3

CHAPTER

Forecasting

CHAPTER OUTLINE

LEARNING OBJECTIVES

After completing this chapter, you should be able to:

LO3.1 List features common to all forecasts.

LO3.2 Explain why forecasts are generally wrong.

LO3.3 List the elements of a good forecast.

LO3.4 Outline the steps in the forecasting process.

LO3.5 Summarize forecast errors and use summaries to make decisions.

LO3.6 Describe four qualitative forecasting techniques.

LO3.7 Use a naive method to make a forecast.

LO3.8 Prepare a moving average forecast.

LO3.9 Prepare a weighted-average forecast.

LO3.10 Prepare an exponential smoothing forecast.

LO3.11 Prepare a linear trend forecast.

LO3.12 Prepare a trend-adjusted exponential smoothing forecast.

LO3.13 Compute and use seasonal relatives.

LO3.14 Compute and use regression and correlation coefficients.

LO3.15 Construct control charts and use them to monitor forecast errors.

LO3.16 Describe the key factors and trade-offs to consider when choosing a forecasting technique.

Weather forecasts are one of the many types of forecasts used by some business organizations. Although some businesses simply rely on publicly available weather forecasts, others turn to firms that specialize in weather-related forecasts. For example, Home Depot, Gap, and JCPenney use such firms to help them take weather factors into account for estimating demand.

Many new car buyers have a thing or two in common. Once they make the decision to buy a new car, they want it as soon as possible. They usually don't want to order it and then have to wait six weeks or more for delivery. If the car dealer they visit doesn't have the car they want, they'll look elsewhere. Hence, it is important for a dealer to *anticipate* buyer wants and to have those models, with the necessary options, in stock. The dealer who can correctly forecast buyer wants, and have those cars available, is going to be much more successful than a competitor who guesses instead of forecasting—and guesses wrong—and gets stuck with cars customers don't want. So how does the dealer know how many cars of each type to stock? The answer is, the dealer *doesn't* know for sure, but by analyzing previous buying patterns, and perhaps making allowances for current conditions, the dealer can come up with a reasonable *approximation* of what buyers will want.

Planning is an integral part of a manager's job. If uncertainties cloud the planning horizon, managers will find it difficult to plan effectively. Forecasts help managers by reducing some of the uncertainty, thereby enabling them to develop more meaningful plans. A **forecast** is an estimate about the future value of a variable such as demand. The better the estimate, the more informed decisions can be. Some forecasts are long range, covering several years or more. Long-range forecasts are especially important for decisions that will have long-term consequences for an organization or for a town, city, country, state, or nation. One example is deciding on the right capacity for a planned power plant that will operate for the next 20 years. Other forecasts are used to determine if there is a profit potential for a new service or a new product: Will there be sufficient demand to make the innovation worthwhile? Many forecasts are short term, covering a day or week. They are especially helpful in planning and scheduling day-to-day operations. This chapter provides a survey of business forecasting. It describes the elements of good forecasts, the necessary steps in preparing a forecast, basic forecasting techniques, and how to monitor a forecast.

3.1 INTRODUCTION

Forecasts are a basic input in the decision processes of operations management because they provide information on future demand. The importance of forecasting to operations management cannot be overstated. The primary goal of operations management is to match supply to demand. Having a forecast of demand is essential for determining how much capacity or supply will be needed to meet demand. For instance, operations needs to know what capacity

Forecast A statement about the future value of a variable of interest.

will be needed to make staffing and equipment decisions, budgets must be prepared, purchasing needs information for ordering from suppliers, and supply chain partners need to make their plans.

Businesses make plans for future operations based on anticipated future demand. Anticipated demand is derived from two possible sources, actual customer orders and forecasts. For businesses where customer orders make up most or all of anticipated demand, planning is straightforward, and little or no forecasting is needed. However, for many businesses, most or all of anticipated demand is derived from forecasts.

Two aspects of forecasts are important. One is the expected level of demand; the other is the degree of accuracy that can be assigned to a forecast (i.e., the potential size of forecast error). The expected level of demand can be a function of some structural variation, such as a trend or seasonal variation. Forecast accuracy is a function of the ability of forecasters to correctly model demand, random variation, and sometimes unforeseen events.

Forecasts are made with reference to a specific time horizon. The time horizon may be fairly short (e.g., an hour, day, week, or month), or somewhat longer (e.g., the next six months, the next year, the next five years, or the life of a product or service). Short-term forecasts pertain to ongoing operations. Long-range forecasts can be an important strategic planning tool. Long-term forecasts pertain to new products or services, new equipment, new facilities, or something else that will require a somewhat long lead time to develop, construct, or otherwise implement.

Forecasts are the basis for budgeting, planning capacity, sales, production and inventory, personnel, purchasing, and more. Forecasts play an important role in the planning process because they enable managers to anticipate the future so they can plan accordingly.

Forecasts affect decisions and activities throughout an organization, in accounting, finance, human resources, marketing, and management information systems (MIS), as well as in operations and other parts of an organization. Here are some examples of uses of forecasts in business organizations:

Accounting. New product/process cost estimates, profit projections, cash management.

Finance. Equipment/equipment replacement needs, timing and amount of funding/borrowing needs.

The Walt Disney World forecasting department has 20 employees who formulate forecasts on volume and revenue for the theme parks, water parks, resort hotels, as well as merchandise, food, and beverage revenue by location.

Human resources. Hiring activities, including recruitment, interviewing, and training; layoff planning, including outplacement counseling.

Marketing. Pricing and promotion, e-business strategies, global competition strategies.

MIS. New/revised information systems, Internet services.

Operations. Schedules, capacity planning, work assignments and workloads, inventory planning, make-or-buy decisions, outsourcing, project management.

Product/service design. Revision of current features, design of new products or services.

In most of these uses of forecasts, decisions in one area have consequences in other areas. Therefore, it is very important for all affected areas to agree on a common forecast. However, this may not be easy to accomplish. Different departments often have very different perspectives on a forecast, making a consensus forecast difficult to achieve. For example, salespeople, by their very nature, may be overly optimistic with their forecasts, and may want to "reserve" capacity for their customers. This can result in excess costs for operations and inventory storage. Conversely, if demand exceeds forecasts, operations and the supply chain may not be able to meet demand, which would mean lost business and dissatisfied customers.

Forecasting is also an important component of *yield management,* which relates to the percentage of capacity being used. Accurate forecasts can help managers plan tactics (e.g., offer discounts, don't offer discounts) to match capacity with demand, thereby achieving high yield levels.

There are two uses for forecasts. One is to help managers *plan the system,* and the other is to help them *plan the use of the system.* Planning the system generally involves long-range plans about the types of products and services to offer, what facilities and equipment to have, where to locate, and so on. Planning the use of the system refers to short-range and intermediate-range planning, which involve tasks such as planning inventory and workforce levels, planning purchasing and production, budgeting, and scheduling.

Business forecasting pertains to more than predicting demand. Forecasts are also used to predict profits, revenues, costs, productivity changes, prices and availability of energy and raw materials, interest rates, movements of key economic indicators (e.g., gross domestic product, inflation, government borrowing), and prices of stocks and bonds. For the sake of simplicity, this chapter will focus on the forecasting of demand. Keep in mind, however, that the concepts and techniques apply equally well to the other variables.

In spite of its use of computers and sophisticated mathematical models, forecasting is not an exact science. Instead, successful forecasting often requires a skillful blending of science and intuition. Experience, judgment, and technical expertise all play a role in developing useful forecasts. Along with these, a certain amount of luck and a dash of humility can be helpful, because the worst forecasters occasionally produce a very good forecast, and even the best forecasters sometimes miss completely. Current forecasting techniques range from the mundane to the exotic. Some work better than others, but no single technique works all the time.

3.2 FEATURES COMMON TO ALL FORECASTS

A wide variety of forecasting techniques are in use. In many respects, they are quite different from each other, as you shall soon discover. Nonetheless, certain features are common to all, and it is important to recognize them.

LO3.1 List features common to all forecasts.

1. Forecasting techniques generally assume that the same underlying causal system that existed in the past will continue to exist in the future.

Comment A manager cannot simply delegate forecasting to models or computers and then forget about it, because unplanned occurrences can wreak havoc with forecasts. For instance, weather-related events, tax increases or decreases, and changes in features or prices of competing products or services can have a major impact on demand. Consequently, a manager must be alert to such occurrences and be ready to override forecasts, which assume a stable causal system.

LO3.2 Explain why forecasts are generally wrong.

2. Forecasts are not perfect; actual results usually differ from predicted values; the presence of randomness precludes a perfect forecast. Allowances should be made for forecast errors.
3. Forecasts for groups of items tend to be more accurate than forecasts for individual items because forecasting errors among items in a group usually have a canceling effect. Opportunities for grouping may arise if parts or raw materials are used for multiple products or if a product or service is demanded by a number of independent sources.
4. Forecast accuracy decreases as the time period covered by the forecast—the *time horizon*—increases. Generally speaking, short-range forecasts must contend with fewer uncertainties than longer-range forecasts, so they tend to be more accurate.

An important consequence of the last point is that flexible business organizations—those that can respond quickly to changes in demand—require a shorter forecasting horizon and, hence, benefit from more accurate short-range forecasts than competitors who are less flexible and who must therefore use longer forecast horizons.

3.3 ELEMENTS OF A GOOD FORECAST

LO3.3 List the elements of a good forecast.

A properly prepared forecast should fulfill certain requirements:

1. The forecast should be **timely.** Usually, a certain amount of time is needed to respond to the information contained in a forecast. For example, capacity cannot be expanded overnight, nor can inventory levels be changed immediately. Hence, the forecasting horizon must cover the time necessary to implement possible changes.
2. The forecast should be **accurate,** and the degree of accuracy should be stated. This will enable users to plan for possible errors and will provide a basis for comparing alternative forecasts.
3. The forecast should be **reliable;** it should work consistently. A technique that sometimes provides a good forecast and sometimes a poor one will leave users with the uneasy feeling that they may get burned every time a new forecast is issued.
4. The forecast should be expressed in **meaningful units.** Financial planners need to know how many *dollars* will be needed, production planners need to know how many *units* will be needed, and schedulers need to know what *machines* and *skills* will be required. The choice of units depends on user needs.
5. The forecast should be **in writing.** Although this will not guarantee that all concerned are using the same information, it will at least increase the likelihood of it. In addition, a written forecast will permit an objective basis for evaluating the forecast once actual results are in.
6. The forecasting technique should be **simple to understand and use.** Users often lack confidence in forecasts based on sophisticated techniques; they do not understand either the circumstances in which the techniques are appropriate or the limitations of the techniques. Misuse of techniques is an obvious consequence. Not surprisingly, fairly simple forecasting techniques enjoy widespread popularity because users are more comfortable working with them.
7. The forecast should be **cost-effective:** The benefits should outweigh the costs.

3.4 FORECASTING AND THE SUPPLY CHAIN

Accurate forecasts are very important for the supply chain. Inaccurate forecasts can lead to shortages and excesses throughout the supply chain. Shortages of materials, parts, and services can lead to missed deliveries, work disruption, and poor customer service. Conversely, overly optimistic forecasts can lead to excesses of materials and/or capacity, which increase costs. Both shortages and excesses in the supply chain have a negative impact not only on customer service but also on profits. Furthermore, inaccurate forecasts can result in temporary increases and decreases in orders to the supply chain, which can be misinterpreted by the supply chain.

Organizations can reduce the likelihood of such occurrences in a number of ways. One, obviously, is by striving to develop the best possible forecasts. Another is through collaborative planning and forecasting with major supply chain partners. Yet another way is through information sharing among partners and perhaps increasing supply chain visibility by allowing supply chain partners to have real-time access to sales and inventory information. Also important is rapid communication about poor forecasts as well as about unplanned events that disrupt operations (e.g., flooding, work stoppages), and changes in plans.

3.5 STEPS IN THE FORECASTING PROCESS

LO3.4 Outline the steps in the forecasting process.

There are six basic steps in the forecasting process:

1. **Determine the purpose of the forecast.** How will it be used and when will it be needed? This step will provide an indication of the level of detail required in the forecast, the amount of resources (personnel, computer time, dollars) that can be justified, and the level of accuracy necessary.
2. **Establish a time horizon.** The forecast must indicate a time interval, keeping in mind that accuracy decreases as the time horizon increases.
3. **Obtain, clean, and analyze appropriate data.** Obtaining the data can involve significant effort. Once obtained, the data may need to be "cleaned" to get rid of outliers and obviously incorrect data before analysis.
4. **Select a forecasting technique.**
5. **Make the forecast.**
6. **Monitor the forecast errors.** The forecast errors should be monitored to determine if the forecast is performing in a satisfactory manner. If it is not, reexamine the method, assumptions, validity of data, and so on; modify as needed; and prepare a revised forecast.

Note too that additional action may be necessary. For example, if demand was much less than the forecast, an action such as a price reduction or a promotion may be needed. Conversely, if demand was much more than predicted, increased output may be advantageous. That may involve working overtime, outsourcing, or taking other measures.

3.6 FORECAST ACCURACY

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Accuracy and control of forecasts is a vital aspect of forecasting, so forecasters want to minimize forecast errors. However, the complex nature of most real-world variables makes it almost impossible to correctly predict future values of those variables on a regular basis. Moreover, because random variation is always present, there will always be some residual error, even if all other factors have been accounted for. Consequently, it is important to include an indication of the extent to which the forecast might deviate from the value of the variable that actually occurs. This will provide the forecast user with a better perspective on how far off a forecast might be.

Decision makers will want to include accuracy as a factor when choosing among different techniques, along with cost. Accurate forecasts are necessary for the success of daily activities of every business organization. Forecasts are the basis for an organization's schedules, and unless the forecasts are accurate, schedules will be generated that may provide for too few or too many resources, too little or too much output, the wrong output, or the wrong timing of output, all of which can lead to additional costs, dissatisfied customers, and headaches for managers.

Some forecasting applications involve a series of forecasts (e.g., weekly revenues), whereas others involve a single forecast that will be used for a one-time decision (e.g., the size of a power plant). When making periodic forecasts, it is important to monitor forecast errors to determine if the errors are within reasonable bounds. If they are not, it will be necessary to take corrective action.

"I recommend our 'wild' expectations be downgraded to 'great.'"

Error Difference between the actual value and the value that was predicted for a given period.

Forecast **error** is the difference between the value that occurs and the value that was predicted for a given time period. Hence, Error = Actual − Forecast:

$$e_t = A_t - F_t \tag{3–1}$$

where

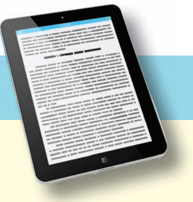
t = Any given time period

Positive errors result when the forecast is too low, negative errors when the forecast is too high. For example, if actual demand for a week is 100 units and forecast demand was 90 units, the forecast was too low; the error is $100 - 90 = +10$.

Forecast errors influence decisions in two somewhat different ways. One is in making a choice between various forecasting alternatives, and the other is in evaluating the success or failure of a technique in use. We shall begin by examining ways to summarize forecast error over time, and see how that information can be applied to compare forecasting alternatives.

High Forecasts Can Be Bad News

READING



Overly optimistic forecasts by retail store buyers can easily lead retailers to overorder, resulting in bloated inventories. When that happens, there is pressure on stores to cut prices in order to move the excess merchandise. Although customers delight in these markdowns, retailer profits generally suffer. Furthermore, retailers will naturally cut back on new orders while they work off their inventories, creating a ripple effect that hits the entire supply chain, from shippers, to producers, to suppliers of raw materials. Moreover, the cutbacks to the supply chain could be misinterpreted. The message is clear: Overly optimistic forecasts can be bad news.

Summarizing Forecast Accuracy

Forecast accuracy is a significant factor when deciding among forecasting alternatives. Accuracy is based on the historical error performance of a forecast.

