**Lecture Notes**

**Topic 6: Forecasting Demand**

Overview

In order to predict future events, it is necessary to have historical data and projecting them into the future with some sort of mathematical model. It may be a subjective or intuitive prediction. Or it may involve a combination of these - that is a mathematical model adjusted by a manager’s good judgement.

There are a number of forecasting techniques but what works on one firm may not work in another firm. There are limits as to what can be expected from forecasts. They are seldom perfect and costly and time-consuming to prepare and monitor.

Learning Outcomes

By the end of this topic, you will be able to:

1. explain the importance of forecasting demand for decision making.
2. distinguish the forecasting approaches for quantitative and qualitative purposes.
3. apply the three techniques for forecasting- judgemental, time series and associative models (regression & correlation analysis).

Introduction

6.1 Features common to all forecasts and elements of a good forecast.

6.2 The strategic importance of forecasting and the seven steps in the forecasting system and

 limitations.

6.3 Common approaches in forecasting : jury of executive opinion, Delphi method, sales

 force composite and consumer market survey.

6.4 forecasting techniques are classified into three categories:

1. Judgemental forecasts
2. Time-series forecasts
3. Associate models using statistical approaches like regression and correlation analysis.
4. Forecasting in the service sector is more challenging than in the product sector.

**Lecture Notes**

**6. Forecasting Demand**

What is forecasting?

It is the art and science of predicting future events. It may involve historical data and projecting them into the future with some sort of mathematical model. It may be a subjective or intuitive prediction. Or it may involve a combination of these - that is, a mathematical model adjusted by a manager’s good judgement.

There are a number of forecasting techniques but what works in one firm may not work in another firm. There are limits as to what can be expected from forecasts. They are seldom perfect and costly and time-consuming to prepare and monitor.

Features common to all Forecasts (The Limitations)

1. Forecasting techniques generally assume that the same underlying causal system that

 existed in the past will continue to exist in the future.

1. Forecasts are rarely perfect; actual results usually differ from predicted values.
2. Forecasts for groups of items tend to be more accurate than forecasts for individual items because forecasting errors among items in a group usually have a cancelling effect.
3. Forecast accuracy decreases as the time period covered by the forecast – the time horizon- increases. This is because of greater uncertainty with longer-range forecasts than short-range forecasts. (However flexible business organisations require a shorter forecasting horizon and they get better benefits from short-range forecasts.)

Elements of a good forecast

1. The forecast should be timely.
2. The forecast should be reliable in the sense that it works constantly.
3. The forecast should be accurate and the degree of accuracy must be stated.
4. The forecast should be expressed in meaningful units.
5. The forecast should be in writing.
6. The forecast technique should be simple to understand and use.

The Strategic Importance of Forecasting

The forecast is the only estimate of demand until actual demand becomes known. Forecasts of demand therefore drive decisions in many areas such as:

1. human resources - hiring, training and laying off workers all depend on anticipated demands.
2. capacity - if the capacity is inadequate it results in shortages and can lead to the loss of customers and market shares.
3. supply-chain management - the advantages of supply of materials and parts, and of prices depend on actual forecasts and coordination.

Seven Steps in the Forecasting System

1. Determine the purpose/use of the forecast.
2. Select the items to be forecasted.
3. Determine the time horizon of the forecast.
4. Select the forecasting technique/model(s).
5. Gather the data needed to make the forecast.
6. Make the forecast.
7. Validate and implement the results (Monitor the forecast).

These seven steps involve three different aspects: initiating, designing and implementing a forecasting system.

Limitations in forecasting system:

* Forecasts are seldom perfect.
* Most forecasting techniques assume that there is some underlying stability in the system.
* Both product family and aggregated forecasts are more accurate than individual product forecasts.

