DESIGNING INVENTORY PLANNING FOR STOCHASTIC DEMAND AT APPAREL'S LABEL INDUSTRY, CIKARANG

By

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THESIS ADVISOR
RECOMMENDATION LETTER

This thesis entitled **"Designing Inventory Planning for Stochastic Demand at Apparel's Label Industry, Cikarang"** prepared and submitted by **Indah Dwidayanti Putri** in partial fulfillment of the requirements for the degree of Bachelor Degree in the Faculty of Engineering has been reviewed and found to have satisfied the requirements for a thesis fit to be examined. I therefore recommend this thesis for Oral Defense.

Cikarang, Indonesia, February 14th, 2018

Anastasia Lidya Maukar, S.T., M.Sc., M.MT.

DECLARATION OF ORIGINALITY

I declare that this thesis, entitled **"Designing Inventory Planning for Stochastic Demand at Apparel's Label Industry, Cikarang"** is, to the best of my knowledge and belief, an original piece of work that has not been submitted, either in whole or in part, to another university to obtain a degree.

Cikarang, Indonesia, February 14th, 2018

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ABSTRACT

This research discusses about designing new inventory planning for stochastic demand at apparel's label industry in Cikarang, especially for RFID product. It begin with observation regarding to the material availability and current forecasting data from global headquarter which cause the material shortage. The core value of this research is to determine the best inventory planning by using total cost as the parameter. Since the data plot of this problem shows trend, seasonal, and cyclic as well, ARIMA is chosen as a proposed forecast method which can solve any pattern behavior of time series data with high accuracy. The selected ARIMA model will be used to forecast RFID demand for several periods a head. EOQ approach is used to calculate the optimum order quantity, reorder point, safety stock, and total cost that incurred in the inventory. The result of this research shows that the proposed forecast method successfully reduce the forecast error by 23.5%, and the inventory planning can reduce the total cost from IDR 8,793,333,100 to IDR 7,670,128,874 or by 12.8%. Moreover, the implementation of (Q,R) model with optimization approach by using ocean freight offers the lowest total cost for the next periods with the total cost IDR 7,827,704,823.

Keywords: *forecasting, ARIMA, Economic Order Quantity, re-order point, safety stock*

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Stochastic	:	A tool for estimating probability distributions of potential outcomes by allowing for random variation in one or more inputs over time. The random variation is usually based on fluctuations observed in historical data for a selected period using standard time-series techniques.
Stationarity	:	The assumption that the time series data contain no trends.
Akaike Information Criterion (AIC)	:	an estimator of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection.
Schwarz Bayesian Information Criterion (BIC)	:	a criterion for model selection among a finite set of models, the model with the lowest BIC is preferred.
Service Quality Level	:	Comparison between expectation and performance, which calculate by ability of the company to fulfil the customer's order based on customer request date and company promised data.
Difference	:	An approach to remove trend in the time series data

White Noise	:	A stationary process, this process is defined as a random array of independent, identical, and distributed random variables.
Autoregressive (AR)	:	A representation of a type of random process; as such, it is used to describe ceritin time-varying process.
Moving Average (MA)	:	This technique can refine the data by creating a consecutive average overall from a group of observations over a period of time.
Autocorrelation Function (ACF)	:	the interdependent correlation of observations of a time series, whereas the autocorrelation function is a plot of correlations.
Partial Autocorrelation Function (PACF)	:	the interdependent correlation of observations of a time series of observations. Partial autocorrelation measures the closeness between experiences of a time series.
Re-order Point	:	The level of inventory which triggers an action to replenish that particular inventory stock. In other word, when stock falls to this amount, the item must be ordered.
Safety Stock	:	A level of extra stock that is maintained to mitigate risk of stockout (shortfall in material or packaging) due to uncertainties in supply and demand.

CHAPTER I
INTRODUCTION

1.1 Problem Background

Nowadays, the dynamic of apparel industry is changing dramatically over the time. This trend happens not only in any specific country but also spread in growth country around the world. Most of the global companies are trying to deal with the customers that have different degrees of demand variability toward the apparel itself. At a baseline level, there is a fast-moving nature of fashion, which requires companies to jump on trends right away and gives the apparel business a unique set of challenges. Therefore, the company should have a sustainable supply chain that involves in the process, such as raw material supplier, garment industry for production, label and packaging company, logistic company, and retails. One of the industries which affected by the development of fashion business is label and packaging company.

According to Coyle *et.al.* (2003), an effective inventory flow management in supply chains is one of the key factors for the success company's operations. In managing the inventory, the big challenge is to balance the amount of supply between inventory and the demand. Ideally, a company want to have enough inventories which will satisfy the demands of its customers-no lost sales due to inventory stock-outs. But, on the other hand, the company would pay high amount of money for the holding cost if there are too much inventory staying on hand.

PT. X Indonesia is one of branch of multnational company, located in United States that focuses on label and packaging for well-known brand around the world. There are more than three thousand items that produced in different layout, material, and process. A fluctuating demand and short lead times make label and packaging company must create an accurate planning. Not only that, but also a make-to-order system with zero finished goods inventory become one of the challenges for the company. In order to maintain the continuity of the company's operations, the company are required to be more efficient in facing of more intense competition among the companies that running a business in the same sectors. The continuity of the production process within a company will be influenced by various factors including capital, machine (technology), materials, method, man power, and information.

After do the analyzing regarding the lower service quality level of PT. X Indonesia which is always below 70%, it has been found that the main problem is related to the material shortage of RFID product. The material shortage problem happened due to lack of inventory planning which caused by poor forecast result. The poor forecast result is caused by the lack of local demand data of RFID. Currently, the local company is using the global demand data for forecasting and it is done by the company headquarter as well. In line with this problem, the company tends to pay more for the procurement either caused by penalty cost, subcontract cost or urgent ordering cost by using air freight. In 2016, the total order intake of RFID product is only 65% or 4.8 Million pieces out of 7.4 Million pieces. There are 5% of the customer's order are lost, and 30% of the order was routed to the PT. X Vietnam, with the total loss IDR 5.92 Billion.

Reflecting to the current condition at PT. X Indonesia, the company desperately needs to design the best inventory planning which suitable with the characteristics of the RFID product especially for HM-RT01. This kind of activity can reduce the penalty cost and other losses that caused by material shortage.

1.2 Problem Statements

Based on the problem that faced by PT. X Indonesia, this research is done to answer these following questions.

- What are the causes of raw material shortage problem in RFID product (HM-RT01)?
- How does the ARIMA model can be the best forecast method for RFID product?

- What is the economic order quantity, re-order point, safety stock, and total cost for RFID product?

1.3 Objectives

The objectives of this research that want to be achieved are below.

- To identify the causes of raw material shortage problem in RFID product especially for HM-RT01 item.
- To identify the quality of demand forecast by using ARIMA model.
- To determine the economic order quantity, reorder point, safety stock, and minimum total cost for RFID product.

1.4 Scopes

Due to limited time and resources, there are some following scopes of this research.

- The demand data of RFID Product (HM-RT01) were taken from August 2015 until October 2017 at PT. X Indonesia.
- The data is only applicable to be used in Supply Chain department especially for RFID Product (HM-RT01) at PT. X Indonesia as a label and packaging company.
- This research will focus to improve the inventory management that affecting the service quality level, without discussing the service quality level in depth.

1.5 Assumption

The assumptions that were defined to help this research are:

- The demand of RFID product is a regular order or no missing of historical data.
- There is no other constraints related to inventory control and management, such as inventory turnover, limitation of budget and space.
- Supplier stocks are alaways available.
- The unfulfilled order will be directly routed to PT. X Vietnam (the company do the subontract).
- Supplier lead time is fixed, for air freight is 1 week, and for ocean freight is 3 weeks.

- There are 5 working days per week.
- Lead time from company to the customer is 4 days.

1.6 Research Outline

Chapter I	**Introduction** This chapter consists of problem background, problem statements, objectives, scope, assumptions and research outline of this research. In each sub-chapter, it contains a brief explanation regarding to the problem and the way to solve it.
Chapter II	**Literature Study** This chapter delivers the explanation related to the study for the whole research such as demand, forecasting method, time series analysis, ARIMA model, and inventory management.
Chapter III	**Research Methodology** This chapter contains the flow process that should be done in order to know the problem in details, to collect the data and the way to carried out the problem to be solved.
Chapter IV	**Data Collection and Analysis** This chapter consists of all the data that was collected by doing direct observation and interview. Also in this section, the data will be analyzed based on the study literature in chapter II.
Chapter V	**Conclusion and Recommendation** This chapter come up with conclusion of analyzed data from previous chapter. Also give some recommendation inputs for future research.

CHAPTER II
LITERATURE STUDY

This chapter consist of the basic theory and literature study that can be useful to solve the problem research. The sources are come from several books, article, journal and other virtual media that can support the research theory. The information covered in this chapter is related to the theoretical explanation about demand, the types of demand and its management. Also, the forecasting method that will be used. Since there are many forecasting methods are built to modelling the demand, the best forecasting method will be chosen to predict the future demand accurately. Forecasting technique that will be used is time series analysis. One of the most well-known time series model is the Autoregressive Integrated Moving Average (ARIMA) model developed by George E. P. Box and Gwilym M. Jenkins or usually called as the Box-Jenkins Model.

2.1 Demand

Demand is the amount of goods or services desired by a consumer or group of consumers for a certain price or demand is the sum of the needs of all potential customers (market participants) for a particular product over a period of time and within a given market. Many factors affect the demand of a good or service. While, it is not possible to identify all of these factors, some of the things that usually affect the level of demand for a good or service are as follows (Arnold dan Chapman 2004):

- General business conditions and economic circumstances.
- Competitive factors.
- Market trends that control the demand.
- Internal business enterprises such as promotion, advertising, price and the product itself.

2.2 Demand Management

According to (Arnold dan Chapman 2004), the main purpose of running a business is to serves the customers, besides the ultimate goal is running the company activities to meet the customer’s needs. Demand management is a function of arranging and managing all product requests. These activities can be in short-term, medium, and long-term management. For the long-term activity, the projection of the demand is required for business strategy planning. In the medium-term, the goal of demand management is to project the number of requests as a function of production planning. Lastly, for the short-term, demand management is that management is needed to combine demand with production scheduling (master production scheduling). Demand management consist of four main activities:

1. Demand forecasting

Forecasting can be used as a fundamental part in determining the future business strategy, production planning and production scheduling. The purpose of business strategy planning is to provide and prepare enough time to plan the resources, such as factory expansions, equipment purchases and other needs. In manufacturing activities, forecasting is used to determine matters relating to manufacturing process such as capital, manpower planning, raw material procurement, inventory levels, and others. While, the production scheduling focus on production activities from the present to the next few months. Forecasting is done for individual items, raw materials, number of components, and others.

2. Order processing

The ordering process occurs when orders from consumers are received. The products to be shipped might be come from warehouse of finished goods or when the product is still in the production process. The sales order will be processed, then the goods from the warehouse immediately enter the shipping stage. Production planner need to know what kind of item that should to be produced, the quantity, and when the product should be delivered.

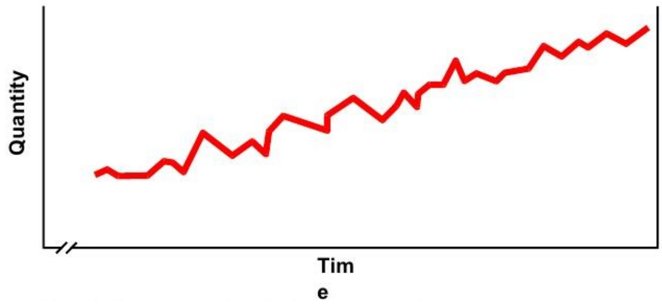
3. Making delivery promises and Confirmation of production planning with market conditions.

