CHAPTER TWO

FORECASTING

Every day, health care managers must make decisions about service delivery without knowing what will happen in the future. Forecasts enable them to anticipate the future and plan accordingly. Good forecasts are the basis for short-, medium-, and long-term planning, and are essential input to all types of service production systems. Forecasts have two primary uses: to help managers plan the system, and also to help them plan the use of the system. Planning the system itself is long-range planning: about the kinds of services supplied and the number of each to offer, what facilities and equipment to have, which location optimizes service delivery to the particular patient population, and so on. Planning the use of the system is short-range and medium-range planning for supplies and workforce levels, purchasing and production, budgeting, and scheduling.

All of the above plans rely on forecasts. Forecasting is not an exact science, however; its results are rarely perfect, and the actual results usually differ. For the best possible forecasts, a health care manager must blend experience and good judgment with technical expertise.

All forecasts have certain common elements regardless of the technique used. The underlying assumption is that past events will continue. It also is a given that errors will occur because of the presence of randomness, and that actual results are more than likely to be different from those predicted. Forecasts of a group of items (aggregate forecasts) tend to be more accurate than those for individual items. For example, forecasts made for a whole hospital would tend to be more accurate than a departmental forecast, because forecasting errors among a group tend to cancel each other. Finally, it is generally accepted that forecast accuracy decreases as the time horizon (the period covered) increases. Short-range forecasts face fewer uncertainties than longer-range forecasts do, so they tend to be more accurate. A flexible health care organization, which responds quickly to changes in demand, makes use of a shorter, more accurate forecasting horizon than do less flexible competitors, who must use longer forecast horizons.

Steps in the Forecasting Process

Many forecasting methods are available to health care managers for planning, to estimate future demand or any other issues at hand. However, for any type of forecast to bring about later success, it must follow a step-by-step process comprising five major steps: 1) goal of the forecast and the identification of resources for conducting it; 2) time horizon; 3) selection of a forecasting technique; 4) conducting and completing the forecast; and 5) monitoring the accuracy of the forecast.

Identify the Goal of the Forecast

This indicates the urgency with which the forecast is needed and identifies the amount of resources that can be justified and the level of accuracy necessary.

Establish a Time Horizon

Decide on the period to be covered by the forecast, keeping in mind that accuracy decreases as the time horizon increases.

Select a Forecasting Technique

The selection of a forecasting model will depend on the computer and financial resources available in an organization, as well as on the complexity of the problem under investigation.

Conduct the Forecast

Use the appropriate data, and make appropriate assumptions with the best possible forecasting model. Health care managers often have to make assumptions based on experience with a given situation, and sometimes by trial and error. In forecasting, analyzing appropriate data refers to a) the availability of relevant historical data; and b) recognizing the variability in a given data set.

Monitor Accuracy

Since there is an arsenal of techniques available, appropriate for different situations and data representations, health care managers must examine their data and circumstances carefully to select the appropriate forecasting approach. Be prepared to use another technique if the one in use is not providing acceptable results. Health care managers must also be alert to how frequently the forecast should be updated, especially when trends or data change dramatically.

Forecasting Approaches

In its simplest forms, forecasting includes judgments, whether individual or juries of opinions. Although this is not a sophisticated mathematical model, a brief explanation of such approaches is prudent.

Judgmental Forecasts

Judgmental forecasts rely on analysis of such subjective inputs as executive opinions, contracts/insurance/HMO/PPO/POS company estimates, consumer surveys, mental estimates of the market, intuition, outside (consultant) opinions, and the opinions of managers and staff. A health care manager may use staff to generate a judgmental forecast or several forecasts from which to choose. Examples of judgmental forecasting include the Delphi method, jury of executive opinion, and naive extrapolation.

The Delphi method, which obtains the opinions of managers and staff who have relevant knowledge, is frequently used. A series of questionnaires are circulated to a group of "experts," with each successive questionnaire developed from the previous one, in order to achieve a consensus on a question, for example, the potential of a new high-technology health service. The Delphi method is useful for forecasting technological changes and their impacts; often the goal is to predict when a certain event will occur. Use of the Delphi method has certain advantages. It saves costs to use questionnaires rather than an assembly of many experts. Furthermore, the isolation of each participant helps to eliminate a "bandwagon effect," and since the anonymity of each participant is preserved, honest responses are likely. The Delphi is not without weaknesses, however: ambiguous questions may lead to a false consensus; anonymity may diminish the sense of accountability and responsibility by the respondents; and panel members may change if the process takes a long time (for example, one year or more) to complete. Finally, studies have not proven or disproved the accuracy of Delphi forecasts.

The jury of executive opinion model uses the consensus of a group of experts, often from several functional areas within a health care organization, to develop a forecast. It differs from the Delphi method in its reach, scope, and time horizons: opinions are sought from health care organization's members rather than from an external source, and the forecast may take much less time. The participants are far more likely to interact with each other under the jury of executive opinion model.

A naive extrapolation involves making a simple assumption about the economic outcome of the next period, or a subjective extrapolation from the results of current events.

At the other end of the forecasting spectrum are mathematical and statistical techniques using historical data, called time series.

Time-Series Approach

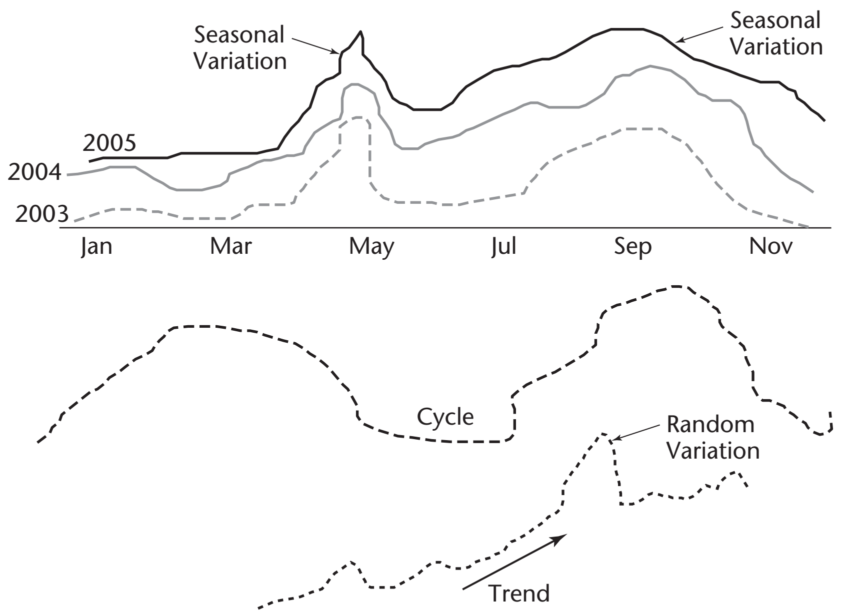
A time series is a sequence of evenly spaced observations taken at regular intervals over a period of time (such as daily, hourly, weekly, monthly, or yearly). An example of a time series is the monthly admissions to a multisystem hospital. Forecasts from time-series data assume that future values of the series can be predicted from past values. Analysis of a time series can identify the behavior of the series in terms of trend, seasonality, cycles, irregular variations, or random variations. A trend is a gradual, long-term, upward or downward movement in data. Seasonality refers to short-term, relatively frequent variations generally related to factors such as weather, holidays, and vacations; health care facilities often experience weekly and even daily "seasonal" variations.

Cycles are patterns in the data that occur every several years, often in relation to current economic conditions. Such cycles often exhibit wavelike characteristics that mimic the business cycle. Irregular variations are "spikes" in the data caused by chance or unusual circumstances (examples: severe weather, labor strike, use of a new high-technology health service); they do not reflect typical behavior and should be identified and removed from the data whenever possible. Random variations are residual variations that remain after all other behaviors have been accounted for. Graphing the data provides clues to a health care manager for selecting the right forecasting method. Figure 2.1 illustrates these common variations in data.

Techniques for Averaging

Historical data usually contain a certain amount of noise (random variation) that tends to obscure patterns in the data. Randomness arises from a multitude of

FIGURE 2.1. VARIATION CHARACTERISTICS.



relatively unimportant factors that cannot possibly be predicted with any certainty. The optimal situation would be to completely remove randomness from the data and leave only "real" variations (for example, changes in the level of patient demand). Unfortunately, it is usually impossible to distinguish between these two kinds of variations. The best one can hope for is that the small variations are random and the large variations actually mean something. Averaging techniques smooth out some of the fluctuations in a data set; individual highs and lows are "averaged" out. A forecast based on an average shows less variability than the original data set does. The result of using averaging techniques is that minor variations are treated as random variations and essentially "smoothed" out of the data set. Although the larger variations, those deemed likely to reflect "real" changes, are also smoothed, it is to a lesser degree. Three techniques for averaging are described in this section: naive forecasts, moving averages, and exponential smoothing.

Naive Forecasts. The simplest forecasting technique is termed the naive method. A naive forecast for any period simply projects the previous period's actual value. For example, if demand for a particular health service was 100 units last week, the naive forecast for the upcoming week is 100 units. If demand in the upcoming week turns out to be 75 units, then the forecast for the following week would be 75 units. The naive forecast can also be applied to a data set that exhibits seasonality or a trend. For example, if the seasonal demand in October is 100 units, then the naive forecast for *next October* would equal the actual demand for *October of this year.*

Although this technique may seem too simplistic, its advantages are low cost and ease of preparation and comprehension. Its major weakness, of course, is its inability to make highly accurate forecasts. Another weakness is that it simply replicates the actual data, with a lag of one period; it does not smooth the data. However, the decision to use naive forecasts certainly has merit if the results *experienced* are relatively close to the forecast (if the resulting accuracy is deemed acceptable). The accuracy of a naive forecast can serve as a standard against which to judge the cost and accuracy of other techniques; the health care manager can decide whether or not the increase in accuracy of another method is worth its additional cost.

Moving Averages (MA). While a naive forecast uses data from the previous period, a moving average forecast uses a number of the most recent actual data values. The moving average forecast is found using the following equation:

$$F_t = \text{MA}_n = \frac{\sum A_i}{n} \qquad [2.1]$$

where

F_t = Forecast for time period t
MA_n = Moving average with n periods
A_i = actual value with age i
i = "age" of the data (i = 1, 2, 3 . . .)
n = number of periods in moving average

Example 2.1

An OB/GYN clinic has the following yearly patient visits, and would like to predict the volume of business for the next year for budgeting purposes.

