

Industrial Engineering
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Module - 04
Lecture - 05
Sales Forecasting - II

A very warm welcome to, all of you on the second lecture on Sales Forecasting, in the last lecture on sales forecasting one, we have seen why a forecasting is important we have seen is forecasting a black art, what are the advantages of doing forecasting and how the forecasting data is used by the industries for the planning purposes. So, the forecast that the companies make is very, very important for their well being. Either forecast goes right the planning is immaculate and the profits are there, if the forecast goes wrong, then the company has to suffer a huge amount of losses.

In the last class, we have also seen the classification of different types of forecasting methods, in which we have seen that there are qualitative and quantitative methods. So, in quantitative method there are a series of other forecast methods, which can be used in order to generate the forecast. In the last class, we have seen that there is a subjective method or there is qualitative method called the Delphi method of forecasting. So, we have seen, what are the advantages and disadvantages of the Delphi method.

So, in today's lecture I will focus majorly on the quantitative methods of sales forecasting. Focusing on their basic principle and then trying to address the problem with the help of certain numerical problems, so that you are able to understand that, how the data is available to us and how we can manipulate that data or how we can process the data to generate a forecast. So, let us review, what we have discussed in the last class.

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So, business time cycles you can see on your screen that on a y axis it is the demand and on the x axis it is the time. So, demand and time in this kind of a trend we can see it is a straight line on your screen you can see this is an increasing trend. Similarly, the demand can also decrease, so this is a decreasing trend that with time the demand for particular items is decreasing.

Similarly, we can have seasonal variations also that on y axis the demand is there and on x axis the time is there, so there is a seasonal variation like this on your screen you can see. Similarly, we can have time cyclic variations with demand varying with time and we can have a erratic demand in which the erratic or random variation of demand with time takes place.

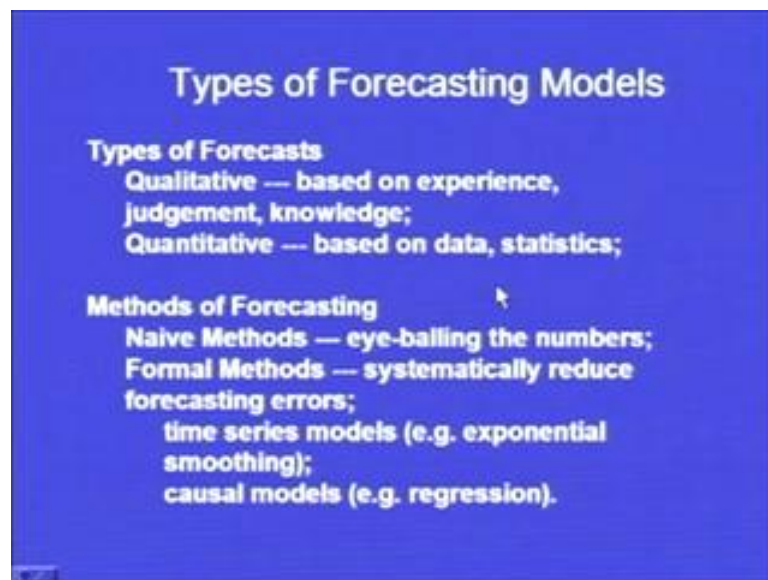
So, if the problem is simple that is there is an increasing trend or a decreasing trend, depending upon the past data we can very easily forecast that the trend is increasing, then we can forecast the next year the sales or the demand for the product is going to be more. Similarly, if the trend is decreasing we can say that for 10 years that trend has been decreasing for the 11th year also the trend would be same and the demand is going to decrease.

Similarly, if a cyclic variation is there very easily we can predict, but the major problem arises when there is an erratic or random variation on your screen this last curve shows that sometimes the demand is high, other time the demand is less and somewhere in

between also. So, what is happening here is that the demand is randomly changing or is changing at an erratic behavior. If we see, this is the 5th year in time scale then if we see for 5th year the demand is more if we say same demand will be there for the 6th year we will forecast this much, but the actual demand is comparatively less.

So for these type of scenario, we need to develop certain methods which would helps us to forecast properly that this is going to be the demand for the next year, so that all the planning activity in the organizations can be carried out in the best possible manner. So, what are the different types of methods that are used to address this type of a problem, where the demand is erratic or the variation is not known with respect to time.

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So, there are different types of forecasting models like types of forecasts can be either qualitative on your screen you can see these qualitative methods are based on experience judgment or knowledge. So, certain individuals who have an experience of working in a particular sector will have certain kind of knowledge available with them which they will use in order to generate the forecast for the subsequent year or for the next year. So, the method that is or the type of forecast that is used is a qualitative in which it is based on experience knowledge or judgment.

Similarly, there are certain quantitative methods also that are based on data and statistics. So, today in sales forecasting two our major thrust our major focus will be on the quantitative methods of sales forecasting in which we will be using certain amount of

past data which is available with us and use the principle of statistics or use simple mathematical tools to generate the forecast.

Similarly, methods of forecasting can further be classified into new methods those are eye-balling the numbers and formal methods like systematically reduce the forecasting errors. So, we will today see, what is a MAD, what is bias and how these can be used in order to minimize the data like, how these are the measures of the accuracy of the forecasting method. Then, time series models like exponential smoothing this we will see in today's class and causal methods such as regression can also be use for generating the forecast based on certain amount of data or certain historical data which is available with us.

Now first that, we are first model that we are going to cover today is the simple moving average model. So, one thing prior to this I would like to focus on is a simple moving average model holds it is precedence from a simple average model, now simple moving average is an advanced stage of a moving simple average method. In averaging out, we say that suppose we want to generate a forecast for the 11th year, we have the data for the last 10 years already available with us. So, what we are going to do in simple average simple mathematics, we are going to take a average of the last 10 years and we are going to say that this is going to be the forecast for the 11th year. So, the average has been taken of all the data which is already available with us, so that is basically a simple average. But, in simple moving average we want sometimes it is, so happens that in the last 10 year the trend has been increasing.

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Simple Moving Average

$$F_{t+1} = \frac{1}{n} (D_t + D_{t-1} + \dots + D_{t-1-n})$$
$$F_{t+1} = \frac{1}{n} \sum_{i=t-1-n}^t D_i$$

Forecast F_t is average of n previous observations or actuals D_t

It is an increasing trend as has been shown in the very first slide today in the business cycles. So, when the trend is increasing and we have the data for the last 10 years, why should we give equal weight age to last 10 years, we would like to give a weight age to the last 3 years or may be 8th year 9th year and 10th year to generate a forecast for the 11th year.