2.2.1 Characteristics of Demand

The demand for a product can show different amounts, so that it has certain characteristics within a certain period. When the demand is depicted in a graph, the historical data will show the various forms and patterns of the demand level (Arnold dan Chapman 2004). The demand level usually forms the following patterns:

1. Trend

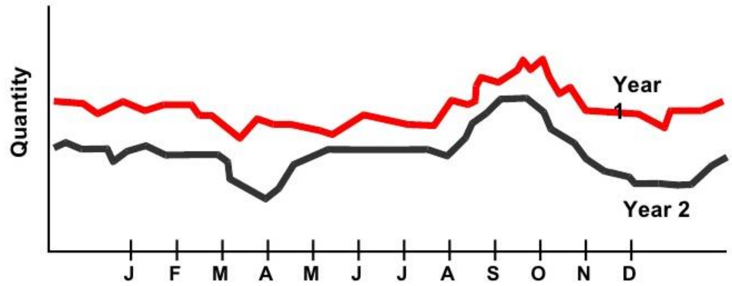
The pattern of trend is usually experienced by new products that experiencing the prosperity in a product life cycle. At such a period, the pattern of the demand tends to positive (rising) trend. But, if the product reach the limit of product life cycle, the pattern of the demand tends to negative (declining) trend. The example can be seen in Figure 2.1.



Source: https://www.slideshare.net/anandsubramaniam/demand-management
Figure 2.1 Example of Demand With Trend

2. Seasonality

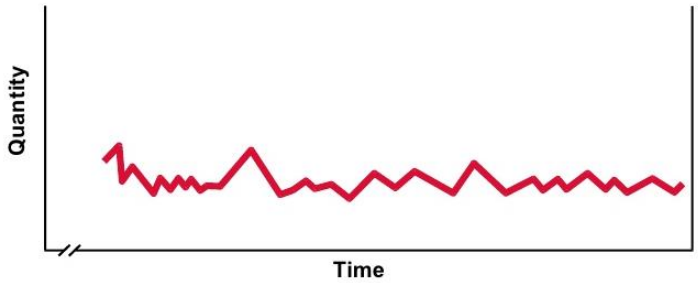
Seasonal patterns are usually formed by demand with products whose rate of demand is affected by weather or holiday season. The basis periods for seasonal demand is usually within the annual timeframe, also monthly and weekly can form a seasonal demand pattern. The example can be seen in Figure 2.2.



Source: https://www.slideshare.net/anandsubramaniam/demand-management
Figure 2.2 Example of Seasonal Demand

3. Random

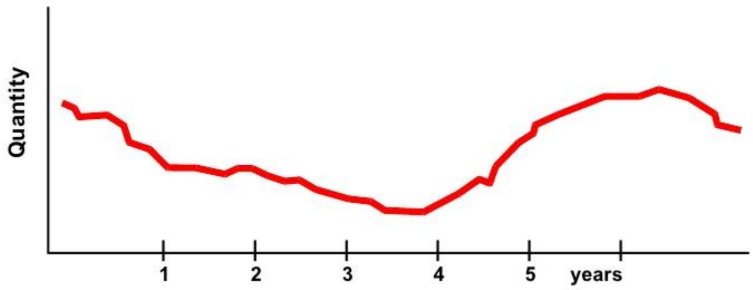
Random patterns usually occur in products whose level of demand is influenced by many factors in a given period. Variations that occur may be very small, but form a random pattern that is uncertain. The example can be seen in Figure 2.3.



Source: https://www.slideshare.net/anandsubramaniam/demand-management
Figure 2.3 Example of Random Demand

4. Cycle

The cyclical pattern is almost similar to the seasonal demand pattern. However, cyclical demand patterns are formed over a longer period of time, such as the seasonal patterns formed over the years or decades. The example can be seen in Figure 2.4.



Source: https://www.slideshare.net/anandsubramaniam/demand-management
Figure 2.4 Example of Cyclic Demand

2.2.2 Dependent and Independent Demand

The independent demand is a such of demand level which not affected by the other goods or service. The independent demand is influenced by the market conditions which can not controlled by the operations. This kind of demand is call for a replenishment philosophy, which means that orders are made to replenish the inventory. While the dependent demand for goods or services occurs when the level of demand for goods or services is obtained if the goods or services of others are also ordered. The demand will related to demand of another item, for example parts and raw materials as a complement of final goods. This kind of demand is call for a requirements philosophy, which means that the orders are made based on the requirement for final product (Sipper and Bulfin, Jr. 1997).

2.3 Forecasting

2.3.1 Definition and Basic Concept of Forecasting

Forecasting is an activity that tries to predict future circumstances with the use of past data from a variable or a set of variables Chase *et al.* (2004). Forecasting is a vital part of any business organization that can be a reference for the organization for significant management decision making. Forecasting can be the basis for short-term planning and long-term company.

Forecasting techniques are widely used in production management and inventory systems to see frequent variations in parts such as quality and process control, financial planning, marketing, investment analysis, and distribution planning Montgomery *et al.* (2015). Forecasting becomes one of the parts of the decision-making process. The ability to predict uncontrollable aspects makes the decision-making process supposed to take decisions on something that has been made based on the interrelationships of the variables. Based on this, the management system for planning and controlling operations by performing the function of forecasting is more defined. Here is an example of the use of forecasting in a manufacturing company Montgomery *et al.* (2015):

1. Inventory Management. In controlling the inventory or purchase of components, keep in mind how much each component needs to determine the lot sizes procurement.

2. Production Planning. Plotting production lines in a production process requires forecasting of the number of requests and units sold for the next period. This forecasting is to predict the number of finished goods, components, raw materials, workers and others so that the entire manufacturing system can be scheduled.

3. Financial Planning. The financial manager will show the company's cash flow to predict the amount of assets and capital held, when the cash flow will rise or decrease over the present and future time that can assist in the decision-making process.

4. Staff Scheduling. Forecasting predicts the number of products to be created, so managers can plan the number of production lines, workers and equipment needed more efficiently.

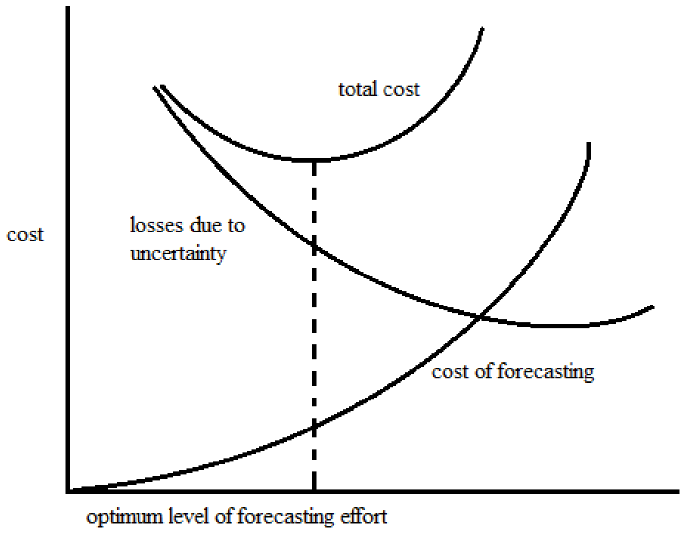
5. Facilities Planning. Decisions on new facilities are required for long-term planning based on forecasting or current circumstances. It is necessary to design the facility and estimate the investment required.

6. Process Control. Forecasting is also an important part of process control. By monitoring the variables of the key processes and predicting the behavior of the upcoming process, it is possible to determine the optimal time and determine the appropriate control measures.

The purpose of forecasting is to reduce the risk of decision making. Forecasting is usually wrong, but the magnitude of forecast errors depends on the forecasting method used. By using many aspects to forecast, the accuracy of forecasting should be improved and reduce some aspects of uncertainty in the decision-making process based on the results of such forecasting.

This concept is illustrated in Figure 2.5, where the cost of forecasting increases, but the risk (uncertainty) is reduced. In some levels the cost of forecasting will decrease. The conceptual model of Figure 2.5, based on the assumption of declining marginal values of forecasting may not have much impact. However, it is possible to reduce forecasting errors. Since forecasting can not absolute reduce risk, explicit decision process is needed to consider the uncertainty of the forecast error. The conceptual of forecasting is illustrated by:

$$actual\ decision = assuming\ forecast + allowance\ for\ forecast\ error$$



(source: Montgomery, 2015 page: 3)

Figure 2.5 Forecasting Trade-off

Ideally the forecasting process should produce a prediction of the probability of predictable spread of variables. However, forecasting does not end in a single process. Forecasting is part of a broad management system and as a subsystem that interacts with other components of the whole system to determine overall performance.

2.3.2 Principle of Forecasting

Forecasting has four characteristics or principles. Understanding the principles of forecasting can help to get more effective forecasts (Arnold dan Chapman 2004).

1. Forecasting is usually wrong. Forecasting tries to see an unknown future and is usually wrong in some assumptions or estimates. The error must be predictable and it cannot be inevitable.
2. Each forecast should include an error estimate that can be measured as a level of confidence, it can be a percentage (plus or minus) of forecasting as a range of minimum and maximum values.
3. Forecasting will be more accurate for the group. The behavior of individual items in a group is random, even when the group is in a stable state. For example, accurately predicting a student in a class is more difficult than forecasting for the overall average of the class. In other words, forecasting is more genuine to be done on groups or groups rather than individual items.
4. Forecasting is more accurate for a shorter period of time. To predict the future to be foreseen in the long time has a higher uncertainty than predicted for a short period. Most people are more confident to predict what they will do next week than predict what they will do next year. Once with a business, demand for the near term for the company is easier to forecast than to predict for the long term.

2.3.3 Forecast Methods

There are two methods or techniques of forecasting that can be used, namely qualitative and quantitative forecasting techniques. Qualitative forecasting techniques focus more on judgment and human intuition in the forecasting process, so the existing historical data becomes less important. While, qualitative forecasting techniques relied on human judgments and intuition more than manipulation of past historical data or methods based on grading and intuition, not on the processing of historical data. Makridakis *et al.* (1998).

Quantitative forecasting techniques rely heavily on historical data. This quantitative technique is usually categorized into two, namely statistical techniques and deterministic techniques.

1. Statistical techniques focus on patterns, pattern changes, and disturbance factors caused by random effects. Included in this technique are the smoothing technique, decomposition, and Box-Jenkins technique.
2. Deterministic techniques include the identification and determination of the relationship between variables to be estimated with other variables that will influence it. Included in this technique are simple regression techniques, multiple regression, autoregression, and input output models.

According to Makridakis *et al.* (1998), the approach of quantitative forecasting techniques consists of three approaches:

- Time Series Analysis
  This forecasting method uses time series as the basis for forecasting. Required data is needed to determine the appropriate forecasting method. Some examples with time series analysis approach are moving average, winter method, decomposition, exponential smoothing, ARIMA (Autoregressive Integrated Moving Average), Kalman Filter, Bayesian Method, and others.
- Causal Methods
  This method uses a causal approach and aims to predict future circumstances by finding and measuring some important independent variables and their effects on non-free variables to be foreseen. In causal methods there are two frequently used methods:

  1. Regression and correlation method, using least squares technique and variable in mathematical formulation. This method is often used for short-term prediction. For example: forecasting the relationship between

the amount of credit given with demand deposits, deposits and public savings or forecasting the ability to forecast sales of a product based on its price.

2. Output input method, commonly used for long-term national economic planning. For example: forecast economic growth such as gross domestic growth for some period five until ten years ahead.

- Simulation Analysis

  The econometric method is based on a simultaneously approximated regression equation. This method is often used for national economic planning in the short and long term. For example: forecasting the magnitude of monetary indicators for the next few years, this is often done by the Bank Indonesia (BI) every year.

2.3.4 Forecast Error

Time series analysis will provide forecasting of future value based on past data. The success rate and accuracy of forecasting can be measured by calculating forecasting errors. Measurement of forecasting accuracy can be measured by some forecasting error indicators Makridakis *et al.* (1998) which are:

1. Mean Error

Mean error is a simple technique in describing the error rate of a process. Errors or errors indicate the difference between the actual value and the predicted value, $e_t = X_t - F_t$. With the equation, the error value can be positive or negative. Negative if the forecast value exceeds the actual value and is positive, if the actual forecast value is smaller. The mean error can be denoted in the equation (2-1).

$$ME = \frac{\sum_{t=1}^{n}(dt - dt')}{n} \tag{2-1}$$

When used to calculate the overall average value of the sum of the total, then the positive and negative values will mutually weaken or add error. This means that the mean error is difficult to describe the average error of any forecasting process that is calculated.

