Improvement of Inventory Policy for Furniture Fittings Manufacturer

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ณัฐชยา สันติภิรมย์กุล : การปรับปรุงนโยบายการจัดการสินค้าคงคลังในโรงงานผลิตชิ้นส่วนเฟอร์นิเจอร์ . (Improvement of Inventory Policy for Furniture Fittings Manufacturer) อ.ที่ปรึกษาหลัก : ผศ. ดร. พิศิษฏ์ จารุมณีโรจน์

วัตถุประสงค์ของการทำวิทยานิพนธ์ฉบับนี้ มุ่งเน้นไปที่การปรับปรุงการบริหารคงคลังของบริษัทผู้ผลิตชิ้นส่วนเฟอร์นิเจอร์ ซึ่งปัญหาส่วนใหญ่เกิดจากการจัดเก็บสินค้าบางประเภทมาก หรือน้อยเกินความจำเป็น ส่งผลให้เกิดการจัดเก็บคงคลังสินค้าไม่เหมาะสมในที่สุด จากการศึกษาเบื้องต้น ผู้วิจัยพบว่า ปัญหาดังกล่าวส่วนหนึ่งเกิดจากการวางแผนการผลิต และการวางแผนการจัดเก็บวัตถุดิบที่ไม่มีประสิทธิภาพ ผู้วิจัยจึงได้นำเสนอการปรับปรุงโดยแบ่งออกได้เป็น 2 ส่วน คือ การพยากรณ์ความต้องการต้องการสินค้าที่มีความแม่นยำ และการควบคุมระดับคงคลังวัตถุดิบสำหรับสินค้าดังกล่าวให้มีความสอดคล้องกันมากยิ่งขึ้น

ในส่วนของการพยากรณ์ความต้องการนั้น ผู้วิจัยได้เริ่มจากการจัดกลุ่มสินค้าออกเป็น 6 กลุ่ม ตามมูลค่าของสินค้า และระยะเวลานำในการผลิต จากนั้นจึงได้เลือกสินค้าขึ้นมา 3 กลุ่ม กลุ่มละ 10 SKUs โดยสินค้ากลุ่มดังกล่าวเป็นสินค้าที่ใช้ระยะเวลาในการยาวนาน และมีมูลค่าแตกต่างกัน (สินค้ากลุ่ม A, B, และ C) เมื่อแบ่ง และเลือกกลุ่มสินค้าแล้วเสร็จ สินค้าดังกล่าวจะถูกนำไปทดสอบกับวิธีการพยากรณ์แบบต่างๆ ตามลักษณะของความต้องการของสินค้านั้นๆ ทั้งนี้ ผู้วิจัยพบว่า วิธีการพยากรณ์แบบ Autoregressive Integrated Moving Average (ARIMA) เป็นวิธีพยากรณ์ที่ให้ค่าความคลาดเคลื่อนต่ำที่สุดในสินค้าในกลุ่ม A และ B โดยวัดจาก Mean Squared Error (MSE) Mean Absolute Error (MAE) และ Mean Absolute Percentage Error (MAPE) ในขณะที่สินค้ากลุ่ม C นั้น วิธีการพยากรณ์ของ Croston จะมีความเหมาะสมกว่า โดยวิธีดังกล่าวให้ค่าความคลาดเคลื่อน Mean Absolute Scaled Error (MASE) ต่ำที่สุด

นอกเหนือไปจากการพยากรณ์ความต้องการสินค้าแล้ว ผู้วิจัยยังได้ทำการพัฒนาปรับปรุงระบบการควบคุมคงคลังของวัสดุ หรือส่วนประกอบ ต่างๆ ซึ่งผู้วิจัยพบว่า การประยุกต์ใช้วิธีการควบคุมระดับคงคลังที่เหมาะสมจะช่วยลดต้นทุนการจัดเก็บลงได้ 32% สำหรับวัสดุ หรือส่วนประกอบเฉพาะที่มีมูลค่าสูงภายใต้การทบทวนระดับคงคลังอย่างต่อเนื่อง และสามารถลดต้นทุนการจัดเก็บลงได้ 43% สำหรับวัสดุ หรือส่วนประกอบทั่วไปภายใต้การทบทวนคงคลังทุกๆ 30 วัน

สาขาวิชา	การจัดการทางวิศวกรรม	ลายมือชื่อนิสิต ....
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Natchaya Suntipiromkul : Improvement of Inventory Policy for Furniture Fittings Manufacturer . Advisor: Asst. Prof. Pisit Jarumaneeroj, Ph.D.

The objective of this research is to improve the management of inventory in a furniture fittings manufacturer so that shortage and overstock could be reduced. Based on our initial investigations, such inventory problems were caused not only by inefficient production planning but also a lack of inventory control system that linked those plans with the stocks of raw material required. To better address the issues, two different models have been therefore proposed, namely more accurate demand forecasting models for products with different demand patterns and inventory control models for raw materials of those products.

Regarding the development of more accurate demand forecasting models, we first classify the products into six groups based on value of items and lead time. We then select ten products in each of three subgroups for further analysis, where a number of demand forecasting models have been applied to each product group according to their demand patterns. The study reveals that the Autoregressive Integrated Moving Average (ARIMA) model provides the least forecasting errors, as measured by Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), for products in Groups A and B, while Croston's model is the most appropriate forecasting model for products in Group C as it provides the least forecasting errors as measured by Mean Absolute Scaled Error (MASE).

We also evaluate inventory policies and determine stock levels of the company's raw material under two different systems, i.e. continuous and periodic reviews. We find that, with proper inventory control model, the company could save up to 32% for special raw materials/components under continuous review and about 43% for common raw materials/components under 30 days periodic review.

Field of Study: Engineering Management		Student's Signature ....
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Natchaya Suntipiromkul

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1. INTRODUCTION

1.1 Company Overview

The selected company to be studied is located in Thailand and was established for over 40 years. The company started with the spare parts manufactured from rubber latex and become the specialist in rubber spare part manufacturer. At the beginning, the spare parts for industry factory and automobile parts were produced as core products of company. With an increase of competition in the market, company expand their products types in order to serve the rubber spare parts for more industries which are food industry, electronics industry, and packaging industry. The materials to be manufactured also increase; there are PVC, PE, aluminium, and steel.

1.1.1 Product portfolio

Figure 1-1: Example of products produced by studied company

The studied company has the products about 700 SKUs, the example of products is shown in Figure 1-1, which can be divided into two types of products based on the served customers.

- Furniture: Products in this group are both parts, spare parts, and finished goods that will be offered to customers such as casters, clothesline, and hinge seal.

- Factory: This group of products are typically offer to the factory customers. The products are the parts or spare parts of mechanical machines, automobile, and the machine in food industry as the studied company can manufactured the food grade parts/ spare parts. For example, O-ring, rubber seals, rubber gaskets.

The products for factory customers are generally made-to-stock as these products are produced through the company's production line. While furniture trader will be mostly processed through the assembly line of the company, the parts are generally purchased and assemble with the made-to-stock parts.

1.2 Statement of Problem

There are two major problems occurred in studied company which are shortage and overstock of raw materials. The stated problems will be determined as followed with nine selected types of raw material/ component of the products based on the best seller products as example.

1.2.1 Shortage of Raw Materials

By analysing the historical data from year 2018, it demonstrates that there were shortage of raw materials to be assembled and become finished goods which cause the loss in opportunity to serve consumers' demand, and low utilisation of capacity. Figure 1-2 illustrates that the percentage of shortage of six raw material types out of nine are inadequate to serve the assemble operation. Raw materials B is the highest percentage of no inventory for usage with 25 percent.

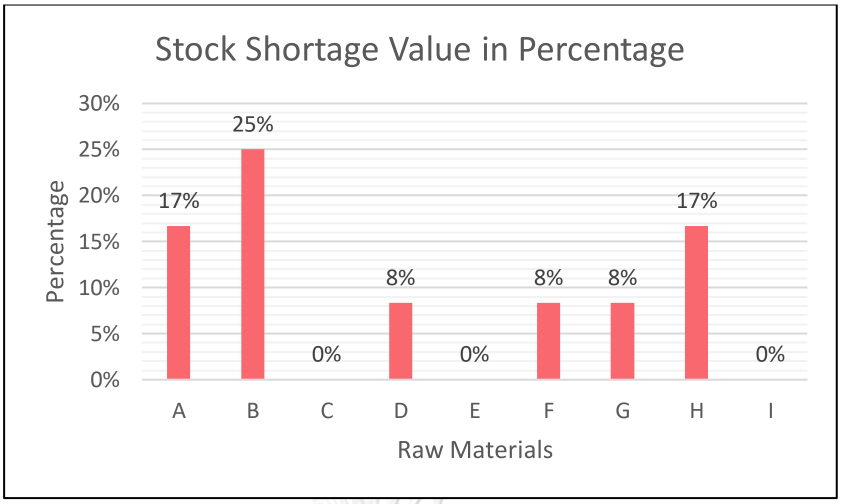


Figure 1-2: Bar graph of raw materials shortage in percentage

1.2.2 Overstock of Raw Materials

On the other hand, the number of raw materials inventories over the usage and requirement are shown in Figure 1-3. The zero percent of shortage in raw materials demonstrated in Figure 1-2 do not imply that the raw materials stocks are optimal except raw material I. The analysis of these raw materials is calculated and analysed with addition of 1-standard deviation as a confidence interval in order to ensure that the stock is excessive and will effect to finance of company. Raw materials C and E are the items that overstock.

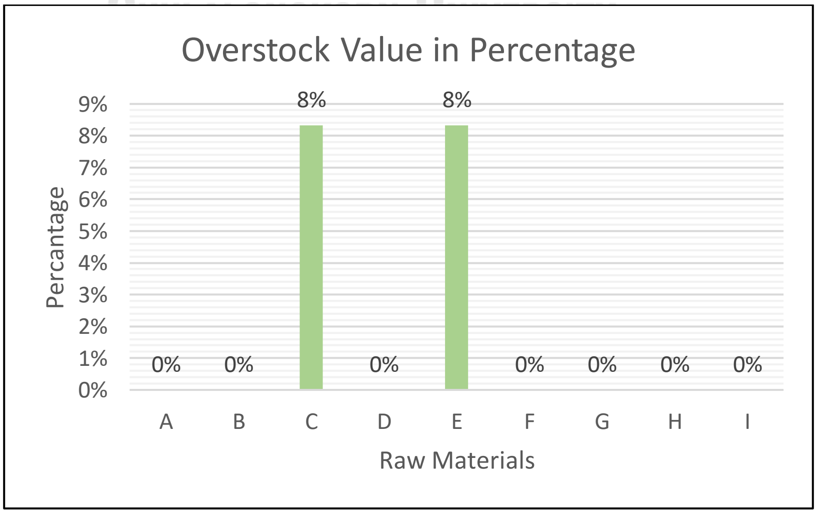


Figure 1-3: Bar graph of raw materials overstock in percentage

1.3 Objectives

Based on the stated problem, the objective of this study is to propose inventory policy that provides better inventory management for furniture fittings manufacturer in order to reduce the inventory shortage and overstock.

The key performance index (KPIs) for these objectives are the forecast performance measurement based on the forecast error, service level, inventory related cost, and the inventory level.

1.4 Scope of Research

This research focuses on the inventory part of studied company according to objectives that aim to propose the inventory policy and improve accuracy in demand forecasting. As the company produces and offers variety of products to customers, the scopes of research are defined:

- Product 104 SKUs will be studied and classified into group to ease manage and proposed
- Finished goods will be focused on demand forecasting while raw materials/ components will be focused on inventory control model.
- Three out of five forecasting techniques will be selected based on demand pattern in order to fit with the data and compare to find the best one that has lowest forecast error.
- Appropriate inventory control model will be proposed to the raw materials/ components.
- 30 months from January 2017 to June 2019 will be inputs as historical data to fit with the selected demand forecasting models.
- Proposed inventory policy will be focuses on inventory quantity, review period, safety stock, and reorder point from July 2019 until October 2019.

1.5 Expected Outcomes

- Demand forecasting model that appropriate to demand characteristic and provide the lowest forecasting error to studied company.
- Up-to-date and accurate inventory data that be able to be tracked and monitored.

1.6 Research Structure

In order to achieve the objectives of research, project planning and how to achieve the stated objectives are required. The flow chart will illustrate how the research is structured and the work steps of this research.

1.6.1 Flow Chart

Figure 1-4 shows the workflow and structure of this study.

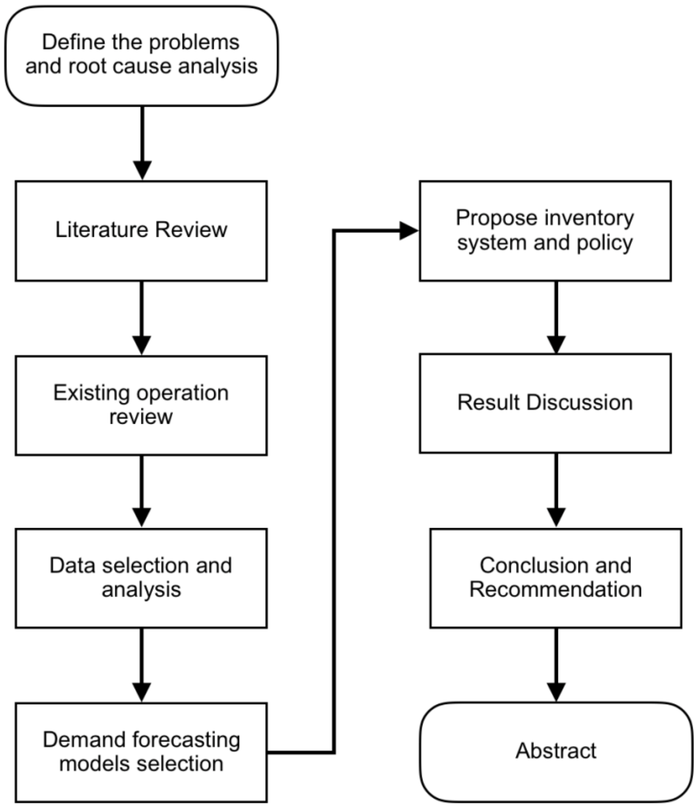


Figure 1-4: Flow Chart

Problem and Root Causes

Starting with defining the problem and analysing the root causes, the problem and root causes will be analysed and stated to be able to understand the situations and things to be solved along with the source of those situations to scope down the research.

Literature Review

After understanding the problem, related theories and researches to the problems will be reviewed and studied to find out the solutions that should be applied to improve the selected company to achieve the defined objectives. Researches and tools relate to inventory will be studied, also the parameters and factors that are associated to the problems.

Existing Operations Review

Next step is the review section of existing operation of studied company. This step is to acknowledge current conditions of the operations and workflows of the company and discover where to be more focused to improve. Planning and warehousing departments are the core for operations review.

Data Selection, Forecasting Models, and Inventory Control Models

Required data will be selected and analyse in order to get the most appropriate data to consider and to be inputs to the three selected forecasting models which is the step after. Appropriate inventory system will be proposed in order to set up the inventory policy.

Implementation and Result Discussion

Last but not least, all the result will be analysed and discussed to obtain the information or factor that can support and improve those stated problems. The measurement of forecasting performance will be generated in order to acquire the most accurate forecasting model out of three selected models. Comparing the forecasting error between those three forecasting models will be shown in this step. The percentage of improvement from proposed forecasting model, inventory system and inventory policy will also be generated with the reasons of outcome.

Conclusion and Recommendation

Lastly, this paper will be summarised with what have been explored, the recommendation and limitation that should be concerned if those proposed methods are applied.

2. LITERATURE REVIEW

2.1 Inventory Management

2.1.1 Inventory

According to Jacobs and Chase (2013), inventory is the goods or resources as buffers that organisations stock them in order to be used and serve the variation of customers' demand. In financial aspect, inventory is defined as current assets shown in the balance sheet which can be implied that inventory is valuable and associate to money.

The types of inventory typically are classified as raw materials, work-in-process, and finished goods (Muller, 2003). These three types of inventory are defined as followed:

- **Raw materials:** Items that will be parts of finished goods by processing through the production line.
- **Work-in-process:** Items that are known as WIP. These can be the partial products or subassemblies items that once were raw materials and wait to be processed till the end of the production line. Their statuses are generally between raw materials and finished goods.
- **Finished Goods:** Completed products that are ready to be purchased or serve the customers' demand. Basically, composed of raw materials and work-in-process

Besides, inventory can be classified based on its functional uses such as spare parts. Spare parts inventory is the part that necessary stock for after-market, it is associated to the maintenance service. With the characteristics of spare parts, these items can be predicted the quantity differently from other types of inventory and do not be defined as dead stock (Muller, 2003).

2.1.2 Inventory Cost

As suggested by Abbasi (2011), there are three major costs that should be focused and effect to inventory management and control. Costs relate to inventory are ordering cost, holding cost, and shortage cost.

- **Ordering Cost:** The ordering cost is occurred when the order is placed whether it be the external purchase e.g. raw materials purchased from the supplier or the internal order such as the requisition from the production order. This type of inventory cost is calculated from every action and process relate to the order and overheads.
- **Holding Cost:** This cost is also known as carrying cost. It is consisted of costs that relate to the space/store that kept the items, insurance, taxes, depreciation, etc. Therefore, the higher the inventory level, the higher the inventory holding cost. As mentioned by Mollering (2007), inventory holding cost is normally defined by the percentage of unit cost of the product; about 10%.
- **Shortage Cost:** In the opposite to holding cost that is the opportunity cost of capital, shortage cost is the cost which is charged when the firm lose the opportunity to meet the customers' demand and satisfaction.

2.1.3 Inventory Management

As defined in the previous section, it can be intimated that inventory can cause the critical effect to the organisations as it is associated to demand serving ability and organisations' finance, and inventory also relate to every department of organisations. Thus, the inventory management is necessary to be applied properly. As researched from 188 micro and small enterprises by Atnafu and Balda (2018) about how the performance of inventory management can cause an effect to the competitiveness of firm, research shows that the more efficiency of inventory management practice can lead to the better competitiveness of firms and be able to improve the performance of company.

In detail, the reasons of necessity of inventory management are following :

- To balance between demand and supply. Since there is the variation and uncertainty in demand, monitoring and managing the supply will be the actions that can cope with those uncertainties.
- To decrease the failure of supply from delivery time. Besides the variation in demand, there is also the time variation in supplier side to provide the raw materials which can cause the effect in delay of production line and low utilisation of machines.
- To be able to minimise the cost of inventory. By maintaining and stocking the inventory whether it be raw materials, work-in-process, and finished goods; there is cost that organisations have to take in account. Thus, the cost can be controlled and monitored when the inventory management approach is applied. The cost of inventory will be reviewed in the later section.

Hence, inventory management is the activity which offers the organisations to have right items based on the specification or requirement, in the right quantity that can meet the demand and able to deal with the supply-demand variation, at the right time when needed, and in the right place where the items can be immediately accessed.

2.2 Demand

Demand is the quantity of products or services that customers willing to purchase, it is also defined as the willingness and ability to pay in order to obtain the products or services. And since demand is related to desire of human, the demand rate can be increased or decreased. According to Sharma (2017), the increase and decrease in demand can occur from factors such as the taste of customers, price competitiveness, and advertisement. Generally, demands usually associate with the period of time such as day, week, month, and year.

2.2.1 Types of Demand

Based on Jacobs and Chase (2013), demand can be categorized into two types which are independent demand and dependent demand. An independent demand is the demand of the products that is irrelevant to each other, it is a higher-level demand. This type of demand is uncertain and need the data from market research and sales information. While the dependent demand can be illustrated as the subset of independent demand since it can be defined by calculating in the basis of high-level demand of each product or service that are required. Moreover, the requirement of dependent demand will affect to other part. For example, there is demand of 100 bicycles that organisation need to produce which one bicycle composed of two wheels and one handle grip. Thus, 100 bicycles which is the independent demand will need 200 wheels and 100 handle grips that defined as dependent demand.

2.2.2 Demand Pattern

Chase (2013) stated that demand patterns can be determined into four patterns which are trend, seasonality, cyclical, and irregular. First three patterns are associated with time while the occurrence of irregular demand pattern is by chance and uncertain. Each pattern is plotted as an example shown in Figure 2-1 and defined as followed:

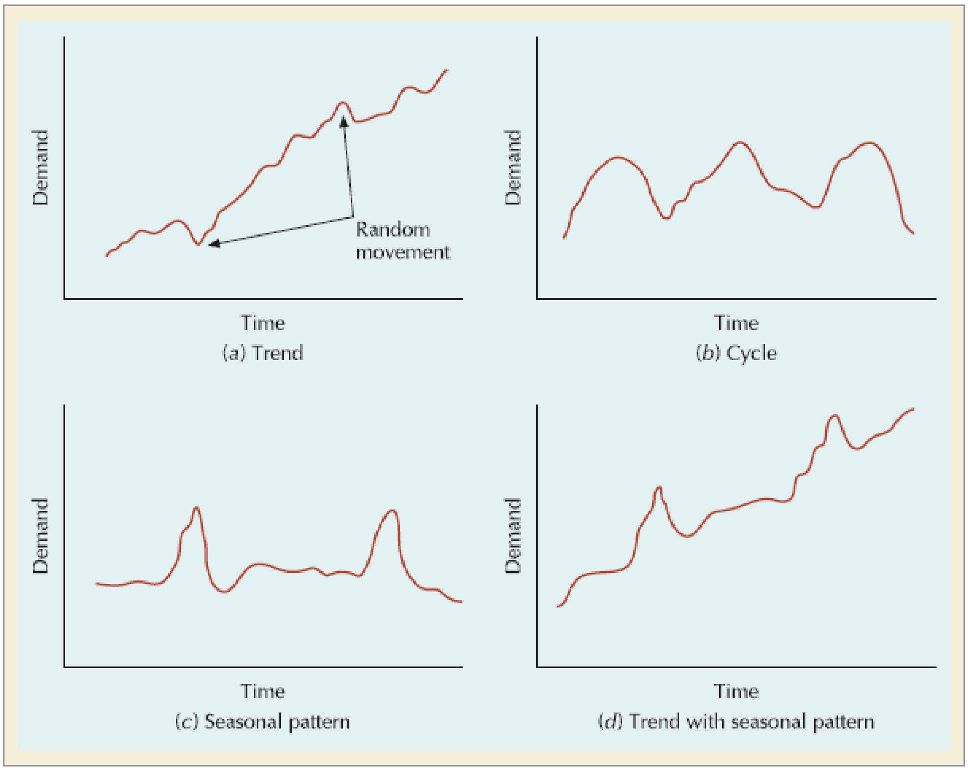


Figure 2-1: Demand Patterns

(Source: Russell and Taylor, 2011)

- Trend: The direction of demand that continuously growth or decreasing over time. This type of demand pattern normally takes long period of time when occurred
- Seasonality: The variation of demand that occurred repeatedly in term of series of time e.g. days, weeks, months. In common, seasonality mostly affected by the season change or customers' interest.
- Cycle: The repetitive occurrence of demand which may influenced by the political factors as example and do not occur regularly depend on period of time.
- Irregular: Irregular demand is the component in forecasting that influenced by other factors such as price, promotion, or competitors' activities which is not occurred based on the period of time. This demand can be implied as randomness.

Intermittent demand

Apart from stated demand patterns, there is a characteristic of demand that has not occurred every time period or contain number of periods that has zero demands which is called intermittent demand (Babai et al., 2019). This pattern of demand is generally happened with the products that in the last stage of their product life cycle where the products are not able to capture the market interest.

2.3 Demand forecasting

Forecasting is the determination of what will happen in the future by using the historical experience or data as a key to calculate and define the direction of advanced circumstance. Demand forecasting is the fundamental process that significant to the decision making of management team as one of the factors that is determined to establish the strategic and operational planning. By considering the demand forecasting purpose, there are two purposes of demand forecasting: strategic forecasts and tactical forecasts (Jacobs and Chase, 2013). The strategic forecasts can be implied as the forecasting that taking into account to analyse the dependent demand which is the high-level demand. While tactical forecasts are associated to day-to-day decisions in order to meet demand in operational level, for example, the inventory replenishment. Hence, predicting the demand of the future in advance will allow every department in organisation to prepare and plan their work to deal with the future demand such procurement planning, inventory planning and scheduling of the production function.

2.3.1 Types of demand forecasting

In the process of forecasting the demand, there are two main categories of forecasting types which are qualitative and quantitative methods. Figure 2-2 demonstrates the types of forecasting method and their techniques.

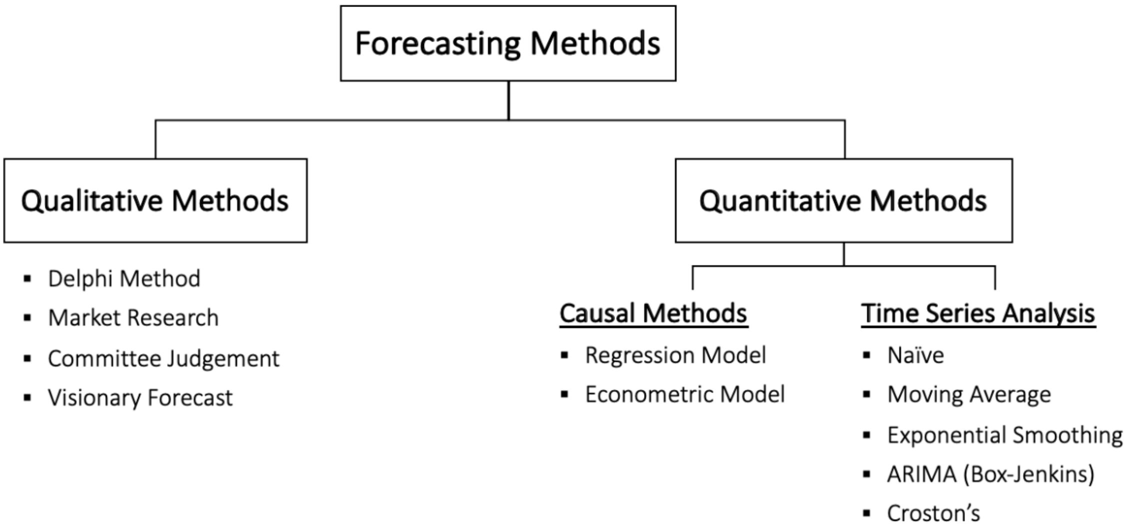


Figure 2-2: Forecasting Types and Techniques

(Adapted from Chambers et al., 1971)

1) Qualitative Methods

The forecasting methods that are subjective and judgmental, the prediction is typically based on the opinion and rating scheme by group of people such as experts in order to interpret the qualitative information to quantitative data. This type of forecasting method is regularly applied when, for example, launching new products or services that prior demand data are unavailable. The acquainted techniques in the category of qualitative methods are:

- Delphi method
- Market research
- Committee judgment
- Visionary forecast

2) Quantitative Methods

On the other hand, the quantitative methods are objective and focus on applying the statistic to determine the future demand. The mathematical models are adopted by using quantitative data as historical demand to project the demand; thus, the availability of historical data is significant to these methods. Based on Chase (2013), quantitative methods can be classified into two groups based on its dimension analysis: multidimensional and one-dimensional methods. In addition to the past sales information, other variables that effect demand rate are considered simultaneously and defined as multidimensional analysis; this is called causal forecasting. While the one-dimensional methods, that historical data set are a core and focus on analysing it, are called time series analysis.

2.1) Causal

As stated above, causal forecasting methods consider more than one dimension. This forecasting will look into the factors or events that cause the changes and fluctuations in demand. Causal still uses the historical data to determine the future circumstance but with the addition of relationship between factors. The economic conditions, social force, competitive market, and substitutions are the example of factors, indicated as independent variables that can affect to the demand (Chambers et al., 1971). Causal forecasting provides short to medium term forecasting more accurately when compare to another method under quantitative category, time series analysis (Chase, 2013). It allows the forecaster to understand and achieve cause-and-effect analysis as it considers the relationship between dependent variable, which is demand, and independent variables. However, causal forecasting is not familiarly use in general according to its complexity and the crucial of independent variables accuracy required. The most well-known statistical technique of causal forecasting is the regression model.