Period (t)	Age	Visits
1	5	15,908
2	4	15,504
3	3	14,272
4	2	13,174
5	1	10,022

Solution: Using formula [2.1], the three-period moving average (MA_3) for period 6 is

$$F_6 = MA_3 = (14{,}272 + 13{,}174 + 10{,}022) \div 3 = 12{,}489.$$

With the available data a health care manager can back forecast earlier periods; this is a useful tool for assessing accuracy of a forecast, as will be explained later. Computation of 3-period moving averages for the OB/GYN visits then would look like this:

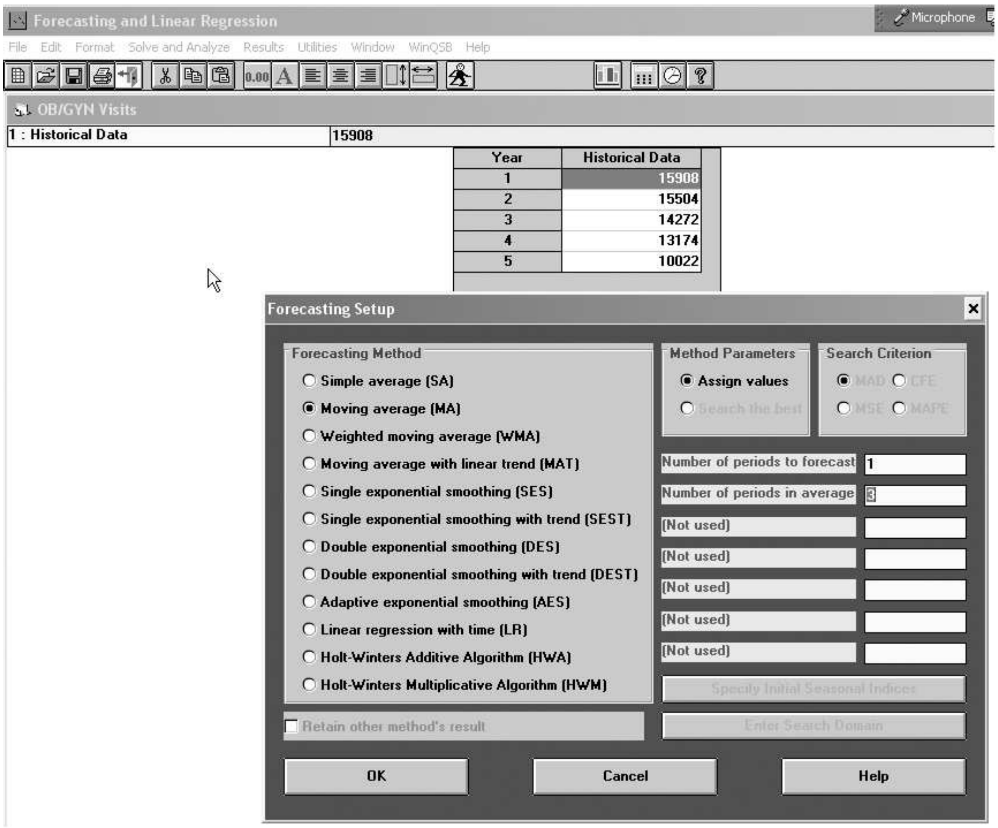
Period (*t*)	**Age**	**Visits**	**Forecast**
1	5	15,908	
2	4	15,504	
3	3	14,272	
4	2	13,174	15,228
5	1	10,022	14,317
6			12,489

This technique derives its name from the fact that as each new actual value becomes available, the forecast is updated by adding the newest value and dropping the oldest and then recalculating the average. Thus the forecast "moves" by reflecting only the most recent values. For instance, to calculate the forecasted value of 15,228 for period 4 (F_4), the visits from periods 1 through 3 were averaged; to calculate F_5, visits from period 1 were dropped, but visits from period 4 were added to the average. ■

A health care manager can incorporate as many data points as desired in the moving average. The number of data points used determines the sensitivity of the forecasted average to the new values being added. The fewer the data points in an average, the more responsive the average tends to be. If a manager seeks responsiveness from the forecast, only a few data points should be used. It is important to point out, however, that a highly sensitive forecast will also be more responsive to random variations (less smooth). On the other hand, moving averages based on many data points will be smoother, but less responsive to "real" changes. The decision maker must consider the cost of responding more slowly to changes in the data against the cost of responding to what may be simply random variations.

WinQSB software evaluation for this problem is shown in Figure 2.2, with the problem set up for three-period moving averages. The first pane (top) shows historical data, with the command "Solve and Analyze"; the second pane (bottom) is the "Forecasting Setup" window, which allows one to select the method and

FIGURE 2.2. WINQSB SETUP: MOVING AVERAGE (MA_3) FOR OB/GYN CLINIC.



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enter the associated parameters. Here the selection is MA with one period to forecast, with the number of periods in the average equal to 3.

After clicking OK, the results shown in Figure 2.3 would confirm the results obtained earlier.

Actual data and the MA_3 forecast for years 4 through 6 (as shown 3-MA) can be observed in columns 1 and 2, respectively. (The information in the other columns and rows will be discussed later in the chapter.) In addition to tabular forecasting results, the graph in Figure 2.4 provides pictorial information on the forecast. The graph is obtained by clicking "Results," then "Show Forecasting in Graph."

FIGURE 2.3. WINQSB SOLUTION: MOVING AVERAGE (MA_3) FOR OB/GYN CLINIC.

Forecasting and Linear Regression

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Forecast Result for OB/GYN Visits

01-16-2004 Year	Actual Data	Forecast by 3-MA	Forecast Error	CFE	MAD	MSE	MAPE (%)	Tracking Signal	R-square
1	15908.0000								
2	15504.0000								
3	14272.0000								
4	13174.0000	15228.0000	-2054.0000	-2054.0000	2054.0000	4218916.0000	15.5913	-1.0000	
5	10022.0000	14316.6700	-4294.6670	-6348.6670	3174.3340	11331540.0000	29.2219	-2.0000	
6		12489.3300							
CFE		-6348.6670							
MAD		3174.3340							
MSE		11331540.0000							
MAPE		29.2219							
Trk.Signal		-2.0000							
R-square									
		m=3							

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Determining a Reasonable Number of Periods for the Moving Average. The health care manager faces the problem of selecting an appropriate number of periods for the moving average forecast. Of course the decision depends upon the number of periods available, and also on the behavior of the data that would yield the best forecast for a given situation. In general, the more periods in a moving average, the less responsive the forecast will be to changes in the data, creating a lag response. To illustrate this, an example with twenty-eight periods of historical data is described in Example 2.2, below.

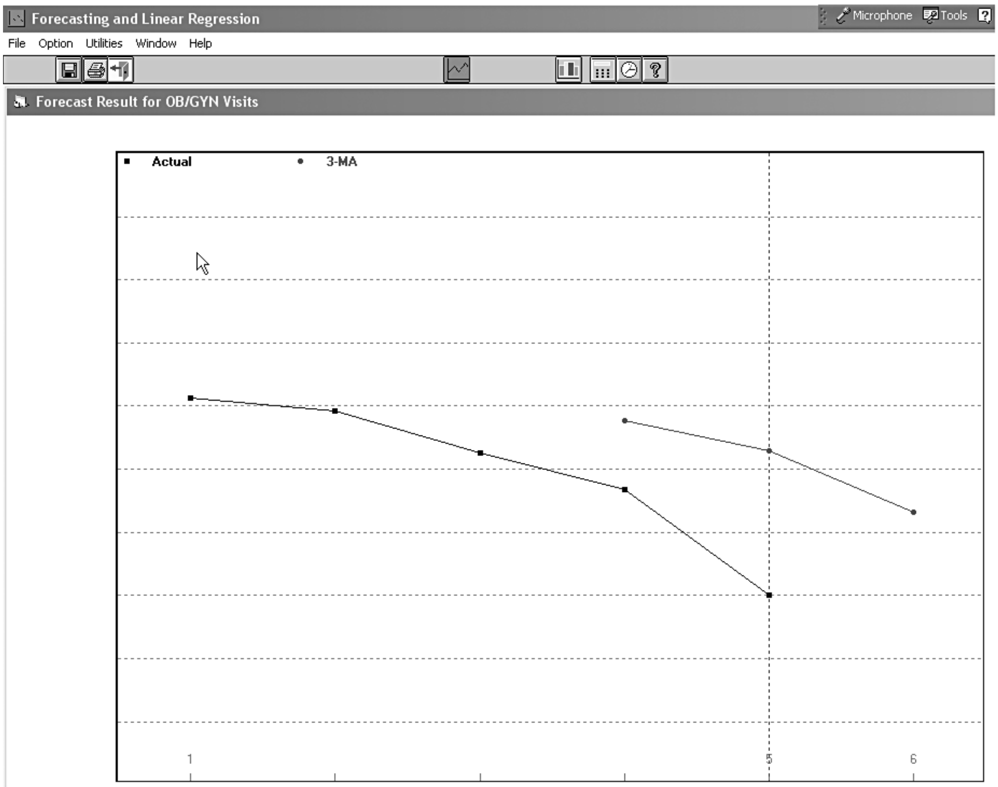
EXAMPLE 2.2

A pediatric clinic manager would like to find the best moving average forecast for the next month's visits. The past data contain the last twenty-eight months.

Solution: The solution to this problem requires calculation of moving averages for various periods (for instance: MA_3 through MA_7). Two approaches can be used to identify the best MA period: 1) graph; and 2) minimum forecasting errors.

For the graph, the results of each MA_n would be graphed, and then the moving average forecast that fits or represents the original data best would be selected. The second method, which will be discussed later in the chapter, would evaluate the actual versus the forecast (errors); at this point it suffices to show how responsive the various MA_n forecasts are to the actual data. In Figure 2.5,

FIGURE 2.4. WINQSB GRAPHICAL SOLUTION: MOVING AVERAGE (MA_3) FOR OB/GYN CLINIC.



