Decision Support System for Managers
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Week - 03
Module - 04
Lecture - 14
Decision Support Systems for Forecasting (Contd.)

Hi, welcome to our 4th module of week 3 on "Decision Support Systems"! We had been discussing 'forecasting' as a means for decision support for managers. Particularly, we will be interested in looking into the different quantitative techniques which are deployed in forecasting DSS as models; ok.

So, we had discussed some simple models like moving average techniques, simple exponential smoothing techniques, and we had seen some examples of those techniques.

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Today, we are basically going to discuss the following concepts, that is, forecasting of demand pattern where there is a trend either upward or downwards. Then we will be discussing something related to forecast errors and associated forecasting accuracy, then we will be discussing the role of tracking signals mainly to detect whether the forecasting model is stable and the results that we are getting are consistent or not.

And, then we will take up one example where there is some evidence of seasonal demand pattern; ok. We will find out the seasonal factors and then deployed at in forecasting demand pattern for the next planning horizon.

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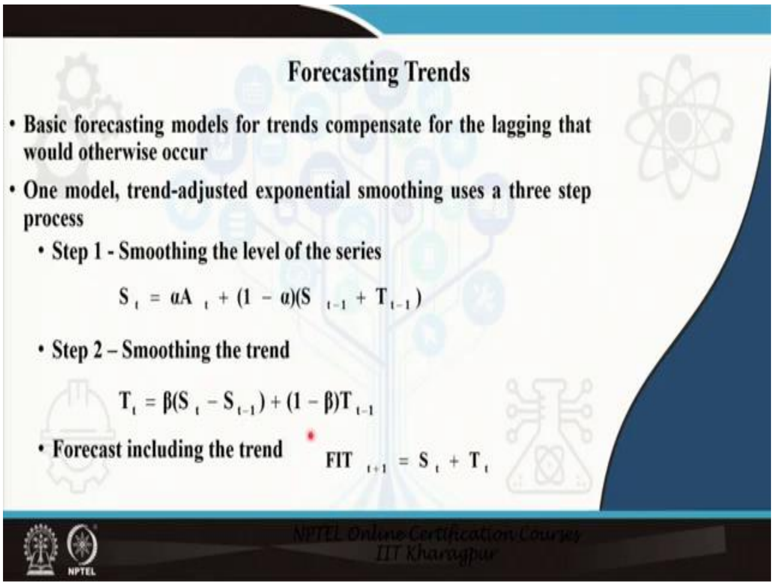

See, the basic forecasting models for trends whatever we had discussed earlier they compensate for the lagging that would otherwise occur because in the last week we had discussed about simple moving average, weighted moving average, we have discussed about simple exponential smoothing models.

Now, what we have basically discussed that these kind of models they take care of smoothing the random fluctuations around the average level of demand. But, these models they cannot take care of the trend in the demand pattern. In fact, single exponential smoothing model they lag behind this trend by a factor of alpha by 1 minus alpha, where alpha is the smoothing constant.

So, in order to take care of this trend in a demand pattern particularly for time series related data, lots of techniques have been devised. One of the techniques is double exponential smoothing model, there is Holt's model; so many models are there. So, that these basic forecasting models for particularly trend they compensate for the lagging that would have occurred if we had deployed only single exponential smoothing models.

One such particular model which is basically known as trend adjusted exponential smoothing uses the following 3 steps. In the first step what we do is that we smooth the average level of the series it something what we had discussed in the last week. The smoothed value of the level at the t-th period, it is given by S t.

S t represent the smoothed value of the level at the t-th period, that is basically equal to alpha which is a smoothing constant into the actual demand in period t which is given by A t plus 1 minus alpha into the smoothed value of the level 1 period ago which is denoted by S t minus 1. Plus the trend factor which was computed 1 period ago and denoted by t subscript T minus 1 T t minus 1.

Once again in the first step we compute the smoothed value of the average level which is given by S t equals alpha which is a smoothing constant times the actual demand in the t-th period denoted by A t plus 1 minus alpha times S t minus 1 that is the smoothed value of the level computed 1 period before plus the smoothed value of trend which is denoted by T t minus 1 which is computed 1 period ahead of the period t. Is that thing will be cleared when we take up one example?

And, in this particular model which is trend adjusted exponential smoothing we need to introduce another smoothing constant which is denoted by beta and this smoothing constant is basically used for smoothing the trend. So, the smoothed value of the trend factor at the period t is given by t subscript t which is nothing, but beta the new smoothing constant multiplied by S t minus S t minus 1, where S t is given by this formula plus 1 minus beta into the trend factor computed 1 period ago and denoted by T subscript t minus 1.

So, once we compute the smoothed value of the level and the trend at the period t then, the forecast value including the trend for the period t plus 1 that is 1 period ahead standing at the end of period t if given by FI FTT t plus 1 which is nothing, but the sum of S t plus the trend smoothed value of the trend T t computed at the end of period t this is the third step.

Now, let us look at one example which will make things absolutely clear.

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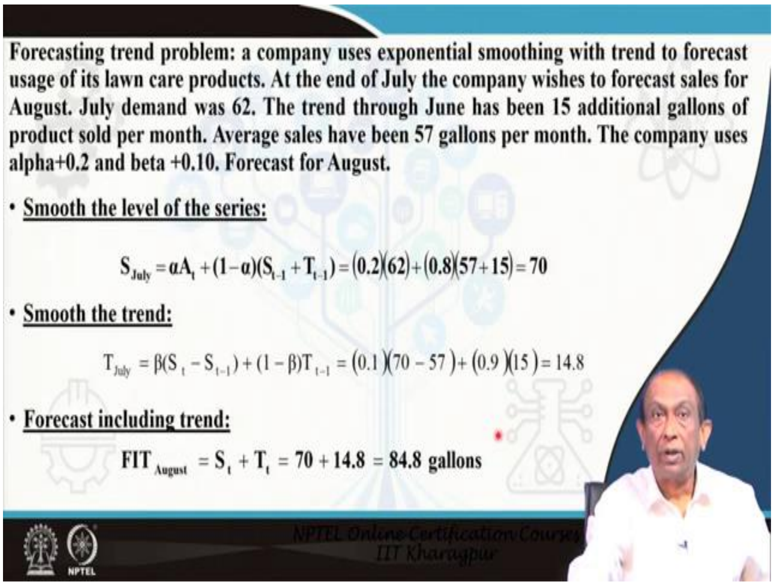

Here is one problem a company uses exponential smoothing techniques with trend to forecast usage of it is lawn care products. At the end of July the company wishes to forecast sales for the month of August. The demand for the month of July was 62 and they have observed that the trend through June has been 15 additional gallons of product sold per month. So, there is an upward trend and they had already computed that the average sales have been 57 gallons per month that is the average level of demand.