2.2) Time Series

The analysis of time series is another method that adopt bunch of statistical techniques. These are forecasting methods that consider only the historical demand data and determine the future demand from trend that random fluctuations are smoothed out completely. Opposite to the causal forecasting, time series analysis is suitable to predict a short-term forecasting in order to provide the accuracy in result. Besides the ease of apply this method, there is also a drawback that can lead to critical forecasting error. Since the main step in time series analysis is to exclude the irregular in data set, it will lead to the unusable demand forecasts if the randomness that smoothing out have a relationship to the demand data.

a. Naïve

The technique is the simplest technique in forecasting approach. Naïve technique predicts the future demand by making an assumption that the forecast demand will have the same quantity as the current demand. For example, the demand of January is 1,000 units then the next month's demand, February will have the same number which is 1,000 units.

$$F_{t+1} = Y_t \tag{1}$$

where $\mathrm{Y_t}$ is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_{t+1}}$ is forecast demand at period of time t+1 when t = 1, 2, 3, …

b. Moving Average

Similar to naïve technique, moving average also utilize historical demand data to predict the forthcoming demand by making the assumption that nearby data will have similarity in value (Kolassa and Siemsen, 2014). But different from naïve that assumes upcoming data will certainly the same as past data, moving average forecasts the demand by averaging the past data from the certain number of periods. Forecasting demand by this technique, a smoothing technique is applied. Smoothing technique will help to smooth out the randomness in demand for better comprehending the demand pattern. Nonetheless, Chase (2013) claimed that seasonality demand pattern is not appropriated to be forecasted by moving average.

$$F_{t+1} = \frac{1}{k} \sum_{i=t-k+1}^{t} Y_t \tag{2}$$

where Y_t is actual demand at period of time t when t = 1, 2, 3, …

F_{t+1} is forecast demand at period of time t+1 when t = 1, 2, 3, …

k is number of periods in the moving average

The essential procedure of moving average is to determine the number of periods to be averaged. The longer of the number of periods included for forecasting, the smoother the estimation of future demand. Even if the foundation of moving average is to smooth out the randomness, eliminate too much randomness may cause the error in forecasting which the information or terms that are critical may be also removed. Later in other time series techniques, it can be seen that moving average is the basic principle to other technique particularly about the smoothing approach.

c. Exponential Smoothing

Exponential smoothing is the most widely used of forecasting techniques according to its ease to understand and provide the logical result. As stated by Jacobs and Chase (2013), exponential smoothing techniques are commonly selected by retail, wholesale, and service industries to forecast the inventory. The randomness in demand still be smoothing out in this technique but not completely omit from the demand data set. Exponential smoothing define the recent data as the data that will cause the critical effect to the future demand thus, weighting the data is added which the past data will be weigh less than the recent data. The weight of data is decreased exponentially. Difference from two previous techniques, naïve and moving average; exponential smoothing techniques are applied when the demand show the pattern of trend and seasonal obviously.

There are three exponential smoothing techniques which are single exponential smoothing, Holt's two-parameters, and Holt's-winters' three-parameter. The first two types will be review for this study.

c.1 Single Exponential Smoothing

Single exponential smoothing is the simplest method of exponential smoothing. It is extended from the moving average. As defined in moving average section, the moving average method gives all data the same weight which can be implied that every data point will cause the same effect to the future forecast while single exponential smoothing focus on the recent data. The more the data is recent, the more weight to the data. Therefore, one more variable, alpha(α), is added to the formula as a weight factor.

$$F_{t+1} = F_t + \alpha(Y_t - F_t) \qquad (3)$$

where α is smoothing constant value from 0 to 1

Y_t is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_{t+1}}$ is forecast demand at period of time t+1 when t = 1, 2, 3, …

Alpha(α), which is also known as smoothing constant parameter, has value between 0 to 1. The α closer to 0 can be interpreted that the forecasts of future demand neglect the fluctuations or swing in previous demand. In the opposite, the value of α closer to 1 means that the forecasted demand will be based on the past demand data (Chase, 2013).

Thing to be considered and as a key in the equation of simple exponential smoothing is the weight. As mentioned above, the weight of data is decreased exponentially since the old data are not further in focus. Thus, the graph of weight should demonstrate the exponential decreases. Nonetheless, the sum of weight of every demand in data set should be nearer to 1.

c.2 Holt's two-parameters

While the simple exponential smoothing neglect the trend pattern by smoothing it out and make an assumption that the demand data have no trend, the Holt's two-parameters can deal with trend of demand better and deliver small error of forecasting than the simple exponential smoothing. Besides the α variable as smoothing constant, beta (β) variable is added to this technique as another smoothing constant in order to smoothing out the randomness once more after using the α. The variable β is the same as α, it has the value from 0 to 1.

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1})$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (4)$$

$$F = L_t + b_t m$$

where α and β are constant values from 0 to 1

Y_t is actual demand at period of time t when t = 1, 2, 3, …

F is forecast for m period ahead

L_t is estimation of the level series at time t

$\mathrm{b_t}$ is estimation of the slope of the data series at time t

d. Autoregressive Integrated Moving Average

This technique of time series is known as ARIMA which Geoge Box and Gwilym Jenkins developed this model and became popular since 1970s; it is also known as Box-Jenkins approach. ARIMA is consisted of three components which are Autoregressive, Integration, and Moving Average as model's name (Fattah et al, 2018).

$$z_t = \beta_0 + \emptyset_1 z_{t-p} + \cdots + \emptyset_p z_{t-p} + e_t + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} \quad (5)$$

Autoregressive (AR)

$$y_t = \beta_0 + \emptyset_1 y_{t-1} + \cdots + \emptyset_q y_{q-2} + e_t \tag{6}$$

The principle of this component demonstrates that current demand is related to its preceding demand in term of mathematical function. Parameter of autoregressive term is *p* which is notified as the number of times lagged in the past.

Integrated (I)

$$y_t - y_{t-1} = z_t \tag{7}$$

Second component is integrated which its parameter is *d*. The parameter of integrated component is defined as the degree of demand data differencing. The differencing procedure to demand data is to eliminate the trends pattern from demand data and make the data to be more stationary.

Moving Average (MA)

$$y_t = \beta_0 + e_t + \theta_1 e_{t-1} + \cdots + \theta_p e_{p-2} \tag{8}$$

And the last component in this model is moving average where its parameter is *q*. The moving average in ARIMA is different from moving average technique in previous section. Moving average for demand forecasting assumes that the previous demand can used to estimate the next demand while ARIMA's moving average has an assumption that the forthcoming demand can be estimated by using the previous error between actual and forecast demand. Thus, q will be the variable to illustrate the number of previous models of forecast error. (Kolassa and Siemsen, 2014)

According to Chase (2013), ARIMA model is appropriate to use with both trend and seasonality demand pattern to make a demand forecasting since it is the combination of major components from both types of demand forecasting which are causal model, regression technique, and time series.

e. Croston's Forecasting Method

This forecasting method is proposed by Croston in 1972; Croston's forecasting method is known as the forecasting method to apply with the slow-moving items and zero demand available in data set. It is an alternative forecasting model instead of the traditional forecasting methods, moving average and exponential smoothing methods, to forecast (Teunter and Duncan, 2009).

$$\text{If } Y_t \neq 0 \text{ then } \quad \begin{aligned} Z_{t+1} &= \alpha Y_t + (1-\alpha) Z_t \\ V_{t+1} &= \alpha q + (1-\alpha) V_t \\ F_{t+1} &= \frac{Z_{t+1}}{V_{t+1}} \end{aligned} \tag{9}$$

$$\text{If } Y_t = 0 \text{ then } \quad \begin{aligned} Z_{t+1} &= Z_t \\ V_{t+1} &= V_t \\ F_{t+1} &= F_t \end{aligned} \tag{10}$$

where α is smoothing constant value from 0 to 1

Y_t is actual demand at period of time t when t = 1, 2, 3, …

F_{t+1} is forecast demand at period of time t+1 when t = 1, 2, 3, …

Z_t is estimate of average non-zero demand size

V_t is estimate of average interval size between demands with non-zero

q is number of zero-demand periods consecutive available

Rather than directly forecast the demand based on its period of time, Croston's method separately forecast the demand quantity and occurrence interval of demand before predicting the demand calculated by formula. The different formulas to forecast the future demands are applied when the data point equal to zero (0).

2.3.2 Measurement of Errors

Even if the technique of demand forecasting is neatly selected, the possibility that forecast errors will be occurred is still happen. The error of forecast can be noticed when there is the difference between actual demand and forecast demand.

$$\mathrm{e_t} = \mathrm{A_t} - \mathrm{F_t} \tag{11}$$

where $\mathrm{e_t}$ is forecast error

$\mathrm{A_t}$ is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_t}$ is forecast demand at period of time t when t = 1, 2, 3, …

Nevertheless, every forecast data will be contained with the forecast error then the confidence limit is applied to allow the forecast error interval that is acceptable error value (Wild, 2018). The measurement of error or can be known as the forecast performance measurement can help the practitioner to analyse the source of error and to improve the accuracy of demand forecasting. In addition, the measurement of errors can use to compare between different demand forecasting methods in order to find the best fitted technique. There are five statistical error terms that will be reviewed in this section.

1) Mean Absolute Deviation (MAD)

This measure of forecast error also known as Mean Absolute Error (MAE). This scale-dependent measure is the forecast error that neglects the negative/positive sign of the values, absolute values, and averaged by the number of points in data set as shown in following formula.

$$\mathrm{MAD} = \frac{1}{n}\sum_{t=1}^{n}[|A_t - F_t|] \tag{12}$$

where n is total number of observations in selected time period

$\mathrm{A_t}$ is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_t}$ is forecast demand at period of time t when t = 1, 2, 3, …

| | is symbol defining the absolute value

2) Mean Squared Error (MSE)

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}[|A_t - F_t|]^2 \tag{13}$$

where n is total number of observations in selected time period

$\mathrm{A_t}$ is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_t}$ is forecast demand at period of time t when t = 1, 2, 3, …

| | is symbol defining the absolute value

Another scale-dependent measures besides the mean absolute deviation measurement is mean squared error (Hyndman and Koehler, 2006). Different from MAD, this type of forecast accuracy measures is based on the squared errors.

3) Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error is the measure of error that calculates the average error relate to average demand as a percentage. This measurement is the most common used for measuring the accuracy of forecast data. Nevertheless, there is also limitation of this metric. According to Hyndman and Koehler (2006), the application of MAPE in M3-competition test revealed the infinite value of error when the data set contain zero as data point.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{[|A_t - F_t|]}{A_t} \times 100 \tag{14}$$

where n is total number of observations in selected time period

$\mathrm{A_t}$ is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_t}$ is forecast demand at period of time t when t = 1, 2, 3, …

| | is symbol defining the absolute value

4) Tracking Signal

In order to find out the bias of forecast demand, the tracking signal is adopted. Tracking signal is one of the forecast performance measurements that utilize the MAD value to observe the direction of forecast demand where the forecast demand keeps the pace with the variation of demand, upward or downward or not. Plotting graph is a tool to illustrate the tracking signal compare with the forecast. If the graph illustrates that there is a big gap between tracking signal and forecast, then the existing forecast is not useful and appropriate to project the future demand.

$$\mathrm{TS} = \frac{\mathrm{RSFE}}{\mathrm{MAD}} \tag{15}$$

where RSFE is the Running Sum of Forecast Errors

5) Mean Absolute Scaled Error (MASE)

An alternative forecast performance measurement instead of using MAPE is Mean Absolute Scaled Error offered by Hyndman and Koehler (2006). Since MAPE is the forecast accuracy measuring by percentage comparing the error with the actual demand, this measure will give the infinite value of measurement when the data set contain zero value, therefore. While MASE is the measures that consist of the MAE as part of its formula, this metric will allow the practitioner to compare the forecast performance of each forecasting model that apply to data set includes of zero observations. Scaled error, is indicated as q_t, is calculated in prior and averaged with the number of observations in data set. As shown in formula (10) and as aforementioned, there are MAE from Naïve forecasting model and error at period of time t as parts of the formula.

$$q_t = \frac{A_t - F_t}{\frac{1}{n-1}\sum_{i=2}^{n}|A_i - A_{i-1}|} \tag{16}$$

$$\text{MASE} = \frac{1}{n}\sum_{t=1}^{n}(|q_t|) \tag{17}$$

where n is total number of observations in selected time period

$\mathrm{A_t}$ is actual demand at period of time t when t = 1, 2, 3, …

$\mathrm{F_t}$ is forecast demand at period of time t when t = 1, 2, 3, …

| | is symbol defining the absolute value

2.3.3 Demand Forecasting and Inventory Relationship

Demand is defined as one of the inventory parameters that plays as a significant role in inventory management as a main data to be considered. Romero-Gelvez (2019)'s study stated that be able to know the future demand of goods will allow the backward planning process. It allows the practitioner to plan the quantity of raw materials to be used and then, relate to the quantity to be stocked to be able to adequate to serve the demand. According to Klaus et al (2016), it has been pointed out that by lowering the parameter of forecast accuracy, the cost can be saved about 10% thus, the improvement of accuracy in demand forecasting is one of inventory policy that will allow better performance of inventory management.

2.4 Inventory Control Systems

In inventory management, inventory control systems are the major approach to be considered. The inventory systems offer the organisations with the policies to maintain, monitor, and control the items in stock. The systems are the framework to establish the inventory policy that suits well with the organisation's strategies. Inventory systems mainly concern on time, quantity, and location. For time, it is related to the lead time. Quantity relates to the number of items needed and number of remaining stock and to be ordered. And location is about where the items are kept and where the current placement of the items. In accordance with Jacobs and Chase (2013), there are two systems classification based on the number of times for purchasing decision: single-period inventory system and multi-period system.

2.4.1 Single-Period System

Single-period model is the policy of inventory management that the decision making is for one-time purchase items. The items or products that are applied with this type of inventory model are usually have value when needed at a certain time such as newspaper, directory for the exhibition or events, and fashion items also considered as the products that should be applied a single-period model as inventory policy. By using the single-period model, the practitioners should take the risk such as 50-50 percent out-of-stock or overstock into consideration since these situations will lead to inventory cost.

2.4.2 Multi-Period Systems

1) Fixed-Order Quantity System

Fixed-order quantity system is one of the multi-period systems; it is also named as Q model.

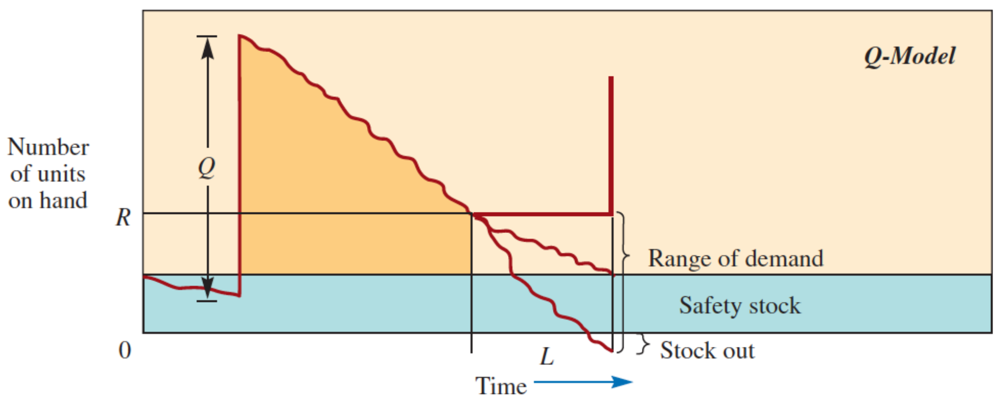


Figure 2-3: Fixed-Order Quantity System

(Source: Jacobs and Chase, 2013)

The model uses the event like some amount of remaining quantity as a trigger to reorder the items to put into the inventory, which is referred to reorder point (R). The order quantity is constant every time the order is made. Reorder point (R) is where inventory decrease to certain point, the replenishment is required.

$$\text{Reorder Point (R)} = \bar{d}L + z\sigma_L \tag{18}$$

where $\bar{d}$ is average daily demand

L is lead time

z is number of standard deviations at service level probability

σ_L is standard deviation of demand during lead time

Every time the items are withdrawn or added to the inventory system, the inventory record should be updated and closely monitored in order to not make any fault when the reorder point is reached. In this system, the continuous review is applied (Silver et al., 2017). Hence, fixed-order quantity system appropriate with the items with high value or critical parts that can lead to the negative or positive outcome to organisation.

<u>Economic Order Quantity (EOQ)</u>

Based on the principle of inventory management that take account in financial section of organisation (Muller, 2003), and Q-model's characteristic is to place order with the same amount of quantity; the optimal order quantity should be take into consideration. Economic order quantity is a model which allows organisation to calculate the certain quantity to be ordered at the minimum cost in both ordering cost and holding cost. Nonetheless, the ordering cost and holding cost must be trade-off. By ordering large number of items will lead to low ordering cost while the holding cost to stock those order items will be high. Thus, organisation should consider what cost to focus when applied this approach.

$$EOQ = \sqrt{\frac{2DK}{H}} \tag{19}$$

where D is demand

K is setup cost or cost of placing order

H is annual holding cost

(H = iC, where i is percent carrying cost and C is cost/unit)

As researched by Keskin and Capar (2013), economic order quantity model can help support designing the supply chain and improve the supply chain operation in the areas of location, transportation and inventory. For location, it is long term strategic decision making. By applying the EOQ model will assist the organisation to fully utilise its location with less holding cost. The transportation or logistic is part of supply chain; ordering at optimal quantity can help to manage mode of transportation, times, and freight. Lastly, an adequate order quantity will reduce the risk of overstock that affects the inventory holding cost and stock shortage that affects in service level of production and customers.

2) Fixed-Time Period System

Another system under multi-period systems is fixed-time period model; it can be called P-model. This model is quite contrast with the fixed-order quantity model.

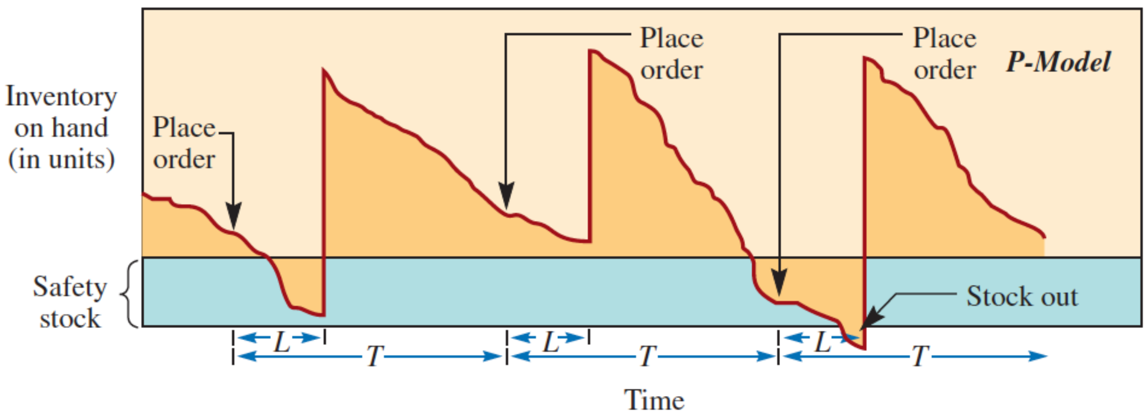


Figure 2-4: Fixed-Time Period System

(Source: Jacobs and Chase, 2013)

While the previous system reviews every time there is the movement in inventory, P-model will be review when the specified time as set has arrived which can be indicated as periodic review (Silver et al., 2017). Thus, the amount of inventory to be stocked is relatively high when compare to the Q-model since the record will be monitored and updated when the review period (T) is reached.

$$\text{Order Quantity(Q)} = \bar{d}(T + LT) + z\sigma_{T+LT} - Inventory\ on\ hand \qquad (20)$$

where $\bar{d}$ is average daily demand

L is lead time

T is review period

z is number of standard deviations at service level probability

σ_{T+LT} is standard deviation of demand during review period and Lead time

Regarding to the amount of purchase, it varies in every order based on the requirement of usage. With this type of inventory system, it allows an ease in stock counting planning and transportation cost management. Nonetheless, there is the weakness in this model. According to the characteristic of fixed-time period system, the chance of running out of stock can occur unnoticed before the review period has reached and cause the struggle in meeting the customers' demand.

2.4.3 Safety Stock

In general, demand has its own pattern and fluctuation as stated in section 2.2.2. Demand was not constant at every period of time as assumed in fixed-order quantity system; hence, the amount of inventory must be carried as a safety stock. Safety stock is the parameter of quantity remained in stock and it is the additional from the predicted demand. The objective of keeping the safety stock is to avoid the stock out situation which can lead to loss in opportunity and reduce the satisfaction from customers (Radasanu, 2016). By keeping the safety stock, organisation has to trade off with the inventory cost minimisation. As same as the economic order quantity model, the safety stock should be controlled not be too much to tie up the capital of organisation unreasonable and not to be too low that cannot serve customers' expectation.

According to King (2011), demand and lead time are variables to determine the appropriate amount of safety stock. For fixed-order quantity system where demand is deterministic and lead time is the primary concern, the formula will be as followed:

$$Safety\ Stock = z \times \sigma_{LT} \tag{21}$$

where z is the number of standard deviations of safety stock

σ_{LT} is standard deviation of demand during lead time

On the other hand, the formula will be derived as shown below when the lead time including the review period is fixed and there is variability in demand.

$$Safety\ Stock = z \times \sigma_{T+LT} \tag{22}$$

where z is the number of standard deviations of safety stock

σ_{T+LT} is standard deviation of demand during review period and lead time

When both demand and lead time are constant and equal, safety stock are not necessary to be acquired and kept which is the ideal case that difficult to occur.

2.4.4 Service Level

Service level is a probability approach use as indicator to know the level that organisations can serve their customers and can use it to approximate the level of inventory stock that will lead to low probability that inventory will run out of stock (Jacobs and Chase, 2013). Besides using the service level as a metric to indicate the ability to serve external demand, this probability approach can use as criteria to service internal demand such as when production line need the raw materials to produce, do raw materials are available to be produced or not.

Since 100% service level is ideal and difficult to be achieved, 95% service level is the percentage that organisations select as their inventory policy claimed by King, 2011. Nonetheless, Radasanu (2016) suggested that each group/type of products/parts in inventory should have different service level because this indicator relates to safety stock which is the items defined in previous section and can effect to the cost of inventory.

2.5 ABC Classification

In organisations that serve variety of products, the management of products classification is essential since it can allow the organisations to manage their SKUs at ease such as easier in fulfilment the inventory, locating the SKUs, and prevent to retard the deterioration of products. It is also associated with the financial part of organisations as each item has value, be able to group the high value items will help the organisations to manage the cost.

An activity-based costing classification or well-known as ABC classification is an approach that widely used for classifying the inventory. This approach divides the finished goods or raw materials into three classes as its name which are A, B, and C. Each group is classified based on the items' importance, value of items. The quantities of items are also a metric in this approach because the ABC classification adapted from Pareto principle (Basu and Wright, 2008). As illustrated in Figure 6, class A is where the SKUs that have high value but low quantity are grouped together. This is the most important class with the assumption that the quantity of SKUs is assumed to be small percentage about 20 percent while the value account for 80 percent from overall SKUs in general. The medium value defined as B class, it is the class that the value is approximately at 15 percent and quantity close to 30 percent of total inventory. And the third class is C class which is the low-value class with only 5 percent but take up to 50 percent of total quantity of inventory.

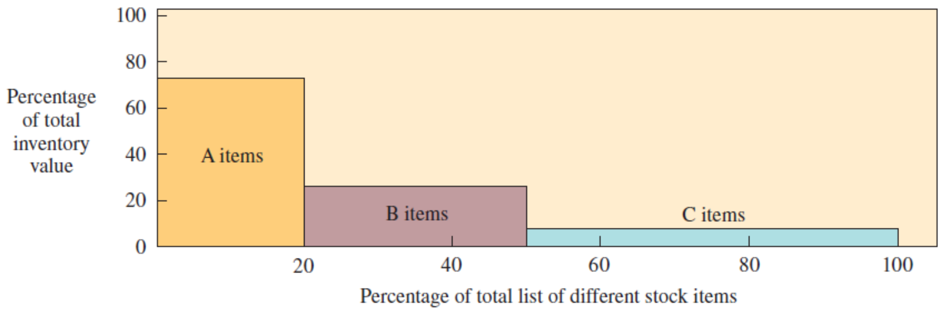


Figure 2-5: ABC Inventory Classification

(Source: Jacobs and Chase, 2013)

Since each class has its own characteristic based on its importance in term of value, the inventory policy for each class will be different as followed:

- A Class: Bases on its high value, A class should be monitored frequently and tight control with high security should be adopted in order to have high accuracy in inventory record. The loss or deterioration of items in this class can affect significantly to organisation's finance and reliability to customers.
- B Class: As an intermediate class between A and C, the inventory policy should be applied the same as A class. The continuous review should still be adopted but with less frequency for example, once every two weeks.
- C Class: With the high number of items in this class, periodic review should be applied because the stock counting and checking in this class takes time. The security may not have to be high as A class since the items' value are low, investing in prevention will not be worthwhile.

2.5.1 Multi-Criteria

Additionally, there are other criteria to classify the inventory into A, B, C class. The traditional ABC analysis approach divides the items mainly based on the money value of items as stated previously, while Flores et al. (1992) suggested that apply multi-criteria to inventory classification allow the practitioner to manage the inventory appropriately and efficiently. Other criteria to classify the inventory are based on the type of organizations, for example, the criticality of items to patients can be second criteria besides the money value of items for the healthcare industry while the organization in technology industry may give important in classification the inventory based on the outdated of items. For the manufacturing business, lead time may be other criteria in inventory classification that is effective to inventory management.

3. DEFINE PHASE

3.1 Organisation Chart and Business Operations

Studied company organizes the company structure based on the working processes as shown in Figure 3-1.

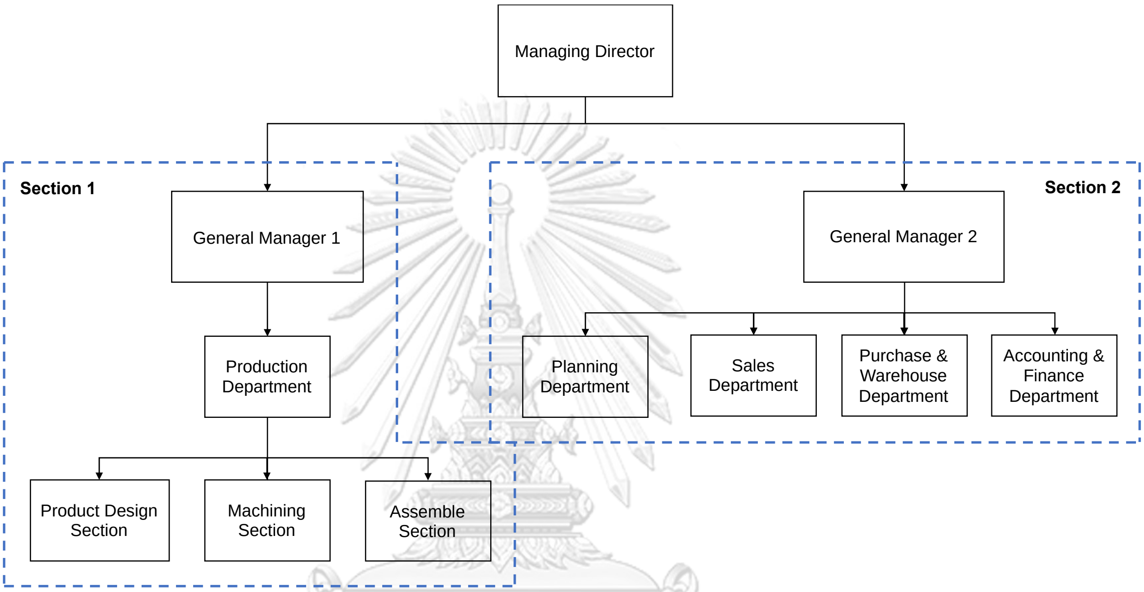


Figure 3-1: Studied Company's Organisation Chart

There are two major section managed by two general manager which are production part and planning part. The production part is consisted of the production department, things or processes related to produce the products are responsible by this department. Concurrently, the production plan is responsible by the second section of the company. The section 2 is where can be called the front office, it is the part they are in charge of contacting with the customers and received the customers' requirement. Nevertheless, planning department is the central department to deal with both back and front office. Figure 3-2 illustrates how the operations flow in studied company.