Three commonly used measures for summarizing historical errors are the **mean absolute deviation (MAD)**, the **mean squared error (MSE)**, and the **mean absolute percent error (MAPE)**. MAD is the average absolute error, MSE is the average of squared errors, and MAPE is the average absolute percent error. The formulas used to compute MAD,[1] MSE, and MAPE are as follows:

$$\text{MAD} = \frac{\Sigma|\text{Actual}_t - \text{Forecast}_t|}{n} \tag{3–2}$$

$$\text{MSE} = \frac{\Sigma(\text{Actual}_t - \text{Forecast}_t)^2}{n-1} \tag{3–3}$$

$$\text{MAPE} = \frac{\Sigma\frac{|\text{Actual}_t - \text{Forecast}_t|}{\text{Actual}_t} \times 100}{n} \tag{3–4}$$

Example 1 illustrates the computation of MAD, MSE, and MAPE.

Mean absolute deviation (MAD) The average absolute forecast error.

Mean squared error (MSE) The average of squared forecast errors.

Mean absolute percent error (MAPE) The average absolute percent error.

LO3.5 Summarize forecast errors and use summaries to make decisions.

EXAMPLE 1

eXcel
mhhe.com/stevenson12e

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Compute MAD, MSE, and MAPE for the following data, showing actual and forecasted numbers of accounts serviced.

Period	Actual	Forecast	(A − F) Error	|Error|	Error^2	[|Error| ÷ Actual] × 100
1	217	215	2	2	4	.92%
2	213	216	−3	3	9	1.41
3	216	215	1	1	1	.46
4	210	214	−4	4	16	1.90
5	213	211	2	2	4	.94
6	219	214	5	5	25	2.28
7	216	217	−1	1	1	.46
8	212	216	−4	4	16	1.89
			−2	22	76	10.26%

SOLUTION

Using the figures shown in the table,

$$\text{MAD} = \frac{\Sigma|e|}{n} = \frac{22}{8} = 2.75$$

$$\text{MSE} = \frac{\Sigma e^2}{n-1} = \frac{76}{8-1} = 10.86$$

$$\text{MAPE} = \frac{\Sigma\left[\frac{|e|}{\text{Actual}} \times 100\right]}{n} = \frac{10.26\%}{8} = 1.28\%$$

From a computational standpoint, the difference between these measures is that MAD weights all errors evenly, MSE weights errors according to their *squared* values, and MAPE weights according to relative error.

[1] The absolute value, represented by the two vertical lines in Formula 3–2, ignores minus signs; all data are treated as positive values. For example, −2 becomes +2.

One use for these measures is to compare the accuracy of alternative forecasting methods. For instance, a manager could compare the results to determine one which yields the *lowest* MAD, MSE, or MAPE for a given set of data. Another use is to track error performance over time to decide if attention is needed. Is error performance getting better or worse, or is it staying about the same?

In some instances, historical error performance is secondary to the ability of a forecast to respond to changes in data patterns. Choice among alternative methods would then focus on the cost of not responding quickly to a change relative to the cost of responding to changes that are not really there (i.e., random fluctuations).

Overall, the operations manager must settle on the relative importance of historical performance versus responsiveness and whether to use MAD, MSE, or MAPE to measure historical performance. MAD is the easiest to compute, but weights errors linearly. MSE squares errors, thereby giving more weight to larger errors, which typically cause more problems. MAPE should be used when there is a need to put errors in perspective. For example, an error of 10 in a forecast of 15 is huge. Conversely, an error of 10 in a forecast of 10,000 is insignificant. Hence, to put large errors in perspective, MAPE would be used.

3.7 APPROACHES TO FORECASTING

There are two general approaches to forecasting: qualitative and quantitative. Qualitative methods consist mainly of subjective inputs, which often defy precise numerical description. Quantitative methods involve either the projection of historical data or the development of associative models that attempt to utilize *causal (explanatory) variables* to make a forecast.

Qualitative techniques permit inclusion of *soft* information (e.g., human factors, personal opinions, hunches) in the forecasting process. Those factors are often omitted or downplayed when quantitative techniques are used because they are difficult or impossible to quantify. Quantitative techniques consist mainly of analyzing objective, or *hard,* data. They usually avoid personal biases that sometimes contaminate qualitative methods. In practice, either approach or a combination of both approaches might be used to develop a forecast.

The following pages present a variety of forecasting techniques that are classified as judgmental, time-series, or associative.

Judgmental forecasts Forecasts that use subjective inputs such as opinions from consumer surveys, sales staff, managers, executives, and experts.

Time-series forecasts Forecasts that project patterns identified in recent time-series observations.

Associative model Forecasting technique that uses explanatory variables to predict future demand.

Judgmental forecasts rely on analysis of subjective inputs obtained from various sources, such as consumer surveys, the sales staff, managers and executives, and panels of experts. Quite frequently, these sources provide insights that are not otherwise available.

Time-series forecasts simply attempt to project past experience into the future. These techniques use historical data with the assumption that the future will be like the past. Some models merely attempt to smooth out random variations in historical data; others attempt to identify specific patterns in the data and project or extrapolate those patterns into the future, without trying to identify causes of the patterns.

Associative models use equations that consist of one or more *explanatory* variables that can be used to predict demand. For example, demand for paint might be related to variables such as the price per gallon and the amount spent on advertising, as well as to specific characteristics of the paint (e.g., drying time, ease of cleanup).

3.8 QUALITATIVE FORECASTS

LO3.6 Describe four qualitative forecasting techniques.

In some situations, forecasters rely solely on judgment and opinion to make forecasts. If management must have a forecast quickly, there may not be enough time to gather and analyze quantitative data. At other times, especially when political and economic conditions are changing, available data may be obsolete and more up-to-date information might not yet be available. Similarly, the introduction of new products and the redesign of existing products or packaging suffer from the absence of historical data that would be useful in forecasting. In such instances, forecasts are based on executive opinions, consumer surveys, opinions of the sales staff, and opinions of experts.

Executive Opinions

A small group of upper-level managers (e.g., in marketing, operations, and finance) may meet and collectively develop a forecast. This approach is often used as a part of long-range planning and new product development. It has the advantage of bringing together the considerable knowledge and talents of various managers. However, there is the risk that the view of one person will prevail, and the possibility that diffusing responsibility for the forecast over the entire group may result in less pressure to produce a good forecast.

Salesforce Opinions

Members of the sales staff or the customer service staff are often good sources of information because of their direct contact with consumers. They are often aware of any plans the customers may be considering for the future. There are, however, several drawbacks to using salesforce opinions. One is that staff members may be unable to distinguish between what customers would *like* to do and what they actually *will* do. Another is that these people are sometimes overly influenced by recent experiences. Thus, after several periods of low sales, their estimates may tend to become pessimistic. After several periods of good sales, they may tend to be too optimistic. In addition, if forecasts are used to establish sales quotas, there will be a conflict of interest because it is to the salesperson's advantage to provide low sales estimates.

Consumer Surveys

Because it is the consumers who ultimately determine demand, it seems natural to solicit input from them. In some instances, every customer or potential customer can be contacted. However, usually there are too many customers or there is no way to identify all potential customers. Therefore, organizations seeking consumer input usually resort to consumer surveys, which enable them to *sample* consumer opinions. The obvious advantage of consumer surveys is that they can tap information that might not be available elsewhere. On the other hand, a considerable amount of knowledge and skill is required to construct a survey, administer it, and correctly interpret the results for valid information. Surveys can be expensive and time-consuming. In addition, even under the best conditions, surveys of the general public must contend with the possibility of irrational behavior patterns. For example, much of the consumer's thoughtful information gathering before purchasing a new car is often undermined by the glitter of a new car showroom or a high-pressure sales pitch. Along the same lines, low response rates to a mail survey should—but often don't—make the results suspect.

If these and similar pitfalls can be avoided, surveys can produce useful information.

Other Approaches

A manager may solicit opinions from a number of other managers and staff people. Occasionally, outside experts are needed to help with a forecast. Advice may be needed on political or economic conditions in the United States or a foreign country, or some other aspect of importance with which an organization lacks familiarity.

Another approach is the **Delphi method**, an iterative process intended to achieve a consensus forecast. This method involves circulating a series of questionnaires among individuals who possess the knowledge and ability to contribute meaningfully. Responses are kept anonymous, which tends to encourage honest responses and reduces the risk that one person's opinion will prevail. Each new questionnaire is developed using the information extracted from the previous one, thus enlarging the scope of information on which participants can base their judgments.

Delphi method An iterative process in which managers and staff complete a series of questionnaires, each developed from the previous one, to achieve a consensus forecast.

The Delphi method has been applied to a variety of situations, not all of which involve forecasting. The discussion here is limited to its use as a forecasting tool.

As a forecasting tool, the Delphi method is useful for *technological* forecasting, that is, for assessing changes in technology and their impact on an organization. Often the goal is to predict *when* a certain event will occur. For instance, the goal of a Delphi forecast might be to predict when video telephones might be installed in at least 50 percent of residential homes or when a vaccine for a disease might be developed and ready for mass distribution. For the most part, these are long-term, single-time forecasts, which usually have very little hard information to go by or data that are costly to obtain, so the problem does not lend itself to analytical techniques. Rather, judgments of experts or others who possess sufficient knowledge to make predictions are used.

3.9 FORECASTS BASED ON TIME-SERIES DATA

Time series A time-ordered sequence of observations taken at regular intervals.

A **time series** is a time-ordered sequence of observations taken at regular intervals (e.g., hourly, daily, weekly, monthly, quarterly, annually). The data may be measurements of demand, earnings, profits, shipments, accidents, output, precipitation, productivity, or the consumer price index. Forecasting techniques based on time-series data are made on the assumption that future values of the series can be estimated from past values. Although no attempt is made to identify variables that influence the series, these methods are widely used, often with quite satisfactory results.

Analysis of time-series data requires the analyst to identify the underlying behavior of the series. This can often be accomplished by merely *plotting the data* and visually examining the plot. One or more patterns might appear: trends, seasonal variations, cycles, or variations around an average. In addition, there will be random and perhaps irregular variations. These behaviors can be described as follows:

Trend A long-term upward or downward movement in data.

Seasonality Short-term regular variations related to the calendar or time of day.

Cycle Wavelike variations lasting more than one year.

Irregular variation Caused by unusual circumstances, not reflective of typical behavior.

Random variations Residual variations after all other behaviors are accounted for.

1. **Trend** refers to a long-term upward or downward movement in the data. Population shifts, changing incomes, and cultural changes often account for such movements.
2. **Seasonality** refers to short-term, fairly regular variations generally related to factors such as the calendar or time of day. Restaurants, supermarkets, and theaters experience weekly and even daily "seasonal" variations.
3. **Cycles** are wavelike variations of more than one year's duration. These are often related to a variety of economic, political, and even agricultural conditions.
4. **Irregular variations** are due to unusual circumstances such as severe weather conditions, strikes, or a major change in a product or service. They do not reflect typical behavior, and their inclusion in the series can distort the overall picture. Whenever possible, these should be identified and removed from the data.
5. **Random variations** are residual variations that remain after all other behaviors have been accounted for.

These behaviors are illustrated in Figure 3.1. The small "bumps" in the plots represent random variability.

The remainder of this section describes the various approaches to the analysis of time-series data. Before turning to those discussions, one point should be emphasized: A demand forecast should be based on a time series of past *demand* rather than unit sales. Sales would not truly reflect demand if one or more *stockouts* occurred.

Naive Methods

Naive forecast A forecast for any period that equals the previous period's actual value.

LO3.7 Use a naive method to make a forecast.

A simple but widely used approach to forecasting is the naive approach. A **naive forecast** uses a single previous value of a time series as the basis of a forecast. The naive approach can be used with a stable series (variations around an average), with seasonal variations, or with trend. With a stable series, the last data point becomes the forecast for the next period. Thus, if demand for a product last week was 20 cases, the forecast for this week is 20 cases. With seasonal variations, the forecast for this "season" is equal to the value of the series last "season." For example, the forecast for demand for turkeys this Thanksgiving season is equal to

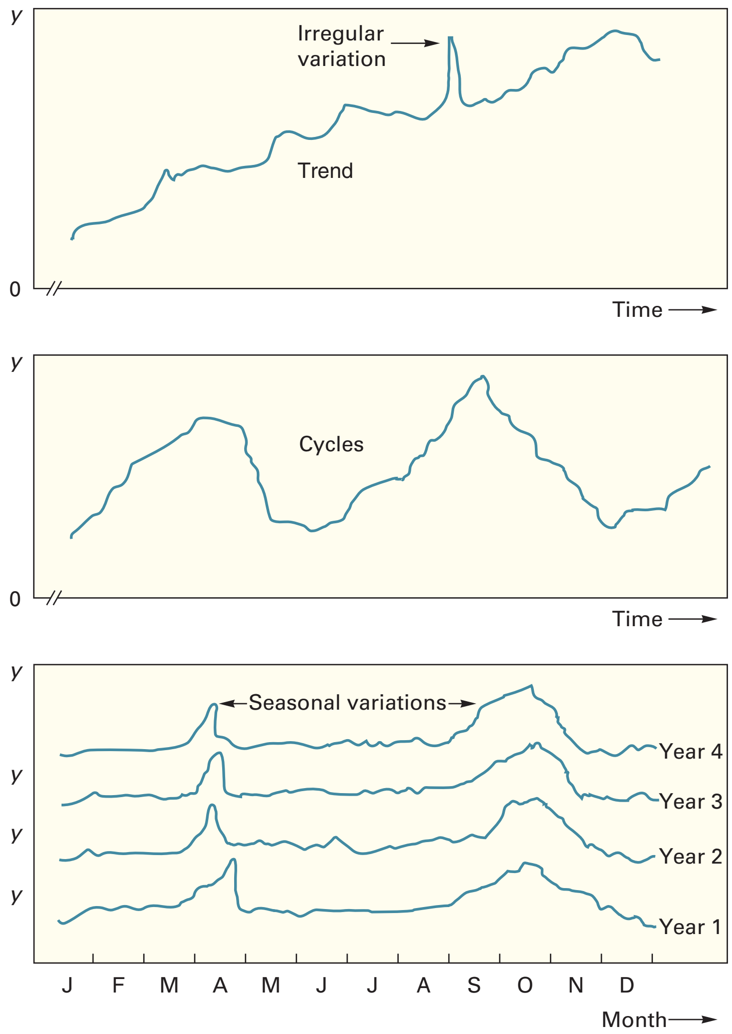


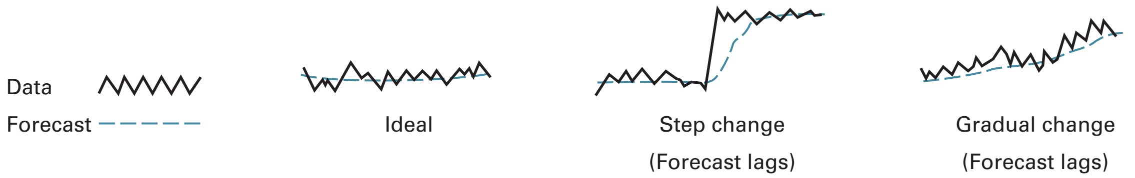
FIGURE 3.1
Trend, cyclical, and seasonal data plots, with random and irregular variations

demand for turkeys last Thanksgiving; the forecast of the number of checks cashed at a bank on the first day of the month next month is equal to the number of checks cashed on the first day of this month; and the forecast for highway traffic volume this Friday is equal to the highway traffic volume last Friday. For data with trend, the forecast is equal to the last value of the series plus or minus the difference between the last two values of the series. For example, suppose the last two values were 50 and 53. The next forecast would be 56:

Period	Actual	Change from Previous Value	Forecast
1	50		
2	53	+3	
3			53 + 3 = 56

Although at first glance the naive approach may appear *too* simplistic, it is nonetheless a legitimate forecasting tool. Consider the advantages: It has virtually no cost, it is quick and easy to prepare because data analysis is nonexistent, and it is easily understandable. The main objection to this method is its inability to provide highly accurate forecasts. However, if resulting accuracy is acceptable, this approach deserves serious consideration. Moreover, even if other forecasting techniques offer better accuracy, they will almost always involve a greater cost. The accuracy of a naive forecast can serve as a standard of comparison against which to judge the cost and accuracy of other techniques. Thus, managers must answer the question: Is the increased accuracy of another method worth the additional resources required to achieve that accuracy?