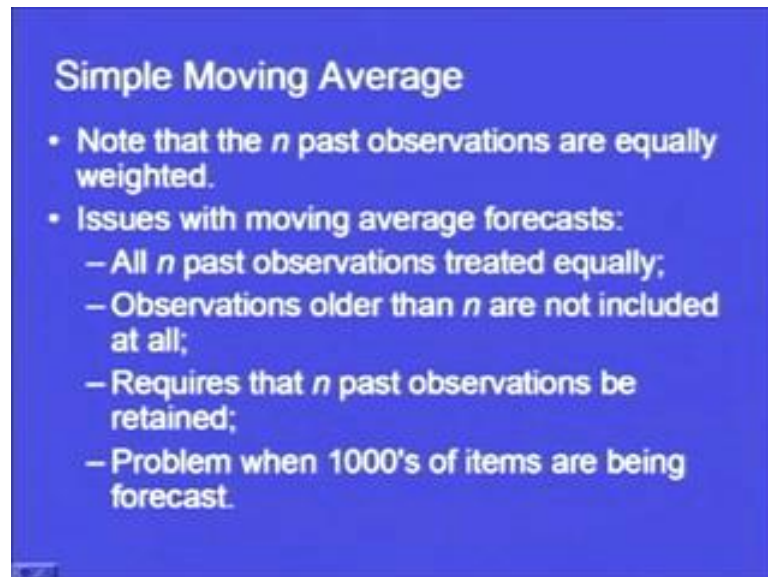
So, that basically turns out to be an average is moving with a period of time and that we call as the simple moving average. So, on your screen you can see that simple moving average is a step ahead of the simple average, because here the average is moving suppose we want to forecast for the 11th year and we are using 3 year moving average principle we will be making use of the data of the last 3 years only.

So, on your screen you can see a simple expression suppose we want to forecast for t plus 1th year. Suppose t is 10, then we will take that, how n can be 3 n can be 4 n can be 5, and this can be taken this decision can be taken by the person who is making the forecast that whether he is going to take into account a three period moving average five period moving average or 8 period moving average and D_t is the demand of the last period.

So, if n is 3, this will 3 quantities will be here, if it is 5 then 5 quantities will be here. So, we can $F_{t+1} = \frac{1}{n} (D_t + D_{t-1} + \dots + D_{t-1-n})$, so n is the period and I goes from t plus 1 minus n to t and then D_i . So, I goes from t plus one minus n to t means that we will be

taking care of the 3 previous or 5 previous or 7 previous readings or the data which is already available with us and from that data we are going to generate the forecast for the $t + 1$ th time segment or $t + 1$ th year. So, forecast F_t is an average of n previous observations is actual D_t 's

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Simple Moving Average

- Note that the n past observations are equally weighted.
- Issues with moving average forecasts:
 - All n past observations treated equally;
 - Observations older than n are not included at all;
 - Requires that n past observations be retained;
 - Problem when 1000's of items are being forecast.

So, simple moving average some points to note regarding the simple moving average are note that the n past observations are weighed equally or are equally weighed. So, the weight age given to each and every observation of the previous years is same, the weights are not varying. So, we will see a problem in which the weights can be assigned to the previous observation. So, in simple moving average n past observations are equally weighed, so that is the first point to be taken into account. Second is the issue with moving average forecast all n past observation are treated equally, so that is a first point.

Observations older than n are not included at all that I have already told in simple average we take the average of last ten years. But, in moving average if we say it is a three period moving average or 3 years moving average, then we are going to consider the observations of year number 8 year number 9 and year number 10 in order to generate the forecast for the 11th year.

So, the older observations means observation for year number 1 2 going on till 7 are excluded in simple moving average. Requires that n past observations be retained, so n

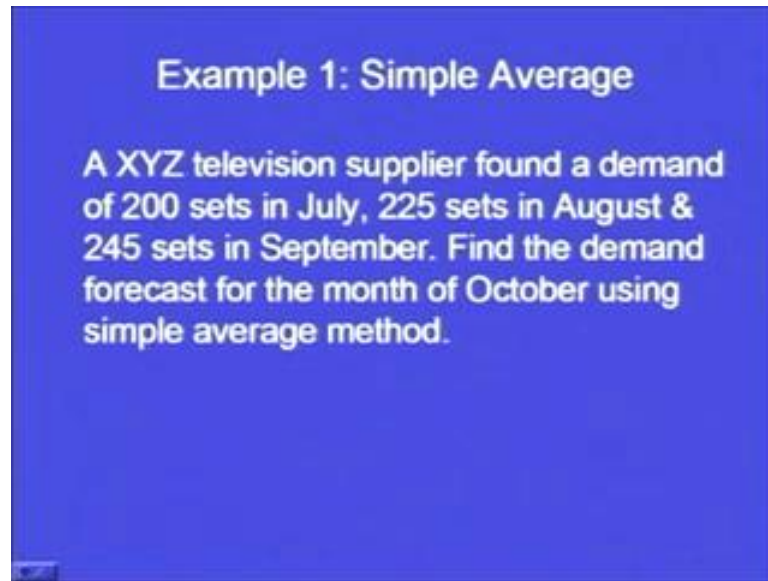
past observations have to be retained, so that those will be used for generating the forecast. The problem when 1000's of items are being forecast, so when the forecasting problem is very big and a large verity of items have to be forecasted, then the problem becomes a little bit very more complex.

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Now, here you can see a simple moving average. So, this include an most recent observations and the weight is given equally all observations are given equal weight and older observations are usually neglected, so that I have already explained in the previous slide and previous to previous slide. So, we can say these are the observations this is the data the weight given is constant and same weight is being given to all the previous observations.

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Example 1: Simple Average

A XYZ television supplier found a demand of 200 sets in July, 225 sets in August & 245 sets in September. Find the demand forecast for the month of October using simple average method.

Now, let us take an example of a simple average problem, then we will see try to see the difference between a simple average and a moving average problem. Now, let us go through the problem first, an XYZ type television supplier found a demand of 200 sets in July. So, the first observation is 200 sets in July, second observation is 225 sets in August and the third observation is 245 sets in September. So, important point to note here is that, we have the data available for 3 particular months of the year; these are July August and September.

And, you can see from the data 200 sets in July, 225 sets in August and 245 sets in September, this means that the increasing trend is there, because 200 in July 225 an increase of 5 sets in August and 245 sets in September. Now, we want to find the demand forecast for the month of October using a simple average method, now what we are going to do is we are going to add up all these three demand data and divided by 3.

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The average demand for the month of October is

$$\begin{aligned} SA &= \left(\frac{D_1 + D_2 + D_3}{3} \right) \\ &= \left(\frac{200 + 225 + 245}{3} \right) \\ &= 223.33 \\ &\approx 224 \text{ units} \end{aligned}$$

Now let us see, the average demand for the month of October can be very easily calculated that simple average is given by D_1 plus D_2 plus D_3 divided by 3. Now, D_1 we can say this is the data for the month of August and September and we are finding out the data for the month of October. So, the average demand for the month of October can be calculated like this July, August and September data is available, 200 plus 225 plus 245 divided by 3, 223.33 units we get which can be rounded off to 224 units.