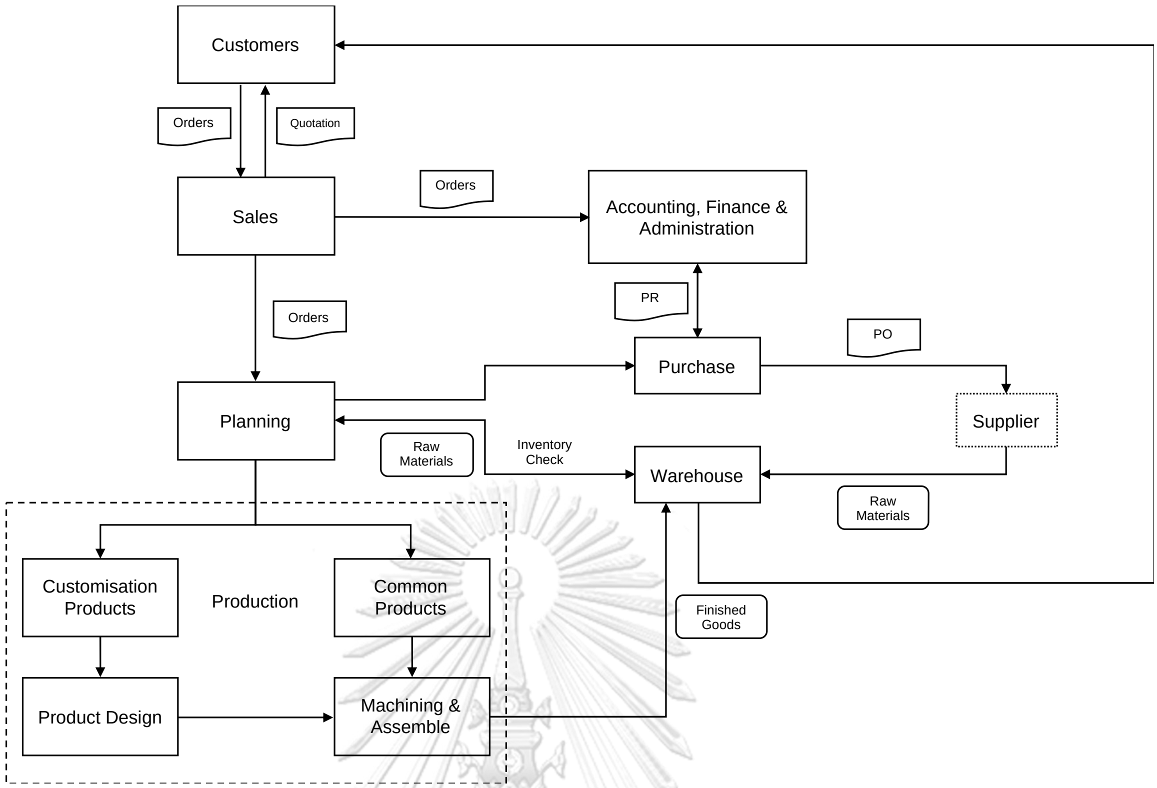


Figure 3-2: Studied Company's Operations Chart

Sales Department

This department is the first contact point with the customers. The customers' order and requirement will be collected by sales employee, also the quantity of products in need and date to be delivered. Preparing the quotation and retaining the relationship with the customers are also the responsibility of sales.

Accounting and Finance Department

All financial related is responsible by accounting and finance department. Administration is also part of this department; bills, receipts, and documents are controlled and processed by the accounting and finance department.

Planning Department

Based on operation flow in Figure 3-2, it can be seen that the planning department is the center of operations in the company. The production will be planned and established by this department. By doing the plan, orders received from sales will be interpreted and transformed into the details such as the bill of materials, production capacity, labours' shift, and technical sheet. Planning department also in charge of inventory management, coordinate with the purchase and warehousing department. Becoming the central department, planning department has to coordinate with all department in the company

Purchase and Warehouse Department

The purchase and warehouse are counted as a department for the studied company since these two sections' responsibility are overlapped. Purchase section is the area where purchase requisition document is managed and purchase order document is established when the planning department notices with the requirement; in the first point, purchase team responsible in specification and price correction before the order is placed to the supplier. Warehouse section is the section which is directly responsible in inventory management; inventory checking, recording, and updating are main responsibility of warehouse section. Receiving and quality checking the order from supplier are also what warehouse section do by coordinating with the purchased section. This department also has an authorize to order the raw materials to be stocked. Lastly, when there are the order placed from customers, products will be delivered from this department.

Production Department

Apart from the planning department, production department plays an important role in studied company since this department is where the products are produced to meet the customers' satisfaction. As stated previously, the production plan and technical sheet are provided by planning team for the production department to start the process.

There are two main processes to produce the products which are machining process and assembling process.

- **Machining process**: This process starts from bringing the raw materials such as plastic discarded/ rubber to the compounding and mixing with chemical filler before extruding to the designed shape and size through the roller die. Injection mold is another manufacturing process to produce the products in studied company. The products produced by machining process are mostly the products that has rubber and plastic as their raw materials e.g. door/ window seal, O-ring, and gasket.
- **Assembling process**: For the assembling line, it is majorly where the components/ parts are purchased from the suppliers and be assemble by the studied company. There are also some products that the components/ parts are received from the machining line to be assembled with the purchased parts.

In addition, there is the product design section that knew as research and develop in generally. This section is responsible in both internal and external requirement which internal requirement is to explore new products to serve the market while external requirement is from the customers that request for the customisation.

3.2 Problem Analysis

By studying and analyzing the existing operations of company, there are problems that occurred from the department that responsible and relate to inventory as followed:

3.2.1 Planning Department

According to the department's operation that responsible in planning the type and quantity of products to be produced to be stocked and to be served to customers' requirement, the quantity is planned to be produced base on the employee's experience and sometimes base on past data. There is no certainty in the method to predict the demand systematically. An inaccuracy of demand estimation can lead to two inventory problems which are stock shortage and overstock: both finished goods and raw materials.

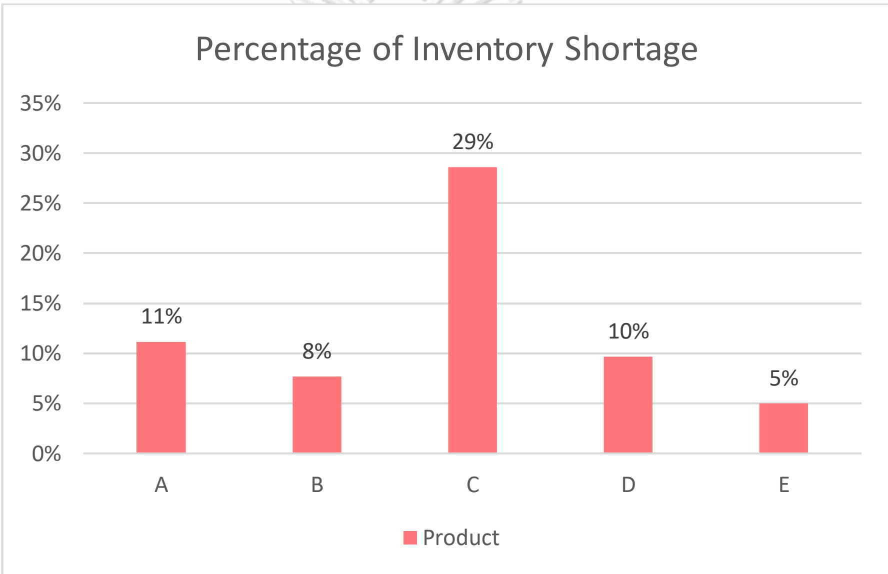


Figure 3-3: Percentage of Inventory Shortage

With the existing procedure of how planning department work on estimating the demand to be produced and to be stocked, it leads to the issue of inadequate of products to meet the customers' satisfaction, inventory shortage. Figure 3-3 shows the percentage of inventory shortage of the products. And also the overstock of inventory, for example, product A is produced in large amount according to the comment of planning department but the customers' need at that time is product B; therefore, the product A will be overstocked and effect to the financial part. This problem of finished goods inventory is occurred from the inaccuracy of demand estimation can affect to the stock of raw materials/ parts to be machined and assembled.

3.2.2 Purchase and Warehouse Department

Apart from ordering the raw materials from the purchase requisition from planning department, purchase and warehouse department sometimes order the raw materials to the inventory when they see fit; and this leads to the problem. There are the issues which the stock is short and over periodically based on the existing operation of the department. Currently, there is no certain time period of stock checking and updating, these activities are mostly done when the manager requested for the report. The order of raw materials/ components is occasionally placed repeatedly since there is no standard of time and quantity to be placed. Based on how the department currently operates, there are cases that the stock is short and sometimes is over. Figure 3-4 reveals the percentage of inventory that kept too much.

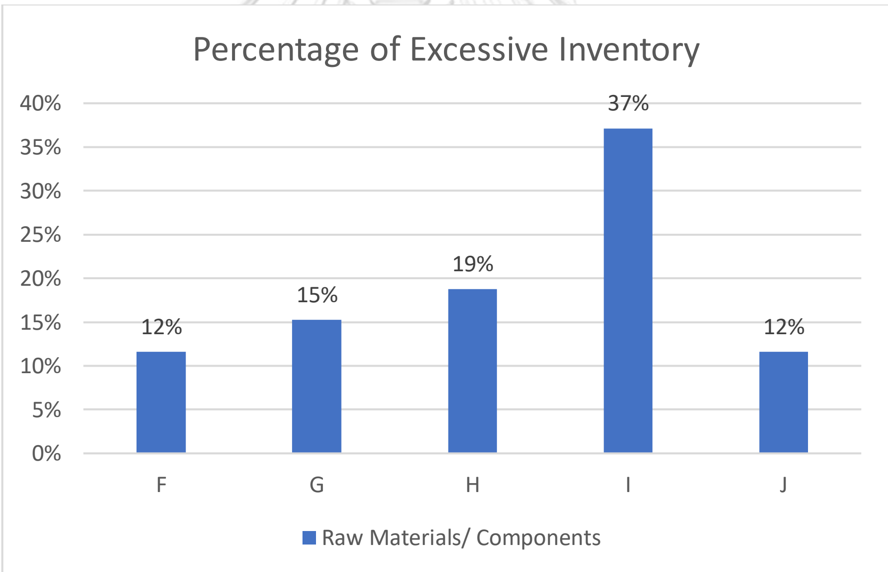


Figure 3-4: Percentage of Excessive Inventory

4. PROPOSED PHASE

In this chapter, it is included of three sections which are inventory classification, demand forecasting, and inventory control. Since There are two types of inventory in studied company which is raw materials and finished goods as stated in Defined Phase, finished goods will be focused to be classified into group and in the part of demand forecasting. For the inventory control part, the data of raw materials will be used.

4.1 Inventory Classification

Before constructing the demand, forecasting models, inventory will be classified into different group to visualise how each group cause an impact to the company and which inventory policy should be applied to manage the inventory. Since there are number of finished goods, 104 SKUs that company allowed to be studied, that company serve to the customers; ABC analysis framework will be applied to classify the inventory. Theoretically, this tool divide inventory into three groups according to their value as reviewed in Chapter 2. Nevertheless, multi-criteria is also applied to ABC analysis and will be applied to this study. There are two criteria as followed:

- **Value of item** – In this study, the value of item to be a criterion of inventory classification is sales value of its item. The unit cost of products and the sales in studied company will be considered. This criterion is selected to this study according to the impact that can cause to the financial part of studied company.
- **Process** – As recommended by Flores et al. (1992), lead time is another criterion that suitable to be applied to manage the inventory items. In this case, the exact lead time of each item is not collected precisely therefore, the process of the items will be considered instead as it is directly related to lead time. Process is divided into machining (M) and assembling (A) as reviewed in Defined Phase with an assumption that

product that is produced by machining process has longer lead time than assembling process. Range of machining's lead time is about 3-5 days while it is about 0.5-1 days for assembling process.

In order to classify the inventory into group, the first step to be done is the data collection. Data which are quantity of use, unit cost, and value of item from year 2018 will be collected to fill in each blank in the Table 4-1.

Table 4-1: ABC Classification Table Format

No.	Item Code	Quantity of Use (Unit/Year)	Unit Cost (THB)	Value of Item (THB)
1	FG-BL-SEAL			
.	.			
.	.			
.	.			
104	FG-TW-CASTER			

Since there are two criteria with groups stated above to be considered, there will be 6 groups as outcome of classification. The value of items will be considered first to classify finished goods into A, B, and C as shown in Table 4-2. The full information of Table 4-2 is shown in Appendix.

Table 4-2: Part of ABC Classification – First Classification with First Criteria

No.	Item Code	Quantity of Use (Unit/Year)			Value of Item (THB)			Class
		Annual	%	Total %	Annual	%	Total %	
12	FG-BL-SEAL04	124249	2%	2%	8200434	8%	8%	A
14	FG-BL-SEAL02	98128	2%	4%	6908211.2	7%	14%	A
70	FG-1.5-SEAL	14355	0.2%	35.3%	1220175	1%	74%	B
44	FG-H-DL	29709	0.5%	35.8%	1188360	1%	75%	B
26	FG-HCL-CASTER	63000	1.0%	51.8%	630000	1%	90%	C
45	FG-BL-SEAL	27590	0.4%	52.2%	606980	1%	91%	C

Then, each item in each group will be categorized into its process; machining and assemble. Table 4-3 reveals an example of how each item is classified the process criteria. Full table can be seen in Appendix.

Table 4-3: Part of ABC Classification – Second Classification with Second Criteria

No.	Rearranged No.	Item Code	Class	Process
12	1	FG-BL-SEAL04	A	M
14	2	FG-BL-SEAL02	A	M
70	23	FG-1.5-SEAL	B	M
44	24	FG-H-DL	B	A
26	42	FG-HCL-CASTER	C	M
45	43	FG-BL-SEAL	C	M

After classifying each item into group, the graph (Figure 4-1) is plotted. From the data collected and analysis, the graph illustrated like the Pareto principle as reviewed in Chapter 2. The graph shows that the items in group A are the items that take part as the highest value of all the item's value which is 73%, which can be implied that this group can cause the highest impact to company in both financial part and customers' relationship. While group B and group C contribute only 17% and 10% respectively to the total inventory value. Nonetheless, group A is only 35.1% of inventory quantity, on the other hand, group B take part in inventory quantity with 15.6% and group C is 49.30%.

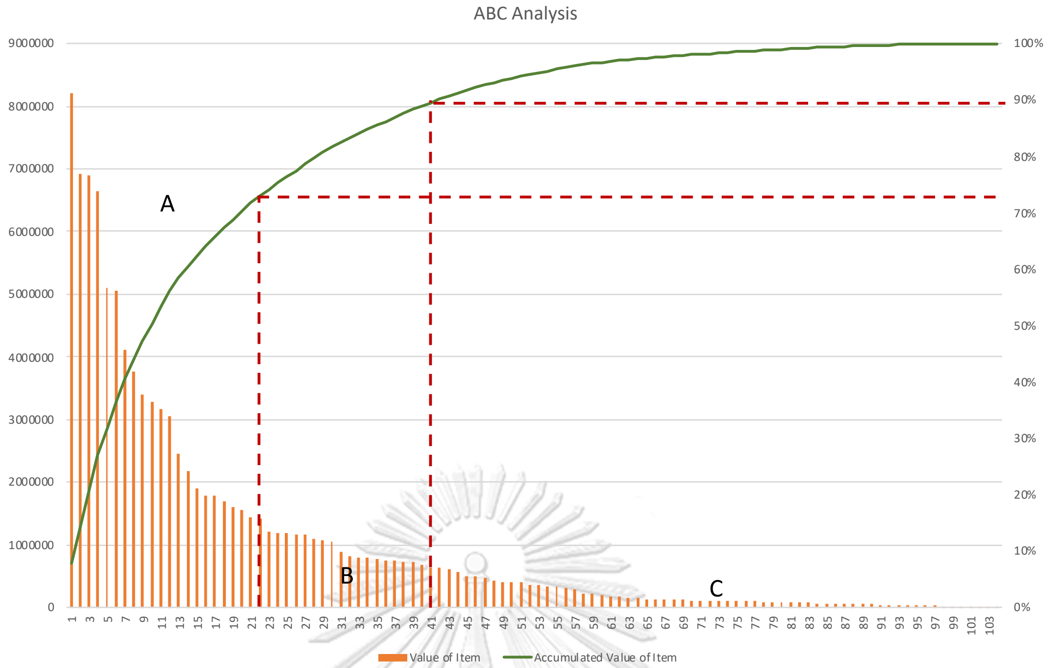


Figure 4-1: ABC Classification Based on Pareto Plot

At the end, the number of items in each group is shown as followed:

Table 4-4: ABC Groups

<table>
<tr><th>Group</th><th>Machining</th><th>Assembling</th></tr>
<tr><td>A</td><td>14</td><td>8</td></tr>
<tr><td>B</td><td>12</td><td>7</td></tr>
<tr><td>C</td><td>32</td><td>31</td></tr>
<tr><td rowspan="2">Total</td><td>58</td><td>46</td></tr>
<tr><td colspan="2">104</td></tr>
</table>

Items in group A with machining will be defined as A-M, which take the same to group B and C with B-M and C-M thereinafter in this study.

4.2 Demand Forecasting

To propose the forecasting model that able to provide better accuracy in predicting the quantity of demand, forecasting model-fitting is selected as a procedure to get the suitable forecasting model for studied company. The model-fitting is included of six steps as followed with the description of each step and will be computed by Microsoft Excel and R Studio software:

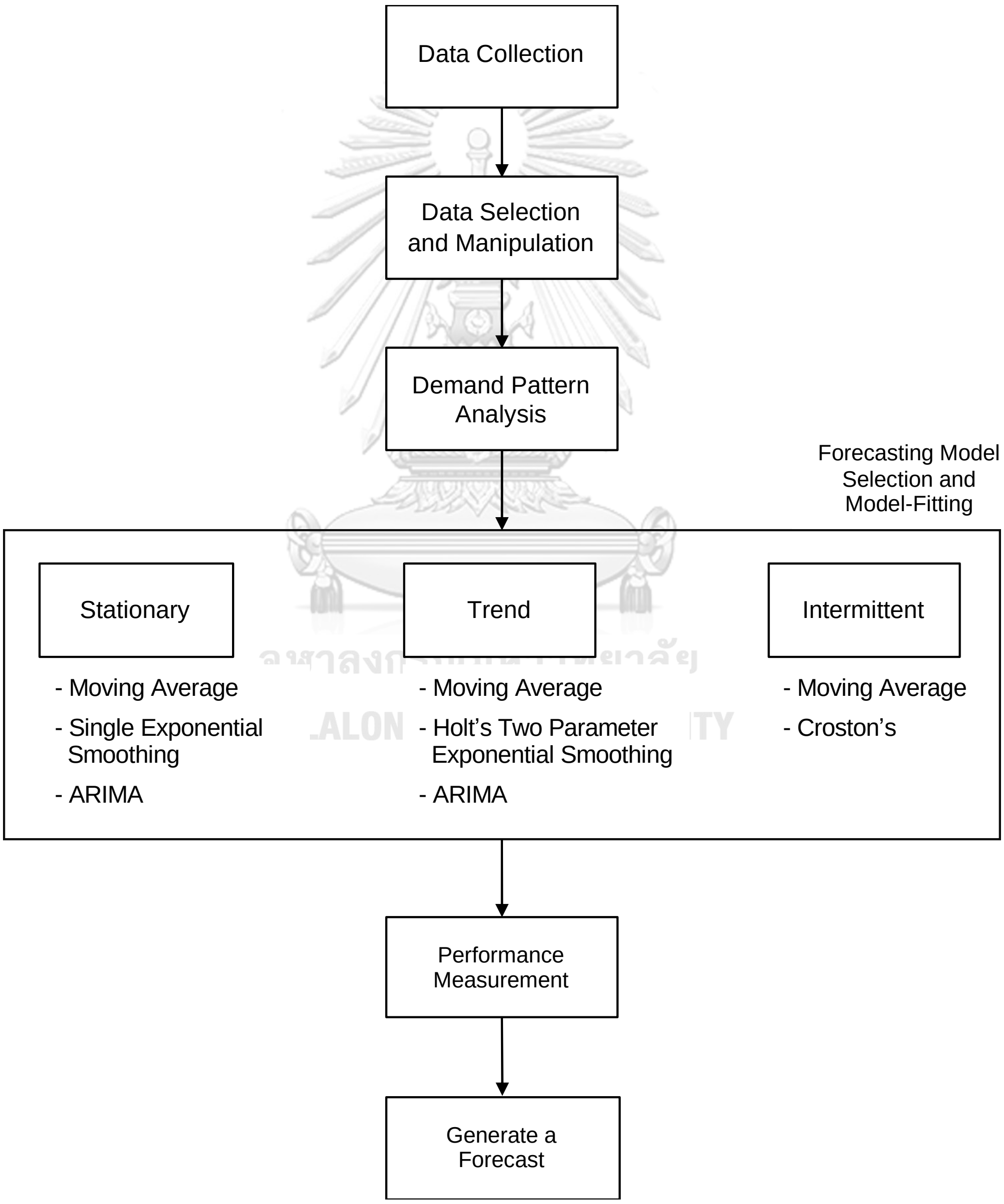


Figure 4-2: Demand Forecasting Model-Fitting Flow Chart

4.1.1 Data Collection

First step to generate the demand forecasting model is to collect the appropriate data set. As Time Series Forecasting models will be selected in this study, history data set of demand is essential to be collected with as accurate as possible which can be implied that source of data should be reliable and sequential. In this study, the demand data set is monthly collected from customer order history. Moreover, amount of data which is data point should be adequately collected.

4.2.2 Data Selection and Manipulation

Three years of history demand data will be selected to apply by model-fitting procedure which are the data from January, 2017 to December, 2019. Data set will be divided into two sections which are in-sample and out-of-sample.

- In-sample data: 30 monthly demand data which are January, 2017 to June, 2019 will be in-sample data that will be used for fitting the forecast model to explore the model that perform the least forecasting error.
- Out-of-sample: Monthly demand data from July, 2019 to October, 2019 are out-of-sample data to compare between the actual demand and forecasted demand that generate from the selected forecasting model.

In evaluating the best forecasting models, ten items from group A-M, B-M, and C-M that is classified in the inventory classification section will be chose to run the forecasting models thereinafter. The items from group A, B, and C that are produced by machining process are selected to implement in this study is because these products have long lead time and the capacity of machine and labors are required to be planned in order to has the optimal utilization. Furthermore, the products with machining process are over 50% of total number of products. Hence, to be able to know the future prediction of demand can help in determine and delegate the work and machine.

4.2.3 Demand Pattern Analysis

In this step, in-sample data will be analysed by plotting the graphs in order to consider what type of demand pattern that the item is. By considering the pattern of demand can guide the practitioner to choose the appropriate forecasting technique to the data set. There are three types of demand pattern to be focused in this study which are stationary, trend, and intermittent. Seasonal pattern is negligible in this case since the products of studied company are not the type of product that in need based on the season or repeated in demand by period of time. The graphs that will be applied as tools to examine the pattern of demand are time series plots and autocorrelation function plot (ACF). Coefficient of Variation (CV) is also used to define the fluctuation of item's demand. As stated by Chase (2013), stationarity of demand is the demand that has similar variance in every period interval therefore, the data set that has low variation can be implied that the data set has stationary pattern.

4.2.4 Forecasting Models Selection and Model-Fitting

After considering the pattern of in-sample data set in previous step, choosing the forecasting models to fit the data will based on the demand pattern defined as stated earlier. Forecasting models that suit with the analysed pattern will be applied to in-sample data of each item. As suggested by Chase (2013), there should be more than one forecasting model to do the model-fitting in order to make a comparison and find the appropriate forecasting model. Thus, each type of demand pattern will be fitted to at least two models. Selected items' data will be fitted to the selected forecasting models as followed to illustrate the plot of actual demand values versus the fitted values.

- Stationary
    - Moving Average
    - Single Exponential Smoothing
    - ARIMA

- Trend
    - Moving Average
    - Holt's Two Parameter (Double Exponential Smoothing)
    - ARIMA
- Intermittent Pattern
    - Moving Average
    - Croston's

Moving average, single exponential smoothing, Holt's two parameters, and Croston's will be computed in Microsoft Excel. And ARIMA will be computed in R Studio.

4.2.5 Performance Measurement

For the purpose of exploring the forecasting technique that can perform the better accuracy, performance of the forecasting model will be evaluated by using the forecasting performance metrics. An error value which is determined from difference between the fitted values and actual values will be the core parameter in measure the performance of forecasting model by applying to the as followed:

- Mean Squared Error (MSE)
- Mean Absolute Deviation/ Mean Absolute Error (MAD/ MAE)
- Mean Absolute Percentage Error (MAPE)
- Mean Absolute Scaled Error (MASE)

The first two metrics of forecasting performance will be applied to determine forecast accuracy in every pattern of demand while MAPE and MASE will be applied differently; MAPE will be applied with the item that its characteristic is stationary or trend pattern while intermittent demand pattern items that in the model-fitting will be evaluated with MASE. This is because of the limitation of MAPE that cannot generate the percentage error of data contain with no demand as referred in Chapter 2. After achieving the result of forecast accuracy measurement of each forecasting method, the one that able to present the least error will be selected to proceed in the next step.

4.2.6 Generate a Forecast

From the first step until the evaluation of forecasting model performance, the selected technique that can establish the better accuracy is finalised through model-fitting procedure. At this step which is the final point of demand forecasting model propose, selected model from the previous step is deployed to generate four months demand projection; July 2019 to October 2019. Four months demand prediction is generated as the selected forecasting models are the models that appropriate to project the short-term forecasting. The out-of-sample data set, actual demand data set, is compared to the established forecasting demand. The accuracy metrics from step 5 will again apply in order to check the ability of selected forecasting model.

At the end, there will be one type of forecasting model that able to generate the least error forecast demand and suit best with each demand pattern that proposed to the studied company. Products from both group A and B will go through until this step while products in group C will finish at step 5 according to the lack of information.

4.3 Inventory Control

In this section, the inventory control model will be set up to match with the demand of raw materials by applying the theories that were reviewed in Chapter 2. The raw materials/components will be classified by looking through the bill of materials of finished goods in each class. Raw materials/components that mostly used as component of group A is classified as the special raw materials/components, and the rest of raw materials/components are defined as common raw materials/components that are generally be the part of most of the products. Since each group of raw materials have different requirement in use, different model of inventory control will be applied.

Continuous review model is proposed to the special raw material/components while Periodic review is proposed to the raw materials in common raw materials/components.

4.3.1 Continuous Review

Continuous review is also known as fixed order quantity (Q-model), it is the inventory control model that the inventory is checked and updated every time there is a movement occurred; in and out of items, as this type of control of inventory is mainly based on the reorder point (R) and quantity to be ordered as reviewed in Literature Review section.

This type of inventory control system allows the person in charge of inventory management, planner, warehouse, and purchaser; in this case, to have a closer looks and control in the items because of the stated principle of the model. Therefore, the inventory control model called Continuous Review is proposed to the raw materials that are mostly component of finished goods in group A; nevertheless, these raw materials are also the component of other items in group B but with small percentage when compared with the group A. Continuous Review model is proposed to these raw materials because the raw materials of this class is highly required to be adequate to serve the production department when needed in order to seize the opportunity to produce the products as planned and serve the customers' satisfaction. High demand of group A's finished goods is also the reason that the Q-model is proposed. Moreover, Q-model has quite low safety stock when compared to the periodic review model according to the continuous review of the model which is one of its advantages. It can help to improve the inventory holding cost that the value of items is distributed to the cost. In this study, the value of raw materials for items in group A are likely high according to the specific of materials' type and they are conformed with the value of finished goods in group A which has high value.

In order to set up and implement the continuous review inventory control model, there are steps how Q-model works shown in Figure 4-3.

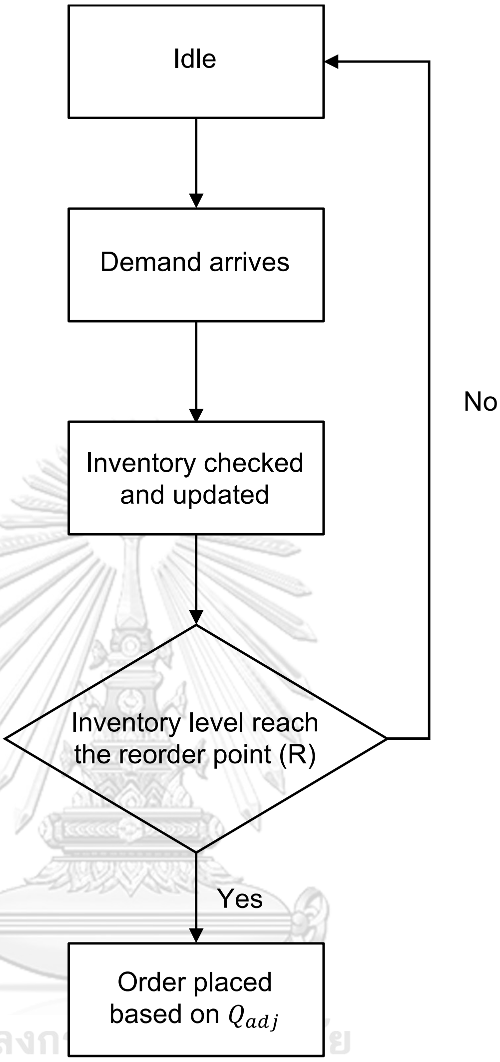


Figure 4-3: Q-Model Flow Chart

Data of raw materials for the items in group A are collected by the use of bill of materials (BOM). Five raw materials are selected to be studied and be input to the continuous review model simulation.

