Supply Chain Analytics
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Lecture-11
Bullwhip Effect and Time Series Analytics

So, welcome participants, we are already discussing the role of analytics in the supply chain, and as part of the discussion, in our last session discussed the role of demand forecasting in the supply chain. And now we are moving to discuss some of the quantitative techniques which are the part of analytics to discuss the forecasting in an supply chain environment. As, we have discussed in last many sessions that forecasting is one of the primary building block for supply chain decisions.

And for that purpose it is very important to have a good forecast. We already know that forecasting is not the 100% accurate. There are always some errors involved, because we are predicting for the future, but how far we can predict correctly, how far we can minimise that error, that is what we are looking in an supply chain environment. Because, one of the very important factor which we have discussed in our earlier sessions also.

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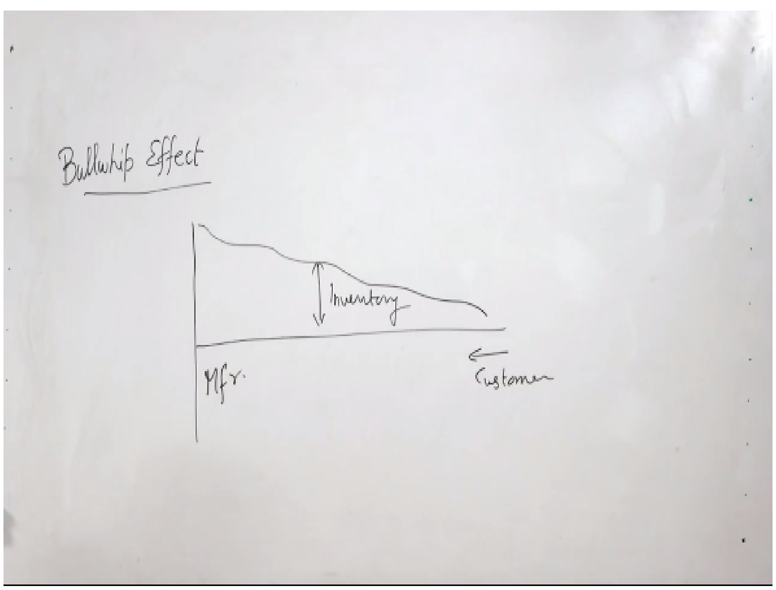

And, it is worthwhile to mention that again that is this bullwhip effect. This is one of the important you can say parasite, to the profit of a supply chain, because of poor forecasting, because of lack of trust in an supply chain, we do individual forecasting at different stages, and as we move from the customer side to the manufacturer side, you keep on pilling the inventories. And as a result of these inventories, the profit of your supply chain goes down.

So, now with the help of forecasting and forecasting particularly in a supply chain is to be the collaborative forecasting. We have different individuals manufacturers are there, wholesalers are there, retailers are there. So these are the individuals, and if I talk of country like India, where we have large number of supply chains which are unorganised. If I am a Maruti, if I am Hero, if I am Amazon, so, I have an organised supply chain.

But, in most of the cases we have highly unorganised supply chains, and, in those cases, the lack of trust, the lack of information sharing between various entities, result into this kind of bullwhip effect and because of this as I mentioned the profits of your supply chain goes down. So, therefore it is very important to understand that we do forecasting where you can have one forecast for all the partners, all the entities, all the actors of your supply chain.

And, that is what we are going to see that what are those techniques through which we can do this type of collaborative forecasting, and we can minimize these types of bullwhip effect, particularly the role of IT is worth mentioning in these types of activities, because of IT's involvement, information technologies involvement, I am ready to share the information from the retailers and to the manufacturers and at the same point of time.