So, we can very easily say that in the month of October, we are going to have a demand or we are going to sell 224 units of the television. But this data may be correct and may not also be correct, because you see that there is an increasing trend, but by averaging out what we are doing, we are getting a value which is 224. If we see by intuition by our mind we see the data for the last 3 months we see it was 200, then it increased to 225 and further it increased 245.

So, we may say that it can be more than 245 in the month of October, but a simple average method not the moving average, I am here only giving a problem that is simple average, a simple average method is forecasting to 224 units which may be wrong. So for in order to further use different methods or further study that, how this type of discrepancy can be overcome, we will see some other methods of forecasting like the moving average method and the exponential smoothing method.

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Simple Moving Average :
A XYZ refrigerator supplier has experienced the following demand for refrigerator during past five months.

Month	Demand
February	20
March	30
April	40
May	60
June	45

Now, a problem of a simple moving average, simple moving average already I have explained, what is simple moving average, with the help of certain expression. Move simple average method we have seen, how it can generate a forecast in the previous problem. We have seen we had three observations available with us for three months data and we were able to forecast for the month of October based upon the last three months data.

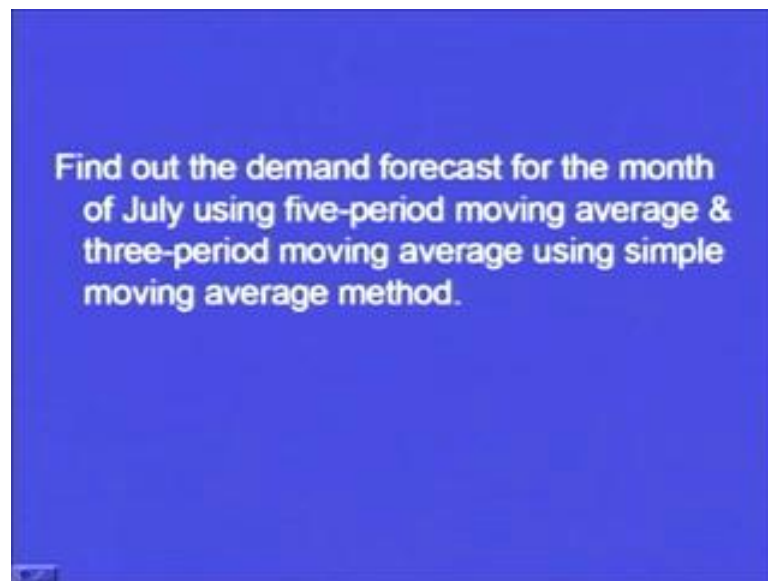
Now, we come on to another problem in which we are going to see the simple moving average. So, moving average means that here the average will be moving in the past problem the average was for the all the previous data that was available with us, so what was the data, that was available with us that was the 3 months data. So, here we are not going to use all the data which is available with us, but depending upon the time period that we select we are going to use the data.

Now, you can see this problem simple moving average problem, a XYZ refrigerator supplier has experienced the following demand for refrigerators during past five months. Now, in this problem we have a data of the last five months available with us. Now, you can see for the month of February, the demand was 20 refrigerators march 30, April 40, May 60 and June 45. So here, we can see that the trend is not at all increasing, if you see the trend of the data which is available with us although 20, it increased to 30 increased to 40 increased to 60. But suddenly, there was a decrease in the demand and that was 45.

So, the trend is not increasing, it is a we can say a cyclic trend or if we have more amount of data available with us, we would be very easily able to find out that, what type of trend is available with us. So, whether it is a cyclic trend or it is a random variation or it is a very erratic type of variation it is a seasonal variation, so depending upon the data availability we can be very easily able to establish that, what type of variation is there in the demand with respect to time.

But here, in this problem we cannot say that, whether it is a increasing trend or a decreasing trend, although by the first four months data we can say yes it is increasing, but the 5th month data is decreasing. So, there is no data available or no substantial data available with us on the basis of which we can make a very judicious decision related to the variation of demand with respect to time. So such type of data, we can say a simple moving average method would be very helpful to us in order to generate a forecast in such type of a scenario.

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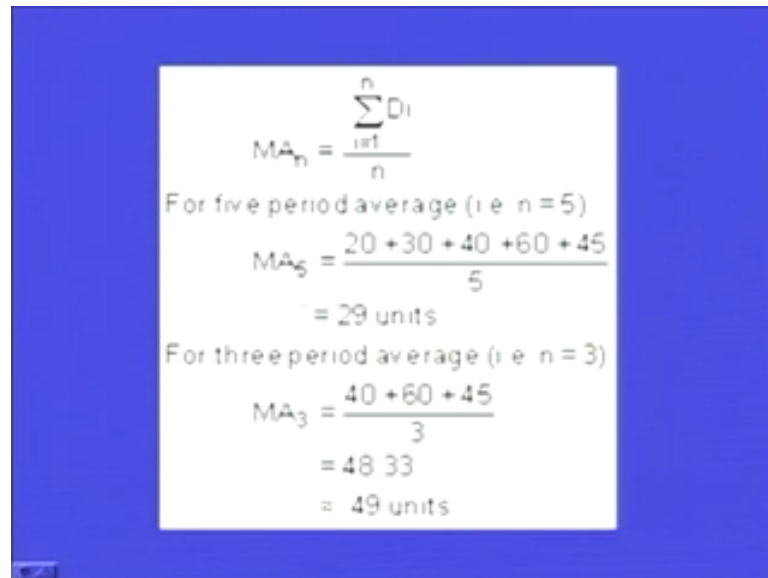


Now, the problem is find out the demand forecast for the month of July using five period moving average and a three period moving average using moving average method. So, that the period has been decided whether a five period moving average or a three period moving average.

In three period moving average, we are going to take the last three years like we are finding the forecast for the month of July, you can see find out the demand forecast for

the month of July. So, when we are finding the forecast for the month of July in a three period moving average, we would only be considering the observations for June, April and May. So, April May June data will be used in three period moving average and in five period moving average, we will be using the 5 previous months data in order to generate the forecast for the month of July.

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$$MA_n = \frac{\sum_{i=1}^n D_i}{n}$$

For five period average (i.e. n = 5)

$$MA_5 = \frac{20 + 30 + 40 + 60 + 45}{5}$$
$$= 29 \text{ units}$$

For three period average (i.e. n = 3)

$$MA_3 = \frac{40 + 60 + 45}{3}$$
$$= 48.33$$
$$\approx 49 \text{ units}$$

Now, here the moving average for n period moving average, now n in first case is 5. So, D_i is the data which is already available with us, so I go from one to n means 1 to n 1 to 5. So, for five period moving average that is n is equal to 5, we are using all the 5 months data available with us that is 20 plus 30 plus 40 plus 60 plus 45 divided by 5. So, simple moving average using a period of 5, we are able to generate a forecast of 29 units, so we can say in the month of July we will be able to sell 29 units of refrigerators.