Table 4-5: Data of Special Raw Materials

Code	Unit	Price/Unit	Annual Demand (D)
RM-1	Kg	38.5	1116500
RM-2	Kg	22.5	722951
RM-3	Kg	44	505998
RM-4	Kg	24	330705
RM-5	Kg	18	305600

The core of inventory control model set up is to be able to determine the quantity to be order and when to order. Even if the demand is varied time-to-time, Karteek and Jyoti (2014) suggested that the equation of economic order quantity can be applied to the case where the demand is not deterministic. Therefore, the quantity to be ordered for Q-model's simulation in this research, it can be determined by the formula of economic order quantity (EOQ) reviewed in Chapter 2 as it can estimate the optimal order quantity. The formula is as followed:

$$EOQ = \sqrt{\frac{2DK}{H}} \tag{19}$$

According to the formula above, it shows that ordering cost (K) and inventory holding cost (H) are parameters of the equation to determine the quantity to be order. Therefore, these two parameters are required to be determined first.

Table 4-6: Ordering Cost

Administration	Cost	Remark
Purchase Department	1100	Manager and employee who involve in placing an order. The cost is calculated by taking the proportional to their salary
PR and PO Document	500	e.g. PR and PO paper and software for the PR&PO issuing
Related Office Supplies	200	e.g. pen, folder, and stapler
Internet	500	
Telephone	200	
Ordering Cost (THB/order)	2500	

Ordering cost is the cost incurs when there is order placed. It is calculated majorly based on the cost of administration as suggested by Shenoy and Rosas (2018). The cost administration is break down in Table 4-6 based on the range and information given from the studied company. All action, time, and effort expend in placing an order is part of the ordering cost. Each components of administration cost is weighted differently, in this study, it depends on the time and usage related to purchasing the materials. The information such as manager and employees' salary use to determine the ordering cost is collected from the studied company. The estimation of ordering cost is 2,500 Thai Baht per order. In the assumption to calculate the economic order quantity (Sethi, 2015), the ordering cost is constant for any order.

Table 4-7: Economic Order Quantity (EOQ) and Q Adjustment

Code	Annual Demand	K	h	EOQ	Q_{adj}
RM-1	1116500	2500	3.00	43137.38	41800
RM-2	722951	2500	2.25	40081.89	40100
RM-3	505998	2500	4.40	23979.10	24000
RM-4	330705	2500	2.40	26248.21	26300
RM-5	305600	2500	1.80	29135.70	29200

Second parameter that effect the quantity to be ordered is inventory holding cost. As stated by Mollering (2007), the holding cost is calculated as 10% of the unit cost of each items. All parameter related to determine the EOQ is shown in Table 4-7, where Q_{adj} is the adjustment of the EOQ to make the quantity to be ordered is based on the minimum of quantity conditions requested from the suppliers.

Table 4-8: Reorder Point

Code	Annual Demand	σ_{month}	σ_{week}	LT (week)	σ_{LT}	z (SL = 98%)	SS	Avg D during LT	Reorder Point (R)
RM-1	1116500	54772.45	26413.62	2	37354.50	2.054	76717	42942	119659
RM-2	722951	7171.47	3458.39	1	3458.39	2.054	7103	13903	21006
RM-3	505998	8236.61	3972.04	2	5617.32	2.054	11537	19461	30998
RM-4	330705	3872.23	1867.35	1.5	2287.03	2.054	4697	9540	14237
RM-5	305600	6580.32	3173.31	1.5	3886.50	2.054	7982	8815	16797

Following that, the reorder point is consider and shown in Table 4-8, it is the indication point when the order should be placed when the inventory level reach at that inventory level. Reorder point is determined from two parts which are demand during the lead time and safety stock.

$$\text{Reorder Point (R)} = \bar{d}L + z\sigma_L \qquad (18)$$

By including the safety stock as part of reorder point determination, it allows the low risk of shortage that may occur from the uncertainty of demand during lead time (Shenoy and Rosas, 2018); even if the demand during lead time is estimated and add to the level of inventory that the order should be placed, there may be the case that the demand during lead time is higher that the estimation. Thus, safety stock at 98% service level is proposed to the continuous review inventory control model.

$$Safety\ Stock = z \times \sigma_{LT} \tag{21}$$

98% service level will be translated by NORMSINV function in Microsoft Excel in order to establish the z-value in safety stock formula. The level of service is proposed according to the significant of raw materials to the production plan and financial part. Hence, there are 2% chance that the demand of raw materials cannot be met.

4.3.2 Periodic Review

As aforementioned, different class of items should be controlled by different inventory policy. For the raw materials that majorly parts of the common finished goods which are products in class B and C; since they are the parts of finished goods that have lower contributed in total value thus, the periodic review inventory control model is proposed to manage the inventory. Periodic review is also known as Fixed-Time Period System (P-Model) which is opposite to the continuous review. Planners and warehousers interact with the inventory based on specific time. The stock record and order will be updated and placed when the review interval (T) is reached, for example, every three weeks or every end of month. Figure 4-4 shows how the periodic review model works.

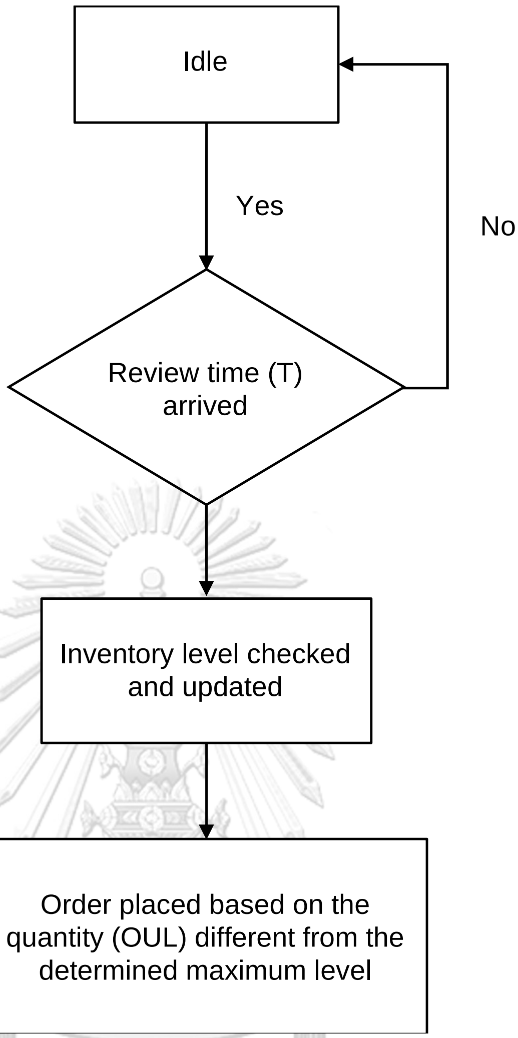


Figure 4-4: P-Model Flow Chart

With P-model, the quantity to be ordered is not fixed and varied due to the determined maximum inventory level; order-up-to-level (OUL). The amount to be ordered is the difference between the inventory on hand (ending inventory level) and the demand during review and lead time interval, plus the safety stock.

$$\text{Order Quantity } (OUL) = \bar{d}(T + LT) + z\sigma_{T+LT} - Inventory\ on\ hand \qquad (20)$$

Safety stock is added in order to cover the possibility of shortage from the uncertainty of demand during the lead time and review interval, similar to the Q-model. For the P-model, 95% service level is selected due to the value of items.

$$Safety\ Stock = z \times \sigma_{T+LT} \tag{22}$$

For studied company and according to the organisation chart of company, the review period is suggested to be every 30 days. The five raw materials that are part of finished goods in class B and C are randomly selected to be studied. Selected five raw materials are listed in Table 4-9 with the variables required for the periodic review simulation.

Table 4-9: Periodic Review Parameters

Code	Annual Demand	$\boldsymbol{\sigma_{month}}$	$\boldsymbol{\sigma_{week}}$	LT (week)	T (week)	$\boldsymbol{\sigma_{LT+T}}$	Avg D during LT+T	z (SL = 95%)	SS	OUL
RM-6	146995	4213	2032	1.5	4	4765	15548	1.64	7838	23386
RM-7	80400	4243	2046	2	4	5012	9277	1.64	8243	17520
RM-8	38154	1097	529	1	4	1183	3669	1.64	1945	5614
RM-9	20384	1030	497	1	4	1111	1960	1.64	1827	3787
RM-10	15220	1631	787	1.5	4	1845	1610	1.64	3035	4644

5. IMPLEMENTATION AND RESULT DISCUSSION

5.1 Demand Forecasting

5.1.1 Group A

In this study, ten items of finished goods out of 14 items from group A are selected to explore the forecasting method that appropriate to group A's data type. Selected items are the top ten items that have high annual number of units sold in group A. Code A-M-1 to A-M-10 are defined to each item. One item out of ten will be demonstrated through the steps proposed in Chapter 4, in this section.

1) Data Collection, Selection and Manipulation

Demand data of A-M-4 in each month from January 2017 to June 2019 are collected from the monthly sales history record. A-M-4 finished goods are chose to demonstrate in detail since this item has high percentage of shortage in year 2018 with 29%. Bar chart in Figure xx displays the demand quantity versus the time period stated previously of A-M-4.

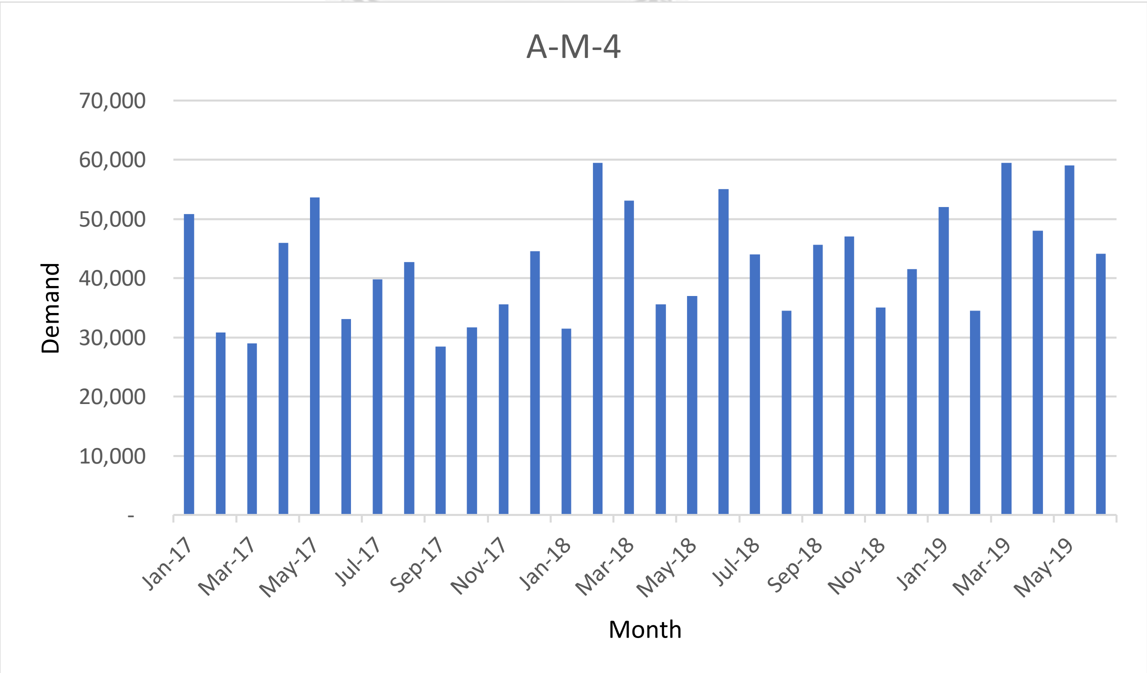


Figure 5-1: A-M-4 Bar Chart

2) Demand Pattern Analysis

As displayed in bar chart and time series plot of A-M-4, Figure 5-1 and 5-2 respectively, the demands of A-M-4 to the market is slightly steady and also demonstrates no trend. Apart from judging the pattern of demand by observing the graph characteristic, coefficient of variation (CV) is calculated in order to check the stability of demand. With the data of A-M-4, coefficient of variation is 0.22 that can be implied that the data set has low fluctuation.

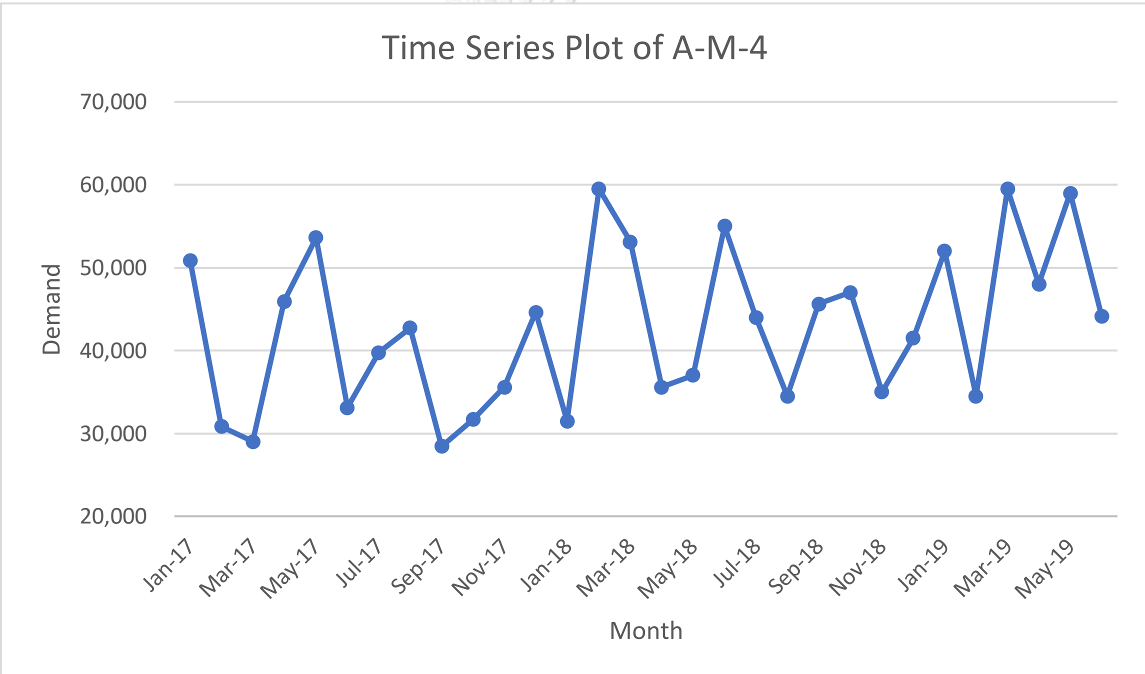


Figure 5-2: Time Series Plot of A-M-4

Autocorrelation Function (ACF) is also plotted to check the stationarity in time series of A-M-4, shown in Figure 5-3. As demonstrated in ACF, it helps to ensure that the demand pattern of A-M-4 is stationary and has no trend since the plot illustrates no spike.

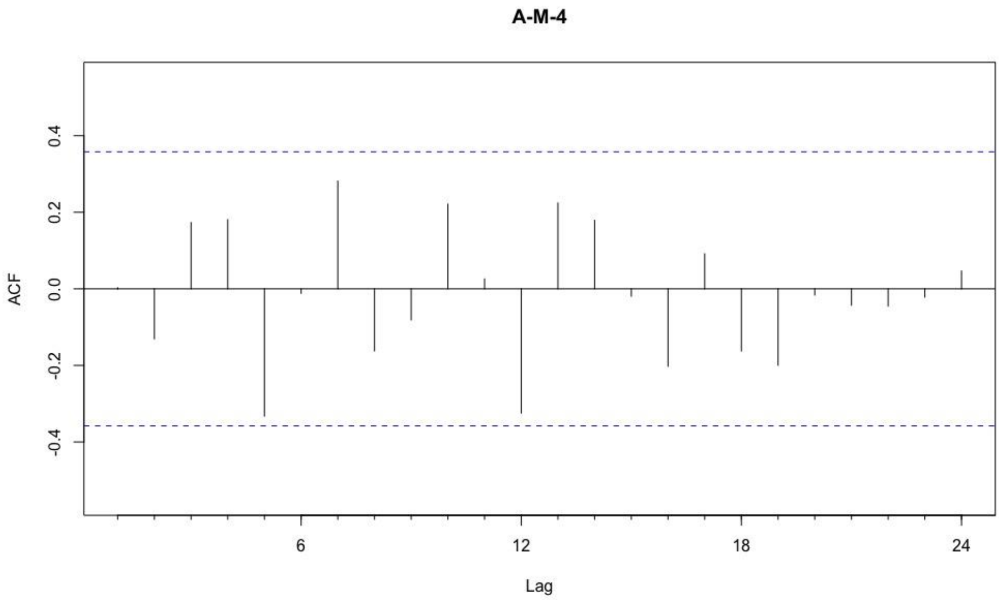


Figure 5-3: Autocorrelation Function of A-M-4

3) Forecasting Models Selection and Model-Fitting

By examining and acknowledging the pattern of demand in prior step, with the stationary demand pattern, three (3) forecasting models proposed will be applied to establish the model-fitting.

- Moving Average
- Single Exponential Smoothing
- Autoregressive Integrated Moving Average (ARIMA)

Naïve model will be shown in this step as an existing forecasting model of studied company.

3.1) Naïve Forecasting Model

The existing method of demand estimation of studied company by planning department is mostly depend on the opinion and experience from planning department and also estimate based on the old demand data which can be implied that the team uses part of qualitative method and quantitative method. According to the current operations stated earlier, the Naïve forecasting model is selected as forecasting model that represents the current method of studied company since the principle of this model is forecast the future demand by assuming that the demand in the future time period will be the same as current demand.

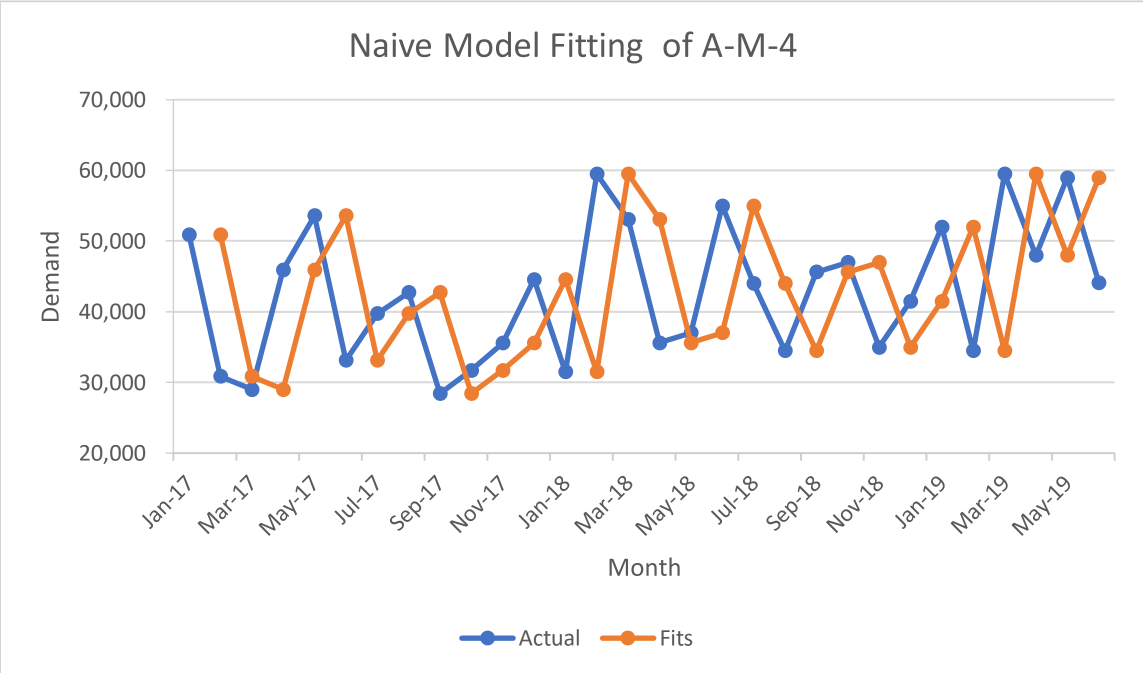


Figure 5-4: Naïve Model Fitting of A-M-4

When fitted the collected data with the Naïve model, the model-fitting is illustrated in Figure 5-4. It can be seen that the plot of fits line is one-step ahead from actual values entirely because of the aforementioned concept of Naïve method.

3.2) Moving Average Forecasting Model

In this model, three months is the number of time periods that will be averaged to project the demand of next month. As outlined in Literature Review section, the longer the time periods to be averaged the smoother the of future demand projection; and smoother the fit values can lead to the missing of critical values or terms. For this reason, the three months is selected in this study since it is the number of period that be able to propose the next month demand estimation by neglecting some randomness but still maintain some randomness that may be critical factor that effects to the future demand value as can be observed in Figure 5-5. The Figure above presents the plot of 3-month moving average model of item A-M-4.

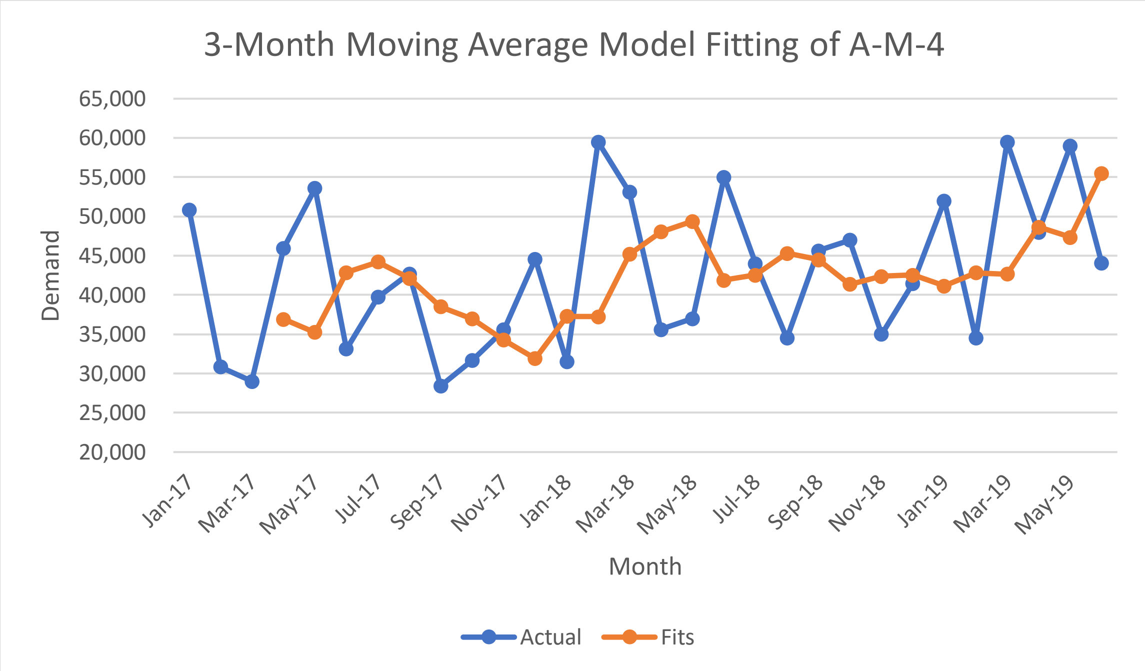


Figure 5-5: 3-Month Moving Average Model Fitting of A-M-4

3.3) Single Exponential Smoothing

Single Exponential Smoothing model is a forecasting model that is developed from Moving Average forecasting technique as reviewed in Literature Review section. This model is adjusted from Moving Average model by adding one more constant factor, alpha(α). By adding smoothing constant factor, each point of observation is weight given with the principle that the most recent data has higher weight and the weight is exponentially decreased as its past of data.

Figure 5-6 shows the model-fitting of A-M-4 by applying the Single Exponential Smoothing method.

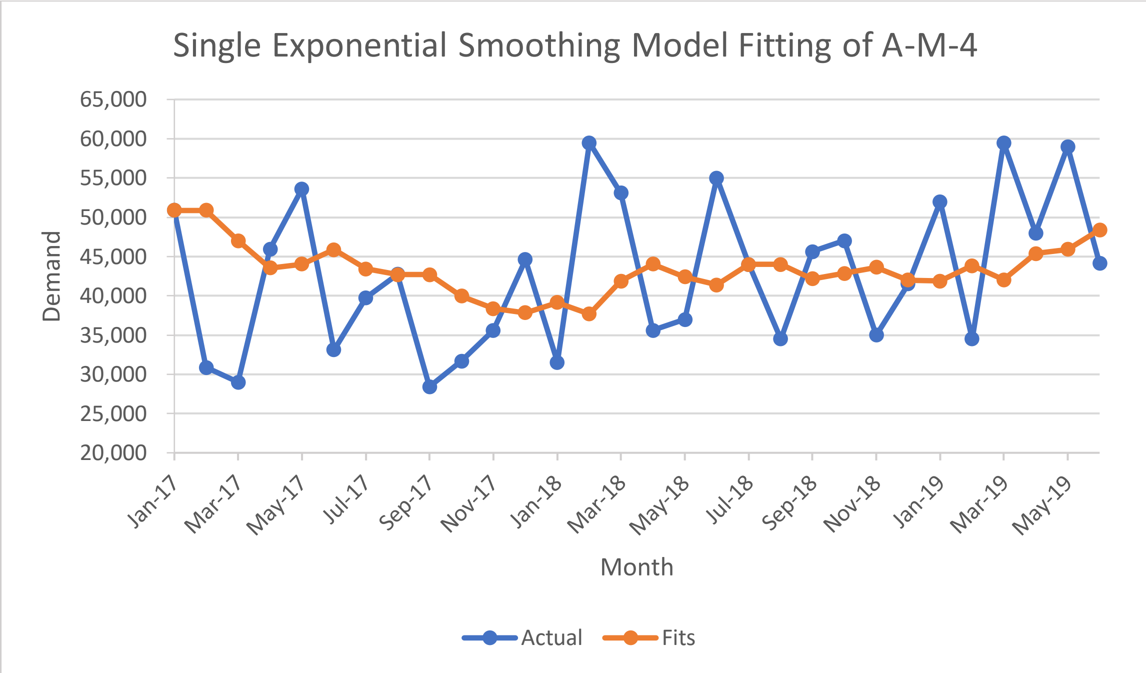


Figure 5-6: Single Exponential Smoothing Model Fitting of A-M-4

By using the solver parameter tool in Excel, the smoothing constant factor (α) for this fitting is 0.192 which is the suitable value of alpha that provide the least error to model-fitting of A-M-4 data set. With this constant factor value, the randomness of data is not completely omitted from data set which allow the model to fit with the actual data properly which is proved in Figure 5-6.

