Line for the Sales and Advertising Data Using POM for Windows

DECISION POINT

The supply chain manager decided to use the regression model as input to planning production levels for month 6. As the advertising expenditure will be $1,750, the forecast for month 6 is $Y = -8.135 + 109.229(1.75) = 183.016$ or 183,016 units.

Often several independent variables may affect the dependent variable. For example, advertising expenditures, new corporation start-ups, and residential building contracts all may be important for estimating the demand for door hinges. In such cases, *multiple regression analysis* is helpful in determining a forecasting equation for the dependent variable as a function of several independent variables. Such models can be analyzed with POM for Windows or OM Explorer and can be quite useful for predicting turning points and solving many planning problems.

Time-Series Methods

Rather than using independent variables for the forecast as regression models do, time-series methods use historical information regarding only the dependent variable. These methods are based on the assumption that the dependent variable's past pattern will continue in the future. Time-series analysis identifies the underlying patterns of demand that combine to produce an observed historical pattern of the dependent variable and then develops a model to replicate it. In this section, we focus on time-series methods that address the horizontal, trend, and seasonal patterns of demand. Before we discuss statistical methods, let us take a look at the simplest time-series method for addressing all patterns of demand—the naive forecast.

Naive Forecast

naive forecast

A time-series method whereby the forecast for the next period equals the demand for the current period, or Forecast = D_t

A method often used in practice is the **naive forecast**, whereby the forecast for the next period equals the demand for the current period (D_t). So if the actual demand for Wednesday is 35 customers, the forecasted demand for Thursday is 35 customers. Despite its name, the naive forecast can perform well.

The naive forecast method may be adapted to take into account a demand trend. The increase (or decrease) in demand observed between the last two periods is used to adjust the current demand to arrive at a forecast. Suppose that last week the demand was 120 units and the week before it was 108 units. Demand increased 12 units in 1 week, so the forecast for next week would be 120 + 12 = 132 units. The naive forecast method also may be used to account for seasonal patterns. If the demand last July was 50,000 units, the forecast for this July would be 50,000 units. The method works best when the horizontal, trend, or seasonal patterns are stable and random variation is small.

Estimating the Average

We begin our discussion of statistical methods of time-series forecasting with demand that has no trend, seasonal, or cyclical patterns. The horizontal pattern in a time series is based on the mean of the demands, so we focus on forecasting methods that estimate the average of a time series of data. The forecast of demand for *any* period in the future is the average of the time series computed in the current period. For example, if the average of past demand calculated on Tuesday is 65 customers, the forecasts for Wednesday, Thursday, and Friday are 65 customers each day.

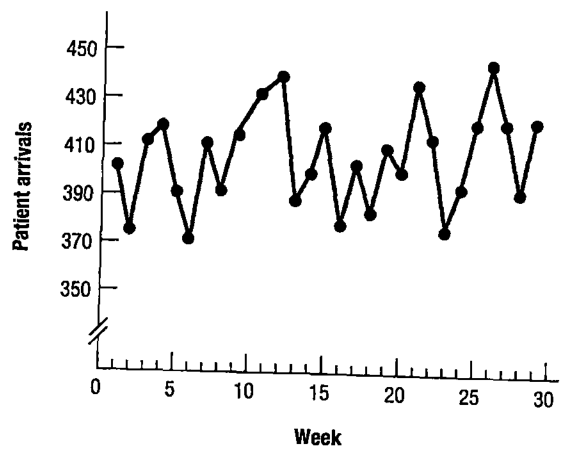


FIGURE 13.4 ▲
Weekly Patient Arrivals at a Medical Clinic

Consider Figure 13.4, which shows patient arrivals at a medical clinic over the past 28 weeks. Assuming that the time series has only a horizontal and random pattern, the statistical techniques useful for forecasting such a time series are (1) simple moving averages, (2) weighted moving averages, and (3) exponential smoothing.

Simple Moving Averages The **simple moving average method** simply involves calculating the average demand for the n most recent time periods and using it as the forecast for future time periods. For the next period, after the demand is known, the oldest demand from the previous average is replaced with the most recent demand and the average is recalculated. In this way, the n most recent demands are used, and the average "moves" from period to period.

Specifically, the forecast for period $t+1$ can be calculated at the end of period t (after the actual demand for period t is known) as

$$F_{t+1} = \frac{\text{Sum of last } n \text{ demands}}{n} = \frac{D_t + D_{t-1} + D_{t-2} + \cdots + D_{t-n+1}}{n}$$

simple moving average method

A time-series method used to estimate the average of a demand time series by averaging the demand for the n most recent time periods.

where

D_t = actual demand in period t

n = total number of periods in the average

F_{t+1} = forecast for period $t+1$

For any forecasting method, it is important to measure the accuracy of its forecasts. **Forecast error** is simply the difference found by subtracting the forecast from actual demand for a given period, or

forecast error

The difference found by subtracting the forecast from actual demand for a given period.

$$E_t = D_t - F_t$$

where

E_t = forecast error for period t

D_t = actual demand for period t

F_t = forecast for period t

EXAMPLE 13.2 Using the Moving Average Method to Estimate Average Demand

a. Compute a *three-week* moving average forecast for the arrival of medical clinic patients in week 4. The numbers of arrivals for the past three weeks were as follows:

Week	Patient Arrivals
1	400
2	380
3	411

b. If the actual number of patient arrivals in week 4 is 415, what is the forecast error for week 4?

c. What is the forecast for week 5?

PEARSON myomlab

Active Model 13.2 in myomlab provides insight on the impact of varying n using the example in *Figure 13.4*.

PEARSON myomlab

Tutor 13.1 in myomlab provides another example to practice making forecasts with the moving average method.

SOLUTION

a. The moving average forecast at the end of week 3 is

$$F_4 = \frac{411 + 380 + 400}{3} = 397.0$$

b. The forecast error for week 4 is

$$E_4 = D_4 - F_4 = 415 - 397 = 18$$

c. The forecast for week 5 requires the actual arrivals from weeks 2 through 4, the three most recent weeks of data.

$$F_5 = \frac{415 + 411 + 380}{3} = 402.0$$

DECISION POINT

Thus, the forecast at the end of week 3 would have been 397 patients for week 4, which fell short of actual demand by 18 patients. The forecast for week 5, made at the end of week 4, would be 402 patients. In addition, at the end of week 4, the forecast for week 6 and beyond is also 402 patients.

The moving average method may involve the use of as many periods of past demand as desired. Large values of n should be used for demand series that are stable, and small values of n should be used for those that are susceptible to changes in the underlying average.

weighted moving average method

A time-series method in which each historical demand in the average can have its own weight; the sum of the weights equals 1.0.

Weighted Moving Averages In the simple moving average method, each demand has the same weight in the average—namely, $1/n$. In the **weighted moving average method**, each historical demand in the average can have its own weight. The sum of the weights equals 1.0. For example, in a *three-period* weighted moving average model, the most recent period might be assigned a weight of 0.50, the second most recent might be weighted 0.30, and the third most recent might be weighted 0.20. The average is obtained by multiplying the weight of each period by the value for that period and adding the products together:

$$F_{t+1} = 0.50D_t + 0.30D_{t-1} + 0.20D_{t-2}$$

PEARSON myomlab

Tutor 13.2 in **myomlab** provides a new practice example for making forecasts with the weighted moving average method.

For a numerical example of using the weighted moving average method to estimate average demand, see Solved Problem 2 and Tutor 13.2 of OM Explorer in my**om**lab.

The advantage of a weighted moving average method is that it allows you to emphasize recent demand over earlier demand. (It can even handle seasonal effects by putting higher weights on prior years in the same season.) The forecast will be more responsive to changes in the underlying average of the demand series than the simple moving average forecast.

exponential smoothing method

A weighted moving average method that calculates the average of a time series by giving recent demands more weight than earlier demands.

Exponential Smoothing The **exponential smoothing method** is a sophisticated weighted moving average method that calculates the average of a time series by giving recent demands more weight than earlier demands. It is the most frequently used formal forecasting method because of its simplicity and the small amount of data needed to support it. Unlike the weighted moving average method, which requires n periods of past demand and n weights, exponential smoothing requires only three items of data: the last period's forecast; the actual demand for this period; and a smoothing parameter, alpha (α), which has a value between 0 and 1.0. To obtain an exponentially smoothed forecast, we simply calculate a weighted average of the most recent demand and the forecast calculated last period. The equation for the forecast is

$$F_{t+1} = \alpha(\text{Demand this period}) + (1-\alpha)(\text{Forecast calculated last period})$$
$$= \alpha D_t + (1-\alpha)F_t$$

An equivalent equation is

$$F_{t+1} = F_t + \alpha(D_t - F_t)$$

This form of the equation shows that the forecast for the next period equals the forecast for the current period plus a proportion of the forecast error for the current period.

The emphasis given to the most recent demand levels can be adjusted by changing the smoothing parameter. Larger α values emphasize recent levels of demand and result in forecasts more responsive to changes in the underlying average. Smaller α values treat past demand more uniformly and result in more stable forecasts. This approach is analogous to adjusting the value of n in the moving average method except that in that method, smaller values of n emphasize recent demand and larger values give greater weight to past demand. In practice, various values of α are tried and the one producing the best forecasts is chosen.

Exponential smoothing requires an initial forecast to get started. There are several ways to get this initial forecast, such as by using last period's actual demand or, if some historical data are available, by calculating the average of several recent periods of demand. The effect of the initial estimate of the average on successive estimates of the average diminishes over time.

EXAMPLE 13.3 Using Exponential Smoothing to Estimate Average Demand

PEARSON myomlab

Active Model 13.3 in my**om**lab provides insight on the impact of varying α in Figure 13.4.

PEARSON myomlab

Tutor 13.3 in my**om**lab provides a new practice example of how to make forecasts with the exponential smoothing method.

a. Reconsider the patient arrival data in Example 13.2. It is now the end of week 3. Using $\alpha = 0.10$, calculate the exponential smoothing forecast for week 4.

b. What was the forecast error for week 4 if the actual demand turned out to be 415?

c. What is the forecast for week 5?

SOLUTION

a. The exponential smoothing method requires an initial forecast. Suppose that we take the demand data for the first two weeks and average them, obtaining $(400 + 380)/2 = 390$ as an initial forecast. (POM for Windows and OM Explorer simply use the actual demand for the first week as a default setting for the initial forecast for period 1, and do not begin tracking forecast errors until the second period). To obtain the forecast for week 4, using exponential smoothing with $\alpha = 0.10$ and the initial forecast of 390, we calculate the average at the end of week 3 as

$$F_4 = 0.10(411) + 0.90(390) = 392.1$$

Thus, the forecast for week 4 would be 392 patients.

b. The forecast error for week 4 is

$$E_4 = 415 - 392 = 23$$

c. The new forecast for week 5 would be

$$F_5 = 0.10(415) + 0.90(392.1) = 394.4$$

or 394 patients. Note that we used F_4, not the integer-value forecast for week 4, in the computation for F_5. In general, we round off (when it is appropriate) only the final result to maintain as much accuracy as possible in the calculations.

DECISION POINT

Using this exponential smoothing model, the analyst's forecasts would have been 392 patients for week 4 and then 394 patients for week 5 and beyond. As soon as the actual demand for week 5 is known, then the forecast for week 6 will be updated.

Because exponential smoothing is simple and requires minimal data, it is inexpensive and attractive to firms that make thousands of forecasts for each time period. However, its simplicity also is a disadvantage when the underlying average is changing, as in the case of a demand series with a trend. Like any method geared solely to the assumption of a stable average, exponential smoothing results will lag behind changes in the underlying average of demand. Higher α values may help reduce forecast errors when there is a change in the average; however, the lags will still occur if the average is changing systematically. Typically, if large α values (e.g., > 0.50) are required for an exponential smoothing application, chances are good that another model is needed because of a significant trend or seasonal influence in the demand series.

Including a Trend

Let us now consider a demand time series that has a trend. A *trend* in a time series is a systematic increase or decrease in the average of the series over time. Where a significant trend is present, exponential smoothing approaches must be modified; otherwise, the forecasts tend to be below or above the actual demand.

To improve the forecast, we need to calculate an estimate of the trend. We start by calculating the *current* estimate of the trend, which is the difference between the average of the series computed in the current period and the average computed last period. To obtain an estimate of the long-term trend, you can average the current estimates. The method for estimating a trend is similar to that used for estimating the demand average with exponential smoothing.

trend-adjusted exponential smoothing method

The method for incorporating a trend in an exponentially smoothed forecast.

The method for incorporating a trend in an exponentially smoothed forecast is called the **trend-adjusted exponential smoothing method**. With this approach, the estimates for both the average and the trend are smoothed, requiring two smoothing constants. For each period, we calculate the average and the trend:

$$A_t = \alpha(\text{Demand this period}) + (1-\alpha)(\text{Average} + \text{Trend estimate last period})$$
$$= \alpha D_t + (1-\alpha)(A_{t-1} + T_{t-1})$$
$$T_t = \beta(\text{Average this period} - \text{Average last period})$$
$$+ (1-\beta)(\text{Trend estimate last period})$$
$$= \beta(A_t - A_{t-1}) + (1-\beta)T_{t-1}$$
$$F_{t+1} = A_t + T_t$$

where

A_t = exponentially smoothed average of the series in period t

T_t = exponentially smoothed average of the trend in period t

α = smoothing parameter for the average, with a value between 0 and 1

β = smoothing parameter for the trend, with a value between 0 and 1

F_{t+1} = forecast for period $t + 1$

To make forecasts for periods beyond the next period, we multiply the trend estimate (T_t) by the number of additional periods that we want in the forecast, and add the results to the current average (A_t). Thus, trend-adjusted exponential smoothing differs from the previous methods covered. For those methods, the forecast for all future periods is the same as the forecast for the next period.