And for this particular problem the company uses smoothing constant alpha as 0.2 and beta as 0.10. The problem is to compute the forecast for the month of August. So, what we have discussed just now that, at the first step we have to smooth the level of the series.

So, standing at the end of July the smoothed value of the level denoted by S July is alpha times actual demand for July plus 1 minus alpha into the smoothed value which was computed 1 period ahead that is the average value of sales till the month of June plus the rate of growth or the upward trend that has been observed in the month of June.

So, what we have done? We have taken alpha equals 0.2, but in the problem it is very clearly given the average value of sales had been for the month of July was 62. So, we have put in that plus 1 minus betas. So, beta is actually in this problem it is not 1 minus beta would have been 0.9 sorry, 1 minus alpha. So, 1 minus 0.2 that is 0.8 correct, plus

57 average sales have been 57 gallons per month ok. So, 57 plus the trend factor 15. So, this total becomes 70.

Once again let us see 0.2 is alpha value and the actual demand for the month of July was 62 we have put in that plus 1 minus alpha that is 0.8 because 1 minus 0.2 is 0.8 multiplied by S t minus 1 which is the average sales is 57, plus the trend through June has been 15 additional gallons of products so, 15; so, this is 70. So, this is the first step smoothed value of the level at the end of July.

Second step is to smooth the trend the smoothed value for the trend factor end of July denoted by T July equals beta multiplied by the smoothed value of the average level in the month of July minus the same value computed 1 period ahead plus 1 minus beta into the trend factor 1 period ahead; that means June.

So, what we have done? We have substituted beta equals 0.1 because beta has been given as 0.1 multiplied by the smoothed value of the average level which is 70 which was computed in the first step minus the smoothed value of the average level till 1 period back that is up to June which is given as 57 gallons per month plus 1 minus beta that is 0.9 multiplied by the trend factor through June which is 15. So, this comes out to be 14.8.

So, forecast including the trend for the month of August standing at end of July equals the sum of these 2 components S July and T July which is nothing, but 70 plus 14.8 is 84.8 gallons. I think it is now very clear.

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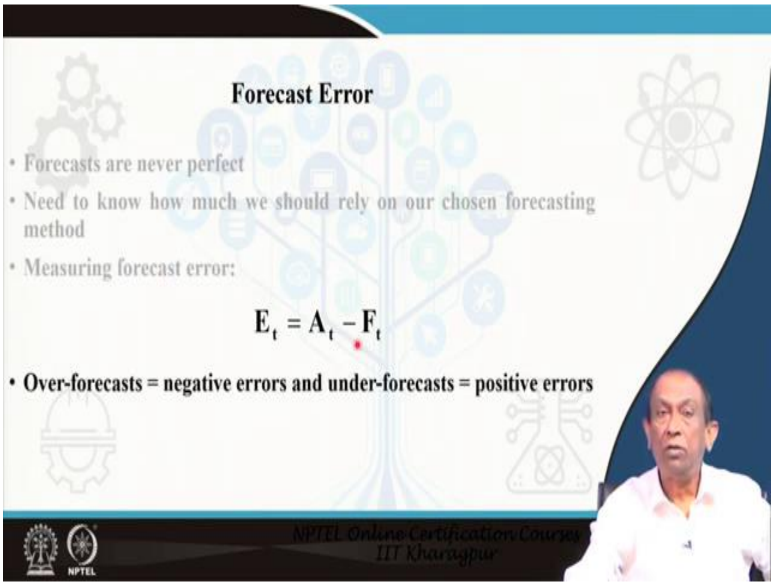

Next we had discussed that the forecast error for the period t is the difference between the actual demand that had observed; that had been observed in the t-th period is A t minus whatever was the forecast demand for the t-th period standing at the end of t minus 1th period which is F t. So, forecast error is given by E t equals A t minus F t.

We had also mentioned that forecasts are never perfect. There is always an error; a forecast is a forecast. So, we need to know how much we should rely on a chosen forecasting method. For this we need to keep track of the errors that get accumulated over several periods of forecast. So, we measure forecast error with this expression of E t equals A t minus F t.

Now, if this value E t comes out to be negative; that means, it is a negative error then it implies that we have over forecasts and if E t comes out to be positive then the forecasts is basically an under forecast.

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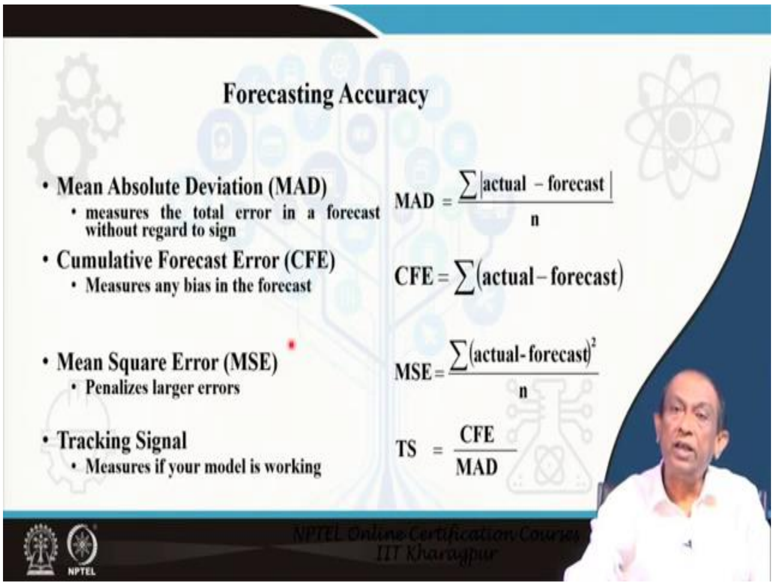

There are several indicators for measuring the accuracy of forecast. The most simple of them is the Mean Absolute Deviation popularly known as MAD. MAD measures the total error in a forecast without regard to sign.

