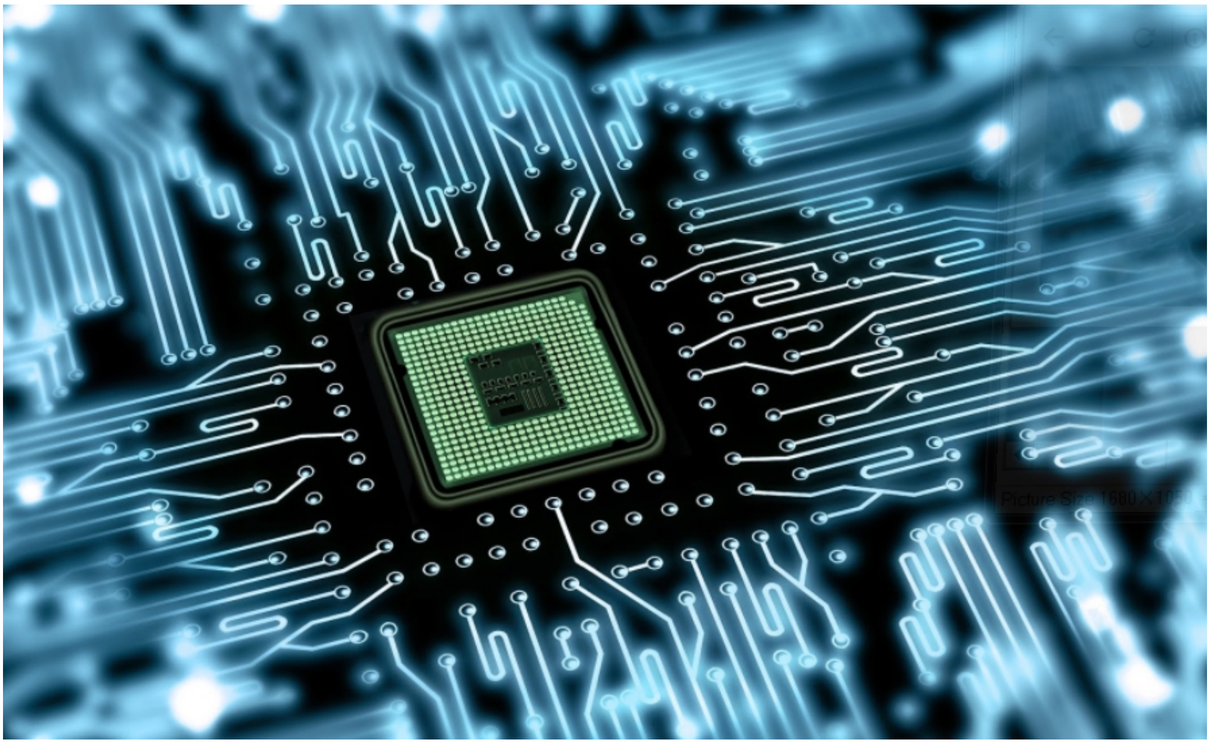
SUBMISSION ENTRY TO MICRON NUS-ISE BUSINESS ANALYTICS CASE COMPETITION 2022



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1. Micron's Role

One reason for the shortage of semiconductors is that the manufacturing process takes a long time from design to mass production (Semiconductor Industry Association, 2021). As one of the biggest chip makers in the industry, Micron plays a role in easing the shortage by investing in new technology or research & development. It can develop leading-edge chips for autonomous cars, IoT, AI, and other areas (McKinsey and Company, 2022). Micron plans to meet demand by upgrading its product lineup to advanced memory technologies, including its 176-layer 3D NAND and 1-alpha node DRAM, which boosts memory density (Micron, 2021). As manufacturing takes the longest time in the supply chain, if Micron manages to boost productivity with new technology, more semiconductors can be delivered to the customer faster, thus increasing the supply and easing the semiconductor shortage.

2. Impacts on Micron

2.1. Positive Impacts

The global shortage of semiconductors causes the Singapore Government to have favourable policies for chipmakers like Micron. Singapore is now having ambitions to grow across the value chain[1] in the semiconductor industry and support areas like research and development and regional distribution (Dylan, 2021). One such example is the opening of Micron's Technology's expanded fabrication plant in 2019. According to Micron, this expansion would be useful for the production of advanced 3D NAND technology to satisfy the rising demand (Eileen, 2019). Consequently, Singapore has seen a surge of inward investment in its semiconductor industry (Misha, 2021). These events indicate the Government had various policies to support the growth of the semiconductor industry as Singapore is trying to catch up with other chip-making powerhouses in Asia (Dylan, 2021). It tries to strengthen the semiconductor ecosystem, which includes the collaboration of the manufacturer and the supplier. Hence, semiconductor manufacturers like Micron are likely to benefit from a stronger ecosystem and easier licensing to build fabrication in the country (Masayuki, 2017).

Another positive impact for Micron is the increase in total revenue. The surge in derived demand for semiconductors is due to the higher demand for technological gadgets for people to work from home. Strong demand and an industry-wide shortage of chips have also allowed

[1] Value chain of semiconductor includes chip design, wafer fabrication, assembly, testing,...

Micron, one of the biggest memory chip suppliers, to charge higher prices (Akash, 2021). Due to a sharp increase in demand, the total revenue of Micron increased, which leads to higher profits assuming costs are the same. As shown in Figure 1, the total revenue of Micron has increased from 2019 to 2021. Hence, Micron will have funds to reinvest in R&D or other fields to increase its capacity in the future to meet rising demand.