2. Mean Absolute Deviation (MAD)

To anticipate the existence of positive and negative values that will mutually weaken or increase the calculation of errors on the sum, then the error used is the absolute value for each difference error. The calculation of error in this way is called Mean Absolute Deviation (MAD). By giving an absolute value on each error, then can be seen the performance of each calculation results, how the value of deviations that occur from the forecasting results. The formula can be shown in equation (2-2)

$$MAD = \frac{\sum_{t=1}^{n} |dt - dt'|}{n} \tag{2-2}$$

3. Mean Squared Error (MSE)

Mean Squared Error uses the squared value for each calculated increment. The difference with mean absolute deviation (MAD) is that MSE assesses errors for more extreme deviations than MAD. For example, the MAD calculation for error value 2 is calculated only twice from the error value 1, but the MSE will be calculated by squaring the value 2, this means the error is calculated four times from error value 1. By adopting the criteria to minimize the value of MSE means the value of deviation will greater than the value of the order when using one deviation. The formula of MSE can be seen in equation (2-3).

$$MSE = \frac{\sum_{i=1}^{n} ei^2}{n} \tag{2-3}$$

4. Percentage Error

Percentage Error is the percentage error of the actual value with the result of calculating the forecast value. The formula is shown is equation (2-4).

$$PE_t = \frac{X_t - F_t}{X_t} \times 100\% \tag{2-4}$$

5. Mean Absolute Percentage Error (MAPE)

MAPE is the average value of error, but gives an absolute value on the difference between the actual value and the forecasting value. MAPE is an indicator value commonly used to show the performance or accuracy of the forecasting process. The formula can be seen in equation (2-5).

$$MAPE = \frac{\sum_{i=1}^{n} |PE_i|}{n} \tag{2-5}$$

Where:

Xt = the actual value at the time t

Ft = forecasting value on time t

e = error (difference from Xt-Ft)

n = number of observations

2.4 Time Series Analysis

2.4.1 Definition

Time series analysis is a forecasting method using a time series approach as the basis of the forecast, which requiring the actual and past data to be predicted to know the data patterns. It is needed to determine the appropriate forecasting method for the current data. A relationship between demand data and time can be formulated ans use to predict the future demand levels. This approach attempts to understand and explain a particular mechanism, predicting a future demand levels with the assumption that the past data can project the future and optimize the control system. The purpose of this analysis is to observe or modeling the existing data series. A characteristic feature of time series analysis is that the observation sequence in a variable is seen as the realization of a randomly distributed variable. That is, it can be assume that a probability function with a random variable is exist Makridakis *et al.* (1998).

2.4.2 Time Series Analysis

In order to do forecasting for time series analysis, there are several method that can be use. Commonly, the method is selected based on the pattern and behavior of the time series data plot. For time series data that has trend and seasonal it can be solve by using Holt-Winter and Box-Jenkins. According to (Octora and Kuntoro 2013), the comparison of Holt-Winter and Box-Jenkins is listed in Table 2.1.

Table 2.1 Comparison between ARIMA and Holt-Winter method

ARIMA	Holt-Winter
Only for Stationary data	Can be used for stationary and non-stationary data
Needs randomness test by considering coefficient of autocorrelation	No need
Based on analysis of model selection in ARIMA for trend and seasonal data	Based on simple time series regression analysis
ARIMA does not make assumptions about the number of terms or the relative weights to be assigned to the terms.	Have 3 parameters only: α, β, γ (smoothing constant for data, trend, and seasonal)

In accordance to the data plot that exist in this problem, it was identified that the data has trend, seasonal, and cyclic. Therefore, ARIMA is prefered to be the best method because it did not require the data pattern so it could be used for all kinds of data pattern such as randomness, trend, seasonality, and cyclic.

Autoregressive and moving average was developed in 1970 by George E. P. Box and Gwilym M. Jenkins through his book Time Series Analysis: Forecasting and Control. The rational for time series is the present observation (Zi) depending on one or more previous observations ($Zi - k$). In other words, the time series model is created because statically there is a correlation (dependent) between series of observations. In order to know the existence of inter-observation dependencies, it can be tested by using autocorrelation function (ACF) which identify the correlation between observations. Montgomery *et al.* (2015).

Considering a time series in which a sequential observation can be denoted by a linear combination of random variables, for example, $\epsilon_t, \epsilon_{t-1}, \epsilon_{t-2\ldots}$ which is illustrated from a stable distributed probability with an average of 0 and variance σ_{ϵ^2}. Distribution of data ϵ_i is normally distributed and sequential from random variables $\epsilon_t, \epsilon_{t-1}, \epsilon_{t-2\ldots}$ or known as white noise process.

Linear combination from ϵ_i can be denoted in the equation (2-6).

$$x_t = \mu + \delta_0 \epsilon_t + \delta_1 \epsilon_{t-1} + \delta_2 \epsilon_{t-2} \quad (2\text{-}6)$$

where δ is the coefficient of autoreggresive or moving average and the value of $j = 0,1,2, \dots$ constant whereas μ are constants that determine the level of the process. Another alternative of Equation (2-7) is defined by another notation, B.

$$B\epsilon_t = \epsilon_{t-1} \tag{2-7}$$

In general, written into:

$$B^j\epsilon_t = \epsilon_{t-j} \tag{2-8}$$

By using the Equation (2-8) then it can be written to be:

$$x_t = \mu + (\delta_0 B^0 + \delta_1 B^1 + \delta_2 B^2 + ..)\epsilon_t \tag{2-9}$$

The equation (2-6) is usually called a linear filter. Consecutive sequence time series x_t is dependent, because the magnitude is determined by other variables ϵ_t normally distributed and ϵ_t normally distributed as well. In the linear view of the model filter, the observer can be defined by time series or known as the transformation of a white noise process into a time series. The equation (2-6) is derived from a stationary or non-stationary time series. If the time series is stationary means that the time series is fluctuating or fluctuating randomly but having constant averages and when the timetable is nonstable, the average has a fairly high range in values. In general, weights δ_j in linear filters are finite or infinite and convergent, in a time series x_t and stationary with average μ. If weight δ_j, infinite and divergent, then the time series formed is non-stationary and μ only a reference value of the original process.

Here are some terms commonly encountered in time series analysis based on Montgomery *et al.* (2015):

- Stationarity. A very important assumption in a time series is the stationarity of the series of observations. A series of observations is said to be stationary if the process does not change with time. That is, the average of observation series over time is always constant. The stationary data has constant mean and variance.

- Autocorrelation Function (ACF). Autocorrelation is the interdependent correlation of observations of a time series, whereas the autocorrelation function is a plot of correlations.
- Partial Autocorrelation Function (PACF). As with the autocorrelation function, partial autocorrelation is the interdependent correlation of observations of a time series of observations. Partial autocorrelation measures the closeness between experiences of a time series.
- Cross Correlations used to analyze the multivariate time series so that there are more than two time series to be analyzed. Similar to cautocorrelation, cross correlation also measures the correlation between time series, but the correlation measured is the correlation of two time series.
- White Noise Process. A stationary process, this process is defined as a random array of independent, identical, and distributed random variables. A white noise process with constant mean and variance, normally and independently distributed and non-autocorrelated. The example of white noise can be seen in Figure 2.6.

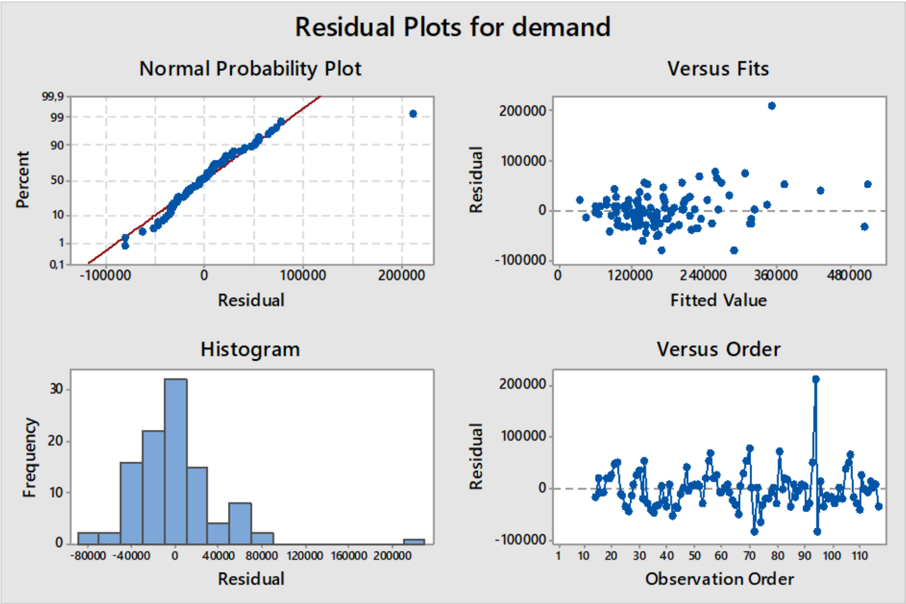


Figure 2.6 Example of white noise

- Trend Analysis. This analysis is used to estimate the trend model of a time series data. There are several models of trend analysis, including linear, quadratic, exponential, growth or decreasing models, and S curve models. Trend analysis is used when time series, no seasonal component.

- Moving Average. This technique can refine the data by creating a consecutive average overall from a group of observations over a period of time.

2.5 Box-Jenkins Method

2.5.1 Autoregressive (AR) Model

The autoregressive (AR) are based on the assumption that each value of the time series data is only depends on the weighted sum of the previous values $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$ and the regression coefficient is $\emptyset_0, \emptyset_1, \dots, \emptyset_p$ plus the value of residual term (ε_t) that represents random events which not explained by the model. An autoregressive model can be considered as a order of p. The equation of autoregressive model can be seen in Equation (2-10).

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t \tag{2-10}$$

The difference between the autoregressive models and other conventional regression model is respect to the assumption of the independence of the error term. Since the independent variables are value of time-lagged for dependent variable, then the assumption od uncorrelated error is easily violated.

2.5.2 Moving Average (MA) model

The fundamental of moving average model is begin with finding the mean for a specified set of values and then using it to do forecast for the next period and correcting for any mistakes made in the last few forecast. The equation of moving average model can be seen in equation (2-11).

$$Y_t = \theta_0 + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{2-11}$$

Where Y_t is the value of time series data at time t, $\theta_0, \theta_1, \dots, \theta_q$ are the weights that applied to previous forecast errors (ε_t).

2.5.3 ARIMA (Autoregressive Integrated Moving Average) Model

The ARIMA model consists of three processes namely autoregressive, integrated, and moving average with order (p, d, q) denoted as ARIMA (p, d, q). Order p are shown the autoregressive process on the model, order d shows the integrated process that must be done first in the data, and order q shows the moving average process. If d = 0 and q = 0, then the autoregressive model is denoted as AR (p), if d = 0 and p = 0, the the moving average model is denoted as MA (q), whereas if in the model there are three processes then the model named autoregressive integrated moving average denoted as ARIMA (p, d, q).

The attraction of ARIMA model is this model provide a general framework for the time series forecasing and other specification of model within the class was determined using data (Raman *et al.*, 2017). To develop an ARIMA model required a large dataset sufficiently. ARIMA model will be able to build if the model have a small error. Therefore, in identifying the existing time series model needs to be done carefully. In ARIMA there are four important processes ranging from correlation identification, determining model parameters, model validation, up to the last stage of forecasting. Montgomery *et al.* (2015).