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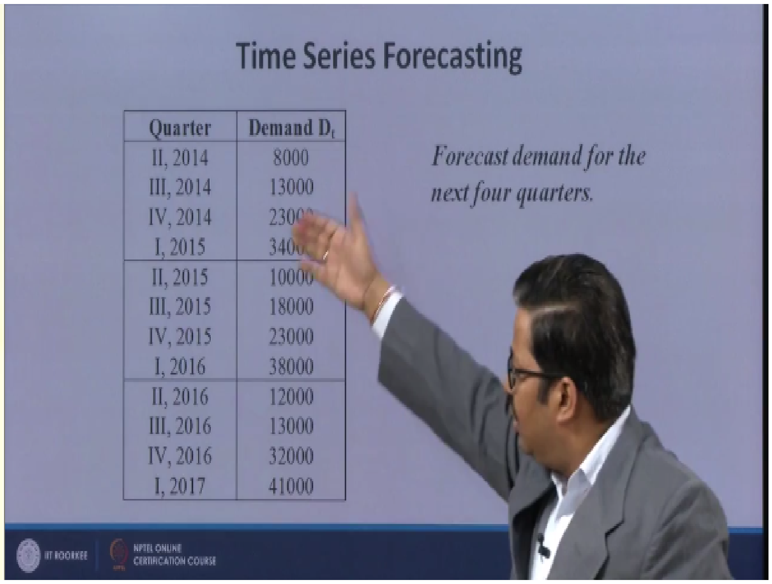

So, we will see that what are those techniques, now for starting because what are the different types of components of time series data, what are the different methodologies which are available we have discuss in our last session. Now we move ahead the some of the techniques which are available for the time series analysis and for doing the forecasting in collaborative environment. Now we have this data available with us on the screen.

This is the sales data and for 2014 to 2016, we have this data available. And now with the help of this data we will see that how can be forecast, we have discussed in our previous session, that time series analysis is one of the most important type of forecasting technique which is available to us. Now in that particular technique, we have also discussed in the last lecture that there are two types of you can say components of your demand data.

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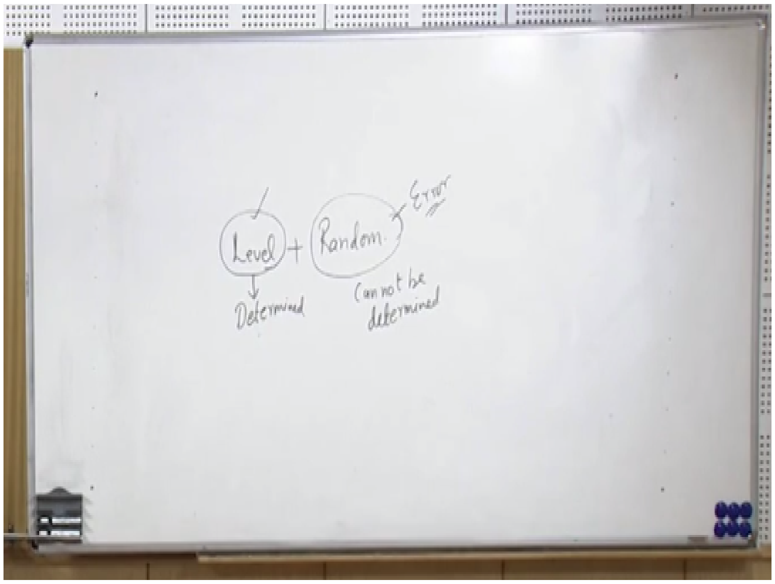

One component is the level component, and another component is the random component. Now this random component we attribute to the forecasting error, and level component is something which can be determined, and this cannot be determined, now it is important for all the students to understand that in all forecasting methods, we are only looking whatever type of model we are going to discuss.

Because, slowly and slowly we will start with the very simple model and then we will move to the complex models, we are only determining the level components, because this is something which we can determine, the random component cannot be determined and therefore this is attributed to the forecasting error. So, you have determined that the forecasting for second quarter of 2017 will be let say 42000.

This is what you have forecasted, but the actual demand happen to be 42500. So, this difference of forecasted value and the actual demand 500 is attributed to the random component. So, we will be not be able to actually forecast, what is going to be the actual demand. So, that is a limitation of the forecasting you can say, now let us try to see that how in the best possible manner we can determine the level components. Now, for that purpose let me start with the simplest method of time series.