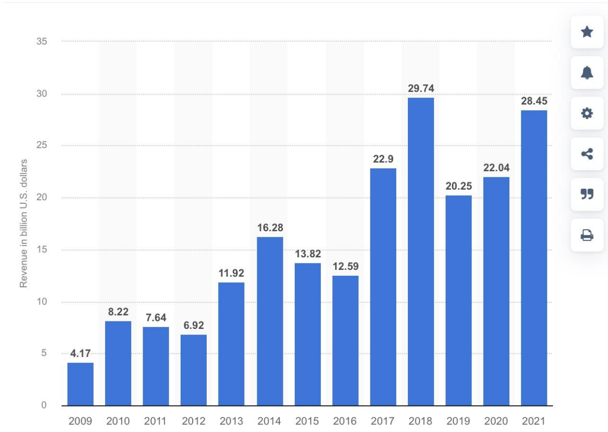

Figure 1. Micron Technology Semiconductor Revenue Worldwide from 2009-2011 (in US$b) (Statista, 2021)

2.2. Negative Impacts

One of the closest competitors of Micron in the area of memory chips is Samsung Electronics (Kim Yoo-Chul, 2020). Samsung produces both semiconductors and electronic gadgets. For example, Samsung produces Exynos chips for its own Galaxy S22 (Ayush J, 2022). From the Supply Chain Management, Samsung is both the manufacturer and the customer of its chips so it can either use or sell them. Meanwhile, since Micron only manufactures chips, it needs to sell them to external customers, which means Micron needs to undergo more steps in the Supply Chain (distributing and retailing). Therefore, Micron experiences a longer delay time than Samsung. Consequently, the Supply Chain management of Micron is less productive as compared to its competitors, so its revenue is lower. More steps in the supply chain also means a higher cost of transportation and risks (Girteka, Logistics, 2021). While Micron needs to go through a full cycle for its supply chain management because it plays only one role in the chain, other firms such as Samsung or even Intel can have shortcuts as they play several roles (Intel is the supplier and manufacturer while Samsung is manufacturer and customer). Hence, Micron generally gains lower profits than other competitors. In terms of memory chips, in 2020, Micron's profit was US$65,52M (Yahoo Finance, 2022) while that of Samsung was US$15,053M (Samsung, 2021).

The chip shortage has prompted the chipmakers to either expand their production or shorten their lead time by investing in R&D (Yangzhi, 2021). Micron, as a semiconductor manufacturer, is also forced into this race to meet rising demand. However, as mentioned, Micron is currently having lower profits than other leading firms in the industry, such as Intel or Samsung. Hence, as compared to these firms, Micron has less financial ability to expand and invest in R&D, which is a huge disadvantage for Microns in this race to increase production. R&D may not give certain results (Will K, 2021), which means that Micron has a higher risk of loss than other firms. Expanding fabrication for higher capacity also takes a lot of time and money, assuming Micron and other chipmakers spend the same amount for expansion, lower profit by Micron will mean larger opportunity cost and Micron will have less funds to invest in other fields like R&D.

II. Task 4.2: Strategies to Handle Chip's Shortage

1. Task 4.2.1: Demand Forecasting

Please refer to the folder named "P_VaaT_Supporting_Document_Q2.1" for the workings of this section.

The demand for microchip is time-series data as it is a series of data points indexed (or listed or graphed) in time order. Hence, time-series forecasting analysis is implemented to study the insights of given historical demand as the use of a model - whether it is computationally calculated or mathematically fitting - is to predict future values based on previously observed values.

In our work, we will explore a few computational models and mathematical models to approximate and curve-fit the given data points of historical demand. With such a foundation, we will be able to choose the best model. Our final model, which is the sinusoidal curve model, utilises all historical data to train. However, in order to see which is the best prediction model, we first need to split our data into training and testing sets. We have split the training and testing data by 70% - 30%. All models are trained using the training data set (Week 1-182) and all models are then evaluated using the testing data set (Week 182-260) to see their performances. Next, a comparison of R-squared and correlation is done to evaluate the most accurate and best-fit model to forecast the demand in the next 2 years.

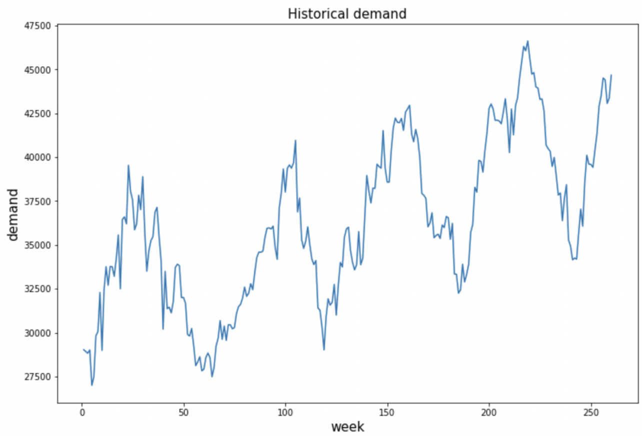

Figure 2. The Plot of Historical Demand

From our inspection, the graph of the historical data of Product suggests that the semiconductor industry is cyclical which coincides with our research (Tagare, 2019). This means that the historical demand features an additive seasonality time-series (Hayes, 2021)

(Figure 2). Hence, several mathematical and computational techniques of time-series analysis and forecasting models have been used to study the insights of given demand data. These include:

- Sinusoidal Curve;
- Holt Winter Seasonal Method;
- Holt Exponential Smoothing;
- Seasonal Auto-Regressive Integrated Moving Average (SARIMA); and
- Multi-Variable Linear Regression.

1.1 Sinusoidal Curve

Since a sinusoidal curve is a periodic function, we believe that the seasonality of the demand of Product A can be modelled to fit a sinusoidal curve. We approach this cyclicality as additive seasonality which can be represented by the general equation:

$$y(t) = T(t) + S(t) + Noise$$

where t represents the number of weeks since 2017-01,

$y(t)$ represents the model time series,

$T(t)$ represents the trend, and

$S(t)$ represents the seasonality.

In this scenario, from inspection, $T(t)$ can be represented with a linear graph while $S(t)$ can be represented with a sinusoidal graph. With noise being randomly generated values, our model will generalise the noise and assume that it is zero for the forecast. Thus, our general equation will be:

$$y(t) = at + b + c \sin sin \, (dt + e)$$

We start off by finding the coefficient of the trend, a, and the vertical intercept, b, first. Using Excel's Linear Regression with our train data set (not full historical data), we found out that the most optimised values of a and b are 39.299 and 30956 respectively.