Forecasting Approaches

1. Jury of executive opinion - a group of high-level experts or managers are pooled to arrive at a group estimate of demand. Statistical models are used.
2. Delphi method - three different types of people (decision makers, staff personnel and respondents) are involved in the decision making process.
* Decision makers (5 to 10 experts) will be making the actual forecast.
* Staff personnel are assisting the decision makers by preparing, distributing, collecting and summarizing a series of questionnaires and survey results.
* The respondents are a group of people, often located in different places, whose judgements are valued. This group provides inputs to the decision makers before the forecast is made.
1. Sales force composite - each salesperson estimates what sales will be in his or her region. These forecasts are then reviewed to ensure they are realistic. Then they are combined at the district and national levels to reach an overall forecast.
2. Consumer market survey - this method solicits input from customers or potential customers regarding future purchasing plans. It can help not only in preparing a forecast but also in improving product design and planning for new products. However this approach can suffer from overly optimistic forecasts that arise from customer input.

**Approaches to Forecasting**

There are two general approaches to forecasting:

1. Qualitative method – involve subjective inputs gathered from participants in a certain

 environment but not from numerical description i.e. from a predetermined theory or

 hypothesis. From the data gathered a theory is then developed.

2. Quantitative method – a theory or hypothesis is first developed and then data are collected

 to support or reject the predetermined theory or hypothesis. Such a method does not

 subject to soft information but on hard data/facts.

In reality, either or both approaches are used to develop a forecast.

**Forecasting techniques can be classified into three aspects:**

1. Judgmental forecasts – where the analysis is based on subjective inputs from various

 sources such as consume surveys – the sales staff, managers and executive and panels of

 experts. It is based on the opinions of these different groups of people.

2. Time-series forecasts – where attempt is made to project past experience into the future.

 Historical data are used to project the future needs (demands).

1. Naive approach
2. Moving averages
3. Exponential smoothing
4. Trend projection

3. Associate models - where equations are used to predict future demands. Here variables

 are used to bring about predictions of demand.

 e.g. Linear regression

**Forecasts based on Time Series**

Analysing time series means breaking down past data into components and then projecting them forward. There are 4 components in a time series.

1. Trend is the upward or downward movement of the data over time.

 Irregular variation

 Trend

1. Seasonality is a data pattern that repeats itself after a period of days, weeks, months or quarters.

 Seasonal variations

 Year 3

 Year 2

 Year 1

1. Cycles are patterns in the data that occur every several years. They are usually tied into the business cycle and are of major importance in short-term business analysis and planning. However predicting business cycles is difficult because they may be affected by political events or by international turmoil.

 Cycles

4. Irregular variations are due to unusual circumstances such as severe weather conditions, strikes, or a major change in a product or service. They do not reflect typical behaviour, and their inclusion in the series can distort the overall picture. Whenever possible, these should be identified and removed from the data.

5. Random variations are “blips” in the data caused by change and unusual situations. They follow no discernible pattern, so they cannot be predicted.

The figure below illustrates a demand over a 4-year period. It shows the average, trend, seasonal components and random variations around the demand curve. The average demand is the sum of the demand for each period divided by the number of data periods.

 Trend

 Component

 Seasonal peaks

 Actual demand line

 Average demand line

 Random variation

a***. Naive Approach***

A forecasting technique which assumes that demand in the next period is equal to demand in the most recent period.

In other words, if the sale of the product says Nokia cell phones were 68 units in January, we can forecast that February’s sale will also be 68 units. This naïve approach seems to be good for some product lines. This then make this naïve approach to be the most cost-effective and efficient objective forecasting model. At least it provides a starting point against which more sophisticated models that follow can be compared.

b***. Moving Averages***

This moving average forecast uses a number of actual data values to generate a forecast. Moving averages are useful if the market demands can stay fairly steady over time. A 4-month moving average is found by simply summing the demand during the past 4 months and dividing by 4. With each passing month, the most recent month’s data are added to the sum of the previous 3 months’ data, and the earliest month is dropped. This practice tends to smooth out short-term irregularities in the data series.

Mathematically the simple moving average (which serves as an estimate of the next period’s demand) is expressed as.

 ∑ demand in previous n periods

 Moving average =

 n

where n is the number of periods in the moving average - for example 4, 5 or 6 months, respectively for a 4, 5 or 6-moving average.

How is moving averages calculated?

For example:

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Month Actual Shed Sales 3-month moving average.