2.5.4 SARIMA Model

In this case, the trend and seasonality is exist. The estimate of seasonal component in th time series data can be biased when the trend are present, and the trend also will affecting the level of overestimation in the seasonal (Hyndman, 2004). Basically, this model is quite similar to the ARIMA model, the differences is regarding the seasonal pattern that data plot shows. Not only that, but also the seasonal sign will be shown in the autocorrelation function (ACF). The specific lag will out from the confidence interval which is 95%. A seasonal ARIMA model is an ARIMA (p, d, q) model whose residuals (ε_t) are further modeled by an ARIMA (P, D, Q)$_s$. Thus, the operators of a seasonal ARIMA model is shown in equation (2-12).

$$(p, d, q)\ x\ (P, D, Q)s \tag{2-12}$$

Where:

p = the non-seasonal autoregressive order

d = the non-seasonal difference order

q = the non-seasonal moving average order

P = the seasonal autoregressive order

D = the seasonal difference order

Q = the seasonal moving average order

S = the number of seasonal lag (s = 12,14,...)

2.5.5 Step of ARIMA model

2.5.5.1 Identification

The aim of identification process is to choose the optimal (p, d, q) structure in an ARIMA model. Generally, a trade-off is exist. The adjusted R^2 will be rise as more as the terms are included in the model, in which the increasing of additional terms will reduce the forecast accuracy. In order to determine the order of ARIMA model, it should to be ensure that the time series data has already stationary. The main analytical tools that will be used is autocorrelation function (ACF) and partial autocorrelation function (PACF) which will identify the order value of *p* and *q* respectively, while the order of d will be determine based on the number of difference process (Michael 2003).

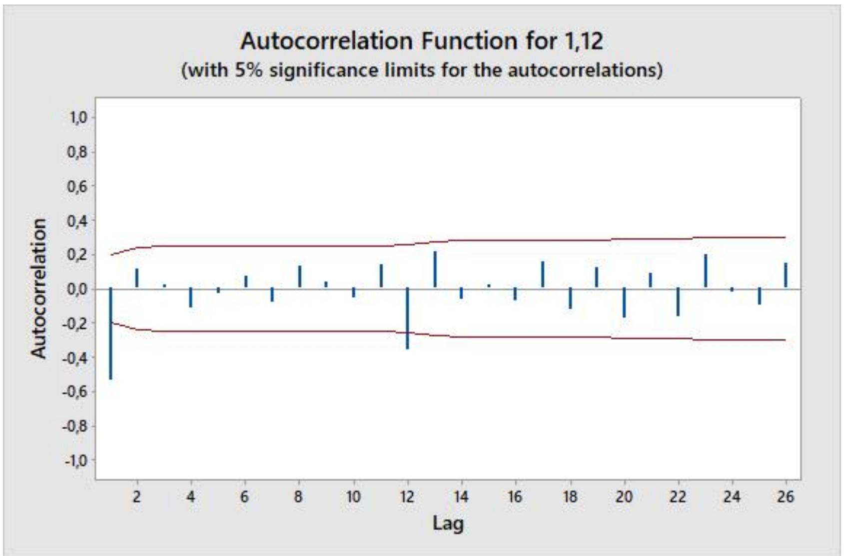


Figure 2.7 Example of autocorrelation function (ACF)

Based on the Figure 2.7 above, the first lag is out of the confidence interval. It means that the value of order q (MA). Thus, the value of MA(q) equal to 1.

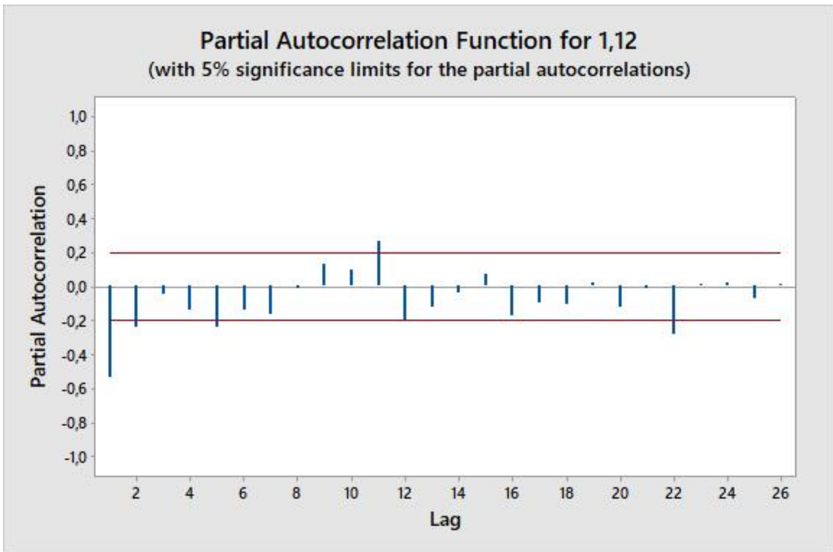


Figure 2.8 Example of Partial Autocorrelation Function (PACF)

The Figure 2.8 above shows the example of partial autocorrelation function (PACF) which will determine the value of order p (AR). Similar to the autocorrelation function (ACF), the can be identified by corresponding to the number of lag that out of confident interval. Thus, the value of AR (p) is 2.

The last step of identification process is model selection. This process will be done by using two goodness of fit which is Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC). The AIC contains a penalty terms which useful to determine the maximum length of lag in an AR model, while the BIC imprises a larger penalty for additional coefficients which useful to determine the maximum lags ofor a mixed ARIMA model. In general, the objective is to select the models that provide the minimum value of AIC and BIC (Michael 2003).

2.5.5.2 Parameter's Estimation

The estimation process includes various methods of removing the time series trend as well as applying the standard least squares methods. The purpose of this process are to ensure that the selected model will be fit to the data series and ensure that there is no additional parameters are present in the ARIMA model . The parameter will be identify as significant contributor to the ARIMA model if the *p*-value is less than 0.05 (α) (Michael 2003). The example of estimated parameters can be seen in Table 2.2.

Table 2.2 Example of Estimted Parameters of ARIMA model

Type	Coef	SE Coef	T	P
SAR 12	-0.360	0.098	-3.660	0.000
MA 1	0.783	0.063	12.510	0.000
Constant	72.100	817.500	0.090	0.930

2.5.5.3 Model Verification

According to (Gaspersz 2005), there are several method that can be used as model verification test, such as verification test which corresponding to moving range (MR) and tracking signal test. The formula of the test are shown in equation (2-13), (2-14), and (2-15).

Moving range

$$\overline{MR} = \frac{\sum_{t=2}^{n} MR_t}{n-1} \tag{2-13}$$

$$MR_t = |(d'_t - d_t) - (d'_{t-1} - d_{t-1})| \tag{2-14}$$

$$UCL\ or\ LCL = \pm 2.66\overline{MR} \tag{2-15}$$

Out of control if:

1. There is a data plot out of Ucl or LCL
2. from 3 consecutive points there are 2 or more points that are in the beginning
3. from 5 consecutive points there are 4 or more points that are in the middle
4. there are 8 consecutive points

Tracking Signal

Control limit vales of signal = ± 4 to ± 6

The formula as listed in equation (2-16).

$$Tracking\ Signal = \frac{RSFE}{MAD} = \frac{\sum_{t=1}^{n}(dt - dt')}{MAD} \tag{2-16}$$

2.5.5.4 Forecast Result

The last step is calculate the forecast result by using selected ARIMA model. The ARIMA procedure is expresses as equation (2-17), (2-18), (2-19), (2-20), and (2-21) follows:

- Non-seasonal autoregressive (AR)p

$$\emptyset_p(B) = 1 - \emptyset_1 B^1 - .\dots. - \emptyset_p B^p \tag{2-17}$$

- Non-seasonal moving average (MA)q

$$\theta(B) = 1 - \theta_1 B^1 - .\dots. - \emptyset_p B^p \tag{2-18}$$

- Seasonal autoregressive (AR)P

$$\emptyset_p(B^s) = 1 - \emptyset_{1,s} B^L - \emptyset_{2,s} B^{2L} - .\dots.. - \emptyset_{P,s} B^{PL} \tag{2-19}$$

- Seasonal moving average (MA)Q

$$\theta_Q(B^s) = 1 - \theta_{1,s} B^s - \theta_{2,s} B^{2s} - .\dots.. - \theta_{Q,s} B^{Qs} \tag{2-20}$$

- Difference

$$\nabla^d = (1 - B)^d \tag{2-21}$$

2.6 Inventory Planning

Inventories are various amount of items, such as raw materials, component, semi-finished, and finished goods which waiting to be processed by manufacturing company. The purpose are to improve the service level of the company, reduce overall logistics cost, to cope with uncertainty in customer demand and lead times, allows the availability of seasonal product, and etc. Basically, the manufacturing company do the forecasting with the aim to predict the number of customer demand in the future. Demand is a part of predictable function of production planning. For example, by forecasting the demand data, the production planning and control can be done. The demand levels will greatly affects the level of production capacity, the financial needs, and other parts of a business (Ballou 2004). In fact, the forecast data is not absolutely accurate to the actual demand data. Commonly, the number of products that has been predicted before is deviate far from the actual demand. therefore, in order to improving the company's efficiency by using demand management function, the forecasting function will be the tools to predict the future demand data. Not only that, but also by analyzing the forecast error, it can be predicted the number of raw material that must be continuously procure as a safety stock that is the amount of inventory needed to anticipate forecasting errors Ghiani *et al.* (2004).

2.6.1 Quantity Decisions

Quantity decision is related to right quantity that should be ordered to the supplier. This decision has a major impact on the inventory level which directly influences the total inventory costs. The most fundamental of all inventory models is Economic Order Quantity (EOQ). This model was introduced in 1915 by Harris, also well-known as the Wilson formula. This model is till one of the most widely used inventory model in the industry, because it serves as a basis for more sophisticated inventory model.

There are some assumption for this decision environment (Sipper and Bulfin, Jr. 1997):

- There is a single iteminventory system.
- No shortages are allowed.
- All the quantity ordered arrives at the same time.

The formula of Economic Order Quantity (EOQ) can be seen in equation (2-22).

$$Q = \sqrt{\frac{2A\bar{D}}{h}} \tag{2-22}$$

Where:

Q = Economic Order Quantity

A = Ordering Cost

D = demand per unit time

h = holding cost

2.6.2 Continuous Review Systems (Q,R) Policy

Continuous review systems is commonly called as fixed re-order quantity policy. This policy will reviewed or monitored the inventory level continuously. When the inventory level reaches the re-order point R (timing decision), then a fixed quantity Q is ordered (quantity decision). The relationship between inventory level and time based on continuous review systems can be seen in Figure 2.9.

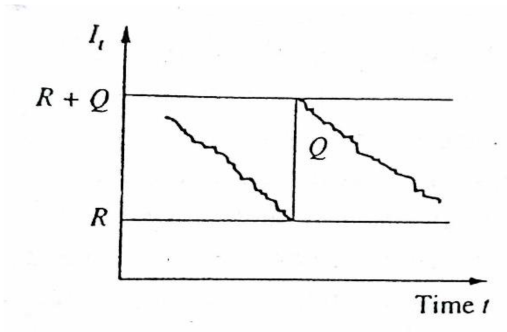


Figure 2.9 Continuous Review Policy

the continuous review policy will consider the lead time to place an order. Therefore, the EOQ approach formula will follow the lead time.

2.6.3 Periodic Review (S,T) Policy

Periodic review has a fixed time interval in reviewing the inventory level. An order will be issued if the inventory level is below a certain predetermined level R (timing decision). The size of order quantity Q is the amount required to bring the inventory to a predetermined level S (quantity decision). The relationship among R, S, and T can be seen in Figure 2.10.

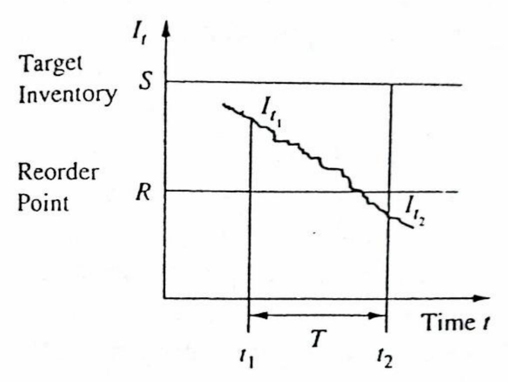


Figure 2.10 Periodic Review Policy

2.6.4 Safety Stock

Safety stock is a buffer or additional inventory which carried in order to meet the objective of the service, which is customers need and satisfaction. By correspondng to the value of service level, the safety stock enable to minimize the customers to experiencing a stockout (Sipper and Bulfin, Jr. 1997).