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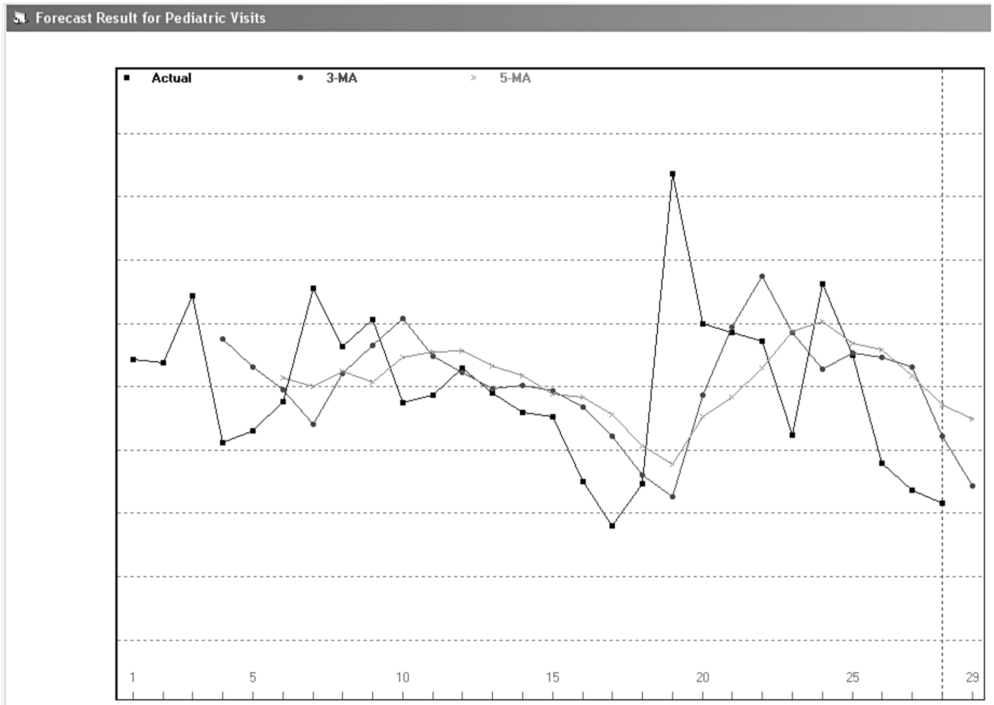
forecasts for the pediatric clinic by both MA_3 and MA_5 show lagged responses to the actual data, but the lag is greater in MA_5. Hence, the MA_3 forecast provides a smoother and more responsive forecast in this case. ■

Weighted Moving Average (WMA). Moving average forecasts are easy to compute and understand; however, all the values are weighted equally. For example, in an eight-year moving average, each value is given a weight of one-eighth. Should data that are ten years old have equal weight (importance) with data collected last year? It certainly depends on the situation that a health care manager faces, but he or she could choose to compute a **weighted average** to assign more weight to recent values. A weighted average is similar to a moving average, except that it assigns more weight to the most recent values in a time series. For example,

FIGURE 2.5. PEDIATRIC VISITS FORECAST USING MA_3 AND MA_5.



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the most recent data might be given a weight of .50, the next most recent value a weight of .30, and .20 for the next. These values are totally subjective (based on the manager's previous experiences with the data in question), with the only requirements being that the weights sum to 1.00, and that the heaviest weights be assigned to the most recent values. Trial and error is used to find an acceptable weighting pattern. The advantage of a weighted average over a simple moving average is that the weighted average is more reflective of the most recent actual results. Formally, weighted moving average is expressed as:

$$F_t = \mathrm{MA}_n = \sum w_i A_i. \qquad [2.2]$$

Example 2.3

Continuing with Example 2.1; since there is a downward trend in visits and in period 5 there is a sharp decline, a weight of .5 or even higher is justified by the health care manager to calculate a weighted average for period 6.

Solution: In this analysis, a weighted average, using formula [2.2], for the OB/GYN clinic for period 6 would be:

$$F_6 = 14{,}272 * .2 + 13{,}174 * .3 + 10{,}022 * .5 = 11{,}818.$$

Period (t)	Age	Visits	Weights	Forecast
1	5	15,908		
2	4	15,504		
3	3	14,272	0.2	
4	2	13,174	0.3	
5	1	10,022	0.5	
6				11,818

■

The WinQSB setup for the OB/GYN problem with weights .2, .3, and .5 is shown in Figure 2.6. After clicking the third option, "Weighed Moving Average," and entering the number of periods to forecast and the number of periods in the average, clicking on the button at "Enter Moving Average Weights" causes a

FIGURE 2.6. WINQSB SETUP FOR OB/GYN EXAMPLE USING WMA_3.

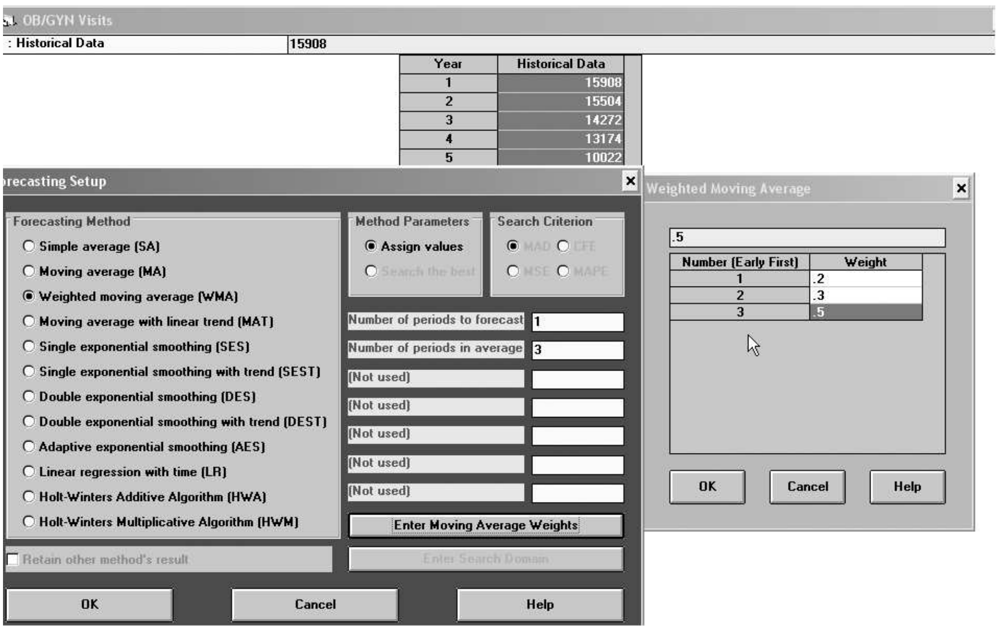

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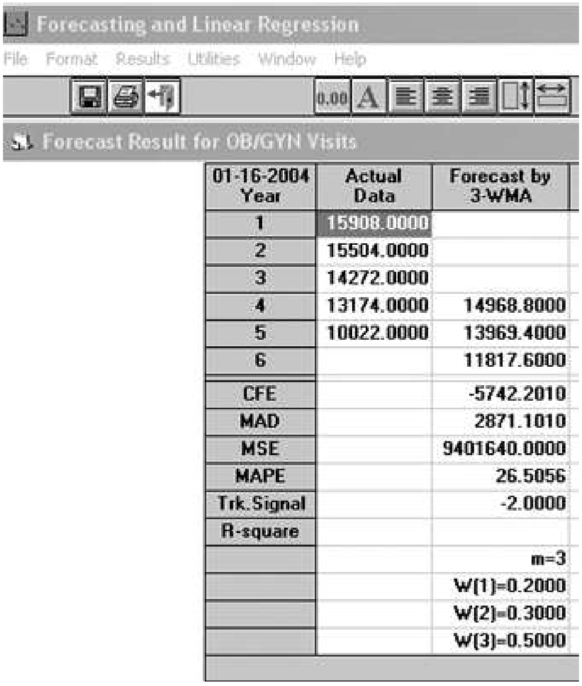
FIGURE 2.7. WINQSB SOLUTION TO OB/GYN EXAMPLE WITH WMA_3.



01-16-2004 Year	Actual Data	Forecast by 3-WMA
1	15908.0000	
2	15504.0000	
3	14272.0000	
4	13174.0000	14968.8000
5	10022.0000	13969.4000
6		11817.6000
CFE		-5742.2010
MAD		2871.1010
MSE		9401640.0000
MAPE		26.5056
Trk.Signal		-2.0000
R-square		
		m=3
		W(1)=0.2000
		W(2)=0.3000
		W(3)=0.5000

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new popup menu to enter the weights. Finally, Figure 2.7 displays the results of the 3-period weighted moving averages for Example 2.3 problem as indicated by WMA_3.

Single Exponential Smoothing (SES). In a single exponential smoothing forecast, 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, expressed as:

$$\text{New forecast} = \text{Old forecast} + \alpha(\text{Actual value} - \text{Old forecast})$$

where, α is the smoothing constant, expressed as a percentage. Formally, the exponential smoothing equation can be written as:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \qquad [2.3]$$

where

F_t = Forecast for period t
F_{t-1} = Forecast for period $t - 1$
α = Smoothing constant
A_{t-1} = Actual value (i.e., patient visits) in period $t - 1$.

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.

Example 2.4

Using the data from Example 2.1, build forecasts with smoothing constant $\alpha = 0.3$.

Solution: Following the previous example and formula [2.3], we can build forecasts for periods as data become available. After period 1 the health care manager would have the number of actual visits, which are recorded as 15,908, and with this information the best one can do for the second period is a naive forecast. Hence 15,908 becomes the forecast for period 2. When period 2 data become available, it will be recorded as actual—in this case, 15,504. Now to forecast period 3, with $\alpha = .3$, the new forecast would be computed as follows:

$$F_3 = 15{,}908 + .30(15{,}504 - 15{,}908) = 15{,}786.8.$$

Then, for period 3, if the actual visits turn out to be 14,272, the next forecast would be:

$$F_4 = 15{,}786.8 + .30(14{,}272 - 15{,}786.8) = 15{,}332.4.$$

Similarly, F_5 and F_6 can be calculated as:

$$F_5 = 15{,}332.4 + .30(13{,}174 - 15{,}332.4) = 14{,}684.9$$
$$F_6 = 14{,}684.9 + .30(10{,}022 - 14{,}684.9) = 13{,}286.0$$

Smoothing constant $\alpha = 0.3$			Error
Period (t)	Actual (Visits)	Forecast	(Actual − Forecast)
1	15,908	—	
2	15,504	15,908	−404.0
3	14,272	15,786.8	−1,514.8
4	13,174	15,332.4	−2,158.4
5	10,022	14,684.9	−4,662.9

The closer the smoothing constant (α) is to one, the faster the forecast is to adjust using forecast errors (the greater the smoothing). Commonly used values for

α range from 0.10 to 0.60 and are usually selected by judgment or trial and error. To illustrate the effect of the higher α values, the same example is shown with $\alpha = 0.50$ below. ■

Example 2.5

Using the data from Example 2.1, build forecasts with smoothing constant $\alpha = 0.5$.

Solution:

Smoothing constant α = 0.5			Error
Period (t)	**Visits**	**Forecast**	**(Actual − Forecast)**
1	15,908	—	
2	15,504	15,908	−404.0
3	14,272	15,706.0	−1,434.0
4	13,174	14,989.0	−1,815.0
5	10,022	14,081.5	−4,059.5

As can be easily noticed, F_6 with $\alpha = 0.5$ is much less than the previous F_6 where α was 0.3. That demonstrates the faster adjustment with respect to the emphasis given recent data.

The smoothing constant value at the lower extreme $\alpha = 0.0$, does not account for errors in predictions and places heavy emphasis on the aged data from old periods (no adjustment to the latest forecast), while at the other extreme, $\alpha = 1.0$, it puts emphasis on the most recent data (greatest adjustment to the latest forecast), thus basically providing a naive forecast, as shown in Example 2.6 below. ■

Example 2.6

Using the data from Example 2.1, build forecasts with smoothing constants $\alpha = 0.0$ and $\alpha = 1.0$.