3.4) Autoregressive Integrated Moving Average (ARIMA)

Different from the preceding forecasting models, Autoregressive Integrated Moving Average or well known as ARIMA is statistical modelled by R Studio software program in this study. According to its name, ARIMA is included of three components which are Autoregressive (AR), Integrated (I), and Moving Average (MA); each component is detailed in Chapter 2. By consisting of three components, there are three parameters that need to be determined in order to run an ARIMA model; the parameters are AR(p), I(d), and MA(q). But fitting the model in R Studio, the function 'auto.arima' is used to provide the ARIMA model with p, d, q parameters that most appropriate to the data set of A-M-4 and has the lowest Akaike's Information Criterion (AIC). By using the 'auto.arima' function, the ARIMA model that fit to A-M-4 data is plotted in Figure 5-7 with ARIMA (0,0,0)

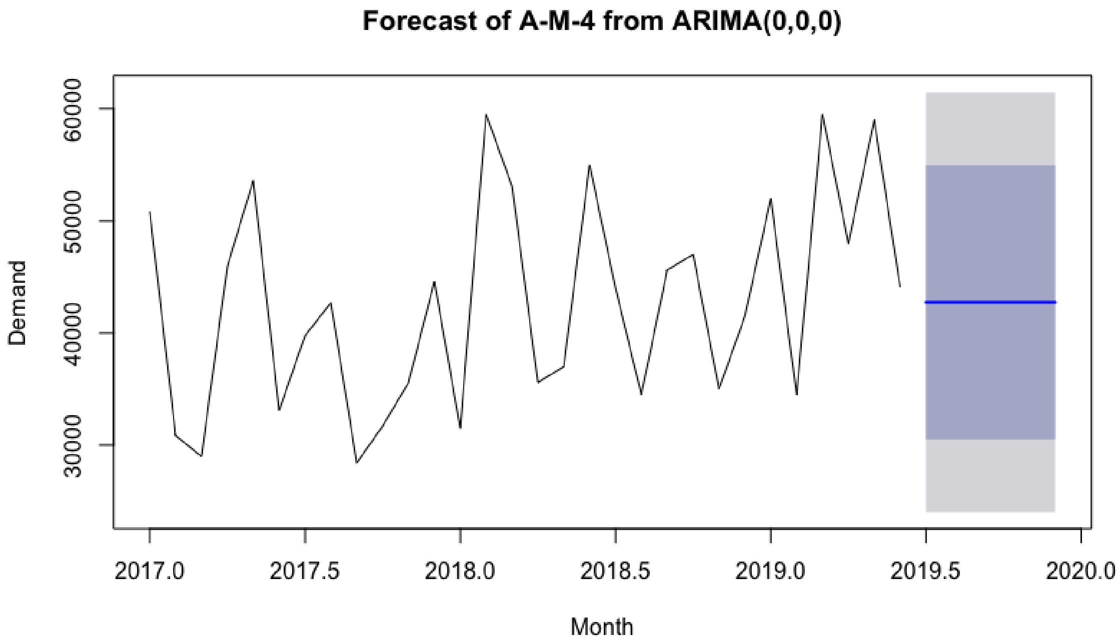


Figure 5-7: Forecast of A-M-4 from ARIMA (0,0,0)

To elaborate the outcome from using 'auto.arima', the autocorrelation function (ACF) plot in Demand Pattern Analysis section (Figure 5-3) pinpoints that this data set of A-M-4 is stationary which is the first point to be considered when constructing the ARIMA model. Since the data is stationary, it is unnecessary to differencing the data and I(d) is determined as zero. Next parameter is AR(p), the ACF plot is observed and it represents that there is no autoregressive (AR) contained in the model since there is no lag spike out of the threshold limit bars.

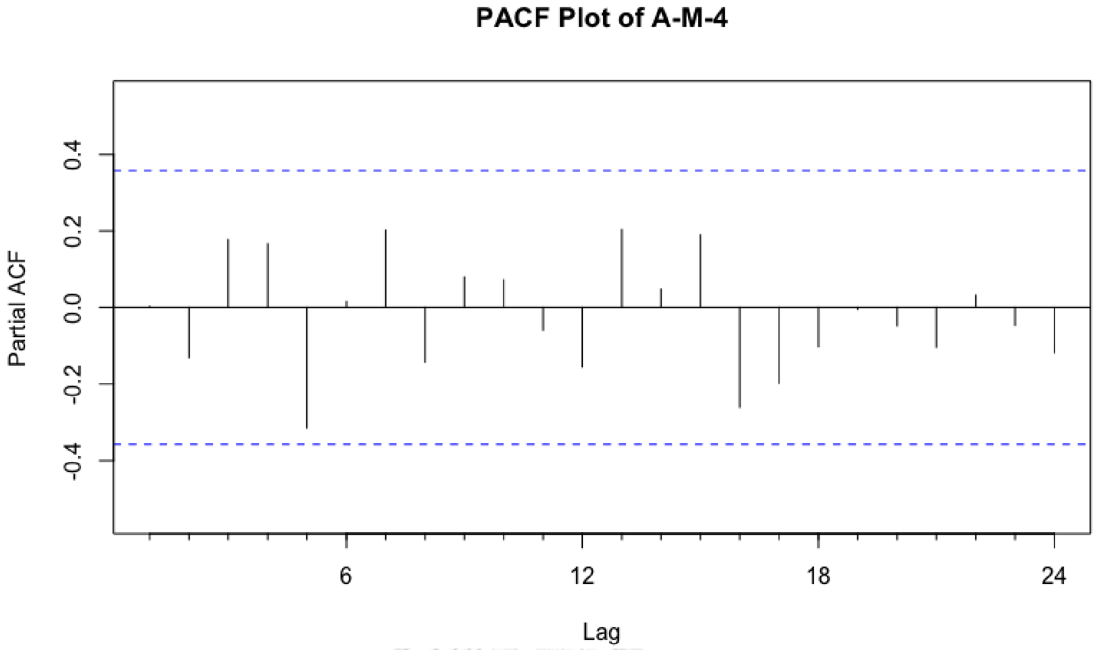


Figure 5-8: Partial Autocorrelation Function of A-M-4

The last parameter to be checked is MA(q). For this parameter, partial autocorrelation function (PACF) is plotted to check. As illustrated in Figure 5-8, there is no significance at any lag of PACF which can be implied that there is no moving average (MA) exists in this data set. After getting the ARIMA (0,0,0) of A-M-4, the residuals of this model are plotted to ensure that the model is appropriate in forecasting the demand of this data set.

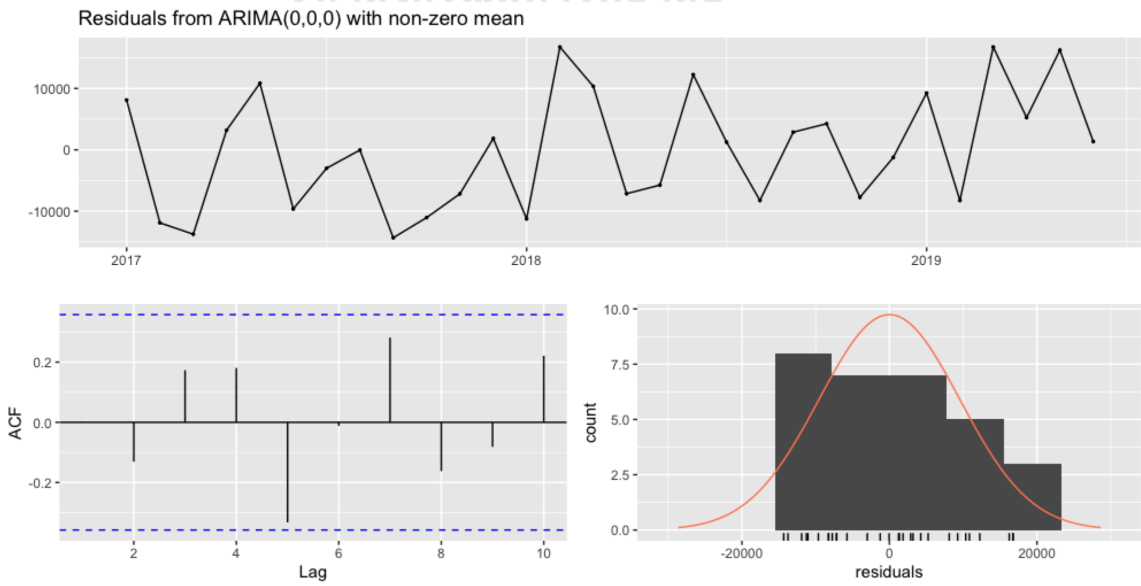


Figure 5-9: Residuals Check for ARIMA (0,0,0)

The ACF of residuals in Figure 5-9 presents that there is not any pattern remains in residuals with the white noise illustrated. Therefore, the suitable ARIMA model of A-M-4 is ARIMA(0,0,0).

4) Performance Measurement

After fitting the data set to the forecasting models, the performance of each model is calculated by measuring the error of forecasting. Mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are three metrics that are applied to calculate the error of each model. These three metrics will be compared; the forecasting method that distributes the smallest error from two out of three metrics will be selected as forecasting model for the next step.

Table 5-1: Result of Performance Measurement of Model-Fitting for A-M-4

Item	Naïve			3-Month Moving Average			Single Exponential Smoothing			ARIMA		
	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
A-M-4	179396897	11494	27.76%	105276820	8616	19.86%	105240853	8616	21.56%	88078600	8037	19.85%

It can be seen in Table 5-1 that among three proposed forecasting methods for item A-M-4, ARIMA forecasting method with model (0,0,0) has the lowest error in three metrics. And when compared with the existing method which is Naïve method, ARIMA model helps to improve the accuracy of demand forecasting to be more accurate with 7.91% decrease of error in MAPE.

5) Generate a Forecast

The selected forecasting model in previous step is adopted to generate a forecast of monthly demand in July 2019 to October 2019, out-of-sample data; and compare with the actual demand in the same time period.

By using the code shown *forecast ()* in R studio software, the forecast values of four months are projected and put in Table 5-2.

Table 5-2: Four Months Demand Forecasting Value of A-M-4

A-M-4			
Month	Naïve	ARIMA (0,0,0)	Actual Demand
Jul-19	44100	42752	42500
Aug-19	42500	42752	48600
Sep-19	48600	42752	46300
Oct-19	46300	42752	41300

Table 5-3: Result of Performance Measurement of Forecasting Models for A-M-4

Item	Naïve			ARIMA (0,0,0)		
	MSE	MAE	MAPE	MSE	MAE	MAPE
A-M-4	17515000	3750	8.35%	12239804	2775	5.95%

From calculating and comparing the forecasting error of Naïve and ARIMA (0,0,0) models, the results in Table 5-3 indicates that the proposed forecasting method gives better accuracy with 5.95% MAPE of the forecasting demand of four months while the existing method uses in the studied company has 8.35% MAPE.

5.1.2 Group B

For the finished goods classified into group B, ten items out of 12 items are studied to determine the forecasting model that appropriate with the data set of this group by applying the steps done with items in group A. Ten items selected from group B are the top ten items of group B. In order to illustrate the procedure of exploring the appropriate forecasting model differently from group A, item with different demand pattern are selected to be processed in detail in this section.

1) Data Collection, Selection and Manipulation

Different from A-M-4, item B-M-2 is a product that contains higher fluctuation in demand as shown in Figure 5-10. It is consisted of the demand data collected monthly from January 2017 until June 2019. In addition, B-M-2 has the issue with inadequate quantity to serve the customers' requirement with 3% shortage in year 2018. And according to the bar chart below, there is an inclination of demand in year 2019.

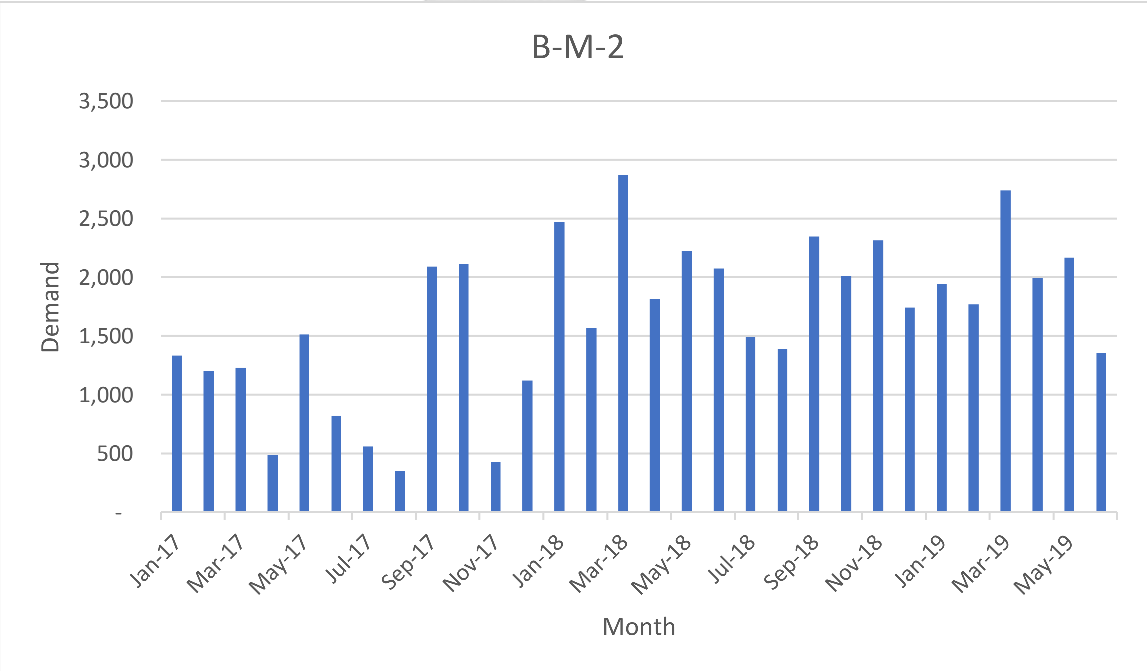


Figure 5-10: B-M-2 Bar Chart

2) Demand Pattern Analysis

As aforementioned and presented in time series plot of B-M-2, it can be perceived that B-M-2 demand pattern contains with a trend unlike the demand pattern of A-M-4. To ensure that the characteristic of B-M-2 has a trend, coefficient of variation (CV) is determined and autocorrelation function (ACF) is plotted. Coefficient of variation of B-M-2 is 0.41, higher than the CV of A-M-4 while the ACF plot (Figure 5-12) shows the exponential decay in each lag which can be implied that this item has higher fluctuation in data set and unstable.

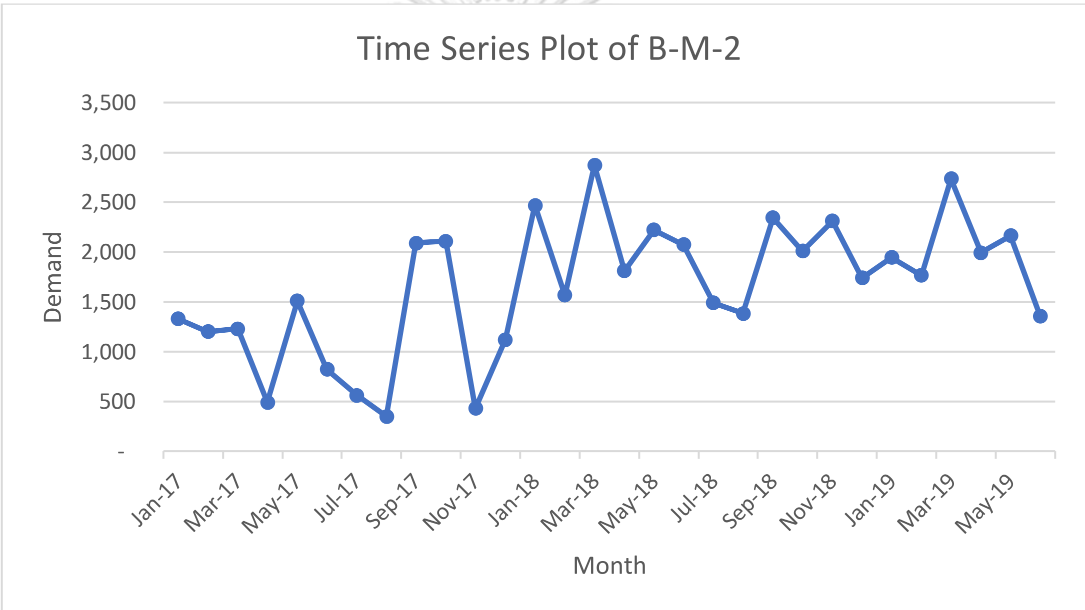


Figure 5-11: Time Series Plot of B-M-2

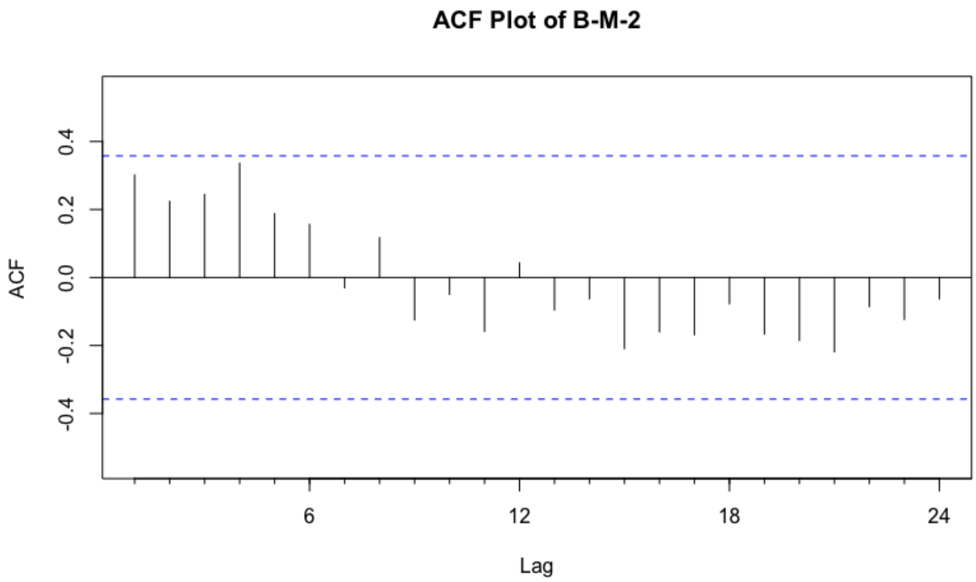


Figure 5-12: Autocorrelation Function of B-M-2

3) Forecasting Models Selection and Model-Fitting

Since item B-M-2 contains a trend in its demand pattern, three proposed forecasting models listed below are selected for proceeding in this step.

- Moving Average
- Holt's Two Parameter (Double Exponential Smoothing)
- Autoregressive Integrated Moving Average (ARIMA)

Naïve model is still applied in this section as an existing forecasting model of studied company.

3.1) Naïve Forecasting Model

For this item, the naïve model fitting is shown in Figure 5-13. Since the principle of naïve model is the future quantity will be the same as current quantity then the fits line of B-M-2 is projected one period ahead from the actual demand.

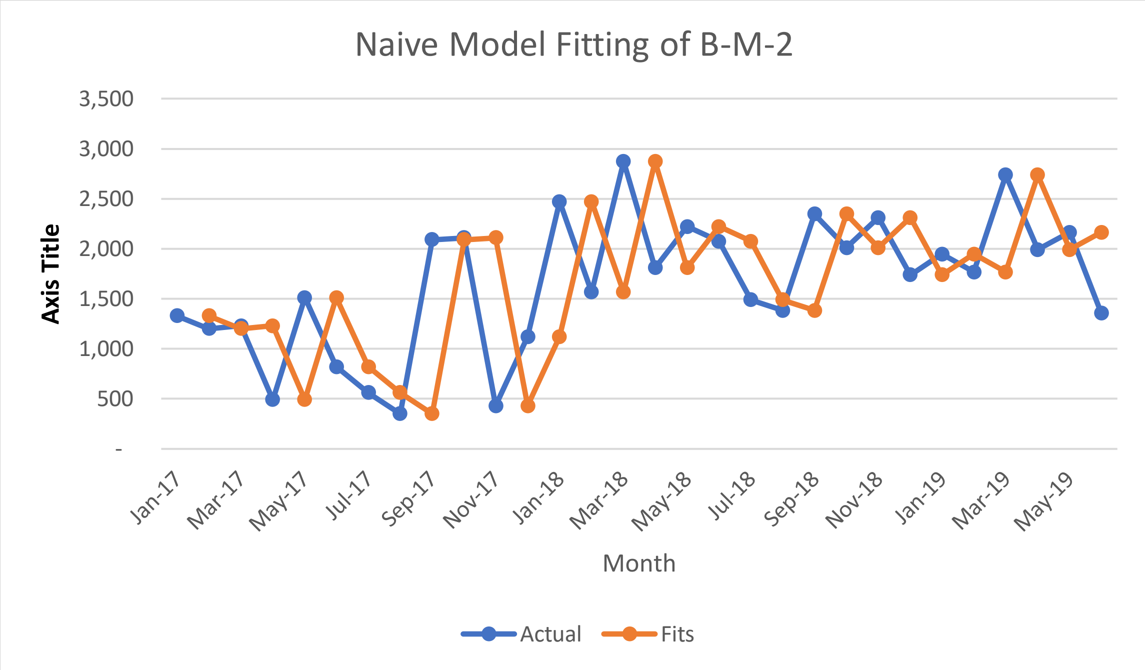


Figure 5-13: Naïve Model Fitting of B-M-2

3.2) Moving Average Forecasting Model

Three months moving average, the same as applying with items in group A, applied to the data set of B-M-2 to establish the fits values. Figure 5-14 demonstrates how the characteristic of fits collate with the actual demand.

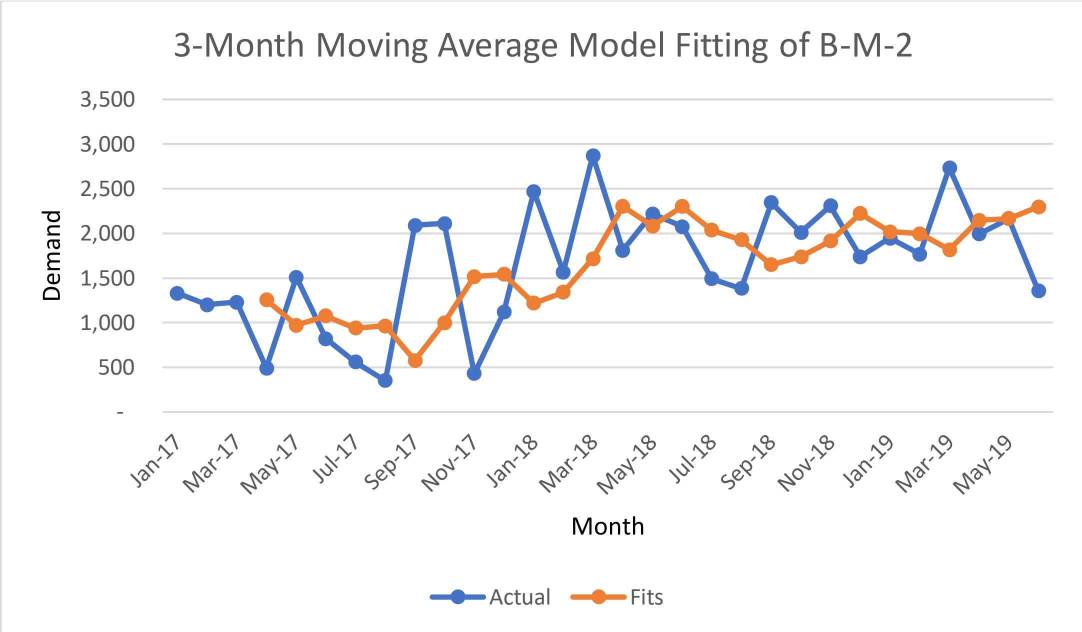


Figure 5-14: 3-Month Moving Average Model Fitting of B-M-2

3.3) Holt's Two Parameter (Double Exponential Smoothing)

By adding one more parameter to involve in calculation, Holt's two parameter is a forecasting model that be able to deal with the data set that has a trend pattern. Developing from single exponential smoothing, smoothing constant factor beta (β) is added as a trend parameter.

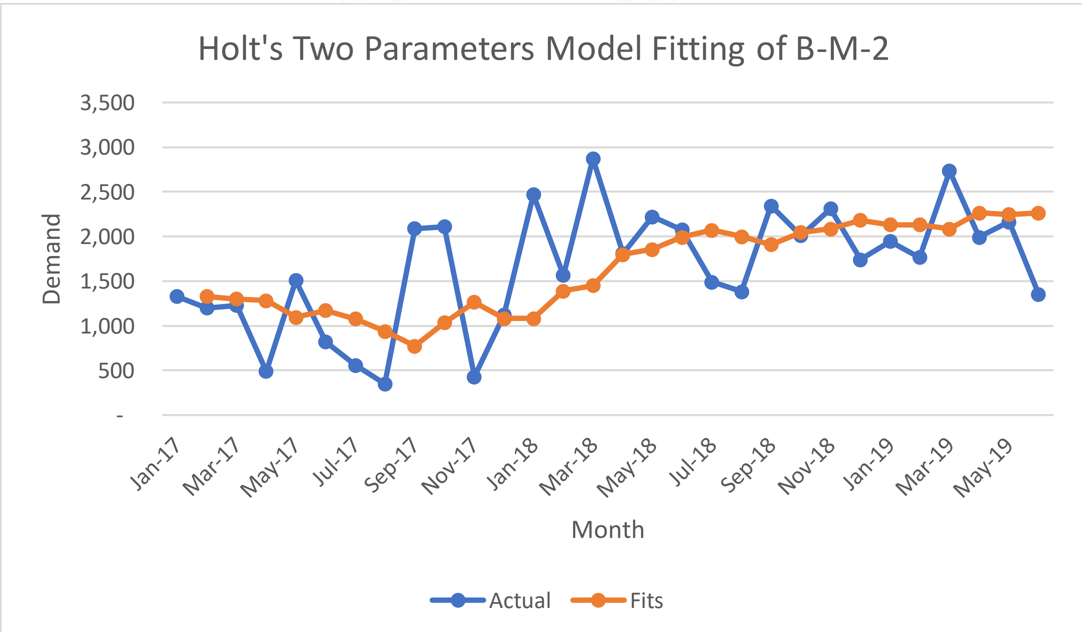


Figure 5-15: Holt's Two Parameters Model Fitting of B-M-2

In order to enhance the smoothing factors that able to determine the values that can fit the actual data, solver parameter in Excel is used. Smoothing constant factor (α) for this fitting is 0.208 while beta (β) is 0.100

3.4) Autoregressive Integrated Moving Average (ARIMA)

In this forecasting model section, stationarity of data set is a first priority to be checked as stated in Chapter 2. At the beginning of B-M-2 demand forecasting section, the time series (Figure 5-11) and ACF (Figure 5-12) plots reveal that the data set of B-M-2 is not stationary and contain trend in it since there is a strong evidence of the increasing of demand and the exponential decreasing to zero of ACF plot.

```
> adf.test(BMA2)

        Augmented Dickey-Fuller Test

data:  BMA2
Dickey-Fuller = -1.8346, Lag order = 3, p-value = 0.6362
alternative hypothesis: stationary
```

Figure 5-16: Augmented Dickey-Fuller Test of B-M-2 before Differencing

Augmented Dickey-Fuller is tested, and the result of p-value is 0.6363 which is higher than 0.05. It can be interpreted that the null hypothesis (H_0), nonstationary, is accepted; the data set is nonstationary. With the result of ACF plot and ADF test, the data set of B-M-2 is required to differencing in order to make the data to be stationary. After the first differencing of studied data, the ADF test generated the p-value that less than statistically significant 0.05; the data set of B-M-2 is now stationary.

```
> adf.test(dBMA2)

        Augmented Dickey-Fuller Test

data:  dBMA2
Dickey-Fuller = -3.7715, Lag order = 3, p-value = 0.03666
alternative hypothesis: stationary
```

Figure 5-17: Augmented Dickey-Fuller Test of B-M-2 after Differencing

Figure 5-18 and Figure 19 represents the ACF and PACF plot of differencing data of B-M-2. It can be observed from ACF plot that the characteristic of exponential decay is not as strong as the ACF of data before differencing. Considering the ACF plot (Figure 5-18), there is significant in lag 1 which indicates that there is AR(p) and the order p can be identified from PACF plot (Figure 19); p is one as there is spike in lag 1.

