

CHAPTER 10

Forecasting

LEARNING OBJECTIVES

After reading this chapter, you should be able to:

- LO10.1** Describe why forecasting is important.
- LO10.2** Describe the four common methods of qualitative forecasting.
- LO10.3** Calculate a moving average and exponential smoothing forecast, and explain when they should be used.
- LO10.4** Evaluate forecast accuracy using a variety of methods.
- LO10.5** Carry out causal forecasting.
- LO10.6** Evaluate factors that impact forecasting method selection.
- LO10.7** Explain the benefits and costs of CPFR.
- LO10.8** Solve advanced forecasting problems.

LO10.1 Describe why forecasting is important.

Forecasting is the art and science of predicting future events. In organizations, managers are usually most interested in predicting future demand. Before appropriate software was available, forecasting was largely an art, but it has more recently developed into a science as well. Although managerial judgment is still required for forecasting, managers today are aided by both simple and sophisticated analytical tools and methods, as well as significant amounts of data from a wide variety of sources. For example, airlines forecast future capacity needs by analyzing their own historical demand data as well as data on the pricing and capacity of their competitors.

Many different methods of forecasting and their uses are described here. Selecting the best forecasting method for a given situation must be done carefully for the particular use it is intended to serve. There is no universal forecasting method for all situations.

Operations Leader

A Winning Forecast for Harrah's Cherokee Casino & Hotel

Harrah's Cherokee Casino & Hotel, located in the town of Cherokee, North Carolina, draws about four million visitors each year. Its alcohol-free facilities include over 1,100 hotel rooms. The Eastern Band of Cherokee Indians contracts with Harrah's, the world's largest gaming company, to manage the casino and hotel. Profits are used to support health care, education, and other initiatives for the local Native American community.



© Medioimages/Alamy

Sophisticated segmentation of customers, analysis of past demand patterns, and focused pricing strategies have helped the hotel achieve an annual occupancy rate of 98.6 percent. How do they do it?

Cherokee first determines *true* customer demand, based on past demand *and* reservation requests that were denied (because facilities were full). True customer demand can be greater than sales due to reservation denials. Customers provide their casino membership number when requesting reservations, making it easy for Cherokee to track both accepted and denied reservation requests.

Next, Cherokee develops its daily forecast based on historical data. For example, the forecast for a particular Saturday might be based on demand for recent Saturdays as well as similar dates in previous years. The forecast model accounts for day of week, seasonality, trends, and other special-event factors.

Based on its forecast and knowledge about the price each customer segment is willing to pay, Cherokee sets a room price for each customer segment on each day. This enables management to maximize the price of every room on every day, resulting in a 60 percent profit margin.

Source: Metters et al., "The 'Killer Application' of Revenue Management: Harrah's Cherokee Casino & Hotel," *Interfaces*, May–June 2008 and www.caesars.com/harrahs-cherokee, 2016.

Forecasts are almost always wrong! It is rare for sales to exactly match the amount forecast. A little variation from the forecast can often be absorbed by extra capacity, inventory, or rescheduling of orders. But large variations can wreak havoc in the business. For example, suppose 100,000 cases of a product are forecast to be sold in a particular year, but only 80,000 cases are actually sold. The extra 20,000 cases can end up in inventory, or workers might be cut to reduce production levels. It is equally painful if the forecast is too low. Then capacity is strained, overtime or extra workers may be added in a rush, or sales may be lost due to stockouts. Consumers often see the results of under- or over-forecasting in retail stores in the form of stockouts or clearance of leftover inventory. From these examples it is clear that forecasting has a strong impact on operations and, indeed, all functions in the business.

In recognition of inherent forecasting error, all forecasts should have at least two numbers: one for the best estimate of demand (e.g., mean, median, or mode) and the other for forecast error (standard deviation, absolute deviation, or range). To produce forecasts with only an average is to ignore error, but this is a common occurrence in practice.

Given the challenge of getting the forecast “right,” there are three main ways for managers to accommodate forecast errors. One is to try to reduce the error through better forecasting. The second is to build more flexibility into operations and the supply chain. The third is to reduce the lead time over which forecasts are required. This is because forecasting error usually increases as the forecasting time horizon increases, so next week’s forecast will usually have less error than next month’s forecast. Even good forecasts will have some error, but the lowest possible error along with reasonable forecasting costs is the goal.

Forecasting occupies a central role in the firm, and throughout the supply chain, because of its complexity and its impact on the business. Harrah’s Cherokee Casino & Hotel performs complex forecasting, as described in the Operations Leader box.

10.1 FORECASTING FOR DECISION MAKING

Although there are many types of forecasting, this chapter will focus on forecasting demand for output from the operations function. Demand and sales, however, are not always the same thing. Whenever the demand is not constrained by capacity or other management policies, the forecasting of demand will be the same as the forecasting of sales. Otherwise, sales may be somewhat below real customer demand.

We should also clarify the difference between forecasting and planning.

We should also clarify the difference between forecasting and planning. Forecasting deals with what we think *will* happen in the future. Planning deals with what we think *should* happen in the future. Thus, through planning, we consciously attempt to alter future events, while we use forecasting only to predict them. Good planning utilizes a forecast as an input. If the forecast is not acceptable, sometimes a plan can be devised to change the course of events.



Forecasting is one input to all types of business planning and control, both inside and outside the operations function. Marketing uses forecasts for planning products and services, promotion, and pricing. Finance uses forecasting as an input to financial planning. Human resources requires forecasts to anticipate hiring decisions and personnel budgets. Forecasting is an input for operations decisions on process design, capacity planning, and inventory. Forecasting is done by firms all along the supply chain.

For process design purposes, forecasting is needed to decide on the type of process and the degree of automation to be used. For example, a low forecast of future demand may indicate that little automation is needed and the process should be kept as simple as possible.

Capacity decisions utilize forecasts for different planning horizons. For planning facilities, a long-range forecast several years into the future is needed. For medium-range capacity decisions, a more detailed forecast by product line or service will be needed to determine hiring plans, subcontracting, and equipment decisions. Short-range capacity decisions, including the assignment of available workers and machines to jobs require a highly accurate forecast.



Operations, Marketing, Finance, and Human Resources collaborate to both create and use forecasts.

© mediaphotos/Getty Images

Inventory decisions resulting in purchasing actions tend to be short range in nature and deal with specific products. The forecasts that lead to these decisions must meet the same requirements as short-range

these decisions must meet the same requirements as short-range scheduling forecasts: They must have a high degree of accuracy and individual product specificity.



There are different types of decisions in operations with different forecasting requirements, as shown in [Table 10.1](#). The table also shows some of the uses of forecasts

in marketing, finance/accounting, and human resources. And it indicates the three types of forecasting methods associated with these decisions: qualitative, time series, and causal.

TABLE 10.1 Forecasting Uses and Methods

	Time Horizon	Accuracy Required	Number of Forecasts	Management Level	Forecasting Method
Uses of Forecasting for Operations Decisions					
Process design	Long	Medium	Single or few	Top	Qualitative or causal
Capacity planning facilities	Long	Medium	Single or few	Top	Qualitative and causal
Aggregate planning	Medium	High	Few	Middle	Causal and time series
Scheduling	Short	Highest	Many	Lower	Time series
Inventory management	Short	Highest	Many	Lower	Time series
Uses of Forecasting in Marketing, Finance, and Human Resources					
Long-range marketing programs	Long	Medium	Single or few	Top	Qualitative
Pricing decisions	Short	High	Many	Middle	Time series
New-product introduction	Medium	Medium	Single	Top	Qualitative and causal
Cost estimating	Short	High	Many	Lower	Time series
Capital budgeting	Medium	High	Few	Top	Causal and time series
Labor planning	Medium	Medium	Few	Lower	Qualitative and time series

In general terms, **qualitative forecasting methods** rely on managerial judgment; they do not use specific quantitative models. Qualitative methods are useful when there is a lack of data or when past data are not reliable predictors of the future.

There are two general types of **quantitative forecasting methods**: time-series and causal forecasting. Quantitative methods utilize an analytical model to arrive at a forecast. The basic assumption for all quantitative forecasting methods is that past data and data patterns are reliable predictors of the future. Forecasting relies on predictive analytics, constructing a useful forecasting model from past demand and other relevant data.

In the remainder of this chapter, we refer to long, medium, and short time ranges. “Long range” will mean two years or more into the future, a common horizon for the planning of facilities and processes. “Medium range” is between six months and two years, the normal time frame for aggregate planning decisions, budgeting, and other resource acquisition and allocation decisions. “Short range” refers to less than six months, where the decisions involve procurement of materials and scheduling of particular jobs and activities.

10.2 QUALITATIVE FORECASTING METHODS

LO10.2 Describe the four common methods of qualitative forecasting.

Qualitative forecasting methods utilize managerial judgment, experience, and relevant data, if available. Because judgment is used, two different managers using qualitative methods may arrive at widely different forecasts.

Some people think that qualitative forecasts should be used only as a last resort. This is not strictly true. Qualitative forecasts should be used when past data are not reliable indicators of future demand, for example, when changes in styles or technologies alter customer preferences. Qualitative forecasting must also be used for new-product and new-service introductions for which historical demand data are not available. In these cases, qualitative methods can be used to develop a forecast by life-cycle analogy or by the use of market research data. Note, a systematic approach to qualitative forecasting is possible even though judgment and experience is used.

Table 10.2 describes four of the best-known qualitative methods. Qualitative methods typically are used for medium- and long-range forecasts for planning process design or the capacity of facilities

methods. Qualitative methods typically are used for medium- and long-range forecasts for planning process design or the capacity of facilities.

TABLE 10.2 Qualitative Forecasting Methods

Qualitative Methods	Description of Method	Uses	Accuracy			Relative Cost
			Short Term	Medium Term	Long Term	
1. Delphi	Forecast developed by a panel of experts answering a series of questions on successive rounds. Anonymous responses are fed back on each round to all participants. Three to six rounds may be used to obtain convergence.	Capacity or facility planning. To assess when technological changes might occur.	Fair to very good	Fair to very good	Fair to very good	Medium to high
2. Market surveys	Panels, questionnaires, test markets, or surveys used to gather data on market conditions.	Total company sales, major product groups, or individual products.	Very good	Good	Fair	High
3. Life-cycles analogy	Prediction based on the introduction, growth, and maturity phases of similar products. Uses the S-shaped sales growth curve.	Long-range sales for capacity or facility planning.	Poor	Fair to good	Fair to good	Medium
4. Informed judgment	Forecast by a group or an individual on the basis of	Total sales and individual products.	Poor to fair	Poor to fair	Poor to fair	Low

experience,
hunches, or
facts about the
situation. No
rigorous
method is
used.

Source: Exhibit adapted from David M. Georgoff and Robert Murdick, "Manager's Guide to Forecasting," *Harvard Business Review*, January–February 1986, pp. 110–120.

Both informed judgment and the Delphi method use expert opinion to arrive at a forecast. When informed judgment is used, a panel will discuss the forecast and arrive at a consensus. The danger of this method is that sometimes not all members of the panel are heard, and one person can dominate the panel in terms of the final forecast.