But, if we use a three period moving average method, so for three periods moving average our n becomes three and the data is considered only the last three months data. So, the moving average by keeping the period three we are able to find out the data as 40 plus 60 plus 45 divided by 3, so it comes out to be 48.3 units or we can say 49 units.

So, what is the difference between a five period moving average, and a three period moving average method. So, if we see in the previous month the forecast or the actual demand was 45 and our next month's forecast is 49 which is very close to the last months demand the data is already available with us.

So, if we use a complete moving complete simple average we have data for the last 5 months available with us and we are doing a simple average of 5 months data that is 20 plus 30 plus 40 plus 60 plus 45 divided by 5 our forecast is 29 units. But, if we are giving weight age to the last three months data or our average is moving with the period like for last 3.

Now, suppose we want to forecast for the next month, this forecast is for the month of July. Now, suppose we want to forecast for the month of August, now what will be our strategy, we will be leaving one data point of the previous month. And now we will be focusing on the actual demand of July actual demand of June and actual demand of May. So, data of May June and July will be used for the forecast of August.

Similarly here, we have use the data of April May and June in order to generate a forecast for the July. So here, the average is moving the time period is moving and only a certain period or certain observations are used in order to generate the forecast.

Now, third is the weighted moving average, so we have seen first simple average, whatever data is available with us we are simply averaging it out and then forecasting for the next month. We have seen a simple moving average in which n was decided by us in problem we have seen n was 5, then n was reduced to three and we have seen, what the difference between the forecast is. Now, we come on to another problem that is a weighted moving average in which the weights are assigned to the previous observations. Now, we will see this we will try to understand this with the help of this very simple example.

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Weighted Moving Average Method :

The manager of a restaurant wants to make decision on inventory and overall cost. He wants to forecast demand for some of the items based on weighted moving average method. For the past three months he experienced a demand for pizzas as follows:

Month	Demand
October	400
November	480
December	550

So, a manager of a restaurant wants to make a decision on inventory and overall cost, he wants to forecast demand for some of the items based on weighted moving average which is the name of this method. For the past three months he experienced a demand for pizzas as follows. So, for October the demand for pizzas was 400, for November it was 480 and for December it was 550.

Now, suppose this problem has to be solve using simple average, in simple average what we will do, we will add 400 plus 480 plus 550 and divide the total sum by three that is that becomes simple average. Now, if we have to solve this problem using a moving average and we take the period to be 2, then what we will be do we will add 480 plus 550 and divide it by 2 and the average will be moving for every two periods. But here, in case of weighted moving average, we would be assigning certain weights to these observations and then we will be forecasting may be for the next month.

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Find the demand for the month of January by assuming suitable weights to demand data.

$$WMA = \sum_{i=1}^n C_i D_i$$

C_i = Weights for Periods
 D_i = Demand for Periods
Let $C_1 = 0.25$, $C_2 = 0.3$, $C_3 = 0.5$
 $WMA = C_1 D_1 + C_2 D_2 + C_3 D_3$
 $= 0.25 * 400 + 0.3 * 480 + 0.5 * 550$
 $= 100 + 144 + 275$
 $= 519$ units.

Now, find the demand for the month of January by assuming suitable weights to demand data. Now, we have to assign the weights to the data, which is already available with us and then we have to make a forecast for the month of January. So, we can see the weighted moving average is I goes from 1 to n, now n suppose is 2 or suppose is 3, then we have to I goes from 1 to n. So, I we can say C_i that is new in our discussion today, C_i are the weights for the periods like we have three periods, three observations available with us and that is C_i will be a weight associated with those observations.

And, D_i is the demand for the periods, now $C_1 D_1$ will be the weight of the demand 1 and D_1 will be demand. So, let C_1 be now the first weight is 0.25, C_2 is 0.3 and C_3 is 0.5, so the weighted moving average will be $C_1 D_1$ plus $C_2 D_2$ plus $C_3 D_3$. So, this should be ideally we C_1 should be 0.02 that is why then the addition of all these weights will turn out to be 1, but somehow it has been put as 0.25.

So, what that is not an important issue, weighted moving average was needed to understand how it is calculated. Now, C_1 as we have already assumed it to be 0.2, we can say 0.25 multiplied by 400, so 400 is the demand for the for the first month.

Just we go to the previous slide for October, we have 400 as the demand. So, D_1 is 400, D_2 is 480, D_3 is 550. So, 0.2 multiplied by 400 plus 0.3 multiplied by 480 plus 0.5 multiplied by 550, so 0.2 0.3 0.5 these are the weights associated with the demand. So,

you can for yourself imagine more weight is given to the demand that is the latest demand.

So, 550 were for the month of December, so more weight is given to that and less weight is given to the previous demands. So, we can see 100 plus 144 plus 275 and it comes out to be 500 and 19 unit, so what we are doing here is that we are assigning certain amount of weights to the observations of the data which is available with us.

So, we are assigning more weights to the demand or to the observations which are just near to the month for which we are forecasting and we are assigning less weight for the data of the months, which are far away from the month which we are forecasting. And this will help us to keep into account the latest variations that are taking place in the actual demand of the particular item.

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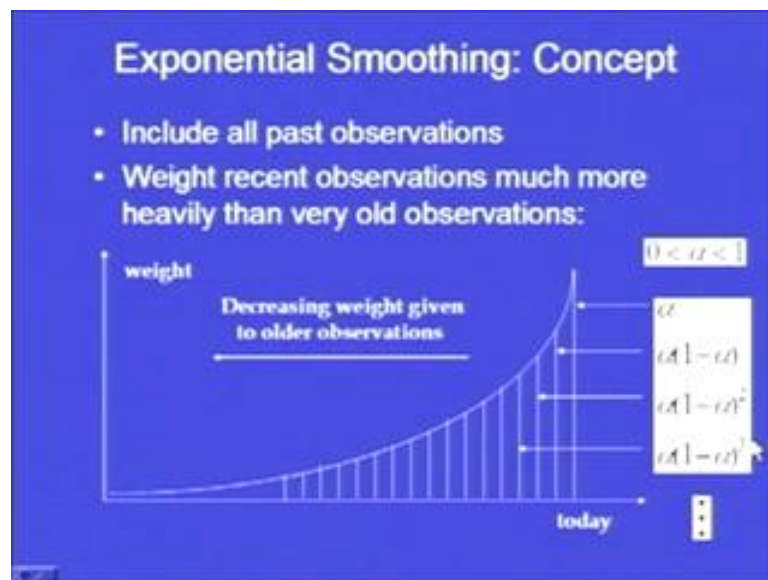
Now, we come on to another important type of forecasting method which is called as the exponential smoothing method. In exponential smoothing method, we include all the past observations, weight recent observations much more heavily than very old observations. In previous weighted moving average, also we assigned weights to some of the observations, which were very near to the month to which we are able or which we are planning to forecast. But here, we are going to include all the past observation and weighing recent observations much more heavily than very old observations, so you can

see on y axis it is the weight and on x axis is the time. So, these are the observations which are there and decreasing weight given to older observation, so this is today.

