

# M6L6b. Seasonal Analysis

## Slide #1



The slide cover is split into two main sections. The left section is a dark grey rectangle containing the Texas A&M University Engineering logo at the top, followed by the title "Seasonal Analysis (Part b)" in white, the name "Dr. Xiaomin Yang" in white, and the course information "TCMT 612 | Technical Management Decision Making" in yellow and white. At the bottom of this section is a red banner with the text "MASTERS OF ENGINEERING TECHNICAL MANAGEMENT" in white. The right section is a light grey image showing a person from behind, looking at a large screen. The screen displays a complex network diagram on the left and several hexagonal icons on the right, each containing a different data visualization: a bar chart, a scatter plot, a network diagram, and a line graph.

ATM  
TEXAS A&M UNIVERSITY  
Engineering

Seasonal Analysis  
(Part b)

Dr. Xiaomin Yang

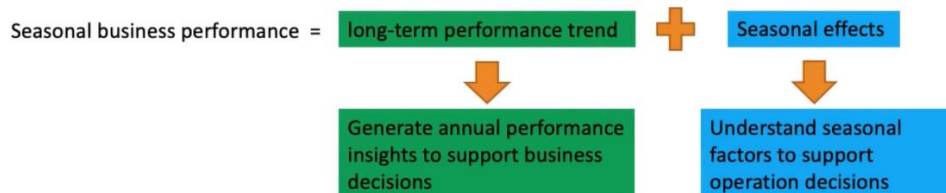
TCMT 612 | Technical Management  
Decision Making

MASTERS OF ENGINEERING TECHNICAL MANAGEMENT

## Slide #2

# Forecasting with Seasonality

Deseasonalizing model: separate long-term trend and seasonal fluctuation



There are several seasonal forecasting methods, but I recommend a decomposition model, which separates the long-term trend and the seasonal effects.

This practical method can distinguish the long-term performance, which is usually due to a company's competitive advantage, and the seasonal patterns, which are due to seasonal factors.

The long-term forecasting generates any performance insights to support business level decisions.

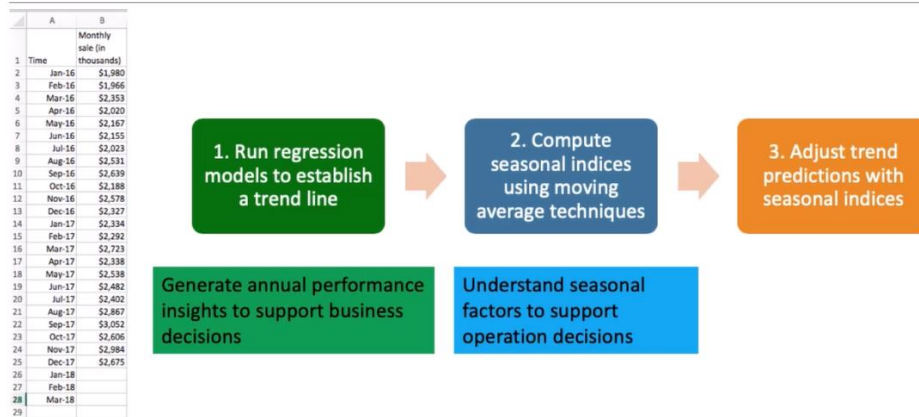
For instance, the annual growth rate can help managers decide the capital investment for additional production capacity, marketing strategy, and research and development spending.

The seasonal effect analysis can help the business understand seasonal factors to support operation decisions.

For example, the optimization of production and inventory, recruitment of temporary workers, and sales force.

### Slide #3

## Forecasting Seasonal Business Performance



The decomposition forecasting method consists of three steps.

The first step is to use a regression model to establish a linear trend line of the sales.

The trend line represents the long-term annual performance of the business or the product.