The Delphi method was developed to correct this situation. It consists of several rounds of anonymous data collection before reaching a forecast. In the first round, each member of the panel anonymously provides a forecast. Then the forecast information from all panel members is fed back to each panel member, again anonymously, along with any reasons or comments about their forecasts. In the second and subsequent rounds members can review the forecasts of the other panel members and then revise their forecasts if they find new information. After three or four rounds of data collection, there is a tendency for the forecast to converge to a range of forecast values, and members no longer adjust their forecasts on the basis of panel feedback. As a result, the Delphi panel arrives not only at a most likely forecast (e.g., mean, median, or mode) but also an estimate of forecast error (e.g., standard deviation, absolute deviation, or range).

Page 191

Market surveys are commonly used to get information from potential customers about willingness to buy a product or service. A variety of methods can be used, including customer responses via phone, mail, or Internet. Also, test markets are an effective way to gauge customer demand.

The life-cycle analogy method is based on the idea that product or service demand has well-defined life stages (introduction, growth, and maturity) that follow an S-shaped curve. To gauge the shape of the curve, an analogy with a similar product or service is used. For example, an estimate of demand for a new website is based on the actual growth curve of similar websites.

Although we are not describing qualitative methods in detail, we note their usefulness in certain situations. Next, we turn to the first type of quantitative model: time-series methods, which are well suited to creating forecasts of a short-range nature.

10.3 TIME-SERIES FORECASTING

Time-series methods make detailed analyses of past demand patterns to predict demand in the future. One of the basic assumptions of all time-series methods is that demand can be decomposed into components such as average **level**, **trend**, **seasonality**, **cycle**, and **random error**. A sample of these components for a representative time series is shown in [Figure 10.1](#). When the components are added together (or in some cases multiplied), they will equal the original time series data pattern.

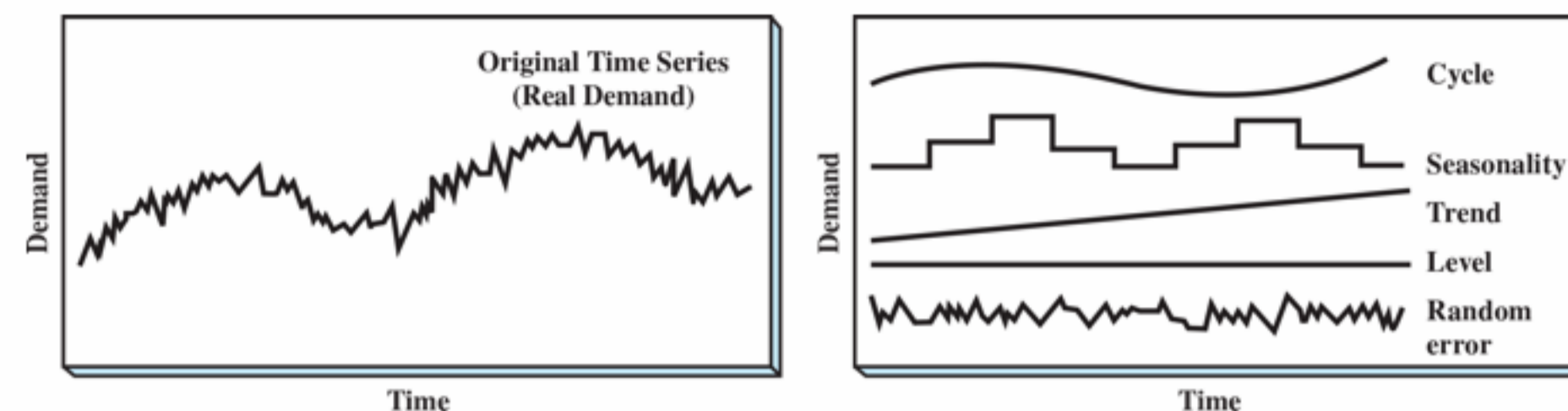


Figure 10.1 Decomposition of time-series data.



Snow skiing is an industry that exhibits several demand patterns. It is primarily a seasonal industry, and over many years the industry has experienced a growth trend. Random factors like snowfall cause abrupt variations in demand.

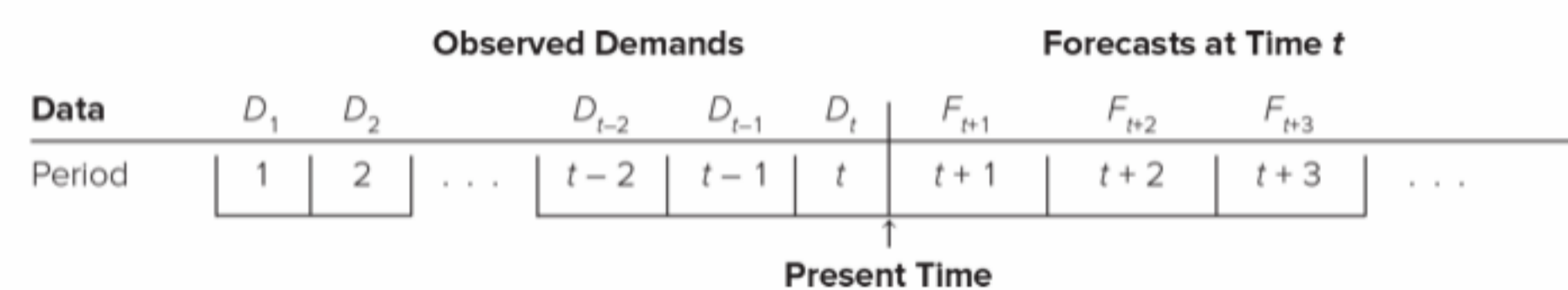
© Randy Lincks/Alamy

The *level* is the relatively constant average demand during a time interval. The *trend* is an increase or decrease in the average demand over time. *Seasonality* is a regularly repeated pattern of increasing and decreasing demand. It can be yearly (such as peak demand at a campus bookstore at the start of each semester), but can also apply to shorter time frames, weekly or daily. For example, a 24-hour call center experiences a seasonal demand pattern on a daily basis. Peak demand occurs during the day, moderate demand in the evening, and very little demand during the

day, moderate demand in the evening, and very little demand during the night. The *cycle* is increasing or decreasing demand over long time periods, often many years. Cyclical changes in demand may be due to changes in the overall economy or changes in product or service life cycles, among other reasons. *Random error* reflects short-term fluctuations in demand that cannot be forecast.

The basic strategy used in time-series forecasting is to identify the magnitude and form of each component on the basis of available past data. These components, except the random error component, are then used to estimate future demand in the form of a forecast.

In discussions of time-series forecasting, the following symbols and terminology are used:



- D_t = demand during period t
- F_{t+1} = forecast demand for period $t + 1$
- $e_t = D_t - F_t$ = forecast error in period t
- A_t = average computed through period t

We are at the end of period t , having just observed actual demand that defines the value of D_t , and are making forecasts for future periods $t + 1$, $t + 2$, $t + 3$, and so on.

10.4 MOVING AVERAGE

LO10.3 Calculate a moving average and exponential smoothing forecast, and explain when they should be used.

The simplest analytics method of time-series forecasting is the **moving average**. For this method, it is assumed that the time series has only a level component plus a random error component. No seasonal pattern, trend, or cycle components are assumed to be present in the demand data. More advanced versions of the moving average can, however, include these additional components.

When the moving average is used, a given number of periods (N) is selected for the computations. Then the average demand, A_t , for the past N periods at time t is computed as follows:

$$A_t = \frac{D_t + D_{t-1} + \dots + D_{t-N+1}}{N} \quad (10.1)$$

Since we are assuming that the time series is level (or horizontal), the best forecast for period $t + 1$ is simply the average demand observed through period t . Thus, we have

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

Each time F_{t+1} is computed, the most recent period of demand is included in the calculation of the average and the oldest period of demand is dropped. This procedure maintains N periods of demand in the forecast and lets the average *move* along as new demand data are observed.

In [Table 10.3](#), a three-period moving average is used for forecasting purposes. Notice how the moving *average* is offset by one period to obtain the moving *forecast*. The forecast error is also shown in the table as the difference between actual and forecast demand. Always use the forecast for period t (F_t) in computing forecast errors, not the average for period t (A_t).

TABLE 10.3 Moving-Average Forecasts

Period	D_t (Demand)	A_t (Three-Period Moving Average)	F_t (Three-Period Forecast)	$D_t - F_t$ (Error)
1	10			
2	18			
3	29	19.0		
4	15	20.7	19.0	-4.0
5	30	24.7	20.7	+9.3
6	12	19.0	24.7	-12.7
7	16	19.3	19.0	-3.0
8	8	12.0	19.3	-11.3
9	22	15.3	12.0	10.0
10	14	14.7	15.3	-1.3
11	15	17.0	14.7	0.3
12	27	18.7	17.0	10.0
13	30	24.0	18.7	11.3
14	23	26.7	24.0	-1.0
15	15	22.7	26.7	-11.7

Example

Using the numbers in [Table 10.3](#) calculate a three-period moving average. The average for period 3, A_3 is just the sum of demands from periods 3, 2, and 1 averaged over these three periods:

$$A_3 = (29 + 18 + 10)/3 = 19$$

The forecast for period 4 is equal to the moving average through period 3; therefore, $F_4 = 19$. Once we know the actual demand in period 4, which is $D_4 = 15$, we can calculate a **forecast error** as follows:

$$e_t = D_t - F_t$$

The forecast error in period 4 is $15 - 19 = -4$. Calculate the three-period moving average, forecast, and error for the remaining periods, for practice.

The graph in [Figure 10.2](#) shows the demand data from the example, the three-period moving average, and a six-period moving average. The six-period moving averages are: $A_6 = 19.0$, $A_7 = 20.0$, $A_8 = 18.3$, $A_9 = 17.2$, and so forth. It is a good idea to plot the data and forecasts when making comparisons. Notice how the six-period moving average responds Page 194 more slowly to demand changes than the three-period moving average. As a general rule, the greater the averaging periods, the slower the response to demand changes. A longer period thus has the advantage of providing stability in the forecast but the disadvantage of responding more slowly to real changes in the demand level. The forecasting analyst must select the appropriate trade-off between stability and response time when selecting the number of periods in N .