That is why we basically take the absolute value of the difference between the actual demand and the forecast and we sum it over n periods that is why this summation symbol and divided by n, the number of periods for which these errors have been considered.

So, MAD stands for mean average Mean Absolute Deviation. We are taking the absolute deviation between the actual demand and the forecast demand, and then trying to take the average value of these absolute demand over n periods. So, it is basically sum over the absolute value of these differences between actual and forecast for period n divided by the number of periods n. So, this is one indicator or one measure of forecast error.

The second one is Cumulative Forecast Error; it measures any bias in the forecast, bias means error. So, cumulative forecast error is summation of the actual demand and the forecast demand over n periods. Here we are not taking absolute value. Whatever is the actual forecast error we are summing it up over n periods and that is why, we are saying that it is a cumulative forecast error.

Then Mean Square Error here we are first taking the difference between actual demand and forecast demand squaring it up and then we are summing this over n period and then divided by n; it is something like variance calculation. And we define tracking signal as TS which is the ratio of the cumulative forecast error divided by the mean absolute deviation.

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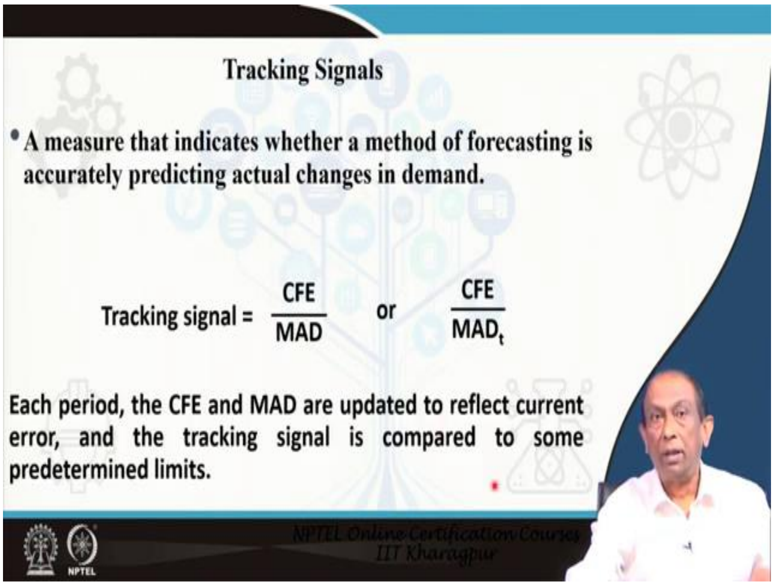

So, tracking signal is a measure that indicates whether a method of forecasting is accurately predicting the actual changes in demand; that means, whether the forecasting system is stable and consistent or not. So, the tracking signal has been defined as the ratio of the cumulative forecasting error divided by the mean absolute deviation.

Each period we compute the cumulative forecast error and the Mean Absolute Deviation MAD to reflect current error; that means we have to update the values of CFE and MAD for every period and then we compare the value of tracking signal with some predetermined limits.

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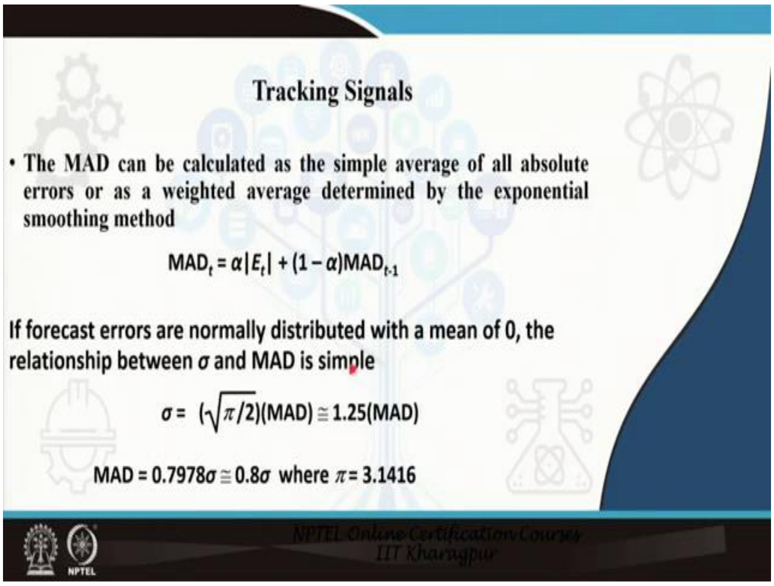

Also, while updating the value of mean absolute deviation we use this particular expression which is nothing but the mean absolute deviation for the period t; denoted by MAD t equals the smoothing constant alpha multiplied by the absolute value of error computed at the period t plus 1 minus alpha into the same value of mad computed 1 period ahead before that is MAD with a subscript t minus 1.

And, if we assume that the forecast errors are normally distributed with a mean of 0, the relationship between the standard deviation of forecast errors and Mean Absolute Deviation is very simple is given by this expression sigma equals root over pi by 2 into mad which is equal to 1.25 into MAD. Therefore, mad is nothing but 0.7978 sigma from this relationship equals almost 0.8 times the standard deviation of the distribution of error and with this expression sometimes we can also compute the mean absolute deviation.