Solution:

	α = 0.0		Error	α = 1.0		Error
Period (t)	**Visits**	**Forecast**	**(Actual − Forecast)**	**Visits**	**Forecast**	**(Actual − Forecast)**
1	15,908	—		15,908	—	
2	15,504	15,908	−404.0	15,504	15,908	−404.0
3	14,272	15,908.0	−1,636.0	14,272	15,504.0	−1,232.0
4	13,174	15,908.0	−2,734.0	13,174	14,272.0	−1,098.0
5	10,022	15,908.0	−5,886.0	10,022	13,174.0	−3,152.0
6		15,908.0			10,022.0	

FIGURE 2.8. WINQSB SOLUTIONS TO THE OB/GYN EXAMPLE, USING SINGLE EXPONENTIAL SMOOTHING (SES).

Forecasting and Linear Regression

File Format Results Utilities Window Help

Forecast Result for OB/GYN Visits

01-16-2004 Year	Actual Data	Forecast by SES	Forecast by SES	Forecast by SES	Forecast by SES	Forecast Error
1	15908.0000					
2	15504.0000	15908.0000	15908.0000	15908.0000	15908.0000	-404.0000
3	14272.0000	15786.8000	15706.0000	15908.0000	15504.0000	-1232.0000
4	13174.0000	15332.3600	14989.0000	15908.0000	14272.0000	-1098.0000
5	10022.0000	14684.8500	14081.5000	15908.0000	13174.0000	-3152.0000
6		13286.0000	12051.7500	15908.0000	10022.0000	
CFE		-8740.0110	-7712.5000	-10660.0000	-5886.0000	
MAD		2185.0030	1928.1250	2665.0000	1471.5000	
MSE		7214634.0000	5498335.0000	11239870.0000	3205437.0000	
MAPE		19.0323	16.7341	23.3881	12.7559	
Trk.Signal		-4.0000	-4.0000	-4.0000	-4.0000	
R-square					0.8023	
		Alpha=0.3	Alpha=0.5	Alpha=0	Alpha=1	
		F(0)=15908	F(0)=15908	F(0)=15908	F(0)=15908	

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The WinQSB results for the above discussions are shown in Figure 2.8. It should be noted that on the setup menus, at lower left bottom there is an option to retain the other method's results. This option was turned on to incorporate four different α values. ■

Techniques for Trend

A trend is a gradual, long-term movement caused by changes in population, income, or culture. Assuming that there is a trend present in a data set, it can be analyzed by finding an equation that correlates to the trend in question. The trend may or may not be linear in its behavior. Plotting the data can give a health care manager insight into whether a trend is linear or nonlinear.

Forecasting Techniques Based on Linear Regression. By minimizing the sum of the squared errors, which is called the least squares method, **regression** analysis can be used to create a representative line that has the form:

$$y = a + b * x \qquad [2.4]$$

where

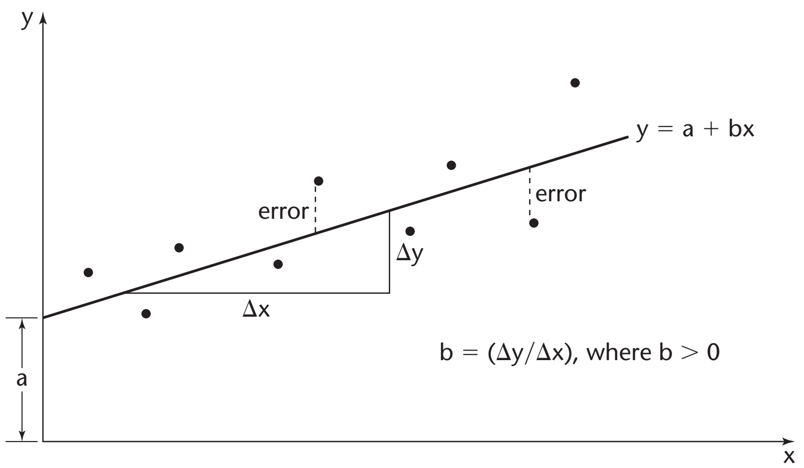
y = the predicted (dependent) variable
x = the predictor (independent) variable
b = the slope (rise/run) of the data line
a = the value of y when x is equal to zero.

Consider the regression equation example $y = 20 + 5x$. The value of y when $x = 0$ is 20, and the slope of the line is 5. Therefore, the value of y will increase by five units for each one-unit increase in x. If $x = 15$, the forecast (y) will be 20 + 5(15), or 95 units. This equation could be plotted on a graph by finding two points on the line. One of those points can be found in the way just mentioned; putting in a value for x. The other point on the graph would be a (i.e. y_x at $x = 0$). The coefficients of the line, a and b, can be found (using historical data) with the following equations:

$$b = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{n\left(\sum x^2\right) - \left(\sum x\right)^2} \quad [2.5]$$

$$a = \frac{\sum y - b\sum x}{n}. \quad [2.6]$$

FIGURE 2.9. LINEAR REGRESSION.



The graph in Figure 2.9 illustrates the regression line concept, showing the errors that are minimized by the least square method by positioning the regression line using the appropriate slope (b) and y-intercept (a).

The Example 2.7 illustrates the linear regression forecast.

Example 2.7

A multihospital system (MHS) owns 12 hospitals. Revenues (x, or the independent variable) and profits (y, or the dependent variable) for each hospital are given below. Obtain a regression line for the data, and predict profits for a hospital with $10 million in revenues. All figures are in millions of dollars.

Multihospital System Revenues and Profits Data

Hospital	Revenue (x)	Profit (y)	$x * y$	x^2
1	7	0.15	1.05	49
2	2	0.10	0.2	4
3	6	0.13	0.78	36
4	4	0.15	0.6	16
5	14	0.25	3.5	196
6	15	0.27	4.05	225
7	16	0.24	3.84	256
8	12	0.20	2.4	144
9	14	0.27	3.78	196
10	20	0.44	8.8	400
11	15	0.34	5.1	225
12	7	0.17	1.19	49
Total	**132**	**2.71**	**35.29**	**1796**

Solution: After calculating $\sum x$, $\sum y$, $\sum xy$, $\sum x^2$, substitute into the Equations [2.5] for a and [2.6] for b, respectively.

$$b = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{n\left(\sum x^2\right) - \left(\sum x\right)^2} = \frac{12(35.29) - 132(2.71)}{12(1796) - 132(132)} = 0.01593$$

$$a = \frac{\sum y - b\sum x}{n} = \frac{2.71 - 0.01593(132)}{12} = 0.0506$$

Hence, the regression line is:

$$y_x = 0.0506 + 0.01593x.$$

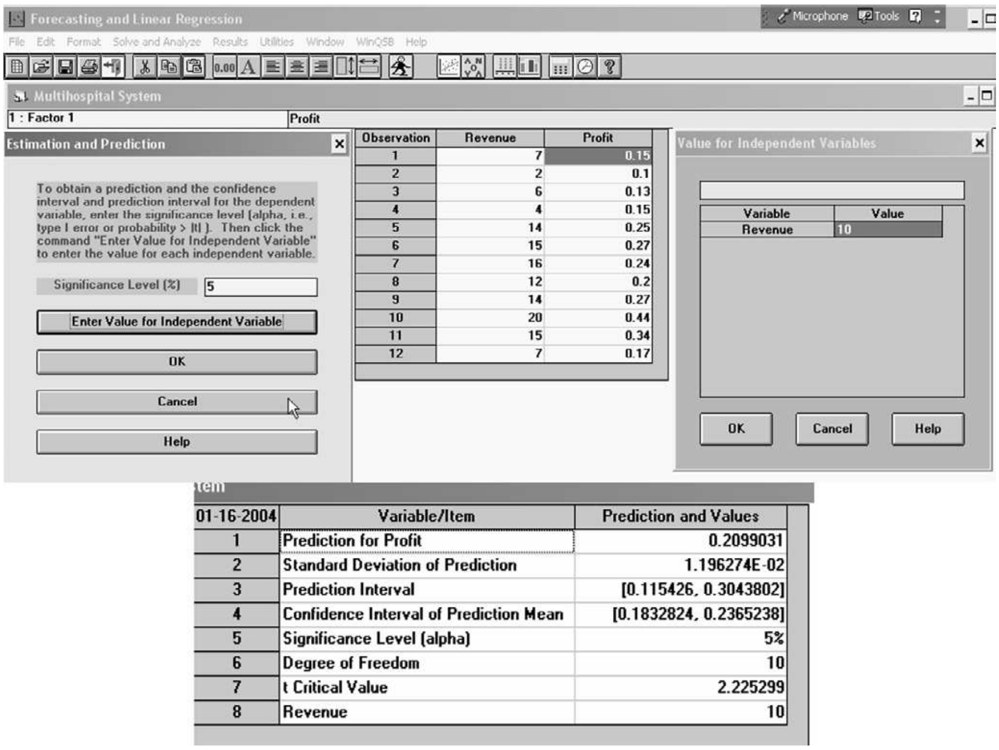
To predict the profits for a hospital with $10 million in revenue, simply plug 10 in as the value of x in the regression equation:

$$\text{Profit} = 0.0506 + 0.01593(10) = .209903.$$

Multiplying this value by one million, the profit level with $10 million in revenue is found to be $209,903. ■

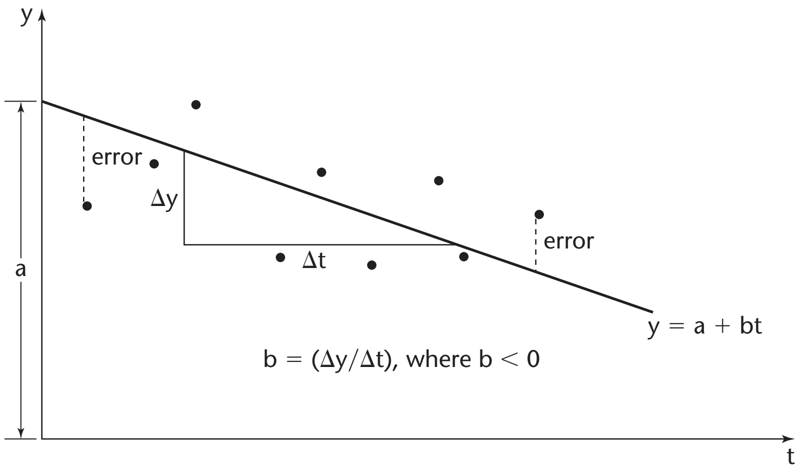
We can observe the same solution from WinQSB as shown in Figure 2.10. The middle pane shows the data; by clicking on "Solve and Analyze" the user can chose "Estimation and Prediction," which is shown on the left pane. This menu has a button to enter a value for the independent variable; when it is clicked a new pop-up menu, shown on the very right pane, opens. A value of 10 (Revenue) was entered. The results are displayed on the bottom pane, where "Prediction for Profit" is shown as .209903, corresponding to the hand calculations above.

FIGURE 2.10. WINQSB SOLUTION TO THE MULTIHOSPITAL SYSTEM EXAMPLE.



Source: Screen shots reprinted by permission from Microsoft Corporation and Yih-Long Chang (author of WinQSB).