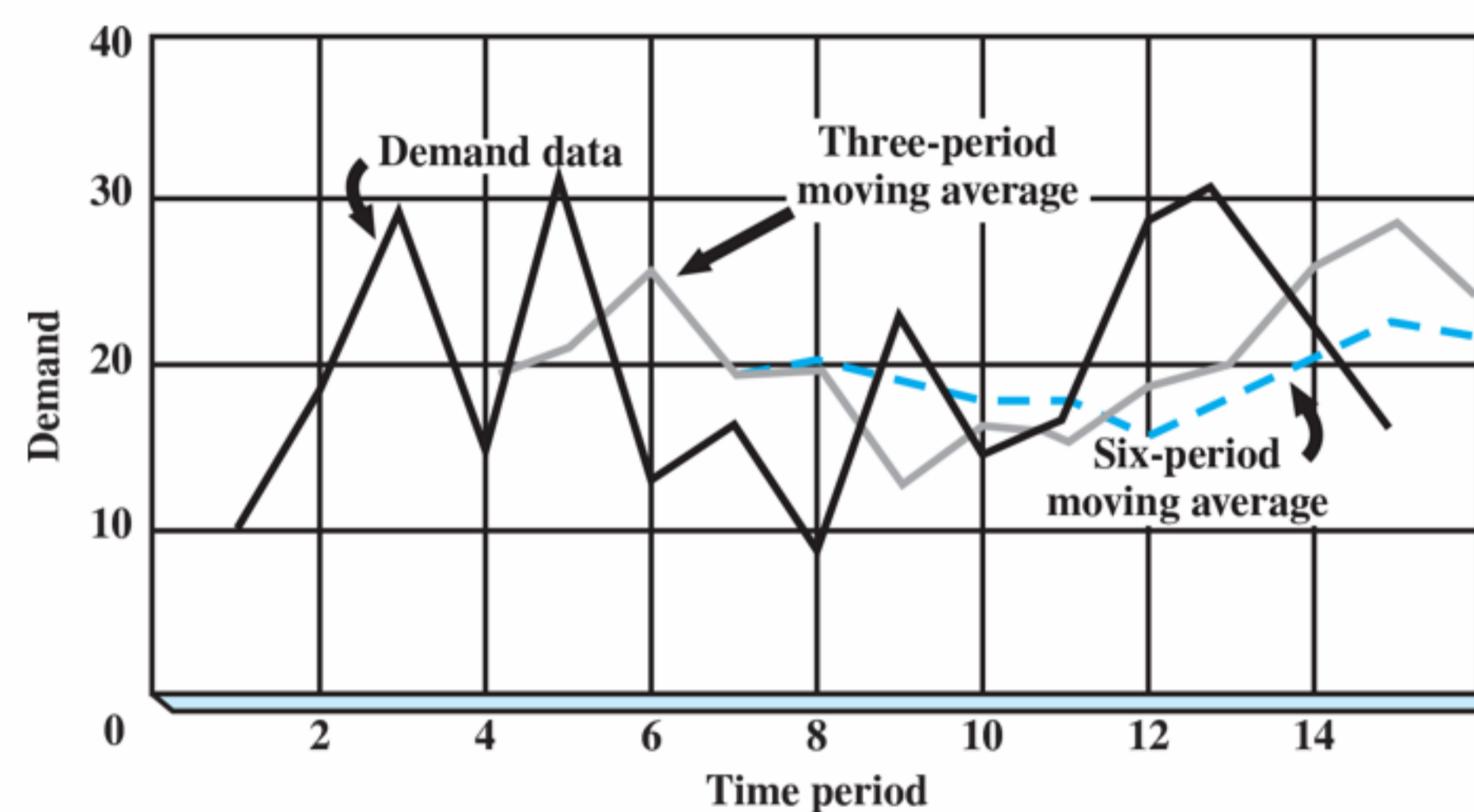


Figure 10.2 Time-series data.

One way to make the moving average respond more rapidly to changes in demand is to place relatively more weight on recent demands than on earlier ones. Any desired weights can be specified so long as they add up to 1. This is called a **weighted moving average**, which is computed as follows:

$$F_{t+1} = A_t = W_1 D_t + W_2 D_{t-1} + \cdots + W_N D_{t-N+1} \quad (10.2)$$

with the condition

$$\sum_{i=1}^N W_i = 1$$

Example

If we have demands $D_1 = 10$, $D_2 = 18$, and $D_3 = 29$, the ordinary three-period moving average is 19.0. With weights of $W_1 = .5$, $W_2 = .3$, and $W_3 = .2$, the three-period weighted moving average is 21.9. In this case, the weight of .5 was applied to the third period, .3 to the

In this case, the weight of .5 was applied to the third period, .3 to the second period, and .2 to the first period. Notice how the weighted moving average responds more rapidly than the ordinary moving average to the increased demand of 29 in the third period. Notice also that the simple moving average is just a special case of the weighted moving average with all weights equal, $W_i = 1/N$.

One of the disadvantages of a weighted moving average is that the entire demand history for N periods must be used in the computation. Furthermore, the responsiveness of a weighted moving average cannot be changed without changing each of the weights. To overcome these difficulties, the method of exponential smoothing has been developed.

10.5 EXPONENTIAL SMOOTHING

The second predictive analytics method for forecasting is useful for reducing the amount of past demand data that must be carried forward. **Exponential smoothing** is based on the simple idea that a new average can be computed from an old average along with the most recent observed demand. Suppose, for example, we have an old average of 20 and we have just observed a demand of 24. The new average will lie between 20 and 24, depending on how much weight we want to assign to the newest demand versus the weight on the old average.

To formalize this logic, we can write

$$A_t = \alpha D_t + (1 - \alpha)A_{t-1} \quad \text{(10.3)}$$

In this case, A_{t-1} is the old average (20), D_t the newest demand (24), and α the proportion of weight placed on the new demand ($0 \leq \alpha \leq 1$).

To illustrate, suppose we use the values $\alpha = .1$, $D_t = 24$, and $A_{t-1} = 20$. Then, from Equation (10.3), we have $A_t = 20.4$. If $\alpha = .5$, we have $A_t = 22$, and if $\alpha = .9$, we have $A_t = 23.6$. Thus A_t varies between the old average of 20 and the newest demand of 24, depending on the value of α used.

If we want A_t to be very responsive to recent demand, we should choose a large value of α . If we want A_t to remain close to the old average, α should be small. Usually, α is given a value between .1 and .3 to maintain reasonable stability.

In **simple exponential smoothing**, just as in the case of moving averages, we assume that the time series is level with no cycles and that there are no seasonal or trend components. Then the exponentially smoothed forecast for the next period is simply the average obtained

through the current period, offset one period from the smoothed average. That is,

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

We can substitute the preceding relationship into Equation (10.3) to obtain the following equation:

$$F_{t+1} = \alpha D_t + (1 - \alpha)F_t \quad \mathbf{(10.4)}$$

Sometimes this alternative form of simple, or first-order, exponential smoothing is more convenient to use than Equation (10.3) because it uses forecasts instead of averages.

Another way to view exponential smoothing is to rearrange the terms on the right-hand side of Equation (10.4) to yield

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

This form indicates that the new forecast is the old forecast plus a proportion of the error between the observed demand and the old forecast. The proportion of error used can be controlled by the choice of α .

Example

Suppose we forecasted for period 5, $F_5 = 100$, and have just observed the demand for period 5, $D_5 = 120$. In this case we have an error of $D_5 - F_5 = 20$. If $\alpha = .1$, then we add only 10 percent of this error to the old forecast to make the adjustment for the fact that demand has exceeded the forecast. Therefore, the forecast for period 6 is $F_6 = 100 + .1(20) = 102$. Note that in using a smoothing constant of .1 we are not overreacting to the fact that we have just observed a demand that exceeded our forecast. However, if we want to react more quickly to demand increases, we could increase the value of α . For example, what is the forecast for period 6 if $\alpha = .5$ or $\alpha = .7$? (Answer: $F_6 = 110$ for $\alpha = .5$ and $F_6 = 114$ for $\alpha = .7$.)

Students often ask why the name “exponential smoothing” has been given to this method. It can be mathematically shown that the weights on each preceding demand data point decrease exponentially, by a factor of $(1 - \alpha)$, until the demand from the first period and the initial forecast F_1 is reached. Since the weights on the previous demands decrease exponentially over time and all the weights add up to 1, exponential smoothing is just a special form of the weighted moving average.

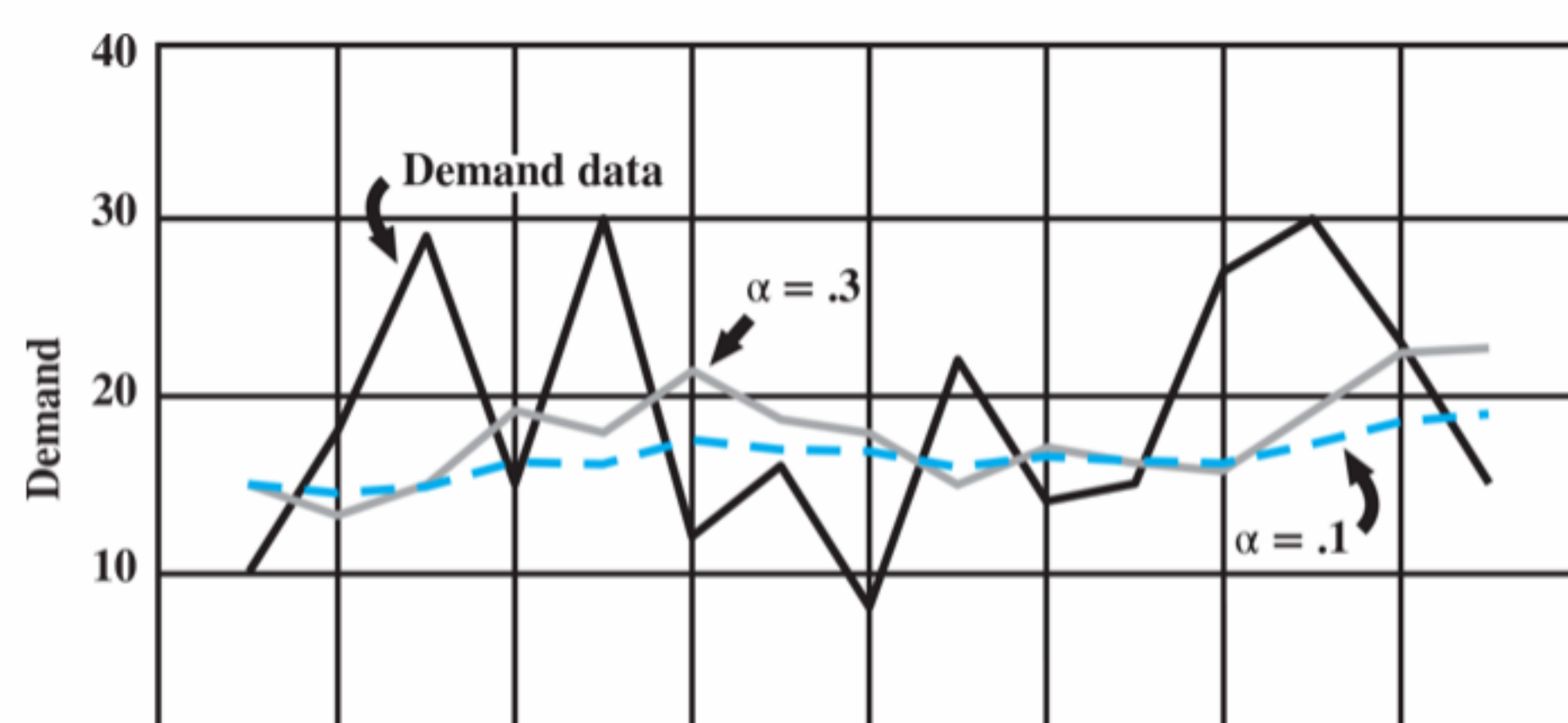
In [Table 10.4](#), two exponentially smoothed forecasts are computed for

In [Table 10.4](#), two exponentially smoothed forecasts are computed for $\alpha = .1$ and $\alpha = .3$, using the same demand data as in [Table 10.3](#). These data are shown graphically in Figure 10.3. As can be seen, the $\alpha = .3$ forecasts respond more rapidly to demand changes but are less stable than $\alpha = .1$. Which of these forecasts is better?