FIGURE 3.2 Averaging applied to three possible patterns



Techniques for Averaging

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Historical data typically contain a certain amount of random variation, or *white noise,* that tends to obscure systematic movements in the data. This randomness arises from the combined influence of many—perhaps a great many—relatively unimportant factors, and it cannot be reliably predicted. Averaging techniques smooth variations in the data. Ideally, it would be desirable to completely remove any randomness from the data and leave only "real" variations, such as changes in the demand. As a practical matter, however, it is usually impossible to distinguish between these two kinds of variations, so the best one can hope for is that the small variations are random and the large variations are "real."

Averaging techniques smooth fluctuations in a time series because the individual highs and lows in the data offset each other when they are combined into an average. A forecast based on an average thus tends to exhibit less variability than the original data (see Figure 3.2). This can be advantageous because many of these movements merely reflect random variability rather than a true change in the series. Moreover, because responding to changes in expected demand often entails considerable cost (e.g., changes in production rate, changes in the size of a workforce, inventory changes), it is desirable to avoid reacting to minor variations. Thus, minor variations are treated as random variations, whereas larger variations are viewed as more likely to reflect "real" changes, although these, too, are smoothed to a certain degree.

Averaging techniques generate forecasts that reflect recent values of a time series (e.g., the average value over the last several periods). These techniques work best when a series tends to vary around an average, although they also can handle step changes or gradual changes in the level of the series. Three techniques for averaging are described in this section:

1. Moving average.
2. Weighted moving average.
3. Exponential smoothing.

Moving average Technique that averages a number of recent actual values, updated as new values become available.

LO3.8 Prepare a moving average forecast.

Moving Average. One weakness of the naive method is that the forecast just *traces* the actual data, with a lag of one period; it does not smooth at all. But by expanding the amount of historical data a forecast is based on, this difficulty can be overcome. A **moving average** forecast uses a *number* of the most recent actual data values in generating a forecast. The moving average forecast can be computed using the following equation:

$$F_t = \text{MA}_n = \frac{\sum_{i=1}^{n} A_{t-i}}{n} = \frac{A_{t-n} + \cdots + A_{t-2} + A_{t-1}}{n} \tag{3–5}$$

where

F_t = Forecast for time period t

MA_n = n period moving average

A_{t-i} = Actual value in period $t - i$

n = Number of periods (data points) in the moving average

For example, MA_3 would refer to a three-period moving average forecast, and MA_5 would refer to a five-period moving average forecast.

EXAMPLE 2

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Compute a three-period moving average forecast given demand for shopping carts for the last five periods.

Period	Demand	
1	42	
2	40	
3	43	the 3 most recent demands
4	40	
5	41	

SOLUTION

$$F_6 = \frac{43 + 40 + 41}{3} = 41.33$$

If actual demand in period 6 turns out to be 38, the moving average forecast for period 7 would be

$$F_7 = \frac{40 + 41 + 38}{3} = 39.67$$

Note that in a moving average, as each new actual value becomes available, the forecast is updated by adding the newest value and dropping the oldest and then recomputing the average. Consequently, the forecast "moves" by reflecting only the most recent values.

In computing a moving average, including a *moving total* column—which gives the sum of the n most current values from which the average will be computed—aids computations. To update the moving total: Subtract the oldest value from the newest value and add that amount to the moving total for each update.

Figure 3.3 illustrates a three-period moving average forecast plotted against actual demand over 31 periods. Note how the moving average forecast *lags* the actual values and how *smooth* the forecasted values are compared with the actual values.

The moving average can incorporate as many data points as desired. In selecting the number of periods to include, the decision maker must take into account that the number of data points in the average determines its sensitivity to each new data point: The fewer the data points in an average, the more sensitive (responsive) the average tends to be. (See Figure 3.4A.)

If responsiveness is important, a moving average with relatively few data points should be used. This will permit quick adjustment to, say, a step change in the data, but it also will cause

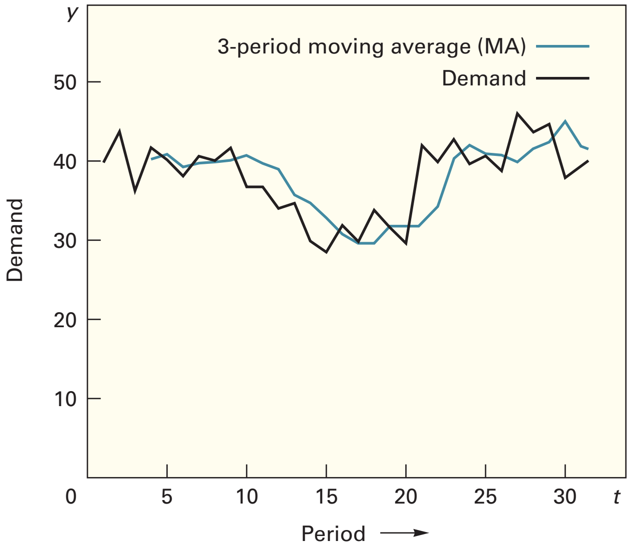
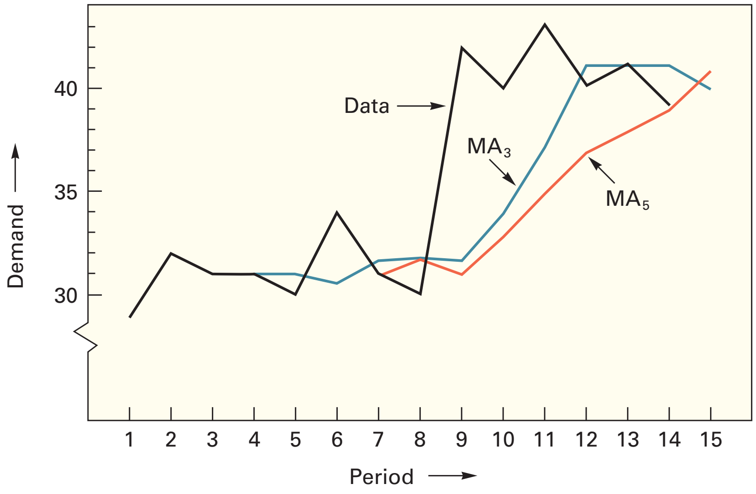


FIGURE 3.3
A moving average forecast tends to smooth and lag changes in the data

FIGURE 3.4A
The more periods in a moving average, the greater the forecast will lag changes in the data



the forecast to be somewhat responsive even to random variations. Conversely, moving averages based on more data points will smooth more but be less responsive to "real" changes. Hence, the decision maker must weigh the cost of responding more slowly to changes in the data against the cost of responding to what might simply be random variations. A review of forecast errors can help in this decision.

The advantages of a moving average forecast are that it is easy to compute and easy to understand. A possible disadvantage is that all values in the average are weighted equally. For instance, in a 10-period moving average, each value has a weight of 1/10. Hence, the oldest value has the *same weight* as the most recent value. If a change occurs in the series, a moving average forecast can be slow to react, especially if there are a large number of values in the average. Decreasing the number of values in the average increases the weight of more recent values, but it does so at the expense of losing potential information from less recent values.

Weighted average More recent values in a series are given more weight in computing a forecast.

Weighted Moving Average. A **weighted average** is similar to a moving average, except that it typically assigns more weight to the most recent values in a time series. For instance, the most recent value might be assigned a weight of .40, the next most recent value a weight of .30, the next after that a weight of .20, and the next after that a weight of .10. Note that the weights must sum to 1.00, and that the heaviest weights are assigned to the most recent values.

LO3.9 Prepare a weighted-average forecast.

$$F_t = w_{t-n}(A_{t-n}) + \cdots + w_{t-2}(A_{t-2}) + w_{t-1}(A_{t-1}) + w_{t-1}(A_{t-1}) + \cdots + w_{t-n}(A_{t-n}) \tag{3–6}$$

where

w_{t-1} = Weight for period $t - 1$, etc.
A_{t-1} = Actual value for period $t - 1$, etc.

EXAMPLE 3

Given the following demand data,

a. Compute a weighted average forecast using a weight of .40 for the most recent period, .30 for the next most recent, .20 for the next, and .10 for the next.

b. If the actual demand for period 6 is 39, forecast demand for period 7 using the same weights as in part *a.*

Period	Demand
1	42
2	40
3	43
4	40
5	41

a. $F_6 = .10(40) + .20(43) + .30(40) + .40(41) = 41.0$

b. $F_7 = .10(43) + .20(40) + .30(41) + .40(39) = 40.2$

SOLUTION

Note that if four weights are used, only the *four most recent* demands are used to prepare the forecast.

The advantage of a weighted average over a simple moving average is that the weighted average is more reflective of the most recent occurrences. However, the choice of weights is somewhat arbitrary and generally involves the use of trial and error to find a suitable weighting scheme.

Exponential Smoothing. **Exponential smoothing** is a sophisticated weighted averaging method that is still relatively easy to use and understand. Each new forecast is based on the previous forecast plus a percentage of the difference between that forecast and the actual value of the series at that point. That is:

Exponential smoothing A weighted averaging method based on previous forecast plus a percentage of the forecast error.

$$\text{Next forecast} = \text{Previous forecast} + \alpha(\text{Actual} - \text{Previous forecast})$$

where (Actual − Previous forecast) represents the forecast error and α is a percentage of the error. More concisely,

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$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \tag{3–7a}$$

where

F_t = Forecast for period t

F_{t-1} = Forecast for the previous period (i.e., period $t - 1$)

α = Smoothing constant (percentage)

A_{t-1} = Actual demand or sales for the previous period

LO3.10 Prepare an exponential smoothing forecast.

The smoothing constant α represents a percentage of the forecast error. Each new forecast is equal to the previous forecast plus a percentage of the previous error. For example, suppose the previous forecast was 42 units, actual demand was 40 units, and $\alpha = .10$. The new forecast would be computed as follows:

$$F_t = 42 + .10(40 - 42) = 41.8$$

Then, if the actual demand turns out to be 43, the next forecast would be

$$F_t = 41.8 + .10(43 - 41.8) = 41.92$$

An alternate form of Formula 3–7a reveals the weighting of the previous forecast and the latest actual demand:

$$F_t = (1 - \alpha)F_{t-1} + \alpha A_{t-1} \tag{3–7b}$$

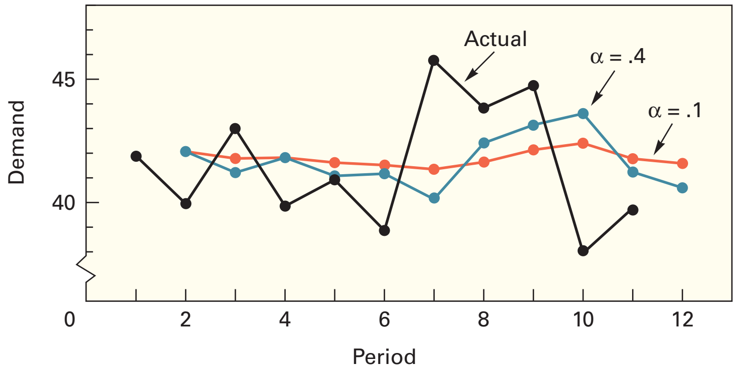
For example, if $\alpha = .10$, this would be

$$F_t = .90F_{t-1} + .10A_{t-1}$$

The quickness of forecast adjustment to error is determined by the smoothing constant, α. The closer its value is to zero, the slower the forecast will be to adjust to forecast errors (i.e., the greater the smoothing). Conversely, the closer the value of α is to 1.00, the greater the responsiveness and the less the smoothing. This is illustrated in Figure 3.4B.

FIGURE 3.4B
The closer α is to zero, the greater the smoothing

Period (t)	Actual Demand	α = .10 Forecast	α = .40 Forecast
1	42 starting forecast	—	—
2	40	42	42
3	43	41.8	41.2
4	40	41.92	41.92
5	41	41.73	41.15
6	39	41.66	41.09
7	46	41.39	40.25
8	44	41.85	42.55
9	45	42.07	43.13
10	38	42.35	43.88
11	40	41.92	41.53
12		41.73	40.92



Selecting a smoothing constant is basically a matter of judgment or trial and error, using forecast errors to guide the decision. The goal is to select a smoothing constant that balances the benefits of smoothing random variations with the benefits of responding to real changes if and when they occur. Commonly used values of α range from .05 to .50. Low values of α are used when the underlying average tends to be stable; higher values are used when the underlying average is susceptible to change.

Some computer packages include a feature that permits automatic modification of the smoothing constant if the forecast errors become unacceptably large.

Exponential smoothing is one of the most widely used techniques in forecasting, partly because of its ease of calculation and partly because of the ease with which the weighting scheme can be altered—simply by changing the value of α.

Note Exponential smoothing should begin several periods back to enable forecasts to adjust to the data, instead of starting one period back. A number of different approaches can be used to obtain a *starting forecast,* such as the average of the first several periods, a subjective estimate, or the first actual value as the forecast for period 2 (i.e., the naive approach). For simplicity, the naive approach is used in this book. In practice, using an average of, say, the first three values as a forecast for period 4 would provide a better starting forecast because that would tend to be more representative.

EXAMPLE 4
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Compare the error performance of these three forecasting techniques using MAD, MSE, and MAPE: a naive forecast, a two-period moving average, and exponential smoothing with α = .10 *for periods 3 through 11,* using the data shown in Figure 3.4B.

SOLUTION

		Naive		Two-period MA		Exponential Smoothing	
Period, *t*	**Demand**	**Forecast**	**Error**	**Forecast**	**Error**	**Forecast**	**Error**
1	42	—	—				
2	40	42	−2			42	−2
3	43	40	3	41	2	41.8	1.2
4	40	43	−3	41.5	−1.5	41.92	−1.92
5	41	40	1	41.5	−0.5	41.73	−0.73
6	39	41	−2	40.5	−1.5	41.66	−2.66
7	46	39	7	40	6	41.39	4.61
8	44	46	−2	42.5	1.5	41.85	2.15
9	45	44	1	45	0	42.07	2.93
10	38	45	−7	44.5	−6.5	42.36	−4.36
11	40	38	2	41.5	−1.5	41.92	−1.92
	MAD		3.11		2.33		2.50
	MSE		16.25		11.44		8.73
	MAPE		7.49%		5.64%		5.98%

If lowest MAD is the criterion, the two-period moving average forecast has the greatest accuracy; if lowest MSE is the criterion, exponential smoothing works best; and if lowest MAPE is the criterion, the two-period moving average method is again best. Of course, with other data, or with different values of α for exponential smoothing, and different moving averages, the best performers could be different.

Other Forecasting Methods

You may find two other approaches to forecasting interesting. They are briefly described in this section.

Focus Forecasting. Some companies use forecasts based on a "best recent performance" basis. This approach, called **focus forecasting**, was developed by Bernard T. Smith, and is described in several of his books.[2] It involves the use of several forecasting methods (e.g., moving average, weighted average, and exponential smoothing) all being applied to the last few months of historical data after any irregular variations have been removed. The method that has the highest accuracy is then used to make the forecast for the next month. This process is used for each product or service, and is repeated monthly. Example 4 illustrates this kind of comparison.

Focus Forecasting Using the forecasting method that demonstrates the best recent success.

Diffusion Models. When new products or services are introduced, historical data are not generally available on which to base forecasts. Instead, predictions are based on rates of product adoption and usage spread from other established products, using mathematical diffusion models. These models take into account such factors as market potential, attention from mass media, and word of mouth. Although the details are beyond the scope of this text, it is important to point out that diffusion models are widely used in marketing and to assess the merits of investing in new technologies.