FIGURE 2.11. LINEAR REGRESSION AS A TREND.



Linear Regression as a Trend Line. Linear regression often is used to describe trends in health care data. The only difference in this application is that the independent variable *x*, takes a value in time and is shown as *t*, and the equation is represented as:

$$y = a + b * t \quad [2.7]$$

where

y = the predicted (dependent) variable
t = the predictor time variable
b = the slope of the data line
a = value of y when t is equal to zero.

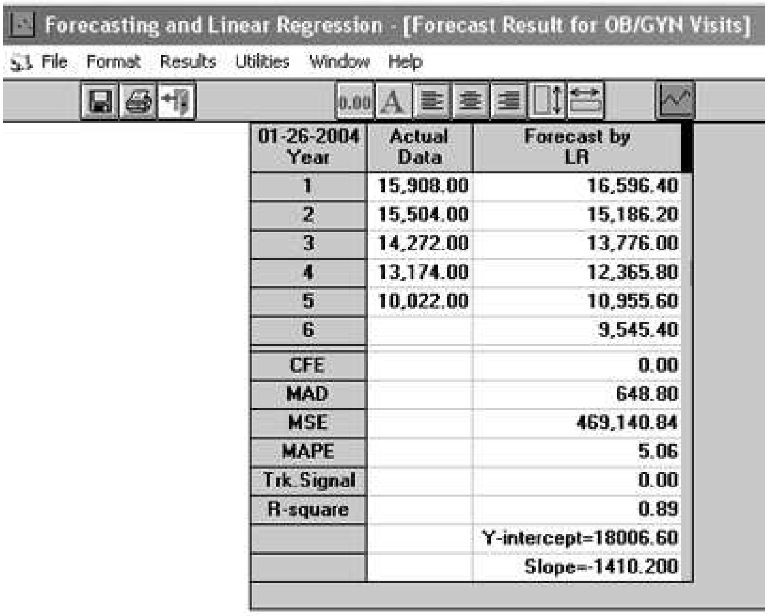
Graphic illustration of a negative trend line (when $b < 0$) is shown in Figure 2.11. If the trend were positive ($b > 0$), it would have looked like that in Figure 2.10.

EXAMPLE 2.8

Referring back to the OB/GYN example, the health care manager can estimate the trend line using regression analysis.

Solution: Figure 2.12 shows the visit data and the regression analysis conducted through WinQSB. The health care manager can observe that the strong R^2, coefficient of determination, value coupled with significant F statistics ($p < 0.015$) provides good predictor confidence for this model. The slope, y-intercept (a) is at 18,006.6, and the slope of line is declining at a yearly rate of 1,410.2 visits (negative value). With this model the health care manager predicts that visits will be at 9,545 in the next period, which is closer to reality than are the results from the other methods predicted so far. ■

FIGURE 2.12. WINQSB LINEAR TREND SOLUTION TO THE OB/GYN EXAMPLE.



01-26-2004 Year	Actual Data	Forecast by LR
1	15,908.00	16,596.40
2	15,504.00	15,186.20
3	14,272.00	13,776.00
4	13,174.00	12,365.80
5	10,022.00	10,955.60
6		9,545.40
CFE		0.00
MAD		648.80
MSE		469,140.84
MAPE		5.06
Trk.Signal		0.00
R-square		0.89
		Y-intercept=18006.60
		Slope=-1410.200

Source: Screen shots reprinted by permission from Microsoft Corporation and Yih-Long Chang (author of WinQSB).

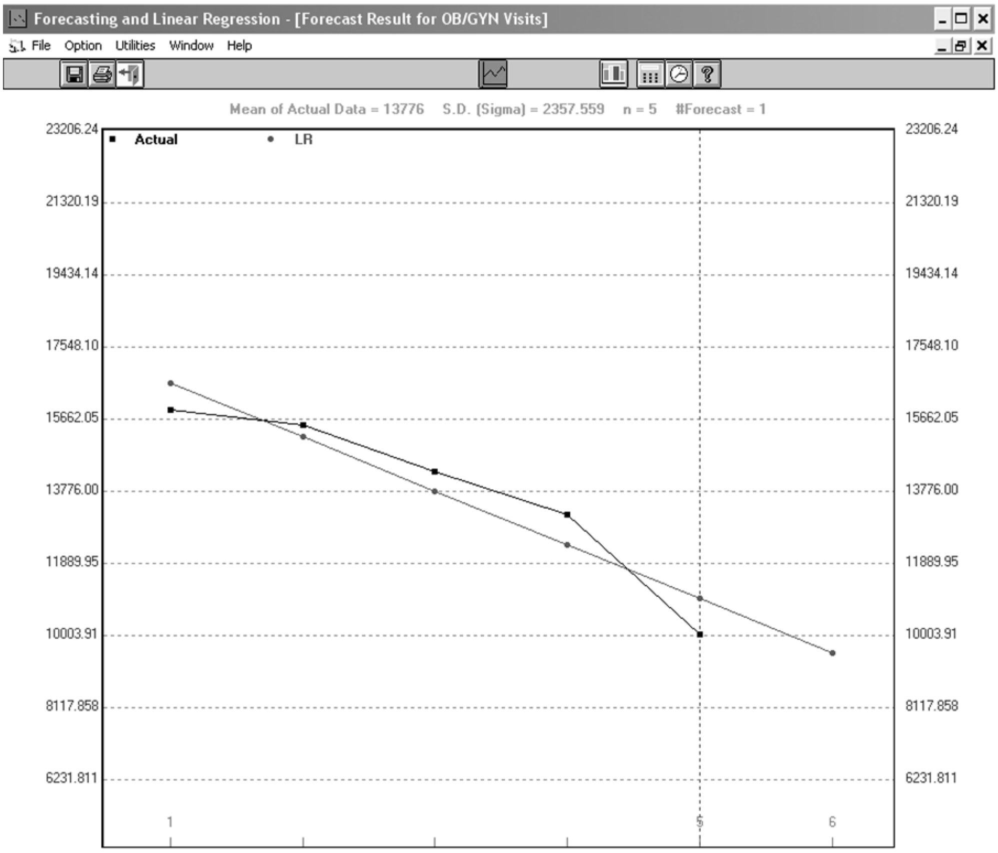
Graphical illustration of the results is shown in Figure 2.13, where both actual and predicted values can be observed.

Trend-Adjusted Exponential Smoothing. A variation of simple exponential smoothing can be used when a time series exhibits a trend. This method is called trend-adjusted exponential smoothing, to differentiate it from simple exponential smoothing. If a data set exhibits a trend, simple smoothing forecasts will reflect it accurately. For example, if the data are increasing, each forecast will be too low. Decreasing data will result in trends that are too high. If the health care manager detects a trend in the data after plotting it on a graph, trend-adjusted smoothing would be preferable to simple smoothing.

A single exponential smoothing with trend (SEST) forecast has two components: smoothed forecast (SF) and trend (T). Thus, the formula for SEST for the next period, $t + 1$, can be written as:

$$\text{SEST}_t = \text{SF}_{t-1} + T_{t-1} \qquad [2.8]$$

FIGURE 2.13. WINQSB LINEAR TREND GRAPHIC SOLUTION TO THE OB/GYN EXAMPLE.



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where

$$SF_{t-1} = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \quad [2.9]$$

previous period's forecast + smoothed error, and

$$T_t = T_{t-1} + \beta(F_t - F_{t-1} - T_{t-1}) \quad [2.10]$$

previous period's trend + smoothed error on trend.

In order to use this set of formulas, the health care manager must decide on the values of smoothing constants of α, β—each would take values between 0 and 1—with the initial forecast and obtain an estimate of trend. The values of smoothing constants can be determined with experimentation. However, a health care manager who experiences relatively stable visits (demand) would want to lessen random and short-term effects using a smaller α; but if visits (demands) are rapidly changing, then larger α values would be more appropriate to capture and follow those changes. Using small versus larger β values to incorporate the effect of a trend follows the same logic. In the absence of a known trend, the health care manager can compute this from available historical data. The SEST model is illustrated in Example 2.9.

EXAMPLE 2.9

Historical data on receipts for a physician office for health insurance billings of the previous 15 months are as follows:

T	Receipts
1	13,125
2	13,029
3	14,925
4	10,735
5	11,066
6	11,915
7	15,135
8	13,484
9	14,253
10	11,883
11	12,077
12	12,857
13	12,162
14	11,600
15	11,480

Using smoothing constant values for $\alpha = .4$ and $\beta = .3$, construct an appropriate SEST model to predict billings for period 16.

Solution: We will use the first half of the data to develop the model ($t = 1$ through 7), and the second half ($t = 8$ through 14) to test the model. Then we will attempt to predict next period ($t = 16$). Two of the unknowns in the model are the trend estimate and the starting forecast. The trend estimate (T_0) can be calculated by averaging the difference between periods $t = 1$ through 7, using $T_0 = (A_n - A_1)/(n - 1)$—or for our example, $T_0 = \frac{13{,}125 - 15{,}135}{7 - 1} = \frac{-2{,}010}{6} = -335$ (*a downward trend*).

The starting forecast (SF_0) for the model test period is the naive forecast using the seventh period plus the trend estimate (T_0). Hence the eighth period can be written as:

$$F_8 = SF_0 + T_0, \quad \text{or}$$

$$F_8 = 15{,}135 - 335.5 = 14{,}800.$$

Calculation of SF_8 and T_8 using smoothing constant values for $\alpha = .4$ and $\beta = .3$, the ensuing forecast values for model testing during periods of 8 through 15 using formulas: [2.8], [2.9], and [2.10]; and the final forecast for period 16 are shown below.

			$SF_t = F_t + \alpha(A_t - F_t)$	$T_t = T_{t-1} + \beta(F_t - F_{t-1} - T_{t-1})$
t	A_t	F_t	$\alpha = 0.4$	$\beta = 0.3$
8	13,484	14,800.00	14,273.60	−335.00
9	14,253	13,938.60	14,064.36	−492.92
10	11,883	13,571.44	12,896.06	−455.19
11	12,077	12,440.87	12,295.32	−657.80
12	12,857	11,637.52	12,125.31	−701.47
13	12,162	11,423.84	11,719.10	−555.13
14	11,600	11,163.97	11,338.38	−466.55
15	11,480	10,871.83	11,115.10	−414.23
16		10,700.87		

The WinQSB graphic solution for forecasting physician office receipts with SEST is shown in Figure 2.14.