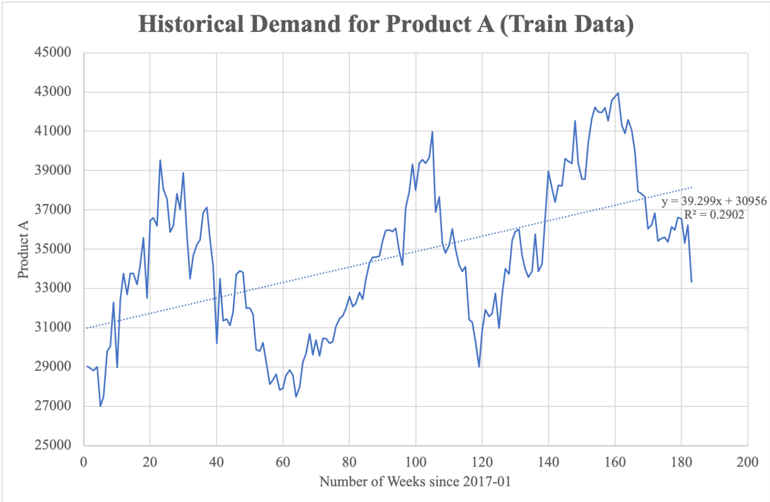

Figure 3. Linear Regression of Train Data

Now, our equation is:

$$y(t) \ = \ 39.299t \ + \ 30956 \ + \ c\,sin\,(dt \ + \ e)$$

Next, we are calculating the seasonality function. After rearranging the equation, we get:

$$y(t) \ - \ 39.299t \ - \ 30956 \ = c\,sin\,(dt \ + \ e)$$

which can be represented graphically as shown below:

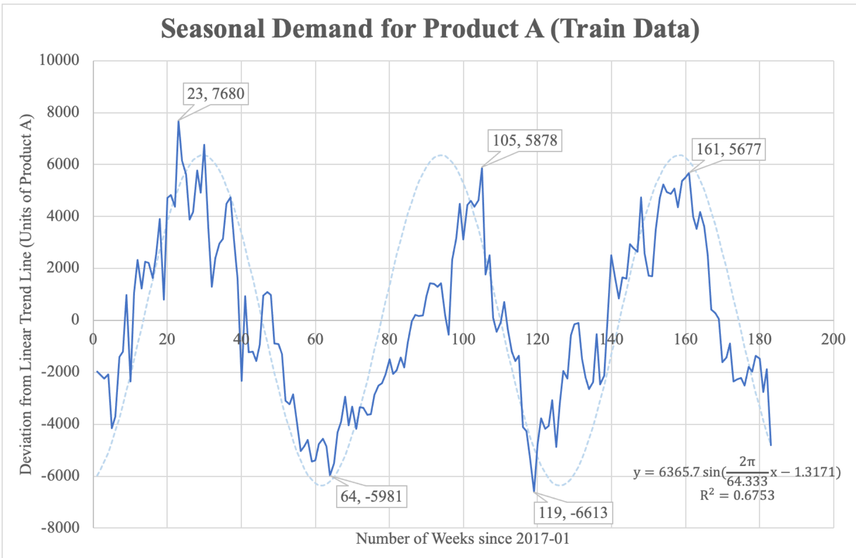

Figure 4. Plotting of Rearranged Equation to Get a Normal Sinusoidal Shape

The value of c is calculated by finding the average amplitude of all peaks and throughs, which comes out as 6365.7. The value of d is calculated by finding the period which is found by the average weeks between all peaks and throughs. The period is 64.333 weeks, which makes d to be $\frac{2\pi}{64.333}$. The value of e is optimised such that the R-squared of our equation with the time-series $y(t)$ is minimum, which comes out as -1.3171.

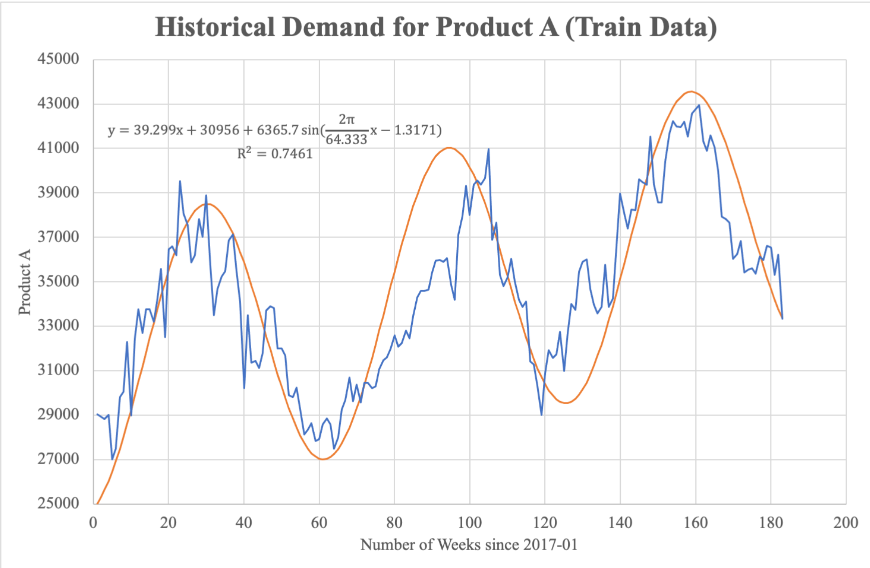

Figure 5. Historical Data Curve-fitting by Sinusoidal Graph

Thus, the final equation for this sinusoidal model is:

$$y\,(t) = 6365.7\,sin\left(\frac{2\pi}{64.333}t - 1.3171\right) + 39.299t + 30956$$

1.2 Holt Exponential Smoothing

Holt Exponential Smoothing (HES) can be used for forecasting time series data that exhibits both a trend and a seasonal variation. HES is built upon Exponential Smoothing - a model that forecasts the next value using a weighted average of all previous values where the weights decay exponentially from the most recent to the oldest historical value.