January 10

February 12

March 13

April 16 (10 + 12 +13)/3 = 112/3

May 19 (12 + 13 + 16)/3 = 132/3

June 23 (13 + 16 + 19)/3 = 16

July 26 (16 + 19 + 23)/3 = 191/3

August 30 (19 + 23 + 26)/3 = 222/3

September 28 (23 + 26 + 30)/3 = 261/3

October 18 (26 + 30 + 28)/3 = 28

November 16 (30 + 28 + 18)/3 = 251/3

December 14 (28 + 18 + 16)/3 = 202/3

Solution: The forecast for December is 202/3 .

 The forecast for January next year is (18 + 16 + 14)/3 = 16

What happen if the actual sales in December were 18 (rather than 14)?

Then the forecast for January should be (18 + 16 + 18)/3 = 171/3

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The monthly sales and the moving averages can be plotted to attain two curves.

* Weighted Moving Average

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

Furthermore if a detectable trend or pattern can be detected, weights can be used to place more emphasis on recent values.

 ∑(Weight for period n) (Demand in period n)

 Weighted Moving average =

 ∑Weights

Using the above table:

 To show an example of how the weighted moving average is calculated.

 For the first three months:

 The weighted moving average in April = (3 x13) + (2 x 12) + (10)/6 = 121/6

**c) Exponential Smoothing**

It is a weighted-moving average forecasting method in which data points are weighted by an exponential function. It involves very little record keeping of past data. The basic expression of the formula is

 **New forecast = Last period’s forecast + α (Last period’s actual demand - Last period’s forecast)**

where α is a weight, or smoothing constant, chosen by the forecaster, that has a value between 0 and 1.

The equation can be written as follows:

 Ft = Ft-1  + α(At-1 - Ft-1)

Where Ft = new forecast

 Ft -1 = previous period’sforecast

 α = smoothing (or weighting) constant (0 ≤ α ≤ 1)

 At - 1 = previous period’s actual demand

The Smoothing Constant “α”

In business application, “α” can range from .05 to .50. When α reaches 1.0 then Ft = 1.0At-1. All the older values drop out and the forecast becomes identical to the naïve model. That is, the forecast for the next period is the same as this period’s demand.

For example:

The previous forecast was 42 units. The actual demand was 40 units and α = 10.

The new forecast would be computed as follows:

 Ft = 42 + .10(40 - 42) = 42 - o.2 = 41.8

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

Ft = 41.8 + .10(43 - 41.8) = 41.8 + 0.12 = 41.92

Measuring Forecast Error

The forecast error is defined as:

 Forecast error = Actual demand – Forecast value

 = At - Ft

Methods commonly used to calculate the overall forecast error are:

1. Mean absolute deviation (MAD)

2. Mean squared error (MSE)

3. Mean absolute percentage error (MAPE)

d) Trend projection

Techniques for Trend

Analysis of trend involves developing an equation that will suitably describe trend. The trend component may be linear or it may not. Some examples of non-linear trend types:

 Parabolic Parabolic

 trend trend

Exponential Growth

curve curve

 Time Time

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

Trend Equation

A linear trend equation has the form: Ft  = a + bt (which is used to develop forecasts)

where

 Ft = Forecast for period t

 a = Value of Ft at t= 0

 b = Slope of the line

 t = Specified number of time periods from t = 0

 y

 ∆ y ∆ y

 b =

 ∆t ∆ t

 a

 t

The coefficients of the line, ‘a’ and ‘b’ can be computed from historical data using the following two equations:

 n∑ty - ∑t∑y ∑y - b∑t

 b = a = or y - bt

 n∑t2 - (∑t)2  n

 where

 n = Number of periods

 y = Value of the time series

Note: These two equations are identical to those used for computing a linear regression line, except that ‘t’ replaces ‘x’ in the equation.

(See work out in separate sheets of paper.)