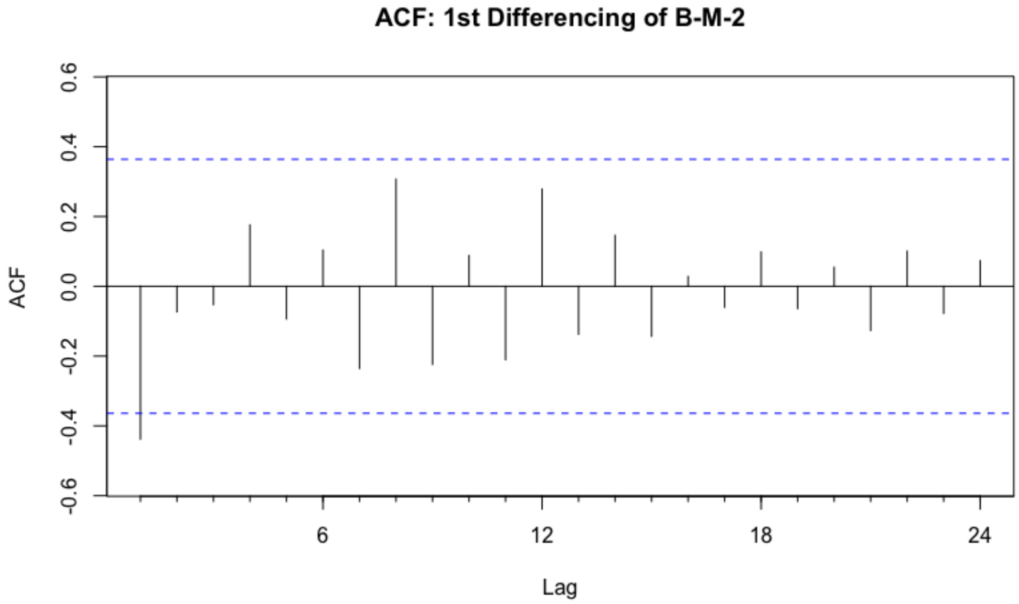


Figure 5-18 Autocorrelation Function of B-M-2 at 1st Differencing

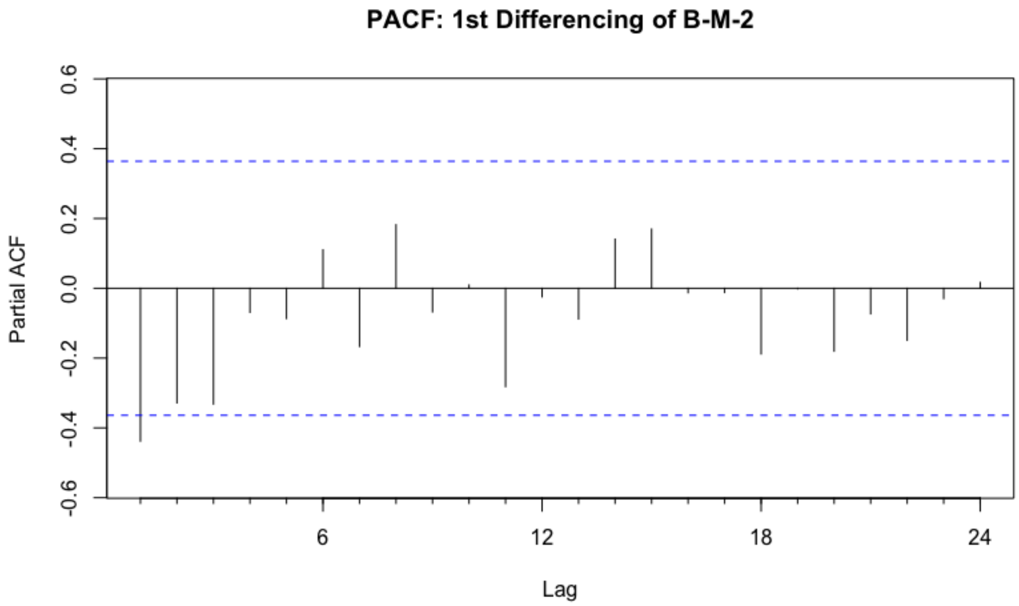


Figure 5-19: Partial Autocorrelation Function of B-M-2 at 1st Differencing

Moreover, the PACF plot is also considered and presents that there is MA(q) in data; and order q is determined by ACF plot which is one (1) according to the significant in lag 1. Thus, the ARIMA model of B-M-2 is (1,1,1) which conclude from the differencing of data, ACF plot, and PACF plots after the data is differencing.

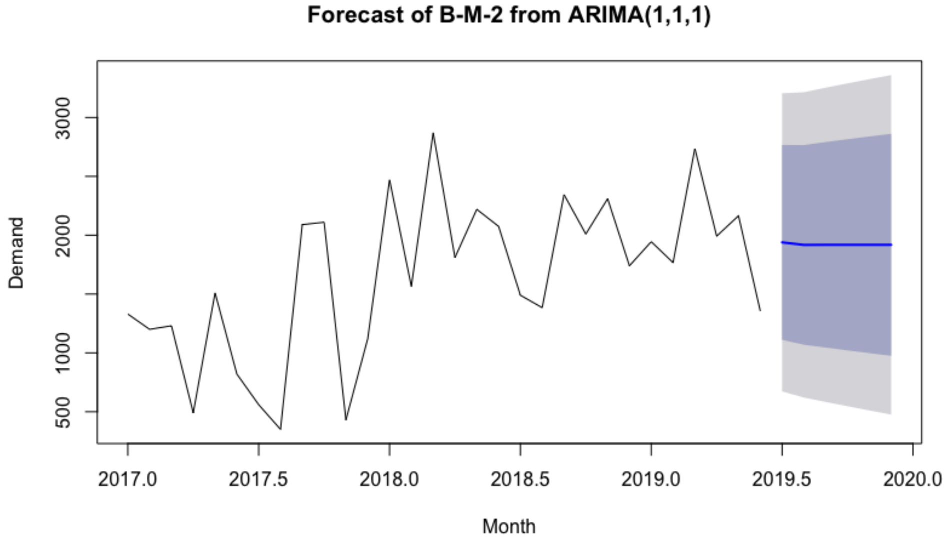


Figure 5-20: Forecast of B-M-2 from ARIMA (1,1,1)

Residuals check is coded in R studio software in order to check the suitability in producing the forecast values of ARIMA (1,1,1), and it shows in Figure 5-20. The ACF plot of residuals illustrates that all the lags are within the threshold limit bars and has a characteristic of white noise with the 0.6781 which help to emphasize that this ARIMA (1,1,1) model suits to establish the forecast of demand for item B-M-2.

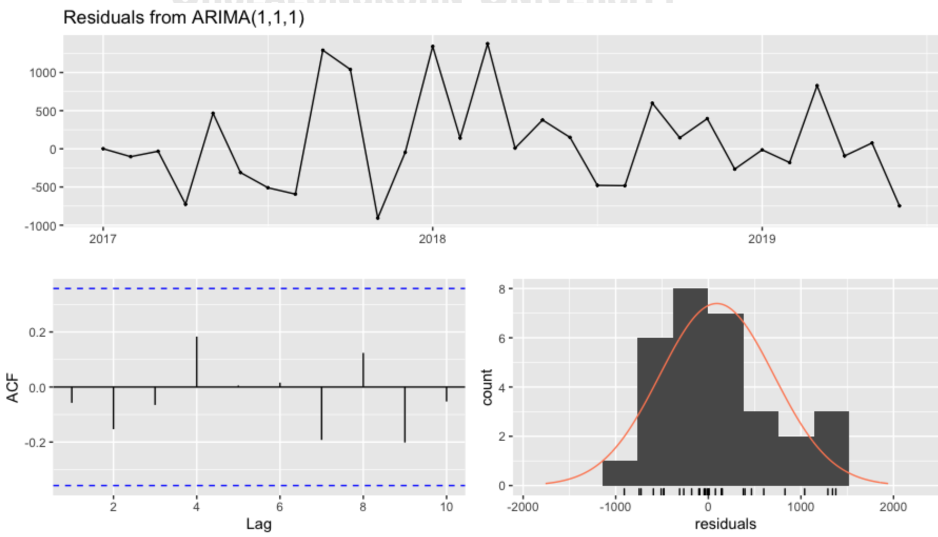


Figure 5-21: Residuals Check for ARIMA (1,1,1)

4) Performance Measurement

The performance of four models are measured and evaluated by using MSE, MAE, and MAPE. All the evaluation of each model is resulted in Table 5-4.

Table 5-4: Result of Performance Measurement of Model-Fitting for B-M-2

Item	Naïve			3-Month Moving Average			Holt's Two Parameter			ARIMA		
	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
B-M-2	628794	632	52.15%	479501	571	48.98%	411155	496	42.64%	375863	457	39.58%

The results of model-fitting evaluation reveal that forecasting the future demand by using ARIMA model can improve the accuracy of existing method of studied company by 12.57% better when looking at MAPE metric. Considering other two metrics, MSE and MAE, it also emphasizes that the ARIMA model can provide better accuracy in forecasting the demand for item B-M-2.

5) Generate a Forecast

After getting the forecasting model that can improve the accuracy in forecasting demand which is ARIMA (1,1,1), the future demand of July 2019 until October 2019 are generated. The demand are forecasted in order to compare with the actual demand and existing forecasting method, and to check that this model can literally help improve the demand forecasting accuracy. The forecasted demand by both Naïve model and ARIMA (1,1,1) model are filled in Table 5-5.

Table 5-5: Four Months Demand Forecasting Value of B-M-2

B-M-2			
Month	Naïve	ARIMA (1,1,1)	Actual Demand
Jul-19	1355	1940	3025
Aug-19	3025	1918	2220
Sep-19	2220	1919	2010
Oct-19	2010	1918	1950

Table 5-6: Result of Performance Measurement of Forecasting Models for B-M-2

Item	Naïve			ARIMA (1,1,1)		
	MSE	MAE	MAPE	MSE	MAE	MAPE
B-M-2	871156.3	686.25	26.25%	319433.5	377.5	13.91%

As the results shown in Table 5-6, all three of performance measurement metrics of ARIMA model indicates that the model can help improve the accuracy of demand forecasting with 12.34% MAPE increased which is about 50% improvement from the method currently apply in studied company.

5.1.2 Group C

1) Data Collection, Selection and Manipulation

The demand of C-M-9 is collected through the sales history from January 2017 to June 2019 to be studied. Item C-M-9 is the item which has excessive quantity over the demand from customers with 37% overstock.

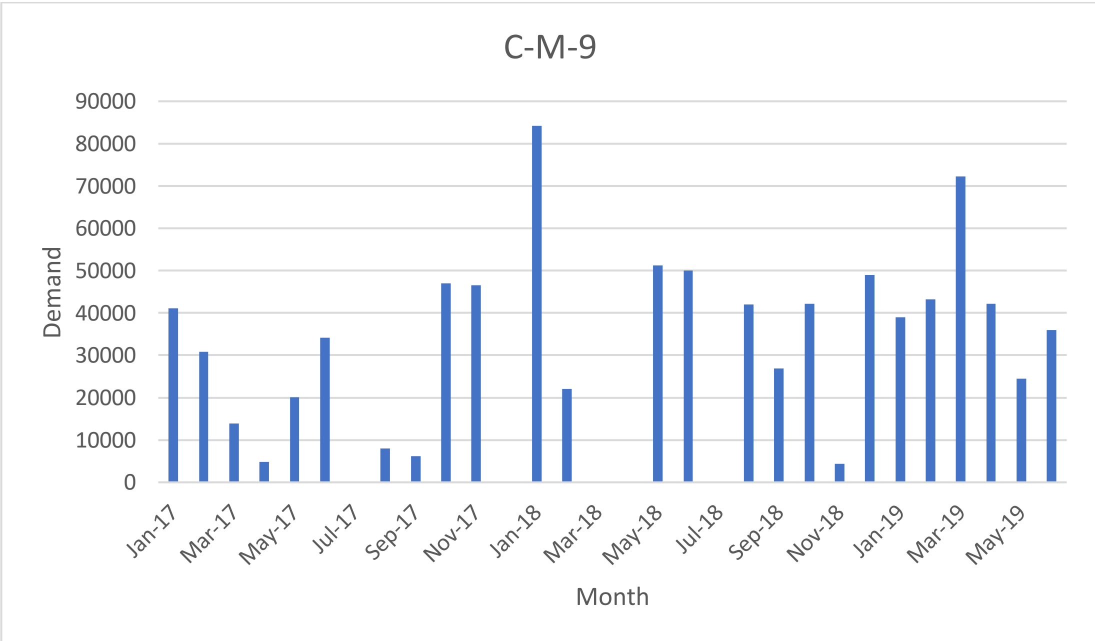


Figure 5-22: C-M-9 Bar Chart

2) Demand Pattern Analysis

From the bar chart of item C-M-9 in Figure 5-22, it shows that there are months that this item has no demand. The demand data set that has zero (0) demand in it can be determined as an intermittent demand data set. And when calculated the coefficient of variation (CV), this item with intermittent demand has CV equal to 0.77 which is the highest among item in group A and B. This is because there is high variation within the data set according to its intermittent characteristic and it is apparent in time series plot of C-M-9 (Figure 5-23).

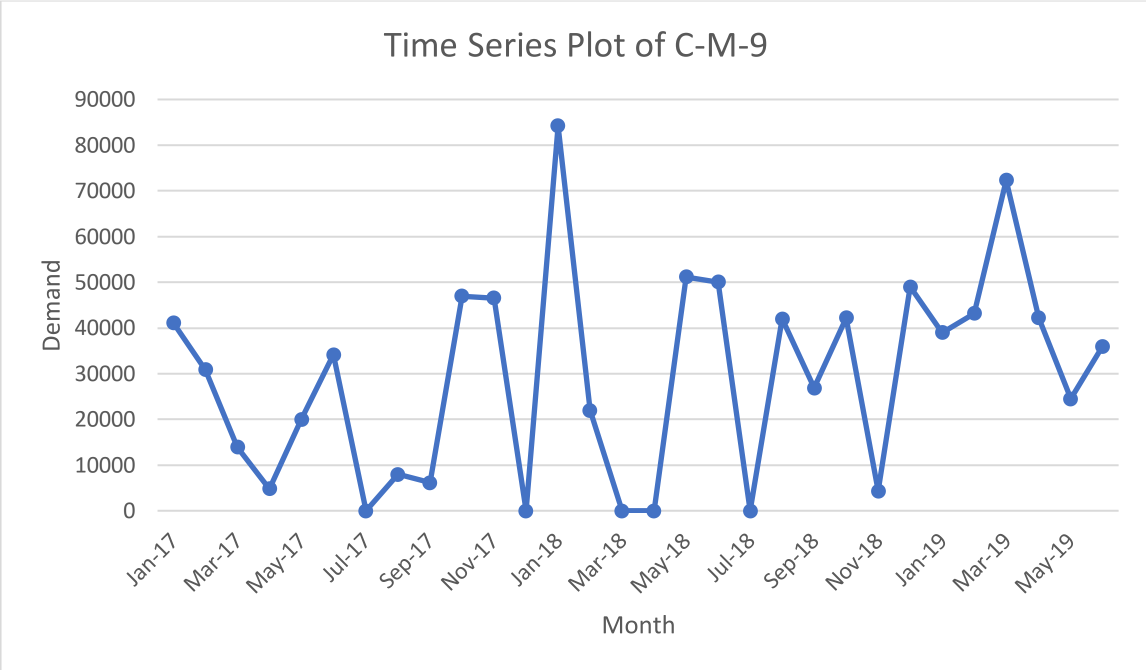


Figure 5-23: Time Series Plot of C-M-9

3) Forecasting Models Selection and Model-Fitting

As proposed in Chapter 4, item with intermittent demand pattern has to fit with the forecasting method as followed:

- Moving Average
- Croston's

Naïve forecasting model is still constructed as the existing forecasting model of studied company shown in Figure 5-24.

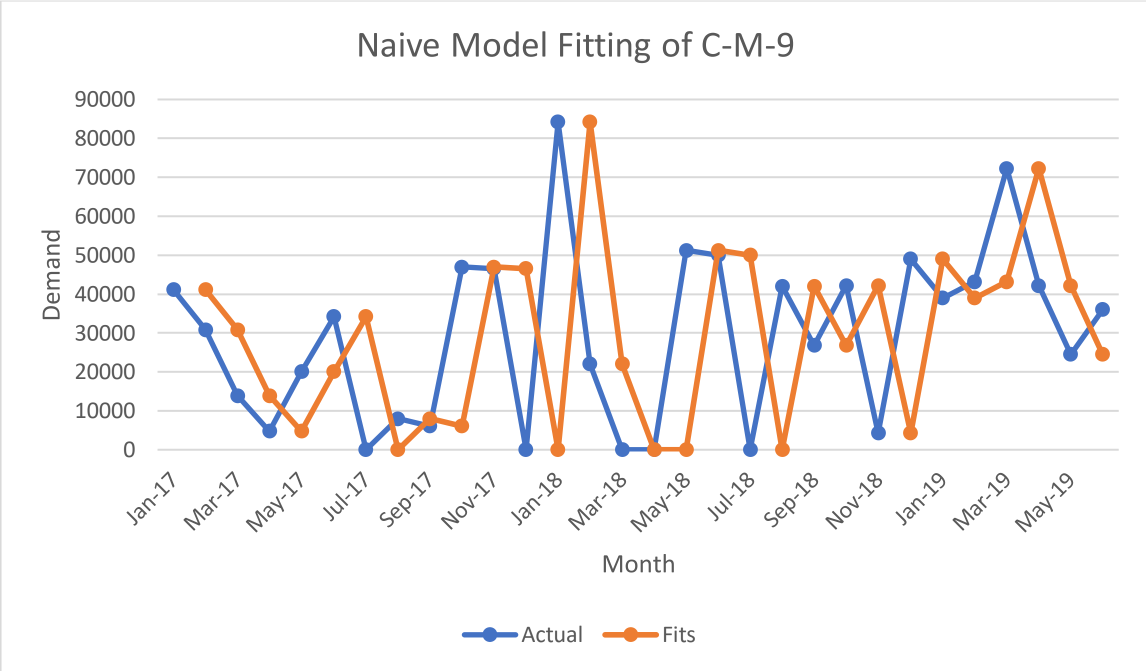


Figure 5-24: Naïve Model Fitting of C-M-9

3.1) Moving Average Forecasting Model

The data of C-M-9 is fitted with the three-month moving average forecasting model. The actual demand and fits values are plotted and illustrated in Figure 5-25.

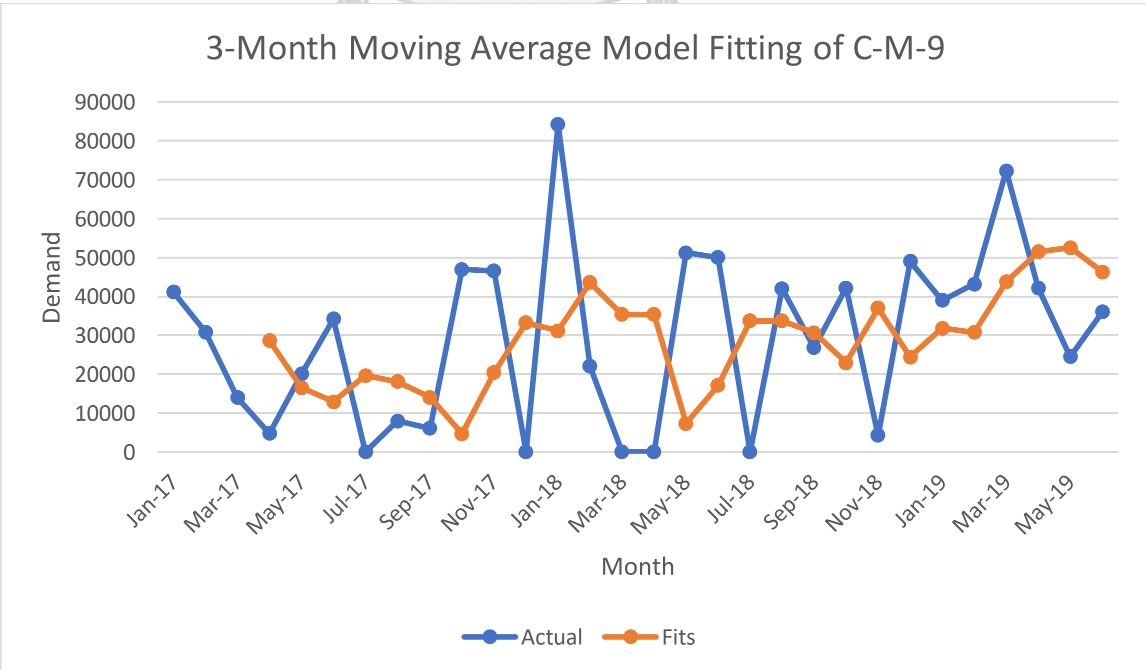


Figure 5-25: 3-Month Moving Average Model Fitting of C-M-9

3.2) Croston's Forecasting Model

Since the data set in group C is consisted of number of zero (0) demand as observation points, Croston's forecasting model is selected to do the forecast. Figure 5-26 shows how the fits value aligned compare with the actual demand. Solver parameter in Excel is also selected as a tool to determine the optimal smoothing constant factor in this forecasting method. The smoothing constant factor for C-M-9 is 0.1, with this value, the white noise is appropriately smooth out and give the effectiveness fits.

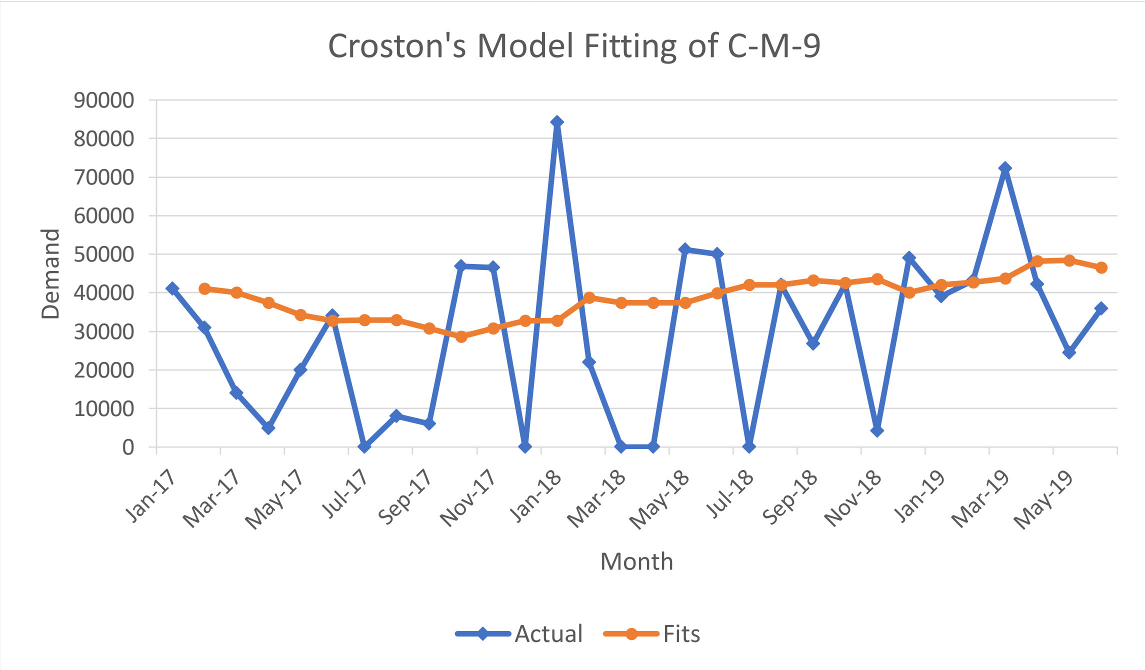


Figure 5-26: Croston's Model Fitting of C-M-9

4) Performance Measurement

For the forecast accuracy measurement in group C, MSE and MAE are the metrics that still apply to determine the error occur from forecast while MAPE is replaced with Mean Absolute Scaled Error (MASE) according to the characteristic of demand pattern that include of zero-demand.

Table 5-7: Result of Performance Measurement of Model-Fitting for C-M-9

Item	Naïve			3-Month Moving Average			Croston's		
	MSE	MAE	MASE	MSE	MAE	MASE	MSE	MAE	MASE
C-M-9	1052460148	25034	0.961	711814183	23272	0.912	594689909	20003	0.784

As highlighted in Table 5-27, fit the C-M-9 data to the Croston's forecasting model gives the smaller error in three measures when compared to the three-month moving average. And compare with the existing method, Croston's gives lower error with 0.2 MASE approximately.

5.1.4 Result Discussion

1) Group A

The other selected nine (9) items from group A are processed through the same steps as item A-M-4. The pattern of demand of each item is shown in Table 5-8; A-M-4 is also included in this Table.

Table 5-8: Demand Pattern of 10 Items in Group A

Item	Demand Pattern
A-M-1	Trend
A-M-2	Stationary
A-M-3	Trend
A-M-4	Stationary
A-M-5	Stationary
A-M-6	Stationary
A-M-7	Trend
A-M-8	Trend
A-M-9	Trend
A-M-10	Trend

With the completion of analysis the demand pattern, the items with small fluctuation in demand were fitted with the same proposed methods as item A-M-4 while the demand with trend were fitted with Moving average, Holt's two parameter, and ARIMA methods. The errors of model-fitting were calculated for each item by applying the MSE, MAE, and MAPE formulas; Table 5-9 and Table 5-10 are contained with the performance of forecasting methods from stationary data set and trend data set respectively.

By considering the Table 5-9, the blue color is highlighted on the forecasting model that can give the least error in each forecasting measures. Four items of group A with stationary pattern, there are two items out of four shows that the ARIMA forecasting model can determine the demand in the future with better accuracy when compared with the existing method while the other two items which are A-M-5 and A-M-6 give the different results.

Table 5-9: Performance Measurement of Model-Fitting for Stationary Items in Group A

Item	Naïve			3-Month Moving Average			Single Exponential Smoothing			ARIMA		
	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
A-M-2	3886004	1588	18.81%	3340998	1554	18.57%	2569434	1335	15.96%	2347450	1318	15.60%
A-M-4	179396897	11494	27.76%	105276820	8616	19.86%	105240853	8616	21.56%	88078600	8037	19.85%
A-M-5	18384423	3404	21.60%	11276379	2684	16.87%	11492299	2934	18.37%	10593209	2958	19.46%
A-M-6	14138078	2876	115.26%	10383494	2822	126.80%	8209758	2354	132.97%	6989060	2132	120.25%

Table 5-9 shows that 3-month moving average has two forecast accuracy metrics that are least error which are MAE and MAPE while MSE of ARIMA is the least one out of three models. For this item, 3-month moving average has ability to predict the future demand with least error since data pattern of A-M-5 which is stationary and has low fluctuation (CV = 0.21); it can be implied that the demand is mostly based on the past history sales. In real situation, the possibility that the future demand will be the same as current demand is low thus, Naïve model which is existing method cannot provide the appropriate forecast demand. Meanwhile, the 3-month moving average that exploit last three months data to generate the forecast can provide better prediction. For the item A-M-6, there are two out of three error metrics which are MSE and MAE defines that ARIMA is the forecasting method that be able to generate the least forecast error when compared to Naïve method. Nevertheless, MAPE shows that the existing method has about 5% better in demand forecasting. But since there are two out of three metrics indicate that the average of squared error and absolute error are the least, ARIMA model is forecasting method that suit the item A-M-6.

Next is the items of group A that their demand characteristics are varied and has higher fluctuation, trend pattern. Blue highlight is applied to the error metrics that have the least error value as shown in Table 5-10. By looking through the results, ARIMA forecasting method is the one that can offer the least forecast error out of three model and better when compared to existing method used by studied company. Nevertheless, there are one item that demonstrates that ARIMA is not the forecasting method that can serve better forecasting value, the item A-M-9.

Table 5-10: Performance Measurement of Model-Fitting for Trend Items in Group A

Item	Naïve			Moving Average			Holt's Two Parameter			ARIMA		
	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
A-M-1	17073244	3180	32.95%	9860000	2388	23.84%	7818939	2059	22.11%	7848682	2011	21.31%
A-M-3	9373487	2646	71.40%	5395068	1835	51.77%	6863893	2202	58.18%	5833177	1822	46.59%
A-M-7	3493920	1606	18.31%	3195192	1529	16.59%	2908298	1453	16.36%	2628276	1365	15.03%
A-M-8	28906398	4556	47.08%	26443698	3911	40.00%	25836721	3873	39.65%	23383569	3680	37.79%
A-M-9	989324	695	103.15%	468681	537	31.03%	738900	588	97.41%	581820	562	80.74%
A-M-10	1851015	1059	77.55%	834199	780	70.95%	1108560	821	80.23%	758385	689	57.82%

Even if the A-M-9 has determined as the item that has trend pattern in demand, there is high variation in the beginning of 2017 and the trend is shown but its trend does not illustrate the extremely slope of trend; the time series of A-M-9 is quite stability increase with low fluctuation after the June 2017. Since measuring the performance of 3-month moving average method started from month 4 to month 30 according to the principle of model that the fit value is determined by averaging the last three months, there are three first month that were neglected to consider. Then, ARIMA is coded in R studio by starting the first data point with month 4 to be the same as moving average. The results reveal that ARIMA has two out three metrics that are better than moving average which are MSE and MAE; 449571 and 512 respectively. And MAPE decrease from 80.74% to 34.28% which is slightly higher than 3-month moving average but this is not significant since there are two metrics define that ARIMA is more appropriate to predict the future demand of A-M-9. Nonetheless, the slightly different of MSE, MAE and MAPE of 3-mongth moving average and ARIMA, it suggests that 3-month moving average can be applied to generate the future demand of this item instead of using the ARIMA in this case.

2) Group B

For group B, the other nine items are determined the pattern of demand by the approaches apply with the B-M-2. Demand pattern of each item is shown in Table 5-11, item B-M-2 is also included in it. Items in group B is similar to the items in group A, there are both stationary and trend patterns mixed in the group. Three items are stationary and the other seven items are trend.