TABLE 10.4 Exponential Smoothing*

Period	D_t (demand)	$\alpha = .1$		$\alpha = .3$		MAD _t ($\alpha = .3$)
		F_t (forecast)	$D_t - F_t$ (error)	F_t (forecast)	$D_t - F_t$ (error)	
1	10	15	-5.0	15	-5.0	6.4
2	18	14.5	3.5	13.5	4.5	5.8
3	29	14.85	14.15	14.85	14.15	8.3
4	15	16.26	-1.26	19.09	-4.09	7.1
5	30	16.14	13.86	17.86	12.14	8.6
6	12	17.52	-5.52	21.50	-9.50	8.8
7	16	16.97	-.97	18.65	-2.65	7.0
8	8	16.87	-8.87	17.85	-9.85	7.9
9	22	15.98	6.02	14.90	7.10	7.6
10	14	16.58	-2.58	17.03	-3.03	6.2
11	15	16.33	-1.33	16.12	-1.12	4.7
12	27	16.19	10.81	15.78	11.22	6.7
13	30	17.27	12.73	19.15	10.85	7.9
14	23	18.54	4.46	22.40	0.60	5.7
15	15	18.99	-3.99	22.58	-7.58	6.4
$\Sigma(D_t - F_t)$ Bias			36.01		17.74	
Σ Absolute Deviation			95.05			103.38

*Assume $F_1 = 15$ as a starting point. Also assume $MAD_0 = 7$. See the text for definitions of MAD and tracking signal.



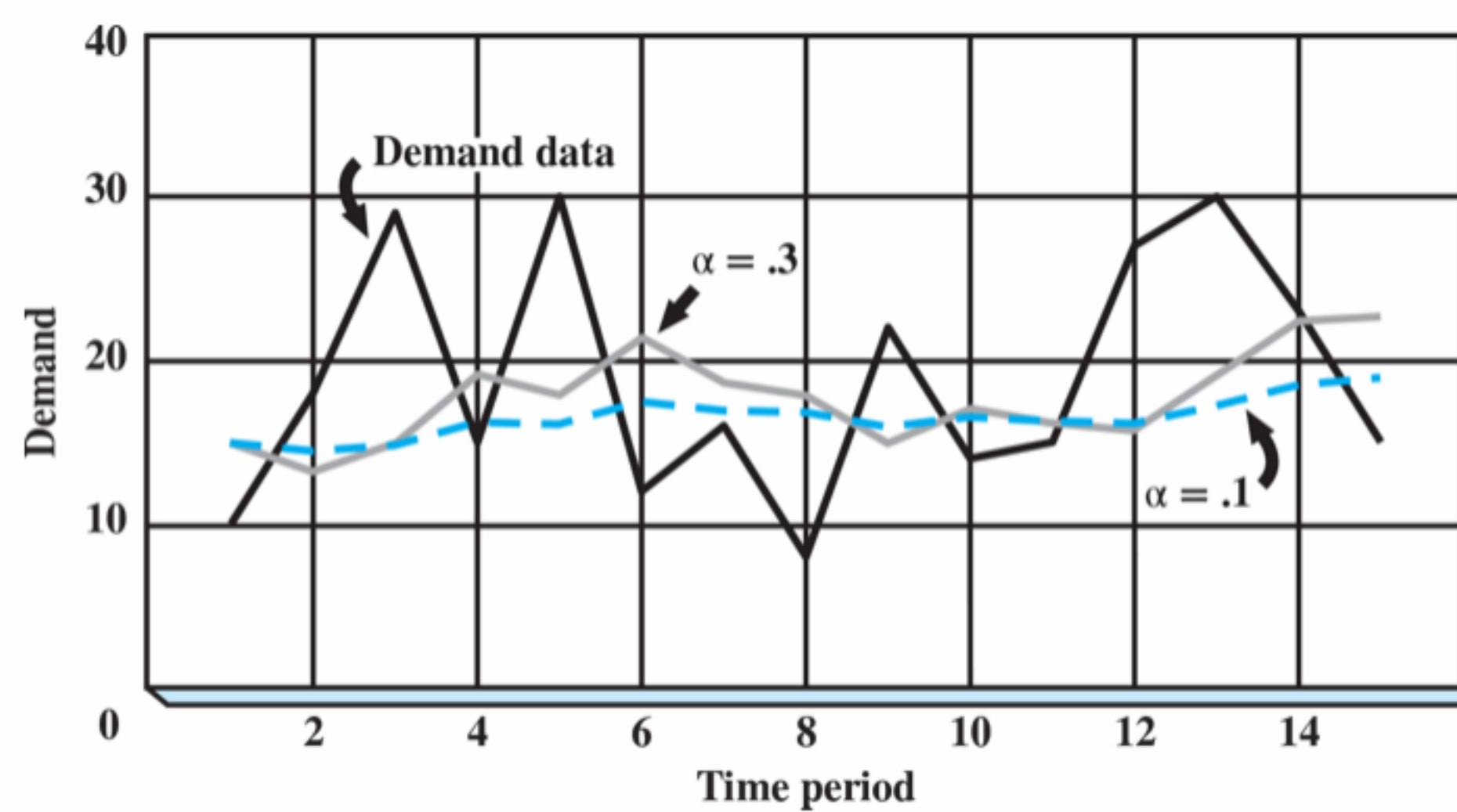


Figure 10.3 Time-series data.

Before answering this question, we'll look at a few rows in [Table 10.4](#). In row 1 the initial forecast for period 1, $F_1 = 15$, is given as a starting value. The demand for period 1 is only 10 units, and so the forecast for period 2 will decrease. For $\alpha = .1$ the new forecast F_2 will be 14.5, and for $\alpha = .3$ the new forecast will be 13.5. (Practice calculating these numbers yourself.) That is why we say that the forecast reacts more quickly to demand changes for higher values of α but is less stable, since we don't know if the underlying long-term average has changed or whether we are just seeing random fluctuation in the first period.

To answer the question of which is the best forecast, we need to look at forecast errors over many periods. Two measures of forecast accuracy are computed in [Table 10.4](#) for 15 periods. One measure is simply the arithmetic sum of all errors, which reflects the **bias** in the forecasting method. Ideally, this sum should be zero, since the positive and negative errors should cancel out over time. In [Table 10.4](#), both methods have a positive bias, with $\alpha = .1$ producing more bias than $\alpha = .3$.

The second measure of forecast error is the **absolute deviation**. In this case the absolute values of the errors are summed, so that negative errors do not cancel positive errors. The result is a measure of variance in the forecasting method. The total absolute deviation for $\alpha = .1$ is less than for $\alpha = .3$.

Thus, we have the interesting result that the $\alpha = .1$ forecast has more bias but less absolute deviation than the $\alpha = .3$ forecast. In this case, there is no clear preference between the two forecasting models; it depends on the manager's evaluation of the importance of bias and deviation. However, if a forecast has both lower deviation and lower bias, it is clearly preferred.

The procedure for choosing a value of α is now clear. A forecast should be computed for several values of α . If one value of α produces a forecast with less bias and less deviation than the others, this value is preferred. If no clear preference exists, trade-offs between bias and deviation must be considered in choosing the preferred value of α .

The exponential smoothing forecast method has the advantage that only

one period of demand and forecast data must be carried forward. This significantly simplifies data storage. Unfortunately, simple exponential smoothing cannot always be used in practice because of trends or seasonal effects in the data. When these effects are present, higher-order smoothing, trend-corrected smoothing, or seasonal smoothing may be used. Some of these more advanced methods are presented in the chapter supplement.

10.6 FORECAST ACCURACY

LO10.4 Evaluate forecast accuracy using a variety of methods.

When exponential smoothing is used, an estimate of **forecast accuracy** should be computed along with the smoothed average. This accuracy estimate might be used for several purposes:

1. To monitor erratic demand observations or outliers, which should be carefully evaluated and perhaps excluded from data analysis.
2. To determine when the forecasting method is no longer tracking actual demand and needs to be reset.
3. To determine the parameter values (e.g., N and α) that provide the forecast with the best accuracy.

There are four ways to measure long-run forecast accuracy over several periods. (Recall that $e_t = D_t - F_t$ is the forecast error for period t .)

Cumulative sum of forecast errors	CFE	$= \sum_{t+1}^n e_t$	
Mean square error	MSE	$= \frac{\sum_{t+1}^n e_t^2}{n}$	
Mean absolute deviation of forecast errors	MAD	$= \frac{\sum_{t+1}^n e_t }{n}$	
Mean absolute percentage errors	MAPE	$= \frac{\sum_{t+1}^n \left \frac{e_t}{D_t} \right 100}{n}$	(expressed as a percentage)

Note that n is the number of past periods used to compute the cumulative error measurements.

We have already referred to the value of CFE as the bias in the forecast. Ideally, the bias will be zero, which occurs if positive errors are offset by

negative errors. However, if the forecast is always low, for example, the error will be positive in each period and the CFE

will be a large positive number, indicating a biased forecast. In this case the

example, the error will be positive in each period and the CFE will be a large positive number, indicating a biased forecast. In this case the chosen starting point is too low and the forecasting method should be reset with a higher starting point.

MSE and MAD measure the variance in the forecast error. The square root of MSE is the well-known standard deviation σ . MSE uses the square of each error term so that positive and negative errors do not cancel each other out. MAD, is computed from the absolute values of the error in each period instead of the squared errors. MAD is just the average error over n periods without regard to the positive or negative sign of the error in each period. In practice, MAD is widely used because it is easy to understand and easy to use.

MAPE normalizes the error by computing a percentage error. This will make it possible to compare forecast errors for different time-series data. For example, if one time series has low demand values and another has much higher demand values, MAPE will be an accurate way of comparing the errors for these two time series.

When exponential smoothing is used, it is common to calculate the smoothed mean absolute deviation period by period, which is defined as follows:

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

In this case, the new MAD_t is simply a fraction α of the current absolute deviation plus $(1 - \alpha)$ times the old MAD. This is analogous to Equation (10.3), since the MAD is being smoothed in the same way as the forecast average. MAD_t is an exponentially weighted average of absolute error terms.

The current MAD_t should be computed for each period along with the forecast average. The MAD_t can then be used to detect an outlier in demand by comparing the observed deviation with the MAD_t . If the observed deviation is greater than $3.75 \times \text{MAD}_t$, we suspect that the demand may be an outlier. This is comparable to determining whether an observed demand value lies outside three standard deviations (σ) for the normal distribution. This is true because $\sigma = 1.25 \times \text{MAD}_t$ for the normal distribution. In [Table 10.4](#), MAD_t was computed for $\alpha = .3$. As can be seen, none of the demand errors fall outside $3.75 \times \text{MAD}_t$, and so no outliers are suspected in the data.

The second use of MAD_t is to determine whether the forecast is tracking with the actual time-series values. To determine this, a tracking signal is computed, as follows:

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

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

The tracking signal is a ratio of bias (cumulative forecast error) in the numerator divided by the most recent estimate of MAD_t . If demand variations are random, control limits of ± 6 on the tracking signal should ensure only a 3 percent probability that the limits will be exceeded by chance.¹ Thus, when the tracking signal exceeds ± 6 , the forecasting method should be reset to more nearly equal observed demand. In [Table 10.4](#), the tracking signal does not exceed ± 6 in any period. Therefore, the forecast is considered to be tracking sufficiently close to actual demand.

As an example of these computations, refer to [Table 10.4](#). In the last two columns of the table we have computed smoothed MAD_t and tracking signal. Starting with the arbitrary assumption that $\text{MAD}_0 = 7$, we can compute MAD_1 using $\alpha = .3$:

$$\text{MAD}_1 = .3|10 - 15| + .7(7) = 6.4$$

The tracking signal for period 1 is the cumulative error divided by MAD_1 :

$$\text{TS} = -5/6.4 = -.8$$

As an exercise, compute MAD_2 and the tracking signal for period 2 and compare your results to [Table 10.4](#).