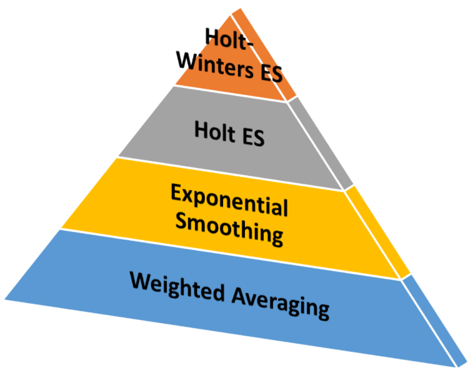

Figure 6. The Foundation of the Holt ES and the Holt-Winters ES Methodologies

A single exponential smoothing line is built to fit the demand data, followed by other 2 exponential smoothing lines (double smoothing line and triple smoothing line). Overall, the triple line model fits the data the best.

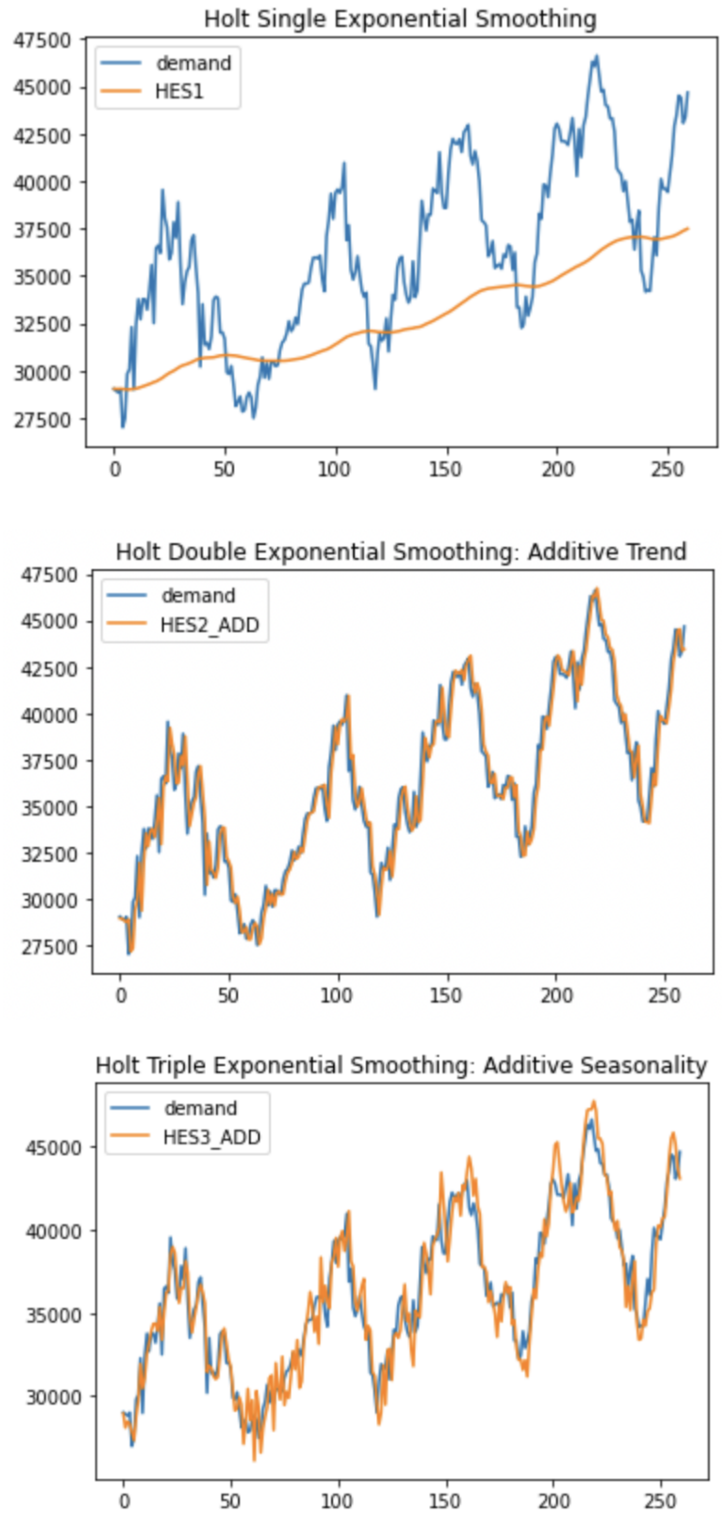

Figure 7. Curve Fitting by HES using Single, Double & Triple Exponential Smoothing

From Figure 7, despite well curve-fitting by triple exponential smoothing of HES, when carrying out the forecast training, the inaccuracy of HES is unfortunately significant (Figure 8).

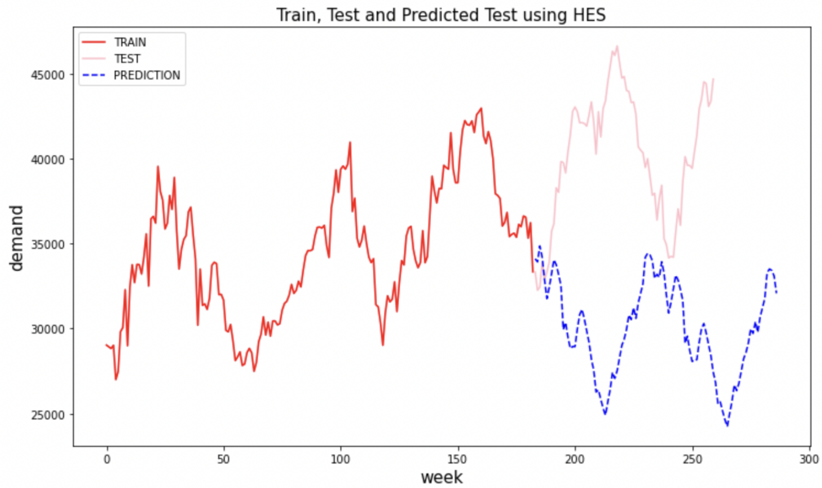

Figure 8. Comparison of the Actual/ Test Data (Pink Line) and Prediction/ Forecast (Dotted Blue Line) of the HES Model

1.3 Holt-Winter Seasonal Method

Holt-Winter Seasonal Method was introduced by Holt (1957) and Winter (1960) to capture seasonality and is built upon HES. The Holt-Winter Seasonal method comprises a forecast equation and 3 smoothing equations - one for trend, one for seasonality and one for residue. The decomposition of additive demand data is as below:

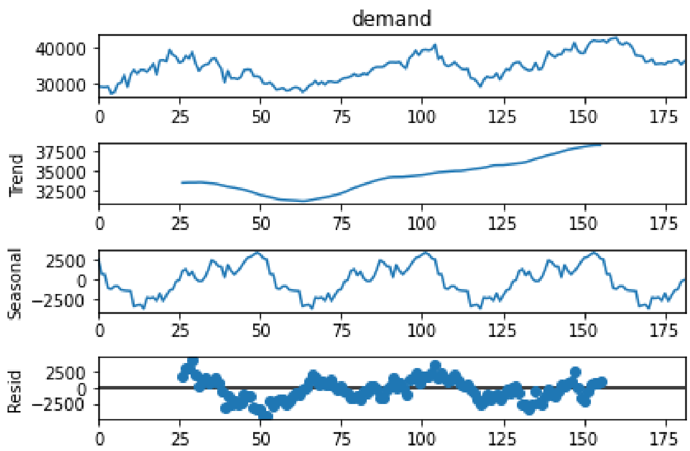

Figure 9. Decomposition of Additive Time Series Demand Data

Computationally fitting the Holt Winter Seasonal (HWS) method into the historical demand data, the model yields a close approximation to historical data (Figure 10a). Although HWS is claimed to be useful for data that has both trend and seasonality — similar to our given historical demand data based on the decomposition of such data, HWS, in this case, is not a suitable model due to large inaccuracy in forecasting despite the small deviation in curve-fitting (Figure 10b).

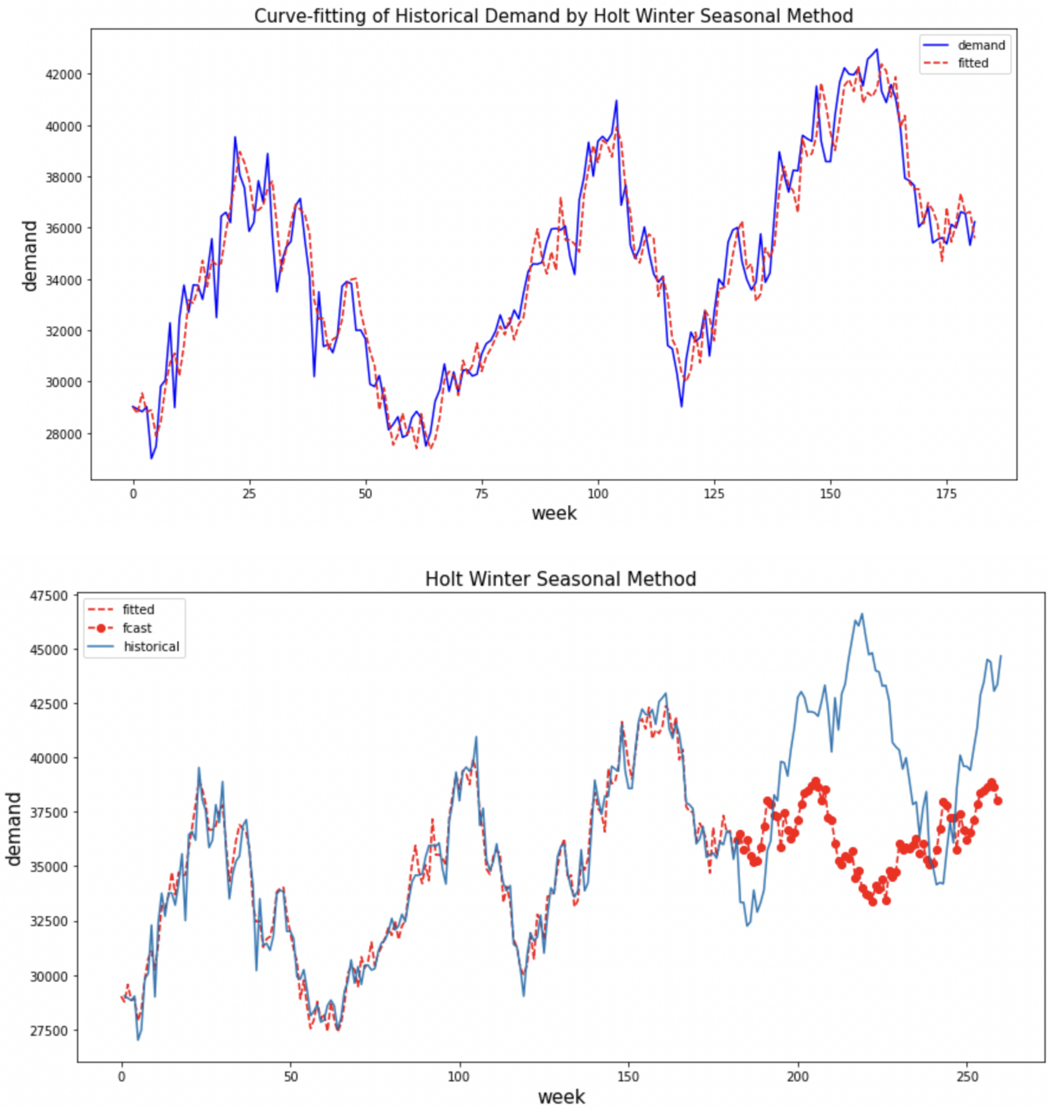

Figure 10. Curve-fitting (a) & Forecast Training by HWS (b)

1.4 Seasonal Auto-Regressive Integrated Moving Average

Similar to HES and HWS, Seasonal Auto-Regressive Integrated Moving Average (SARIMA) is also a popular time-series forecasting model which involves three parts: autoregression, integration, and moving averages. Carrying similar steps in curve-fitting and forecast training to the HES and HWS models, the SARIMA model gives a better prediction due to smaller variance than HWS and HES.