Techniques for Trend

Analysis of trend involves developing an equation that will suitably describe trend (assuming that trend is present in the data). The trend component may be linear, or it may not. Some

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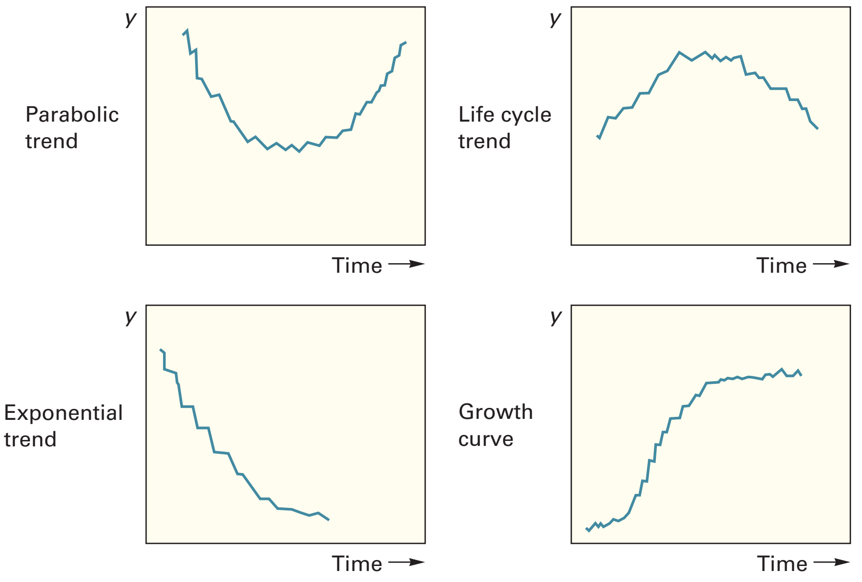
[2]See, for example, Bernard T. Smith and Virginia Brice, *Focus Forecasting: Computer Techniques for Inventory Control Revised for the Twenty-First Century* (Essex Junction, VT: Oliver Wight, 1984).

FIGURE 3.5
Graphs of some nonlinear trends



commonly encountered nonlinear trend types are illustrated in Figure 3.5. A simple plot of the data often can reveal the existence and nature of a trend. The discussion here focuses exclusively on *linear* trends because these are fairly common.

There are two important techniques that can be used to develop forecasts when trend is present. One involves use of a trend equation; the other is an extension of exponential smoothing.

Linear trend equation $F_t = a + bt$, used to develop forecasts when trend is present.

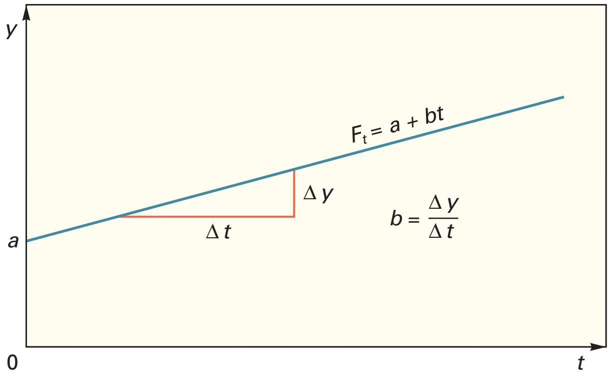
LO3.11 Prepare a linear trend forecast.

Trend Equation. A **linear trend equation** has the form

$$F_t = a + bt \tag{3–8}$$

where

F_t = Forecast for period t
a = Value of F_t at $t = 0$, which is the y intercept
b = Slope of the line
t = Specified number of time periods from $t = 0$



For example, consider the trend equation $F_t = 45 + 5t$. The value of F_t when $t = 0$ is 45, and the slope of the line is 5, which means that, on the average, the value of F_t will increase by five units for each time period. If $t = 10$, the forecast, F_t, is $45 + 5(10) = 95$ units. The equation can be plotted by finding two points on the line. One can be found by substituting some value of t into the equation (e.g., $t = 10$) and then solving for F_t. The other point is a (i.e., F_t at $t = 0$). Plotting those two points and drawing a line through them yields a graph of the linear trend line.

The coefficients of the line, a and b, are based on the following two equations:

$$b = \frac{n\Sigma ty - \Sigma t\Sigma y}{n\Sigma t^2 - (\Sigma t)^2} \tag{3–9}$$

$$a = \frac{\Sigma y - b\Sigma t}{n} \text{ or } \bar{y} - b\bar{t} \tag{3–10}$$

where

n = Number of periods

y = Value of the time series

Note that these two equations are identical to those used for computing a linear regression line, except that t replaces x in the equations. Values for the trend equation can be obtained easily by using the Excel template for linear trend.

EXAMPLE 5

excel

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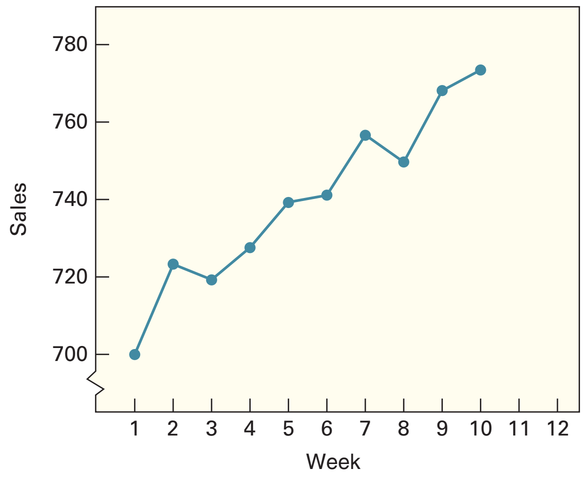
Cell phone sales for a California-based firm over the last 10 weeks are shown in the following table. Plot the data, and visually check to see if a linear trend line would be appropriate. Then determine the equation of the trend line, and predict sales for weeks 11 and 12.

Week	Unit Sales
1	700
2	724
3	720
4	728
5	740
6	742
7	758
8	750
9	770
10	775

SOLUTION

a. A plot suggests that a linear trend line would be appropriate:



b. The solution obtained by using the Excel template for linear trend is shown in Table 3.1.

$b = 7.51$ and $a = 699.40$

The trend line is $F_t = 699.40 + 7.51t$, where $t = 0$ for period 0.

c. Substituting values of t into this equation, the forecasts for the next two periods (i.e., $t = 11$ and $t = 12$) are:

$$F_{11} = 699.40 + 7.51(11) = 782.01$$

$$F_{12} = 699.40 + 7.51(12) = 789.52$$

d. For purposes of illustration, the original data, the trend line, and the two projections (forecasts) are shown on the following graph:

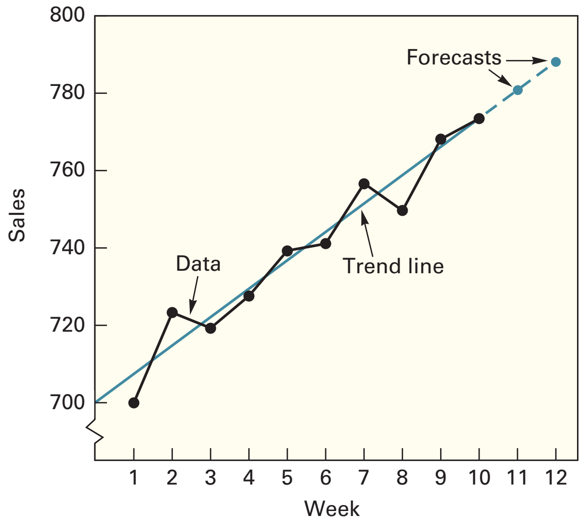
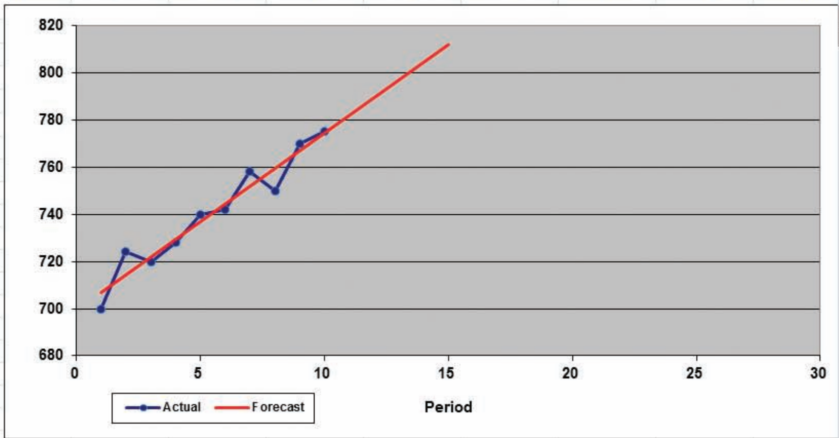


TABLE 3.1 Excel solution for Example 5

A2 | f_x <Back

	A	B	C	D
1	Linear Trend Equation		Basic	Clear
2	<Back			
3	Slope =	7.5091	MAD =	4.44
4	Intercept =	699.4	MSE =	32.91
5				
6	Period	Actual	Forecast	Error
7	1	700	706.90909	-6.9090909
8	2	724	714.41818	9.5818182
9	3	720	721.92727	-1.9272727
10	4	728	729.43636	-1.4363636
11	5	740	736.94545	3.0545455
12	6	742	744.45455	-2.4545455
13	7	758	751.96364	6.0363636
14	8	750	759.47273	-9.4727273
15	9	770	766.98182	3.0181818
16	10	775	774.49091	0.5090909
17	11		782	
18	12		789.50909	
19	13		797.01818	
20	14		804.52727	
21	15		812.03636	
22	16			
23	17			
24	18			



Period: 0

Actual:

Forecast:

Exponential Smoothing | Linear Trend | Trend Adj Expon Smooth | Trend and Seasonal

Ready 100%

Trend-Adjusted Exponential Smoothing

A variation of simple exponential smoothing can be used when a time series exhibits a *linear* trend. It is called **trend-adjusted exponential smoothing** or, sometimes, *double smoothing,* to differentiate it from simple exponential smoothing, which is appropriate only when data vary around an average or have step or gradual changes. If a series exhibits trend, and simple smoothing is used on it, the forecasts will all lag the trend: If the data are increasing, each forecast will be too low; if decreasing, each forecast will be too high.

Trend-adjusted exponential smoothing Variation of exponential smoothing used when a time series exhibits a linear trend.

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LO3.12 Prepare a trend-adjusted exponential smoothing forecast.

The trend-adjusted forecast (TAF) is composed of two elements: a smoothed error and a trend factor.

$$\text{TAF}_{t+1} = S_t + T_t \tag{3–11}$$

where

S_t = Previous forecast plus smoothed error

T_t = Current trend estimate

and

$$\begin{aligned} S_t &= \text{TAF}_t + \alpha(A_t - \text{TAF}_t) \\ T_t &= T_{t-1} + \beta(\text{TAF}_t - \text{TAF}_{t-1} - T_{t-1}) \end{aligned} \tag{3–12}$$

where

α = Smoothing constant for average

β = Smoothing constant for trend

In order to use this method, one must select values of α and β (usually through trial and error) and make a starting forecast and an estimate of trend.

EXAMPLE 6

eXcel

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Using the cell phone data from the previous example (where it was concluded that the data exhibited a linear trend), use trend-adjusted exponential smoothing to obtain forecasts for periods 6 through 11, with $\alpha = .40$ and $\beta = .30$.

SOLUTION

The initial estimate of trend is based on the net change of 28 for the *three changes* from period 1 to period 4, for an average of 9.33. The Excel spreadsheet is shown in Table 3.2. Notice that an initial estimate of trend is estimated from the first four values and that the starting forecast (period 5) is developed using the previous (period 4) value of 728 plus the initial trend estimate:

$$\text{Starting forecast} = 728 + 9.33 = 737.33$$

Unlike a linear trend line, trend-adjusted smoothing has the ability to adjust to *changes* in trend. Of course, trend projections are much simpler with a trend line than with trend-adjusted forecasts, so a manager must decide which benefits are most important when choosing between these two techniques for trend.

Techniques for Seasonality

Seasonal variations in time-series data are regularly repeating upward or downward movements in series values that can be tied to recurring events. *Seasonality* may refer to regular annual variations. Familiar examples of seasonality are weather variations (e.g., sales of winter and summer sports equipment) and vacations or holidays (e.g., airline travel, greeting card sales, visitors at tourist and resort centers). The term *seasonal variation* is also applied to daily, weekly, monthly, and other regularly recurring patterns in data. For example, rush hour

Seasonal variations Regularly repeating movements in series values that can be tied to recurring events.

TABLE 3.2 Using the Excel template for trend-adjusted smoothing

Trend Adjusted Exponential Smoothing

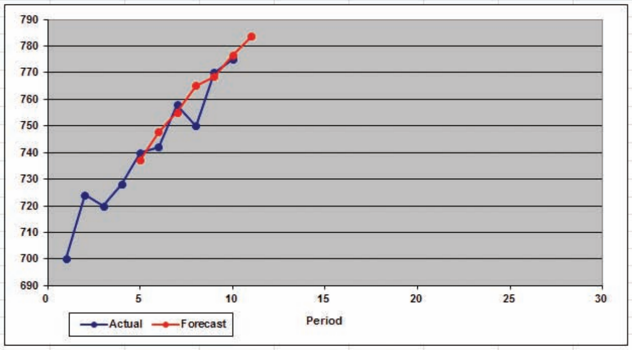
<Back

Clear

Model Initialization:

Period =	5		
Forecast =	737.33	α =	0.4
Trend =	9.33	Δα =	0.1
MAD =	4.94	β =	0.3
MSE =	56.95	Δβ =	0.1

Period	Actual	Forecast	Error
1	700		
2	724		
3	720		
4	728		
5	740	737.33	2.67
6	742	747.728	-5.728
7	758	755.0872	2.9128
8	750	765.21536	-15.21536
9	770	768.44179	1.558208
10	775	776.55181	-1.551808
11		783.6048	
12			
13			
14			
15			
16			
17			
18			
19			
20			
21			
22			



Period: 0

Actual:

Forecast:

Note: To display more data on the above graph, right click on the x-axis, select Format Axis, and set Maximum to higher value. The size of the graph may also be increased.

Moving Average | Exponential Smoothing | Linear Trend | Trend Adj Expon Smooth

traffic occurs twice a day—incoming in the morning and outgoing in the late afternoon. Theaters and restaurants often experience weekly demand patterns, with demand higher later in the week. Banks may experience daily seasonal variations (heavier traffic during the noon hour and just before closing), weekly variations (heavier toward the end of the week), and monthly variations (heaviest around the beginning of the month because of Social Security, payroll, and welfare checks being cashed or deposited). Mail volume; sales of toys, beer, automobiles, and turkeys; highway usage; hotel registrations; and gardening also exhibit seasonal variations.

Seasonality in a time series is expressed in terms of the amount that actual values deviate from the *average* value of a series. If the series tends to vary around an average value, then seasonality is expressed in terms of that average (or a moving average); if trend is present, seasonality is expressed in terms of the trend value.

There are two different models of seasonality: additive and multiplicative. In the *additive* model, seasonality is expressed as a *quantity* (e.g., 20 units), which is added to or subtracted from the series average in order to incorporate seasonality. In the *multiplicative* model, seasonality is expressed as a *percentage* of the average (or trend) amount (e.g., 1.10), which is then used to multiply the value of a series to incorporate seasonality. Figure 3.6 illustrates the two models for a linear trend line. In practice, businesses use the multiplicative model much more widely than the additive model, because it tends to be more representative of actual experience, so we shall focus exclusively on the multiplicative model.