Estimates for last period's average and trend needed for the first forecast can be derived from past data or they can be based on an educated guess if no historical data exist. (POM for Windows and OM Explorer simply use the actual demand for the first week as a default setting for the initial average and 0 for the initial trend, and do not begin tracking forecast errors until the second period). To find values for α and β, often an analyst systematically adjusts α and β until the forecast errors are lowest. This process can be carried out in an experimental setting with the model used to forecast historical demands.

EXAMPLE 13.4 Using Trend-Adjusted Exponential Smoothing to Forecast a Demand Series with a Trend

PEARSON myomlab

Active Model 13.4 in myomlab provides insight on varying α and β using the example in Figure 13.5.

PEARSON myomlab

Tutor 13.4 in myomlab provides another practice example and explanation of how to make forecasts with the trend-adjusted exponential smoothing method.

Medanalysis, Inc., provides medical laboratory services to patients of Health Providers, a group of 10 family-practice doctors associated with a new health maintenance program. Managers are interested in forecasting the number of blood analysis requests per week. Supplies must be purchased and a decision made regarding the number of blood samples to be sent to another laboratory because of capacity limitations at the main laboratory. Recent publicity about the damaging effects of cholesterol on the heart has caused a national increase in requests for standard blood tests. Medanalysis recently ran an average of 28 blood tests per week. The trend has been about three additional patients per week. This week's demand was for 27 blood tests. We use $\alpha = 0.20$ and $\beta = 0.20$ to calculate the forecast for next week.

SOLUTION

$$A_0 = 28 \text{ patients and } T_0 = 3 \text{ patients}$$

The forecast for week 2 (next week) is

$$A_1 = 0.20(27) + 0.80(28 + 3) = 30.2$$
$$T_1 = 0.20(30.2 - 28) + 0.80(3) = 2.8$$
$$F_2 = 30.2 + 2.8 = 33 \text{ blood tests}$$

If the actual number of blood tests requested in week 2 proved to be 44, the updated forecast for week 3 would be

$$A_2 = 0.20(44) + 0.80(30.2 + 2.8) = 35.2$$
$$T_2 = 0.2(35.2 - 30.2) + 0.80(2.8) = 3.2$$
$$F_3 = 35.2 + 3.2 = 38.4 \text{ or 38 blood tests}$$

DECISION POINT

Using this trend-adjusted exponential smoothing model, the forecast for week 2 was 33 blood tests, and then 38 blood tests for week 3. If the analyst makes forecasts at the end of week 2 for periods beyond week 3, the forecast would be even greater because of the upward trend estimated to be 3.2 blood tests per week.

Figure 13.5 shows the trend-adjusted forecast (the blue line) for Medanalysis for a period of 15 weeks. We set α at 0.20, β at 0.20, the initial average at 28, and the initial estimate of the trend at 3. Table 13.1 shows the calculations and forecasts for a period of 15 weeks. At the end of each week, we calculated a forecast for the next week, using the number of blood tests for the current week. Note that they vary less than actual demand because of the smoothing effect of the procedure for calculating the estimates for the average and the trend. By adjusting α and β, we may be able to come up with a better forecast.

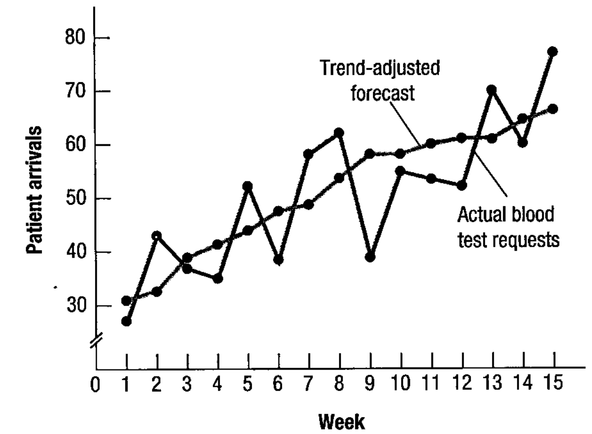


FIGURE 13.5
Trend-Adjusted Forecast for Medanalysis

To make forecasts for periods beyond the next period, we multiply the trend estimate by the number of additional periods that we want in the forecast and add the result to the current average. For example, if we were at the end of week 2 and wanted to estimate the demand for blood tests in week 6 (i.e., 4 weeks ahead), the forecast would be 35.23 + 4(3.28) = 48 tests.

TABLE 13.1 FORECASTS FOR MEDANALYSIS USING THE TREND-ADJUSTED EXPONENTIAL SMOOTHING MODEL

Week	Arrivals	Calculations to Forecast Arrivals for Next Week		Forecast for This Week	Forecast Error
		Smoothed Average	Trend Average		
0	28	28.00	3.00		
1	27	30.20	2.84	28.00 + 3.00 = 31.00	−4
2	44	35.23	3.28	30.20 + 2.84 = 33.04	10.96
3	37	38.21	3.22	35.23 + 3.28 = 38.51	−1.51
4	35	40.14	2.96	38.21 + 3.22 = 41.43	−6.43
5	53	45.08	3.36	40.14 + 2.96 = 43.10	9.90
6	38	46.35	2.94	45.08 + 3.36 = 48.44	−10.44
7	57	50.83	3.25	46.35 + 2.94 = 49.29	7.71
8	61	55.46	3.52	50.83 + 3.25 = 54.08	6.92
9	39	54.99	2.72	55.46 + 3.52 = 58.98	−19.98
10	55	57.17	2.62	54.99 + 2.72 = 57.71	−2.71
11	54	58.63	2.38	57.17 + 2.62 = 59.79	−5.79
12	52	59.21	2.02	58.63 + 2.38 = 61.01	−9.01
13	60	60.99	1.97	59.21 + 2.02 = 61.23	−1.23
14	60	62.37	1.86	60.99 + 1.97 = 62.96	−2.96
15	75	66.38	2.29	62.37 + 1.86 = 64.23	10.77

The trend-adjusted exponential smoothing method accounts for both the average and trend, and might be considered to be a better performer than the ones already covered. This is not necessarily true, and the simpler models can sometimes be better performers.

Seasonal Patterns

Seasonal patterns are regularly repeating upward or downward movements in demand measured in periods of less than one year (hours, days, weeks, months, or quarters). In this context, the time periods are called *seasons*. For example, customer arrivals at a fast-food shop on any day may peak between 11 A.M. and 1 P.M and again from 5 P.M. to 7 P.M.

An easy way to account for seasonal effects is to use one of the techniques already described but to limit the data in the time series to those time periods in the same season. For example, for a day-of-the-week seasonal effect, one time series would be for Mondays, one for Tuesdays, and so on. Such an approach accounts for seasonal effects, but has the disadvantage of discarding considerable information on past demand.

multiplicative seasonal method

A method whereby seasonal factors are multiplied by an estimate of average demand to arrive at a seasonal forecast.

Other methods are available that analyze all past data, using one model to forecast demand for all of the seasons. We describe only the **multiplicative seasonal method**, whereby seasonal factors are multiplied by an estimate of average demand to arrive at a seasonal forecast. The four-step procedure presented here involves the use of simple averages of past demand, although more sophisticated methods for calculating averages, such as a moving average or exponential smoothing approach, could be used. The following description is based on a seasonal pattern lasting one year and seasons of one month, although the procedure can be used for any seasonal pattern and season of any length.

1. For each year, calculate the average demand per season by dividing annual demand by the number of seasons per year.
2. For each year, divide the actual demand for a season by the average demand per season. The result is a *seasonal index* for each season in the year, which indicates the level of demand relative to the average demand. For example, a seasonal index of 1.14 calculated for April implies that April's demand is 14 percent greater than the average demand per month.
3. Calculate the average seasonal index for each season, using the results from step 2. Add the seasonal indices for a season and divide by the number of years of data.
4. Calculate each season's forecast for next year. Begin by forecasting next year's annual demand using the naive method, moving averages, exponential smoothing, trend-adjusted exponential smoothing, or linear regression. Then divide annual demand by the number of seasons per year to get the average demand per season. Finally, make the seasonal forecast by multiplying the average demand per season by the appropriate seasonal index found in step 3.

EXAMPLE 13.5 **Using the Multiplicative Seasonal Method to Forecast the Number of Customers**

The manager of the Stanley Steemer carpet cleaning company needs a quarterly forecast of the number of customers expected next year. The carpet cleaning business is seasonal, with a peak in the third quarter and a trough in the first quarter. Following are the quarterly demand data from the past 4 years:

Quarter	Year 1	Year 2	Year 3	Year 4
1	45	70	100	100
2	335	370	585	725
3	520	590	830	1,160
4	100	170	285	215
Total	1,000	1,200	1,800	2,200

The manager wants to forecast customer demand for each quarter of year 5, based on an estimate of total year 5 demand of 2,600 customers.

SOLUTION

Figure 13.6 shows the solution using the *Seasonal Forecasting* Solver in OM Explorer. (For a numerical example calculated manually, see Solved Problem 4 at the end of this chapter.) For the Inputs sheet (a), forecast for the total demand in year 5 is needed. The annual demand has been increasing by an average of 400 customers each year (from 1,000 in year 1 to 2,200 in year 4, or 1,200/3 = 400). The computed forecast demand is found by extending that trend, and projecting an annual demand in year 5 of 2,200 + 400 = 2,600 customers. The option of a user-supplied forecast is also available if the manager wishes to make a judgmental forecast based on additional information.

The results sheet, sheet (b), shows quarterly forecasts by multiplying the seasonal factors by the average demand per quarter. For example, the average demand forecast in year 5 is 650 customers (or 2,600/4 = 650). Multiplying that by the seasonal index computed for the first quarter gives a forecast of 133 customers (or 650 × 0.2043 = 132.795).

Period: Quarters

Starting Year: 1 Years: 4

Computed Forecast Demand for Year 5: 2600

User-supplied Forecast Demand for Year 5: 2600

Quarter	Year 1	Year 2	Year 3	Year 4
1	45	70	100	100
2	335	370	585	725
3	520	590	830	1160
4	100	170	285	215

(a) Inputs sheet

Quarter	Seasonal Index	Forecast
1	0.2043	132.795
2	1.2979	843.635
3	2.0001	1300.065
4	0.4977	323.505

(b) Results

◀ **FIGURE 13.6**
Demand Forecasts Using the *Seasonal Forecast* Solver of OM Explorer

DECISION POINT

Using this seasonal method, the analyst makes a demand forecast as low as 133 customers in the first quarter and as high as 1,300 customers in the third quarter. The season of the year clearly makes a difference.

additive seasonal method A method in which seasonal forecasts are generated by adding a constant to the estimate of average demand per season.

An alternative to the multiplicative seasonal method is the **additive seasonal method**, whereby seasonal forecasts are generated by adding or subtracting a seasonal constant (say, 50 units) to the estimate of average demand per season. This approach is based on the assumption that the seasonal pattern is constant, regardless of average demand. The amplitude of the seasonal adjustment remains the same regardless of the level of demand.

CHOOSING A TIME-SERIES METHOD

We now turn to factors that managers must consider in selecting a forecasting technique for a particular time series. One important consideration is forecast performance, as determined by forecast errors. Managers need to know how to measure forecast errors and how to detect when something is going wrong with the forecasting system. After examining forecast errors and their detection, we discuss criteria that managers can use to choose an appropriate time-series forecasting method.

Forecast Error

Forecasts almost always contain errors. Forecast errors can be classified as either *bias errors* or *random errors.* Bias errors are the result of consistent mistakes—the forecast is always too high or too low. The other type of forecast error, random error, results from unpredictable factors that cause the forecast to deviate from the actual demand. Forecasting analysts try to minimize the effects of bias and random errors by selecting appropriate forecasting models, but eliminating all forms of errors is impossible.

Measures of Forecast Error Our earlier definition of forecast error for a given time period ($E_t = D_t - F_t$) is the starting point for creating several measures of forecast error that cover a relatively long period of time.

cumulative sum of forecast errors (CFE)

A measurement of the total forecast error that assesses the bias in a forecast.

The **cumulative sum of forecast errors (CFE)** measures the total forecast error:

$$CFE = \sum E_t$$

Large positive errors tend to be offset by large negative errors in the CFE measure. Nonetheless, CFE is useful in assessing *bias* in a forecast. For example, if a forecast is always lower than actual demand, the value of CFE will gradually get larger and larger. This increasingly large error indicates some systematic deficiency in the forecasting approach. The average forecast error, sometimes called the *mean bias*, is simply

$$\bar{E} = \frac{\text{CFE}}{n}$$

mean squared error (MSE)
A measurement of the dispersion of forecast errors.

standard deviation (σ)
A measurement of the dispersion of forecast errors.

mean absolute deviation (MAD)
A measurement of the dispersion of forecast errors.