Now, we want to forecast for the next day or for the next week or for the next month, so we are moving in this direction. Suppose we want to forecast for this day, so this data we are giving more weight and as we move away from the day for which are forecasting we are given lesser and lesser weights.

So, decreasing weight given to older observations, so the older observations in this direction, suppose this is 10 days or 10 months before the actual day. Now, this is the actual day and 10 months before or 10th data is given minimum weight and the latest data is given the maximum weight, this was also used in the weighted moving average also, but there the weights were assumed by us, which may be wrong also. But here, we are we the variation is an exponential variation, so we can see the alpha we can call it as the smoothing coefficient. So, alpha varies between 0 and 1, so this is we are giving a value of alpha. Now, this alpha will keep on decreasing.

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So, in the next we will see, the weight assigned to the next observation is alpha into 1 minus alpha. Similarly, when we move forward the other 2 year back or 2 months back or 2 days back data is given a weight of alpha into 1 minus alpha to the power 2.

So, the variation is exponential, subsequently this will keep on moving the next previous years data is given the weight α into $1 - \alpha$ to the power 3. And similarly, as many observations we will have exponential smoothing and the data or the observations will be assigned a relative weight depending upon their distance from the actual day.

Now, actual day is supposed the month of January, so December data will be given certain weight age which will be considerably more than the other month's observation. Similarly, November will be given certain weight age October will be given certain weight age and similarly going down the previous months will be given the weight age, but this weight age will be moving exponentially and it will be reducing.

So, what is the major aim of doing this type of exponentials smoothing is that, we are giving maximum weight age to the latest data and minimum weight age to the distant data or the data which is very, very far off from the present day? So, we can say that what is happening is that, we are here accounting for all the market conditions all the market scenario whatever changes are taking place in the market that have been accounted for here.

Because, the previous data is or the latest data is given more weight age as compared to the data which was far of may be 2 years back or 3 years back the companies may be having a different type of business environment. Today the companies may be facing a different type of business environment more number of competitors might have entered in. So, there is no point in giving too much of weight age to data of 2 years or 5 year before the actual day.

So, latest data that is the data which takes into account or which incorporates all the business environment should be given more weight age as compare to the data which was far of or which was too late or which was may be 5 years or ten years behind the actual day. So, important point to note here is that exponential smoothing method is more important or is more applicable as compared to a simple average method.

So, let us now discuss the mathematics behind the exponential smoothing, so we have seen that, what is the importance of exponential smoothing, why exponential smoothing is done and how do we assign weights in a exponentially decreasing pattern. So, this is a pattern how the weights on y axis we have weights, so here we have maximum weight this is today and then with the weights are decreasing exponentially along this line.

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Exponential Smoothing

$$F_t = \alpha D_t + \alpha(1-\alpha)D_{t-1} + \alpha(1-\alpha)^2 D_{t-2} + \dots$$
$$F_t = \alpha D_t + (1-\alpha)[\alpha D_{t-1} + \alpha(1-\alpha)D_{t-2} + \dots]$$
$$F_t = \alpha D_t + (1-\alpha)F_{t-1}$$

So, let us now see, now F_t is the forecast that we work to do this is α into D_t plus α minus 1 though these are the weights, α is the weight α into $1 - \alpha$ α into $1 - \alpha$ square weight given to D_{t-2} and α into $1 - \alpha$ α is the weight given to D_{t-1} .

And, if we realign this we find out that α into D_t plus $1 - \alpha$ into all the previous year's demand data which is available with us. So, this we can formulate expression a very simple expression of this type in which the forecast is given as is equal to α the weight given to the previous demand plus $1 - \alpha$ into F_{t-1} .

So, F_{t-1} is the previous forecast F_t is the forecast that we want to do and D_t is the actual demand. So, what is required is the actually demand data is required, previous forecast is required and the value of α which has been assumed by the forecaster or the person who is in charge of calculating the forecast for F_t . So, only 2-3 data points or 2-3 observations are required in order to generate a forecast using the exponential smoothing method. So, F_{t-1} the previous forecast previous demand and α these 3 are three things are require in order to generate the forecast.

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Exponential Smoothing

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

Now, you can see exponential smoothing this is the same thing that we have already discussed.

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- Thus, new forecast is weighted sum of old forecast and actual demand
- Notes:
 - Only 2 values (D_t and F_{t-1}) are required, compared with n for moving average
 - Parameter α determined empirically (whatever works best)
 - Rule of thumb: $\alpha < 0.5$
 - Typically, $\alpha = 0.2$ or $\alpha = 0.3$ work well
- Forecast for k periods into future is:
$$F_{t+k} = F_t$$

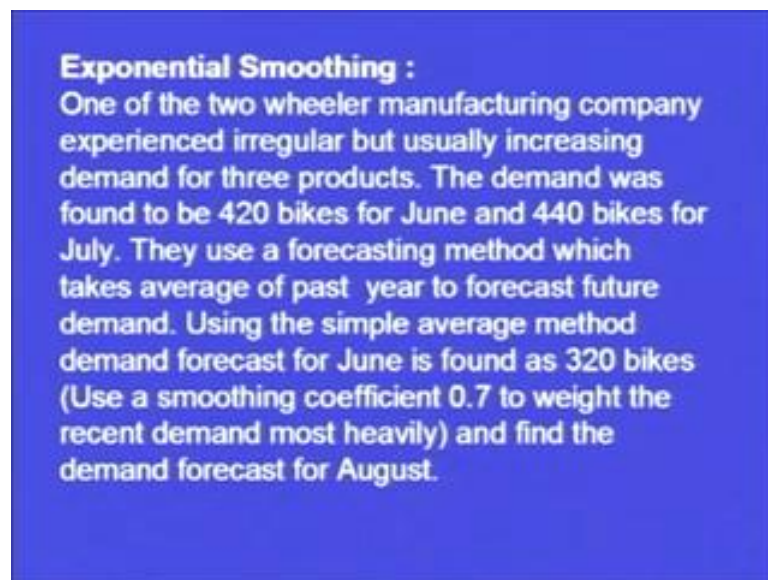
Thus, the new forecast is weighted some of old forecast and actual demand. I have already told F_{t-1} was the old forecast and D_t was the actual demand. Now, there are certain notes certain things that have to be born in mind related to the exponential smoothing method. So, what are these notes, only two values D_t and F_{t-1} are required, so this already I have told that only the actual demand and the forecasted value

that is F_{t-1} , that is required and there that can be use this data can be used for generating the forecast for the next year. Compared with n moving average, so n moving average we require at least 5 year if n is 5 we require 5 years average 5 years observation and that will be then later on averaged out.