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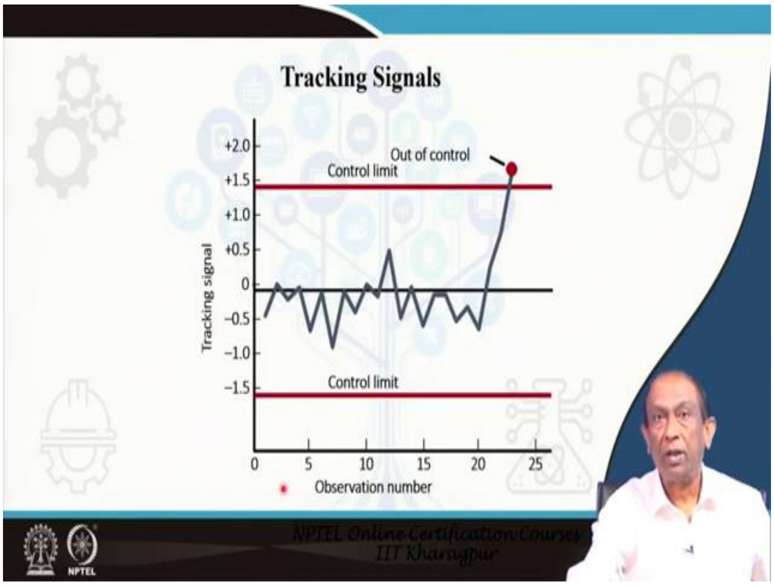

And, then we can draw control charts and plot the forecast errors. And, if any of these values fall outside the control limits then we can basically infer that there is some error that has crypt in, the forecasting system is not stable and we have to really find out what are the assignable causes for that whether the forecasting system needs any division or correction something like that.

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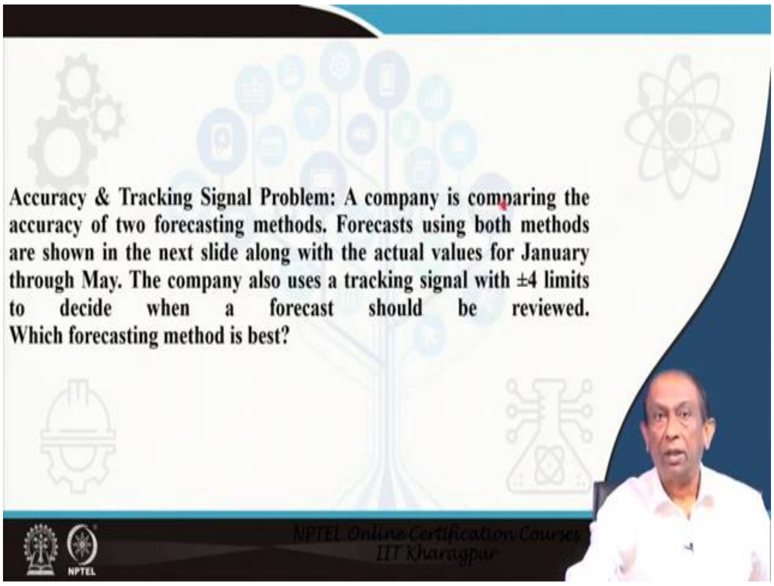

Let us look at this example. A company is comparing the accuracy of 2 forecasting methods. Forecast using both methods are shown in the next slide along with the actual values for January through May. The company also uses a tracking signal with plus minus 4 limits to decide when a forecast should be reviewed. Which forecasting method is best?

So, here you see the control limits value are plus minus 4.

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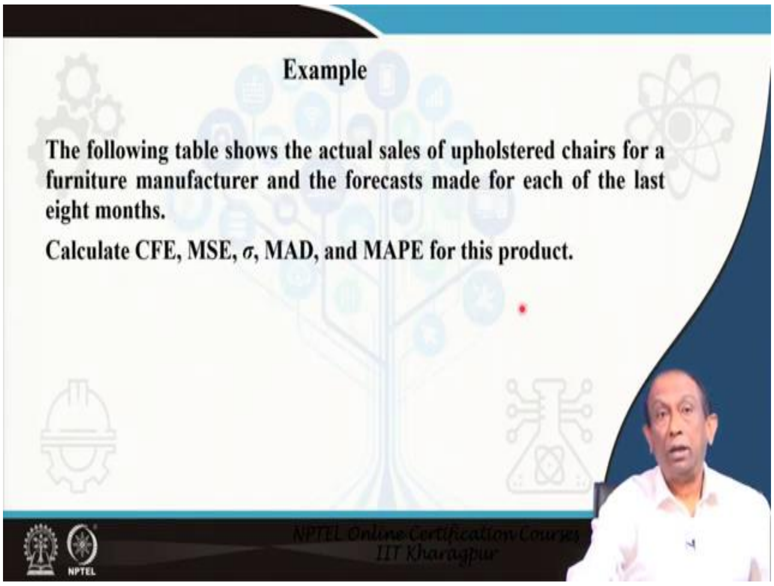

So, we will use the error.

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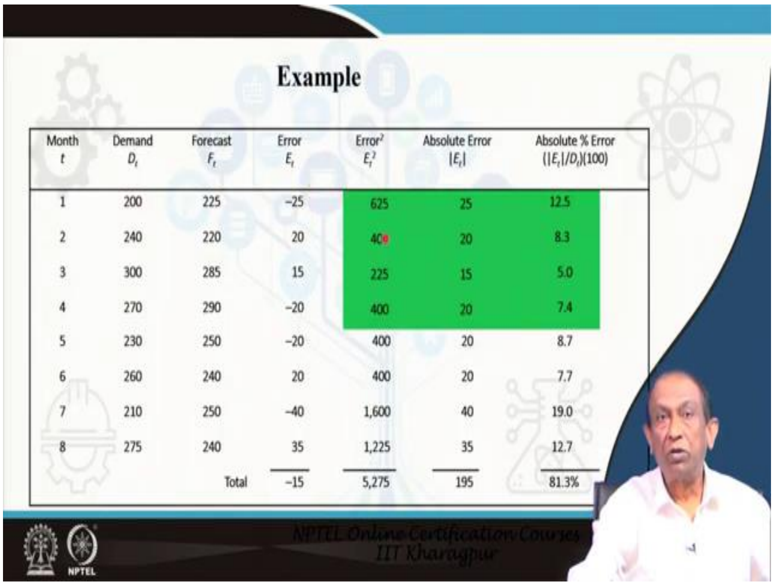

So, basically the values are given here the demand values and the forecast values and you see the errors have been computed for every period. The cumulative forecast error is minus 15 and then for every period we have to compute the square of the errors. So, we compute the square of the errors. We compute the absolute value of error for every period and we also compute the percentage of this absolute error using this expression.