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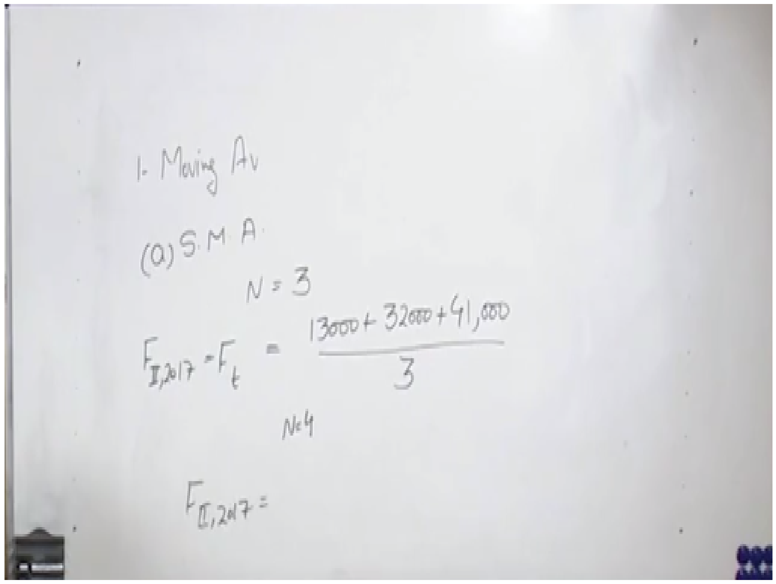

And this simple method is known as moving average method, this is the simplest method of time series. Now, the data is here, data is here for past many periods. So we collect this type of data and with the help of this past data. We will try to predict the feature and when I am saying the moving average method which is the building block of time series forecasting. In that case I take there are further a category of moving average method, which is known as simple moving average.

This is simple moving average and in this simple moving average, moving average means some period I am taking**.** So let us say if, I take a moving average period of N = 3 that is the period of moving average. So what I am going to do for the forecasting of the next period I will take the average of demand of most recent three periods. So here most recent three periods are 13000 + 32000.

And, the latest period is first quarter of 2017 that is 41000. So I will take these three most recent periods and I will take the average of this three periods and that will be the forecast of in fact this is the forecast of second quarter of 2017. So this way I will calculate the forecast for the second quarter. If I am moving average period is of 3. Now for a better forecast more accurate forecast I will like to increase the period of moving average.

If I take N = 4 and for calculating the same forecast for the second period of 2017.I will take the average of most recent 4 periods that is in this case second quarter of 2016, third quarter of 2016, fourth quarter of 2016, and first quarter of 2017. So If I am taking the average of these four recent periods it means my period of moving average N = 4. So, to have a better forecast I need to have higher value of N.

And that is the simplest method of time series forecasting where I am taking simply the average of most recent periods, the method is very simple. Therefore it has very limited applicability, wherever we have simple method it is various categorical statement I am giving you where the simple methods have limited applicability. So we need to see that what are the limitations of this particular method, one limitation is that.

Now you are seeing in this where N is 3 I am taking 13000, 32000, and 41000. Now here just by observation, you can see that there is a kind of seasonality in this data, I have not consider that seasonality in this data, and I have given equal weight, equal weight to all 3 past periods. One logic says. I should give maximum weight to the most recent period ,but, in this particular method.

I am giving equal weight to all 3 past periods. So, this is 1 limitation of this method, and, therefore I am not able to give due regard or due weight to the happenings or to the conditions of the most recent period, and I am giving equal weight. So, that is one limitation, the certain limitation is as I am saying for better forecast we need to have higher values of N.

Now, for higher values of N, I need huge amount of past data, you talk of simple automobile company, one automobile company making a car deals in more than 2000 different types of a smaller components, now when you want to forecast for those 2000 different types of components you need to have data for all those components. Take an example of company like Amazon.

Supplying more than 6 billion items as we used. Now you can imagine the amount of data, these companies need to manage for the forecasting to use this simple moving average method with higher values of N. So therefore it is very costly time consuming affair to have higher values of N, because of better focus. So these are the two very important limiting factor for this particular method. So, now let us go for slightly improvement on the simple moving average method.

And then we have other method which is known as waited moving average method. So, now let us see what is the weighted moving average method, and here in this weighted moving average method we give more weight to the most recent period.