And, if n is 3, we require the data for the previous 3 years, If n is 5 we require the data for the previous 5 years, and then this data will be used to generate the forecast. But here, only two values are required that you can see on your screen that is D_t that is demand and F_{t-1} that is the forecast.

Then, parameter is determined empirically whatever works best, so whatever parameters are alpha that can be usually determined empirically whatever works the best. Then, rule of thumb that is alpha usually it is taken 0.5 may be it can be taken more than that also, but as a rule of thumb people usually use it as less than 0.5, so typically alpha equal to 0.3 or alpha equal to 0.3 work well. Now, forecast for k periods into future is F_{t+k} is equal to F_t that is simple.

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Exponential Smoothing :
One of the two wheeler manufacturing company experienced irregular but usually increasing demand for three products. The demand was found to be 420 bikes for June and 440 bikes for July. They use a forecasting method which takes average of past year to forecast future demand. Using the simple average method demand forecast for June is found as 320 bikes (Use a smoothing coefficient 0.7 to weight the recent demand most heavily) and find the demand forecast for August.

Now, let us see a problem on exponential smoothing. One of the two wheeler manufacturing company, let us first go through this, then we will see what is that data which has been presented in this problem and further we will see how this data will be used to generate a forecast.

So, let us first you read, what is there on your screen, that is one of the two wheeler manufacturing company experienced irregular, but usually increasing. So, we can say it is irregular it is changing, but the trend overall is increasing there can variation, but the variation overall variation if you see it is on the increasing side only.

So, one of the two wheeler manufacturing company one of the two wheeler manufacturing company experienced irregular, but usually increasing demand for three products. The demand was found to be 420 bikes for June 440 bikes for July, they use a forecasting method which takes average of past year to forecast future demand. Using the simple average method, the demand forecast for June is found as 320 bikes, uses a smoothing coefficient of 0.5 to weigh the recent demand most heavily and find the demand forecast for August.

Now you can see what the data which available is; the data available is the demand was found to be 420 bikes. So, the actual demand data is available found to be 2 4 20 bikes for June and 440 bikes for July, so the demand data for 2 months is already available. They use a forecasting method, which takes a average of the past year to forecast future demand.

So, the forecast can be calculated using, what is written here is on your screen, you can say simple average method that was the first method that we discuss today. We have discussed simple average simple moving average weighted moving average and now we are discussing the exponential smoothing. So, the first simple average data we used the previous data averaged it out and then we got the forecast.

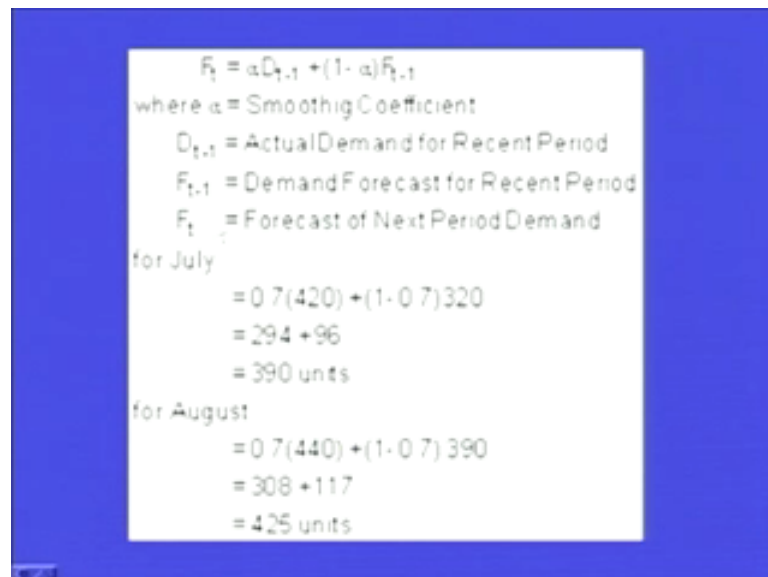
So the forecast they are doing the forecasting using a simple average method and that forecast for the month can be found out as 320 bikes, how 320, because 420 plus 440 and then we are divide. We use a simple average method demand forecast for June is found to be, so demand is already 320 bikes that is available. So, the forecast data or demand forecast is available forecast data is available and previous month's actual demand is also available.

These are the two things that are required in the exponential smoothing method. (Refer Slide Time: 34:50) If you go to the previous slide, you can see that D_t and F_{t-1} , these are the two important things that are required in ordered to generate a forecast using the exponential smoothing method. So here, we have the all these data is already

available 320 is we can say F_{t-1} and D_t can be for the previous month for June is given and for July is give and we have to forecast for August.

So, for July 440 bikes are the actual demands, so D_t is 440 and F_{t-1} is 320. So, from the problem we have formulated a problem which can be solved using the exponential smoothing method and the coefficient or the smoothing coefficient, we can see is also given to be 0.7, so we know the value of alpha, we know the value of F_{t-1} we know the value of D_t . So, using these three values we will very easily able to find out the forecast for the month of August using the exponential smoothing method.

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

where α = Smoothing Coefficient
 D_{t-1} = Actual Demand for Recent Period
 F_{t-1} = Demand Forecast for Recent Period
 F_t = Forecast of Next Period Demand

for July
$$= 0.7(420) + (1 - 0.7)320$$
$$= 294 + 96$$
$$= 390 \text{ units}$$

for August
$$= 0.7(440) + (1 - 0.7)390$$
$$= 308 + 117$$
$$= 425 \text{ units}$$

So, let us now see, the formula is given as F_t is equal to alpha into D_{t-1} plus 1 minus alpha into F_{t-1} . For your easy understanding, we will again see alpha is the smoothing coefficient D_t is actual demand for the recent period. Now, we are forecasting for the month of August, you can see find the demand forecast for the month of August. So, actual demand for the recent period means we need to know the demand for the month of July.

Then, F_{t-1} is the demand forecast for the recent period, now what was the demand forecast, that was calculated using the simple average method and that value was 320. Then, F_t is the forecast of the next period demand, so F_t we can find out for July. But the data which is already available with us we can also use that data for forecasting for the month of July also, because for June. We know that what was the actual demand and

what was the forecast, so 0.7 that is alpha multiplied by 420 that was for the month of June, what was the actual demand, if you see on your screen 420 bikes for the month of June. So, that was the demand was found out to be 420 bikes for the month of June.