And, the sum of the error square is this 5275, the sum of the absolute values of error is this, and the absolute percentage error is this much from this table. So, once we know these values whatever has been asked for in this problem becomes very simple to compute.

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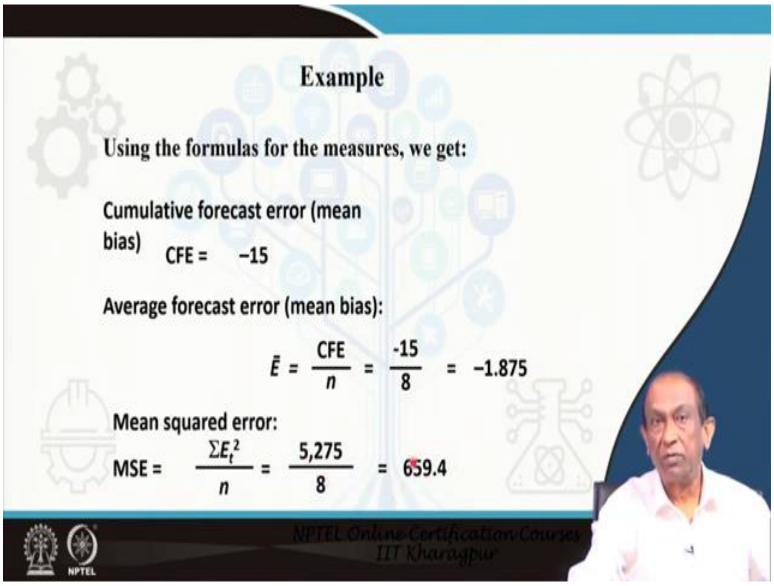

And, as you have seen from the last table that the cumulative forecast error which is also the mean bias is this much, average forecast error is this one and the mean squared error comes out to be this much.

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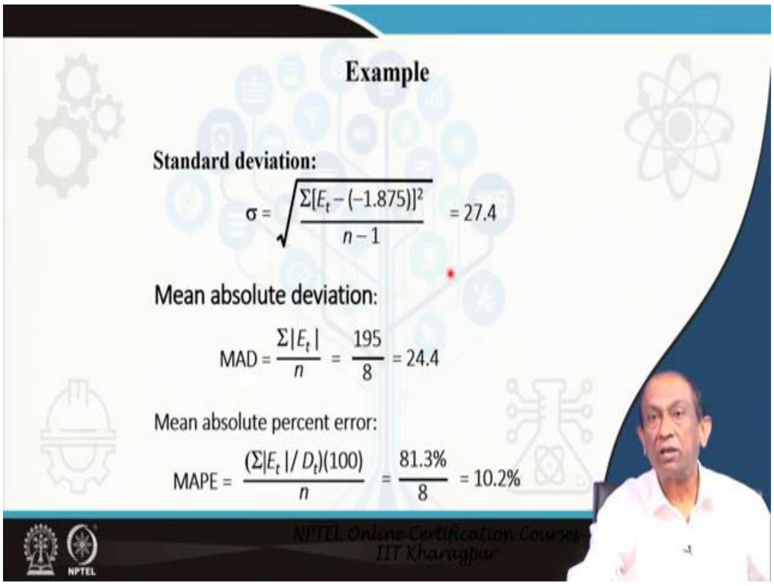

The standard deviation of error is again using the same expression and the data values that we have already computed comes out to be 27.4, mean absolute deviation is 24.4 and mean absolute percentage error from this expression is 10.2 percent. So, all the data's are already computed.

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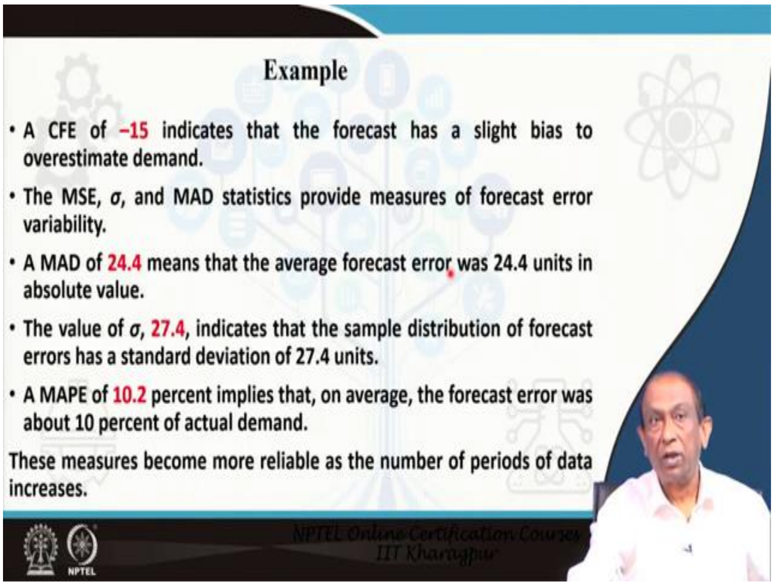

So, basically what is the implications? A cumulative forecast error of minus 15 indicates that the forecast has a slight bias to overestimate the demand. The mean squared error sigma which is the standard deviation of the distribution of errors and the MAD statistics provide measures of forecast error variability. MAD of 24.4 means that the average forecast error was 24.4 units in absolute value.

Similarly, the standard deviation of the distribution of errors has been computed to be 27.4 and the map value is 10.2 percent implies that on an average the forecast error was about 10 percent of the actual demand. Now, these measures become more reliable as the number of periods of data increases so that is why we take beta over a larger horizon.