In computerized forecasting systems, it is extremely important to incorporate error controls of the type discussed above. This will ensure that the system does not run out of control. Instead, the user is notified when outliers in demand are detected or when the tracking signal becomes too large.

10.7 ADVANCED TIME-SERIES FORECASTING

A variation of exponential smoothing is **adaptive exponential smoothing**. In one form, simple exponential smoothing is used but the smoothing coefficient is varied at each forecast by $\pm .05$ to determine which of the three forecasts has the lowest forecast error. The resulting value of α is used for the next-period forecast.

Another type of adaptive smoothing is to continually adjust α on the basis of current forecast error. If there is a large forecasting error, α will be large until the forecast comes back on track. When the error is smaller, α

will also be small and a stable forecast will result. This method appears to work quite well for inventory forecasting situations.

Table 10.5 summarizes four time-series forecasting methods. We have already discussed two of them, moving average and exponential smoothing. The remaining two are described briefly below.

TABLE 10.5 Time-Series Forecasting Methods

Time-Series Methods	Description of Method	Uses	Accuracy			Relative Cost
			Short Term	Medium Term	Long Term	
1. Moving averages	Forecast is based on arithmetic average or weighted average of a given number of past data points.	Short- to medium-range planning for inventories, production levels, and scheduling.	Poor to good	Poor	Very poor	Low
2. Exponential smoothing	Similar to moving average, with exponentially more weight placed on recent data. Well adapted to large number of items to be forecast.	Same as moving average.	Fair to very good	Poor to good	Very poor	Low
3. Analytical models	A linear or nonlinear model fitted to time-series data, usually by regression methods.	Limited, due to expense, to a few products.	Very good	Fair to good	Very poor	Medium
4. Box-Jenkins	Autocorrelation methods are used to identify underlying time series and to fit the "best" model. Requires about	Limited, due to expense, to products requiring very accurate short-range forecasts	Very good to excellent	Fair to good	Very poor	Medium to high

Requires about 60 past data points.
forecasts.

Source: Exhibit adapted from David M. Georgoff and Robert Murdick, "Manager's Guide to Forecasting," *Harvard Business Review*, January–February 1986, pp. 110–120.



At Kellogg USA, demand for cereal is translated into forecasts, useful for inventory planning and meeting supply chain goals.

© Rick Souders/Getty Images

A customized analytical model can be fitted to a time series with level, trend, and seasonal components. For example, a linear regression model or nonlinear methods can be used. In some cases, the resulting model may provide a more accurate forecast than exponential smoothing. However, a custom-fitted model is more expensive because an individual with sophisticated skills will be used to develop it, and so the trade-off between accuracy and model cost must be considered.

Another option, the sophisticated Box-Jenkins method, has been developed for time-series forecasting. This technique permits more precise analysis of proposed models than is possible with the other methods. The Box-Jenkins method requires about 60 periods of past data and is too expensive to use for routine forecasting. For a special forecast involving a costly decision, however, the use of Box-Jenkins may be warranted.

In summary, time-series methods are useful for short- or medium-range forecasts when the demand pattern is expected to remain relatively stable. Time-series forecasts are often inputs to decisions concerning aggregate output planning, budgeting, resource allocation, inventory, and

aggregate output planning, budgeting, resource allocation, inventory, and scheduling.

10.8 CAUSAL FORECASTING METHODS

LO10.5 Carry out causal forecasting.

Page 200

The second type of quantitative forecasting, **causal forecasting methods**, develop a cause-and-effect model between demand and other variables. For example, the demand for ice cream may be related to population, the average summer temperature, and time. Data can be collected on these variables and analysis conducted to determine the validity of the proposed model. One of the best-known causal methods is regression, which is usually taught in statistics courses.

For regression methods, a model must be specified before the data are collected and the analysis is conducted. The simplest case is the following single-variable linear model:

$$\hat{y} = a + bx$$

where

y = estimated demand

x = independent variable (hypothesized to cause)

a = y intercept

b = slope

Data are collected for x and y in this model, and the parameters a and b are estimated. Then estimates of demand can be made from the above equation. Of course, more complicated models with multiple x 's can be developed.

We illustrate linear regression forecasting with a simple example. Suppose we are interested in estimating the demand for bicycles on the basis of local population. The demand for bicycles over the past eight years (y_i) and the corresponding population in a small town (x_i) are shown in [Table 10.6](#). We first compute the values of a and b for the line using one of many statistics packages, such as Excel Minitab, SPSS, JMP, or SAS. The result is $a = -1.34$ and $b = 2.01$. The best (least squares) equation for predicting demand for bicycles is thus $y = -1.34 + 2.01x$. From this equation we can see that the rate of increase in bicycles is 2.01 (thousands) for each 10,000-person increase in population. This rate of increase, or trend, allows us to project bicycle demand in future years from population estimates, assuming that a linear equation continues to be a good fit with population as a predictor variable.

Page 201

TABLE 10.6 Regression Example*

i	y_i	x_i
1	3.0	2.0
2	3.5	2.4
3	4.1	2.8
4	4.4	3.0
5	5.0	3.2
6	5.7	3.6
7	6.4	3.8
8	7.0	4.0
	39.1	24.8

*The demand for bicycles, y_i , is expressed in thousands. The population, x_i , is expressed in ten thousands of people.

Other forms of causal forecasting—econometric models, input-output models, and simulation models—are described in [Table 10.7](#). In general, these models are more complex and more costly to develop than regression models. However, in situations in which it is necessary to model a segment of the economy in detail, an econometric or input-output model may be appropriate.

TABLE 10.7 Causal Forecasting Methods

Causal Methods	Description of Method	Uses	Accuracy			Forecast Horizon
			Short Term	Medium Term	Long Term	
1. Regression	This method relates demand to other external or internal variables that tend to cause demand changes. Uses least squares to obtain a best fit among the variables.	Short- to medium-range planning for aggregate production or inventory involving a few products. Useful where strong causal relationships exist.	Good to very good	Good to very good	Poor	1
2. Econometric model	A system of interdependent regression	Forecast of sales by product	Very good to excellent	Very good	Good	

	equations that describes some sector of economic sales or profit activity.	classes for short- to medium-range planning.			
3. Input-output model	A method of forecasting that describes the flows from one sector of the economy to another. Predicts the inputs required to produce required outputs in another sector.	Forecasts of company- or countrywide sales by industrial sectors.	Not available	Good to very good	Good to very good
4. Simulation model	Simulation of the distribution system describing the changes in sales and flows of product over time. Reflects effects of the distribution pipeline.	Forecasts of companywide sales by major product groups.	Very good	Good to very good	Good

Source: Exhibit adapted from David M. Georgoff and Robert Murdick, "Manager's to Forecasting," *Harvard Business Review*, January–February 1986, pp. 110–120.

Simulation models are especially useful when a supply chain or logistics system is modeled for forecasting purposes. For example, suppose you want to estimate the demand for TVs. A simulation model can be built representing the distribution pipeline from the screen manufacturer, to the assembler, and finally to wholesale and retail distribution; all imports, inventories, and exports from the supply chain would be included. Using this model, a reasonable forecast for TVs several years into the future is obtained.

One of the most important features of causal models is that they are used to predict turning points in the demand function. Because of this ability causal models are usually more accurate for medium- to long-range forecasts than time-series models that only predict trends. Causal models therefore are more widely useful for facility and process planning

therefore are more widely useful for facility and process planning in operations.

10.9 SELECTING A FORECASTING METHOD

LO10.6 Evaluate factors that impact forecasting method selection.

In this section, we present a set of factors to consider for selecting a forecasting method.



1. Use or decision characteristics. The forecasting method must be related to the use or decisions required. The use, in turn, is closely related to characteristics such as accuracy required, time horizon of the forecast, and number of items to be forecast. For example, inventory, scheduling, and pricing decisions by a big box retailer require highly accurate short-range forecasts for a large number of items. Time-series methods are ideally suited to these requirements. By contrast, decisions by an auto manufacturer involving process, facility planning, and marketing programs are long range in nature and require less accuracy. Qualitative or causal methods tend to be more appropriate for those decisions. In the middle time range are aggregate planning, capital-budgeting, and new-product and new-service introduction decisions, which often utilize time-series or causal methods.

2. Data availability. The choice of forecasting method is often constrained by available data. An econometric model may require data that are simply not available in the short run; therefore, another method must be selected. The Box-Jenkins time-series method requires about 60 data points (five years of monthly data). In some cases, data can be collected, but then time and resources must also be considered relative to the importance of the forecast. The quality of the data available is also a concern. Poor data lead to poor forecasts. Data should be checked for extraneous points or outliers.

3. Data pattern. The pattern in the data will affect the type of forecasting method selected. If the time series is level, as we have assumed in most of this chapter, a fairly simple method can be used. However, if the data show trends or seasonal patterns, more advanced methods will be needed. The pattern in the data will also determine whether a time-series method will suffice or whether causal models are needed. If the data pattern is unstable over time, a qualitative method may be selected. One way to detect the pattern is to plot the data on a graph as the first step in forecasting.

An issue concerning the selection of forecasting methods is the

difference between **fit** and **prediction**. When different models are tested, it is often thought that the model with the best fit to historical data (least error) is also the best predictive model. This is not true. For example, suppose demand observations are obtained for the last eight time periods and we want to fit the best time-series model to these data. A polynomial model of degree seven can be made to fit exactly through each of the past eight data points.² However, this model is not necessarily the best predictor of the future.



Retailers like Walmart use Google Analytics to understand changing consumer preferences.

© Montgomery Martin/Alamy

The best predictive model is one that describes the underlying time series but is not force-fitted to the data. The correct way to fit models based on past data is to separate model fit and model prediction. First, the data set is divided into two subsets, one for building the forecasting model and the other hold-out set for testing the predictive ability of the model. Several models based on reasonable assumptions about seasonality, trend, and cycle are then fitted to the first data set. These models are used to predict values for the second data set, and the one with the lowest error on the second set is the best model. This approach utilizes fit on the first data set and prediction on the second as a basis for model selection.

Big data **analytics** are increasingly used in demand forecasting. According to a study by Deloitte, 64 percent of supply chain executives consider big data analytics the most important disruptive technology in supply chain management today. Big data come from sources both inside and outside the firm. Internal data useful for forecasting can include, for example, bar code data and loyalty programs. External data might come from social media, or in the case of Walmart, from Google Analytics. Walmart monitored preholiday food searches to guide forecasting for ingredients to stock in their stores. When searches showed spikes in “tachos”—nachos with tater tots in place of chips—Walmart increased its stock of tater tots and highlighted the dish in their advertising.

Big data analytics are useful for directly building forecast models. Detailed data, as to the quantity and timing of past demand, may be acquired from extremely large data sets, and are useful for developing the types of quantitative models studied earlier in the chapter. Large data sets are also useful for conducting research to inform future forecasting indirectly. For example, less structured data such as call center recordings might be studied, coded, and analyzed for insight into customer needs. This insight can be used to inform forecast models.

Big and small data sets can be helpful for improving forecast models, in most instances. However, managers must be careful to not let detailed analysis of the data slow their decision making, which could degrade supply chain response times. The insight gained from forecast analytics must be balanced against the time and cost of obtaining the information.

10.10 COLLABORATIVE PLANNING, FORECASTING, AND REPLENISHMENT

LO10.7 Explain the benefits and costs of CPFR.