The formula of safety stock can be seen in equation (2-23) and (2-24):

$$\text{safety stock for continuous review} = z\sigma_{\tau}\sqrt{L} \qquad (2\text{-}23)$$

$$\text{safety stock for periodic review} = z_{\alpha}\sigma_{d}\sqrt{T+t} \qquad (2\text{-}24)$$

Where:

Z = Normal Standard

σ = Standard deviation

L = Lead time

T = Order interval

2.6.5 Reorder Point

The re-order point is the inventory level at which a new order is placed bu the company to the supplier. The order should to be made while there is enough stock in place to cover the demand during lead time. Since the problem that exist at PT. X Indonesia is under probabilistic conditions, then the re-order point will include the value of safety stock. There are two kind of re-order point policy: policy 1 which is the service level required is α, while the policy 2 required fill rate (β) as the service level. The formula of re-order point are shown in equation (2-25) and (2-26):

$$ROP\ of\ continuous\ review = R = \overline{D}_\tau L + z\sigma_\tau\sqrt{L} \quad (2\text{-}25)$$

$$max\ inventory\ (S) of\ periodic\ review = S = \overline{D}(T+t) + z_\alpha \sigma_d \sqrt{T+t} \quad (2\text{-}26)$$

2.6.6 Total Inventory Cost

Total inventory cost is any amount of cost incurred to purchase, order, and hold an item that required by the company. Total inventory cost per year incurred based on EOQ calculation can be seen in equation (2-27).

$$TIC = (D \times C) + \left(\frac{D}{Q} \times A\right) + (H\left(\frac{Q}{2} + SS\right)) \quad (2\text{-}27)$$

Where:

D = Annual demand in units

C = Unit price

Q = Order quantity in units

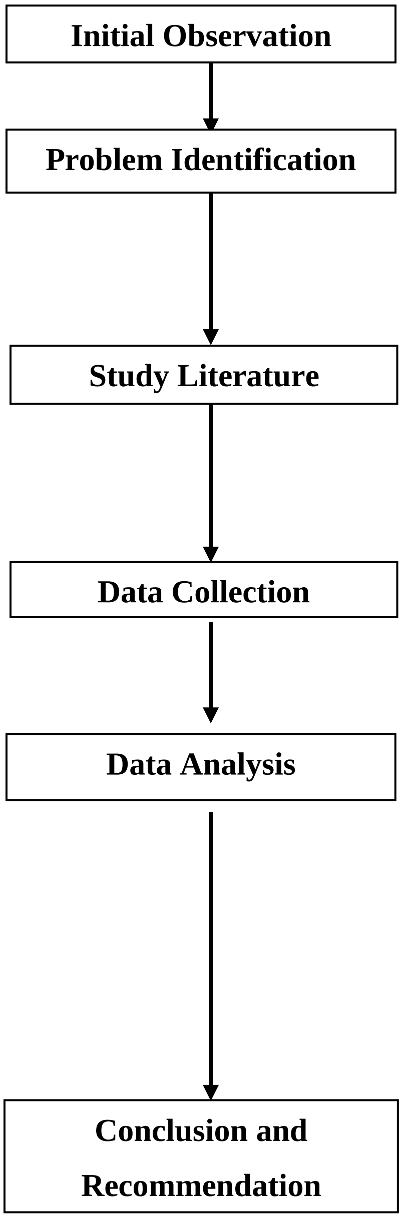
H = Holding cost per year

SS = Safety stock

CHAPTER III
RESEARCH METHODOLOGY

The flow process in this chapter will become a guidance to do the research, so the objectives of this research can be reached.

3.1 Theoretical Framework



<u>Initial Observation</u>
- Observe the supply chain department of PT. X
- Identify the main problem that needs to be improved

<u>Problem Identification</u>
- Identify the problem related to RFID product in current condition
- Define the objective of research, scope and assumptions

<u>Study Literature</u>
- Demand management and forecast methods
- ARIMA Model
- Inventory Model

<u>Data Collection</u>
- Do interview session with operation manager of PT. X Indonesia
- Analyze the procurement and inventory planning of RFID Product

<u>Data Analysis</u>
- Define the causes of material shortage
- Do demand forecast using ARIMA model
- Determine the value of safety stock, order quantity, re-order point, and minimum total cost
- Compare between proposed and current system

<u>Conclusion and Recommendation</u>
- Conclude the result of the research
- Give recommendation for future research

Figure 3.1 Theoretical Framework

3.1.1 Initial Observation

This is the first step of this research by analyzing the supply chain department especially focus on RFID product especially for HM-RT01 item at PT. X Indonesia. The initial observation is done by interviewing the people who involve in RFID, such as operation manager, production manager, inventory planner, people who incharge purchasing, and incharge export-import in order to get depth knowledge and understanding related to the RFID product.

3.1.2 Problem Identification

This is one of the phase in this research which conducted to identify the main problem in the current system at PT. X Indonesia. It is an important aspect to identify the problem at the beginning of the process. The purpose is to identify the main problem that should be improved and also define the objective, scope, and assumption so that the research will be on target. The problem that carried out in this research is related to the inventory management of HM-RT01 item which is RFID for Sweden apparel industry at PT. X Indonesia, which is material shortage that come up with high number of loss cost in recent 2 years. Also do the analyzing about the causes that give direct impact to the material shortage by determining the proper method should be used to solve the problem.

During the problem identification process, the aspect which acts as the cause of the material shortage is inaccurate data of demand forecast. This problem may leads to the high amount of subcontract cost or route cost due to material shortage, since the company has to pay two times of purchase price per unit.

The focus of this research is to increase the accuracy of demand forecast, so the inventory cost and other losses will be decresing. Therefore, to keep this research in line with the problem, the objectives of this research are formulated as below:

- Analyze the current inventory management of RFID for the last twelve periods.
- Set the total inventory cost as the parameter in order to minimize the total losses.

- Define the optimum forecast model which is by using ARIMA model to improve the current demand forecast.
- Minimize the forecast error to designing the new inventory model which better than previous model.
- Compare the proposed improvement model with the current inventory model.

Th scopes of this reasearch are the observation data was taken in supply chain department of PT. X Indonesia start from August 2015 until October 2017, while the assumption is there is no other constraints applied to this research.

3.1.3 Literature Study

By using several references such as journals, books, and websites, the literature study can be used to support the theory in this research. The relevant theories is essential to strengthen the method that used in this research. Thus, based on the topic of this research, the literature study will consist of:

- Definition and basic concept of demand management, forecasting, and inventory management.
- Box-Jenkins forecast model such as AR, MA, ARMA, ARIMA, and SARIMA model which explain the differences among the models.

3.1.4 Data collection

The data collection was taken from the direct observation at PT. X Indonesia. the data will be useful to analyze the problem related to material shortage in RFID product that causes PT. X Indonesia to pay more for subcontract cost and urgent shipping cost. the data that were collected are:

- Data of customer demand during August 2015-October 2017.
- Data of demand forecast in current condition.
- Data of prices incurred in the inventory management.

3.1.5 Data analysis

After obtaining the problem and the relevant data, then the further step is analyzing the data based on the . The detail steps are:

- Identify the pattern and trend of demand data of RFID Product.
- Calculate the forecast error of current demand forecast data.
- Analyze the current inventory management model that the company used for RFID product.
- Implement and analyze the Box-Jenkins method in order to get better demand forecast data.
- Designing the new inventory management model for RFID product based on the forecast data that has obtained from Box-Jenkins method (SARIMA model).
- Compare the result of current inventory management and the proposed inventory management by considering the total cost as the parameter.

3.2 Box-Jenkins Methodology

Generally, Box-Jenkins methodology has three main phase to determine the result of forecast data, which are identification phase, estimation and testing phase, and application phase. According to Makridakis *et al.* (1998), the stage of ARIMA model is shown in Table 3.1, while the detail flow of process for Box-Jenkins method can be seen in Figure 3.2.

Table 3.1 Steps of ARIMA Methodology for Time Series Modeling

Phase I: Identification	Data Preparation	• Transform data to stabilize variance • Difference dta to obtain statinary series
	Model Selection	• Examine data, ACF and PACF to identify potential models
Phase II: Estimation and Testing	Estimating	• Estimate parameters • Select best model if p-value of all model parameters are significant
	Diagnostics	• Check AIC and BIC of residuals • Are residual normally distributed?
Phase III: Application	Forecasting	• Use model to forecast

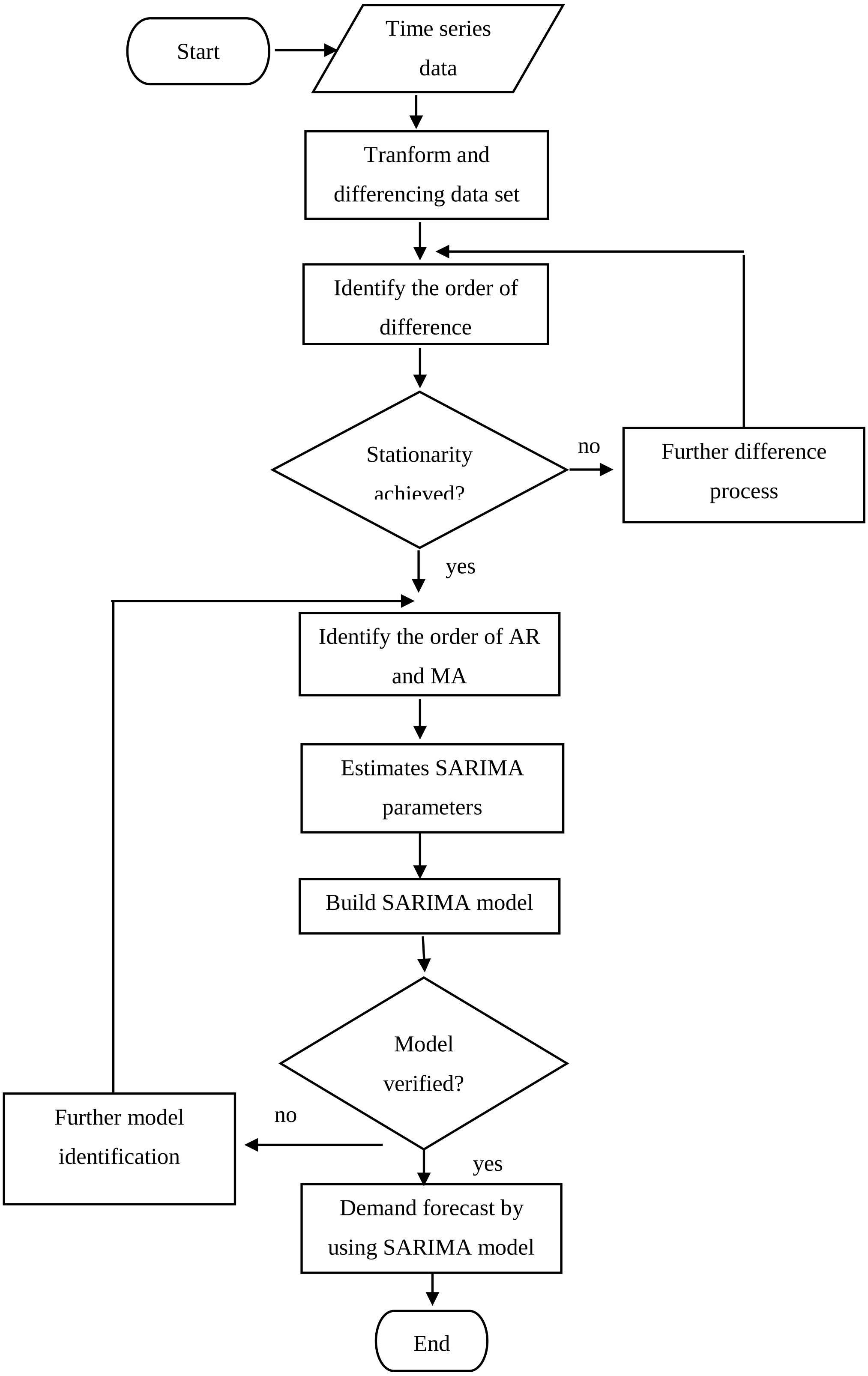


Figure 3.2 Flow Process of Box-Jenkins Method

3.3 Reserach Framework

The research framework will discuss about the flow process that should be done after the Box-Jenkins process. the input of this process is demand forecast data from current system and demand data that was gotten from SARIMA model. The detail process can be seen in Figure 3.3.