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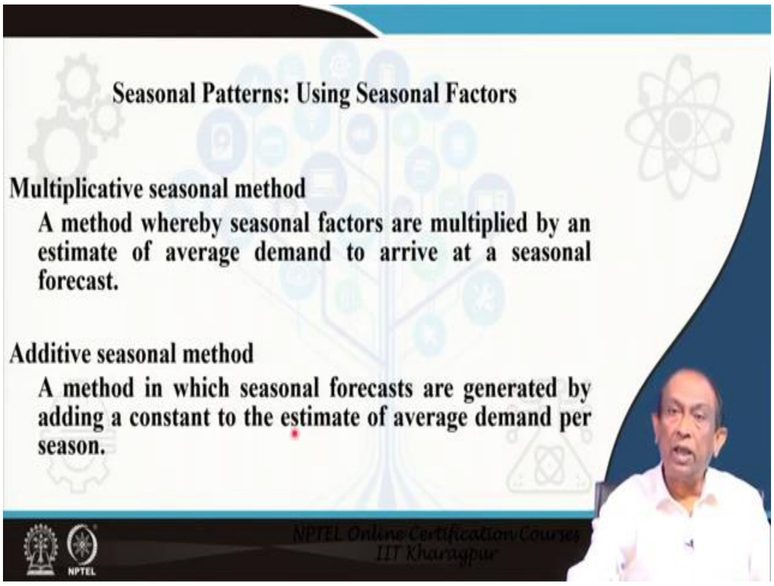

Then the next topic of our discussion is to compute the forecast when there is seasonality. So, there are two methods the first one the multiplicative seasonal method is more widely used. This is a method where the seasonal factors are multiplied by an estimate of average demand to arrive at a seasonal forecast. So, the task is to compute the seasonal factors.

Second method is almost same, only thing instead of multiplication the seasonal forecast are generated by adding a constant to the estimate of average demand per season. So, we will talk about only this multiplicative seasonal method because that is more widely used.

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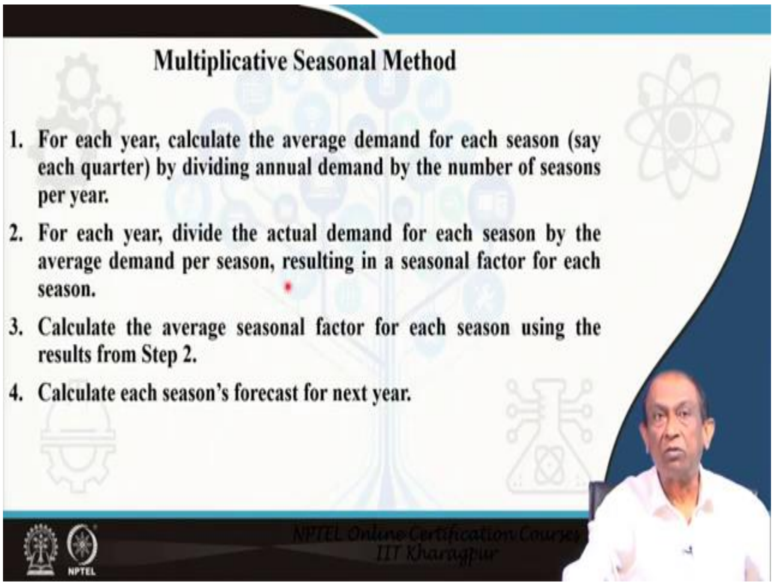

So, in the multiplicative seasonal method for each year first we calculate the average demand for each season, say the season is by quarter. So, for each year we will calculate the average demand for each season say each quarter by dividing the annual demand by the number of seasons per year. So, if it is a; you know if this season extends over a quarter, so, this value will be 4.

For each year, divide the actual demand for each season by the average demand per season resulting in a seasonal factor for each season. Then, we will compute the average seasonal factor for each season using the results from step 2, and then we will calculate the each seasons forecast for the next year.

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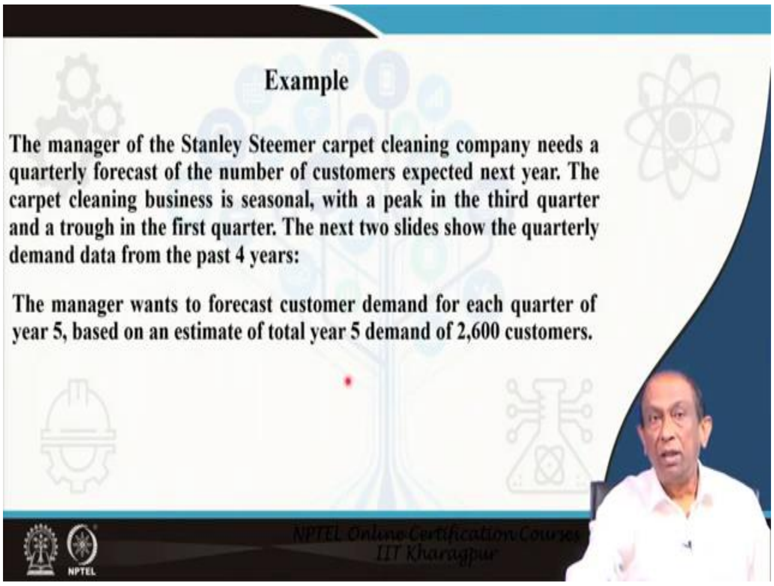

It will very simple if we look at this example. The manager of the Stanley Steemer carpet cleaning company needs a quarterly forecast of the number of customers expected next year. So, the carpet cleaning business is seasonal, with a peak in the third quarter and a trough in the first quarter. The next 2 slides show the quarterly demand data from the past 4 years.

The manager wants to forecast the customer demand for each quarter of year 5 based on an estimate of total year 5, demand of 2,600 customers.