Trend-Adjusted Exponential Smoothing

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

The trend-adjusted forecast (TAF) is composed of two elements:

* a smoothed error and
* a trend factor

 TAFt + 1 = St + Tt

 where

 St = Previous forecast plus smoothed error

 Tt = Current trend estimate

 and

 St = TAFt + α(At - TAFt)

 Tt  = Tt-1  + β(TAFt - TAFt-1 - Tt-1)

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

 (See work out example: Cell Phone in separate sheets of paper)

**Techniques for Seasonality**

Seasonal variations in time-series data are regularly repeating upward or downward movements in series values that can be tied to recurring events. Seasonality may refer to regular annual variations. Familiar examples of seasonality are weather variations (e.g. sales of winter and summer sports equipment) and vacations or holidays (e.g. airline travel, greeting card sales, visitors at tourist and resort centres).

The term seasonal variation is also applied to hourly, daily, weekly, monthly, or other recurring patterns. Fast-food restaurants, experience daily surges at noon and again at 5 p.m. Moves theatres see higher demand on Friday and Saturday evenings.

The understanding of seasonal variations is important for capacity planning in organisations, that handle peak loads. These include electric power companies during extreme cold and warm periods, banks on Friday afternoons, and buses and subways during the morning and evening rush hours.

Time-series forecasts involve reviewing the trend of data over a series of time periods. The presence of seasonality makes adjustments in trend-line forecasts necessary.

Seasonality is expressed in terms of the amount that actual values differ from average values in the time series. Analysing data in monthly or quarterly terms usually makes it easy for statistician to spot seasonal patterns. Seasonal indices can then be developed by several common methods.

There are two different models of seasonality: additive and multiplicative.

Additive model – seasonality is expressed as a quantity (e.g. 20 units) which is added to or subtracted from the series average in order to incorporate seasonality.

 Demand = Trend + Seasonality

In the multiplicative model – seasonality is expressed as a percentage of the average (or trend) amount (e.g. 1,10), which is then used to multiply the value of a series to incorporate seasonality.

 Demand = Trend x Seasonality

E.g. The quantity of toys sold in May at a store is 1.20. This indicates that toy sales for that month are 20% above the monthly average. A seasonal relative of .90 for July indicates that July sales are 90% of the monthly average.

Note: knowledge of seasonal variations is an important factor in retailing planning and scheduling, as well as for capacity planning for systems that must be designed to handle peak loads (e.g. public transportation, electric power plants, highways and bridges).

Knowledge of the extent of seasonality in a time series can enable one to remove seasonality from the data i.e. to seasonally adjust data) in order to discern other patterns or the lack of patterns in the series. Thus, one frequently reads or hears about “seasonally adjusted unemployment” and “seasonally adjusted personal income.”

Using Seasonal Relatives

Seasonal relatives are used in two different ways in forecasting:

1. Deseasonalize data- to remove the seasonal component from the data in order to get a

 clearer picture of the nonseasonal (e.g. the trend) component. Deseasonalizing data is

 accomplished by dividing each data point by its corresponding seasonal relative (e.g.

 divide November demand by the November relative, divide December demand by the

 December relative, and so on).

2. Incorporating seasonality in a forecast - when demand has both trend (or average) and

 seasonal components Incorporating seasonality can be accomplished:

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

For example:

A furniture manufacturer wants to predict quarterly demand for a certain loveseat for periods 15 and 16, which happens to be the second and third quarters of a particular year. The series consists of both trend and seasonality. The trend portion of demand is projected using the equation Ft = 124 + 7.5t. Quarter relatives are Q1 = 1.20, Q2 = 1.10, Q3 = 0.75 and Q4=0.95.

a. Use this information to deseasonalize sales for quarters 1 through 8.

b. Use this information to predict demand for periods 15 and 16.

a.

 Period Quarter Sales ÷ Quarter Relative = Deseasonalized Sales

 1 1 132 1.20 110.00

 2 2 140 1.10 127.27

 3 3 146 0.75 194.67

 4 4 153 0.95 161.05

 5 1 160 1.20 133.33

 6 2 168 1.10 152. 73

 7 3 176 0.75 234.67

 8 4 185 0.95 194.74

b. The trend value at t = 15 and t = 16 are:

 F15 = 124 + 7.5 (15) = 236.5

 F16 = 124 + 7.5(16) = 244.0

 Multiplying the trend value by the appropriate quarter relative yields a forecast that includes both trend and seasonality. Given that t = 15 is a second quarter and t = 16 is a third quarter, the forecasts are:

 Period 15: 236.5(1.10) = 260.15

 Period 16: 244.0(0.75) = 183.00

Computing seasonal relatives

A commonly used method for representing the trend portion of a time series involves moving average. Computations and the resulting values are the same as those for a moving average forecast. However, the values are not projected as in a forecast, instead, they are positioned in the middle of the periods used to compute the moving average. The implication is that the average is most representative of that point in the series. For example, assume the following time-series data:

 Three Period

 Period Demand Centerred Average

 1 40 40 + 46 + 42

 42.67 Average =

 2 46 3

 3 42 = 42.67

The three period average is 42.67. As a positioned at period 2; the average is most representative of the series at that point.

The ratio of demand at period 2 to this centered average at period 2 is an estimate of the seasonal relative at that point. Because the ratio is 46/42.67 = 1.08, the series is about 8 percent above average at that point. To achieve a reasonable estimate of seasonality for any season (e.g. Friday attendance at a theatre), it is usually necessary to compute seasonal ratios for a number of seasons and then average these ratios. In the case of theatre attendance, average the ratios of five or six Fridays for the Friday relative, average five or six Saturdays for the Saturday relative and so on.

Techniques for Cycles

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

Products go through their product life cycles. The demand for products can be based on their life cycles.

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

**Associative forecasting methods (models) based on cause-and-effect relationship (variables): Regression and Correlation Analysis**

Unlike time-series forecasting, ***associative forecasting*** models consider several variables that are related to the quantity being predicted. Once these variables are found, a statistical model is built and used to forecast the item of interest. This approach is of course more powerful than the time-series methods that use historical values for the forecasted variables.

Bear in mind, that in the associative forecasting methods take into consideration many factors such as independent variables and dependable variables. It is important to develop the best statistical relationship between the independent variables and the dependent variables. The most common quantitative associative forecasting model is the linear-regression analysis.

Simple Linear Regression

This is the simplest and most widely used method to relate the relationship between two variables.

The object of a linear regression is to obtain an equation of a straight line that minimizes the sum of squared vertical deviation from the line (i.e. the least squares criterion). This least squares line has the equation

 yc = a + bx

 where

 yc = Predicted (dependent) variable

 x = Predicted (independent) variable

 b = Slop of the line

 a = Value of yc, when x = O (i.e. the height of the line at the y

 intercept).

(Note: Values of predicted (dependent) variable on the y-axis and values of the predictor (independent) variable on the x-axis.)

A general graph of a linear regression line is shown below.

The line intersects the y-axis where y = a and the slope of the line = b.

 yc = a + bx

 y

 Predicted variable

 ∆ y ∆ y

 b =

 ∆t ∆ t

 a

 x

 Predictor variable

 The coefficients of a and b of the line can be determined based on the two equations.

 n(∑xy) – (∑x)(∑y)

 b (the slope of the line) =

 n(∑x2) – (∑x)2

 ∑y - b∑x

 a (intersection at y-axis) = or y – bx

 n

 where n = Number of paired observations.

Many factors can be considered in an associative analysis. E.g. the of Dell PC may be related to Dell’s advertising budget, the company’s prices, competitors’ prices and promotional strategies and even the nation’s economy and unemployment rates.

(See pp.159 – 160 for workout example: Jay Heizer & Barry Render, 2010)

**Standard Error of the Estimate**

To measure the accuracy of the regression estimates, the standard of error of the estimate, S is computed. It measures the error from the dependent variable, yc, to the regression line, rather than to the mean. The computation is known as the ***standard distribution of the regression***.

The formula for computing the standard deviation of an arithmetic mean is:

 ∑(y – yc)2

 Sy,x  =

 $√$ n - 2

 where y = y-value of each data point

 yc = computed value of the dependent variable, from the regression equation

 n = number of data points

 Anther formula to calculate the same thing is:

 ∑y2 - a∑y - b∑xy

 Sy,x =

 √ n - 2

 Sales Regression line

 Dollars

**Correlation Coefficients for Regression Lines**

The regression equation is one way of expressing the nature of the relationship between two variables. Regression lines are not “cause-effect” relationships. They merely describe the relationships among variables. The regression equation shows how one variable relates to the value and changes in another variable.