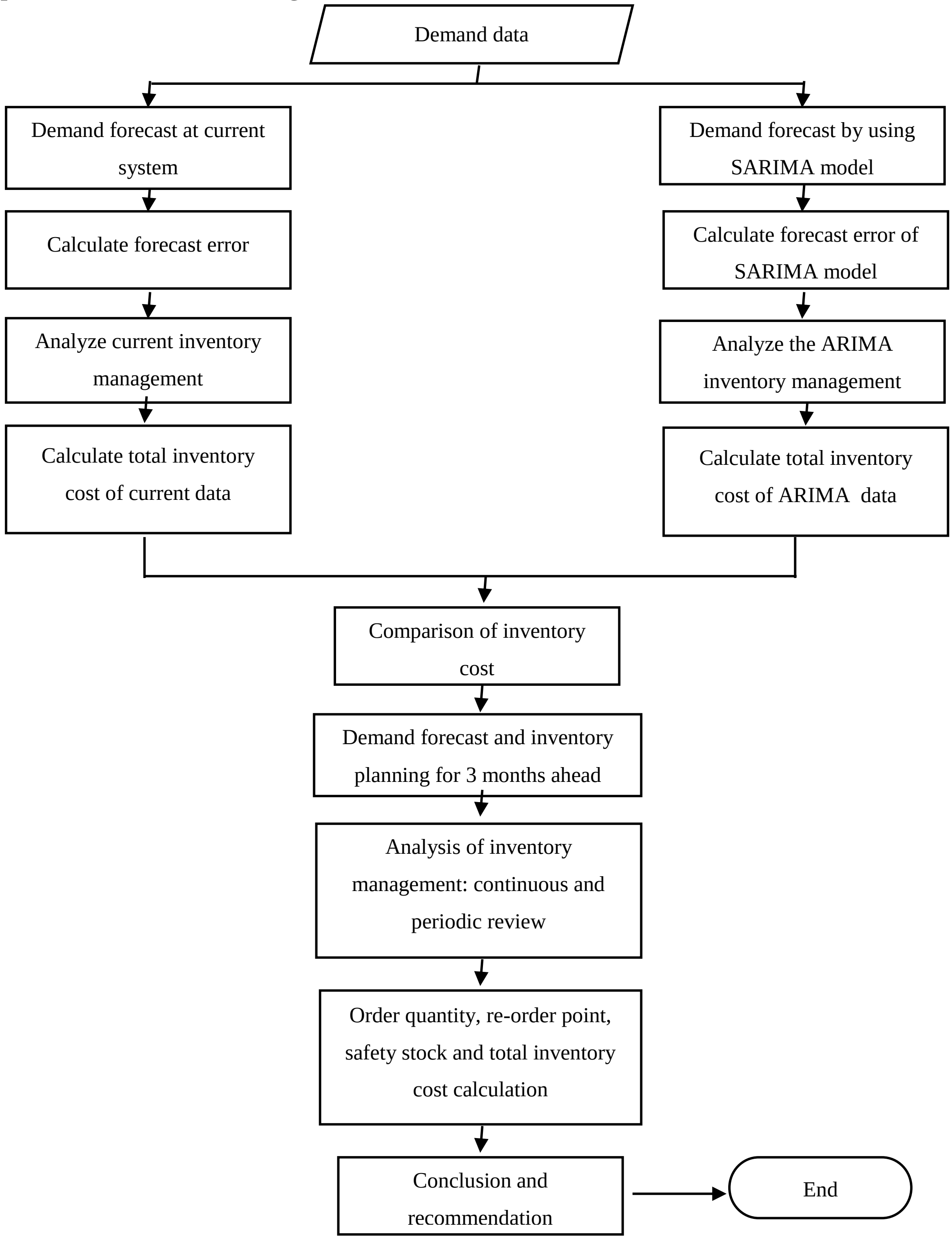


Figure 3.3 Research Framework

CHAPTER IV
DATA COLLECTION AND ANALYSIS

4.1 Data Collection

4.1.1 Product Description

Radio Frequency Identification or RFID is a kind of product that use technology as a fundamental part. RFID market is rapidly growing and have a good potential for many industries especially to make a great economic impacts in the future. Not only that, but also RFID as a revolutioner in supply chain management, logistics, and inventory control. Basically, RFID consist of three system essentials, which are tags, readers, and databases (A. Weis 2007).

In PT. X, there are 20 kinds of RFID product. One RFID is different with another, because there will be a chip in the tag. The in-house production process for RFID is quite simple which is only printing the tag with the right layout. The chip and all the information related to the product is already inserted by the supplier. Therefore, it can be conclude that the demand data of RFID product will be similar to the material request to the supplier, which means that one piece finished goods of RFID will be equal to one piece material of RFID. The RFID product that will be reviewed in this research is HM-RT01 which is for footwear product from Sweden apparel industry. The example of RFID tags can be seen in Figure 4.1.

Figure 4.1 example of RFID tag

4.1.2 Demand Data of the Product

The observation was done at PT. X Indonesia, which is a make-to-order company that produce label and packaging for international (well-kown) apparel industry. In this company, there are three kind of division that produce different type of product with different layout and materials. The newest product that exist in this company is RFID (Radio Frequency Identification). Based on the problem background that has already explain in the chapter 1, shortage material always be the biggest problem for RFID product, then it will makes the service quality level of the company become low. Therefore, this research will try to analyze the stochastic demand of RFID product for a specific item only.

The demand data that was taken is starting from the beginning of the order placed by customer which is August 2015 and ended by demand data of October 2017. Commonly, apparel industry produce seasonal product with the life cycle in the market is about three months, it means that the product will changes over the time. The demand data that was collected from PT. X Indonesia for RFID item will be listed in the Table 4.1 and the data plot in Figure 4.2.

Table 4.1 Monthly Demand Data of RFID Period Aug 2015 – Oct 2017

Year	Month	Actual Demand
2015	August	168,432
	September	395,006
	October	263,008
	November	201,898
	December	827,379
2016	January	396,961
	February	555,571
	March	762,306
	April	381,106
	May	550,357
	June	612,202
	July	328,680
	August	1,014,031
	September	638,229
	October	459,953
	November	949,430
	December	847,056
2017	January	660,458
	February	1,231,130
	March	516,152
	April	909,076
	May	1,389,971
	June	578,830
	July	827,524
	August	1,750,526
	September	709,283
	October	1,313,383

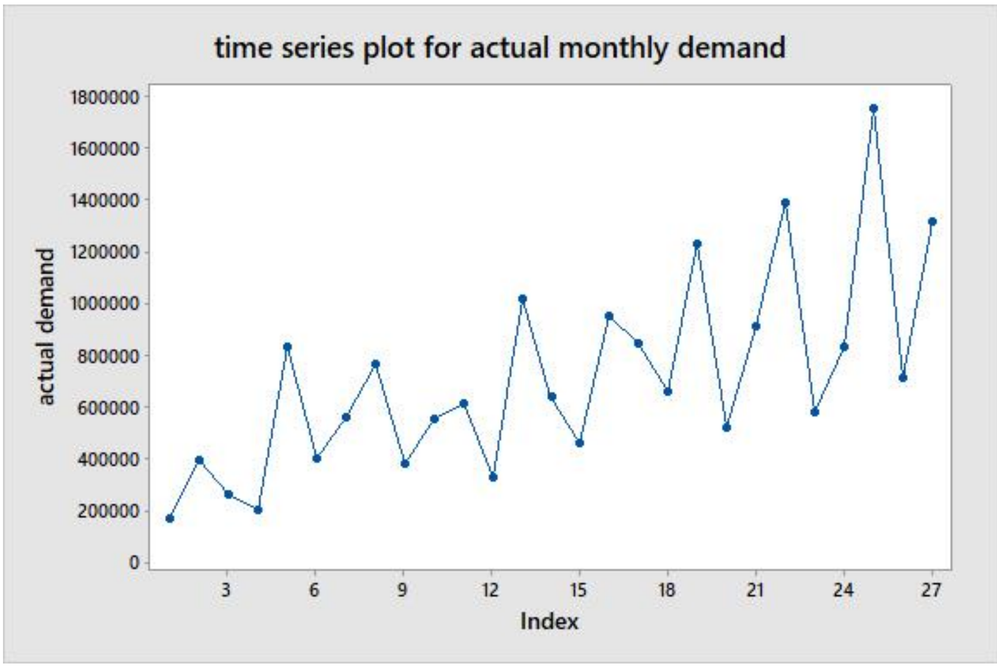


Figure 4.2 Time Series Plot of Actual Demand Data in Monthly

According to the Figure 4.2 above, the demand data of the product is fluctuate and has positive trend over the time. But, the seasonal characteristic can not be identified yet. Due to this reason, the demand data will be separated into week periods. Weekly historical data can be seen in appendix A.

Based on the table of weekly demand data of RFID, the data can be estimated as a seasonal time series data, because the demand tend to increasing after the first 6^{th} periods in every season. Even though the data plot shows the seasonal increasing of customer demand, there is no reason for the causes. The difference between demand of 6^{th} period and 7^{th} period is unknown, but it was significant enough for the company to experiencing a stockout. Reflecting to other RFID product, the order will increse at the end of the season due to the customers will launch new layout for the next season, but it can not be ascertained what function is approaching it. Therefore, this problem assumed to be stochastic demand, whereas at certain moments will reaching the maximum value, while the other reaches a minimal point.

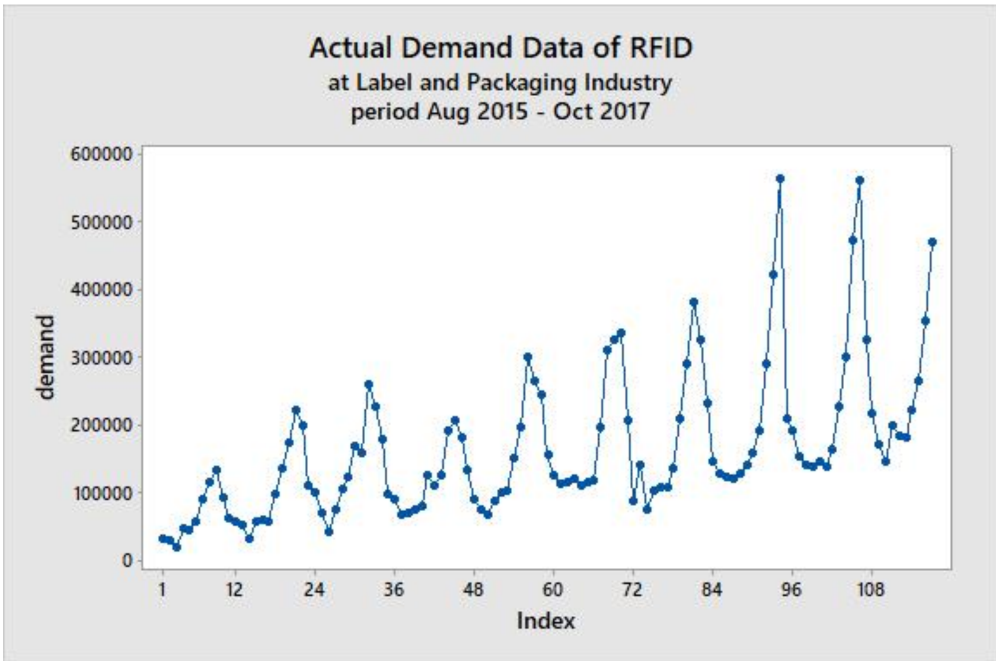


Figure 4.3weekly data plot of actual demand

According to the Figure 4.3 above, it can be estimated that the data is non-stationary with the positive trend over the time. Non-stationary data are unpredictable and difficult to be modeled or forecasted. This data has a variable variance and mean that does not remain near the zero over X-axis, or return to a long-run mean over time. In order to make this data fit with the model that will be used in the analysis phase, the data will tested for variance and mean stationarity test. The detail of the process will be explain in the sub-chapter 4.3.1.