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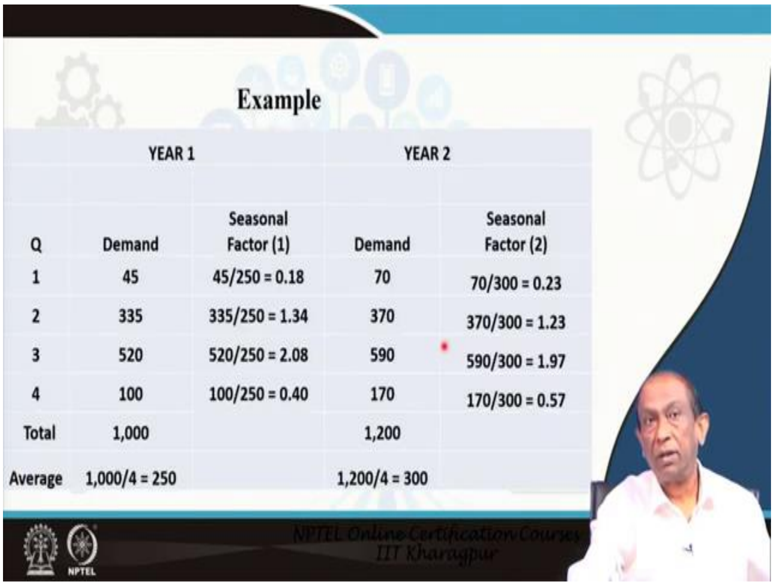

	YEAR 1		YEAR 2	
Q	Demand	Seasonal Factor (1)	Demand	Seasonal Factor (2)
1	45	45/250 = 0.18	70	70/300 = 0.23
2	335	335/250 = 1.34	370	370/300 = 1.23
3	520	520/250 = 2.08	590	590/300 = 1.97
4	100	100/250 = 0.40	170	170/300 = 0.57
Total	1,000		1,200	
Average	1,000/4 = 250		1,200/4 = 300	

So, this is the first year, you see there are 4 quarters. There is a peak in the 3rd quarter 520 and a trough in the first quarter. The sum of the demand for the 4 quarters is 1000. So, average quarterly demand comes out to be 1000 by 4 that is 250. Each quarters demand is then divided by the average demand for the year.

So, the seasonal factors are computed for the first year and have been given as 0.18, 1.34, 2.08, 0.4. We repeat the same for the second year and we calculate the seasonal factors for each quarter in the second year. Like this we compute it for the 3rd year and the 4th year.

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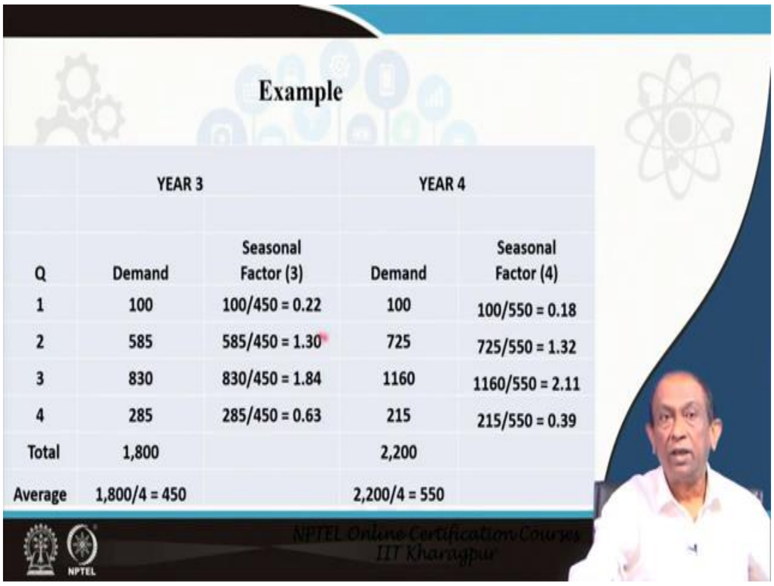

	YEAR 3		YEAR 4	
Q	Demand	Seasonal Factor (3)	Demand	Seasonal Factor (4)
1	100	100/450 = 0.22	100	100/550 = 0.18
2	585	585/450 = 1.30	725	725/550 = 1.32
3	830	830/450 = 1.84	1160	1160/550 = 2.11
4	285	285/450 = 0.63	215	215/550 = 0.39
Total	1,800		2,200	
Average	1,800/4 = 450		2,200/4 = 550	

So, for each year we compute the seasonal factors for every quarter and then what we do? We take these seasonal factors for every year for each quarter and then compute the average of that. That means for the year one for the quarter one we will take the seasonal factor add it with the seasonal factor for the quarter 1, for the year 2. Then add to that the seasonal factor for the quarter 1, for the year 3 that is 0.22 plus say 0.18 computed for the year 4 and then divide it by 4 to get the average value.

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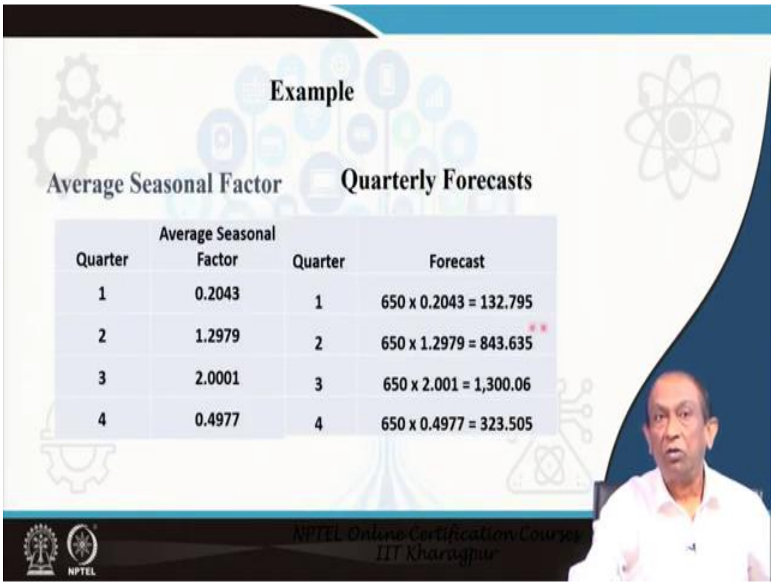

So, the average seasonal factors for all the quarters is computed for the quarter 1 it is 0.2043, for the quarter 2 is 1.2979, for quarter 3 it is 2.0001 and for the 4th quarter it is this. So, you see from the seasonal factors; you see that there is a peak demand in the quarter 3 and for quarter 1, there is a trough.

Now, for the next planning horizon; that means, for the 5th year it has been given that they expect that the total sales will be 2600 units. So, we divide it by 4 to find out the average level that is 650 units, then for each quarter we multiply it by the corresponding average seasonal factor for that quarter to arrive at the estimated demand for that particular quarter considering the seasonality in the demand pattern.