Another way to evaluate the relationship between two variables is to compute the coefficient of correlation. This measure expresses the degree or strength of the linear relationship. Usually identified as r, the coefficient of correlation can be any number between +1 and -1.

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 + + + + + + + +

 + + + + + + +

 r = +1 0 < r <1 r = 0 r = -1

 Perfect positive Positive correlation No correlation Perfect negative

 co√rrelation correlation

To calculate ‘r’ the same data needed to calculate ‘ a’ and ‘b’ for the regression line are used.

To compute ‘r’, the lengthy equation for r is:

 n∑xy - ∑x∑y

 r =

 √ n∑x2 - (∑x)2 n∑y2 – (∑y)2

Although the coefficient of correlation is he measure most commonly used to describe the relationship and is simply the square of the coefficient of correlation- namely r2. The value of r2 will always be a positive number in the range 0 ≤ r2 ≤ 1. The coefficient of determination is the percent of variation in the dependent variable (y) that is explained by the regression equation.

**Monitoring and Controlling Forecasts**

Once a forecast has been completed, it should not be forgotten. No manager wants to be reminded that his or her forecast is horribly inaccurate, but a firm needs to determine why actual demand different significantly from that projected. If the forecast is accurate, that individual usually makes sure that everyone is aware of his or her talents. Very seldom does one read articles in Fortune, Forbes or The Wall Street Journal, however, about money managers who are consistently off by 25% in their stock market forecasts.

One way to monitor forecasts to ensure that they are performing well is to use a tracking signal.

A tracking signal is a measurement of how well a forecast is predicting actual values. As forecasts are updated every week, month or quarter, the newly available demand data are compared to the forecast values.

The tracking signal is computed as the cumulative error divided by the mean absolute deviation (MAD)L

 Cumulative error

 Tracking signal) =

 MAD

 ∑(Actual demand in period I – Forecast demand in period i)

 =

 MAD

 ∑ Actual - Forecast

 where (MAD) =

 n

Positive tracking signals indicate that demand is greater than forecast. Negative signals mean that demand is less than forecast. A good tracking signal – that is, one with a low cumulative error – has about as much positive error as it has negative error. In other words, small deviations are okay, but positive and negative errors should balance one another so that the tracking signal centres closely around zero. A consistent tendency for forecasts to be greater or less than the actual values (that is, for a high absolute cumulative error) is called a bias error. Bias can occur if, for example, the wrong variable or trend line are used or if a seasonal index is misapplied.

Once tracking signals are calculated, they are compared with predetermined control limits. When a tracking signal exceeds an upper or lower limit, there is a problem with the forecasting method, and management may want to reevaluate the way it forecasts demand. See the graph of a tracking signal that is exceeding the range of acceptable variation.

 Signal exceeded limit

 Tracking signal

 Upper control limit

 0 MAD Acceptable range

 Lower control limit

 Time

**Forecasting in the Service Sector**

Forecasting in the service sector is more challenging than in the product sector. A major technique in the retail sector is tracking demand by maintaining good short-term records. E.g. barber shops experience peak flow on Fridays, Saturdays and Sundays. They probably close on Mondays and Tuesdays. Similarly restaurants have similar experience as the barber shops.

Speciality Retail Shops

Flower shops may have other demand patterns and those patterns will differ depending on the holiday. When the Valentine’s Day falls on a weekend flowers cannot be delivered to the offices and those who are romantically inclined are likely to celebrate with outings than with flowers. If the holiday falls in midweek and with busy midweek schedules, makes flowers the optimal way to celebrate.

Due to different demand patterns, many service firms maintain records of sales not only the day of the week but also unusual events, including the weather, so that patterns and correlations that influence demand can be developed.

Fast Food Restaurants

Fast food restaurants are well aware not only of weekly daily and hourly but even 15-minute variations in demands that influence sales. Therefore, detailed forecasts of demands are needed.

Can draw column charts to represent the pattern of demands.