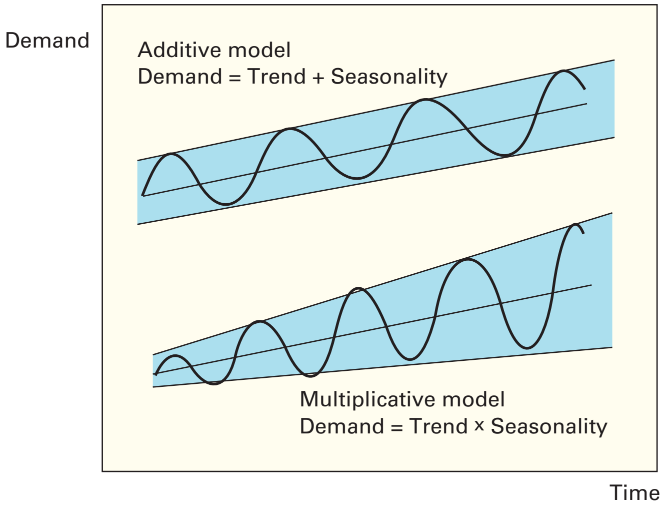


FIGURE 3.6
Seasonality: the additive and multiplicative models compared using a linear trend

The seasonal percentages in the multiplicative model are referred to as **seasonal relatives** or *seasonal indexes.* Suppose that the seasonal relative for the quantity of toys sold in May at a store is 1.20. This indicates that toy sales for that month are 20 percent above the monthly average. A seasonal relative of .90 for July indicates that July sales are 90 percent of the monthly average.

Seasonal relative Percentage of average or trend.

Knowledge of seasonal variations is an important factor in retail planning and scheduling. Moreover, seasonality can be an important factor in capacity planning for systems that must be designed to handle peak loads (e.g., public transportation, electric power plants, highways, and bridges). Knowledge of the extent of seasonality in a time series can enable one to *remove* seasonality from the data (i.e., to seasonally adjust data) in order to discern other patterns or the lack of patterns in the series. Thus, one frequently reads or hears about "seasonally adjusted unemployment" and "seasonally adjusted personal income."

The next section briefly describes how seasonal relatives are used.

Using Seasonal Relatives. Seasonal relatives are used in two different ways in forecasting. One way is to *deseasonalize data;* the other way is to *incorporate seasonality in a forecast.*

LO3.13 Compute and use seasonal relatives.

To deseasonalize data is to remove the seasonal component from the data in order to get a clearer picture of the nonseasonal (e.g., trend) components. Deseasonalizing data is accomplished by *dividing* each data point by its corresponding seasonal relative (e.g., divide November demand by the November relative, divide December demand by the December relative, and so on).

Incorporating seasonality in a forecast is useful when demand has both trend (or average) and seasonal components. Incorporating seasonality can be accomplished in this way:

1. Obtain trend estimates for desired periods using a trend equation.
2. Add seasonality to the trend estimates by *multiplying* (assuming a multiplicative model is appropriate) these trend estimates by the corresponding seasonal relative (e.g., multiply the November trend estimate by the November seasonal relative, multiply the December trend estimate by the December seasonal relative, and so on).

Example 7 illustrates these two techniques.

EXAMPLE 7
eXcel
mhhe.com/stevenson12e

A coffee shop owner wants to estimate demand for the next two quarters for hot chocolate. Sales data consist of trend and seasonality.

a. Quarter relatives are 1.20 for the first quarter, 1.10 for the second quarter, 0.75 for the third quarter, and 0.95 for the fourth quarter. Use this information to deseasonalize sales for quarters 1 through 8.

b. Using the appropriate values of quarter relatives and the equation $F_t = 124 + 7.5t$ for the trend component, estimate demand for periods 9 and 10.

SOLUTION

a.

Period	Quarter	Sales (gal.)	÷	Quarter Relative	=	Deseasonalized Sales
1	1	158.4	÷	1.20	=	132.0
2	2	153.0	÷	1.10	=	139.1
3	3	110.0	÷	0.75	=	146.7
4	4	146.3	÷	0.95	=	154.0
5	1	192.0	÷	1.20	=	160.0
6	2	187.0	÷	1.10	=	170.0
7	3	132.0	÷	0.75	=	176.0
8	4	173.8	÷	0.95	=	182.9

b. The trend values are:

Period 9: $F_t = 124 + 7.5(9) = 191.5$

Period 10: $F_t = 124 + 7.5(10) = 199.0$

Period 9 is a first quarter and period 10 is a second quarter. Multiplying each trend value by the appropriate quarter relative results in:

Period 9: $191.5(1.20) = 229.8$

Period 10: $199.0(1.10) = 218.9$

Centered moving average A moving average positioned at the center of the data that were used to compute it.

Computing Seasonal Relatives. A widely used method for computing seasonal relatives involves the use of a **centered moving average**. This approach effectively accounts for any trend (linear or curvilinear) that might be present in the data. For example, Figure 3.7 illustrates how a three-period centered moving average closely tracks the data originally shown in Figure 3.3.

Manual computation of seasonal relatives using the centered moving average method is a bit cumbersome, so the use of software is recommended. Manual computation is illustrated in Solved Problem 4 at the end of the chapter. The Excel template (on the Web site) is a simple and convenient way to obtain values of seasonal relatives (indexes). Example 8A illustrates this approach.

EXAMPLE 8A

excel

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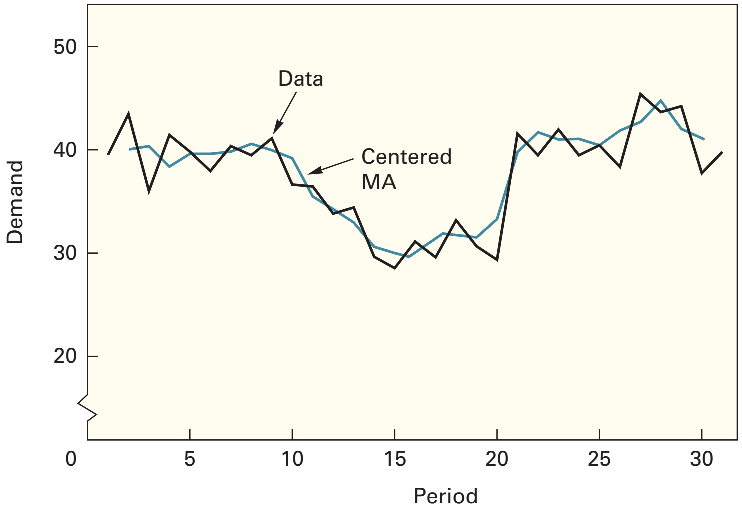
The manager of a call center recorded the volume of calls received between 9 and 10 a.m. for 21 days and wants to obtain a seasonal index for each day for that hour.

Day	Volume	Day	Volume	Day	Volume
Tues	67	Tues	60	Tues	64
Wed	75	Wed	73	Wed	76
Thurs	82	Thurs	85	Thurs	87
Fri	98	Fri	99	Fri	96
Sat	90	Sat	86	Sat	88
Sun	36	Sun	40	Sun	44
Mon	55	Mon	52	Mon	50

FIGURE 3.7
A centered moving average closely tracks the data

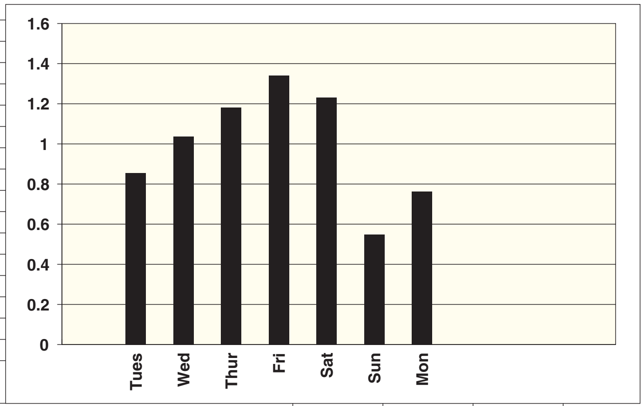


SOLUTION

Compute Seasonal Indexes
<Back
Number of "seasons" = 7

Season	Average Index	Standard Index
Tues	0.8688	0.8690
Wed	1.0460	1.0463
Thur	1.1980	1.1983
Fri	1.3648	1.3652
Sat	1.2383	1.2386
Sun	0.5339	0.5341
Mon	0.7484	0.7486

Clear



Period	Season	Actual	MA	Center	Index
1	Tues	67			
2	Wed	75			
3	Thur	82			
4	Fri	98		71.857143	1.3638171
5	Sat	90		70.857143	1.2701613
6	Sun	38		70.571429	0.5101215
7	Mon	55	71.857143	71	0.7746479
8	Tues	60	70.857143	71.142857	0.8433735
9	Wed	73	70.571429	70.571429	1.034413
10	Thur	85	71	71.142857	1.1947791
11	Fri	99	71.142857	70.714286	1.4
12	Sat	86	70.571429	71.285714	1.2064128
13	Sun	40	71.142857	71.714286	0.5577689
14	Mon	62	70.714286	72	0.7222222
15	Tues	64	71.285714	71.571429	0.8942116
16	Wed	76	71.714286	71.857143	1.0576541
17	Thur	87	72	72.428571	1.2011834
18	Fri	96	71.571429	72.142857	1.3306931
19	Sat	88	71.857143		
20	Sun	44	72.428571		
21	Mon	50	72.142857		

For practical purposes, you can round the relatives to two decimal places. Thus, the seasonal (standard) index values are:

Day	Index
Tues	0.87
Wed	1.05
Thurs	1.20
Fri	1.37
Sat	1.24
Sun	0.53
Mon	0.75

Computing Seasonal Relatives Using the Simple Average Method. The simple average (SA) method is an alternative way to compute seasonal relatives. Each seasonal relative is the average for that season divided by the average of all seasons. This method is illustrated in Example 8B, where the seasons are days. Note that there is no need to standardize the relatives when using the SA method.

The obvious advantage of the SA method compared to the centered MA method is the simplicity of computations. When the data have a stationary mean (i.e., variation around an average), the SA method works quite well, providing values of relatives that are quite close

EXAMPLE 8B

This example illustrates the steps needed to compute seasonal relatives using the SA method.

SOLUTION

Step 1: Compute the season averages

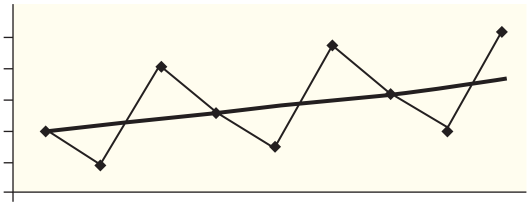
Step 3: Compute the SA relatives

Quarter	Year 1	Year 2	Year 3	Quarter Total	Quarter Average	Quarter Relative
1	20	23	17	60	20	20/20 = 1.00
2	10	12	8	30	10	10/20 = 0.50
3	25	17	22	66	22	22/20 = 1.10
4	28	26	30	84	28	28/20 = 1.40
					80	4.00

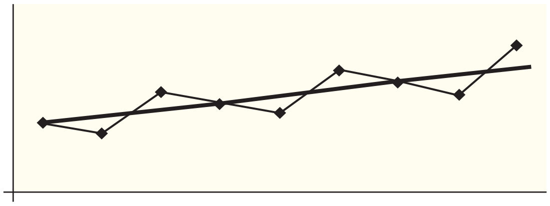
Average of quarter averages = 80/4 = 20

Step 2: Compute the overall average

to those obtained using the centered MA method, which is generally accepted as accurate. Conventional wisdom is that the SA method should not be used when linear trend is present in the data. However, it can be used to obtain fairly good values of seasonal relatives as long as the ratio of the intercept to the slope is large, or when variations are large relative to the slope, as shown below. Also, the larger the ratio, the smaller the error. The general relationship is illustrated in the following figure.



Variations are large relative to the slope of the line, so it is okay to use the SA method.



Variations are small relative to the slope of the line, so it is not okay to use the SA method.

Techniques for Cycles

Cycles are up-and-down movements similar to seasonal variations but of longer duration—say, two to six years between peaks. When cycles occur in time-series data, their frequent irregularity makes it difficult or impossible to project them from past data because turning points are difficult to identify. A short moving average or a naive approach may be of some value, although both will produce forecasts that lag cyclical movements by one or several periods.

The most commonly used approach is explanatory: Search for another variable that relates to, and *leads,* the variable of interest. For example, the number of housing starts (i.e., permits to build houses) in a given month often is an indicator of demand a few months later for products and services directly tied to construction of new homes (landscaping; sales of washers and dryers, carpeting, and furniture; new demands for shopping, transportation, schools). Thus, if an organization is able to establish a high correlation with such a *leading variable* (i.e., changes in the variable precede changes in the variable of interest), it can develop an equation that describes the relationship, enabling forecasts to be made. It is important that a persistent relationship exists between the two variables. Moreover, the higher the correlation, the better the chances that the forecast will be on target.

3.10 ASSOCIATIVE FORECASTING TECHNIQUES

Associative techniques rely on identification of related variables that can be used to predict values of the variable of interest. For example, sales of beef may be related to the price per pound charged for beef and the prices of substitutes such as chicken, pork, and lamb; real estate prices are usually related to property location and square footage; and crop yields are related to soil conditions and the amounts and timing of water and fertilizer applications.

The essence of associative techniques is the development of an equation that summarizes the effects of **predictor variables**. The primary method of analysis is known as **regression**. A brief overview of regression should suffice to place this approach into perspective relative to the other forecasting approaches described in this chapter.

Predictor variables Variables that can be used to predict values of the variable of interest.

Regression Technique for fitting a line to a set of points.

Simple Linear Regression

The simplest and most widely used form of regression involves a linear relationship between two variables. A plot of the values might appear like that in Figure 3.8. The object in linear regression is to obtain an equation of a straight line that minimizes the sum of squared vertical deviations of data points from the line (i.e., the *least squares criterion*). This **least squares line** has the equation

Least squares line Minimizes the sum of the squared vertical deviations around the line.

$$y_c = a + bx \tag{3–13}$$

where

y_c = Predicted (dependent) variable

x = Predictor (independent) variable

b = Slope of the line

a = Value of y_c when $x = 0$ (i.e., the height of the line at the y intercept)

LO3.14 Compute and use regression and correlation coefficients.

(*Note:* It is conventional to represent values of the predicted variable on the y axis and values of the predictor variable on the x axis.) Figure 3.9 is a general graph of a linear regression line.

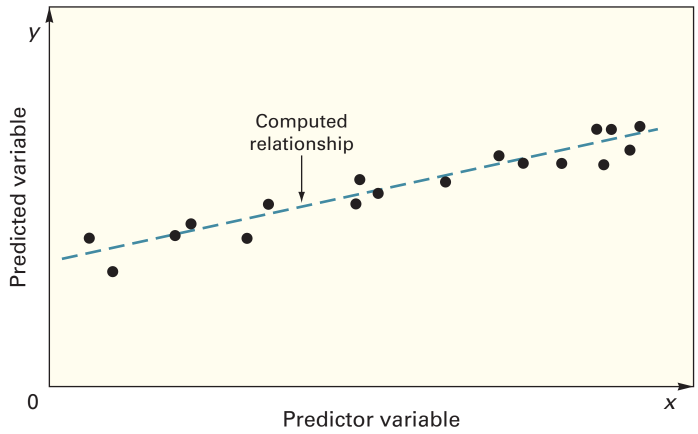


FIGURE 3.8
A straight line is fitted to a set of sample points

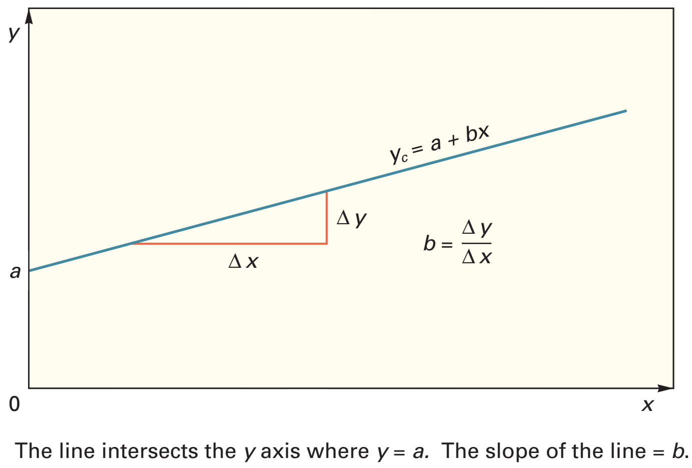


FIGURE 3.9
Equation of a straight line: The line represents the average (expected) values of variable y given values of variable x

The coefficients a and b of the line are based on the following two equations:

$$b = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{n(\Sigma x^2) - (\Sigma x)^2} \quad (3\text{–}14)$$

$$a = \frac{\Sigma y - b\Sigma x}{n} \text{ or } \bar{y} - b\bar{x} \quad (3\text{–}15)$$

where

n = Number of paired observations

EXAMPLE 9

eXcel

mhhe.com/stevenson12e

Healthy Hamburgers has a chain of 12 stores in northern Illinois. Sales figures and profits for the stores are given in the following table. Obtain a regression line for the data, and predict profit for a store assuming sales of $10 million.