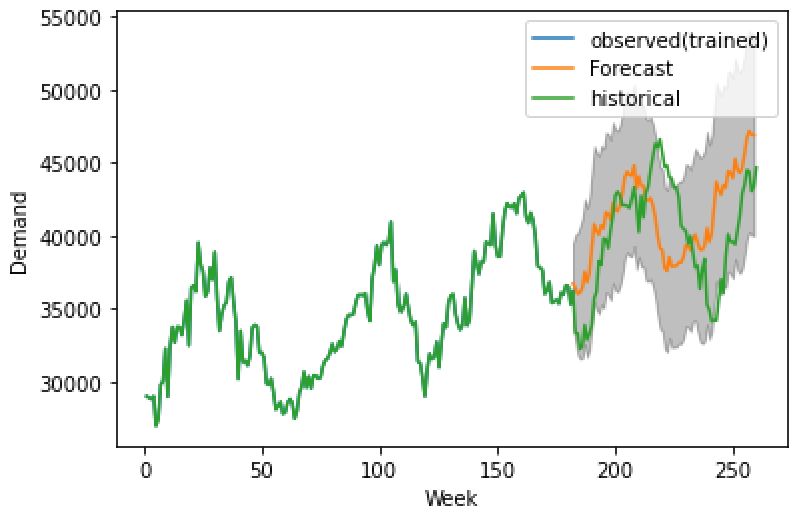

Figure 11. Forecast Training of SARIMA Model

1.5 Multi-Variable Linear Regression

Multi-variable linear regression is one of the most common ways to produce a forecast model when there is seasonality involved. In our training model, we assume a seasonality based on the number of weeks since the start of the year. Hence, we employ a 52-variable linear regression — 51 variables influencing the seasonality and 1 variable influencing the overall trend — and use machine learning to optimise the 52 variables such that the R-square is minimised. However, from Figure 12, we noticed that linear regression based on the week number does not work well since there is little to no trend between the week number and the data of each year.

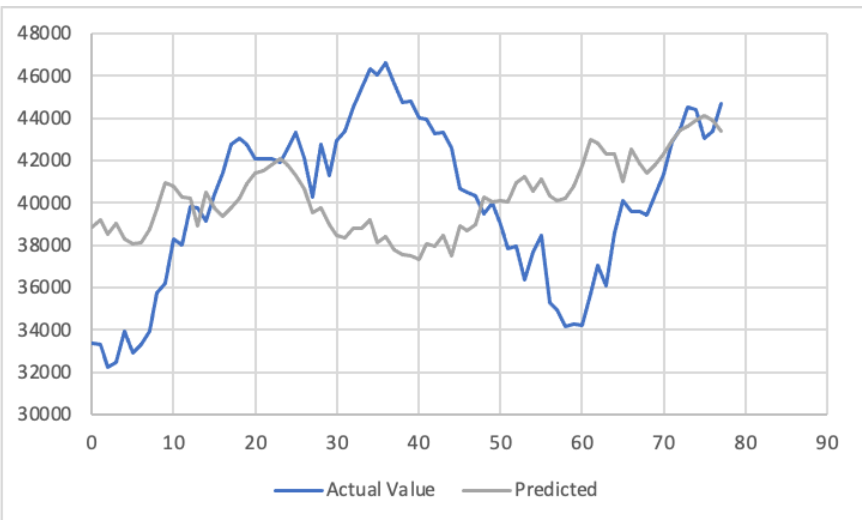

Figure 12. Testing of the Multi-Variable Linear Regression Model

1.6 Choosing the Best Model

A visualisation of all five suggested models is sketched to compare the accuracy among the forecasting models.

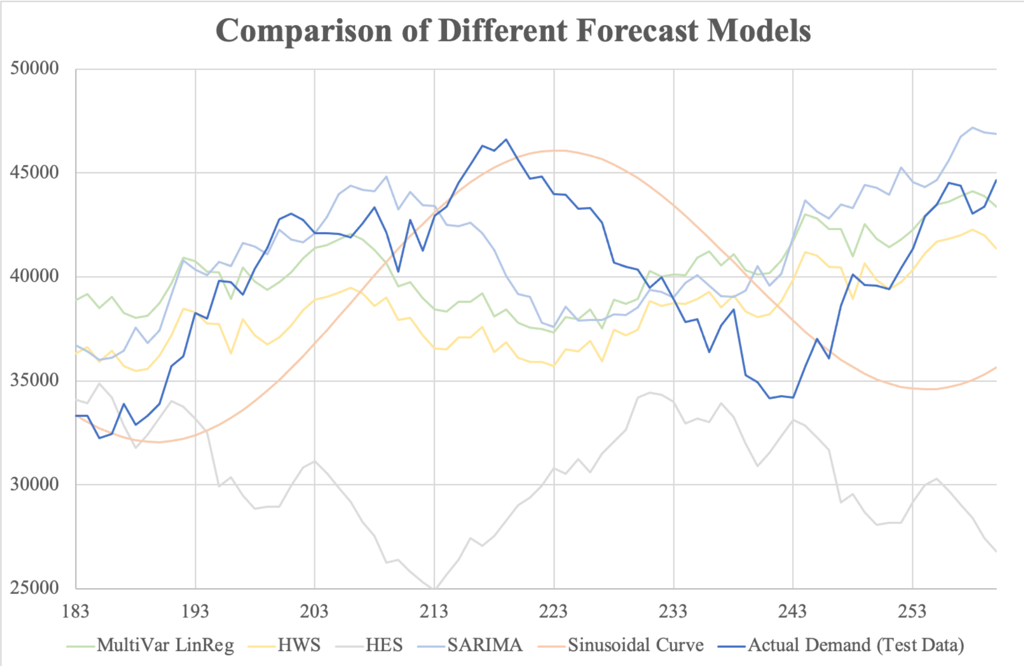

Figure 13. Comparison of Accuracy of the Five Forecasting Models

Statistically, a summary of correlations and R-squared values of the mathematical sinusoidal model and 3 computation forecasting models are studied and presented below:

Model	Sinusoidal	HES	HWS	SARIMA	MultiVar LinReg
R-squared	0.2592	0.4655	0.0100	0.2154	0.0002
Correlation to Actual Data	0.5091	-0.6823	0.1000	0.4641	0.0129

Table 1. Summary of Forecasting Models

R-squared value and the correlation to the actual data of the sinusoidal curve is the highest among the five models, suggesting the greatest accuracy among the suggested four. Despite being hardly seen to be used in prediction models as such mathematical function usually fails to predict the noise that departs from the trend or seasonality (Shah, 2017), we will employ the sinusoidal curve model for our analysis hereafter since it is the best in this case.