The **mean squared error (MSE), standard deviation** (s), and **mean absolute deviation (MAD)** measure the dispersion of forecast errors:

$$\text{MSE} = \frac{\Sigma E_t^2}{n}$$

$$\sigma = \sqrt{\frac{\Sigma(E_t - \bar{E})^2}{n - 1}}$$

$$\text{MAD} = \frac{\Sigma|E_t|}{n}$$

The mathematical symbol | | is used to indicate the absolute value—that is, it tells you to disregard positive or negative signs. If MSE, s, or MAD is small, the forecast is typically close to actual demand; by contrast, a large value indicates the possibility of large forecast errors. The two measures differ in the way they emphasize errors. Large errors get far more weight in MSE and s because the errors are squared. MAD is a widely used measure of forecast error and is easily understood; it is merely the mean of the forecast errors over a series of time periods, without regard to whether the error was an overestimate or an underestimate.

mean absolute percent error (MAPE)
A measurement that relates the forecast error to the level of demand and is useful for putting forecast performance in the proper perspective.

The **mean absolute percent error (MAPE)** relates the forecast error to the level of demand and is useful for putting forecast performance in the proper perspective:

$$\text{MAPE} = \frac{(\Sigma|E_t|/D_t)\ (100)}{n} \quad \text{(expressed as a percentage)}$$

For example, an absolute forecast error of 100 results in a larger percentage error when the demand is 200 units than when the demand is 10,000 units. MAPE is the best error measure to use when making comparisons between time series for different SKUs.

EXAMPLE 13.6 Calculating Forecast Error Measures

The following table shows the actual sales of upholstered chairs for a furniture manufacturer and the forecasts made for each of the last eight months. Calculate CFE, MSE, s, MAD, and MAPE for this product.

Month, t	Demand, D_t	Forecast, F_t	Error, E_t	Error, Squared, E_t^2	Absolute Error $\lvert E_t\rvert$	Absolute Percent Error, $(\lvert E_t\rvert/D_t)(100)$
1	200	225	−25	625	25	12.5%
2	240	220	20	400	20	8.3
3	300	285	15	225	15	5.0
4	270	290	−20	400	20	7.4
5	230	250	−20	400	20	8.7
6	260	240	20	400	20	7.7
7	210	250	40	1,600	40	19.0
8	275	240	35	1,225	35	12.7
		Total	−15	5,275	195	81.3%

SOLUTION

Using the formulas for the measures, we get

Cumulative forecast error (bias):

CFE = −15

Average forecast error (mean bias):

$$\bar{E} = \frac{\text{CFE}}{n} = \frac{-15}{8} = -1.875$$

Mean squared error:

$$\text{MSE} = \frac{\Sigma E_t^2}{n} = \frac{5{,}275}{8} = 659.4$$

Standard deviation:

$$\sigma = \sqrt{\frac{\Sigma[E_t - (-1.875)]^2}{7}} = 27.4$$

Mean absolute deviation:

$$\text{MAD} = \frac{\Sigma|E_t|}{n} = \frac{195}{8} = 24.4$$

Mean absolute percent error:

$$\text{MAPE} = \frac{[\Sigma|E_t|/D_t]\ 100}{n} = \frac{81.3\%}{8} = 10.2\%$$

A CFE of −15 indicates that the forecast has a slight bias to overestimate demand. The MSE, s, and MAD statistics provide measures of forecast error variability. A MAD of 24.4 means that the average forecast error was 24.4 units in absolute value. The value of s, 27.4, indicates that the sample distribution of forecast errors has a standard deviation of 27.4 units. A MAPE of 10.2 percent implies that, on average, the forecast error was about 10 percent of actual demand. These measures become more reliable as the number of periods of data increases.

DECISION POINT

Although reasonably satisfied with these forecast performance results, the analyst decided to test out a few more forecasting methods before reaching a final forecasting method to use for the future.

tracking signal
A measure that indicates whether a method of forecasting is accurately predicting actual changes in demand.

Tracking Signals A **tracking signal** is a measure that indicates whether a method of forecasting is accurately predicting actual changes in demand. The tracking signal measures the number of MADs represented by the cumulative sum of forecast errors, the CFE. The CFE tends to be 0 when a correct forecasting system is being used. At any time, however, random errors can cause the CFE to be a nonzero number. The tracking signal formula is

$$\text{Tracking signal} = \frac{\text{CFE}}{\text{MAD}}$$

Each period, the CFE and MAD are updated to reflect current error, and the tracking signal is compared to some predetermined limits. The MAD can be calculated in one of two ways: (1) as the simple average of all absolute errors (as demonstrated in Example 13.6) or (2) as a weighted average determined by the exponential smoothing method:

$$\text{MAD}_t = \alpha|E_t| + (1 - \alpha)\text{MAD}_{t-1}$$

If forecast errors are normally distributed with a mean of 0, the relationship between s and MAD is simple:

$$\sigma = (\sqrt{\pi/2})(\text{MAD}) \cong 1.25(\text{MAD})$$

$$\text{MAD} = 0.7978\sigma \cong 0.8\sigma$$

where

$$\pi = 3.1416$$

This relationship allows use of the normal probability tables to specify limits for the tracking signal. If the tracking signal falls outside those limits, the forecasting model no longer is tracking demand adequately. A tracking system is useful when forecasting systems are

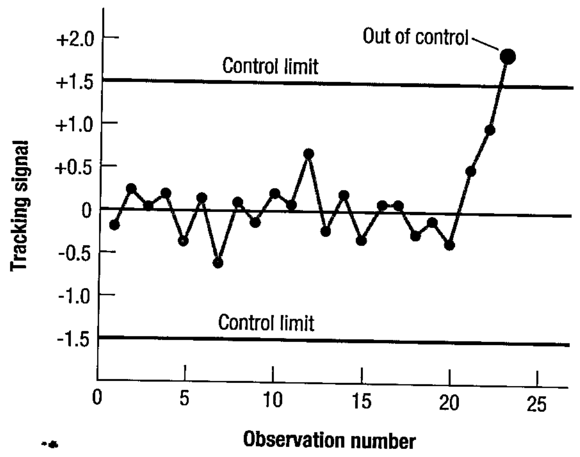


FIGURE 13.7 ▲
Tracking Signal

computerized because it alerts analysts when forecasts are getting far from desirable limits. Figure 13.7 shows tracking signal results for 23 periods plotted on a *control chart*. The control chart is useful for determining whether any action needs to be taken to improve the forecasting model. In the example, the first 20 points cluster around 0, as we would expect if the forecasts are not biased. The CFE will tend toward 0. When the underlying characteristics of demand change but the forecasting model does not, the tracking signal eventually goes out of control. The steady increase after the 20th point in Figure 13.7 indicates that the process is going out of control. The 21st and 22nd points are acceptable, but the 23rd point is not.

Computer Support Computer support, such as from OM Explorer or POM for Windows, makes error calculations easy when evaluating how well forecasting models fit with past data (i.e., the *history file*). They show the various error measures across the entire history file for each method evaluated. They also make forecasts into the future, based on the method selected.

Criteria for Selecting Time-Series Methods

Forecast error measures provide important information for choosing the best forecasting method for a service or product. They also guide managers in selecting the best values for the parameters needed for the method: n for the moving average method, the weights for the weighted moving average method, and α for the exponential smoothing method. The criteria to use in making forecast method and parameter choices include (1) minimizing bias; (2) minimizing MAPE, MAD, or MSE; (3) meeting managerial expectations of changes in the components of demand; and (4) minimizing the forecast error last period. The first two criteria relate to statistical measures based on historical performance, the third reflects expectations of the future that may not be rooted in the past, and the fourth is a way to use whatever method seems to be working best at the time a forecast must be made.

Using Statistical Criteria Statistical performance measures can be used in the selection of a forecasting method. The following guidelines will help when searching for the best time-series models:

1. For projections of more stable demand patterns, use lower α and β values or larger n values to emphasize historical experience.
2. For projections of more dynamic demand patterns using the models covered in this chapter, try higher α and β values or smaller n values. When historical demand patterns are changing, recent history should be emphasized.

holdout set

Actual demands from the more recent time periods in the time series, that are set aside to test different models developed from the earlier time periods.

Often, the forecaster must make trade-offs between bias (CFE) and the measures of forecast error dispersion (MAPE, MAD, and MSE). Managers also must recognize that the best technique in explaining the past data is not necessarily the best technique to predict the future, and that "overfitting" past data can be deceptive. A forecasting method may have small errors relative to the history file, but may generate high errors for future time periods. For this reason, some analysts prefer to use a **holdout set** as a final test. To do so, they set aside some of the more recent periods from the time series and use only the earlier time periods to develop and test different models. Once the final models have been selected in the first phase, they are tested again with the holdout set. Performance measures, such as MAPE and CFE, would still be used but they would be applied to the holdout sample. Whether this idea is used or not, managers should monitor future forecast errors, perhaps with tracking signals, and modify their forecasting approaches as needed. Maintaining data on forecast performance is the ultimate test of forecasting power—rather than how well a model fits past data or holdout samples.

Using Multiple Techniques

We described several individual forecasting methods and showed how to assess their forecast performance. However, we need not rely on a single forecasting method. Several different forecasts can be used to arrive at a final forecast. Initial statistical forecasts using several time-series methods and regression are distributed to knowledgeable individuals, such as marketing directors and sales teams, for their adjustments. They can account for current market and customer conditions that are not necessarily reflected in past data. Multiple forecasts may come from different sales teams, and some teams may have a better record on

forecast errors than others. Finally, the collaborative process of CPFR introduces forecasts from customers and even suppliers.

combination forecasts

Forecasts that are produced by averaging independent forecasts based on different methods or different data or both.

Research during the last two decades suggests that combining forecasts from multiple sources often produces more accurate forecasts. **Combination forecasts** are forecasts that are produced by averaging independent forecasts based on different methods or different data or both. It is intriguing that combination forecasts often perform better over time than even the *best* single forecasting procedure. For example, suppose that the forecast for the next period is 100 units from technique 1 and 120 units from technique 2 and that technique 1 has provided more accurate forecasts to date. The combination forecast for next period, giving equal weight to each technique, is 110 units (or $0.5 \times 100 + 0.5 \times 120$). When this averaging technique is used consistently into the future, its combination forecasts often will be much more accurate than those of any single best forecasting technique (in this example, technique 1). Combining is most effective when the individual forecasts bring different kinds of information into the forecasting process. Forecasters have achieved excellent results by weighting forecasts equally, and this is a good starting point. However, unequal weights may provide better results under some conditions.

OM Explorer and POM for Windows allow you to evaluate several forecasting models, and then you can create combination forecasts from them. The models can be the ones evaluated separately, but they can also include forecasts from the regression, judgment, or naive method. For example, you can create a simple Excel spreadsheet that combines forecasts generated by OM Explorer or POM for Windows to create combination forecasts. To evaluate the judgment method, the forecaster should be given actual demand just one period at a time, preferably as the actual events are happening, and then commit to a forecast for the next period. To be informed, the forecaster should also be aware of how well the other forecasting methods have been performing, particularly in the recent past. Managerial Practice 13.2 describes how Fiskars Brands uses combination forecasts as part of its demand planning system.

focus forecasting

A method of forecasting that selects the best forecast from a group of forecasts generated by individual techniques.

Another way to take advantage of multiple techniques is **focus forecasting**, which selects the best forecast (based on past error measures) from a group of forecasts generated by individual techniques. Every period, all techniques are used to make forecasts for each item. The forecasts are made with a computer because there can be 100,000 SKUs at a company, each needing to be forecast. Using the history file as the starting point for each method, the computer generates forecasts for the current period. The forecasts are compared to actual demand, and the method that produces the forecast with the least error is used to make the forecast for the next period. The method used for each item may change from period to period.

Putting It All Together: Forecasting As a Process

Forecasting is not just a set of techniques, but instead a process that must be designed and managed. While there is no one process that works for everyone, here we describe a comprehensive process that can be quite effective in managing operations and the supply chain.

A Typical Forecasting Process

Many *inputs* to the forecasting process are informational, beginning with the *history file* on past demand. The history file is kept up-to-date with the actual demands. Clarifying notes and adjustments are made to the database to explain unusual demand behavior, such as the impact of special promotions and closeouts. Often the database is separated into two parts: *base* data and *nonbase* data. The second category reflects irregular demands. Final forecasts just made at the end of the prior cycle are entered in the history file, so as to track forecast errors. Other information sources are from salesforce estimates, outstanding bids on new orders, booked orders, market research studies, competitor behavior, economic outlook, new product introductions, pricing, and promotions. If CPFR is used, considerable information sharing will take place with customers and suppliers. For new products, a history database is fabricated based on the firm's experience with prior products and the judgment of personnel.