Collaborative planning, forecasting, and replenishment (**CPFR**) is sharing information between business customers and suppliers in the supply chain during the planning and forecasting process. For example, a customer (e.g., retailer) may have information on planned sales promotions that are not known to the supplier. In this case a supplier's forecast based on time-series data alone would be inaccurate, but it could be adjusted if the retailer information were made available.

Operations Leader

CPFR Creates Waves for West Marine

After 10 years of using collaborative planning, forecasting, and replenishment (CPFR) with 200 of its major suppliers, West Marine has seen forecast accuracy rise 85 percent, and 96 percent of products are in-stock in retail stores during their peak season.



West Marine, the largest boating-supply retail chain in the United States, opened its first store in Palo Alto, California, in 1975. Today, they have sales of more than \$663 million from 300 stores and an active website carrying 75,000 products, from kayaks and anchors to life jackets and wetsuits.

During planning processes, retail stores have primary responsibility for creating the demand forecasts for each item. Retailers base their forecasts on data such as seasonal forecasts, planned promotions, and future retail assortment changes. These forecasts are then integrated with planning at the company's distribution centers and its suppliers.

West Marine gains supplier buy-in for using CPFR by working closely with them to accommodate their materials planning schedules. Suppliers will know about special promotions well in advance so that lead times (often international) can be managed. To make its commitment to CPFR and its suppliers clear, West Marine guarantees it will purchase its forecasts.

Source: Larry Smith. "West Marine: A CPFR Success Story," *Supply Chain Management Review*, March 1, 2006; and westmarine.com, 2016.

Using CPFR, the customer and supplier exchange information on their respective forecasted demands. When there is a discrepancy in the forecasts, a discussion ensues to discover the basis for the difference. After discussion, an agreed forecast is developed that becomes the basis for replenishment planning. Note, this is a forecast and not an actual order from the customer that would typically be placed at a later time. The collaborative forecast gives visibility into the replenishment planning processes beyond the usual ordering cycle.

CPFR works best in B2B relationships. Walmart, for example, shares forecasted orders with its suppliers. As a result the suppliers gain visibility into expected demand shifts and special sales promotions that Walmart is planning. CPFR helps coordinate the Walmart supply chain. See the following Operations Leader box for another example of the use of CPFR.

The important points to remember about CPFR are:

1. All parties must be willing to share sensitive information about demand, future sales promotions, new products, lead times, and so forth. Assurances must be provided that competitors will not have access to this proprietary information.
2. A long-term collaborative relationship that is mutually beneficial is needed. This will require an atmosphere of trust and ongoing management attention.

3. Sufficient time and resources must be provided for CPFR to succeed. In other words, there is a cost to receive the benefits of CPFR.

10.11 KEY POINTS AND TERMS

Demand forecasts are crucial inputs to planning decisions within operations and other parts of business. In this chapter, we have highlighted several important uses and methods of forecasting. Some of the chapter's main points are the following:



- Different decisions require different forecasting methods, including the following in operations: process design, capacity planning, aggregate planning, scheduling, and inventory management. Some of the decisions outside of operations that require forecasts are long-range marketing programs, pricing, new-product and new-service introduction, cost estimating, and capital budgeting. The available methods may be classified as qualitative, time-series, and causal methods.
- Four of the most important qualitative methods are Delphi, market surveys, life-cycle analogy, and informed judgment. These methods are most useful when historical data are not available or are not reliable in predicting the future. Qualitative methods are used primarily for long- or medium-range forecasting involving process design, facilities planning, and marketing programs.
- Time-series forecasting is used to decompose demand data into their underlying components and to project the historical pattern forward in time. The primary uses are short- to medium-term forecasting for inventory, scheduling, pricing, and costing decisions. Some time-series techniques are the moving average, exponential smoothing, mathematical models, and the Box-Jenkins method.
- Causal forecasting methods include regression, econometric models, input-output models, and simulation models. These methods are used in an attempt to establish a cause-and-effect relationship between demand and other variables. Causal methods can help in predicting turning points in time-series data and are therefore most useful for medium- to long-range forecasting.
- Two measures of accuracy in forecasting are bias and deviation. Both should be monitored routinely to control the accuracy of the forecasts obtained. For forecasting applications, tracking signal and MAD are two methods used to determine if bias and deviation, respectively, are well controlled.
- A forecasting method should be selected on the basis of five factors:

- A forecasting method should be selected on the basis of five factors: user and system sophistication, time and resources available, use or decision characteristics, data availability, and data pattern.
- CPFR is a method used to share and improve forecasts between customers and suppliers along the supply chain and thereby reduce forecasting errors.

Key Terms

[Qualitative forecasting methods 189](#)

[Quantitative forecasting methods 189](#)

[Time-series methods 191](#)

[Level 191](#)

[Trend 191](#)

[Seasonality 191](#)

[Cycle 191](#)

[Random error 191](#)

[Moving-average 192](#)

[Forecast error 193](#)

[Weighted moving average 194](#)

[Exponential smoothing 194](#)

[Simple exponential smoothing 195](#)

[Bias 196](#)

[Absolute deviation 196](#)

[Forecast accuracy 197](#)

[Adaptive exponential smoothing 199](#)

[Causal forecasting methods 200](#)

[Fit 202](#)

[Prediction 202](#)

[Analytics 203](#)

[CPFR 203](#)



This site contains a description of the ForecastPro software. Read the description and take a quick tour. Write a short summary report on the features of the software.

2. Institute for Business Forecasting and Planning
www.ibf.org

Review this website and determine the purpose of this professional organization. This site provides a listing of jobs in the forecasting field. Examine the listing to understand the types of positions offered and the companies that are looking for forecasting professionals.

3. Delphus
www.delphus.com

Examine the types of software available from this company. Prepare a short report on the various features available in its forecasting systems.

SOLVED PROBLEMS

Problem

1. **Moving Average, Weighted Moving Average, and Exponential Smoothing** The weekly demand for chicken wings at a local restaurant during the past six weeks has been

Week	1	2	3	4	5	6
Demand	650	521	563	735	514	596

- a. Forecast the demand for week 7 using a five-period moving average.
- b. Forecast the demand for week 7 using a three-period weighted moving average. Use the following weights: $W_1 = .5$, $W_2 = .3$, $W_3 = .2$.
- c. Forecast the demand for week 7 using exponential smoothing. Use an α value of .1 and assume the forecast for week 6 was 600 units.
- d. What assumptions are made in each of the above forecasts?

Solution

- a.

$$D_6 + D_5 + D_4 + D_3 + D_2$$

Solution

a.

$$\begin{aligned} F_7 &= A_6 = \frac{D_6 + D_5 + D_4 + D_3 + D_2}{n} \\ &= \frac{596 + 514 + 735 + 563 + 521}{5} \\ &= 585.8 \end{aligned}$$

$$\begin{aligned} F_7 &= A_6 = (W_1 \times D_6) + (W_2 \times D_5) + (W_3 \times D_4) \\ &= (.5 \times 596) + (.3 \times 514) + (.2 \times 735) \\ &= 599.2 \end{aligned}$$

$$\begin{aligned} F_7 &= A_6 = [(\alpha) \times D_6] + [(1 - \alpha) \times F_6] \\ &= [(.1) \times 596] + [(1 - .1) \times 600] \\ &= 599.6 \end{aligned}$$

- d. We assumed the following: Future demand will be like past demand. No trend, seasonality, or cyclical effects are present. In the weighted-moving-average model, the more recent demand is considered more important than older demand. In the exponential smoothing model, an α value of .1 puts very little weight on current demand (10 percent), while most of the weight is put on past demand (90 percent).

Problem

2. **Exponential Smoothing, Exponentially Smoothed MAD, and Tracking Signal** The XYZ Company was flooded by a thunderstorm and lost part of its forecasting data. Positions in the table that are marked [a], [b], [c], [d], [e], and [f] must be recalculated from the remaining data.

Period	D_t (demand)	$F_t(\alpha = .3)$ (forecast)	$e_t = D_t - F_t$ (error)	$\alpha = .3$ (MAD _t)	Tracking Signal
0				10.0	
1	120	100.0	20.0	[a]	1.5
2	140	106.0	34.0	19.3	[b]
3	160	[c]	[d]	[e]	[f]

Solution

$$\begin{aligned} \text{MAD}_t &= (\alpha \times |D_t - F_t|) + [(1 - \alpha) \times \text{MAD}_{t-1}] \\ \text{MAD}_1 &= (\alpha \times |D_1 - F_1|) + [(1 - \alpha) \times \text{MAD}_0] \\ &= (.3 \times |120 - 100|) + [(1 - .3) \times 10.0] \\ &= 13.0 \end{aligned}$$

$$\begin{aligned} \text{TS}_t &= \frac{\text{CEF}}{\text{MAD}_t} \\ \text{TS}_2 &= \frac{(D_1 - F_1) + (D_2 - F_2)}{\text{MAD}_2} \\ &= \frac{20.0 + 34.0}{19.3} \\ &= 2.8 \end{aligned}$$

$$\begin{aligned} F_{t+1} &= (\alpha \times D_t) + [(1 - \alpha) \times F_t] \\ F_3 &= (\alpha \times D_2) + [(1 - \alpha) \times F_2] \\ &= (.3 \times 140) + [(1 - .3) \times 106.0] \\ &= 116.2 \end{aligned}$$

$$\begin{aligned} e_t &= D_t - F_t \\ e_3 &= D_3 - F_3 \\ &= 160 - 116.2 \\ &= 43.8 \end{aligned}$$

$$\begin{aligned} \text{MAD}_t &= (\alpha \times |D_t - F_t| + [(1 - \alpha) \times \text{MAD}_{t-1}]) \\ \text{MAD}_3 &= (\alpha \times |D_3 - F_3| + [(1 - \alpha) \times \text{MAD}_2]) \\ &= (.3 \times |160 - 116.2|) + [(1 - .3) \times 19.3] \\ &= 26.7 \end{aligned}$$

$$\begin{aligned} \text{TS}_t &= \frac{\text{CFE}}{\text{MAD}_t} \\ \text{TS}_3 &= \frac{(D_1 - F_1) + (D_2 - F_2) + (D_3 - F_3)}{\text{MAD}_3} \\ &= \frac{20.0 + 34.0 + 43.8}{26.7} \\ &= 3.7 \end{aligned}$$

Discussion Questions

1. Is there a difference between forecasting demand and forecasting sales? Can demand be forecast from historical sales data?
2. What is the distinction between forecasting and planning?
3. Qualitative forecasting methods should be used only as a last resort. Agree or disagree? Comment.
4. Describe the uses of qualitative, time-series, and causal forecasts.
5. Qualitative forecasts and causal forecasts are not particularly useful as inputs to inventory and scheduling decisions. Why is this statement true?
6. What type of time-series components would you expect for the following products and services?
 - a. Monthly sales of a retail florist.
 - b. Monthly sales of milk in a supermarket.
 - c. Daily demand in a call center.
7. What are the advantages of exponential smoothing over the moving average and the weighted moving average?
8. How should the choice of α be made for exponential smoothing?
9. Describe the difference between *fit* and *prediction* for forecasting models.
10. In the Stokely Company, marketing makes a sales forecast by developing a sales force composite. Meanwhile, operations makes a forecast of sales based on past data, trends, and seasonal components. The operations forecast usually turns out to be 20 percent less than the forecast of the marketing department. How should forecasting in this company be done?
11. Explain how CPFR can be used to reduce forecasting error.
12. Under what circumstances might CPFR be useful, and when is it not useful?