1.7 Using the Best Model to Forecast

After deciding the best modelling method, which is the sinusoidal curve method, we follow the steps outlined in Section 1.1 and found out the final forecasting model that we will be using hereafter:

$$y(t) = 6425.9sin\left(\frac{2\pi}{62.5}t - 1.3171\right) + 41.524t + 30809$$

where t represents the number of weeks since 2017-01.

The equation is then used to forecast the demand for Product A for the next 2 years starting from 2022-01, which is recorded in "P_VaaT_Supporting_Document_Q2.1_Forecasted_ Demand.csv".

2. Task 4.2.2: Machine Capacity

Please refer to the folder named "P_VaaT_Supporting_Document_Q2.2" for the workings of this section.

2.1 Key Assumptions

1. Utilisation (%) and Availability (%) always stay constant over time.
2. Every machine has already been working for a period of time. Thus, no extra time is required to start the machines.
3. Transportation time between machines is negligible.
4. Wafers are transported between machines using a Front Opening Unified Pod (FOUP). There are an unlimited number of FOUPs available.
5. A machine cannot process two steps at the same time.

2.2. Calculations

In order to calculate the number of wafers that can be produced by each machine per week, we calculate the total time that one machine can work, divided by the total time taken to produce one batch of wafers, and times the number of wafers per batch. We take the floor of the value since the number of wafers to be produced is an integer.

$$Machine\ Capacity\ (Per\ Week) = \left\lfloor \frac{7 \times 24 \times 60 \times Utilisation\% \times RPT\ Basis \times Load\ Size}{Sum\ of\ RPT\ of\ Steps\ using\ the\ Workstation} \right\rfloor$$

Hence, $$Number\ of\ Machines\ Needed = \left\lceil \frac{Weekly\ Wafer\ Output}{Machine\ Capacity\ (Per\ Week)} \right\rceil$$

We apply this formula to every type of machine and for every forecasted weekly wafer output (The total wafer output divided by the number of wafers that one machine can create per week, and we take the ceiling of that value as the number of machines needed is an integer.). As such, Figure 14 shows the number of machines calculated for the demand of each week.

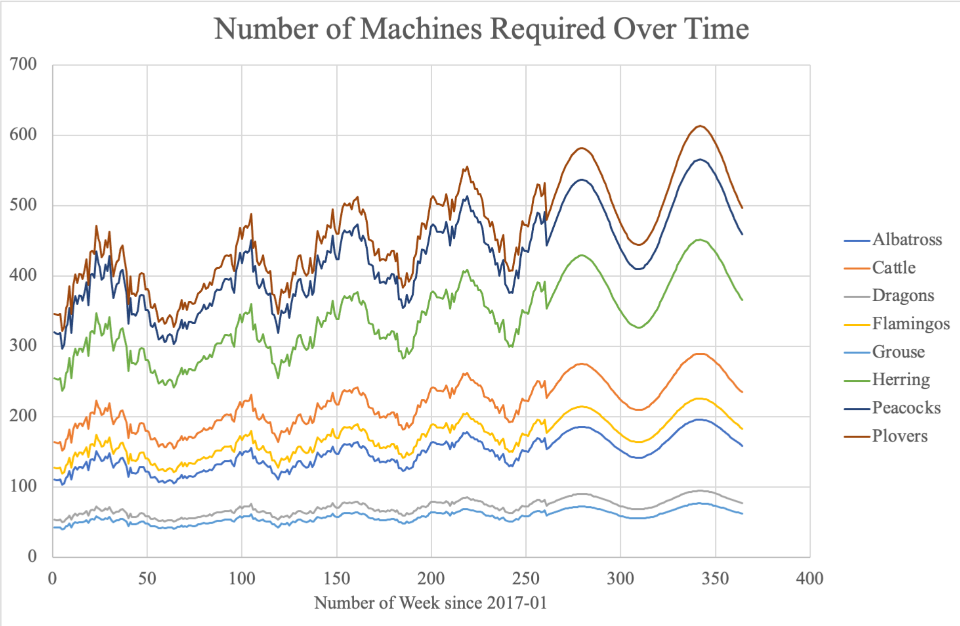

Figure 14. Number of Each Type of Machines Required Over Time

3. Task 4.2.3: Ability to Meet Demand

Please refer to the folder named "P_VaaT_Supporting_Document_Q2.3" for the workings of this section.

3.1 Key Assumptions

1. There will never be a delay in the delivery, inspection, and installation process.
2. Micron will always delay the order if possible and will only order the machines when it is absolutely necessary (i.e. if Micron does not order the machines at that time, Micron will not be able to keep up with the forecasted demand at some point of time in the future). This is due to the Time Value of Money and the opportunity cost of the capital investment.
3. There is no difference between ordering at the beginning of the week (e.g. Monday) and ordering at the end of a week (e.g. Friday) since everything is calculated on a weekly basis.

3.2. Assessment

Step 1: Based on our forecasted demand, **Micron will not be able to meet the demand in the next two years with the currently available machines that it has**. Using the same forecasted demand model, we are able to calculate the required number of each machine each week.

Step 2: We calculate the total amount of time required for each type of machine to be ready, from the moment it is ordered to the moment it is ready to be included in the production chain by adding up the "Order Lead Time" and "Machine Installation". From this, we have a total time of X weeks.

Step 3: We calculate the "Total Machine" available for a week which includes the working machines, installing machines, and ordered machines by adding up the "Total Machine" of the previous week and the number of machines to be ordered in that week.

Step 4: In order to calculate the number of machines to be ordered in a week, we look at the required machines of X weeks after the current week. If the value is larger than the "Total Machine" of the current week, the difference is the number of machines to be ordered; if not, the number of machines to be ordered is 0.

Step 5: Continue Steps 1 - 4 for the rest of the weeks and for every type of machine.