Table 5-11: Demand Pattern of 10 Items in Group B

Item	Demand Pattern
B-M-1	Trend
B-M-2	Trend
B-M-3	Trend
B-M-4	Trend
B-M-5	Stationary
B-M-6	Trend
B-M-7	Stationary
B-M-8	Stationary
B-M-9	Trend
B-M-10	Trend

The three items with stationary pattern are listed in Table 5-12 where red highlight is to define the performance metrics that are the least among these four models. As results of model-fitting, ARIMA model is the technique that has ability to generate the future demand with least error. Three metrics determined from the ARIMA models in these three items shows the least error except MAPE of ARIMA of item B-M-7. For the MAPE value of item B-M-7 that the MAPE of ARIMA is higher than MAPE of 3-month moving average while the other two metrics of ARIMA are lower than 3-month moving average, it is because of the principle of MAPE that use the actual as a divider in order to give the percentage result. The first three month of B-M-7 had small quantity of demand, nearly to zero, ARIMA model coded by R studio also include those three month to do the model-fitting and calculate the forecast accuracy, on the contrary, evaluating the forecast accuracy of 3-month moving average was determined from month 4. Therefore, the neglect of first three month can affect the result of forecast accuracy.

Table 5-12: Performance Measurement of Model-Fitting for Stationary Items in Group B

Item	Naïve			3-Month Moving Average			Single Exponential Smoothing			ARIMA		
	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
B-M-5	1898580	978	185.07%	1023771	787	200.45%	1001628	748	177.77%	566970	569	147.95%
B-M-7	3709628	1614	223.27%	3163950	1538	85.85%	2145362	1203	206.19%	749472	688	117.23%
B-M-8	264805	436	68.68%	149253	327	51.57%	132054	305	44.61%	106403	262	42.35%

Interestingly, for high percentage of MAPE which is over 100% as a result. This is based on the actual data. The smaller the demand quantity data, the higher the percentage of MAPE. A reasonable explanation of high percentage of MAPE can base on the calculation of MAPE that the actual demand is used as a divider, it follows that the result will be looked too high and excessive. B-M-7 also has high percentage of MAPE since there are the data points with small quantity as aforementioned. It goes the same to item B-M-5 for stationary table, there are many point of observation that near to zero and they were occurred after month 3 hence, the MAPE of 3-month moving average is also over 100%. Correspondingly occur to item B-M-9 in Table 5-13.

Table 5-13: Performance Measurement of Model-Fitting for Trend Items in Group B

Item	Naïve			3-Month Moving Average			Holt's Two Parameter			ARIMA		
	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE
B-M-1	179759	320	33.29%	44589	171	16.60%	46538	174	16.51%	39973	160	15.45%
B-M-2	628794	632	52.15%	479501	571	48.98%	411155	496	42.64%	375863	457	39.58%
B-M-3	13303841	2826	35.45%	12059110	2851	38.54%	11440535	2830	36.27%	10210319	2584	33.52%
B-M-4	161115	335	69.38%	105890	260	61.22%	84795	232	50.20%	91360	231	47.74%
B-M-6	178550	340	53.93%	101966	245	35.76%	99508	229	35.11%	81979	216	32.82%
B-M-9	335396	468	253.21%	235536	400	218.99%	192638	347	193.70%	189582	326	195.71%
B-M-10	73679	220	33.50%	44950	175	24.74%	54845	188	28.42%	46805	185	26.91%

There are seven items in group B with trend pattern, and six out of seven are appropriate to be determined the future demand by using the ARIMA model. For the item B-M-10, it is different from item A-M-9 and item B-M-7. According to what have been mentioned, the measurement of forecast performance of 3-month moving average used the data from month 4 to month 30 to calculate while ARIMA coded by R studio evaluate the error from month 1 to month 30. In case of A-M-9, there are two metrics that ARIMA can give smaller error but in the case of B-M-10; moving average model is able to offer slightly better accuracy of demand forecasting in three metrics when compared with the ARIMA model that calculated the forecast accuracy with the same number of observation to moving average.

3) Group C

The results of performance measurement of model-fitting in group C is show in Table 5-14. According to the demand pattern of items in group C that contain zero demand in it which MAPE cannot use as forecast accuracy metrics as mentioned in Chapter 2 thus, MASE is applied to determine the forecast accuracy. The least error measures values are highlighted with green color. As shown in Table above, Croston's model is the forecasting model that be able to determine the future demand with better accuracy, except the item C-M-10. With two out of three error measures, 3-month moving average is the technique that able to provide least error values.

Table 5-14: Performance Measurement of Model-Fitting for Items in Group C

Item	Naïve			3-Month Moving Average			Croston's		
	MSE	MAE	MASE	MSE	MAE	MASE	MSE	MAE	MASE
C-M-1	88594648	6552	0.972	47433515	5722	0.843	42323774	5601	0.825
C-M-2	1587227	1002	0.940	1289129	936	0.928	1083497	835	0.827
C-M-3	258932	414	1.015	124641	281	0.670	143519	294	0.702
C-M-4	1035840	766	0.987	775421	699	0.887	648195	655	0.831
C-M-5	2894638	1374	1.003	1670588	1016	0.729	1702211	1071	0.768
C-M-6	30529810	4378	0.952	19646512	3728	0.825	16805018	3277	0.726
C-M-7	1493968	872	1.026	2260609	995	1.177	1767683	984	1.164
C-M-8	858056	726	1.012	563918	649	0.923	451224	571	0.812
C-M-9	1052460148	25034	0.961	711814183	23272	0.912	594689909	20003	0.784
C-M-10	2137846	953	1.045	1683515	801	0.849	1544093	861	0.913

In order to ensure that 3-month moving average is the forecasting model that suit with item C-M-10, the error metrics in Croston's forecasting model start to calculate from month four which is the same as metrics in 3-month moving average are calculated. By calculating the error of model-fitting with new number of observations, the MSE of Croston's model is still lower than MSE of moving average. Moreover, the other two metrics of moving average yet lower than the MAE and MAPE of Croston's model.

Therefore, the appropriate forecasting model to item C-M-10 is 3-month moving average.

5.2 Inventory Control Models

In this section, the simulation of inventory control is set up in order to explore how the proposed inventory control model can perform with the inventory of raw materials/ components. The requirement of raw materials/ components, which is defined by the planning team, is used as the internal demand. Collected data is in monthly basis thus, the daily internal demand will be randomly and be generated from the *RAND()* function in Microsoft Excel since the production department is set to run every day except the weekend. The daily internal demand is randomly within the range of monthly demand. The simulation is run through four months, from July 2019 to October 2019.

5.2.1 Continuous Review

For continuous review inventory control model, the quantity to be ordered and when to order are based on the EOQ and reorder point that are determined in Define Phase. Figure 5-27 illustrates how continuous review is simulated and how the format was constructed in Microsoft Excel.

Inventory Control Model: Continuous Review									
		EOQ	41800		**Reorder (R)**	119659		**Lead Time**	14 Days
RM-1		**Actual**	**Proposed**						
2019		**Ending Inventory**	**Inventory On-Hand**	**Received**	**Demand**	**Ending Inventory**	**Order**	**Lead Time**	**Ordering cost**
Month	**Date**								
July	**1**	139390	143000		3610	139390	No		
July	**2**	138360	139390		1030	138360	No		
July	**3**	133430	138360		4930	133430	No		
July	**4**	126763	133430		6667	126763	No		
July	**5**	153988	126763		2775	123988	No		
July	**6**	153988	123988		0	123988	No		
July	**7**	153988	123988		0	123988	No		
July	**8**	152045	123988		1944	122045	No		

Figure 5-27: Continuous Review Simulation Format in Microsoft Excel -1

Inventory on-hand of 1st of July is the actual ending inventory from June 2019. For Q-model, the inventory is checked continuously when the inventory level has movement. The order will be placed when the inventory level is at or under the reorder point, after placing the order, the lead time will be counted until the day 0 that the inventory will be received and added to the ending inventory.

July	7	153988	123988		0	123988	No		
July	8	152045	123988		1944	122045	No		
July	9	148550	122045		3495	118550	Yes	14	2500
July	10	146089	118550		2460	116089	Yes	13	
July	11	139422	116089		6667	109422	Yes	12	
July	12	132477	109422		6946	102477	Yes	11	
July	13	132477	102477		0	102477	Yes	10	
July	14	132477	102477		0	102477	Yes	9	
July	15	127422	102477		5055	97422	Yes	8	
July	16	120682	97422		6740	90682	Yes	7	
July	17	117989	90682		2692	87989	Yes	6	
July	18	110924	87989		7065	80924	Yes	5	
July	19	107336	80924		3589	77336	Yes	4	
July	20	107336	77336		0	77336	Yes	3	
July	21	107336	77336		0	77336	Yes	2	
July	22	106296	77336		1040	76296	Yes	1	
July	23	102406	76296	41800	3890	114206	Yes	0	

Figure 5-28: Continuous Review Simulation Format in Microsoft Excel -2

As part of the simulation shown in Figure 5-28, the continuous review applied to item RM-1, the order is placed to the supplier as the ending inventory level is lower than the reorder point. The lead time is counted down and the EOQ is received at day 0. The inventory data of RM-1 to RM-5 are the input of this inventory control simulation.

5.2.2 Periodic Review

The simulation structure of periodic review in Microsoft Excel (Figure 5-29) is similar to the format of continuous review.

Inventory Control Model: Periodic Review										
		OUL	17520		Review Period (T)	30 Days		Lead Time	14 Days	
RM-7		Actual	Proposed							
2019		Ending Inventory	Inventory On-Hand	Received	Demand	Proposed	Order Quantity	Review Period	Lead Time	Ordering cost
Month	Date									
July	1	15980	16092		112	15980		30	13	
July	2	15635	15980		345	15635		29	12	
July	3	15186	15635		448	15186		28	11	
July	4	14873	15186		313	14873		27	10	
July	5	14745	14873		128	14745		26	9	
July	6	14595	14745		150	14595		25	8	
July	7	14346	14595		248	14346		24	7	

Figure 5-29: Periodic Review Simulation Format in Microsoft Excel -1

There are different points according to the different parameters in P-Model. EOQ is replaced with OUL (Order-up-to-Level) which is the maximum of inventory to be kept; and instead of ordering when the inventory level reach at some point, the order will be constantly placed when the review period is arrived. In this study, the review period is 30 days as proposed in Chapter 5.

July	28	12969	9533		136	9397		3		
July	29	12265	9397		704	8693		2		
July	30	11602	8693		664	8030	9490	1	14	2500
July	31	11092	8030		510	7520			13	
Aug	1	10994	7520		98	7423		30	12	
Aug	2	20823	7423		171	7252		29	11	
Aug	3	20583	7252		240	7011		28	10	
Aug	4	20449	7011		134	6878		27	9	
Aug	5	20353	6878		97	6781		26	8	
Aug	6	20255	6781		98	6683		25	7	
Aug	7	20255	6683		0	6683		24	6	
Aug	8	20255	6683		0	6683		23	5	
Aug	9	20255	6683		0	6683		22	4	
Aug	10	20255	6683		0	6683		21	3	
Aug	11	20255	6683		0	6683		20	2	
Aug	12	20255	6683		0	6683		19	1	
Aug	13	20255	6683	9490	0	16174		18	0	

Figure 5-30: Periodic Review Simulation Format in Microsoft Excel -2

An example of periodic review inventory control simulation of RM-7 shown in Figure 5-23. It can be seen that the order is placed when the review period is reached, every 30 days, then the quantity to be ordered is determined by subtracting the inventory on hand from the maximum quantity (OUL) to be stocked.

5.2.3 Result Discussion

By inputting the data of RM-1 to RM-5, five raw materials/ components, to simulate the continuous review inventory control model, Figure 5-23 illustrates how the proposed inventory control model performs compare with the actual ending inventory level of each item in each month for four months.

The plots show that proposed model has lower number of time that the order is placed while the actual lines in plots illustrate number of time that the order is placed and randomly placed. There is also time period that the order is placed repeatedly without receiving the prior lot first. This leads to the high accumulation of inventory level. Meanwhile, there is point that the order is not placed at the right time, and then, there is a case of running out of stock e.g. RM-5 is going to short on the beginning of July 2019.

According to continuous review principle, the order is placed more often and number of times during these four months. With this characteristic of Q-model, it properly suits with the raw materials/ components of group A since there will be the adequate quantity to serve the internal demand to produce the products without the opportunity lose. At the same time, the number of keeping stock is at the level that is not cause high cost to financial part of the company.

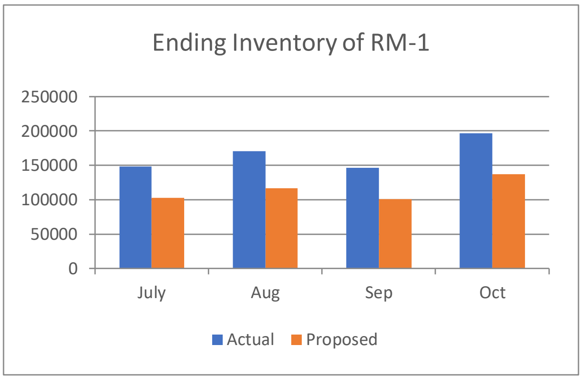
Figure 5-31: Inventory Level Plots from Continuous Review Simulation

For RM-6 to RM-10, the periodic review inventory control model is proposed to control the stock. Figure 5-32 demonstrates the comparison of actual inventory level against the inventory level with the proposed quantity and the time period to be ordered.

Figure 5-32: Inventory Level Plots from Periodic Review Simulation

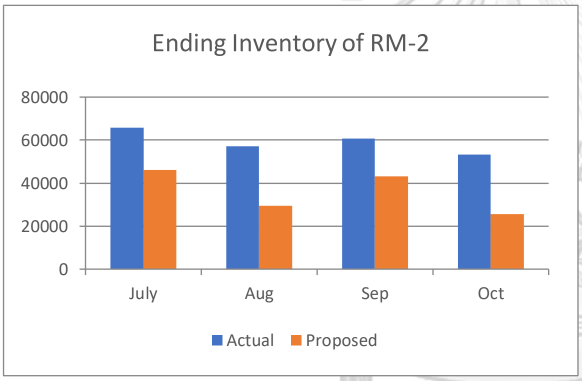
The plots show that some items are ordered with the quantity that is not well-determined which lead to multiple and repetitive of orders in a month in order to have stock to serve the internal demand. Some items are ordered multiplicative over the demand required which leads to overstock. Considering the proposed plots, the number of orders within these four months period is quite constant since the review period is every 30 days as proposed.

Figure 5-33 demonstrates how the proposed models can help to reduce the inventory level in bar charts with the ending inventory quantity. Three items from continuous review and three items from periodic review are selected to be demonstrated here, the rest are shown in Appendix xx. Overall, the proposed methods, both continuous review and periodic review, can control the inventory level to be lower than the how the studied company works. By applying the continuous review control model, the ending inventory level is decreased about 30% in average. The ordering cost is also decreased. Also, since there are the indication of when to order, the time of order during these periods is also reduced which lead to the inventory related cost. As shown in Figure below, the ordering cost during these four months of RM-1 from 25,000 THB to 12,500 THB which is 50% lower. The total ordering cost of using the continuous review model is varied, conversely to the total ordering cost in periodic review model. Looking to the results in Figure 5-34, the ordering cost occurred from July 2019 to October 2019 is maximum at 10,000 THB. The stated ordering cost is mostly the ordering cost of common raw materials/components, there are possibility that the ordering cost will be lower than stated during this time period; for example, RM-9. The lower the demand of use of raw materials/ component, can be implied that there will be lower ordering cost since the stock is over the maximum inventory level then, there is no need to order more. By considering the selected data to be analysed and simulated in periodic review model, the results of proposed reveals that it can help improve the inventory management by reducing the inventory level from the actual 50% averagely.



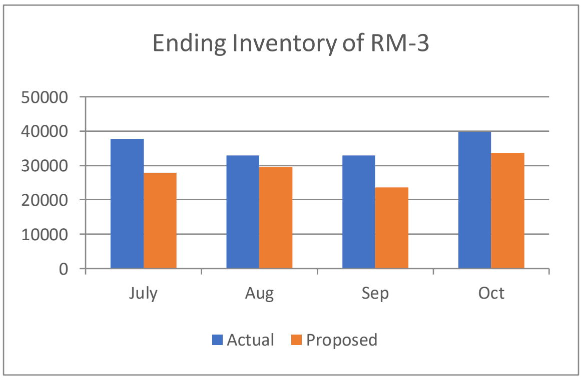
Month (2019)	Ending Inventory: RM-1		
	Actual	Proposed	% diff
July	148393	102300	-31%
Aug	170893	116600	-32%
Sep	146893	101200	-31%
Oct	196404	137511	-30%
Average	165646	114403	-31%

Ordering Cost (THB)	
Actual	Proposed
25000	12500



Month (2019)	Ending Inventory: RM-2		
	Actual	Proposed	% diff
July	65865	46065	-30%
Aug	57165	29465	-48%
Sep	60735	43235	-29%
Oct	53135	25735	-52%
Average	59225	36125	-40%

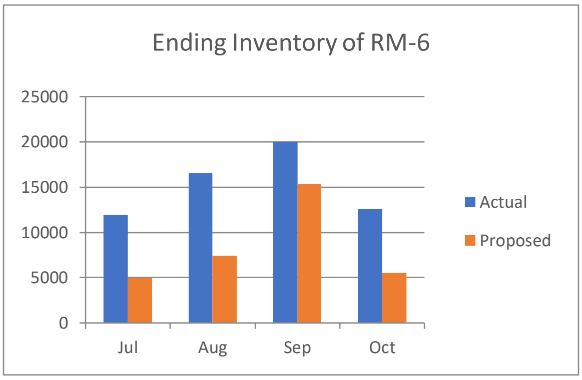
Ordering Cost (THB)	
Actual	Proposed
20000	15000



Month (2019)	Ending Inventory: RM-3		
	Actual	Proposed	% diff
July	37705	27905	-26%
Aug	32905	29605	-10%
Sep	33003	23703	-28%
Oct	39878	33578	-16%
Average	35873	28698	-20%

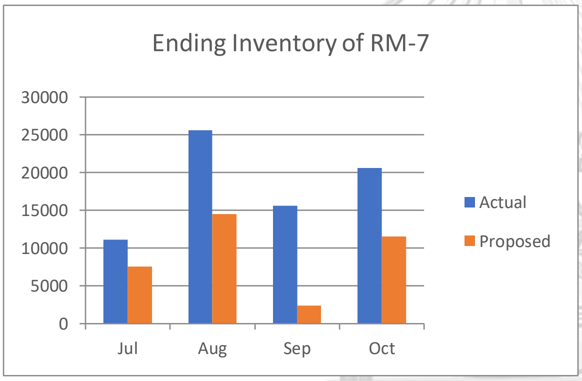
Ordering Cost (THB)	
Actual	Proposed
25000	15000

Figure 5-33: Results of Continuous Review Simulation



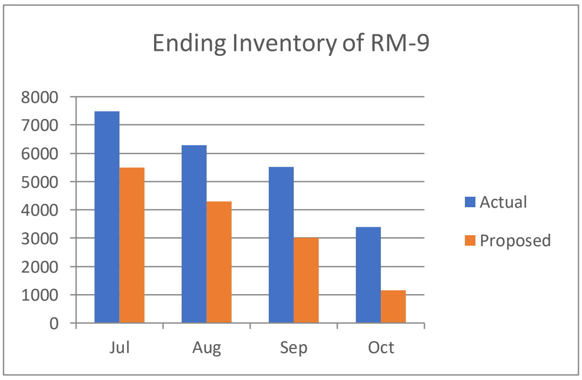
Month (2019)	Ending Inventory: RM-6		
	Actual	Proposed	% diff
July	11945	4981	-58%
Aug	16545	7406	-55%
Sep	19969	15320	-23%
Oct	12619	5536	-56%
Average	15269	8311	-48%

Ordering Cost (THB)	
Actual	Proposed
15000	10000



Month (2019)	Ending Inventory: RM-7		
	Actual	Proposed	% diff
July	11092	7520	-32%
Aug	25592	14511	-43%
Sep	15592	2417	-85%
Oct	20592	11520	-44%
Average	18217	8992	-51%

Ordering Cost (THB)	
Actual	Proposed
15000	10000



Month (2019)	Ending Inventory: RM-9		
	Actual	Proposed	% diff
July	11092	7520	-32%
Aug	25592	14511	-43%
Sep	15592	2417	-85%
Oct	20592	11520	-44%
Average	18217	8992	-51%

Ordering Cost (THB)	
Actual	Proposed
10000	5000

Figure 5-34: Results of Periodic Review Simulation

6. CONCLUSION AND RECOMMENDATION

6.1 Conclusion

Objectives of this study is to be able to present the inventory policy that help to allow the studied company to have better performance in inventory management in order to reduce the inventory shortage and overstock. The inventory shortage and overstock are the issues that cause the negative effect to the company such as losing the customers' satisfaction and customers' relationship, and financial related. In order to propose the inventory policy to achieve the objectives of this research, this study starts with understanding of the overview of studied company; it includes of the type of business, products, and inventory types. Next part is the reviewal of inventory related literature to be able to translate those theories in literature review to applicable with the problems that are defined in define phase. The proposed phase is the part where the inventory classification, demand forecasting, and inventory control are proposed in order to achieve the objectives of research.

For inventory classification, ABC classification with the multi-criteria is proposed to group the products based on two criteria; value of items and process. These two criteria were selected because their impact to the company, value of items is related to financial part directly while the process is the one that related to lead time of the products which is directly related to customers' satisfaction and indirectly related to financial part. From 104 SKUs, they are grouped into six groups which are A-Machining, B-Machining, C-Machining, A-Assembling, B-Assembling, and C-Assembling. Classifying to group allows the company to manage and control the inventory easier since they are able to acknowledge that which group of products can cause the impact to the company. Group A-Machining (A-M), B-Machining (B-M), and C-Machining (C-M) are the groups that were chose to study in this research because these products have longer lead time.

Demand forecasting is proposed in this research in order to provide the forecasting model that can predict future demand of each product with better accuracy; and support the company to be able to prepare and plan for the production in advanced. Time series analysis, which is part of quantitative methods, was selected to forecast the demand of products. This particular forecasting method was selected since the method allows users to predict the future demand by applying the statistical techniques and provide the short-term forecasting with more accuracy. In time series analysis, there are several models of forecasting; the forecasting models are selected according to the pattern of demand. Products in studied company are included of three types of demand which are stationary, trend, and intermittent demand. Demand pattern of each item in machining group was determined by observing and considering the time series plot, autocorrelation function plot, and coefficient of variation (CV). After analysing the demand pattern, top ten items from each selected group was fitted with three forecasting models fore group A-M and B-M while C-M was fitted with two forecasting models depend on the analysed demand pattern. Three-month moving average is the forecasting method that was applied to three demand patterns and ARIMA was applied to stationary and trend pattern. There are three forecasting models that were applied to each demand type; single exponential smoothing was applied to stationary pattern, Holt's two parameters was applied to trend pattern, and intermittent demand was forecasted by applying the Croston's forecasting model.

Table 6-1: Result Summary from Demand Forecasting Section

Demand Pattern	Stationary	Trend	Intermittent
Selected Forecasting Models	3-Month Moving Average	3-Month Moving Average	3-Month Moving Average
	Single Exponential Smoothing	Holt's Two Parameters	Croston's Forecasting Model
	ARIMA	ARIMA	

By implementing the procedure and forecasting models from proposed phase, the results of performance measurement indicate that ARIMA is the forecasting model that be able to generate forecast with the least error for stationary and trend patterns which are the patterns that mostly occur with the products in group A and B. ARIMA model can improve the accuracy of future demand prediction reduce the performance error about 26% from the existing method. For group C which has intermittent demand, Croston's forecasting model is the one that appropriate to predict the future demand since it provide the least error and reduce the forecast error about 16% from the existing method. This can be implied that the lower the error of forecast, the better the ability in planning for production to kept in stock with suitable quantity that be able to meet the customers' satisfaction but still not excessive that effect to the financial part of company. Finished goods are selected to be focused is because knowing the demand of end products, it allows the planners to be able to backward to the material requirement planning instead of statistical computing the number of items in raw materials/ components.

For raw materials/ components, these items are selected to be focused in the area of inventory control. The inventory control models which are continuous review (Q-model) and periodic review (P-model) are proposed to the studied company. Two models of inventory control are proposed in this research because all types of raw materials should not be controlled with the same model in order to reduce the chance of shortage or overstock, and also overload to the employees. Q-model is proposed to the special raw materials that are mostly the parts of products in group A since this type of model suit well with the items that require to be closely looked and adequate to be processed at all time. According to the continuous review simulation on five raw materials which are RM-1 to RM-5, the results in Table 6-2 demonstrates that the proposed model can help in decrease the inventory level about 33% in 4-month average inventory level of five items. The inventory related cost which is one of the key performance index of this study also indicates that the Q-model is able to reduce the cost that occurred from inventory. Ordering cost is 40% decrease and cost to kept those items is 32% lower from how the studied company currently operates. The possibility of stock shortage which relate to the delay in production of studied company will be supported by this proposed inventory control model as these raw materials will be strictly monitored and updated.

Table 6-2: Results Summary from Continuous Review Simulation

Items	4-Month Average Inventory Level			Ordering Cost (THB)			Holding Cost (THB)		
	Actual	Proposed	% diff	Actual	Proposed	% diff	Actual	Proposed	% diff
RM-1	165646	114403	-31%	25,000	12,500	-50%	637,737.10	440,451.55	-31%
RM-2	59225	36125	-40%	20,000	15,000	-25%	133,256.25	81,281.25	-39%
RM-3	35873	28698	-20%	25,000	15,000	-40%	157,841.20	126,271.20	-20%
RM-4	34284	22309	-37%	15,000	7,500	-50%	82,281.60	53,541.60	-35%
RM-5	28989	19289	-35%	15,000	10,000	-33%	52,180.20	34,720.20	-33%
			-33%			-40%			-32%

For the common raw materials/ components, P-model is proposed according to the value of the items. The results from simulation of RM-6 to RM-10 are defined in Table 6-3. The average inventory level from four months of these five items is reduced about 43% which influence the cost from holding the inventory to be lower about 41%, at the same time, ordering cost is 41% saver with the determined time period to be order and the maximum inventory level to be stocked. P-model will support the studied company by having the scheduled of inventory monitoring which reduce the workload of employee but increase the accuracy in data since every 30 days, stock count is formally done and in detailed.

Table 6-3: Results Summary from Periodic Review Simulation

Items	4-Month Average Inventory Level			Ordering Cost (THB)			Holding Cost (THB)		
	Actual	Proposed	% diff	Actual	Proposed	% diff	Actual	Proposed	% diff
RM-6	15269	8311	-48%	15,000	10,000	-33%	19,086.25	10,388.75	-46%
RM-7	18217	8992	-51%	15,000	10,000	-33%	11,841.05	5,844.80	-51%
RM-8	4149	2509	-46%	20,000	10,000	-50%	9,335.25	5,645.25	-40%
RM-9	18217	8992	-51%	10,000	5,000	-50%	18,672.43	9,216.80	-51%
RM-10	4378	3623	-17%	12,500	7,500	-40%	3,830.75	3,170.13	-17%
			-43%			-41%			-41%

By comparing total ordering cost between two types of inventory control, it can be seen that the continuous review has higher ordering cost than periodic review and more vary in range. Periodic review has the maximum range of ordering cost at 10,000 THB for four months, this is because of the characteristic of model. Inventory is reviewed, monitored and updated when determined time period is reached; also the order placing. Therefore, the proposed review period is every 30 days will limit the ordering cost at 10,000 THB. It allows the studied company to be able to control both inventory level and financial part. On the other hand, the variation of ordering cost in Q-model trade off with the ability to achieve 98% service level and customers' satisfaction which relate to the company's reputation and creditability. The lose opportunity to produce the product to serve the customers will lead to high cost since those are special raw materials of products with high value.

Finally, to be able to forecast the future demand with least error will lead to the better plan in production and material requirement, also the ability to manage and control inventory of raw materials/ components will allow the better internal service level directly and indirect to external service level. In addition, the reduction of issues of shortage and overstock that relate to inventory cost.

6.2 Recommendation

In this section, the recommendation is stated base on the studies and limitations in this research. There are two areas, which are demand forecasting and inventory control, that are proposed in order to improve the inventory management of studied company.