Outputs of the process are forecasts for multiple time periods into the future. Typically they are on a monthly basis and are projected out from six months to two years. Most software packages have the ability to "roll up" or "aggregate" forecasts for individual stock-keeping units (SKUs) into forecasts for whole product families. Forecasts can also be "blown down" or "disaggregated" into smaller pieces. In a make-to-stock environment, forecasts tend to be more detailed and can get down to specific individual products. In a

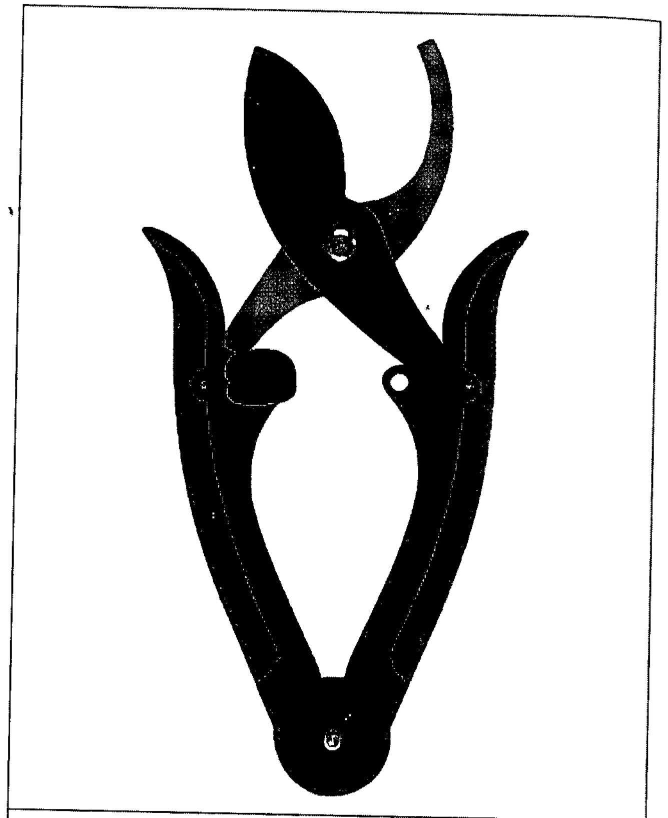
MANAGERIAL PRACTICE 13.2 Combination Forecasts and the Forecasting Process

Fiskars Brands, Inc., totally overhauled its forecasting process. It serves 2,000 customers ranging from large discounters to local craft stores providing about 2,300 finished SKUs. Its parent company, Fiskars Corporation, is the second oldest incorporated entity in the world and produces a variety of high-quality products such as garden shears, pruners, hand tools, scissors for preschoolers, ratchet tools, screwdrivers, and the like. Business is highly seasonal and prices quite variable. About 10 percent to 15 percent of the annual revenue comes from one-time promotions, and 25 percent to 35 percent of its products are new every year.

It introduced a statistical-based analysis along with a Web-based business intelligence tool for reporting. It put much more emphasis on combination forecasts. Instead of asking members of the sales staff to provide their own forecasts, forecasts were sent to them, and they were asked for their validation and refinement. Their inputs are most useful relative to additions, deletions, and promotions. Converting multiple forecasts into one number (forecasts from time-series techniques, sales input, and customer input) creates more accurate forecasts by SKU. Fiskars's software has the ability to weigh each input. It gives more weight to a statistical forecast for in-line items, and inputs from the sales staff get much more weight for promoted products and new items.

It also segments SKUs by value and forecastability so as to focus forecasting efforts on SKUs that have the biggest impact on the business. High-value items ("A" items identified with ABC analysis in Chapter 12, "Inventory Management") that also have high forecastability (stable demand with low forecast errors to date) tend to do well with the time-series techniques, and judgmental adjustments are made with caution. High-value items with low forecastability get top priority in the forecasting effort, such as with CPFR. Much less attention is given to improving forecasts for "C" items for which there is some history and fairly steady demand.

Finally, Fiskars instituted a Web-based program that gives the entire company visibility to forecast information in whatever form it needs. For example, Finance wants monthly, quarterly, and yearly projections in dollars, whereas Operations wants projections in units as well as accuracy measures. Everybody can track updated forecast information by customer, brand, and SKU.

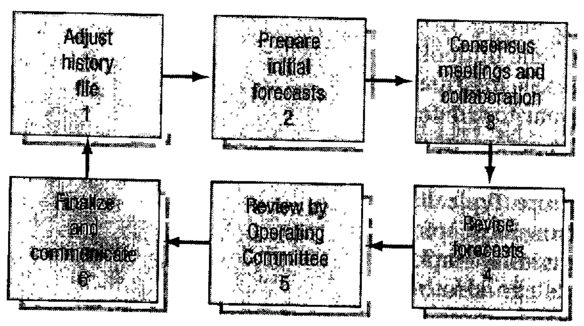


This power-point bypass pruner is one of 2,300 SKUs for which Fiskars Brands needs demand forecasts. Sales are quite seasonal and one-time promotions can be a factor. This garden tool is especially designed for people with limited hand strength. Combination forecasts that modify statistical forecasts with judgmental inputs from the sales staff improved their forecasting process.

Sources: David Montgomery, "Flashpoints for Changing Your Forecasting Process," *The Journal of Business Forecasting*, (Winter 2006–2007), pp. 35–37; http://www.fiskars.com, July 6, 2008.

make-to-order environment, the forecasts tend to be for groups of products. Similarly, if the lead times to buy raw materials and manufacture a product or provide a service are long, the forecasts go further out into the future.

The forecast process itself, typically done on a monthly basis, consists of structured steps. These steps often are facilitated by someone who might be called a demand manager, forecast analyst, or demand/supply planner. However, many other people are typically involved before the plan for the month is authorized.



Step 1. The cycle begins mid-month just after the forecasts have been finalized and communicated to the stakeholders. Now is the time to update the history file and review forecast accuracy. At the end of the month, enter actual demand and review forecast accuracy.

Step 2. Prepare initial forecasts using some forecasting software package and judgment. Adjust the parameters of the software to find models that fit the past demand well and yet reflect the demand manager's judgment on irregular events and information about future sales pulled from various sources and business units.

Step 3. Hold consensus meetings with the stakeholders, such as marketing, sales, supply chain planners, and finance. Make it easy for business unit and field sales personnel to make inputs. Use the Internet to get collaborative information from key customers and suppliers. The goal is to arrive at consensus forecasts from all of the important players.

Step 4. Revise the forecasts using judgment, considering the inputs from the consensus meetings and collaborative sources.

Step 5. Present the forecasts to the operating committee for review and to reach a final set of forecasts. It is important to have a set of forecasts that everybody agrees upon and will work to support.

Step 6. Finalize the forecasts based on the decisions of the operating committee and communicate them to the important stakeholders. Supply chain planners are usually the biggest users.

As with all work activity, forecasting is a process and should be continually reviewed for improvements. A better process will foster better relationships between departments such as marketing, sales, and operations. It will also produce better forecasts. This principle is the first one in Table 13.2 to guide process improvements.

Forecasting as a Nested Process

Forecasting is not a stand-alone activity, but instead part of a larger process that encompasses the remaining chapters. After all, demand is only half of the equation—the other half is supply. Future plans must be developed to supply the resources needed to meet the forecasted demand. Resources include the workforce, materials, inventories, dollars, and equipment capacity. Making sure that demand and supply plans are in balance begins in the next chapter, Chapter 14, "Operations Planning and Scheduling" and continues with Chapter 15, "Resource Planning."

TABLE 13.2 | SOME PRINCIPLES FOR THE FORECASTING PROCESS

- Better processes yield better forecasts.
- Demand forecasting is being done in virtually every company, either formally or informally. The challenge is to do it well—better than the competition.
- Better forecasts result in better customer service and lower costs, as well as better relationships with suppliers and customers.
- The forecast can and must make sense based on the big picture, economic outlook, market share, and so on.
- The best way to improve forecast accuracy is to focus on reducing forecast error.
- Bias is the worst kind of forecast error; strive for zero bias.
- Whenever possible, forecast at more aggregate levels. Forecast in detail only where necessary.
- Far more can be gained by people collaborating and communicating well than by using the most advanced forecasting technique or model.

Source: Adapted from Thomas F. Wallace and Robert A. Stahl, *Sales Forecasting: A New Approach* (Cincinnati, OH: T. E. Wallace & Company, 2002), p. 112.

INTERNET RESOURCES

myomlab and the Companion Website at **www.pearsonhighered.com** contain many tools, activities, and resources designed for this chapter.

KEY EQUATIONS

1. Linear regression: $Y = a + bX$
2. Naive forecasting: Forecast $= D_t$
3. Simple moving average:

$$F_{t+1} = \frac{D_t + D_{t-1} + D_{t-2} + \cdots + D_{t-n+1}}{n}$$

4. Weighted moving average:

$$F_{t+1} = \text{Weight}_1(D_t) + \text{Weight}_2(D_{t-1}) + \text{Weight}_3(D_{t-2}) + \cdots + \text{Weight}_n(D_{t-n+1})$$

5. Exponential smoothing:

$$F_{t+1} = \alpha D_t + (1-\alpha)F_t$$

$$F_{t+1} = F_t + \alpha(D_t - F_t)$$

6. Trend-adjusted exponential smoothing:

$$A_t = \alpha D_t + (1-\alpha)(A_{t-1}+T_{t-1})$$

$$T_t = \beta(A_t - A_{t-1}) + (1-\beta)T_{t-1}$$

$$F_{t+1} = A_t + T_t$$

7. Forecast error:

$$E_t = D_t - F_t$$

$$\text{CFE} = \Sigma E_t$$

$$\bar{E} = \frac{\text{CFE}}{n}$$

$$\text{MSE} = \frac{\Sigma E_t^2}{n}$$

$$\sigma = \sqrt{\frac{\Sigma(E_t - \bar{E})^2}{n-1}}$$

$$\text{MAD} = \frac{\Sigma|E_t|}{n}$$

$$\text{MAPE} = \frac{(\Sigma|E_t|/D_t)(100\%)}{n}$$

8. Tracking signal: $\frac{\text{CFE}}{\text{MAD}}$ or $\frac{\text{CFE}}{\text{MAD}_t}$

9. Exponentially smoothed error:

$$\text{MAD}_t = \alpha|E_t| + (1-\alpha)\text{MAD}_{t-1}$$

KEY TERMS

SOLVED PROBLEM 1

Chicken Palace periodically offers carryout five-piece chicken dinners at special prices. Let Y be the number of dinners sold and X be the price. Based on the historical observations and calculations in the following table, determine the regression equation, correlation coefficient, and coefficient of determination. How many dinners can Chicken Palace expect to sell at $3.00 each?

Observation	Price (X)	Dinners Sold (Y)
1	$ 2.70	760
2	$ 3.50	510
3	$ 2.00	980
4	$ 4.20	250
5	$ 3.10	320
6	$ 4.05	480
Total	$19.55	3,300
Average	$ 3.258	550

SOLUTION

We use the computer to calculate the best values of a, b, the correlation coefficient, and the coefficient of determination.

$$a = 1{,}454.60$$
$$b = -277.63$$
$$r = -0.84$$
$$r^2 = 0.71$$

The regression line is

$$Y = a + bX = 1{,}454.60 - 277.63X$$

The correlation coefficient ($r = -0.84$) shows a negative correlation between the variables. The coefficient of determination ($r^2 = 0.71$) is relatively small, which suggests that other variables (in addition to price) might appreciably affect sales.

If the regression equation is satisfactory to the manager, estimated sales at a price of $3.00 per dinner may be calculated as follows:

$$Y = a + bX = 1{,}454.60 - 277.63(3.00)$$
$$= 621.71 \text{ or } 622 \text{ dinners}$$

SOLVED PROBLEM 2

The Polish General's Pizza Parlor is a small restaurant catering to patrons with a taste for European pizza. One of its specialties is Polish Prize pizza. The manager must forecast weekly demand for these special pizzas so that he can order pizza shells weekly. Recently, demand has been as follows:

Week	Pizzas	Week	Pizzas
June 2	50	June 23	56
June 9	65	June 30	55
June 16	52	July 7	60

a. Forecast the demand for pizza for June 23 to July 14 by using the simple moving average method with $n = 3$. Then repeat the forecast by using the weighted moving average method with $n = 3$ and weights of 0.50, 0.30, and 0.20, with 0.50 applying to the most recent demand.

b. Calculate the MAD for each method.

SOLUTION

a. The simple moving average method and the weighted moving average method give the following results:

Current Week	Simple Moving Average Forecast for Next Week	Weighted Moving Average Forecast for Next Week
June 16	$\frac{52 + 65 + 50}{3} = 55.7$ or 56	$[(0.5 \times 52) + (0.3 \times 65) + (0.2 \times 50)] = 55.5$ or 56
June 23	$\frac{56 + 52 + 65}{3} = 57.7$ or 58	$[(0.5 \times 56) + (0.3 \times 52) + (0.2 \times 65)] = 56.6$ or 57
June 30	$\frac{55 + 56 + 52}{3} = 54.3$ or 54	$[(0.5 \times 55) + (0.3 \times 56) + (0.2 \times 52)] = 54.7$ or 55
July 7	$\frac{60 + 55 + 56}{3} = 57.0$ or 57	$[(0.5 \times 60) + (0.3 \times 55) + (0.2 \times 56)] = 57.7$ or 58

Forecasts in each row are for the next week's demand. For example, the simple moving average and weighted moving average forecasts (both are 56 units) calculated after learning the demand on June 16 apply to June 23's demand forecast.

b. The mean absolute deviation is calculated as follows:

		Simple Moving Average		Weighted Moving Average	
Week	Actual Demand	Forecast for This Week	Absolute Errors $\lvert E_t \rvert$	Forecast for This Week	Absolute Errors $\lvert E_t \rvert$
June 23	56	56	$\lvert 56-56 \rvert = 0$	56	$\lvert 56-56 \rvert = 0$
June 30	55	58	$\lvert 55-58 \rvert = 3$	57	$\lvert 55-57 \rvert = 2$
July 7	60	54	$\lvert 60-54 \rvert = 6$	55	$\lvert 60-55 \rvert = 5$
			$\text{MAD} = \frac{0+3+6}{3} = 3.0$		$\text{MAD} = \frac{0+2+5}{3} = 2.3$

For this limited set of data, the weighted moving average method resulted in a slightly lower mean absolute deviation. However, final conclusions can be made only after analyzing much more data.