4.1.3 Current Forecast Data and Calculation Of Forecast Error

The forecast data of PT. X Indonesia is performed by the global management that placed in hongkong. The forecast data will be shared directly to the inventory planner of every site that responsible to produce RFID, then the information sharing is only between the global planner and local inventory planner. At the present time, the accuracy of forecast data is quite small, which is below 80%. Therefore, the forecast data of RFID item for Sweden apparel industry will be analyzed in this report. The current forecast data will be listed in the appendix A.

The table of current forecast data and error in appendix A shows the forecast data and forecast error toward demand data of RFID since Aug 2015 – Oct 2017. The residual error value is getting from the difference between demand and forecast data. The negative value in residual error means that the value off demand data is less than the forecast data. In order to calculate the forecast error, there are several method that can be used, such as Mean Error (ME), Mean Absolute Error (MAD), and Mean Absolute Percentage Error (MAPE). The sum value of Mean Error (ME) indicates the total number of material shortage for 126 periods, which is 6,725,167 pieces. According to Dekker *et. al*. (2004), the calculation of forecast error by using Mean Error (ME) and Mean Absolute Error (MAD) will less accurate than Mean Absolute Percentage Error (MAPE) whether in reviewing some forecast methods and data through direct comparison or not. Based on the data, the forecast error of the current system is about 38.79% which means the accuracy of the forecast demand is 61.21%.

4.1.4 Ordering Cost

Ordering cost are all the expenses incurred whenever the company wants to place an order to the supplier, which applied since the company creating a purchase requision to the availability of goods. The average cost that will be charged per order for RFID item by using air shipping mode is IDR 10,000,000. This value includes delivery order document fee, collection fee (2% of freight cost), customs clearance, electronic data interchange of import item (EDI-PIB) free, terminal storage cost, custom inspection cost, delivery charge for trucking, an rush handling cost. Meanwhile, the ordering cost that incurred by using sea mode shipping is a half of air mode, which is IDR 5,000,000.

4.1.5 Holding Cost

Holding cost are the amount of money that the company spent to maintain and store each unit of goods in the storage. Essentially, any cost that include to the holding cost are the rent's space cost, materials, labor, taxes, insurance, and other cost that related to carrying the item. Based on the company's policy, the total inventory cost will be charged at 5% of the price of unit ordered. Since the material ordered from the supplier per piece and the holding cost applied for one seasons (12 weeks or three months), then the holding cost per season is

$$holding\ cost = i \times c = 5\% \times IDR\ 2000 = IDR\ 100$$

Based on the calculation above, it can be concluded that the holding cost for twelve periods is IDR 100 per pieces of RFID stored in the storage or IDR 8.333 per pieces of RFID per period.

4.1.6 Route Cost

Route cost or transfer cost is the cost that included in the total inventory cost wherein the company experiencing a shortage material. This cost is quite the same with subcontract cost, the differences is the product will not send back to the company, but directly ship to the customers. In order to fulfil the customers order, the company will route or transfer the order to other company, which is PT. X Vietnam. The cost that will incurred for this activity is twice of purchase price per unit of RFID or equal to IDR 4000 per pieces and the additional cost to delivery the item to the customer, which is the average delivery cost is IDR 2,000,000.

4.1.7 Current Inventory Planning

In the current inventory planning of PT. X Indonesia, it was identified that there were unbalance amount between supply and demand of RFID product. According to the data of PT. X Indonesia, the service quality level is always below 70%, it was measure based on the ability of PT.X to fulfil the customer's order either corresponding to the customers request date or company's promised date. Thus, the percentage of service level will propotionally affected to the customers experiencing a stockout. The current inventory planning model can be seen in table Table 4.2.

Table 4.2 Current Inventory Planning of period 115 until period 126

Period	Forecast	Orders				Inventory		
		Total Order Received at the end of week (pcs)	Total Complete Order (pcs)	Total Incomplete Order on Hand (pcs)	Total Order Route to PT. X Vietnam	Inventory Balance	Open PO at Supplier (optional)	
							Monday	Thursday
114						**52,500**	**60,000**	**50,200**
115	158,000	264,434	162,700	101,734	101,734	-	100,000	100,000
116	204,800	355,248	200,000	155,248	155,248	-	195,000	155,000
117	349,060	472,126	350,000	122,126	122,126	-	250,000	200,000
118	496,085	599,475	450,000	149,475	149,475	-	250,000	150,000
119	347,320	322,091	322,091	-	-	77,909	-	78,000
120	149,078	238,912	155,909	83,003	83,003	-	75,000	97,000
121	166,950	221,079	172,000	49,079	49,079	-	65,000	100,000
122	150,030	177,620	165,000	12,620	12,620	-	100,000	90,000
123	189,431	219,839	190,000	29,839	29,839	-	160,000	50,000
124	188,506	201,118	201,118	-	-	8,882	100,000	45,000
125	142,105	216,940	153,882	63,058	63,058	-	100,000	100,000
126	197,540	231,069	200,000	31,069	31,069			
Total	**2,738,905**	**3,519,951**	**2,722,700**		**797,251**			

On the Table 4.2, the current inventory planning at PT. X Indonesia for RFID is listed for the recent twelve period in 2017, which is period 115 until period 126. The forecast result is getting from the current demand forecast which has been done by the headquarter. The total order received is the number or customers order that the company received until at the last day in those week, which means that if the are five working days in a week, the customers order will recorded until Friday. The next is total complete order, which means that the number of customers order that has been processed in that week by corresponding to the number of inventory balance and materials from supplier that has already ordered in the previous period. There is two days available for the company to place an order to the supplier, which are on Monday and Thursday. Since the lead time from company to the customer is only 4 days, it means that there will be late of delivery if the company place an order on Thursday. The last is total imcomplete order on hand, which is the value of total order received subtract by total complete order. The total material ordered to the supplier is quite similar to the total demand forecast. In the current inventory planning, there are 10 imcomplete or unfulfilled order that will directly routed to PT. X Vietnam, which means that the company will pay more to complete the customers order corresponding to route cost and also experiencing late of delivery to the customers.

4.2 Proposed Forecast Method

4.2.1 Data Analysis Using the ARIMA (Box-Jenkins method)

The autoregressive integrated moving average or usually called as ARIMA model, is the most sophisticated method to do forecasting in time series data context (Pankratz 1983). This type of forecasting method was developed by Box and Jenkins (1970), where the autoregressive (AR) and movung average (MA) term are combining in used to forecast the demand data. This method was selected due to the characteristics of the demand data, which is a non-stationary dataset. There are four major steps to run Box and Jenkins model and The step of analyzing process will be described below:

1. Model Identification

2. Parameter’s Estimation for Model
3. Model Evaluation
4. Forecast Result

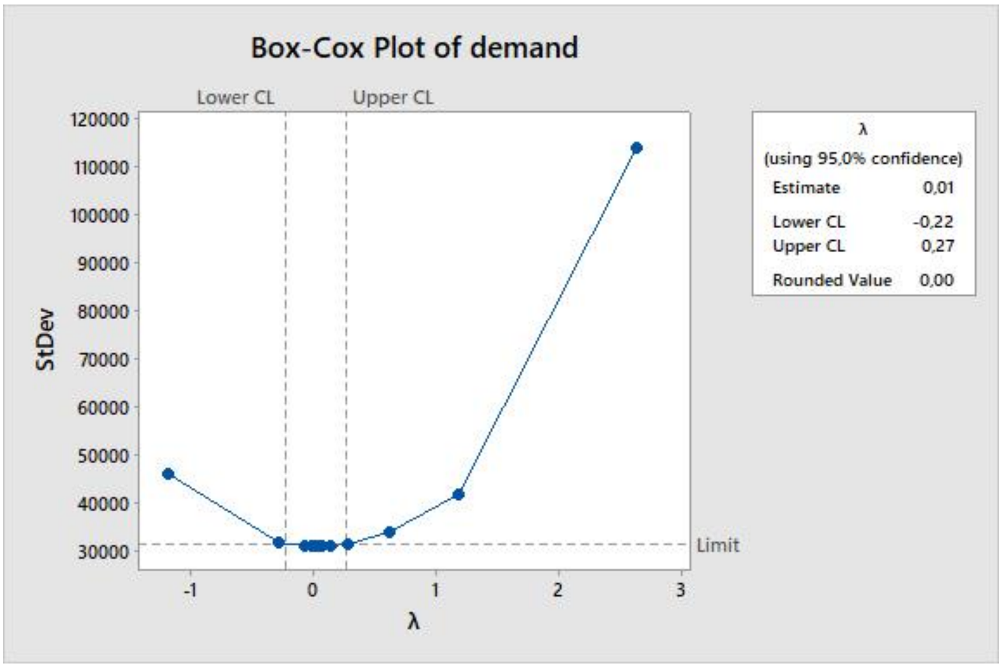
4.2.1.1 Model Identification

At the beginning of the data analysis procedures, the first thing that should be done is model identification. The aim of this step are to identify the trend of the demand data, check the stationarity of the data, and determine the order for autoregressive (AR) and moving average (MA). The identification prosess of the non-stationary data consist of detecting which transformation must be applied to obtain a stationary ARIMA process with constant variance and mean. To have a data series that will be stationary toward variance (constant variance), the data should to be transform. Besides, to have a data series that will be stationary toward mean (constant mean), the data should to be differentiate.

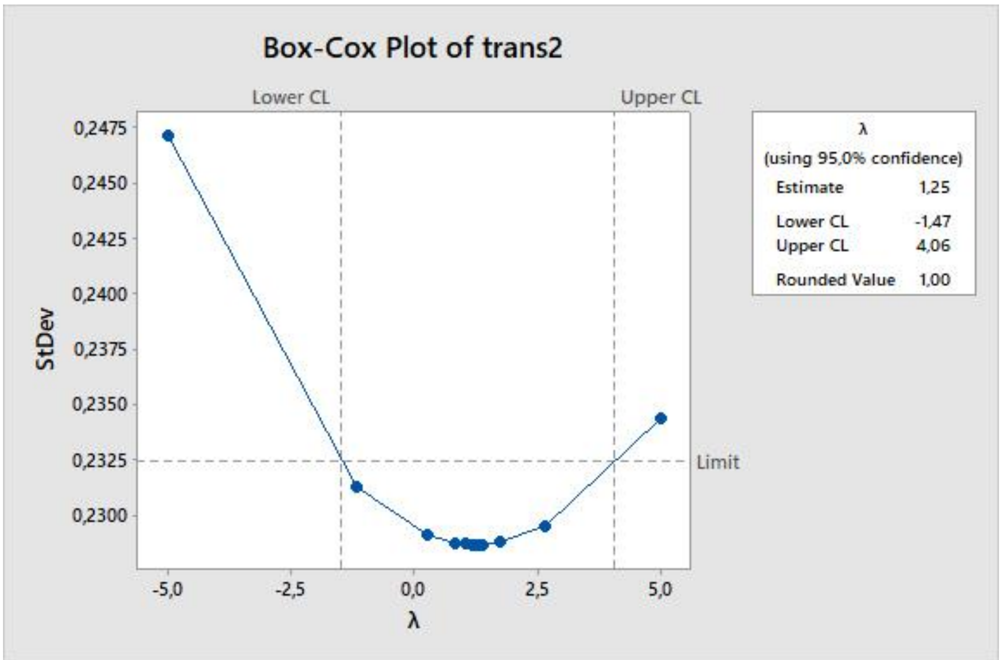
Cheking the stationary of the demand data

a. stationarity based on variance

according to the figure (graph of demand data), the data plot of demand shows that the data is non-stationary toward variance, due to there are variables variance happened to the data. By using Box-Cox control chart, the actual demand data shows that the rounded value equal to 0.00. Therefore, the data should to be transform until it has rounded value equal to 1. Here is the comparison between the current Box-Cox plot data with the Box-Cox plot data after transformation process.