Unit Sales, x (in $ millions)	Profits, y (in $ millions)
$ 7	$0.15
2	0.10
6	0.13
4	0.15
14	0.25
15	0.27
16	0.24
12	0.20
14	0.27
20	0.44
15	0.34
7	0.17

SOLUTION

First, plot the data and decide if a linear model is reasonable. (That is, do the points seem to scatter around a straight line? Figure 3.10 suggests they do.) Next, using the appropriate Excel template on the text Web site, obtain the regression equation $y_c = 0.0506 + 0.0159x$ (see Table 3.3). For sales of $x = 10$ (i.e., 10 million), estimated profit is $y_c = 0.0506 + 0.0159(10) = .2099$, or $209,900. (Substituting $x = 0$ into the equation to produce a predicted profit of $50,600 may appear strange because it seems to suggest that amount of profit will occur with no sales. However, the value of $x = 0$ is *outside the range of observed values.* The regression line should be used only for the range of values from which it was developed; the relationship may be nonlinear outside that range. The purpose of the a value is simply to establish the height of the line where it crosses the y axis.)

FIGURE 3.10
A linear model seems reasonable

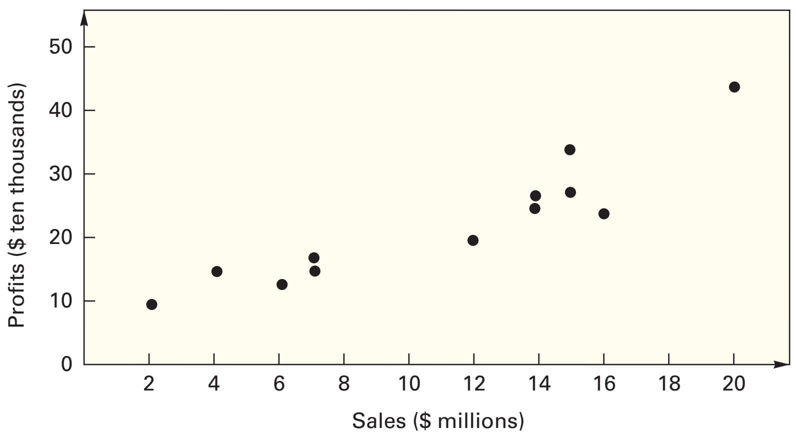


TABLE 3.3 Using the Excel template for linear regression

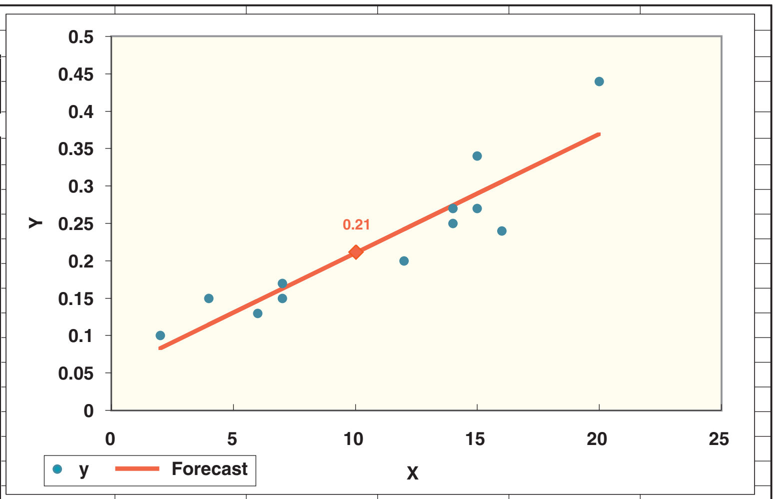
Simple Linear Regression

<Back

Clear

Slope =	0.0159	r =	0.9166657
Intercept =	0.0506008	r^2 =	0.840276

x	y	Forecast	Error
7	0.15	0.1621124	−0.0121124
2	0.1	0.0824612	0.0175388
6	0.13	0.1461822	−0.0161822
4	0.15	0.1143217	0.0356783
14	0.25	0.273624	−0.023624
15	0.27	0.2895543	−0.0195543
16	0.24	0.3054845	−0.0654845
12	0.2	0.2417636	−0.0417636
14	0.27	0.273624	−0.003624
20	0.44	0.3692054	0.0707946
15	0.34	0.2895543	0.0504457
7	0.17	0.1621124	0.0078876



x = 10

Δx = 1

Forecast: 0.2099031

One indication of how accurate a prediction might be for a linear regression line is the amount of scatter of the data points around the line. If the data points tend to be relatively close to the line, predictions using the linear equation will tend to be more accurate than if the data points are widely scattered. The scatter can be summarized using the **standard error of estimate**. It can be computed by finding the vertical difference between each data point and the computed value of the regression equation for that value of *x*, squaring each difference, adding the squared differences, dividing by $n - 2$, and then finding the square root of that value.

Standard error of estimate A measure of the scatter of points around a regression line.

$$S_e = \sqrt{\frac{\Sigma(y - y_c)^2}{n - 2}} \tag{3–16}$$

where

S_e = Standard error of estimate

y = y value of each data point

n = Number of data points

For the data given in Table 3.3, the error column shows the $y - y_c$ differences. Squaring each error and summing the squares yields .01659. Hence, the standard error of estimate is

$$S_e = \sqrt{\frac{.01659}{12 - 2}} = .0407 \text{ million}$$

One application of regression in forecasting relates to the use of indicators. These are uncontrollable variables that tend to lead or precede changes in a variable of interest. For example, changes in the Federal Reserve Board's discount rate may influence certain business activities. Similarly, an increase in energy costs can lead to price increases for a wide range of products and services. Careful identification and analysis of indicators may yield insight into possible future demand in some situations. There are numerous published indexes and Web sites from which to choose.[3] These include:

Net change in inventories on hand and on order.

Interest rates for commercial loans.

[3]See, for example, *The National Bureau of Economic Research, The Survey of Current Business, The Monthly Labor Review,* and *Business Conditions Digest.*

Industrial output.

Consumer price index (CPI).

The wholesale price index.

Stock market prices.

Other potential indicators are population shifts, local political climates, and activities of other firms (e.g., the opening of a shopping center may result in increased sales for nearby businesses). Three conditions are required for an indicator to be valid:

1. The relationship between movements of an indicator and movements of the variable should have a logical explanation.
2. Movements of the indicator must precede movements of the dependent variable by enough time so that the forecast isn't outdated before it can be acted upon.
3. A fairly high correlation should exist between the two variables.

Correlation A measure of the strength and direction of relationship between two variables.

Correlation measures the strength and direction of relationship between two variables. Correlation can range from -1.00 to $+1.00$. A correlation of $+1.00$ indicates that changes in one variable are always matched by changes in the other; a correlation of -1.00 indicates that increases in one variable are matched by decreases in the other; and a correlation close to zero indicates little *linear* relationship between two variables. The correlation between two variables can be computed using the equation

$$r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{n(\Sigma x^2) - (\Sigma x)^2}\sqrt{n(\Sigma y^2) - (\Sigma y)^2}} \tag{3–17}$$

The square of the correlation coefficient, r^2, provides a measure of the percentage of variability in the values of y that is "explained" by the independent variable. The possible values of r^2 range from 0 to 1.00. The closer r^2 is to 1.00, the greater the percentage of explained variation. A high value of r^2, say .80 or more, would indicate that the independent variable is a good predictor of values of the dependent variable. A low value, say .25 or less, would indicate a poor predictor, and a value between .25 and .80 would indicate a moderate predictor.

Comments on the Use of Linear Regression Analysis

Use of simple regression analysis implies that certain assumptions have been satisfied. Basically, these are as follows:

1. Variations around the line are random. If they are random, no patterns such as cycles or trends should be apparent when the line and data are plotted.
2. Deviations around the average value (i.e., the line) should be normally distributed. A concentration of values close to the line with a small proportion of larger deviations supports the assumption of normality.
3. Predictions are being made only within the range of observed values.

If the assumptions are satisfied, regression analysis can be a powerful tool. To obtain the best results, observe the following:

1. Always plot the data to verify that a linear relationship is appropriate.
2. The data may be time-dependent. Check this by plotting the dependent variable versus time; if patterns appear, use analysis of time series instead of regression, or use time as an independent variable as part of a *multiple regression analysis.*
3. A small correlation may imply that other variables are important.

In addition, note these weaknesses of regression:

1. Simple linear regression applies only to linear relationships with *one* independent variable.
2. One needs a considerable amount of data to establish the relationship—in practice, 20 or more observations.
3. All observations are weighted equally.

EXAMPLE 10

eXcel

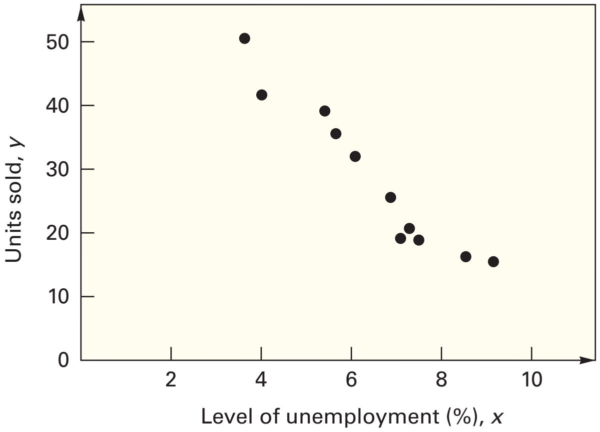
mhhe.com/stevenson12e

Sales of new houses and three-month lagged unemployment are shown in the following table. Determine if unemployment levels can be used to predict demand for new houses and, if so, derive a predictive equation.

Period	1	2	3	4	5	6	7	8	9	10	11
Units sold	20	41	17	35	25	31	38	50	15	19	14
Unemployment % (three-month lag)	7.2	4.0	7.3	5.5	6.8	6.0	5.4	3.6	8.4	7.0	9.0

SOLUTION

1. Plot the data to see if a *linear* model seems reasonable. In this case, a linear model seems appropriate *for the range of the data.*



2. Check the correlation coefficient to confirm that it is not close to zero using the Web site template, and then obtain the regression equation:

$$r = -.966$$

This is a fairly high negative correlation. The regression equation is

$$y = 71.85 - 6.91x$$

Note that the equation pertains only to unemployment levels in the range 3.6 to 9.0, because sample observations covered only that range.

Nonlinear and Multiple Regression Analysis

Simple linear regression may prove inadequate to handle certain problems because a linear model is inappropriate or because more than one predictor variable is involved. When nonlinear relationships are present, you should employ nonlinear regression; models that involve more than one predictor require the use of multiple regression analysis. While these analyses are beyond the scope of this text, you should be aware that they are often used. Multiple regression forecasting substantially increases data requirements.

3.11 MONITORING FORECAST ERROR

LO3.15 Construct control charts and use them to monitor forecast errors.

Many forecasts are made at regular intervals (e.g., weekly, monthly, quarterly). Because forecast errors are the rule rather than the exception, there will be a succession of forecast errors. Tracking the forecast errors and analyzing them can provide useful insight on whether forecasts are performing satisfactorily.

There are a variety of possible sources of forecast errors, including the following:

1. The model may be inadequate due to (*a*) the omission of an important variable, (*b*) a change or shift in the variable that the model cannot deal with (e.g., sudden appearance of a trend or cycle), or (*c*) the appearance of a new variable (e.g., new competitor).
2. Irregular variations may occur due to severe weather or other natural phenomena, temporary shortages or breakdowns, catastrophes, or similar events.
3. Random variations. Randomness is the inherent variation that remains in the data after all causes of variation have been accounted for. There are always random variations.

A forecast is generally deemed to perform adequately when the errors exhibit only random variations. Hence, the key to judging when to reexamine the validity of a particular forecasting technique is whether forecast errors are random. If they are not random, it is necessary to investigate to determine which of the other sources is present and how to correct the problem.

Control chart A visual tool for monitoring forecast errors.

A very useful tool for detecting nonrandomness in errors is a **control chart**. Errors are plotted on a control chart in the order that they occur, such as the one depicted in Figure 3.11. The centerline of the chart represents an error of zero. Note the two other lines, one above and one below the centerline. They are called the upper and lower control limits because they represent the upper and lower ends of the range of acceptable variation for the errors.

In order for the forecast errors to be judged "in control" (i.e., random), two things are necessary. One is that all errors are within the control limits. The other is that no patterns (e.g., trends, cycles, noncentered data) are present. Both can be accomplished by inspection. Figure 3.12 illustrates some examples of nonrandom errors.

Technically speaking, one could determine if any values exceeded either control limit without actually plotting the errors, but the visual detection of patterns generally requires plotting the errors, so it is best to construct a control chart and plot the errors on the chart.

FIGURE 3.11
Conceptual representation of a control chart

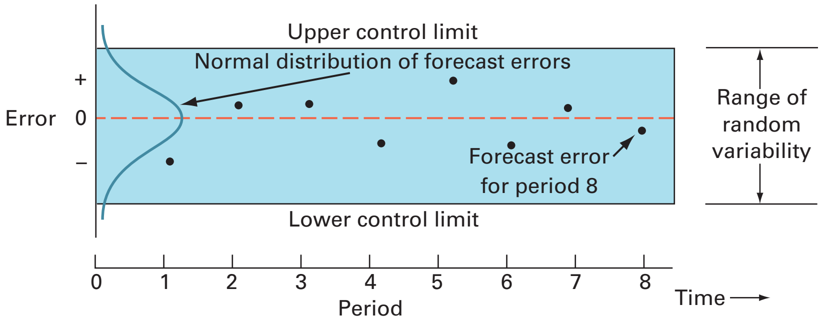
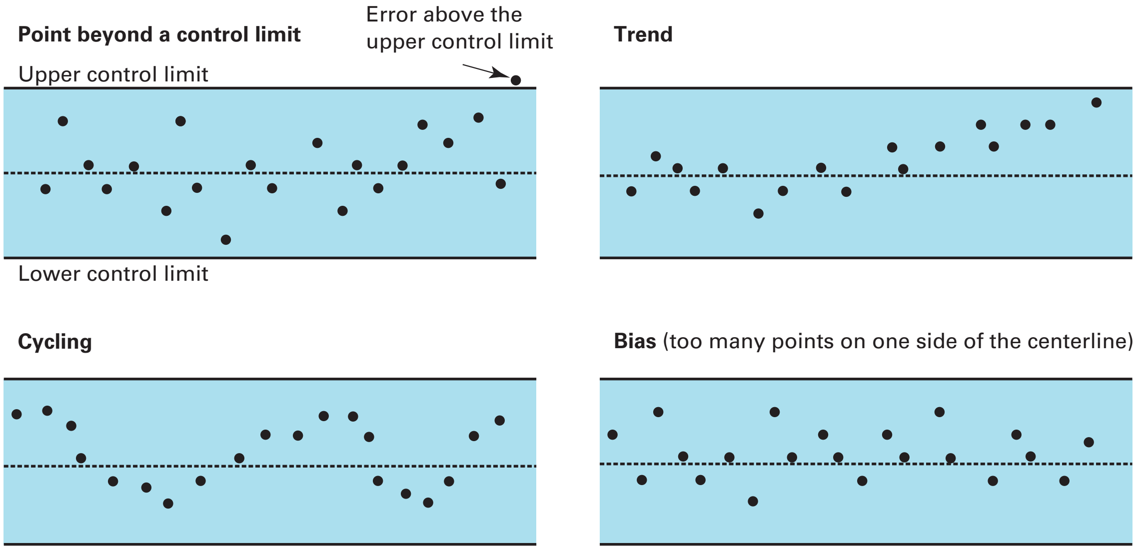


FIGURE 3.12 Examples of nonrandomness



To construct a control chart, first compute the MSE. The square root of MSE is used in practice as an estimate of the standard deviation of the distribution of errors.[4] That is,

$$s = \sqrt{\text{MSE}} \qquad (3\text{–}18)$$

Control charts are based on the assumption that when errors are random, they will be distributed according to a normal distribution around a mean of zero. Recall that for a normal distribution, approximately 95.5 percent of the values (errors in this case) can be expected to fall within limits of $0 \pm 2s$ (i.e., 0 ± 2 standard deviations), and approximately 99.7 percent of the values can be expected to fall within $\pm 3s$ of zero. With that in mind, the following formulas can be used to obtain the upper control limit (UCL) and the lower control limit (LCL):

$$\text{UCL: } 0 + z\sqrt{\text{MSE}}$$

$$\text{LCL: } 0 - z\sqrt{\text{MSE}}$$

where

z = Number of standard deviations from the mean

Combining these two formulas, we obtain the following expression for the control limits:

$$\text{Control limits: } 0 \pm z\sqrt{\text{MSE}} \qquad (3\text{–}19)$$

EXAMPLE 11

Compute $2s$ control limits for forecast errors when the MSE is 9.0.