SOLVED PROBLEM 3

The monthly demand for units manufactured by the Acme Rocket Company has been as follows:

Month	Units	Month	Units
May	100	September	105
June	80	October	110
July	110	November	125
August	115	December	120

a. Use the exponential smoothing method to forecast the number of units for June to January. The initial forecast for May was 105 units; $\alpha = 0.2$.

b. Calculate the absolute percentage error for each month from June through December and the MAD and MAPE of forecast error as of the end of December.

c. Calculate the tracking signal as of the end of December. What can you say about the performance of your forecasting method?

SOLUTION

a.

Current Month, t	Calculating Forecast for Next Month $F_{t+1} = \alpha D_t + (1-\alpha) F_t$	Forecast for Month $t + 1$
May	$0.2(100) + 0.8(105) = 104.0$ or 104	June
June	$0.2(80) + 0.8(104.0) = 99.2$ or 99	July
July	$0.2(110) + 0.8(99.2) = 101.4$ or 101	August
August	$0.2(115) + 0.8(101.4) = 104.1$ or 104	September
September	$0.2(105) + 0.8(104.1) = 104.3$ or 104	October
October	$0.2(110) + 0.8(104.3) = 105.4$ or 105	November
November	$0.2(125) + 0.8(105.4) = 109.3$ or 109	December
December	$0.2(120) + 0.8(109.3) = 111.4$ or 111	January

b.

Month, t	Actual Demand, D_t	Forecast, F_t	Error, $E_t = D_t - F_t$	Absolute Error, $\lvert E_t \rvert$	Absolute Percentage Error, $(\lvert E_t \rvert / D_t)(100\%)$
June	80	104	−24	24	30.0%
July	110	99	11	11	10.0
August	115	101	14	14	12.0
September	105	104	1	1	1.0
October	110	104	6	6	5.5
November	125	105	20	0	16.0
December	120	109	11	11	9.2
Total	765		39	87	83.7%

$$\text{MAD} = \frac{\Sigma \lvert E_t \rvert}{n} = \frac{87}{7} = 12.4 \text{ and } \text{MAPE} = \frac{(\Sigma \lvert E_t \rvert / D_t)(100)}{n} = \frac{83.7\%}{7} = 11.96\%$$

c. As of the end of December, the cumulative sum of forecast errors (CFE) is 39. Using the mean absolute deviation calculated in part (b), we calculate the tracking signal:

$$\text{Tracking signal} = \frac{\text{CFE}}{\text{MAD}} = \frac{39}{12.4} = 3.14$$

The probability that a tracking signal value of 3.14 could be generated completely by chance is small. Consequently, we should revise our approach. The long string of forecasts lower than actual demand suggests use of a trend method.

SOLVED PROBLEM 4

The Northville Post Office experiences a seasonal pattern of daily mail volume every week. The following data for two representative weeks are expressed in thousands of pieces of mail:

Day	Week 1	Week 2
Sunday	5	8
Monday	20	15
Tuesday	30	32
Wednesday	35	30
Thursday	49	45
Friday	70	70
Saturday	15	10
Total	224	210

a. Calculate a seasonal factor for each day of the week.

b. If the postmaster estimates 230,000 pieces of mail to be sorted next week, forecast the volume for each day of the week.

SOLUTION

a. Calculate the average daily mail volume for each week. Then for each day of the week divide the mail volume by the week's average to get the seasonal factor. Finally, for each day, add the two seasonal factors and divide by 2 to obtain the average seasonal factor to use in the forecast (see part [b]).

	Week 1		Week 2		
Day	Mail Volume	Seasonal Factor (1)	Mail Volume	Seasonal Factor (2)	Average Seasonal Factor [(1) + (2)]/2
Sunday	5	5/32 = 0.15625	8	8/30 = 0.26667	0.21146
Monday	20	20/32 = 0.62500	15	15/30 = 0.50000	0.56250
Tuesday	30	30/32 = 0.93750	32	32/30 = 1.06667	1.00209
Wednesday	35	35/32 = 1.09375	30	30/30 = 1.00000	1.04688
Thursday	49	49/32 = 1.53125	45	45/30 = 1.50000	1.51563
Friday	70	70/32 = 2.18750	70	70/30 = 2.33333	2.26042
Saturday	15	15/32 = 0.46875	10	10/30 = 0.33333	0.40104
Total	224		210		
Average	224/7 = 32		210/7 = 30		

b. The average daily mail volume is expected to be 230,000/7 = 32,857 pieces of mail. Using the average seasonal factors calculated in part (a), we obtain the following forecasts:

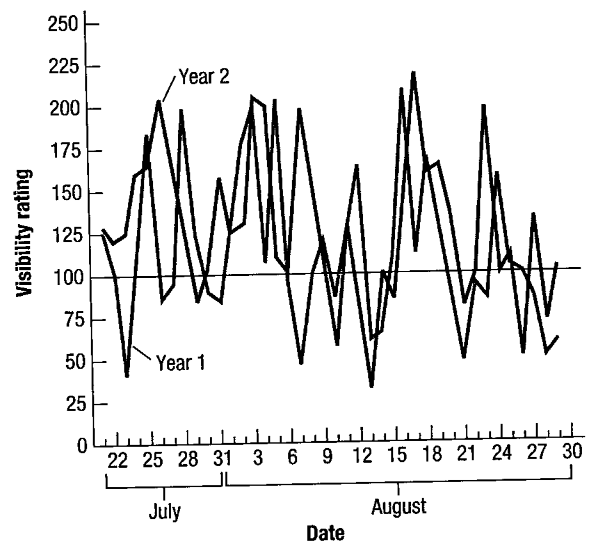
Day	Calculation	Forecast
Sunday	0.21146(32,857) =	6,948
Monday	0.56250(32,857) =	18,482
Tuesday	1.00209(32,857) =	32,926
Wednesday	1.04688(32,857) =	34,397
Thursday	1.51563(32,857) =	49,799
Friday	2.26042(32,857) =	74,271
Saturday	0.40104(32,857) =	13,177
	Total	230,000

DISCUSSION QUESTIONS

1. Figure 13.8 shows summer air visibility measurements for Denver, Colorado. The acceptable visibility standard is 100, with readings above 100 indicating clean air and good visibility, and readings below 100 indicating temperature inversions caused by forest fires, volcanic eruptions, or collisions with comets.

   a. Is a trend evident in the data? Which time-series techniques might be appropriate for estimating the average of these data?

   b. A medical center for asthma and respiratory diseases located in Denver has great demand for its services when air quality is poor. If you were in charge of developing a short-term (say, three-day) forecast of visibility, which causal factor(s) would you analyze? In other words, which external factors hold the potential to significantly affect visibility in the *short term*?



▲ FIGURE 13.8

   c. Tourism, an important factor in Denver's economy, is affected by the city's image. Air quality, as measured by visibility, affects the city's image. If you were responsible for development of tourism, which causal factor(s) would you analyze to forecast visibility for the *medium term* (say, the next two summers)?

   d. The federal government threatens to withhold several hundred million dollars in Department of Transportation funds unless Denver meets visibility standards within eight years. How would you proceed to generate a *long-term* judgment forecast of technologies that will be available to improve visibility in the next 10 years?

2. Kay and Michael Passe publish *What's Happening?*—a biweekly newspaper to publicize local events. *What's Happening?* has few subscribers; it typically is sold at checkout stands. Much of the revenue comes from advertisers of garage sales and supermarket specials. In an effort to reduce costs associated with printing too many papers or delivering them to the wrong location, Michael implemented a computerized system to collect sales data. Sales-counter scanners accurately record sales data for each location. Since the system was implemented, total sales volume has steadily declined. Selling advertising space and maintaining shelf space at supermarkets are getting more difficult.

   Reduced revenue makes controlling costs all the more important. For each issue, Michael carefully makes a forecast based on sales data collected at each location. Then he orders papers to be printed and distributed in quantities matching the forecast. Michael's forecast reflects a downward trend, which *is* present in the sales data. Now only a few papers are left over at only a few locations. Although the sales forecast accurately predicts the actual sales at most locations, *What's Happening?* is spiraling toward oblivion. Kay suspects that Michael is doing something wrong in preparing the forecast but can find no mathematical errors. Tell her what is happening.

PROBLEMS

Software, such as OM Explorer, Active Models, and POM for Windows, is available in **myomlab**. Check with your instructor on how best to use it. In many cases, the instructor wants you to understand how to do the calculations by hand. At most, the software provides a check on your calculations. When calculations are particularly complex and the goal is interpreting the results in making decisions, the software replaces entirely the manual calculations.

1. The owner of a computer store rents printers to some of her preferred customers. She is interested in arriving at a forecast of rentals so that she can order the correct quantities of supplies that go with the printers. Data for the last 10 weeks are shown here.

Week	Rentals	Week	Rentals
1	23	6	28
2	24	7	32
3	32	8	35
4	26	9	26
5	31	10	24

a. Prepare a forecast for weeks 6 through 10 by using a five-week moving average. What is the forecast for week 11?

b. Calculate the mean absolute deviation as of the end of week 10.

2. Sales for the past 12 months at Dalworth Company are given here.

Month	Sales ($ millions)	Month	Sales ($millions)
January	20	July	53
February	24	August	62
March	27	September	54
April	31	October	36
May	37	November	32
June	47	December	29

a. Use a three-month moving average to forecast the sales for the months May through December.

b. Use a four-month moving average to forecast the sales for the months May through December.

c. Compare the performance of the two methods by using the mean absolute deviation as the performance criterion. Which method would you recommend?

d. Compare the performance of the two methods by using the mean absolute percent error as the performance criterion. Which method would you recommend?

e. Compare the performance of the two methods by using the mean squared error as the performance criterion. Which method would you recommend?

3. Karl's Copiers sells and repairs photocopy machines. The manager needs weekly forecasts of service calls so that he can schedule service personnel. Use the actual demand in the first period for the forecast for the first week so error measurement begins in the second week. The manager uses exponential smoothing with $\alpha = 0.20$. Forecast the number of calls for week 6, which is next week.

Week	Actual Service Calls
1	24
2	32
3	36
4	23
5	25

4. Consider the sales data for Dalworth Company given in Problem 2.

a. Use a three-month weighted moving average to forecast the sales for the months April through December. Use weights of (3/6), (2/6), and (1/6), giving more weight to more recent data.

b. Use exponential smoothing with $\alpha = 0.6$ to forecast the sales for the months April through December. Assume that the initial forecast for January was $20 million. Start error measurement in April.

c. Compare the performance of the two methods by using the mean absolute deviation as the performance criterion, with error measurement beginning in April. Which method would you recommend?

d. Compare the performance of the two methods by using the mean absolute percent error as the performance criterion, with error measurement beginning in April. Which method would you recommend?

e. Compare the performance of the two methods by using the mean squared error as the performance criterion, with error measurement beginning in April. Which method would you recommend?

5. A convenience store recently started to carry a new brand of soft drink in its territory. Management is interested in estimating future sales volume to determine whether it should continue to carry the new brand or replace it with another brand. At the end of April, the average monthly sales volume of the new soft drink was 700 cans and the trend was +50 cans per month. The actual sales volume figures for May, June, and July are 760, 800, and 820, respectively. Use trend-adjusted exponential smoothing with $\alpha = 0.2$ and $\beta = 0.1$ to forecast usage for June, July, and August.

6. Community Federal Bank in Dothan, Alabama, recently installed a new automatic teller machine to perform the standard banking services and handle loan applications and investment transactions. The new machine is a bit complicated to use, so management is interested in tracking its past use and projecting its future use. Additional machines may be needed if projected use is high enough.

At the end of April, the average monthly use was 600 customers and the trend was +60 customers per month. The actual use figures for May, June, and July are 680, 710, and 790, respectively. Use trend-adjusted exponential smoothing with $\alpha = 0.3$ and $\beta = 0.2$ to forecast usage for June, July, and August.

7. The number of heart surgeries performed at Heartville General Hospital has increased steadily over the past several years. The hospital's administration is seeking the best method to forecast the demand for such surgeries in year 6. The data for the past five years are shown.