So, this is 420 that was the demand for the month of June, so what we are doing, we are calculating the forecast for the month of July. The demand for the month of June will be used here plus 1 minus alpha into the F_{t-1} by simple average we have found out that the forecast for the month of June was 320. So, if we say 0.7 multiplied by 420 multiplied by 1 minus 0.7 multiplied by 320, we found that 294 plus 96 comes out to be 390 units.

Now, let us understand the very difference between simple average and exponential smoothing. We know that for the month of July the demand was 440 units. On your previous screen you can see the actual demand was 440 bikes for July, the demand was found to be 420 bikes for June and 440 bikes for July.

So, 440 bikes were actually demanded for July, what was the forecast using simple average a simple average forecast was 320. So, 440 was desired or demanded by the customer the forecast was 320 we can see, what the difference between the two is, but if we would have used the exponential smoothing method for generating the forecast for the month of July our forecast would have been 390 units.

So, we can very easily distinguish between the accuracy of the two methods, simple average gives us 320 moving average would have given us something else. Exponential smoothing is giving us 390, which is pretty much closer to 440 which was the actual demand for July. So, we can see if we weigh the latest demands more heavily our forecast will be more accurate as compare to simple average method.

Now let us see, what will be forecast for the month of August, For August smoothing coefficient we have taken as same as 0.7. Demand for July has been 440 which are known with certainty, 1 minus 0.7 that is one minus alpha and the forecast is F_t is 390. For June we have calculated using exponential smoothing.

So here, we are not using a simple average method we are using the exponential smoothing method for forecasting. So, whatever was forecasted for the month of July we

are using that value or that observation here as 390, so for August our forecast comes out to be 425 unit.

So, we have seen that exponential smoothing is a much better method as compared to simple average method. Because, the forecast that has been generated using this method relate more closely to the actual demand that was there, but this we cannot say in each and every case that this method is going to be beneficial.

There will be certain business cycles in which the simple averaging out of all the previous observations which would be much more beneficial as compared to the exponential smoothing method. But depending upon the business environment always a decision has to be taken that which type of method should be used under which type of circumstances.

So, simple moving average will be used if large amount of data is available with us and we want to concentrate only on the last 4 years or last 5 years or last 6 years data. Exponential smoothing will be used where we want to give a large amount of weight age to the previous readings and want to give a less amount of weight age to the distant readings or the readings that are far off from today's readings.

So depending upon the requirements; depending upon the type of business environment; depending upon the kind of market scenario prevailing; depending upon a large number of other factors that influence the forecast. We have to take a judicious decision that our forecast is very, very accurate and we have to take a judicious decision that which type of method or forecasting method we should use in order to generate a forecast.

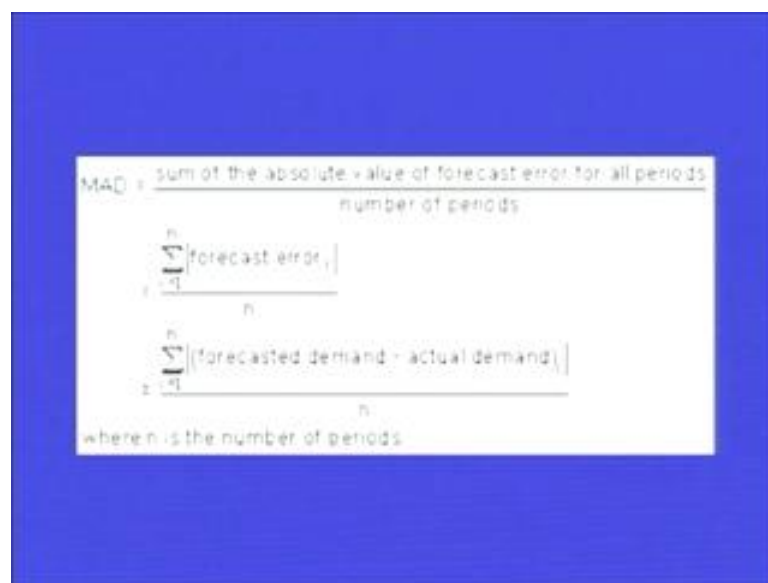
Already, in the start of sales forecasting lecture number one, I have told I have put a question that is forecasting a black art, why I am coming to that point again. Because, we have seen there are, so many method subjective method we have seen that was a Delphi method.

Then, we came across so many methods which use the previous data like the simple average simple moving average weighted moving average exponential smoothing method. We will see in brief two or three other method, which are used for forecasting, so we have to select the most appropriate method for forecasting. But still, there is a point is forecasting a black art which means that the forecast that we are generating or

deviating from the actual demand say in this problem itself we can say. The forecast is was 320 and the actual demand was not 320 it was more than that.

Similarly, for the month of July we can see that there a variation between the forecast and actual demand. So, how to account for this type of variation; basically we would select a method which could minimize this variation. So, how to check, what the parameters are? That is used for checking the deviation there we use MAD and bias, so we will see, what is MAD and what is bias.

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$$\text{MAD} = \frac{\text{sum of the absolute value of forecast error for all periods}}{\text{number of periods}}$$
$$\frac{\sum_{i=1}^n |\text{forecast error}_i|}{n}$$
$$\frac{\sum_{i=1}^n |(\text{forecasted demand} - \text{actual demand})|}{n}$$

where n is the number of periods

Now, MAD is the sum of the absolute value of forecast errors for all periods, so all periods' means that suppose we are seen 10 different periods. So for period number 1 what was the actual demand, what was the forecast for that period, what is the difference between the two.

Then, this will be added up to the period number 2, for period number 2 again we will calculate that, what the forecast was, what was the actual demand and what is the difference. So, sum of the absolute value, so here absolute is very, very important. So, we are considering the absolute value, so sum of absolute value of the forecast error for all periods divided by the number of period.

So, would tell us that, how much we are deviating for those number of period, that was either we were under forecasting or we were over forecasting and how should we do the

point tuning our forecasting method. To reach to a particular value or a particular confidence level that yes if we use this type of a forecasting method, we would be very close to the actual demand that will be generated in the market.

So we can say mathematically, we can represent this MAD by summation of 1 to n forecast error for the period I, for I goes from 1 to n for all the n periods we are going to calculate the forecast error. And then, we are going to divide it by a total number of periods therefore, which we are calculating the value of MAD.

And, how this forecast error will be calculated, we will calculate the forecast error for one particular period. Suppose, for period I as forecasted demand, we have forecasted the demand may be using any of the methods that we have discussed till now and this will be subtracting means actual demand that was there.

Now, suppose we have forecasted that next year or may be in 2009 5000 cars will be sold. So, what is this 5000, for 5000 is the forecasted demand, we say 5000 cars will be sold in the next year 2009. Now, suppose after 2009, we say there was a sale of 4500 cars only, so what was the actual demand for the year 2009 that was 4500.