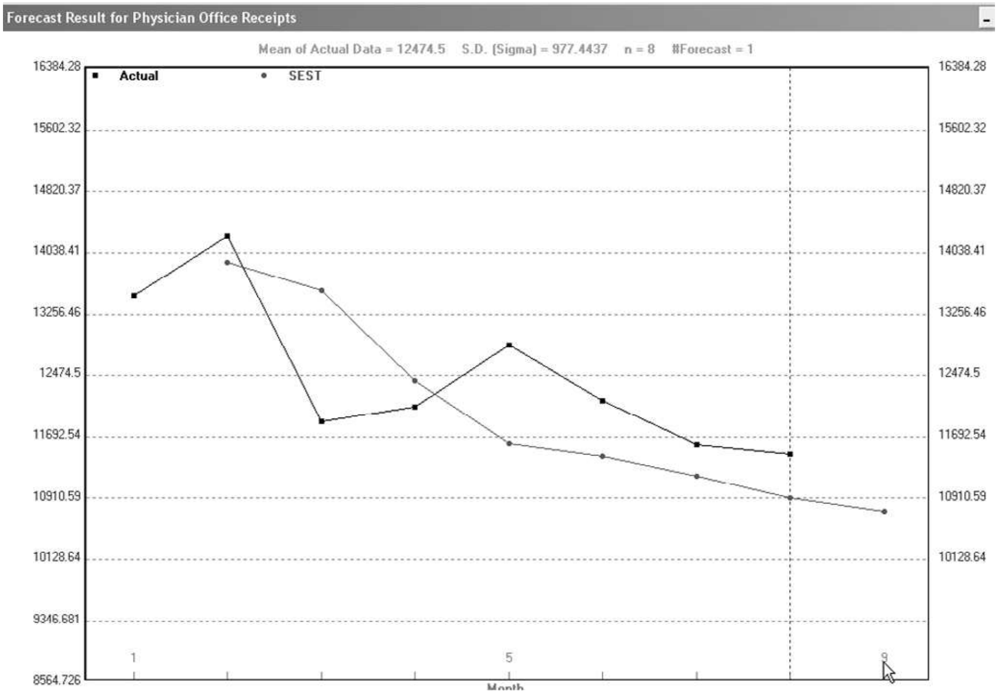
Techniques for Seasonality

Knowledge of seasonal variations is an important factor in demand planning and scheduling. Seasonality is also useful in planning capacity for systems that must be designed to handle peak loads. **Seasonal variations** in a data set consistently repeat upward or downward movements of the data values that can be traced to recurrent events. The term can also mean daily, weekly, monthly, or other regularly recurring patterns in data. Seasonality in a data set is expressed in terms of the amount that actual values deviate from the average value of a series. Seasonality is expressed in two models: additive and multiplicative. In the **additive** model, seasonality is expressed as a quantity (example: 5 units), which is added or subtracted from the series average in order to incorporate seasonality. In the **multiplicative** model, seasonality is expressed as a percentage of the average amount (example: 1.15), which is then multiplied by the value of a series to incorporate seasonality. The multiplicative model is used much more often than the additive model.

The seasonal percentages in the multiplicative model are referred to as seasonal indexes. Suppose that the seasonal index for the number of heart bypass surgeries at a hospital in October is 1.12. This indicates that bypass surgeries for that month are 12 percent above the monthly average. A seasonal index of .88 indicates that surgeries in a given month are at 88 percent of the monthly average.

If time series data contain trend and seasonality, the health care manager can remove (decompose) the seasonality by using seasonal indices to discern a clearer

FIGURE 2.14. FORECAST OF PHYSICIAN OFFICE RECEIPTS WITH SEST.



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picture of the trend. Removing seasonality in the multiplicative model is done by dividing each data point by its seasonal index (relative). Calculation of a seasonal index depends upon the period being considered which identifies the index (such as: quarterly indices, monthly indices, or daily indices). In each case, the health care manager must collect enough seasonal data to calculate averages for the season, and then divide that by the overall average to find the seasonal index or relative. In Example 2.10, the indices for various seasonal values are illustrated.

EXAMPLE 2.10

To prepare plans and budgets, "HEAL-ME" Hospital management wants to forecast the inpatient demand for the coming year. But, they would like to know what kind of seasonal variations are exhibited in the data shown in Table 2.1, which depict the average daily patient count for the past 28 months (from July, Year 1 to October, Year 3).

TABLE 2.1. HEAL-ME HOSPITAL AVERAGE DAILY PATIENT DAYS.

MONTHS	Saturday	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Average per Day
1 JULY	493	478	500	506	520	534	531	507
2 AUGUST	489	471	507	542	542	542	533	521
3 SEPTEMBER	499	480	499	526	536	550	540	519
4 OCTOBER	502	480	501	533	547	550	544	520
5 NOVEMBER	478	468	496	530	535	530	510	508
6 DECEMBER	503	484	499	523	533	537	539	516
7 JANUARY	532	530	535	550	558	567	559	547
8 FEBRUARY	514	491	514	537	541	552	551	529
9 MARCH	483	461	484	507	525	528	517	500
10 APRIL	500	475	493	524	537	540	540	515
11 MAY	483	459	470	508	519	525	514	499
12 JUNE	491	479	499	526	529	535	528	510
13 JULY	487	470	504	533	541	528	519	513
14 AUGUST	502	476	503	534	540	545	545	522
15 SEPTEMBER	540	509	527	545	566	573	572	545
16 OCTOBER	537	516	546	573	587	587	581	563
17 NOVEMBER	508	503	532	557	555	546	542	534
18 DECEMBER	509	480	505	517	523	535	536	514
19 JANUARY	528	517	538	565	558	568	564	550
20 FEBRUARY	541	516	539	558	575	575	577	554
21 MARCH	537	522	549	572	576	584	576	558
22 APRIL	530	510	529	550	564	572	562	546
23 MAY	512	487	504	531	538	552	550	526
24 JUNE	530	510	532	563	582	584	574	551
25 JULY	503	489	516	559	564	558	531	534
26 AUGUST	514	496	528	560	567	562	549	538
27 SEPTEMBER	532	512	514	548	563	564	557	541
28 OCTOBER	516	490	514	556	574	575	553	541
Grand Means	510	491	514	541	550	553	546	529

TABLE 2.2. QUARTERLY INDICES FOR HEAL-ME HOSPITAL.

	Year				
Quarter	1	2	3	Quarterly Average	Quarterly Index
1		525	554	540	1.020
2		519	541	530	1.001
3	516	527	538	527	0.996
4	515	537		526	0.994
Overall Average				529	

Solution:

Quarterly Indices Technique. The data in Table 2.1 can be reorganized in quarters by combining averages for the values January–March (Q1), April–June (Q2) July–September (Q3), and October–December (Q4), as shown in Table 2.2. As can be observed, two values of Q1, Q2, and Q4 are averaged over Years 2 and 3; Q3 had three values in its average. Then quarterly averages are divided by the overall average (530), yielding the quarterly index. Here, the index values do not differ much from each other, so for these data seasonal adjustment on a quarterly basis is not justified. ■

Monthly Indices Technique. In the absence of quarterly variation, a health care manager may want to investigate monthly variation in the historical data. The data are organized in similar manner in Table 2.3, where index values exhibit

TABLE 2.3. MONTHLY INDICES FOR HEAL-ME HOSPITAL.

	Year				
Month	1	2	3	Monthly Average	Monthly Index
JANUARY		547	550	549	1.036
FEBRUARY		529	554	542	1.023
MARCH		500	558	529	0.999
APRIL		515	546	531	1.002
MAY		499	526	513	0.968
JUNE		510	551	531	1.002
JULY	507	513	534	518	0.979
AUGUST	521	522	538	527	0.996
SEPTEMBER	519	545	541	535	1.011
OCTOBER	520	563	541	541	1.023
NOVEMBER	508	534		521	0.984
DECEMBER	516	514		515	0.973
Overall Average				529	

TABLE 2.4. DAILY INDICES FOR HEAL-ME HOSPITAL.

Days	Daily Average	Daily Index
Monday	514	0.972
Tuesday	541	1.023
Wednesday	550	1.040
Thursday	553	1.045
Friday	546	1.032
Saturday	510	0.964
Sunday	491	0.928
Overall Average	529	1.000

more variation than the quarterly indices showed in Table 2.2. The health care manager now can divide each of the monthly values by monthly indices to discern the trend in the data. For example, the seasonal (monthly) effect removed from July year 1 data by dividing the historical value for that period (507) by the monthly index of July (0.979), yields a non-seasonal July demand for year 1 of 518 ($507 \div 0.979 = 518$). The remaining periods can be similarly calculated and then the appropriate forecasting technique (such as trend analysis) can be employed to predict the trend more accurately.

Daily Indices Technique. Daily variation in hospitalization, especially in an emergency department, is a very common occurrence in the health care industry. Daily indices for HEAL-ME Hospital are calculated similarly, this time by dividing only daily averages into the overall average, as shown in Table 2.4. As can be observed, there is even greater variation within the week (for instance, Sundays versus Thursdays) in this particular example. ■

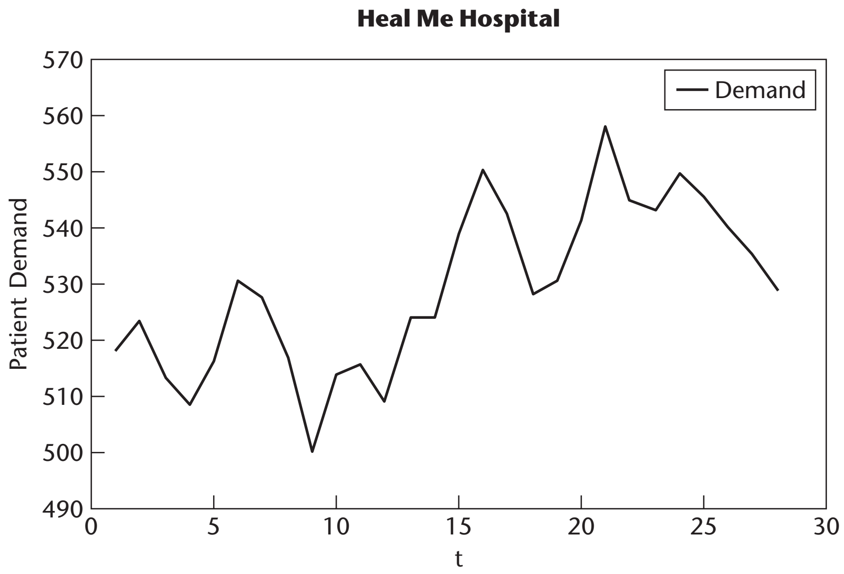
Employing Seasonal Indices in Forecasts

Earlier, in the discussion of the monthly indices technique (Example 2.10), it was noted that indices may be used to remove or decompose the seasonal variations in order to discern trends and other effects in the data. If a trend is detected, the health care manager can use historical data with the seasonal effect removed in the forecasting model. That will improve its forecasting accuracy. (The next section discusses the problem of accuracy.) In Example 2.10, after the seasonal effect is removed, the twenty-eight-month data have an upward linear trend, as seen in Figure 2.15.

A forecast for this data based on linear regression yields the following trend equation:

$$\text{Demand } (Y_t) = 511.06 + 1.259t.$$

FIGURE 2.15. SEASONALITY-REMOVED TREND DATA FOR HEAL-ME HOSPITAL PATIENT DEMAND.