So, we do that and we find that the forecast for quarter 1 is 139.795 units for the 5th year and look at the demand estimated demand for the 3rd quarter for the 5th year is 1300.06. So, you see there is a peak here and there is a trough here and you will see that the sum of all these will lead to the total estimated demand for the fifth year which is 2600 units.

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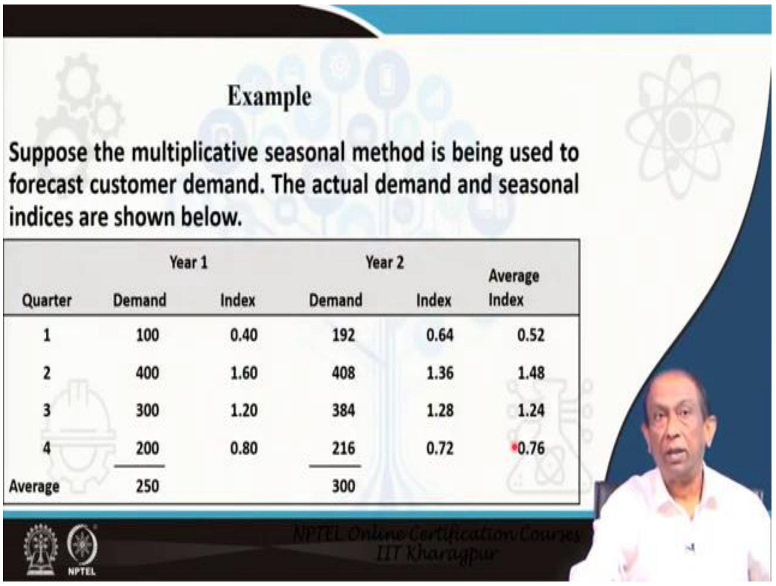

Similarly, another example. Suppose the multiplicative seasonal method is being used to forecast customer demand. The actual demand and the seasonal indices are shown; ok.

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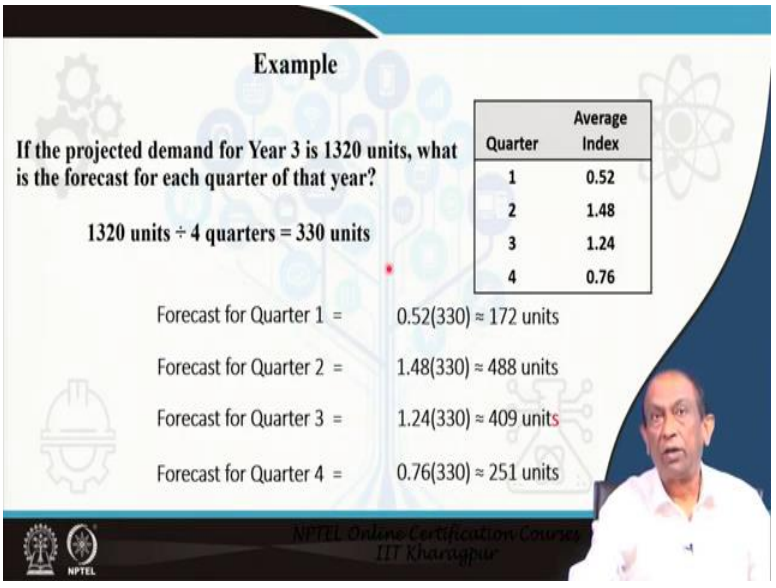

So, if the projected demand for year 3 is 1320 units. The problem is what is the forecast for each quarter of that year. So, we have found out this average index for each quarter then multiply it by this 330 units to get the forecast for quarter 1, quarter 3 and then quarter 4 the absolutely. This is easiest method, most simple way in handling seasonality ok. There are other complicated models like winters method for handling seasonality.

This is a versatile model to take care of both trend and seasonality. The only thing we need to introduce 3 smoothing constant alpha, beta and gamma.

And in any textbook on say, 'production and operations management' or any textbook on 'forecasting' extensively deals with that is Winter's method for forecasting. And, once we you know decide that we will deploy this kind of models in our decision support systems, we can easily you know there are lots of software course available. We can incorporate that in our forecasting system.

But, the idea is that once we get this results then the managers they have to basically review it and validate the outcome of this model and maybe it may call for refinement based on managers intuition, judgment and you know based on also the other factors that might influence is decision.

So, this is the essence of this kind of forecasting system.

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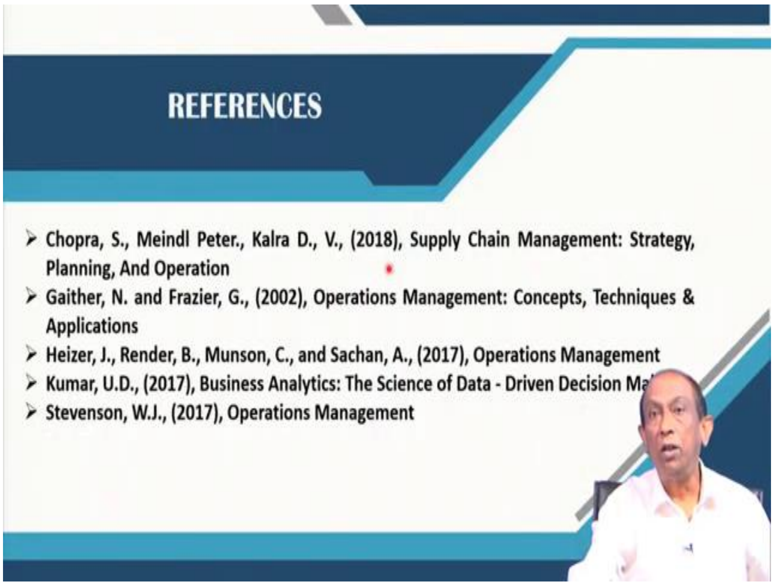

Thank you all! We have used these references for you know, explaining you this particular system. Well, there are lots of, you know, books on forecasting. So, I have consulted these books and basically from there, I have, you know, explained you this particular.

Thank you! Thank you all for the patience!