So, actual demand was 4500 forecasted demand was 5000, so 5000 minus 4500 that comes out to with a difference between the forecasted and the actual demand for 2009. Similarly, if we have the similar kind of data which is available to us for the last 10 years, similarly for 2008 2007 2006 2005 and similarly going back the line.

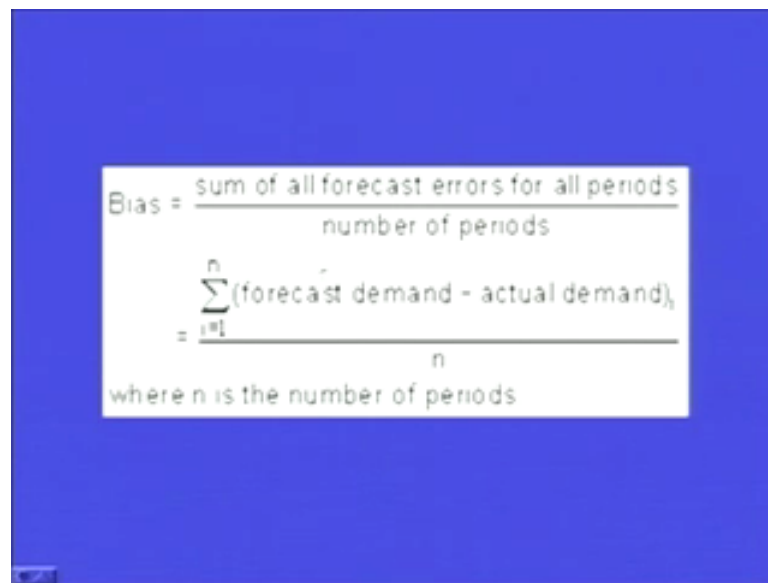
If we have all this difference between the forecasted demand and the actual demand data or the observation available with us, we will add these all observations and divide it by the number of period that we are selected. Suppose for the last 10 years we are going to evaluate this data then n turn out to be 10. And we will be able to find out the value of MAD which would tell us that, whether our forecasting is good or poor or should we need to switch over to some other type of forecasting method. Because the errors that, we are generating are too much and that is having a bearing on our profitability.

Already, I have told that if we are not able to forecast properly, our planning will not be appropriate or accurate and we will have to suffer a huge amount of losses. But, if our forecasts are current the planning that it dependent upon these types of forecast will be

very very correct well in time and this will result in huge amount of profits for the company.

So, forecasting accuracy is having a direct bearing on the profitability of the organization or the company. So, we need to understand by these type of parameter that whether we are forecasting correctly or not or is the difference between the forecasting and the actual demand is much more and if the difference is more then we should switch over to some other type of forecasting method.

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$$\text{Bias} = \frac{\text{sum of all forecast errors for all periods}}{\text{number of periods}}$$
$$= \frac{\sum_{i=1}^n (\text{forecast demand} - \text{actual demand})}{n}$$

where n is the number of periods

A one more method of evaluating the performance of the forecasting is the bias. Now, bias is the sum of all forecast errors for all periods divided by the number of periods, so in MAD also we were dividing by the number of periods. Here also we are dividing by the number of periods.

So here, we can say the forecast demand minus the actual demand for the period I and I goes from 1 to n, n is the number of periods that we have chosen divided by n. So basically, if we say the formula is same.

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$$\text{MAD} = \frac{\text{sum of the absolute value of forecast error for all periods}}{\text{number of periods}}$$
$$\frac{\sum_{t=1}^n |\text{forecast error}_t|}{n}$$
$$\frac{\sum_{t=1}^n |(\text{forecasted demand} - \text{actual demand})|}{n}$$

where n is the number of periods

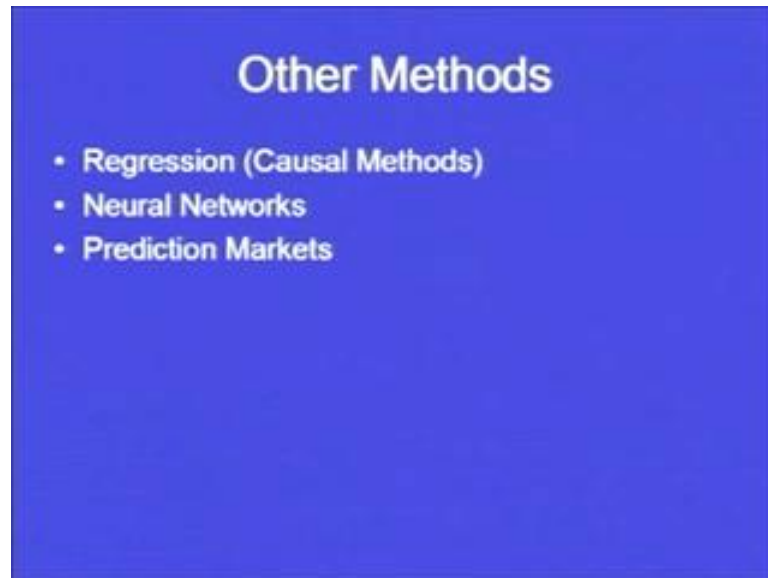
But in previous performance measure, we have seen this is the giving the absolute value. MAD is giving the absolute value and bias is not giving the absolute value. So, the difference between MAD and bias lies in the absolute value being taken in case of MAD and in case of bias we are taking the general value or the value that is coming out. So, we can have a negative value also, and we can have a positive value also and a direction we can say that always we have been under forecasting or always we have been over forecasting.

So, in bias we will be able to gauge the direction of forecasting also whether positive or negative. So, these two performance criterion will be used to judge the performance of our forecasting methods, so number of forecasting methods we have seen today and these two criteria, there can be other criterion also on the basis of which we can see that the methods that we are using for forecasting are appropriate accurate precise or not.

If they are accurate and precise we can continue with using those methods for forecasting. But if the values for MAD and bias are not coming within the limits, then we will think of changing our method of forecasting may be sometimes, we may even decide to change the method from a subjective method to a quantitative method or from a subjective method to objective type of method, in which we would be using the previous data and the statistics to generate the forecast for the subsequent years.

Lately, we have seen that there are so many types of other methods which have been used by the researchers engineer scientist in order to do the forecasting.

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So here, we see there are three other methods, the regression although is a very common technique. But, we have not covered regression in sales forecasting one and sales forecasting two, but this is a very simple method in which we frame a linear equation may be y is equal to ax plus b and can be used for forecasting depending upon the number of parameters which influence the forecast.

Then, there are other techniques like neural networks and prediction markets which have been used by people in order to generate the forecast. So here, I would like to conclude that although there are number of methods available with us in order to generate the forecast.

But it depends on the judicious selection of the method in order to arrive at a particular forecast, which is very, very close to the actual demand, because this closeness will result in a huge amount of profit for the organization. So, we have seen subjective and objective methods and we have seen try to understand with the help of certain numerical problems that how these methods work.

Thank you.