Hence, the forecast of demand for the next 3 months would be:

$$Y_{29} = 511.06 + 1.259\,(29) = 547.6$$
$$Y_{30} = 511.06 + 1.259\,(30) = 548.8$$
$$Y_{31} = 511.06 + 1.259\,(31) = 550.1.$$

Having forecast the next three months, the health care manager needs to incorporate seasonality back into those forecasts. The periods $t = 29$, 30, and 31 represent the months of November, December and January, respectively, with corresponding monthly indices 0.984, 0.973, and 1.036. Monthly adjustments to those forecasts are calculated:

$$\text{Monthly Adjusted Forecast } (t)\text{: Forecast} * \text{Monthly Index} \qquad [2.11]$$

for the HEAL-ME hospital example:

Period 29 (November): 547.6 (0.984) = 538.8

Period 30 (December): 548.9 (0.973) = 534.1

Period 31 (January): 550.1 (1.036) = 569.9.

The next step in adjustment of the forecasted demand would be for daily fluctuations. As was shown in Table 2.4, HEAL-ME Hospital experiences daily

TABLE 2.5. MONTHLY AND DAILY ADJUSTED FORECASTS FOR HEAL-ME HOSPITAL.

Week Days	Daily Index	November	December	January
Monday	0.972	523.7	519.1	553.9
Tuesday	1.023	551.2	546.3	583.0
Wednesday	1.040	560.4	555.4	592.7
Thursday	1.045	563.1	558.0	595.5
Friday	1.032	556.1	551.1	588.1
Saturday	0.964	519.4	514.8	549.4
Sunday	0.928	500.0	495.6	528.9

variation in demand. Thus, the monthly index adjusted forecasts should be further adjusted for daily variations.

$$\text{Daily Adjusted Forecast} = \text{Monthly Adjusted Forecast } (t) * \text{Daily Index} \qquad [2.12]$$

For example, for November (period 29), the adjusted forecasts for Monday and Tuesday are:

$$\text{Monday, November: } 538.8 * (0.972) = 523.7$$

$$\text{Tuesday, November: } 538.8 * (1.023) = 551.2.$$

The remaining periods and days for the complete adjusted forecasts are shown in Table 2.5.

Depending upon the forecasting horizon, a health care manager can develop a printed calendar of forecasts for care units and disseminate it so that division managers can adjust their resources according to the forecasted daily patient demand.

Accuracy of Forecasts

The complex nature of most real-world variables makes it nearly impossible to regularly forecast the future values of those variables correctly. Errors may be caused by an inadequate forecasting model, or the technique may be used improperly. Errors also result from irregular variations beyond the manager's control, such as severe weather, shortages or breakdowns, catastrophes, and so on. Random variations in the data, too, may create forecasting errors. **Forecast error** equals the actual value minus the forecast value:

$$\text{Error} = \text{Actual} - \text{Forecast} \qquad [2.13]$$

Forecast values that are too low result in a positive error value; forecast values that are too high result in negative error values. For example, if the actual demand for a week is 200 patients and the forecast demand was 220 patients, the forecast was too high; the error was 200 − 220 = −20. The issue of forecast errors influences two important decisions: making a choice among the forecasting alternatives, and evaluating the success or failure of a technique in use.

Two aspects of forecast accuracy have the potential to influence a choice among forecasting models. One aspect is the historical error performance of a forecast model, and the other is the ability of a forecast model to respond to changes. Two commonly used measures of historical errors are the **mean absolute deviation (MAD)** and the **mean absolute percent error (MAPE)**. MAD is the average absolute error, and MAPE is the absolute error as a percentage of actual value. The formulas used to compute MAD and MAPE are:

$$\text{MAD} = \frac{\sum|\text{Actual} - \text{Forecast}|}{n} \qquad [2.14]$$

$$\text{MAPE} = \frac{\sum|\text{Actual} - \text{Forecast}|}{\sum \text{Actual}}. \qquad [2.15]$$

MAD places equal weight on all errors; thus the lower the value of MAD relative to the magnitude of the data, the more accurate the forecast. On the other hand, MAPE measures the absolute error as a percentage of actual value, rather than per period. That avoids the problem of interpreting the measure of accuracy relative to the magnitudes of the actual and the forecast values. Using the previous Example 2.4 from SES with $\alpha = 0.3$, we observe the necessary error calculations in Table 2.6. Here sums are calculated over only four periods ($t = 2$ through 5) where both actual and forecast have values.

TABLE 2.6. ERROR CALCULATIONS.

	Smoothing Constant $\alpha = 0.3$		Error	Absolute Error
Period t	**Actual**	**Forecast**	**(Actual − Forecast)**	**|Actual − Forecast|**
1	15,908	—		
2	15,504	15,908	−404.0	404.0
3	14,272	15,786.8	−1,514.8	1,515.0
4	13,174	15,332.4	−2,158.4	2,158.0
5	10,022	14,684.9	−4,662.9	4,662.9
6		13,286		
Sum Σ	**52,972**			**8,740.1**

Using the data from Table 2.6,

$$MAD = 8740.1 \div 4 = 2185.03 \quad \text{and}$$
$$MAPE = 8740.1 \div 52972 = 0.165 \quad \text{or} \quad 16.5 \text{ percent.}$$

A health care manager can use these measures to choose among forecasting alternatives for a given set of data by selecting the one that yields the lowest MAD or MAPE. Another decision health care managers have to make, however, is whether a forecast's responsiveness to change is more important than error performance. In such a situation, the selection of a forecasting method would assess the cost of not responding quickly to a change versus the cost of responding to changes that are not really there (but simply random variations).

To illustrate the influence of MAD and MAPE on the selection of a forecasting method appropriate for a given situation, the WinQSB evaluation of Example 2.9 (a physician office's health insurance receipts) is shown in Figure 2.16,

FIGURE 2.16. ALTERNATIVE FORECASTING METHODS AND ACCURACY, MEASURED BY MAD & MAPE.

Forecast Result for Physician Office Receipts

01-26-2004 Month	Actual Data	Forecast by 3-MA	Forecast by 5-MA	Forecast by 4-WMA	Forecast by SES	Forecast by SES	Forecast by SEST	Forecast by LR
1	13125.0000							13231.6300
2	13029.0000				13125.0000	13125.0000	13125.0000	13148.3100
3	14925.0000				13096.2000	13077.0000	13081.8000	13064.9900
4	10735.0000	13693.0000			13644.8400	14001.0000	13896.8400	12981.6700
5	11066.0000	12896.3300		12689.8000	12771.8900	12368.0000	12736.0900	12898.3500
6	11915.0000	12242.0000	12576.0000	11934.8000	12260.1200	11717.0000	11772.3500	12815.0400
7	15135.0000	11238.6700	12334.0000	11725.3000	12156.5900	11816.0000	11373.8400	12731.7200
8	13484.0000	12705.3300	12755.2000	12915.2000	13050.1100	13475.5000	12625.0500	12648.4000
9	14253.0000	13511.3300	12467.0000	13423.7000	13180.2800	13479.7500	13134.4400	12565.0800
10	11883.0000	14290.6700	13170.6000	13964.9000	13502.0900	13866.3800	13889.5000	12481.7600
11	12077.0000	13206.6700	13334.0000	13239.4000	13016.3700	12874.6900	13406.0600	12398.4500
12	12857.0000	12737.6700	13366.4000	12594.7000	12734.5600	12475.8400	12926.5000	12315.1300
13	12162.0000	12272.3300	12910.8000	12567.8000	12771.2900	12666.4200	12814.3800	12231.8100
14	11600.0000	12365.3300	12646.4000	12325.6000	12588.5000	12414.2100	12429.5400	12148.4900
15	11480.0000	12206.3300	12115.8000	12067.7000	12291.9500	12007.1100	11867.1200	12065.1700
16		11747.3300	12035.2000	11790.1000	12048.3700	11743.5500	11379.3600	11981.8600
CFE		-4718.6660	-830.2002	-1536.9030	-3588.7760	-2762.8950	-2477.5030	-0.0010
MAD		1315.8890	1146.1800	1061.5550	1175.8090	1129.9080	1280.4680	977.1576
MSE		3063111.0000	1756081.0000	2005935.0000	2184751.0000	2382130.0000	2814970.0000	1561803.0000
MAPE		10.6614	8.7912	8.3001	9.4137	9.0290	10.1583	7.6976
Trk.Signal		-3.5859	-0.7243	-1.4478	-3.0522	-2.4452	-1.9348	0.0000
R-square		0.4807	0.1236	0.2980	0.1400	0.2968	0.3041	0.0766
		m=3	m=5	m=4	Alpha=0.3	Alpha=0.5	Alpha=0.3	Y-intercept=13314.94
				W(1)=0.1000	F(0)=13125	F(0)=13125	Beta=0.5	Slope=-83.3180
				W(2)=0.2000			F(0)=13125	
				W(3)=0.3000			T(0)=0	
				W(4)=0.4000				

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which includes MA_3, MA_5, WMA_4, SES (with $\alpha = .3$, $\alpha = .5$), SEST, and Linear Regression.

Examination of the MAD and MAPE errors across the forecasting techniques in Figure 2.16 reveals that the lowest errors are provided by linear regression (MAD = 977, MAPE = 7.7 percent), followed by four-period moving averages [(WMA_4 with weights .1, .2, .3, and .4) MAD = 1061, MAPE = 8.3 percent].

Forecast Control

Whatever the forecasting method used, the health care manager must ensure that it provides consistent results or continues to perform correctly. Forecasts can go out of control for a variety of reasons: changes in trend behavior, cycles, new

FIGURE 2.17. TRACKING SIGNAL FOR PATIENT VISIT FORECAST, HEAL-ME HOSPITAL.