Problems

Four Excel spreadsheets are provided on Connect for assistance in solving the chapter problems and supplement.

1. Daily demand for marigold flowers at a large garden store is shown

1. Daily demand for marigold flowers at a large garden store is shown below. Compute:
 - a. A three-period moving average for each period.
 - b. A five-period moving average for each period.

Period	Demand
1	85
2	92
3	71
4	97
5	93
6	82
7	89

2. The number of daily calls for the repair of Speedy copy machines has been recorded as follows:

October	Calls
1	92
2	127
3	106
4	165
5	125
6	111
7	178
8	97

- a. Prepare three-period moving-average forecasts for the data. What is the error on each day?
 - b. Prepare three-period weighted-moving-average forecasts using weights of $w_1 = .5$, $w_2 = .3$, $w_3 = .2$.
 - c. Which of the two forecasts is better?
3. The ABC Floral Shop sold the following number of geraniums during the last two weeks:

Day	Demand	Day	Demand
1	200	8	154

3. The ABC Floral Shop sold the following number of geraniums during the last two weeks:

Day	Demand	Day	Demand
1	200	8	154
2	134	9	182
3	147	10	197
4	165	11	132
5	183	12	163
6	125	13	157
7	146	14	169

Develop a spreadsheet for the following.

- Calculate forecasts using a three- and five-period moving average.
 - Graph these forecasts and the original data using Excel. What does the graph show?
 - Which of the above forecasts is best? Why?
4. The Handy-Dandy Department Store had forecast sales of \$110,000 for the previous week. The actual sales were \$130,000.
- What is the forecast for this week, using exponential smoothing and $\alpha = .1$?
 - If sales this week turn out to be \$120,000, what is the forecast for next week?
5. The Yummy Ice Cream Company uses the exponential smoothing method. Last week the forecast was 100,000 gallons of ice cream, and 90,000 gallons was actually sold.
- Using $\alpha = .1$, prepare a forecast for next week.
 - Calculate the forecast using $\alpha = .2$ and $\alpha = .3$. Which value of α gives the best forecast, assuming actual demand is 95,000 gallons?
6. Using the data in problem 2, prepare exponentially smoothed forecasts for the following cases:
- $\alpha = .1$ and $F_1 = 90$
 - $\alpha = .3$ and $F_1 = 90$
7. Compute the errors of bias and absolute deviation for the forecasts in problem 6. Which of the forecasting models is the best?

11. A grocery store sells the following number of frozen turkeys during the week prior to Thanksgiving:

Turkeys Sold	
Monday	80
Tuesday	53
Wednesday	65
Thursday	43
Friday	85
Saturday	101

- a. Prepare a forecast of sales for each day, starting with $F_1 = 85$ and $\alpha = .2$.
 - b. Compute the MAD and the tracking signal in each period. Use $MAD_0 = 0$.
 - c. On the basis of the criteria given in the text, are the MAD and tracking signal within tolerances?
 - d. Recompute parts a and b using $\alpha = .1, .3, \text{ and } .4$. Which value of α provides the best forecast?
12. The famous Widget Company uses simple exponential smoothing to forecast the demand for its best-selling widgets. The company is considering whether it should use $\alpha = .1$ or $\alpha = .3$ for forecasting purposes. Use the following data for daily sales to arrive at a recommendation:

Day	Demand	Day	Demand
1	35	8	39
2	47	9	24
3	46	10	26
4	39	11	36
5	26	12	43
6	33	13	46
7	24	14	29

Develop an Excel spreadsheet to answer the following questions.

- a. For the first seven days of data compare the absolute deviation for forecasts using $\alpha = .1$ and $\alpha = .3$. Start with $A_0 = 33$. Which method is best?

is best?

- b. Use the second week of data to make the same comparison. Use $A_7 = 32$. Which method is best now?
- c. What does this example illustrate?
13. The Easyfit tire store had demand for tires shown below. Assume $F_1 = 198$.
- a. Develop a spreadsheet using the first seven days of demand to determine the best exponential smoothing model for values of $\alpha = .2$, $\alpha = .3$, and $\alpha = .4$. Select the model with the smallest absolute deviation for seven periods.
- b. Develop another spreadsheet using the second seven days to compare the best exponential smoothing model found in part a with a three-period moving-average model. Compare the predictions on the basis of the total absolute deviation.
- c. What principles does this problem illustrate?

Day	Demand	Day	Demand
1	200	8	208
2	209	9	186
3	215	10	193
4	180	11	197
5	190	12	188
6	195	13	191
7	200	14	196

14. The ABC Floral Shop from problem 3 is considering fitting various forecasting models on the first seven days of demand and using the second seven days as a hold-out sample for comparing the prediction accuracy of the models. They have decided to use $\alpha = .25$, but aren't sure what starting value of forecast, F_1 , to use.
- a. Try values of $F_1 = 160$, $F_2 = 170$, and $F_3 = 180$ to determine the best exponential model for the first seven days using the minimum total absolute deviation as the criterion. You may modify the spreadsheet from problem 8 for the calculations.
- b. Compare the best model from part a to a three-period moving average model on the second set of data. Which one has the smallest sum of absolute errors?
- c. What principles does this problem illustrate?

Advanced Methods

LO10.8 Solve advanced forecasting problems

This supplement describes three additional methods for time-series forecasting that have trend and seasonal components. These methods are extensions of the techniques described in the chapter.

When the time-series model has a trend component, an exponential smoothing model can be developed that is based on updating two variables in each time period: an average level and a trend. The average level is computed as an expanded version of the first-order equation to include trend, as follows:

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

This average is then, in turn, used to update the estimate of trend by taking the difference in averages and smoothing this difference with the old trend. The updated trend is thus

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

In this case, the smoothing constant β , which can be the same as or different from the constant α used for level, is used for trend. The model requires initial estimates of A_0 and T_0 to get started. These estimates can be based either on judgment or on past data.

Using the above values, we can compute forecasts for the future. The procedure is now slightly different from the first-order case, because a constant trend is assumed in the time series. The forecast for period $t+K$ in the future is therefore

$$F_{t+k} = A_t + KT_t \quad K = 1, 2, 3, \dots$$

One unit of trend is added for each period into the future. An example using these formulas is shown in [Table S10.1](#).

Time series that have both trend and seasonal components can be forecast. In this case, three variables—average, trend, and a seasonal factor—are updated for each time period.

TABLE S10.1

Trend-Adjusted Exponential Smoothing*

t	D_t (demand)	A_t (average)	T_t (trend)	F_t (forecast)	$D_t - F_t$ (error)
-----	-------------------	--------------------	------------------	---------------------	------------------------

1	85	85	15	85	0
2	105	100.5	15.05	100	5.00
3	112	115.2	15.01	115.55	-3.55
4	132	130.4	15.03	130.21	1.79
5	145	145.4	15.03	145.43	-.43

*Assume $A_0 = 70$, $T_0 = 15$, $\alpha = .1$, $\beta = .1$.

The average is computed for period t as follows:

$$A_t = \alpha \left(\frac{D_t}{R_{t-l}} \right) + (1 - \alpha) (A_{t-1} + T_{t-1})$$

In this case, the demand is adjusted by the seasonal ratio and smoothed with the old average and old trend. The trend for period t is

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

The seasonal ratio for period t is

$$R_t = \gamma \left(\frac{D_t}{A_t} \right) + (1 - \gamma) R_{t-L}$$

In this case, we are assuming that the seasonal cycle is L periods. Page 212
 There are L seasonal ratios, one for each period. If the demand is monthly and the seasonal cycle repeats on an annual basis, $L = 12$. Each month, one of the seasonal ratios will be updated to a new value, along with the trend and average.

The model requires initial estimates of A_0 , T_0 and $R_0, R_{-1}, \dots, R_{-L+1}$. These initial estimates can be based on judgment or data if available.

According to the updated values, the forecast for future periods in period t is

$$F_{t+K} = (A_t + KT_t)(R_{t-L+K})$$

An example of this method is shown in [Table S10.2](#).

TABLE S10.2

Seasonal Exponential Smoothing Method*

t	D_t (demand)	A_t (average)	T_t (trend)	R_t (seasonal ratio)	F_t (forecast)	$D_t - F_t$ (error)
1	66	80.5	10.1	.804	64	2.0

1	66	80.5	10.1	.804	64	2.0
2	106	90.1	10.0	1.195	108.7	-2.7
3	78	99.5	9.9	.799	80.4	-2.4
4	135	110.1	10.0	1.201	130.7	4.3

*Assume $A_0 = 70$, $T_0 = 10$, $L = 2$, $R_{-1} = .8$, $R_0 = 1.2$, $\alpha = .2$, $\beta = .2$, $\gamma = .2$.

If there is no trend, this method can be used with seasonal factors alone. In this case, the above trend equation and T_t values are simply dropped.

One of the techniques used frequently in time-series forecasting is *classical decomposition*. This involves decomposing a time series into level, trend, seasonal, and possibly cyclic components. Decomposition is illustrated by an example with three years of quarterly data from a store that sells children's toys. It is assumed that the seasonal pattern is quarterly in nature, and there may be trend and level components in the data as well. Since only three years of data are available, no cyclic component will be estimated.

The quarterly data on the sales of toys are shown in [Table S10.3](#). The biggest sales of toys, by far, are in the fourth quarter, at Christmastime. Visual inspection of the data indicates an upward trend—but how can this trend be disentangled from the seasonality of the data? This is done by first computing a four-quarter moving average. Decomposition requires the same number of periods in the moving average as the seasonality of the data (i.e., 4 periods for quarterly seasonality and 12 periods for monthly seasonality). This is done to average out the high periods and the low periods of demand over the seasonal cycle. The four-period moving average is shown in the third column of [Table S10.3](#). These moving averages are centered between periods, because a four-period average should represent a point with two periods on each side. From column 3, the upward trend is clear, because the seasonality has been removed from the data.

TABLE S10.3

Classical Decomposition Method

Quarter	Sales*	Four-Period Moving Average	Two-Period Moving Average	Seasonal Ratio
1	30			
2	42			
3	55	56.75	57.4	.958
4	100	58	58.5	1.709
5	35	59	59.5	.588
6	46	60	62.5	.736
7	59	65	66.0	.894
8	120	67	68.4	1.754
9	43	69.75	71.3	.603
10	57	72.75	75.5	.755
11	71	78.25		
12	142			

Quarter	Sales*	Four-Period Moving Average	Two-Period Moving Average	Seasonal Ratio
1	30			
2	42			
3	55	56.75	57.4	.958
4	100	58	58.5	1.709
5	35	59	59.5	.588
6	46	60	62.5	.736
7	59	65	66.0	.894
8	120	67	68.4	1.754
9	43	69.75	71.3	.603
10	57	72.75	75.5	.755
11	71	78.25		
12	142			

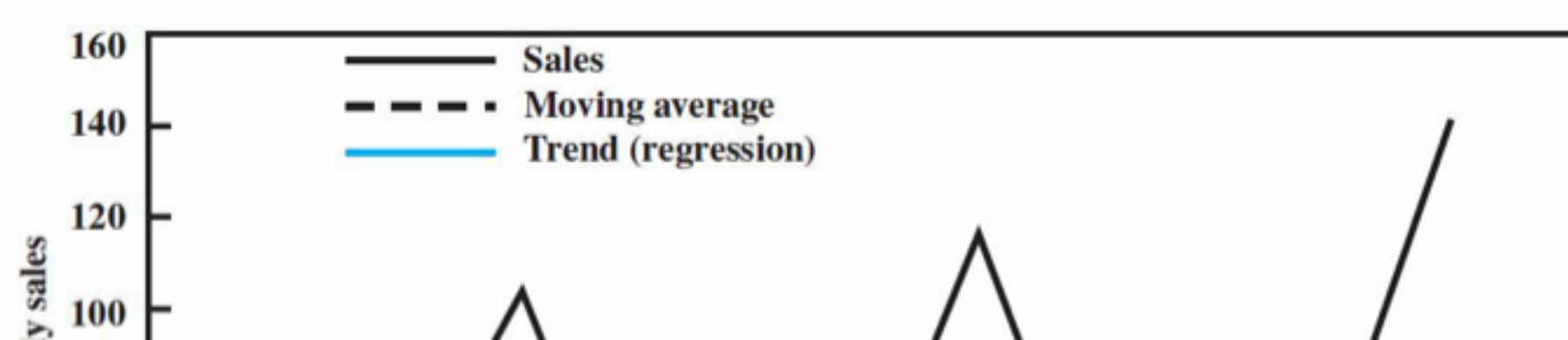
Seasonal Ratios Quarter				
	1	2	3	4
			.958	1.709
	.588	.736	.894	1.754
	.603	.755		
Average	<u>.596</u>	<u>.746</u>	<u>.926</u>	<u>1.732</u>

*Sales are in thousands of dollars.