Year	Demand
1	45
2	50
3	52
4	56
5	58

The hospital's administration is considering the following forecasting methods. Begin error measurement in year 3, so all methods are compared for the same years.

i. Exponential smoothing, with $\alpha = 0.6$. Let the initial forecast for year 1 be 45, the same as the actual demand.

ii. Exponential smoothing, with $\alpha = 0.9$. Let the initial forecast for year 1 be 45, the same as the actual demand.

iii. Trend-adjusted exponential smoothing, with $\alpha = 0.6$ and $\beta = 0.1$. Use the actual demand for year 1 for the initial average for the first year and 0 for the initial trend.

iv. Two-year moving average.

v. Two-year weighted moving average, using weights 0.6 and 0.4, with more recent data given more weight.

vi. Regression model, $Y = 42.6 + 3.2X$, where Y is the number of surgeries and X is the index for the year (e.g., $X = 1$ for year 1, $X = 2$ for year 2, and so forth).

a. If MAD is the performance criterion chosen by the administration, which forecasting method should it choose?

b. If MSE is the performance criterion chosen by the administration, which forecasting method should it choose?

c. If MAPE is the performance criterion chosen by the administration, which forecasting method should it choose?

8. The following data are for calculator sales in units at an electronics store over the past five weeks:

Week	Sales
1	46
2	49
3	43
4	50
5	53

Use trend-adjusted exponential smoothing with $\alpha = 0.2$ and $\beta = 0.2$ to forecast sales for weeks 3 through 6. Assume that the average of the time series was 45 units and that the average trend was +2 units per week just before week 1.

9. The demand for Krispee Crunchies, a favorite breakfast cereal of people born in the 1940s, is experiencing a decline. The company wants to monitor demand for this product closely as it nears the end of its life cycle. The trend-adjusted exponential smoothing method is used with $\alpha = 0.1$ and $\beta = 0.2$. At the end of December, the updated estimate for the average number of cases sold per month, A_t, was 900,000 and the updated trend, T_t, was −50,000 per month. The following table shows the actual sales history for January, February, and March. Generate forecasts for February, March, and April.

Month	Sales
January	890,000
February	800,000
March	825,000

10. Forrest and Dan make boxes of chocolates for which the demand is uncertain. Forrest says, "That's life." On the other hand, Dan believes that some demand patterns exist that could be useful for planning the purchase of sugar, chocolate, and shrimp. Forrest insists on placing a surprise chocolate-covered shrimp in some boxes so that "You never know what you'll get." Quarterly demand (in boxes of chocolates) for the last three years follows:

Quarter	Year 1	Year 2	Year 3
1	3,000	3,300	3,502
2	1,700	2,100	2,448
3	900	1,500	1,768
4	4,400	5,100	5,882
Total	10,000	12,000	13,600

a. Use intuition and judgment to estimate quarterly demand for the fourth year.

b. If the expected sales for chocolates are 14,800 cases for year 4, use the multiplicative seasonal method to prepare a forecast for each quarter of the year. Are any of the quarterly forecasts different from what you thought you would get in part (a)?

11. The manager of Snyder's Garden Center must make the annual purchasing plans for rakes, gloves, and other gardening items. One of the items the company stocks is Fast-Grow, a liquid fertilizer. The sales of this item are seasonal, with peaks in the spring, summer, and fall months. Quarterly demand (in cases) for the past two years follows:

Quarter	Year 1	Year 2
1	40	60
2	350	440
3	290	320
4	210	280
Total	890	1,100

If the expected sales for Fast-Grow are 1,150 cases for year 3, use the multiplicative seasonal method to prepare a forecast for each quarter of the year.

12. The manager of a utility company in the Texas panhandle wants to develop quarterly forecasts of power loads for the next year. The power loads are seasonal, and the data on the quarterly loads in megawatts (MW) for the last four years are as follows:

Quarter	Year 1	Year 2	Year 3	Year 4
1	103.5	94.7	118.6	109.3
2	126.1	116.0	141.2	131.6
3	144.5	137.1	159.0	149.5
4	166.1	152.5	178.2	169.0

The manager estimates the total demand for the next year at 600 MW. Use the multiplicative seasonal method to develop the forecast for each quarter.

13. Demand for oil changes at Garcia's Garage has been as follows:

Month	Number of Oil Changes
January	41
February	46
March	57
April	52
May	59
June	51
July	60
August	62

a. Use simple linear regression analysis to develop a forecasting model for monthly demand. In this application, the dependent variable, Y, is monthly demand and the independent variable, X, is the month. For January, let $X = 1$; for February, let $X = 2$; and so on.

b. Use the model to forecast demand for September, October, and November. Here, $X = 9$, 10, and 11, respectively.

14. At a hydrocarbon processing factory, process control involves periodic analysis of samples for a certain process quality parameter. The analytic procedure currently used is costly and time consuming. A faster and more economical alternative procedure has been proposed. However, the numbers for the quality parameter given by the alternative procedure are somewhat different from those given by the current procedure, not because of any inherent errors but because of changes in the nature of the chemical analysis.

Management believes that if the numbers from the new procedure can be used to forecast reliably the corresponding numbers from the current procedure, switching to the new procedure would be reasonable and cost effective. The following data were obtained for the quality parameter by analyzing samples using both procedures:

Current (Y)	Proposed (X)	Current (Y)	Proposed (X)
3.0	3.1	3.1	3.1
3.1	3.9	2.7	2.9
3.0	3.4	3.3	3.6
3.6	4.0	3.2	4.1
3.8	3.6	2.1	2.6
2.7	3.6	3.0	3.1
2.7	3.6	2.6	2.8

a. Use linear regression to find a relation to forecast Y, which is the quality parameter from the current procedure, using the values from the proposed procedure, X.

b. Is there a strong relationship between Y and X? Explain.

15. Ohio Swiss Milk Products manufactures and distributes ice cream in Ohio, Kentucky, and West Virginia. The company wants to expand operations by locating another plant in northern Ohio. The size of the new plant will be a function of the expected demand for ice cream within the area served by the plant. A market survey is currently under way to determine that demand.

Ohio Swiss wants to estimate the relationship between the manufacturing cost per gallon and the number of gallons sold in a year to determine the demand for ice cream and, thus, the size of the new plant. The following data have been collected:

a. Develop a regression equation to forecast the cost per gallon as a function of the number of gallons produced.

Plant	Cost per Thousand Gallons (Y)	Thousands of Gallons Sold (X)
1	$1,015	416.9
2	973	472.5
3	1,046	250.0
4	1,006	372.1
5	1,058	238.1
6	1,068	258.6
7	967	597.0
8	997	414.0
9	1,044	263.2
10	1,008	372.0
Total	$10,182	3,654.4

b. What are the correlation coefficient and the coefficient of determination? Comment on your regression equation in light of these measures.

c. Suppose that the market survey indicates a demand of 325,000 gallons in the Bucyrus, Ohio, area. Estimate the manufacturing cost per gallon for a plant producing 325,000 gallons per year.

ADVANCED PROBLEMS

16. The past demands at a medical clinic follow:

Week	Demand	Week	Demand
1	400	15	383
2	380	16	402
3	411	17	387
4	415	18	410
5	393	19	398
6	375	20	433
7	410	21	415
8	395	22	380
9	406	23	394
10	424	24	412
11	433	25	439
12	391	26	416
13	396	27	395
14	417	28	419

The clinic's administration is considering the following forecasting methods. Use OM Explorer or POM for Windows to evaluate each one. Start error measurement in the fourth week, so all methods are evaluated over the same periods.

(i) Naive (1-Period Moving Average)

(ii) 3-Period Weighted Moving Average, using weights of 0.70, 0.20, and 0.10, with more recent data given more weight

(iii) Exponential smoothing, with $\alpha = 0.10$

(iv) Trend-adjusted exponential smoothing, with $\alpha = 0.10$ and $\beta = 0.10$. Use 400 for the initial average and an initial trend of 0.

a. If CFE (or mean bias) is the performance criterion chosen by the administration, which forecasting method should it choose?

b. If MAD is the performance criterion chosen by the administration, which forecasting method should it choose?

c. If MSE is the performance criterion chosen by the administration, which forecasting method should it choose?

d. If MAPE is the performance criterion chosen by the administration, which forecasting method should it choose?

17. Create an Excel spreadsheet on your own that can create a combination forecast for Problem 16, using the three techniques that seem best based on MAD. Give equal weight to each technique. Calculate MAD for the combination forecast. Is it better or worse than the forecasting techniques identified in Problem 16?

18. The director of a large public library must schedule employees to reshelve books and periodicals checked out of the library. The number of items checked out will determine the labor requirements. The following data reflect the number of items checked out of the library for the past three years:

Month	Year 1	Year 2	Year 3
January	1,847	2,045	1,986
February	2,669	2,321	2,564
March	2,467	2,419	2,635
April	2,432	2,088	2,150
May	2,464	2,667	2,201
June	2,378	2,122	2,663
July	2,217	2,206	2,055
August	2,445	1,869	1,678
September	1,894	2,441	1,845
October	1,922	2,291	2,065
November	2,431	2,364	2,147
December	2,274	2,189	2,451

The director needs a time-series method for forecasting the number of items to be checked out during the next month. Find the best simple moving average forecast you can. Decide what is meant by "best" and justify your decision.

19. Using the data in Problem 18, find the best exponential smoothing solution you can. Justify your choice.

20. Using the data in Problem 18, find the best trend-adjusted exponential smoothing solution you can. Compare the performance of this method with those of the best moving average method and the exponential smoothing method. Which of the three methods would you choose?

21. Cannister, Inc., specializes in the manufacture of plastic containers. The data on the monthly sales of 10-ounce shampoo bottles for the past five years are as follows:

Year	1	2	3	4	5
January	742	741	896	951	1,030
February	697	700	793	861	1,032
March	776	774	885	938	1,126
April	898	932	1,055	1,109	1,285
May	1,030	1,099	1,204	1,274	1,468
June	1,107	1,223	1,326	1,422	1,637
July	1,165	1,290	1,303	1,486	1,611
August	1,216	1,349	1,436	1,555	1,608
September	1,208	1,341	1,473	1,604	1,528
October	1,131	1,296	1,453	1,600	1,420
November	971	1,066	1,170	1,403	1,119
December	783	901	1,023	1,209	1,013

a. Using the multiplicative seasonal method, calculate the monthly seasonal indices.

b. Develop a simple linear regression equation to forecast annual sales. For this regression, the dependent variable, Y, is the demand in each year and the independent variable, X, is the index for the year (i.e., $X = 1$ for year 1, $X = 2$ for year 2, and so on until $X = 5$ for year 5).

c. Forecast the annual sales for year 6 by using the regression model you developed in part (b).

d. Prepare the seasonal forecast for each month by using the monthly seasonal indices calculated in part (a).

22. The Midwest Computer Company serves a large number of businesses in the Great Lakes region. The company sells supplies and replacements and performs service on all computers sold through seven sales offices. Many items are stocked, so close inventory control is necessary to assure customers of efficient service. Recently, business has been increasing, and management is concerned about stockouts. A forecasting method is needed to estimate requirements several months in advance so that adequate replenishment quantities can be purchased. An example of the sales growth experienced during the last 50 months is the growth in demand for item EP-37, a laser printer cartridge, shown in Table 13.3.

a. Develop a trend-adjusted exponential smoothing solution using POM for Windows for forecasting demand. Find the "best" parameters and justify your choices. Forecast demand for month 51.

b. A consultant to Midwest's management suggested that new office building leases would be a good leading indicator for company sales. The consultant quoted a recent university study finding that new office building leases precede office equipment and supply sales by three months. According to the study findings, leases in month 1 would affect sales in month 4, leases in month 2 would affect sales in month 5, and so on. Use POM for Windows' linear regression module to develop a forecasting model for sales, with leases as the independent variable. Forecast sales for month 51.

c. Which of the two models provides better forecasts? Explain.

23. A certain food item at P&Q Supermarkets has the demand pattern shown in the table at the bottom of the next page. Find the "best" forecast you can for month 25 and justify your methodology. You may use some of the data to find the best parameter value(s) for your method and the rest to test the forecast model. Your justification should include both quantitative and qualitative considerations.

TABLE 13.3 | EP-37 SALES AND LEASE DATA

Month	EP-37 Sales	Leases	Month	EP-37 Sales	Leases
1	80	32	26	1,296	281
2	132	29	27	1,199	298
3	143	32	28	1,267	314
4	180	54	29	1,300	323
5	200	53	30	1,370	309
6	168	89	31	1,489	343
7	212	74	32	1,499	357
8	254	93	33	1,669	353
9	397	120	34	1,716	360
10	385	113	35	1,603	370
11	472	147	36	1,812	386
12	397	126	37	1,817	389
13	476	138	38	1,798	399
14	699	145	39	1,873	409
15	545	160	40	1,923	410
16	837	196	41	2,028	413
17	743	180	42	2,049	439
18	722	197	43	2,084	454
19	735	203	44	2,083	441
20	838	223	45	2,121	470
21	1,057	247	46	2,072	469
22	930	242	47	2,262	490
23	1,085	234	48	2,371	496
24	1,090	254	49	2,309	509
25	1,218	271	50	2,422	522

Month	Demand	Month	Demand
1	33	13	37
2	37	14	43
3	31	15	56
4	39	16	41
5	54	17	36
6	38	18	39
7	42	19	41
8	40	20	58
9	41	21	42
10	54	22	45
11	43	23	41
12	39	24	38

24. The data for the visibility chart in Discussion Question 1 are shown in Table 13.4. The visibility standard is set at 100. Readings below 100 indicate that air pollution has reduced visibility, and readings above 100 indicate that the air is clearer.

a. Use several methods to generate a visibility forecast for August 31 of the second year. Which method seems to produce the best forecast?

b. Use several methods to forecast the visibility index for the summer of the third year. Which method seems to produce the best forecast? Support your choice.