Our additional recommendation is to follow our ordering schedule that is recorded in the csv file "P_VaaT_Supporting_Document_Q2.3_New_Purchase_Order" so that Micron will be able to keep up with the future demand should the forecast model be true.

III. Task 4.3: Machines' Optimised Work Schedule

Please refer to the excel file named "P_VaaT_Supporting_Document_Q3.xlsx" for this section.

There are a total of 48 decision variables, each variable represents a possible machine usage pattern.

Decision Variable	Meaning
x1	The number of machines X that will be used from 1AM to 11PM and rest from 11PM to 1AM
x2	The number of machines X that will be used from 2AM to 12AM and rest from 12PM to 2AM
x3	The number of machines X that will be used from 3AM to 1AM and rest from 1AM to 3AM
…	…
x24	The number of machines X that will be used from 12AM to 10PM and rest from 10PM to 12AM
y1	The number of machines Y that will be used from 1AM to 11AM, rest from 11AM to 1PM, used from 1PM to 11PM, and rest from 11PM to 1AM
…	…
z1	The number of machines Z that will be used from 1AM to 10AM, rest from 10AM to 1PM, used from 1PM to 10PM, and rest from 10PM to 1AM
…	…

Since the three types of machines produce the same product in the exact same way, we are able to formulate a system of linear inequalities for each time slot to represent the minimum number of machines required. For example, the total number of machines that are working from 1AM to 2AM is represented by:

$x1 + x4 + x5 + ... + x24 + y1 + y4 + y5 + ... + y12 + z1 + z5 + z6 + ... + z12 \geq 172$

The linear program is now represented as such:

$$x1 + x4 + x5 + ... + x24 + y1 + y4 + y5 + ... + y12 + z1 + z5 + z6 + ... + z12 \geq 172$$
$$x1 + x2 + x5 + x6 + ... + x24 + y1 + y2 + y5 + y6 + ... + y12 + z1 + z2 + z6 + z7 + ... + z12 \geq 205$$
$$x1 + x2 + x3 + x6 + x7 + ... + x24 + y1 + y2 + y3 + y6 + y7 + ... + y12 + z1 + z2 + z3 + z7 + z8 + ... + z12 \geq 201$$
$$x1 + x2 + ... + x4 + x7 + x8 + ... + x24 + y1 + y2 + ... + y4 + y7 + y8 + ... + y12 + z1 + z2 + ... + z4 + z8 + z9 + ... + z12 \geq 190$$
$$x1 + x2 + ... + x5 + x8 + x9 + ... + x24 + y1 + y2 + ... + y5 + y8 + y9 + ... + y12 + z1 + z2 + ... + z5 + z9 + z10 + ... + z12 \geq 170$$
$$...$$
$$x3 + x4 + ... + x24 + y3 + y4 + ... + y12 + z4 + z5 + ... + z12 \geq 188$$

The constraints are that, for $all\ decision\ variables \in Z^{+}$ and that

$$\sum_{i=1}^{48} x_i \leq 100,\ \sum_{i=1}^{24} y_i \leq 100,\ \sum_{i=1}^{24} z_i \leq 100$$

The objective is to minimise the total daily operating cost, c,

$$\text{where } c = 10,400 \times \sum_{i=1}^{48} x_i + 9,000 \times \sum_{i=1}^{24} y_i + 8,200 \times \sum_{i=1}^{24} z_i\, c.$$

By using the Excel Solver, Simplex LP, we found out that the following solution is the most optimal in minimising the total daily operating cost. The following work schedule is the most optimised for the scenario given:

Decision Variable	Meaning	Amount
x1	The number of machines X that will be used from 1AM to 11PM and rest from 11PM to 1AM	79
x10	The number of machines X that will be used from 10AM to 8AM and rest from 8AM to 10AM	14
x12	The number of machines X that will be used from 12PM to 10AM and rest from 10AM to 12PM	7

y1	The number of machines Y that will be used from 1AM to 11AM, rest from 11AM to 1PM, used from 1PM to 11PM, and rest from 11PM to 1AM	3
y2	The number of machines Y that will be used from 2AM to 12PM, rest from 12PM to 2PM, used from 2PM to 12AM, and rest from 12AM to 2AM	10
y3	The number of machines Y that will be used from 3AM to 1PM, rest from 1PM to 3PM, used from 3PM to 1AM, and rest from 1AM to 3AM	12
y5	The number of machines Y that will be used from 5AM to 3PM, rest from 3PM to 5PM, used from 5PM to 3AM, and rest from 3AM to 5AM	15
y6	The number of machines Y that will be used from 6AM to 4PM, rest from 4PM to 6PM, used from 6PM to 4AM, and rest from 4AM to 6AM	11
y8	The number of machines Y that will be used from 8AM to 6PM, rest from 6PM to 8PM, used from 8PM to 6AM, and rest from 6AM to 8AM	8
y9	The number of machines Y that will be used from 9AM to 7PM, rest from 7PM to 9PM, used from 9PM to 7AM, and rest from 7AM to 9AM	14
y10	The number of machines Y that will be used from 10AM to 8PM, rest from 8PM to 10PM, used from 10PM to 8AM, and rest from 8AM to 10AM	10
y11	The number of machines Y that will be used from 11AM to 9PM, rest from 9PM to 11PM, used from 11PM to 9AM, and rest from 9AM to 11AM	16

z2	The number of machines Z that will be used from 2AM to 11AM, rest from 11AM to 2PM, used from 2PM to 11PM, and rest from 11PM to 2AM	11
z5	The number of machines Z that will be used from 5AM to 2PM, rest from 2PM to 5PM, used from 5PM to 2AM, and rest from 2AM to 5AM	3
z6	The number of machines Z that will be used from 6AM to 3PM, rest from 3PM to 6PM, used from 6PM to 3AM, and rest from 3AM to 6AM	4
z9	The number of machines Z that will be used from 9AM to 6PM, rest from 6PM to 9PM, used from 9PM to 6AM, and rest from 6AM to 9AM	6

In conclusion, the minimised total daily operating cost is achieved at **$2,127,800** by using **100 machine X's, 99 machine Y's, and 24 machine Z's** by following the optimised schedule stated.

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