In the part of demand forecasting, forecasting techniques selected are part of time series analysis which is the statistical computation of future demand based on the past data and by neglecting and smoothing out the randomness from the data set. According to the stated characteristics of this type of quantitative forecasting method, its limitation is there might be an opportunity those critical factors that can cause the impact accuracy of prediction. Qualitative forecasting methods are suggested to apply along with the proposed forecasting methods in order to include the external factors such as current market trend, consumers' behavior, and experience of experts in the industry in making decision in future demand quantity. This is because forecasting has to encounter with the demand/ customers' requirement which there is uncertainty in it, the uncertainty of demand is the core that leads to the inventory problem. By applying both quantitative and qualitative methods, it will help in shaping and generating the demand quantity that suitable with that time period and more up-to-date to the competitive market. Reviewing the pattern of demand and macro-environment are also recommended in order to adjust with the changes properly. An example to demonstrate how applying time series only can be the limitation can be the situation when there is a pandemic of virus. Relying on the history sales data might cause negative impact to the financial part of company as the economic is impacted and customers' behavior has certainly change from the past.

For inventory control that is simulated in this research with two types which are continuous review and periodic review, the outcomes might not be the representative of the real situation since the simulation of both types are done with ideal environment. Human error and data error are neglected while the daily demand as input to the simulation is functioning from RAND() in Microsoft Excel. In the real situation, there is possibility that the internal demand might has higher fluctuation than the data in simulation according to external factor such as customers' requirement and internal factor such as defects from production. Lead time is constant which is also ideal; there is the chance of delay of delivery from suppliers that may lead to stock shortage even if the safety stock is determined. According to the mentioned limitation, safety stock may need to be reviewed and updated instead of the constant level of safety stock. Penalty cost is suggested to be determined for further study in order to understand the trade-off between holding cost and cost of not able to meet the customers' requirement. Using the predicted demand data from selected demand forecast section as input to simulate the inventory control model is further work that is recommended to be done which would help to verify that the inventory level will be lower that the proposed; even if, the simulation in this study already shows that it can reduce the inventory level.

Lastly, it can be acknowledged through this research that the proposed principles, methods, and models to improve the inventory management started with the data collection hence, data is the main components of overall which the assumption can be made that the accuracy of data plays an important role in inventory management. Properly apply the proposed inventory policy also part of the inventory policy improvement. Therefore, the inventory related strategy and commitment from management level is suggested to be applied. With the inventory related strategy from management level, it will not only effective in data collection with more accuracy but also effective in the term of more efficient in implement the proposed inventory policy. Developing the internal communication between departments is also recommended in order to has better in coordination and data update.

REFERENCES

Abbasi, M., 2011. Storage, Warehousing, and Inventory Management. *Logistics Operations and Management*, pp.181-197. https://doi.org/10.1016/B978-0-12-385202-1.00010-4

Accenture (2008). *Role of Forecast Analytics in Inventory Management*. [online] S3.amazonaws.com. Available at: https://s3.amazonaws.com/images.chaptermanager.com/chapters/daa5e330-f68e-a26c-03fa-d8d709d940dd/files/napm-denver-presentation-df-analytics-for-im.pdf [Accessed 19 Oct. 2019].

Atnafu, D. and Balda, A., 2018. The impact of inventory management practice on firms' competitiveness and organizational performance: Empirical evidence from micro and small enterprises in Ethiopia. *Cogent Business & Management*, 5(1). https://doi.org/10.1080/23311975.2018.1503219

Basu, R. and Wright, J. (2008). *Total supply chain management*. Amsterdam: Butterworth-Heinemann.

Braglia, M., Grassi, A. and Montanari, R. (2004), "Multi-attribute classification method for spare parts inventory management", *Journal of Quality in Maintenance Engineering*, Vol. 10 No. 1, pp. 55-65. https://doi.org/10.1108/13552510410526875

Chambers, J., Mullick, S. and Smith, D. (1971). *How to Choose the Right Forecasting Technique*. [online] Harvard Business Review. Available at: https://hbr.org/1971/07/how-to-choose-the-right-forecasting-technique [Accessed 19 Oct. 2019].

Chase, C. (2013). *Demand-Driven Forecasting*. 2nd ed. Hoboken, New Jersey: John Wiley & Sons, Inc.

Chase, C. (2016). *Next Generation Demand Management: People, Process, Analytics, and Technology*. Hoboken, New Jersey: John Wiley & Sons, Inc.

Fattah, J., Ezzine, L., Aman, Z., El Moussami, H. and Lachhab, A. (2018). Forecasting of demand using ARIMA model. *International Journal of Engineering Business Management*, 10. https://doi.org/10.1177/1847979018808673

Ganesan, R. (2015). *The Profitable Supply Chain: a practitioner's guide*. Berkeley, CA: Apress, pp.23-85.

Hyndman, R. and Koehler, A., 2006. Another look at measures of forecast accuracy. International Journal of Forecasting. *International Journal of Forecasting*, 22(4), pp.679-688. https://doi.org/10.1016/j.ijforecast.2006.03.001

Hyndman, R. and Athanasopoulos, G. (2016). *Forecasting: Principles & Practice*. [Heathmont]: OTexts.

Jacobs, F. and Chase, R. (2013). *Operations and supply chain management*. 3rd ed. New York: McGraw-Hill Irwin.

Karteek, P. and Jyoti, K. (2014). Deterministic and Probabilistic models in Inventory Control. *International Journal of Engineering Development and Research*. [online] 2(3). Available at: https://www.academia.edu/12285059/Deterministic_and_Probabilistic_models_in_Inventory_Control [Accessed 29 Oct. 2019].

King, P. (2011). CRACK THE CODE: Understanding Safety Stock and Mastering its Equations. *APICS*, [online] (July/August 2011), pp.33-36. Available at: http://web.mit.edu/2.810/www/files/readings/King_SafetyStock.pdf.

Klaus A., Thomas F., and Herbert J. (2016) Effects of forecast errors on optimal utilisation in aggregate production planning with stochastic customer demand, *International Journal of Production Research*, 54:12, 3718-3735

Montgomery, D., Jennings, C. and Kulahci, M. (2008). *Forecasting and time series analysis*. New York: Wiley.

Montgomery, D., Jennings, C. and Kulahci, M. (2008). *Introduction to time series analysis and forecasting*. Hoboken, N.J.: Wiley-Interscience.

Muller, M. (2003). *Essentials of inventory management*. 10th ed. New York: American Management Association, pp.1-4.

Möllering, K., 2007. Inventory Rationing. Wiesbaden, Germany: Springer Gabler, Wiesbaden.

Radasanu, A. (2016). Inventory Management, Service Level and Safety Stock. *Journal of Public Administration, Finance and Law*, [online] 9(9), pp.145-153. Available at: http://www.jopafl.com/uploads/issue9/INVENTORY_MANAGEMENT_SERVICE_LEVEL_AND_SAFETY_STOCK.pdf.

Russell, R. and Taylor, B. (2011). *Operations management creating value along the supply chain*. 7th ed. Hoboken, New Jersey: John Wiley & Sons.

Sharma, S. (2017). *Inventory Parameters*. Singapore: Springer.

Sheakh, Dr.Tariq. (2018). A Study of Inventory Management System Case Study. *Journal of Dynamical and Control Systems*. 10. 1176-1190.

Shen, H., Deng, Q., Lao, R. and Wu, S., 2016. A Case Study of Inventory Management in a Manufacturing Company in China. *Nang Yan Business Journal*, 5(1), pp.20-40.

Silver, E., Pyke, D. and Douglas, T. (2017). *Inventory and production manegment in supply chains*. 4th ed. Boca Raton: Taylor & Francis Group, LLC.

Singha, K., Buddhakulsomsiri, J. and Parthanadee, P., 2017. Mathematical Model of (R,Q) Inventory Policy under Limited Storage Space for Continuous and Periodic Review Policies with Backlog and Lost Sales. Mathematical Problems in Engineering, 2017, pp.1-9.

Thomopoulos, N. (2015). *Demand Forecasting for Inventory Control*. Cham: Springer, p.00.

Wensing, T. (2011). *Periodic Review Inventory Systems*. Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg.

Wild, A. (2018). *Best Practice in Inventory Management*. 3rd ed. New York: Routledge.

Zare, A., Abouee-Mehrizi, H. and Berman, O., 2017. Exact analysis of the(R,Q)inventory policy in a two-echelon production–inventory system. *Operations Research Letters*, 45(4), pp.308-314.

APPENDICES

Appendix A: ABC Analysis

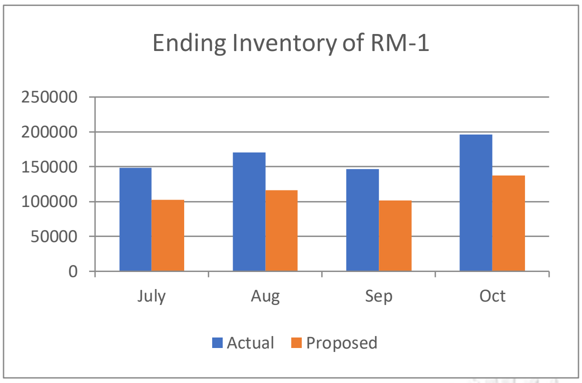
Table 0-1: ABC Classification with 1st Criteria

No.	Rearranged No.	Item Code	Quantity of Use (Unit/Year)			THB Usage			Class	Process
			Annual	%	Total %	Annual	%	Total %		
12	1	FG-BL-SEAL04	124249	2.0%	2.0%	8200434	8%	8%	A	M
14	2	FG-BL-SEAL02	98128	1.6%	3.6%	6908211.2	7%	14%	A	M
29	3	FG-KEY-W	53003	0.9%	4.5%	6890390	6%	21%	A	A
16	4	FG-BL-SEAL05	107880	1.8%	6.2%	6645408	6%	27%	A	M
1	5	FG-CA-PP	509330	8.3%	14.5%	5093300	5%	32%	A	M
8	6	FG-HA-BRZ	202399	3.3%	17.8%	5059975	5%	37%	A	M
37	7	FG-KEY-T	31582	0.5%	18.3%	4105660	4%	40%	A	A
17	8	FG-SA	99310	1.6%	19.9%	3773780	4%	44%	A	M
49	9	FG-KEY-W	26084	0.4%	20.3%	3390920	3%	47%	A	A
11	10	FG-AL-W	142922	2.3%	22.6%	3287206	3%	50%	A	M
20	11	FG-DL-W	79288	1.3%	23.9%	3171520	3%	53%	A	A
10	12	FG-CA-GR	203621	3.3%	27.2%	3054315	3%	56%	A	M
58	13	FG-KEY-ROT	18939	0.3%	27.5%	2462070	2%	59%	A	A
42	14	FG-BL-SEAL021	30863	0.5%	28.0%	2172755.2	2%	61%	A	M
22	15	FG-AL-T	82750	1.3%	29.4%	1903250	2%	62%	A	A
39	16	FG-BL-SEAL12	32495	0.5%	29.9%	1787225	2%	64%	A	M
7	17	FG-CADD	178000	2.9%	32.8%	1780000	2%	66%	A	M
32	18	FG-CA-PP01	48212	0.8%	33.6%	1687420	2%	67%	A	M
76	19	FG-KEY-B	12329	0.2%	33.8%	1602770	2%	69%	A	A
33	20	FG-SW-T	38825	0.6%	34.4%	1553000	1%	70%	A	A
48	21	FG-BL-SEAL10	26142	0.4%	34.8%	1437810	1%	72%	A	M
61	22	FG-BLGR-SEAL	16060	0.3%	35.1%	1413280	1%	73%	A	M
70	23	FG-BL-SEAL0316	14355	0.2%	35.3%	1220175	1%	74%	B	M
44	24	FG-W-R	29709	0.5%	35.8%	1188360	1%	75%	B	A
40	25	FG-BL-DL	29490	0.5%	36.3%	1179600	1%	76%	B	A
52	26	FG-BL-SEAL06	24290	0.4%	36.7%	1175636	1%	77%	B	M
15	27	FG-CA-K	116000	1.9%	38.6%	1160000	1%	79%	B	M
51	28	FG-HA-BR	27724	0.5%	39.0%	1108960	1%	80%	B	A
4	29	FG-H-R	269100	4.4%	43.4%	1076400	1%	81%	B	A
101	30	FG-KEY-RZ	8112	0.1%	43.5%	1054560	1%	82%	B	A
86	31	FG-BL-SEAL15	10001	0.2%	43.7%	880088	1%	82%	B	M
91	32	FG-BL-SEAL0313	15049	0.2%	43.9%	827695	1%	83%	B	M
82	33	FG-BL-SEAL011	11395	0.2%	44.1%	802208	1%	84%	B	M
35	34	FG-H-T	31780	0.5%	44.6%	794500	1%	85%	B	M
79	35	FG-BL-SEAL01	11048	0.2%	44.8%	777779.2	1%	85%	B	M
9	36	FG-HC	189802	3.1%	47.9%	759208	1%	86%	B	A
68	37	FG-BL-SEAL061	15511	0.3%	48.1%	750732.4	1%	87%	B	M
34	38	FG-AL-B	31800	0.5%	48.7%	731400	1%	88%	B	A
95	39	FG-LKB	10400	0.2%	48.8%	728000	1%	88%	B	M
84	40	FG-PPW	12308	0.2%	49.0%	676940	1%	89%	B	M
18	41	FG-AL-S	105819	1.7%	50.7%	634914	1%	90%	B	M

Table 0-2: ABC Classification with 2nd Criteria

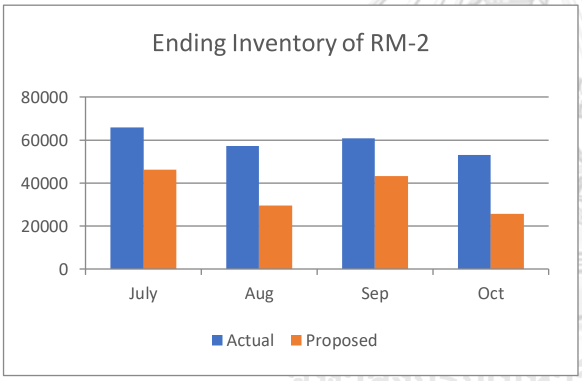
No.	Rearranged No.	Item Code	Quantity of Use (Unit/Year)			THB Usage			Class	Process
			Annual	%	Total %	Annual	%	Total %		
26	42	FG-HCL	63000	1.0%	51.8%	630000	1%	90%	C	M
45	43	FG-BL-SEAL07	27590	0.4%	52.2%	606980	1%	91%	C	M
13	44	FG-H	143900	2.3%	54.6%	575600	1%	91%	C	A
92	45	FG-W-SEAL10	9236	0.1%	54.7%	507980	0%	92%	C	M
85	46	FG-REC	12415	0.2%	54.9%	496600	0%	92%	C	M
53	47	FG-CA-R	20316	0.3%	55.2%	487584	0%	93%	C	M
77	48	FG-H-BR	10790	0.2%	55.4%	431600	0%	93%	C	A
90	49	FG-W-L	10250	0.2%	55.6%	410000	0%	93%	C	A
25	50	FG-ABS-W	79900	1.3%	56.9%	399500	0%	94%	C	M
89	51	FG-B-L	9923	0.2%	57.0%	396920	0%	94%	C	A
24	52	FG-GD	90500	1.5%	58.5%	362000	0%	95%	C	A
69	53	FG-AIR	17666	0.3%	58.8%	353320	0%	95%	C	M
67	54	FG-HD-W	13589	0.2%	59.0%	339725	0%	95%	C	M
2	55	FG-PL-90	469173	7.6%	66.6%	328421.1	0%	95%	C	M
59	56	FG-AL-W	20401	0.3%	67.0%	326416	0%	96%	C	A
80	57	FG-AIR-CU	15832	0.3%	67.2%	284976	0%	96%	C	M
36	58	FG-BA-W	31800	0.5%	67.7%	222600	0%	96%	C	A
46	59	FG-BA-B	30650	0.5%	68.2%	214550	0%	96%	C	A
3	60	FG-WI-6	275700	4.5%	72.7%	206775	0%	97%	C	M
54	61	FG-CA-NO	29900	0.5%	73.2%	179400	0%	97%	C	M
47	62	FG-LO-R	43500	0.7%	73.9%	174000	0%	97%	C	A
98	63	FG-AL-T-1	9330	0.2%	74.0%	149280	0%	97%	C	A
71	64	FG-BA-T	21200	0.3%	74.4%	148400	0%	97%	C	A
97	65	FG-AL-W-1	8402	0.1%	74.5%	134432	0%	97%	C	A
96	66	FG-AL-B-1	8400	0.1%	74.7%	134400	0%	98%	C	A
19	67	FG-CI-B	88000	1.4%	76.1%	132000	0%	98%	C	M
55	68	FG-O-GD	31300	0.5%	76.6%	125200	0%	98%	C	A
104	69	FG-AIR-PO	7552	0.1%	76.7%	120832	0%	98%	C	M
21	70	FG-CI-W	78602	1.3%	78.0%	117903	0%	98%	C	M
38	71	FG-LO-AG	29200	0.5%	78.5%	116800	0%	98%	C	A
41	72	FG-LE-GO	27300	0.4%	78.9%	109200	0%	98%	C	A
43	73	FG-C3-AG	31170	0.5%	79.4%	109095	0%	98%	C	A
93	74	FG-AIR-DI	10657	0.2%	79.6%	106570	0%	98%	C	M
5	75	FG-W-SE	354000	5.7%	85.3%	106200	0%	99%	C	M
66	76	FG-LO-BL	25800	0.4%	85.8%	103200	0%	99%	C	A
83	77	FG-BA-BR	14600	0.2%	86.0%	102200	0%	99%	C	A
75	78	FG-DU-BL	24100	0.4%	86.4%	96400	0%	99%	C	A
57	79	FG-DU-14	24000	0.4%	86.8%	96000	0%	99%	C	A
28	80	FG-REC-W	62002	1.0%	87.8%	93003	0%	99%	C	M
23	81	FG-REC-B	61600	1.0%	88.8%	92400	0%	99%	C	M
60	82	FG-DU-YL	23000	0.4%	89.2%	92000	0%	99%	C	A
73	83	FG-ABS-BR	18300	0.3%	89.5%	91500	0%	99%	C	M
74	84	FG-LOCK-WH	17716	0.3%	89.7%	70864	0%	99%	C	M
6	85	FG-SE-BL	217000	3.5%	93.3%	65100	0%	99%	C	M
64	86	FG-DU-PP	15100	0.2%	93.5%	60400	0%	99%	C	A
65	87	FG-LOCK-BL	14900	0.2%	93.8%	59600	0%	99%	C	M
87	88	FG-ABS-T	11900	0.2%	93.9%	59500	0%	100%	C	M
88	89	FG-DU-AG	13800	0.2%	94.2%	55200	0%	100%	C	A
72	90	FG-H-G	15400	0.2%	94.4%	53900	0%	100%	C	A
27	91	FG-RU-1	72915	1.2%	95.6%	51040.5	0%	100%	C	M
81	92	FG-DU-NA	12200	0.2%	95.8%	48800	0%	100%	C	A
30	93	FG-PL-WD	62700	1.0%	96.8%	43890	0%	100%	C	M
62	94	FG-LO-YL	9700	0.2%	97.0%	38800	0%	100%	C	A
100	95	FG-DU-GR	9400	0.2%	97.1%	37600	0%	100%	C	A
99	96	FG-C2-AG	10400	0.2%	97.3%	36400	0%	100%	C	A
103	97	FG-DU-PK	7600	0.1%	97.4%	30400	0%	100%	C	A
63	98	FG-CI-T	16700	0.3%	97.7%	25050	0%	100%	C	M
78	99	FG-REC-T	14900	0.2%	97.9%	22350	0%	100%	C	M
31	100	FG-SE-GR	70000	1.1%	99.1%	21000	0%	100%	C	M
50	101	FG-SE-GY	44000	0.7%	99.8%	13200	0%	100%	C	M
94	102	FG-มุREC-AL1	8412	0.1%	99.9%	12618	0%	100%	C	M
102	103	FG-REC-G	4700	0.1%	100.0%	7050	0%	100%	C	M
56	104	FG-C-GO	200	0.0%	100.0%	800	0%	100%	C	A

Appendix B: Inventory Control Models



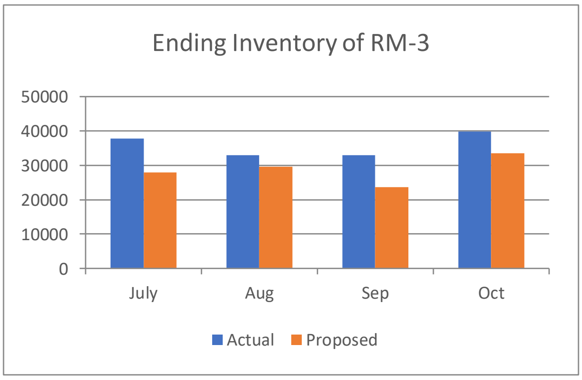
Month (2019)	Ending Inventory: RM-1		
	Actual	Proposed	% diff
July	148393	102300	-31%
Aug	170893	116600	-32%
Sep	146893	101200	-31%
Oct	196404	137511	-30%
Average	165646	114403	-31%

Ordering Cost (THB)	
Actual	Proposed
25000	12500



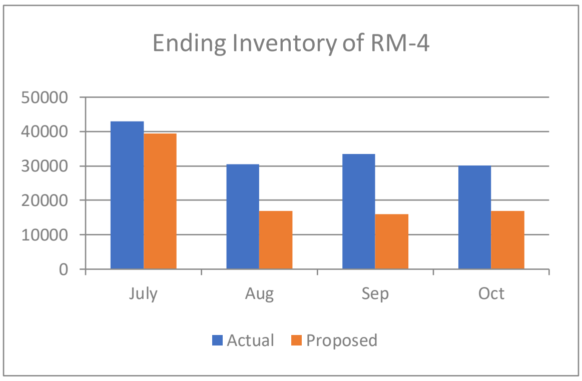
Month (2019)	Ending Inventory: RM-2		
	Actual	Proposed	% diff
July	65865	46065	-30%
Aug	57165	29465	-48%
Sep	60735	43235	-29%
Oct	53135	25735	-52%
Average	59225	36125	-40%

Ordering Cost	
Actual	Proposed
20000	15000



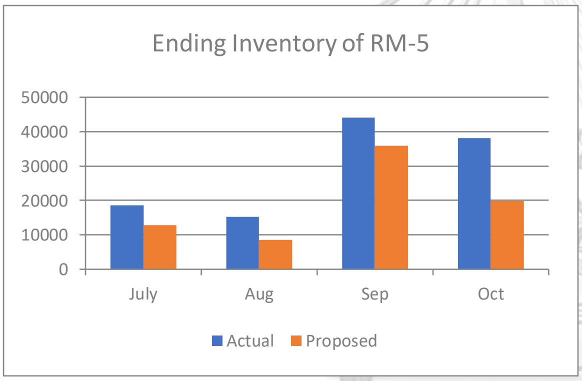
Month (2019)	Ending Inventory: RM-3		
	Actual	Proposed	% diff
July	37705	27905	-26%
Aug	32905	29605	-10%
Sep	33003	23703	-28%
Oct	39878	33578	-16%
Average	35873	28698	-20%

Ordering Cost	
Actual	Proposed
25000	15000



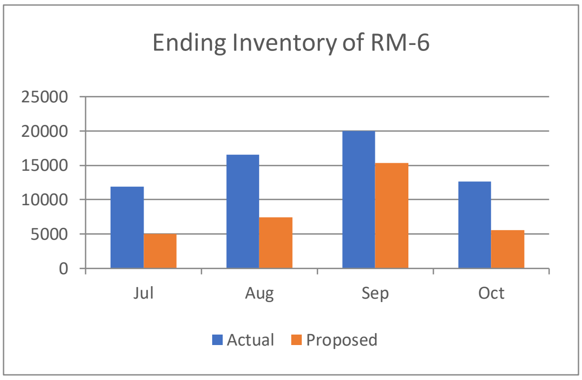
Month (2019)	Ending Inventory: RM-4		
	Actual	Proposed	% diff
July	43055	39355	-9%
Aug	30545	16845	-45%
Sep	33440	16040	-52%
Oct	30095	16995	-44%
Average	34284	22309	-37%

Ordering Cost (THB)	
Actual	Proposed
15000	7500



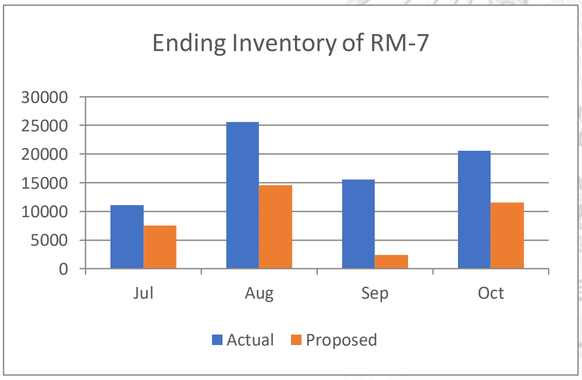
Month (2019)	Ending Inventory: RM-5		
	Actual	Proposed	% diff
July	18539	12739	-31%
Aug	15239	8639	-43%
Sep	44039	35839	-19%
Oct	38139	19939	-48%
Average	28989	19289	-35%

Ordering Cost (THB)	
Actual	Proposed
15000	10000



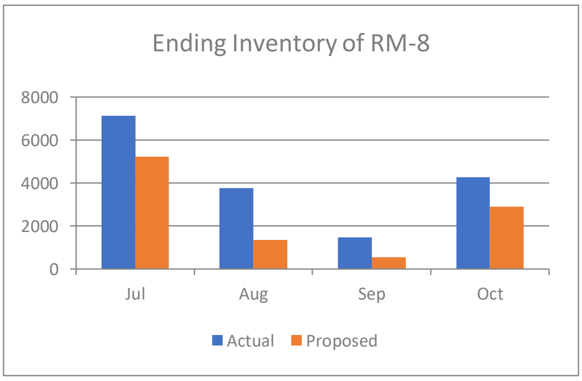
Month (2019)	Ending Inventory: RM-6		
	Actual	Proposed	% diff
July	11945	4981	-58%
Aug	16545	7406	-55%
Sep	19969	15320	-23%
Oct	12619	5536	-56%
Average	15269	8311	-48%

Ordering Cost (THB)	
Actual	Proposed
15000	10000



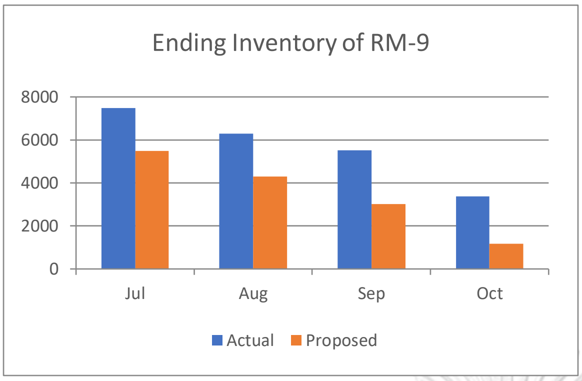
Month (2019)	Ending Inventory: RM-7		
	Actual	Proposed	% diff
July	11092	7520	-32%
Aug	25592	14511	-43%
Sep	15592	2417	-85%
Oct	20592	11520	-44%
Average	18217	8992	-51%

Ordering Cost (THB)	
Actual	Proposed
15000	10000



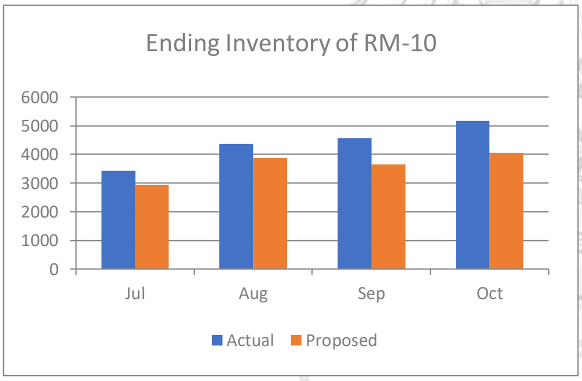
Month (2019)	Ending Inventory: RM-8		
	Actual	Proposed	% diff
July	7114	5214	-27%
Aug	3760	1359	-64%
Sep	1460	550	-62%
Oct	4260	2914	-32%
Average	4149	2509	-46%

Ordering Cost (THB)	
Actual	Proposed
20000	10000



Month (2019)	Ending Inventory: RM-9		
	Actual	Proposed	% diff
July	11092	7520	-32%
Aug	25592	14511	-43%
Sep	15592	2417	-85%
Oct	20592	11520	-44%
Average	18217	8992	-51%

Ordering Cost (THB)	
Actual	Proposed
10000	5000



Month (2019)	Ending Inventory: RM-9		
	Actual	Proposed	% diff
July	3430	2930	-15%
Aug	4360	3874	-11%
Sep	4560	3644	-20%
Oct	5160	4044	-22%
Average	4378	3623	-17%

Ordering Cost (THB)	
Actual	Proposed
12500	7500

VITA

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