SOLUTION

$$s = \sqrt{\text{MSE}} = 3.0$$

$$\text{UCL} = 0 + 2(3.0) = +6.0$$

$$\text{LCL} = 0 - 2(3.0) = -6.0$$

[4] The actual value could be computed as $s = \sqrt{\dfrac{\Sigma(e - \bar{e})^2}{n - 1}}$.

Tracking signal The ratio of cumulative forecast error to the corresponding value of MAD, used to monitor a forecast.

Bias Persistent tendency for forecasts to be greater or less than the actual values of a time series.

Another method is the **tracking signal**. It relates the cumulative forecast error to the average absolute error (i.e., MAD). The intent is to detect any **bias** in errors over time (i.e., a tendency for a sequence of errors to be positive or negative). The tracking signal is computed period by period using the following formula:

$$\text{Tracking signal}_t = \frac{\Sigma(\text{Actual}_t - \text{Forecast}_t)}{\text{MAD}_t} \tag{3–20}$$

Values can be positive or negative. A value of zero would be ideal; limits of $\pm$ 4 or $\pm$ 5 are often used for a range of acceptable values of the tracking signal. If a value outside the acceptable range occurs, that would be taken as a signal that there is bias in the forecast, and that corrective action is needed.

After an initial value of MAD has been determined, MAD can be updated and smoothed (SMAD) using exponential smoothing:

$$\text{SMAD}_t = \text{MAD}_{t-1} + \alpha\left(|\text{Actual} - \text{Forecast}|_t - \text{MAD}_{t-1}\right) \tag{3–21}$$

EXAMPLE 12

eXcel

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Monthly attendance at financial planning seminars for the past 24 months, and forecasts and errors for those months, are shown in the following table. Determine if the forecast is working using these approaches:

1. A tracking signal, beginning with month 10, updating MAD with exponential smoothing. Use limits of $\pm$ 4 and α = .2.
2. A control chart with 2s limits. Use data from the first eight months to develop the control chart, and then evaluate the remaining data with the control chart.

Month	*A* (Attendance)	*F* (Forecast)	*A* − *F* (Error)	|*e*|	Cumulative |*e*|
1	47	43	4	4	4
2	51	44	7	7	11
3	54	50	4	4	15
4	55	51	4	4	19
5	49	54	−5	5	24
6	46	48	−2	2	26
7	38	46	−8	8	34
8	32	44	−12	12	46
9	25	35	−10	10	56
10	24	26	−2	2	58
11	30	25	5	5	
12	35	32	3	3	
13	44	34	10	10	
14	57	50	7	7	
15	60	51	9	9	
16	55	54	1	1	
17	51	55	−4	4	
18	48	51	−3	3	
19	42	50	−8	8	
20	30	43	−13	13	
21	28	38	−10	10	
22	25	27	−2	2	
23	35	27	8	8	
24	38	32	6	6	
			−11		

SOLUTION

1. The sum of absolute errors through the 10th month is 58. Hence, the initial MAD is 58/10 = 5.8. The subsequent MADs are updated using the formula $MAD_{new} = MAD_{old} + \alpha(|e| - MAD_{old})$. The results are shown in the following table.

The tracking signal for any month is

$$\frac{\text{Cumulative error at that month}}{\text{Updated MAD at that month}}$$

t (Month)	|e|	MADt = MADt₋₁ + .2(|e|− MADt₋₁)	Cumulative Error	Tracking Signal = Cumulative Errort ÷ MADt
10			−20	−20/5.800 = −3.45
11	5	5.640 = 5.8 + .2(5 − 5.8)	−15	−15/5.640 = −2.66
12	3	5.112 = 5.640 + .2(3 − 5.64)	−12	−12/5.112 = −2.35
13	10	6.090 = 5.112 + .2(10 − 5.112)	−2	−2/6.090 = −0.33
14	7	6.272 = 6.090 + .2(7 − 6.090)	5	5/6.272 = 0.80
15	9	6.818 = 6.272 + .2(9 − 6.272)	14	14/6.818 = 2.05
16	1	5.654 = 6.818 + .2(1 − 6.818)	15	15/5.654 = 2.65
17	4	5.323 = 5.654 + .2(4 − 5.654)	11	11/5.323 = 2.07
18	3	4.858 = 5.323 + .2(3 − 5.323)	8	8/4.858 = 1.65
19	8	5.486 = 4.858 + .2(8 − 4.858)	0	0/5.486 = 0.00
20	13	6.989 = 5.486 + .2(13 − 5.486)	−13	−13/6.989 = −1.86
21	10	7.591 = 6.989 + .2(10 − 6.989)	−23	−23/7.591 = −3.03
22	2	6.473 = 7.591 + .2(2 − 7.591)	−25	−25/6.473 = −3.86
23	8	6.778 = 6.473 + .2(8 − 6.473)	−17	−17/6.778 = −2.51
24	6	6.622 = 6.778 + .2(6 − 6.778)	−11	−11/6.622 = −1.66

Because the tracking signal is within ± 4 every month, there is no evidence of a problem.

2. a. Make sure that the average error is approximately zero, because a large average would suggest a biased forecast.

$$\text{Average error} = \frac{\Sigma \text{ errors}}{n} = \frac{-11}{24} = -.46$$

b. Compute the standard deviation:

$$s = \sqrt{\text{MSE}} = \sqrt{\frac{\Sigma e^2}{n-1}}$$

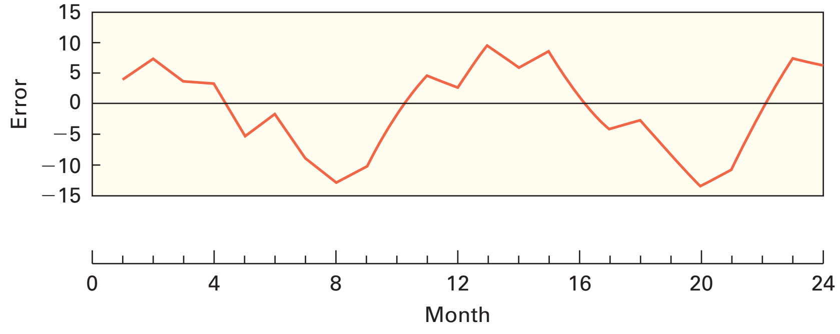
$$= \sqrt{\frac{4^2 + 7^2 + 4^2 + 4^2 + (-5)^2 + (-2)^2 + (-8)^2 + (-12)^2}{8-1}} = 6.91$$

c. Determine 2*s* control limits:

$$0 \pm 2s = 0 \pm 2(6.91) = -13.82 \text{ to } +13.82$$

d. (1) Check that all errors are within the limits. (They are.)

(2) Plot the data (see the following graph), and check for nonrandom patterns. Note the strings of positive and negative errors. This suggests nonrandomness (and that an improved forecast is possible). The tracking signal did not reveal this.



A plot helps you to visualize the process and enables you to check for possible patterns (i.e., nonrandomness) *within the limits* that suggest an improved forecast is possible.[5]

Like the tracking signal, a control chart focuses attention on deviations that lie outside predetermined limits. With either approach, however, it is desirable to check for possible patterns in the errors, even if all errors are within the limits.

If nonrandomness is found, corrective action is needed. That will result in less variability in forecast errors, and, thus, in narrower control limits. (Revised control limits must be computed using the resulting forecast errors.) Figure 3.13 illustrates the impact on control limits due to decreased error variability.

Comment The control chart approach is generally superior to the tracking signal approach. A major weakness of the tracking signal approach is its use of cumulative errors: Individual errors can be obscured so that large positive and negative values cancel each other. Conversely, with control charts, every error is judged individually. Thus, it can be misleading to rely on a tracking signal approach to monitor errors. In fact, the historical roots of the tracking signal approach date from before the first use of computers in business. At that time, it was much more difficult to compute standard deviations than to compute average deviations; for that reason, the concept of a tracking signal was developed. Now computers and calculators can easily provide standard deviations. Nonetheless, the use of tracking signals has persisted, probably because users are unaware of the superiority of the control chart approach.

3.12 CHOOSING A FORECASTING TECHNIQUE

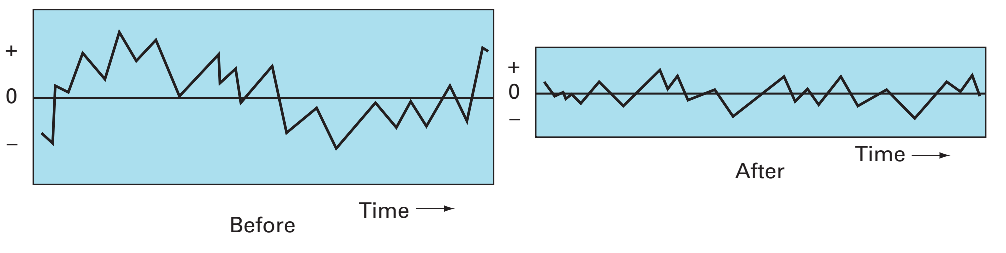
LO3.16 Describe the key factors and trade-offs to consider when choosing a forecasting technique.

Many different kinds of forecasting techniques are available, and no single technique works best in every situation. When selecting a technique, the manager or analyst must take a number of factors into consideration.

The two most important factors are *cost* and *accuracy.* How much money is budgeted for generating the forecast? What are the possible costs of errors, and what are the benefits that might accrue from an accurate forecast? Generally speaking, the higher the accuracy, the higher the cost, so it is important to weigh cost–accuracy trade-offs carefully. The best forecast is not necessarily the most accurate or the least costly; rather, it is some combination of accuracy and cost deemed best by management.

Other factors to consider in selecting a forecasting technique include the availability of historical data; the availability of computer software; and the time needed to gather and analyze data and to prepare the forecast. The forecast horizon is important because some techniques are more suited to long-range forecasts while others work best for the short range. For example, moving averages and exponential smoothing are essentially short-range techniques, since they produce forecasts for the *next* period. Trend equations can be used to project over much longer time periods. When using time-series data, *plotting the data* can be very helpful in choosing an appropriate method. Several of the qualitative techniques are well suited to

FIGURE 3.13
Removal of a pattern usually results in less variability, and, hence, narrower control limits



[5]The theory and application of control charts and the various methods for detecting patterns in the data are covered in more detail in Chapter 10, on quality control.

long-range forecasts because they do not require historical data. The Delphi method and executive opinion methods are often used for long-range planning. New products and services lack historical data, so forecasts for them must be based on subjective estimates. In many cases, experience with similar items is relevant. Table 3.4 provides a guide for selecting a forecasting method. Table 3.5 provides additional perspectives on forecasts in terms of the time horizon.

TABLE 3.4 A guide to selecting an appropriate forecasting method

Forecasting Method	Amount of Historical Data	Data Pattern	Forecast Horizon	Preparation Time	Personnel Background
Moving average	2 to 30 observations	Variation around an average	Short	Short	Little sophistication
Simple exponential smoothing	5 to 10 observations	Variation around an average	Short	Short	Little sophistication
Trend-adjusted exponential smoothing	10 to 15 observations	Trend	Short to medium	Short	Moderate sophistication
Trend models	10 to 20; for seasonality at least 5 per season	Trend	Short to medium	Short	Moderate sophistication
Seasonal	Enough to see 2 peaks and troughs	Handles cyclical and seasonal patterns	Short to medium	Short to moderate	Little sophistication
Causal regression models	10 observations per independent variable	Can handle complex patterns	Short, medium, or long	Long development time, short time for implementation	Considerable sophistication

Source: Adapted from J. Holton Wilson and Deborah Allison-Koerber, "Combining Subjective and Objective Forecasts Improves Results," *Journal of Business Forecasting,* Fall 1992, p. 4.

TABLE 3.5
Forecast factors, by range of forecast

Factor	Short Range	Intermediate Range	Long Range
1. Frequency	Often	Occasional	Infrequent
2. Level of aggregation	Item	Product family	Total output Type of product/service
3. Type of model	Smoothing Projection Regression	Projection Seasonal Regression	Managerial judgment
4. Degree of management involvement	Low	Moderate	High
5. Cost per forecast	Low	Moderate	High

In some instances, a manager might use more than one forecasting technique to obtain independent forecasts. If the different techniques produced approximately the same predictions, that would give increased confidence in the results; disagreement among the forecasts would indicate that additional analysis may be needed.

3.13 USING FORECAST INFORMATION

A manager can take a *reactive* or a *proactive* approach to a forecast. A reactive approach views forecasts as probable future demand, and a manager reacts to meet that demand (e.g., adjusts production rates, inventories, the workforce). Conversely, a proactive approach seeks to actively influence demand (e.g., by means of advertising, pricing, or product/service changes).

Generally speaking, a proactive approach requires either an explanatory model (e.g., regression) or a subjective assessment of the influence on demand. A manager might make two forecasts: one to predict what will happen under the status quo and a second one based on a "what if" approach, if the results of the status quo forecast are unacceptable.

3.14 COMPUTER SOFTWARE IN FORECASTING

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SCREENCAM TUTORIAL

Computers play an important role in preparing forecasts based on quantitative data. Their use allows managers to develop and revise forecasts quickly, and without the burden of manual computations. There is a wide range of software packages available for forecasting. The Excel templates on the text Web site are an example of a spreadsheet approach. There are templates for moving averages, exponential smoothing, linear trend equation, trend-adjusted exponential smoothing, and simple linear regression. Some templates are illustrated in the Solved Problems section at the end of the chapter.

3.15 OPERATIONS STRATEGY

Forecasts are the basis for many decisions and an essential input for matching supply and demand. Clearly, the more accurate an organization's forecasts, the better prepared it will be to take advantage of future opportunities and reduce potential risks. A worthwhile strategy can be to work to improve short-term forecasts. Better short-term forecasts will not only enhance profits through lower inventory levels, fewer shortages, and improved customer service, they also will enhance forecasting *credibility* throughout the organization: If short-term forecasts are inaccurate, why should other areas of the organization put faith in long-term forecasts? Also, the sense of confidence accurate short-term forecasts would generate would allow allocating more resources to strategic and medium- to longer-term planning and less on short-term, tactical activities.