25. Tom Glass forecasts electrical demand for the Flatlands Public Power District (FPPD). The FPPD wants to take its Comstock power plant out of service for maintenance when demand is expected to be low. After shutdown, performing maintenance and getting the plant back on line takes two weeks. The utility has enough other generating

TABLE 13.4 | VISIBILITY DATA

Date	Year 1	Year 2	Date	Year 1	Year 2	Date	Year 1	Year 2
July 22	125	130	Aug 5	105	200	Aug. 19	170	160
23	100	120	6	205	110	20	125	165
24	40	125	7	90	100	21	85	135
25	100	160	8	45	200	22	45	80
26	185	165	9	100	160	23	95	100
27	85	205	10	120	100	24	85	200
28	95	165	11	85	55	25	160	100
29	200	125	12	125	130	26	105	110
30	125	85	13	165	75	27	100	50
31	90	105	14	60	30	28	95	135
Aug 1	85	160	15	65	100	29	50	70
2	135	125	16	110	85	30	60	105
3	175	130	17	210	150			
4	200	205	18	110	220			

capacity to satisfy 1,550 megawatts (MW) of demand while Comstock is out of service. Table 13.5 shows weekly peak demands (in MW) for the past several autumns. When next fall should the Comstock plant be scheduled for maintenance?

26. A manufacturing firm has developed a skills test, the scores from which can be used to predict workers' production ratings factors. Data on the test scores of various workers and their subsequent production ratings are shown.

Worker	Test Score	Production Rating	Worker	Test Score	Production Rating
A	53	45	K	54	59
B	36	43	L	73	77
C	88	89	M	65	56
D	84	79	N	29	28
E	86	84	O	52	51
F	64	66	P	22	27
G	45	49	Q	76	76
H	48	48	R	32	34
I	39	43	S	51	60
J	67	76	T	37	32

a. Using POM for Windows' least squares-linear regression module, develop a relationship to forecast production ratings from test scores.

b. If a worker's test score was 80, what would be your forecast of the worker's production rating?

c. Comment on the strength of the relationship between the test scores and production ratings.

27. The materials handling manager of a manufacturing company is trying to forecast the cost of maintenance for the company's fleet of over-the-road tractors. The manager believes that the cost of maintaining the tractors increases with their age. The following data was collected:

Age (years)	Yearly Maintenance Cost ($)	Age (years)	Yearly Maintenance Cost ($)
4.5	619	5.0	1,194
4.5	1,049	0.5	163
4.5	1,033	0.5	182
4.0	495	6.0	764
4.0	723	6.0	1,373
4.0	681	1.0	978
5.0	890	1.0	466
5.0	1,522	1.0	549
5.5	987		

a. Use POM for Windows' least squares-linear regression module to develop a relationship to forecast the yearly maintenance cost based on the age of a tractor.

b. If a section has 20 three-year-old tractors, what is the forecast for the annual maintenance cost?

TABLE 13.5 | WEEKLY PEAK POWER DEMANDS

	August		September						October			November	
Year	1	2	3	4	5	6	7	8	9	10	11	12	13
1	2,050	1,925	1,825	1,525	1,050	1,300	1,200	1,175	1,350	1,525	1,725	1,575	1,925
2	2,000	2,075	2,225	1,800	1,175	1,050	1,250	1,025	1,300	1,425	1,625	1,950	1,950
3	1,950	1,800	2,150	1,725	1,575	1,275	1,325	1,100	1,500	1,550	1,375	1,825	2,000
4	2,100	2,400	1,975	1,675	1,350	1,525	1,500	1,150	1,350	1,225	1,225	1,475	1,850
5	2,275	2,300	2,150	1,525	1,350	1,475	1,475	1,175	1,375	1,400	1,425	1,550	1,900

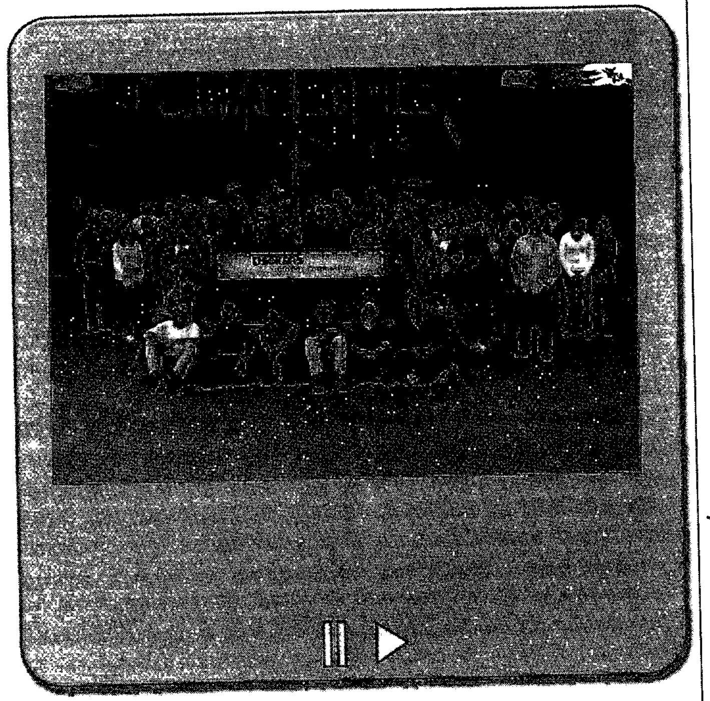
VIDEO CASE — Forecasting and Supply Chain Management at Deckers Outdoor Corporation

Deckers Outdoor Corporation's footwear products are among some of the most well-known brands in the world. From UGG sheepskin boots and Teva sport sandals to Simple shoes, Deckers flip-flops, and Tsubo footwear, Deckers is committed to building niche footwear brands into global brands with market leadership positions. Net sales for fiscal year 2007 were close to $449 million. In addition to traditional retail store outlets for Deckers' footwear styles, the company maintains an active and growing "direct to consumer" e-commerce business. Since most retail stores cannot carry every style in every color and size, the company offers the full line for each of its brands directly to consumers through the brands' individual Web sites. Online sales at its virtual store are handled by its e-commerce group. Customers who want a pair of shoes not available at the retail store can always buy from the virtual store.

Founded in 1973, the company manufactured a single line of sandals in a small factory in Southern California. The challenges of managing the raw materials and finished goods inventories were small compared to today's global sourcing and sales challenges for the company's various brands. Today, each brand has its own development team and brand managers who generate, develop, and test-market the seasonal styles that appear on the shelves of retailers such as Nordstrom, Lord & Taylor, REI, the Walking Company, and the company's own UGG brand retail stores in the United States and Japan.

At Deckers, forecasting is the starting point for inventory management, sales and operations planning, resource planning, and scheduling—in short, managing its supply chain. It carries a considerable amount of seasonal stock. Shoes with seasonal demand that are left over at the end of their season must be sold at heavily discounted prices. Its products fall into three categories: (1) carry-over items that were sold in prior years, (2) new items that look similar to past models, and (3) completely new designs that are fashionable with no past history.

Twice a year, the brand development teams work on the fall and spring product lines. They come up with new designs about one year in advance of each season. Each brand (UGG, Teva, Simple, Tsubo, and Deckers) contains numerous products, called stock keeping units (SKUs). The materials for new designs are selected and tested in prototypes. Approved designs are put into the seasonal line-up. Forecasts must be made at both the SKU and aggregate levels months before the season begins. "Bottoms-up" forecasts for each SKU begin by analyzing any available history files of past demand. Judgment forecasts are also important inputs, particularly for the second and third categories of shoes that are not carry-overs. For example, Char Nicanor-Kimball is an expert in spotting trends in shoe sales and makes forecasts for the virtual store. For new designs, historical sales on similar items are used to make a best guess on demand for those items. This process is facilitated by a forecasting and inventory system on the company's Intranet. At the same time, the sales teams for each brand call on their retail accounts and secure customer orders of approved designs for the coming season. Then the virtual store forecasts are merged with orders from the retail store orders to get the total seasonal demand forecasted by SKU. Next, the SKU forecasts are "rolled up" by category and "top down" forecasts are also made.



The Deckers Family.

These forecasts then go to top management where some adjustments may be made to account for financial market conditions, consumer credit, weather, demographic factors, and customer confidence. The impact of public relations and advertising must also be considered.

Actually, forecasting continues on throughout the year on a daily and weekly basis to "get a handle" on demand. Comparing actual demand with what was forecasted for different parts of the season also helps the forecasters make better forecasts for the future and better control inventories.

Based on initial demand forecasts, the company must begin sourcing the materials needed to produce the footwear. The company makes most of its products in China and sources many of the raw materials there as well. For UGG products sheepskin sourcing occurs in Australia with top grade producers, but the rawhide tanning still takes places in China. With potential suppliers identified and assurance from internal engineering that the footwear can be successfully made, the engineering and material data are handed over to the manufacturing department to determine how best to make the footwear in mass quantities. At this point, Deckers places a seasonal "buy" with its suppliers.

The orders for each SKU are fed into the manufacturing schedules at the Chinese factories. All the SKUs for a given brand are manufactured at the same factory. While Deckers agents negotiate the raw materials contracts early in the development process, the factories only place the orders for the raw materials when the company sends in the actual orders for the finished goods. No footwear is made by the factories until orders are received.

At the factories, finished goods footwear is inspected and packaged for the month-long ocean voyage from Hong Kong to ports in the United States. Deckers ships fifty containers a week from its Chinese manufacturing sources, each holding approximately 5,000 pairs of shoes. Ownership of the finished goods transfers from the factories to Deckers in Hong Kong.

When the shipping containers arrive in the United States, the footwear is transferred to Deckers' distribution centers in Southern California. Teva products are warehoused in Ventura, California; all other products are handled by the company's state-of-the-art facility in Camarillo, California. Typically, Deckers brings product into the distribution centers two to three months in advance of expected needs so that the production at the suppliers' factories and the labor activities at the distribution centers are leveled. There are definitive spikes in the demand for footwear, with Teva spiking in Quarter 1 and UGG spiking in Quarter 4. The leveling approach works to keep costs low in the supply chain. However, it also means that Deckers must maintain sizeable inventories. Most shipments from suppliers come in to the distribution centers and are stored in inventory for one to two months awaiting a customer order. By the time the footwear is stocked in the distribution center, the company knows which retail customers will be getting the various products, based on the orders booked months earlier. Then, according to delivery schedules negotiated with the customers, the company begins filling orders and shipping products to retail locations. The warehouse tracks incoming shipments, goods placed on the shelves for customers, and outgoing orders. The inventory system helps manage the customer order filling process.

Because the booked orders are a relatively large proportion of the total orders from retailers, and the number of unanticipated orders is very small, only small safety stocks are needed to service the retailers. Occasionally, the purchase order from Deckers to one of its suppliers matches the sales order from the customer. In such a case, Deckers uses a "cross-dock" system. When the shipment is received at the distribution center, it is immediately checked in and loaded on another truck for delivery to customers. Cross docking reduces the need to store vast quantities of product for long periods of time and cuts down on warehousing expenses for Deckers. The company has been successful in turning its inventory over about four times a year, which is in line with footwear industry standards.

The online sales traffic is all managed centrally. In fact, for ordering and inventory management purposes, the online side of the business is treated just like another major retail store account. As forecasted seasonal orders are generated by each brand's sales team, a manufacturing order for the online business is placed by the e-commerce sales team at the same time. However, unlike the retail outlets that take delivery of products on a regular schedule, the inventory pledged to the online business is held in the distribution center until a Web site order is received. Only then is it shipped directly to the consumer who placed the online order. If actual demand exceeds expected demand, Char checks if more inventory can be secured from other customer orders that have scaled back.

The forecasting and supply chain management challenges now facing Deckers are two-fold. First, the company plans to grow the brands that have enjoyed seasonal sales activity into year-round footwear options for consumers by expanding the number of SKUs for those brands. For example, most sales for UGG footwear occur in the fall/winter season. Sales for Teva historically have been in the spring and summer. Product managers are now working to develop styles that will allow the brands to cross over the seasons. Second, the company plans to expand internationally, and will have retail outlets in Europe, China, and other Asian locations in the very near future. Company managers are well aware of the challenges and opportunities such global growth will bring, and are taking steps now to assure that the entire supply chain is prepared to forecast and handle the demand when the time comes.

QUESTIONS

1. How much does the forecasting process at Deckers correspond with the "typical forecasting process" described at the end of this chapter?
2. Based on what you see in the video, what kinds of information technology are used to make forecasts, maintain accurate inventory records, and project future inventory levels?
3. What factors make forecasting at Deckers particularly challenging? How can forecasts be made for seasonal, fashionable products for which there is no history file? What are the costs of over-forecasting demand for such items? Under-forecasting?
4. How does the concept of *postponement* get implemented at Deckers by having online sales and positioning inventory at the DCs for every model, color, and size?
5. Where in the supply chain are cycle, pipeline, safety stock, and anticipation inventories being created?
6. What are the benefits of leveling aggregate demand by having a portfolio of SKUs that create 365-day demand?
7. Deckers plans to expand internationally, thereby increasing the volume of shoes it must manage in the supply chain and the pattern of material flows. What implications does this strategy have on forecasting, order quantities, logistics, and relationships with its suppliers and customers?