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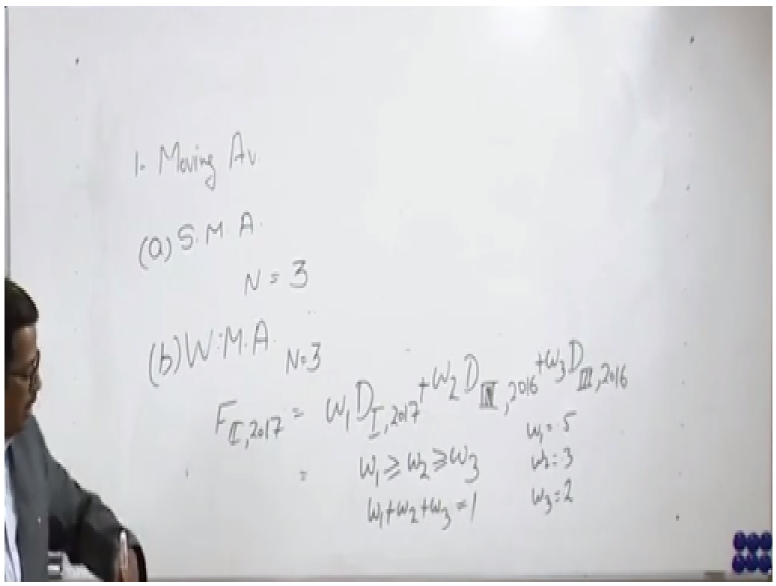

Again take an example where the period of moving average is 3, in this case also the period of moving average is 3 and is equals to 3, but, here I give more weight or maximum weight to the most recent period. So, the first quarter of 2000. If I am forecasting for the second quarter, I am forecasting for the second quarter of 2017. So, I will give maximum weight to the first quarter of 2017 and my weights will decrease.

As I go ahead from the most recent period to the furthest period. So, I have weights like W1which I will give to the demand of first quarter of 2017+W2 that is the weight given to the fourth quarter of 2016 and then W3 which is the weight given to the third quarter of 2016. And in this way we will determine the forecast, but I have to be careful that my W1 is greater than or equal to W2, we should be greater than or equal to W3.

And, another condition should be that W1, W2 and W3 sum of these 3 weights should be equal to 1. So, by this let say I give W1 as 0.5, W2 is 0.3, and W3 as 0.2. And then if I substitute these values Ws these values of weights in this particular equation I get a forecast where I am overcoming one of the limitation of my earlier method, that I am giving more weights to my most recent demand and my weights are decreasing, as I am moving away from first period to the further periods.

Again, the issue of better forecast will remain here in this case also, and, I can increase, by improving the values of N. So if I keep N equals to 4, so, I will have W1, W2, W3, W4 and accordingly I can follow the same rule to have weights differently. There is no set rule, to give the values of this weights, normally experts on their own, give the weights and with the experienced, with the exposure in a particular field.

With the exposure of a particular market, with the exposure of the external environment, experts are good enough to give these weights. Though there are some types of fiji mathematics systems are available to decide these weights when we invite some experts, and this experts may be in a group, and can think of what should be the appropriate weight, but here also there is a problem.

In this method, we have overcome one of the limitation that we are giving maximum weight is weight to the most recent period, and the weights are decreasing. But here also you have 2 important issues one there may be some reason, there may be a temporary reason because of which demand of a particular product in a particular duration has increased.

Recently in the October-November month of 2016 there was a problem around deepavali time in NCR reason, when a smog was there, and the result of that smog the demand of air filters, the demand of mask has increased drastically in that area. That is what a regular feature, that was a very temporary phenomena but, due to that temporary phenomena that demand has increased drastically for those products. But now if I am following the time series method of forecasting.

And, if that October, November data is there, where the demand has increased all of a sudden to a very high level, and I give maximum weight to that period. So, what will happen that, the same will carry to the next period also, but actually in the next period that phenomena of a smog is not going to be there, and therefore demand will going to be on a very low level. So, in some this exceptional situations I should know that I should not be assigning the maximum weights to the most recent period.

Because of the temporary nature of particular phenomena and therefore, we need improvement over this weighted moving average method also, that these types of temporary phenomena can also be handled. And therefore we move to the next category of time series analysis, where we can very well handle these types of temporary phenomena and these category of time series methods are known as exponential smoothing methods.

That there are certain reasons which may be permanent like if I talk of government employees in India. So, there was sixth pay commission and now over last 2 years employees are moving towards seventh pay commission and as a result of that the purchasing power of employees, government employees are increasing and therefore the demands of certain products may increase, but this phenomena is a permanent phenomena.

So, I need to incorporate this phenomenon in my forecasting model. So, there are certain things which are of temporary nature like the smog problem in NCR, I should not include those things in my forecasting method, and there are certain permanent issues like increasing the purchasing power of your customers. And that must include in my forecasting model. So, as a forecasting manager, as a supply chain manger I must understand that what is to be included permanently in my forecasting methods.