To calculate seasonal ratios, we need an average for each period. This is done in column 4 of [Table S10.3](#) by constructing a two-period moving average of column 3. These new averages are then once again centered on the periods of data instead of between periods. Column 4 then represents the best average of the data for estimating the trend. It is also used to calculate seasonal ratios directly by dividing sales by column 4 to produce the seasonal ratios in column 5. Interpretation of these ratios is as follows: Demand in the third quarter is 95.8 percent of the annual average, demand in the fourth quarter is 170.9 percent of the yearly average, and so on. To obtain a best estimate of the seasonal ratios, we simply average the ratios for corresponding quarters. This calculation is shown on the bottom of [Table S10.3](#). Note that the seasonal ratios are quite stable in this example, but we have a minimal amount of data to work with. Ordinarily, at least four years of data should be used to establish seasonal ratios.

The original sales data and the deseasonalized moving average, from column 4, are plotted in [Figure S10.1](#). The moving average indicates an upward trend line. Actually, the trend might be slightly nonlinear, but let us assume for this example a linear trend line. Then a regression line can be fitted to the eight moving-average points shown on the graph. The result is

$$Y(t) = 47.8 + 2.63t$$



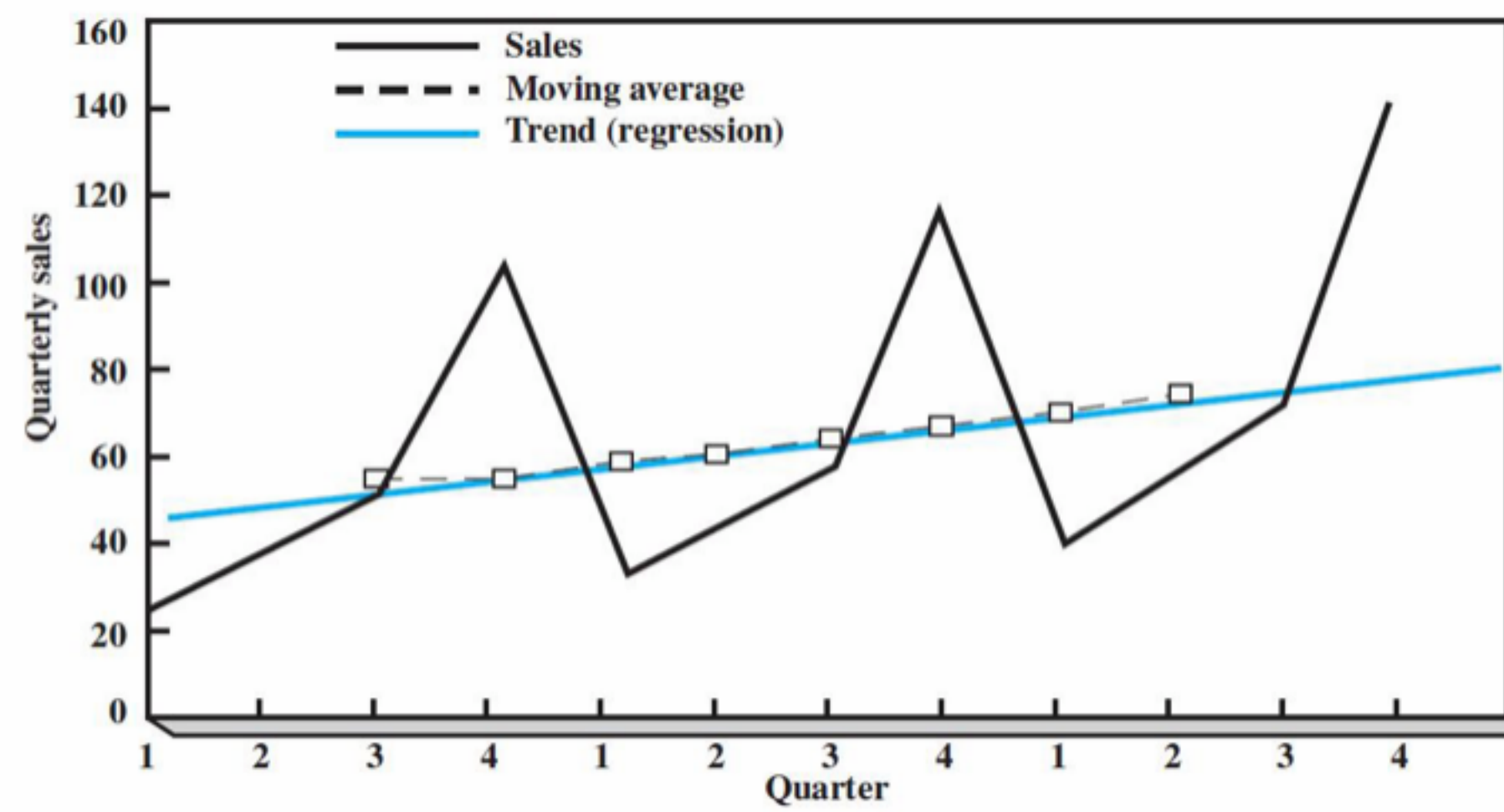


FIGURE S10.1 Seasonal toy sales.

where $\gamma(t)$ = sales and t = time.

A trend line could also be fitted to the original sales data, but it is customary in classical decomposition to use moving averages before fitting the trend line. This seems to give a slightly more stable forecast.

To forecast sales for the coming year, the following method is used. First, use the trend-line equation to predict the average for quarters 13, 14, 15, and 16 by inserting these values of time into the above regression equation. This yields column 2 in [Table S10.4](#). Then multiply the seasonal ratio for each quarter by the predicted average. The result is a forecast for each quarter of the next year, as shown in [Table S10.4](#).

TABLE S10.4

Seasonal Forecast Calculations

Quarter	Predicted Average	×	Seasonal Factor	=	Forecast
13	82.0		.596		48.8
14	84.6		.746		63.1
15	87.2		.926		80.7
16	89.9		1.732		155.7

Supplement Problems

1. Ace Hardware sells spare parts for lawn mowers. The following data were collected for one week in May when replacement lawn-mower blades were in high demand:

Day	Demand
1	10
2	12
3	13
4	15
5	17

5	17
6	20
7	21

- Simulate a forecast for the week, starting with $F_1 = 10$, $T_0 = 2$, $\alpha = .2$, and $\beta = .4$. Use the trend model given in the chapter supplement.
- Compute the MAD and tracking signal for the data. Use $MAD_0 = 0$.
- Are the MAD and tracking signal within tolerances?
- Simulate a forecast using simple smoothing for the week, starting with $F_1 = 10$ and $\alpha = .2$. Plot the forecast and the demand on a graph. Note how the forecast lags behind demand.



- The daily demand for chocolate donuts from the Donut-Hole Shop has been recorded for a two-week period.

Day	Demand	Day	Demand
1	80	8	85
2	95	9	99
3	120	10	110
4	110	11	90
5	75	12	80
6	60	13	65
7	50	14	50

- Simulate a forecast of the demand using trend-adjusted exponential smoothing. Use values of $A_0 = 90$, $T_0 = 25$, and $\alpha = \beta = .2$.
 - Plot the data and the forecast on a graph.
 - Does this appear to be a good model for the data?
- The SureGrip Tire Company produces tires of various sizes and shapes. The demand for tires tends to follow a quarterly seasonal pattern with a trend. For a particular type of tire the company's current estimates are as follows: $A_0 = 10,000$, $T_0 = 1,000$, $R_0 = .8$, $R_{-1} = 1.2$, $R_{-2} = 1.5$, and $R_{-3} = .75$.
 - The company has just observed the first quarter of demand $D_1 = 6000$ and would like to update its forecast for each of the next four quarters using $\alpha = \beta = \gamma = .4$.

- b. When demand is observed for the second quarter, it is $D_2 = 15,000$. How much error is there in the forecast?
- c. Update the forecasts again for the coming year, using the second-quarter demand data.

excel

4. Management believes there is a seasonal pattern in the above data for the Donut-Hole Shop (see problem 2), with the first two days of a week representing one level; the third and fourth days representing a second level; and the fifth, sixth, and seventh days a third level. Thus, three seasonal factors have been suggested: $R_0 = .9$, $R_{-1} = 1.3$, and $R_{-2} = .8$.
- a. Simulate a forecast of demand for days 1 to 7 using $A_0 = 85$, $T_0 = 0$, and $\alpha = \beta = \gamma = .1$.
- b. Comment on the appropriateness of the forecasts developed.
5. Management of the ABC Floral Shop believes that its sales are seasonal in nature with a monthly seasonal pattern and no trend. The demand data and seasonal ratios for the past three years are given as follows.

Page 215

Month	Year 1 Demand	Year 2 Demand	Year 3 Demand	Seasonal Ratio
Jan.	\$12,400	\$11,800	\$13,600	0.8
Feb.	23,000	24,111	21,800	1.8
Mar.	15,800	16,500	14,900	0.9
Apr.	20,500	21,000	19,400	1.6
May	25,100	24,300	26,000	2.0
June	16,200	15,800	16,500	1.0
July	12,000	11,500	12,400	0.7
Aug.	10,300	10,100	10,800	0.6
Sept.	11,800	11,000	12,500	0.7
Oct.	14,000	14,300	13,800	1.2
Nov.	10,700	10,900	10,600	0.9
Dec.	7,600	7,200	8,100	0.6

- a. Calculate a forecast for Year 3 using $A_0 = 15,000$, $\alpha = \gamma = .3$, and the seasonal ratios shown above. For each period, calculate the forecast

- a. Calculate a forecast for Year 3 using $A_0 = 15,000$, $\alpha = \gamma = .3$, and the seasonal ratios shown above. For each period, calculate the forecast and the updated seasonal ratio.
- b. Plot the original data and the forecast on a graph.
- c. Calculate the tracking signals for the past year using $MAD_0 = 0$. Are they within tolerances?
- d. Using the classical decomposition method described in the chapter supplement, calculate the seasonal ratios from the data and determine the trend and average levels. Use these ratios and estimates of trend and level to make a forecast for the next year.