HEALME2

01-26-2004 Month	Actual Data	Forecast by LR	Forecast Error	CFE	MAD	MAPE (%)	Tracking Signal
1	518.0000	512.0961	5.9039	5.9039	5.9039	1.1398	1.0000
2	523.0000	513.3668	9.6332	15.5372	7.7686	1.4908	2.0000
3	513.0000	514.6374	-1.6374	13.8998	5.7249	1.1003	2.4280
4	508.0000	515.9081	-7.9081	5.9917	6.2707	1.2144	0.9555
5	516.0000	517.1787	-1.1787	4.8130	5.2523	1.0172	0.9164
6	530.0000	518.4494	11.5506	16.3636	6.3020	1.2109	2.5966
7	528.0000	519.7200	8.2800	24.6436	6.5846	1.2619	3.7426
8	517.0000	520.9907	-3.9907	20.6528	6.2603	1.2007	3.2990
9	500.0000	522.2614	-22.2614	-1.6085	8.0382	1.5620	-0.2001
10	514.0000	523.5320	-9.5320	-11.1406	8.1876	1.5912	-1.3607
11	515.0000	524.8027	-9.8027	-20.9432	8.3344	1.6196	-2.5129
12	509.0000	526.0734	-17.0734	-38.0166	9.0627	1.7642	-4.1949
13	524.0000	527.3440	-3.3440	-41.3606	8.6228	1.6775	-4.7967
14	524.0000	528.6147	-4.6147	-45.9753	8.3365	1.6206	-5.5149
15	539.0000	529.8853	9.1147	-36.8606	8.3884	1.6253	-4.3943
16	551.0000	531.1560	19.8440	-17.0166	9.1043	1.7488	-1.8691
17	543.0000	532.4267	10.5733	-6.4433	9.1907	1.7605	-0.7011
18	528.0000	533.6973	-5.6973	-12.1406	8.9967	1.7226	-1.3495
19	531.0000	534.9680	-3.9680	-16.1086	8.7320	1.6713	-1.8448
20	542.0000	536.2386	5.7614	-10.3473	8.5835	1.6409	-1.2055
21	558.0000	537.5093	20.4907	10.1434	9.1505	1.7376	1.1085
22	545.0000	538.7800	6.2200	16.3634	9.0173	1.7105	1.8147
23	543.0000	540.0507	2.9493	19.3127	8.7535	1.6598	2.2063
24	550.0000	541.3213	8.6787	27.9915	8.7503	1.6563	3.1989
25	546.0000	542.5920	3.4080	31.3995	8.5366	1.6151	3.6782
26	540.0000	543.8626	-3.8626	27.5369	8.3569	1.5805	3.2951
27	535.0000	545.1333	-10.1333	17.4036	8.4227	1.5921	2.0663
28	529.0000	546.4039	-17.4039	-0.0004	8.7434	1.6527	0.0000
29		547.6746					
30		548.9453					
31		550.2159					

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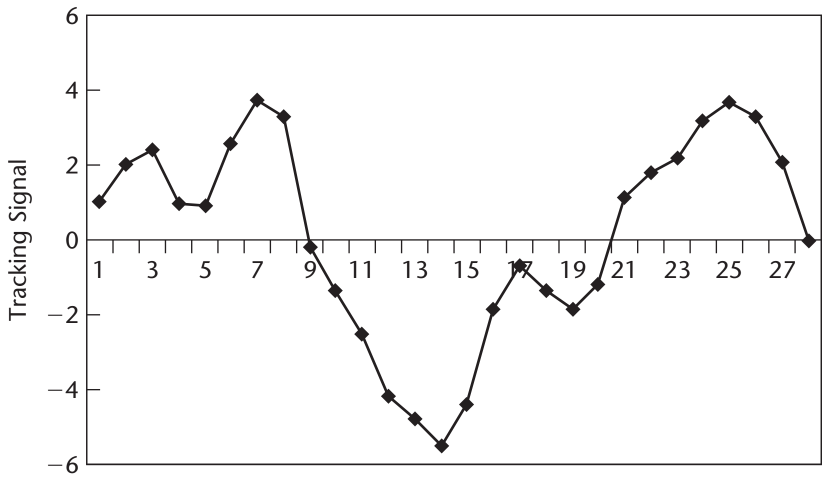
regulations that affect demand, and so on. Thus, a statistical control methodology should monitor the results of the forecast as more periods are added to the data. A method of constructing such statistical control on forecasts is the tracking signal. A tracking signal measures whether forecasts keep pace with up-and-down changes in actual values. A tracking signal is computed for each period, with updated cumulative forecast errors divided by MAD.

$$\text{Tracking signal} = \frac{\sum(\text{Actual} - \text{Forecast})}{\text{MAD}} \quad [2.16]$$

Although it can range from ±3 to ±8, the acceptable limits for tracking signal are in general within ±4, which corresponds roughly to three standard deviations. A statistical control chart can be built to monitor the performance of forecasts. If the tracking signal is positive, it indicates that the actual value is greater than the forecast; if negative, that the actual is less than the forecast. As the gap between actual and forecast gets larger, the tracking signal increases (gets closer to or beyond the control limits). When the tracking signal goes beyond acceptable limits, the health care manager should re-evaluate the forecasting methodology and investigate why it is not performing well, and perhaps try other forecasting methods. Figure 2.17 shows the WinQSB solution to HEAL-ME Hospital patient demand with cumulative errors (CFE), MAD, MAPE and the tracking signal updated for each month.

Figure 2.18 uses the tracking signals reported in Figure 2.17 in a control chart. As can be observed, during periods 12 through 15 the tracking signal went

FIGURE 2.18. TRACKING SIGNAL FOR PATIENT VISIT FORECASTS.



beyond the acceptable control limits (down to −5.51), but recovered at period 16 and stayed within acceptable limits after that. Another observation can be made from Figure 2.18, whether the forecast values are consistently higher or lower than the actual ones. Until period 8 the predicted values were below the actual. That changed from period 9 to period 20, when forecasts were higher than actual data. At the period 21 a return to under-forecast occurred.

Summary

Forecasting is a basic tool for planning in health care organizations. For example, in hospitals, forecasting is applied to number of patient hospitalizations by department or nursing care units, number of outpatient visits, or visits to therapy units. In physician offices, similarly, visits and collections from insurers are examples of forecasting applications. These forecasts can be from short-horizon, a few months ahead, to medium-horizon, for one or two years. The health care manager should keep in mind that the longer the horizon of the forecast, the more prediction errors are likely.

EXERCISES

Exercise 2.1

The monthly ambulatory visits shown in Table EX 2.1 occurred in an outpatient clinic.

TABLE EX 2.1

Months	Visits
July	2,160
August	2,186
September	2,246
October	2,251
November	2,243
December	2,162

a. Predict visits for January, using the naive forecast method.
b. Predict visits for January, using a three-period moving average.
c. Predict visits for January, using a four-period moving average.

Exercise 2.2

Patient days in a hospital were recorded as shown in Table EX 2.2.

TABLE EX 2.2

Month	Patient Days
January	543
February	528
March	531
April	542
May	558
June	545
July	543
August	550
September	546
October	540
November	535
December	529

a. Predict naive forecasts of patient days for February and June.
b. Predict the patient days for January, using a four-period moving average.
c. Predict the patient days for January, using the six-period moving average.
d. Plot the actual data and the results of the four-period and the six-period moving averages. Which method is a better predictor?

Exercise 2.3

Using patient days data from Exercise 2.2:

a. Predict the patient days for January, using a four-period moving average with weights 0.1, 0.2, 0.3, and 0.4.
b. Predict the patient days for January, using a five-period moving average with weights 0.1, 0.1, 0.2, 0.2, and 0.4.

Exercise 2.4

Using the visit data from Exercise 2.1:

a. Prepare a forecast for January visits, using the simple exponential smoothing method with $\alpha = 0.3$.
b. If $\alpha = .5$, what is the predicted value for January visits?
c. If $\alpha = 0.0$, what is the predicted value for January visits?
d. If $\alpha = 1.0$, what is the predicted value for January visits?
e. What other forecasting methods yield results similar to the exponential smoothing forecasts with $\alpha = 1.0$ and $\alpha = 0.0$?

Exercise 2.5

An urgent care center experienced the average patient admissions shown in Table EX 2.5 during the weeks from the first week of December through the second week of April.

TABLE EX 2.5

Week	Average Daily Admissions
1-Dec	11
2-Dec	14
3-Dec	17
4-Dec	15
1-Jan	12
2-Jan	11
3-Jan	9
4-Jan	9
1-Feb	12
2-Feb	8
3-Feb	13
4-Feb	11
1-Mar	15
2-Mar	17
3-Mar	14
4-Mar	19
5-Mar	13
1-Apr	17
2-Apr	13

a. Predict forecasts for the admissions from the third week of April through the fourth week of May, using linear regression.
b. Forecast admissions for the periods from the first week of December through the second week of April. Compare the forecasted admissions to the actual admissions; what do you conclude?

Exercise 2.6

A hospital pharmacy would like to develop a budget for allergy medications that is based on patient days. Cost and patient days data were collected over a 17-month period as shown in Table EX 2.6.

TABLE EX 2.6

Period	Cost	Patient Days
October: Year-1	32,996	516
November: Year-1	34,242	530
December: Year-1	27,825	528
January: Year-2	29,807	517
February: Year-2	28,692	500
March: Year-2	34,449	514
April: Year-2	33,335	515

TABLE EX 2.6 (Continued)

Period	Cost	Patient Days
May: Year-2	38,217	509
June: Year-2	36,690	524
July: Year-2	35,303	524
August: Year-2	33,780	539
September: Year-2	32,843	551
October: Year-2	37,781	543
November: Year-2	27,716	528
December: Year-2	31,876	531
January: Year-3	31,463	542
February: Year-3	29,829	558

a. Develop a linear-regression-based forecasting model to predict costs for future periods.
b. Predict costs for the remainder of Year 3.

Exercise 2.7

Using hospital pharmacy data from Exercise 2.6, develop a trend-adjusted exponential smoothing forecast with $\alpha = .3$ and $\beta = .4$ to predict costs for the March, Year-3 period (eighteenth month). Use the first nine periods to develop the model, and use the last eight periods to test the model.

Exercise 2.8

In an ambulatory care center the average visits per each weekday for each month are shown in Table EX 2.8:

TABLE EX 2.8

	Day				
Month	Monday	Tuesday	Wednesday	Thursday	Friday
April	2,356	2,245	2,213	2,215	1,542
May	2,427	2,312	2,279	2,281	1,588
June	2,309	2,200	2,169	2,171	1,511
July	2,299	2,191	2,160	2,162	1,505
August	2,328	2,218	2,186	2,188	1,523
September	2,391	2,279	2,246	2,248	1,565
October	2,396	2,283	2,251	2,253	1,568
November	2,388	2,275	2,243	2,245	1,563
December	2,302	2,193	2,162	2,164	1,507
January	2,402	2,289	2,256	2,258	1,572
February	2,372	2,261	2,228	2,231	1,553
March	2,382	2,270	2,237	2,239	1,559

a. Develop a linear regression trend forecast based on the average visits in each month.
b. Predict the visits for April through June.
c. Develop daily indices for ambulatory care center visits.
d. Assuming 22 working days in a month, adjust predictions for Monday through Friday from April to June, and present them in a table format.

Exercise 2.9

Using the forecasting results from Exercise 2.1, calculate MAD and MAPE for naive, three-period and four-period forecasts. Which forecast appears more accurate?

Exercise 2.10

Using the forecasting results from exercise 2.2, calculate MAD and MAPE for naive, four-period and six-period forecasts. Which forecast appears more accurate?

Exercise 2.11

Using the forecasting results from Exercise 2.1, calculate MAD and MAPE for exponential smoothing forecasts with $\alpha = 0.3$ and with $\alpha = .5$. Does varying the values of α provide a more accurate forecast?

Exercise 2.12

Using the forecasting results from Exercise 2.2, calculate and graph tracking signal for four-period and six-period forecasts.