Maintaining accurate, up-to-date information on prices, demand, and other variables can have a significant impact on forecast accuracy. An organization also can do other things to improve forecasts. These do not involve searching for improved techniques but relate to the inverse relation of accuracy to the forecast horizon: Forecasts that cover shorter time frames tend to be more accurate than longer-term forecasts. Recognizing this, management might choose to devote efforts to *shortening the time horizon that forecasts must cover.* Essentially, this means shortening the *lead time* needed to respond to a forecast. This might involve building *flexibility* into operations to permit rapid response to changing demands for products and services, or to changing volumes in quantities demanded; shortening the lead time required to obtain supplies, equipment, and raw materials or the time needed to train or retrain employees; or shortening the time needed to *develop* new products and services.

Lean systems are demand driven; goods are produced to fulfill orders rather than to hold in inventory until demand arises. Consequently, they are far less dependent on short-term forecasts than more traditional systems.

In certain situations forecasting can be very difficult when orders have to be placed far in advance. This is the case, for example, when demand is sensitive to weather conditions, such as the arrival of spring, and there is a narrow window for demand. Orders for products or

(continued)

(concluded)

services that relate to this (e.g., garden materials, advertising space) often have to be placed many months in advance—far beyond the ability of forecasters to accurately predict weather conditions and, hence, the timing of demand. In such cases, there may be pressures from salespeople who want low quotas and financial people who don't want to have to deal with the cost of excess inventory to have conservative forecasts. Conversely, operations people may want more optimistic forecasts to reduce the risk of being blamed for possible shortages.

Sharing forecasts or demand data throughout the supply chain can improve forecast quality in the supply chain, resulting in lower costs and shorter lead times. For example, both Hewlett-Packard and IBM require resellers to include such information in their contracts.

The following reading provides additional insights on forecasting and supply chains.

Gazing at the Crystal Ball

READING

Ram Reddy

Disregarding Demand Forecasting Technologies during Tough Economic Times Can Be a Costly Mistake

It's no secret that the IT sector has felt the brunt of the economic downturn. Caught up in the general disillusionment with IT has been demand forecasting (DF) technologies. Many companies blame DF technologies for supply chain problems such as excess inventory. Pinning the blame on and discontinuing DF technologies is the equivalent of throwing out the baby with the bathwater. The DF misunderstanding stems from the fact that, despite sophisticated mathematical models and underlying technologies, the output from these systems is, at best, an educated guess about the future.

A forecast from these systems is only as good as the assumptions and data used to build the forecast. Even the best forecast fails when an unexpected event—such as a recession—clobbers the underlying assumptions. However, this doesn't imply that DF technologies aren't delivering the goods. But, unfortunately, many DF and supply chain technology implementations have recently fallen victim to this mindset. DF is part science and part art (or intuition)—having the potential to significantly impact a company's bottom line. In this column, you'll find an overview of how DF is supposed to work and contrast that with how most companies actually practice it. I'll conclude with suggestions on how to avoid common mistakes implementing and using this particular class of technologies.

The Need for DF Systems

DF is crucial to minimizing working capital and associated expenses and extracting maximum value from a company's capital investments in property, plant, and equipment (PPE). It takes a manufacturing company a lot of lead time to assemble and stage the raw materials and components to manufacture a given number of products per day. The manufacturing company, in turn, generates its sales forecast numbers using data from a variety of sources such as distribution channels, factory outlets, value-added resellers, historical sales data, and general macroeconomic data. Manufacturing companies can't operate without a demand forecast because they won't know the quantities of finished goods to produce. The manufacturing company wants to make sure all or much of its finished product moves off the store shelves or dealer lots as quickly as possible. Unsold products represent millions of dollars tied up in inventory.

The flip side of this equation is the millions of dollars invested in PPE to manufacture the finished products. The company and its supporting supply chain must utilize as close to 100 percent of its PPE investments. Some manufacturing plants make products in lots of 100 or 1,000. Generally, it's cost prohibitive to have production runs of one unit. So how do you extract maximum value from your investments and avoid having money tied up in unsold inventory?

DF and supply chain management (SCM) technologies try to solve this problem by generating a production plan to meet forecasted demand and extract maximum value from PPE, while reducing the amount of capital tied up in inventory. Usually, the demand forecast is pretty close to the actual outcomes, but there are times when demand forecasts don't match the outcomes. In addition to unforeseen economic events, a new product introduction may be a stellar success or an abysmal failure. In the case of a phenomenal success, the manufacturing plant may not be able to meet demand for its product.

Consider the case of the Chrysler PT Cruiser. It succeeded way beyond the demand forecast's projections. Should it have started with manufacturing capacity to fulfill the runaway demand? Absolutely not. Given the additional millions of dollars of investment in PPE necessary to add that capacity, it would've backfired if the PT Cruiser had been a flop. The value provided by DF and supporting SCM technologies in this instance was the ability to add capacity to meet the amended forecast based on actual events. Demand forecasts can and do frequently miss their targets. The point to underscore here is that the underlying DF and supporting SCM technologies are critical to a company's ability to react and respond in a coordinated manner when market conditions change.

The manufacturing company and its supply chain are able to benefit from sharing information about the changed market conditions and responding to them in a coordinated manner. Despite best practices embedded in DF and SCM technologies to support this manner of collaboration, it plays out differently in the real world.

(continued)

(concluded)

How It Works in Real Life—Worst Practices

A company prepares its forecast by taking into account data about past sales, feedback from distribution channels, qualitative assessments from field sales managers, and macroeconomic data. DF and SCM technologies take these inputs and add existing capacities within the company and across the supply chain to generate a production plan for optimum financial performance.

There's been incredible pressure on executives of publicly traded companies to keep up stock prices. This pressure, among other reasons, may cause manufacturing company executives to make bold projections to external financial analysts (or Wall Street) about future sales without using the demand forecast generated from the bottom up. When the company realizes this disparity between the initial projection and the forecast, the forecast is changed to reflect the projections made by the company's officers, negating its accuracy.

The company arbitrarily sets sales targets for various regions to meet Wall Street numbers that are totally out of sync with input provided by the regional sales managers for the DF process. Even though the regional sales managers' input may have a qualitative element (art), they tend to be more accurate, given their proximity to the customers in the region. Unfortunately, the arbitrary sales targets make their way back to the supply chain, and the result is often excessive inventory build-up starting at the distribution channels to the upstream suppliers.

Seeing the inventory pile up, the manufacturing company may decide to shut down a production line. This action affects upstream suppliers who had procured raw materials and components to meet the executive-mandated production numbers, which may cause them to treat any future forecasted numbers with suspicion. Most cost efficiencies that could be obtained through planned procurement of raw materials and components go out the window. It's very likely that the companies try to blame DF and SCM technologies for failing to provide a responsive and efficient supply chain, even though the fault may lie in the company's misuse of the technologies and not the technologies themselves.

Guarding against the Extremes

Earlier in this column, I said that DF is part art or intuition and part science. The art/intuition part comes in when subject-matter experts (SMEs) make educated estimates about future sales. These SMEs could range from distribution outlet owners to sales and marketing gurus and economists. Their intuition is typically combined with data (such as historical sales figures) to generate the forecast for the next quarter or year. During a recession, the SMEs tend to get overly pessimistic. The demand forecasts generated from this mindset lead to inventory shortages when the economy recovers. Similarly, during an economic expansion, the SMEs tend to have an overly rosy picture of the future. This optimism leads to inventory gluts when the economy starts to slow down. In both instances, blaming and invalidating DF and SCM technologies is counterproductive in the long run.

It's very rare that a demand forecast and the actual outcome match 100 percent. If it's close enough to avoid lost sales or create an excess inventory situation, it's deemed a success. DF and supporting SCM technologies are supposed to form a closed loop with actual sales at the cash register providing a feedback mechanism. This feedback is especially essential during economic upturns or downturns. It provides the necessary information to a company and its supply chain to react in a coordinated and efficient manner.

Don't let the current disillusionment with DF and SCM technologies impede the decision-making process within your company. The intelligent enterprise needs these technologies to effectively utilize its capital resources and efficiently produce to meet its sales forecasts.

Ram Reddy is the author of *Supply Chains to Virtual Integration* (McGraw-Hill, 2001). He is the president of Tactica Consulting Group, a technology and business strategy consulting company.

Questions

1. What is DF and why is it important?
2. Why might a company executive make bold predictions about future demand to Wall Street analysts?
3. How might an executive's comments to Wall Street analysts affect demand forecasts, and what are the consequences of doing so?

Source: Ram Reddy, "Gazing at the Crystal Ball," *Intelligent Enterprise,* June 13, 2002.

SUMMARY

Forecasts are vital inputs for the design and the operation of the productive systems because they help managers to anticipate the future.

Forecasting techniques can be classified as qualitative or quantitative. Qualitative techniques rely on judgment, experience, and expertise to formulate forecasts; quantitative techniques rely on the use of historical data or associations among variables to develop forecasts. Some of the techniques are simple, and others are complex. Some work better than others, but no technique works all the time. Moreover, all forecasts include a certain degree of inaccuracy, and allowance should be made for this. The techniques generally assume that the same underlying causal system that existed in the past will continue to exist in the future.

The qualitative techniques described in this chapter include consumer surveys, salesforce estimates, executive opinions, and manager and staff opinions. Two major quantitative approaches are described: analysis of time-series data and associative techniques. The time-series techniques rely strictly on the examination of historical data; predictions are made by projecting past movements of a variable into the future without considering specific factors that might influence the variable. Associative techniques attempt to explicitly identify influencing factors and to incorporate that information into equations that can be used for predictive purposes.

All forecasts tend to be inaccurate; therefore, it is important to provide a measure of accuracy. It is possible to compute several measures of forecast accuracy that help managers to evaluate the performance of a given technique and to choose among alternative forecasting techniques. Control of forecasts involves deciding whether a forecast is performing adequately, typically using a control chart.

When selecting a forecasting technique, a manager must choose a technique that will serve the intended purpose at an acceptable level of cost and accuracy.

The various forecasting techniques are summarized in Table 3.6. Table 3.7 lists the formulas used in the forecasting techniques and in the methods of measuring their accuracy. Note that the Excel templates on the text Web site that accompanies this book are especially useful for tedious calculations.

KEY POINTS

1. Demand forecasts are essential inputs for many business decisions; they help managers decide how much supply or capacity will be needed to match expected demand, both within the organization and in the supply chain.
2. Because of random variations in demand, it is likely that the forecast will not be perfect, so managers need to be prepared to deal with forecast errors.
3. Other, nonrandom factors might also be present, so it is necessary to monitor forecast errors to check for nonrandom patterns in forecast errors.
4. It is important to choose a forecasting technique that is cost-effective and one that minimizes forecast error.

TABLE 3.6 Forecasting approaches

	Approaches	Brief Description
Judgment/opinion:	Consumer surveys	Questioning consumers on future plans
	Direct-contact composites	Joint estimates obtained from salespeople or customer service people
	Executive opinion	Finance, marketing, and manufacturing managers join to prepare forecast
	Delphi technique	Series of questionnaires answered anonymously by knowledgeable people; successive questionnaires are based on information obtained from previous surveys
	Outside opinion	Consultants or other outside experts prepare the forecast
Statistical:	Time series:	
	Naive	Next value in a series will equal the previous value in a comparable period
	Moving averages	Forecast is based on an average of recent values
	Exponential smoothing	Sophisticated form of weighted moving average
	Associative models:	
	Simple regression	Values of one variable are used to predict values of a dependent variable
	Multiple regression	Two or more variables are used to predict values of a dependent variable

TABLE 3.7
Summary of formulas

Technique	Formula	Definitions
MAD	$\text{MAD} = \dfrac{\sum^{n} \lvert e \rvert}{n}$	MAD = Mean absolute deviation e = Error, $A - F$ n = Number of errors
MSE	$\text{MSE} = \dfrac{\sum^{n} e^2}{n - 1}$	MSE = Mean squared error n = Number of errors

Technique	Formula	Definitions
MAPE	$\text{MAPE} = \dfrac{\sum^{n}\left[\dfrac{\lvert e_t \rvert}{\text{Actual}_t} \times 100\right]}{n}$	MAPE = Mean absolute percent error n = Number of errors
Moving average forecast	$F_t = \dfrac{\sum_{i=1}^{n} A_{t-i}}{n}$	A = Demand in period $t - i$ n = Number of periods
Weighted average	$F_t = w_{t-n}(A_{t-n}) + \cdots + w_{t-2}(A_{t-2}) + w_{t-1}$ $(A_{t-1}) + w_{t-1}(A_{t-1}) + \cdots + w_{t-n}(A_{t-n})$	W_t = Weight for the period t A_t = Actual value in period t
Exponential smoothing forecast	$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$	α = Smoothing factor
Linear trend forecast	$F_t = a + b_t$ where $b = \dfrac{n\Sigma ty - \Sigma t \Sigma y}{n\Sigma t^2 - (\Sigma t)^2}$ $a = \dfrac{\Sigma y - b\Sigma t}{n}$ or $\bar{y} - b\bar{t}$	a = y intercept b = Slope
Trend-adjusted forecast	$\text{TAF}_{t+1} = S_t + T_t$ where $S_t = \text{TAF}_t + \alpha(A_t - \text{TAF}_t)$ $T_t = T_{t-1} + \beta(\text{TAF}_t - \text{TAF}_{t-1} - T_{t-1})$	t = Current period TAF_{t+1} = Trend-adjusted forecast for next period S = Previous forecast plus smoothed error T = Trend component
Linear regression forecast	$Y_c = a + bx$ where $b = \dfrac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{n(\Sigma x^2) - (\Sigma x)^2}$ $a = \dfrac{\Sigma y - b\Sigma x}{n}$ or $\bar{y} - b\bar{x}$	y_c = Computed value of dependent variable x = Predictor (independent) variable b = Slope of the line a = Value of y_c when $x = 0$
Standard error of estimate	$S_e = \sqrt{\dfrac{\Sigma(y - y_c)^2}{n - 2}}$	S_e = Standard error of estimate y = y value of each data point n = Number of data points
Tracking signal	$\text{TS}_t = \dfrac{\sum^{n} e}{\text{MAD}}$	
Control limits	$\text{UCL} = 0 + z\sqrt{\text{MSE}}$ $\text{LCL} = 0 - z\sqrt{\text{MSE}}$	$\sqrt{\text{MSE}}$ = standard deviation z = Number of standard deviations; 2 and 3 are typical values

KEY TERMS

associative model, 82
bias, 108
centered moving average, 98
control chart, 106
correlation, 104
cycle, 84
Delphi method, 83
error, 80
exponential smoothing, 89
focus forecasting, 91
forecast, 75
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mean absolute percent error (MAPE), 81
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SOLVED PROBLEMS

Problem 1

Forecasts based on averages. Given the following data:

Period	Number of Complaints
1	60
2	65
3	55
4	58
5	64

Prepare a forecast for period 6 using each of these approaches:

a. The appropriate naive approach.
b. A three-period moving average.
c. A weighted average using weights of .50 (most recent), .30, and .20.
d. Exponential smoothing with a smoothing constant of .40.

Solution
Step by step

a. Plot the data to see if there is a pattern. Here we have only variations around an average (i.e., no trend or cycles). Therefore, the most recent value of the series becomes the next forecast: 64.

b. Use the latest values. $MA_3 = \dfrac{55 + 58 + 64}{3} = 59$

c. $F = .20(55) + .30(58) + .50(64) = 60.4$

d. Start with period 2. Use the data in period 1 as the forecast for period 2, and then use exponential smoothing for successive forecasts.

Period	Number of Complaints	Forecast	Calculations
1	60		[The previous value of the series is used
2	65	60	as the starting forecast.]
3	55	62	$60 + .40(65 - 60) = 62$
4	58	59.2	$62 + .40(55 - 62) = 59.2$
5	64	58.72	$59.2 + .40(58 - 59.2) = 58.72$
6		60.83	$58.72 + .40(64 - 58.72) = 60.83$