CASE Yankee Fork and Hoe Company

The Yankee Fork and Hoe Company is a leading producer of garden tools ranging from wheelbarrows, mortar pans, and hand trucks to shovels, rakes, and trowels. The tools are sold in four different product lines ranging from the top-of-the-line Hercules products, which are rugged tools for the toughest jobs, to the Garden Helper products, which are economy tools for the occasional user. The market for garden tools is extremely competitive because of the simple design of the products and the large number of competing producers. In addition, more people are using power tools, such as lawn edgers, hedge trimmers, and thatchers, reducing demand for their manual counterparts. These factors compel Yankee to maintain low prices while retaining high quality and dependable delivery.

Garden tools represent a mature industry. Unless new manual products can be developed or a sudden resurgence occurs in home gardening, the prospects for large increases in sales are not bright. Keeping ahead of the competition is a constant battle. No one knows this better than Alan Roberts, president of Yankee.

The types of tools sold today are, by and large, the same ones sold 30 years ago. The only way to generate new sales and retain old customers is to provide superior customer service and produce a product with high customer value. This approach puts pressure on the manufacturing system, which has been having difficulties lately. Recently, Roberts has been receiving calls from long-time customers, such as Sears and True Value Hardware Stores, complaining about late shipments. These customers advertise promotions for garden tools and require on-time delivery.

Roberts knows that losing customers like Sears and True Value would be disastrous. He decides to ask consultant Sharon Place to look into the matter and report to him in one week. Roberts suggests that she focus on the bow rake as a case in point because it is a high-volume product and has been a major source of customer complaints of late.

Planning Bow Rake Production

A bow rake consists of a head with 12 teeth spaced 1 inch apart, a hardwood handle, a bow that attaches the head to the handle, and a metal ferrule that reinforces the area where the bow inserts into the handle. The bow is a metal strip that is welded to the ends of the rake head and bent in the middle to form a flat tab for insertion into the handle. The rake is about 64 inches long.

Place decides to find out how Yankee plans bow rake production. She goes straight to Phil Stanton, who gives the following account:

> Planning is informal around here. To begin, marketing determines the forecast for bow rakes by month for the next year. Then they pass it along to me. Quite frankly, the forecasts are usually inflated—must be their big egos over there. I have to be careful because we enter into long-term purchasing agreements for steel, and having it just sitting around is expensive. So I usually reduce the forecast by 10 percent or so. I use the modified forecast to generate a monthly final-assembly schedule, which determines what I need to have from the forging and woodworking areas. The system works well if the forecasts are good. But when marketing comes to me and says they are behind on customer orders, as they often do near the end of the year, it wreaks havoc with the schedules. Forging gets hit the hardest. For example, the presses that stamp the rake heads from blanks of steel can handle only 7,000 heads per day, and the bow rolling machine can do only 5,000 per day. Both operations are also required for many other products.

Because the marketing department provides crucial information to Stanton, Place decides to see the marketing manager, Ron Adams. Adams explains how he arrives at the bow rake forecasts.

> Things do not change much from year to year. Sure, sometimes we put on a sales promotion of some kind, but we try to give Phil enough warning before the demand kicks in—usually a month or so. I meet with several managers from the various sales regions to go over shipping data from last year and discuss anticipated promotions, changes in the economy, and shortages we experienced last year. Based on these meetings, I generate a monthly forecast for the next year. Even though we take a lot of time getting the forecast, it never seems to help us avoid customer problems.

The Problem

Place ponders the comments from Stanton and Adams. She understands Stanton's concerns about costs and keeping inventory low and Adams's concern about having enough rakes on hand to make timely shipments. Both are also somewhat concerned about capacity. Yet she decides to check actual customer demand for the bow rake over the past four years (in Table 13.6) before making her final report to Roberts.

QUESTIONS

1. Comment on the forecasting system being used by Yankee. Suggest changes or improvements that you believe are justified.
2. Develop your own forecast for bow rakes for each month of the next year (year 5). Justify your forecast and the method you used.

TABLE 13.6 | FOUR-YEAR DEMAND HISTORY FOR THE BOW RAKE

	Demand			
Month	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	55,220	39,875	32,180	62,377
2	57,350	64,128	38,600	66,501
3	15,445	47,653	25,020	31,404
4	27,776	43,050	51,300	36,504
5	21,408	39,359	31,790	16,888
6	17,118	10,317	32,100	18,909
7	18,028	45,194	59,832	35,500
8	19,883	46,530	30,740	51,250
9	15,796	22,105	47,800	34,443
10	53,665	41,350	73,890	68,088
11	83,269	46,024	60,202	68,175
12	72,991	41,856	55,200	61,100

Note: The demand figures shown in the table are the number of units promised for delivery each month. Actual delivery quantities differed because of capacity or shortages of materials.

EXPERIENTIAL LEARNING — Forecasting with Holdout Sample

A company's history file, as shown in the following table, gives monthly sales in thousands of dollars "rolled up" into aggregated totals for one of its major product lines.

Your team should input this data into a forecasting routine for POM for Windows. Seek out three models to use in making in-class forecasts of monthly sales for year 9. You should bring to class at least one computer for your team that has loaded on it an Excel spreadsheet for making combination forecasts (see Problem 17). Also bring a one-page document that

- characterizes the monthly sales of the product line in terms of its forecastability.
- identifies the relative importance of four demand patterns: horizontal, trend, seasonal, and cyclical.
- states how much importance you think should be placed on judgmental forecasts in year 9, justifying how you reached this conclusion.
- identifies the forecasting model (models in the case of combination forecasts) that you will use to make the forecasts for year 9. Explain why you made this selection, given that MAD will be used as our error measure.
- makes the January forecast for year 9.

After you hand in your document that gives your January forecast, the month's actual sales for January will be revealed from a *holdout sample.* Using that additional information you will then generate February forecasts using your three models that you selected before class, as well as the combination forecast derived from them. The process will repeat itself until all of the forecasts have been made for year 9. Update your model(s) from one period to the next. At the end of this exercise, create a second one-page document that reports your forecasts for year 9, the corresponding average MAD for last year, whether (and how) you modified your forecasting model as the exercise progressed, and what you learned from this exercise. Submit your report to your instructor at the end of the class session.

Your grade on this exercise will be based on (1) the insights provided in the two documents (50 percent of grade) and (2) the average MAD for year 9 (50 percent of grade).

Yr	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	3,255	3,420	3,482	3,740	3,713	3,785	3,817	3,900	3,878	3,949	4,004	4,035
2	3,892	3,730	4,115	4,054	4,184	4,321	4,307	4,481	4,411	4,443	4,395	4,403
3	4,507	4,400	4,099	4,064	4,002	3,963	4,037	4,162	4,312	4,395	4,540	4,471
4	4,589	4,688	4,566	4,485	4,385	4,377	4,309	4,276	4,280	4,144	4,219	4,052
5	4,084	4,158	4,174	4,225	4,324	4,220	4,267	4,187	4,239	4,352	4,331	4,371
6	4,535	4,477	4,601	4,648	4,860	4,998	5,003	4,960	4,943	5,052	5,107	5,100
7	5,303	5,550	5,348	5,391	5,519	5,602	5,557	5,608	5,663	5,497	5,719	5,679
8	5,688	5,604	5,703	5,899	5,816	5,745	5,921	5,900	5,911	5,987	6,074	6,045

Source: This experiential exercise was adapted from in in-class exercise prepared by Dr. Richard J. Penlesky, Carroll University, as a basis for classroom discussion.

Selected References

Armstrong, J. S. *Long-Range Forecasting: From Crystal Ball to Computer.* New York: John Wiley & Sons, 1995.

Armstrong, J. Scott, and F. Collopy. "Integration of Statistical Methods and Judgment for Time Series Forecasting: Principles from Empirical Research," in G. Wright and P. Goodwin (eds.), *Forecasting with Judgment,* New York: John Wiley and Sons, 1998.

Blattberg, R. C., and S. J. Hoch. "Database Models and Managerial Intuition: 50% Model + 50% Manager." *Management Science,* vol. 36 (1990), pp. 887–899.

Bowerman, Bruce L., and Richard T. O'Connell. *Forecasting and Time Series: An Applied Approach,* 3d ed., Belmont, CA: Duxbury Press, 1993.

Bowman, Robert J. "Access to Data in Real Time: Seeing Isn't Everything." *Global Logistics and Supply-Chain Strategies* (May 2002).

Cederlund, Jerold P., Rajiv Kohli, Susan A. Sherer, and Yuliang Yao. "How Motorola Put CPFR into Action." *Supply Chain Management Review* (October 2007), pp. 28–35.

"Clearing the Cobwebs from the Stockroom." *Business Week* (October 21, 1996), p. 140.

Clemen, R. T. "Combining Forecasts: A Review and Annotated Bibliography." *International Journal of Forecasting,* vol. 5 (1989), pp. 559–583.

Hudson, William J. *Executive Economics: Forecasting and Planning for the Real World of Business.* New York: John Wiley & Sons, 1993.

Jenkins, Carolyn. "Accurate Forecasting Reduces Inventory and Increases Output at Henredon." *APIC—The Performance Advantage* (September 1992), pp. 37–39.

Kakouros, Steve, Dorothea Kuettner, and Brian Cargille. "Measure, Then Manage." *APICS—The Performance Advantage* (October 2002), pp. 25–29.

Kimes, Sheryl E., and James A. Fitzsimmons. "Selecting Profitable Hotel Sites at La Quinta Motor Inns." *Interfaces,* vol. 20, no. 2 (1990), pp. 12–20.

Li, X. "An Intelligent Business Forecaster for Strategic Business Planning." *Journal of Forecasting,* vol. 18, no. 3 (1999), pp. 181–205.

Lim, J. S., and M. O'Connor. "Judgmental Forecasting with Time Series and Causal Information." *International Journal of Forecasting,* vol. 12 (1996), pp. 139–153.

Melnyk, Steven. "1997 Forecasting Software Product Listing." *APICS—The Performance Advantage* (April 1997), pp. 62–65.

Mitchell, Robert L. "Case Study: Unilever Crosses the Data Streams." *Computerworld* (December 17, 2001).

Moon, Mark A., John T. Mentzer, and Dwight E. Thomas Jr. "Customer Demand Planning at Lucent Technologies: A Case Study in Continuous Improvement Through Sales Forecast Auditing." *Industrial Marketing Management,* vol. 29, no. 1 (2000).

Principles of Forecasting: A Handbook for Researchers and Practitioners. J. Scott Armstrong (ed.). Norwell, MA: Kluwer Academic Publishers, 2001. Also visit http://www.forecastingprinciples.com for valuable information on forecasting, including frequently asked questions, a forecasting methodology tree, and a dictionary.

Raghunathan, Srinivasan. "Interorganizational Collaborative Forecasting and Replenishment Systems and Supply-Chain Implications." *Decision Sciences,* vol. 30, no. 5 (1999), pp. 1053–1067.

Sanders, Nada R., and L. P. Ritzman. "Bringing Judgment into Combination Forecasts." *Journal of Operations Management,* vol. 13 (1995), pp. 311–321.

Sanders, Nada R., and Karl B. Manrodt. "Forecasting in Practice: Use, Satisfaction, and Performance." *Interfaces,* vol. 33, no. 5 (2003), pp. 90–93.

Sanders, Nada R., and Larry P. Ritzman. "The Need for Contextual and Technical Knowledge in Judgmental Forecasting." *Journal of Behavioral Decision Making,* vol. 5, no. 1 (1992), pp. 39–52.

Schachtman, Noah. "Trading Partners Collaborate to Increase Sales." *Information Week.com* (October 9, 2000), www.informationweek.com/807/cpfr.htm.

Schoenberger, Chana R. "The Weakest Link." *Forbes* (October 1, 2001), www.forbes.com/forbes/2001/1001/114.print.html.

Seifert, Dirk. *Collaborative Planning, Forecasting, and Replenishment: How to Create a Supply-Chain Advantage.* Bonn, Germany: Galileo Press, 2002.

Smith, Larry. "West Marine: A CPFR Success Story." *Supply Chain Management Review* (March 2006), pp. 29–36.

Smith, Bernard. *Focus Forecasting: Computer Techniques for Inventory Control.* Boston: CBI Publishing, 1984.

Steerman, Hank. "A Practical Look at CPFR: The Sears-Michelin Experience." *Supply Chain Management Review* (July/August 2003), pp. 46–53.

VICS (2002) "Collaborative Planning, Forecasting, and Replenishment," Version 2.0, www.cpfr.org.

Wallace, Thomas F., and Robert A. Stahl. *Sales Forecasting: A New Approach.* Cincinnati, OH: T. E. Wallace & Company, 2002.

Yurkiewicz, Jack. "Forecasting 2000." *OR/MS Today,* vol. 27, no. 1 (2000), pp. 58–65.

Yurkiewicz, Jack. "2003 Forecasting Software Survey." *OR/MS Today* (February 2003).