And what is to be excluded in my forecasting method, and the next method which we are going to discuss the exponential smoothing methods will take care that particular aspect, that what is to be included and what is to be excluded. Moving average methods are very simple calculation vice and these methods have therefore limited applications as I discussed.

But, just to start the concept of the moving methods, just to start to understanding that how methods can be adaptive. Because as you got o second quarter of 2017, you have new data available and then with that new data if you have and equals to 3 again. So, that second quarter sale, the first quarter sale, and the fourth quarter sale of 2016, these 3 sales will be used to predict the sale for third quarter of 2017. So, this method is automatically an adaptive method.

Whatever is the latest data available with you, that latest data is used for forecasting for the future. So, the method is continuously evolving, you do not have a static forecast for all the periods, whatever new data, whatever latest data is available with you, you use that data for moving ahead. So, that is the beauty of time series analysis, therefore the moving average methods whether it is simplest type of time series analysis.

Help us to understand what is the meaning of adaptive forecasting. So, whatever is happening whatever changes are happening there, those changes you are including in your forecasting method and continuously you are updating you forecast for next period.

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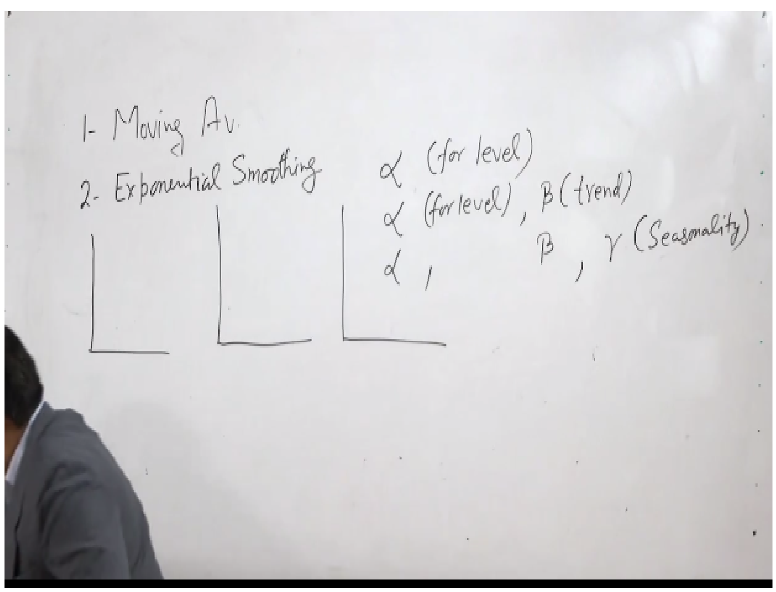

So, now moving to the second category of time series analysis, this is the most popular type of time series analysis which is known as exponential smoothing methods. Now as we discussed in our earlier sessions, that our time series data may have different type of components, time series data may have trend, time series data may have seasonality, time series data may have some kind of cyclic fluctuations. So, I need to see that what type of components my time series data may have.

And, therefore accordingly I will use my particular method of forecasting. But the philosophy of exponential smoothing method is that just to elaborate that this is for the demand data, for some of the periods. Now, you can see that this is not a straight line, this is a slightly zigzag line, now this zigzag line is around a particular dotted line, which is a straight line. So now in exponential smoothing method.

I will try to smoothen**,** the fluctuations of the actual demand data so that it can be represented by this dotted that is what we are doing. So, we use different types of a smoothening constants, we use different types of smoothening constants in this exponential smoothing method and by using those constants we will try to smoothen the fluctuations of actual demand data. So, that it can be represented by this dotted lines.

And, therefore, we need to understand which type of data we have and accordingly the number of smothering constants if there is no other component available in my data. So, I use only one smothering constant alpha, when no other component is available, I use just for level activities, I use 2 smoothening constants if I have trend also in my data and I use 3 smoothening constants one for level, one for trend, and another gamma for smothering the seasonality component.

So, depending upon type of data I have like this data very clearly shows the kind of seasonality I have, the demand in the first quarter of each month, each year increases to very high level, like here it is 34000, here it is 38000, and here it is 41000. And then in the second quarter of each year like here it is 8000, here it is 10000 and here it is 12000 decreases to a low level. So, this data just by observation without going for any kind of mathematics you can see that.