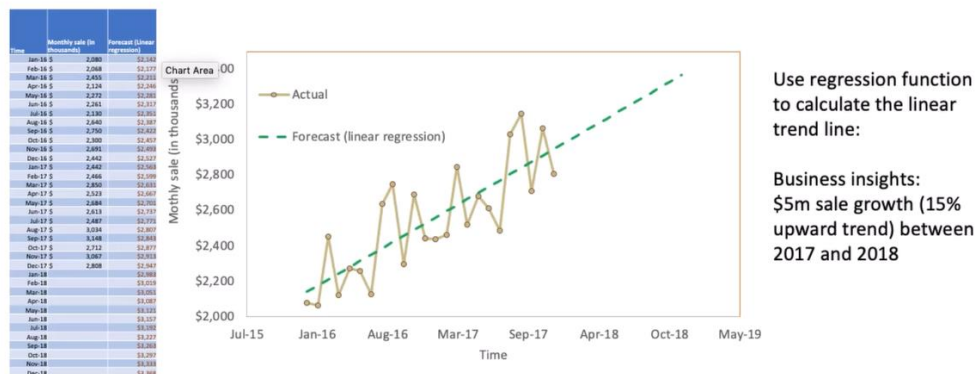
The second step is to compute a seasonal index of each month using the moving average methods. The seasonal index represents the seasonal effect of each month. The identified seasonal effect shall give operation managers some business insights to support operation decisions.

The last step is to adjust the trend prediction with the seasonal index to forecast the long-term future sales in each month.

Clearly, the decomposition method will not only forecast the future sales, but also provide business insights that managers can use to make business level decisions and operation level decisions based on the long-term trend and the seasonal fluctuations respectively.

## Slide #4

# Forecasting: Linear Regression



The first step of seasonal forecasting is the linear regression.

It is the same as we discussed in the previous lecture.

The linear function represents the relationship between monthly sales and time. The monthly sale of OCT machines grows at a consistent pace, which leads to an annual sale increase of 5 million. The projected annual growth rate between 2017 and 2018 is 15%.

The Microsoft Excel linear regression analysis is very simple, but we can still derive significant business insights from the linear trend analysis.

From this chart, we can clearly see the long-term growth of OCT sales between January 2016 and October 2017. And we can project the same trend into the future, into 2018 and even 2019.

Also, the graph shows a very regular pattern of fluctuation around the trend line. In 2016, sales were low in January and February. It increased in March and remained low in the second quarter of the year. The monthly sales jumped in August and it remained low in December. The pattern repeated in 2017.

## Slide #5

# Seasonal Indices

Sale forecast = sale trend forecast x seasonal indices

$$\text{Seasonal index}_{\text{month}} = \frac{\text{Actual sale}_{\text{month}}}{\text{Tme series moving average sale}_{12 \text{ months}}}$$

E.g. 12 month moving average

$$\text{Seasonal index}_{\text{Jan}} = \frac{\text{Actual sale}_{\text{Jan}}}{(\text{Average sale}_{\text{July 2016} - \text{June 2017}} + \text{Average sale}_{\text{Aug 2016} - \text{July 2017}})/2}$$

2016												2017											
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec

The second step is to compute the seasonal indexes of 12 months using the moving average method.

We use the multiplicative model to forecast the monthly sale with the below formula.

Forecast equals the sale trend forecast multiplied by the seasonal indexes.

A simple and effective way of modeling multiplicative seasonal effects is to develop seasonal indexes that reflect the average percentage by which sales in each month differ from their projected trend value.

We use the concept of moving average smoothing technique to calculate the seasonal index of each month.

The seasonal index of a specific month equals to the actual sale in that month divided by the moving average sale in the 12-month window.

The center of the 12 month window is the specific month.

We choose 12 month moving average window because the seasonal pattern repeats every year.

If the seasonal window is shorter than a year, you can choose a narrower moving average window.

I do not recommend a moving average window broader than a year because the older data may not represent the current business situation.

Since a year includes 12 months, the middle point is not at the exact center of the 12 data points.

There are 6 data points in the first half and another 6 data points in the second half.

So the middle of the year is either in the first half or the second half.

So we use the average of two adjacent 12 month windows.

For instance, to calculate the seasonal index of January 2017, we use the average of the moving average numbers of two 12-month time series windows.

One is between August 2016 and July 2017. The other window is between July 2016 and June 2017.

The two 12-month windows are shown in this spreadsheet table.

And we can see that January is at the beginning of the second half of the first 12-month window and it is also at the end of the first half of the second 12-month window.

That is the reason we use two 12 month moving average windows to calculate the time series moving average sale in 12 months.