The kind of data we have represented here, is showing a type of seasonality into this. Now when this types of seasonality is built in to the data, we need to use different type of a smothering models, when only trend is there we need to use different type of smoothening model and when nothing is there only plane horizontal demand is there, and some kind of regular fluctuations are there. So, only one type of smothering constants are required that is alpha.

So, now let it may show you the representation of different types of curves which are possible because of this different type of components which are present in the demand data and you will appreciate that as my data will change the type of model will also be required to change. Now we can have nine possible combinations let me clear the board first, so that we can understand it in a better way.

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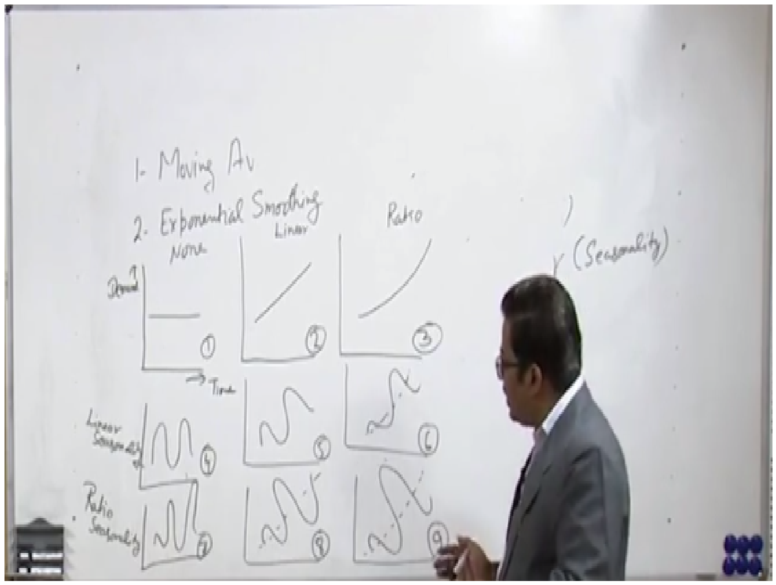

Now this is the demand data where know this X axis represents this time Y axis represents the demand. So there is no trend, no seasonality. So, demand is represented as a horizontal straight line with respect to time. Now you can have few more curves and these curves will help you to understand different types of components. Now first is there is a linear trend, linear trend like this over a period of time.

And then you can have multiple trend are the ratio trend, so which is represented like this way where demand is increasing in a multiple manner, and in all these three curves figure number 1, figure number 2, figure number3. You have only trend component present, here there is no trend, here is linear or additive, here it is ratio or multiple relative. Then come to figure number 4, here there is no trend but some kind of seasonality is present.

That demand increases to a high value in a particular period but there is no trend. Then you have demand where you have linear trend but linear seasonality also. So, here your curve is represented like this. And here you have linear trend but ratio seasonality, so around this curve you can think of this type of actual demand data. Then you have here I can write is the linear seasonality, and then you have ratio seasonality. In ratio seasonality you have demand increasing in season like here 34, 38, 41.

This type of increasing seasonality data is like a constant increasing data 4000, 3000 so it is more like a linear seasonality this type of seasonality, but it is possible that it is here 30000, 34000 then here it is like 60000 then it is 70000 or 750000. So the demand may increase in a ratio term also in the seasonal periods. So this is the ratio seasonality and when this ratio seasonality is compelled with the linear seasonality.

So you can think of the curve something like this. So which is earth and then you have the most extreme case where you have the ratio seasonality and ratio trend. So you will have the actual curve around this like this. So this is the ninth figure. So in all you have these nine different types of demand data sets which are possible and in our next session we will discuss the exponential smoothering method for some of this model and rest of the models you can develop on your own.

But we will see that how exponential is smothering method can we used for some of the models which we have discuss some of these different characteristics of demand data which are possible. So there are two important duties which are there, one is to identify the characteristic of your data that just by seeing it is almost impossible that what type of characteristics your data is showing and once you identifying the characteristic then appropriately use that model which is suitable for that particular case.

And the third thing will be the use of well use of alpha beta gamma as for the case may be. So these are the two three important things which we will discuss in our next session. Thank you very much.