a) Box-Cox plot of current demand data



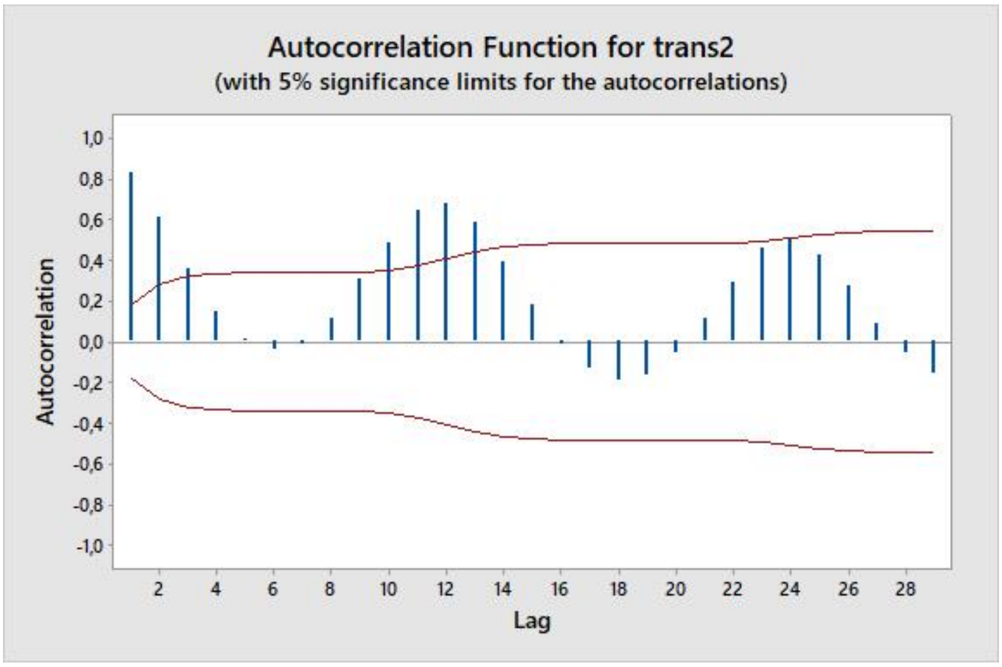
b) Box-Cox plot of demand data after 2nd transformation

Figure 4.4 Comparison between current and after transformation

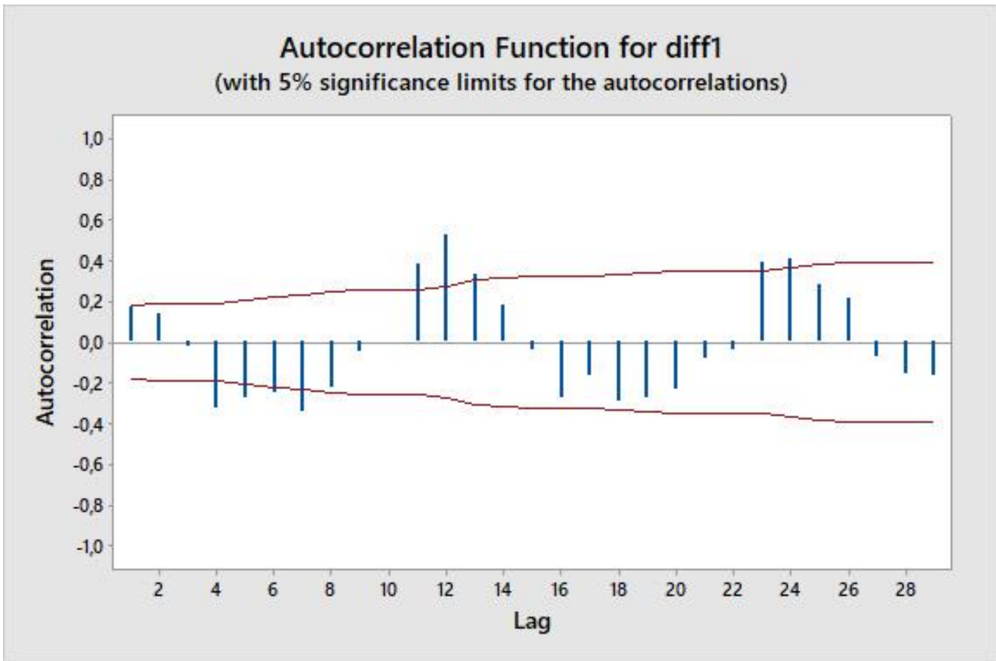
Figure 4.4(a) shows that the data has a rounded value equal to 0.00. It means that the data is non-stationary toward variance and should to be transformed. In the second process of transformation, the data has the optimal rounded value which is equal to 1 Figure 4.4(b). It can be conclude that the data has a optimal rounded value at the second transformation, then those data will be checked to mean stationarity.

b. stationarity based on mean

In order to find the stationarity of data based on mean, the main analytical tools that used is the autocorrelation function (ACF). The data series that has a stationary pattern usually have less than three lag that out of confidence level (confidence level = 95%) or non-stationarity is often indicated by an autocorrelation plot with very slow decay. Not only that, but also the data series that has a non-stationary pattern will have the value of the first lag is very close to one. The Figure 4.5 below will comparing the autocorrelation plot for non-stationary data series and stationary data series after difference process.



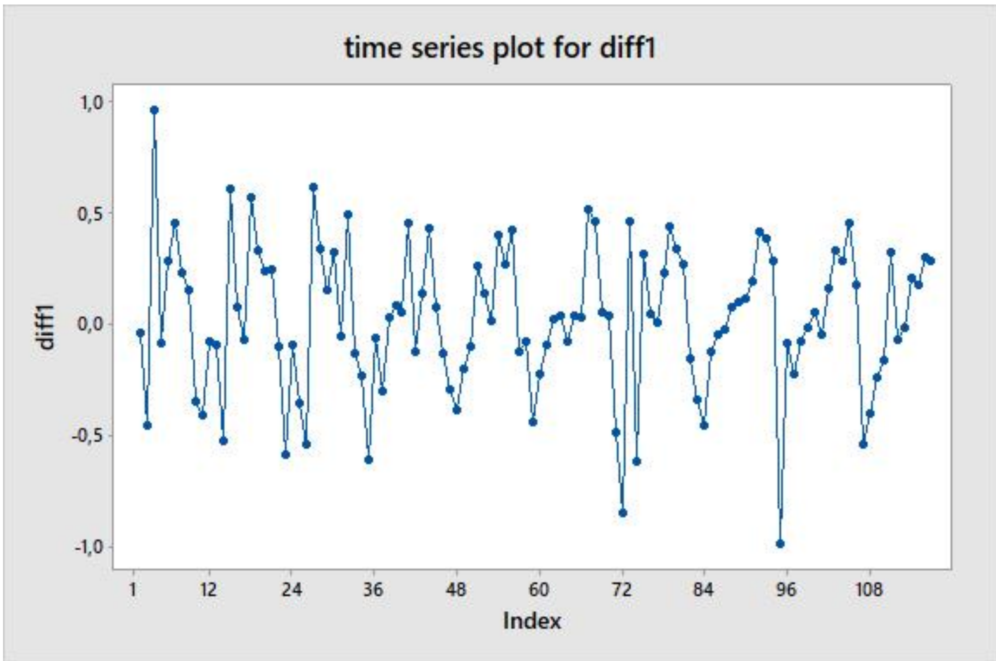
a) Autocorrelation before differentiation



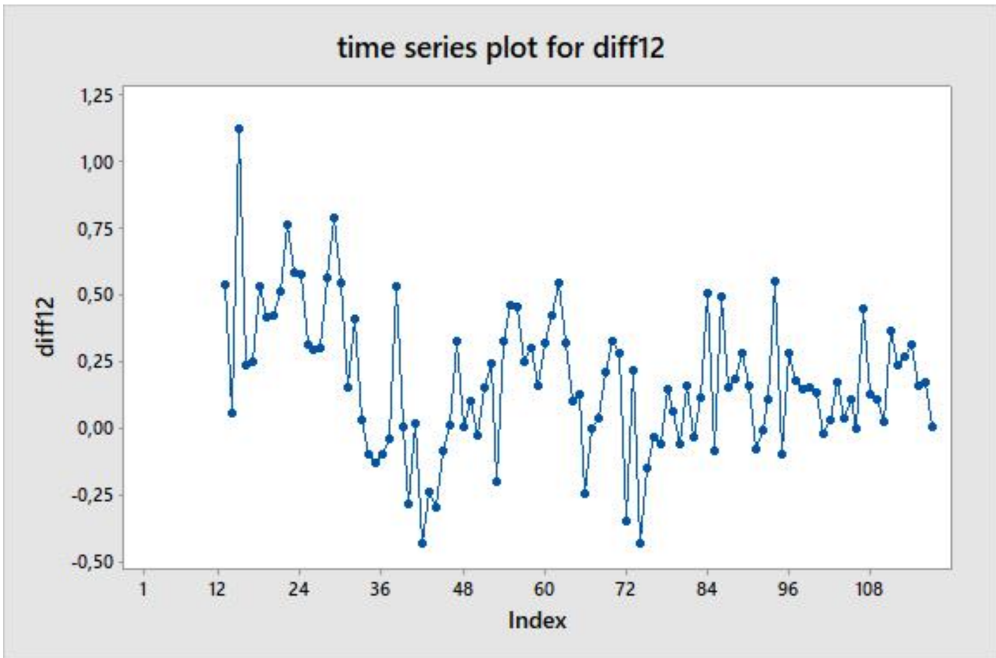
b) autocorrelation after 1st differencing

Figure 4.5 comparison of autocorrelation function toward stationary test

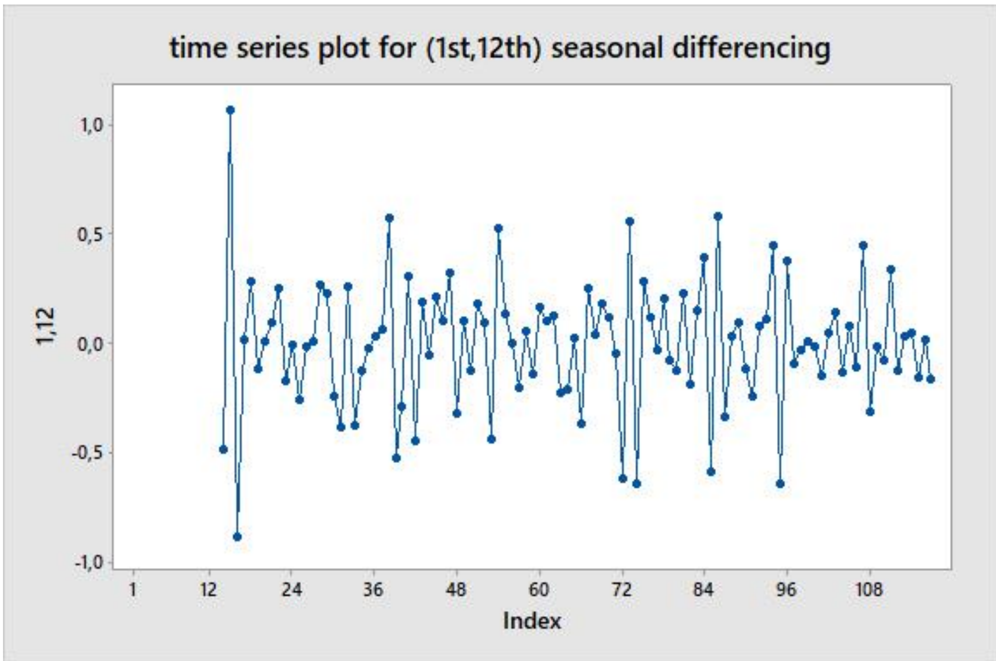
According to the Figure 4.5a above, it shows that the autocorrelation function for the previous data or second transformation, the data is not stationary yet due to there are three lag in the beginning that exit from confidence interval, and also the value first lag is very close to one which 0.8, and Figure 4.5b shows the autocorrelation after 1st differecing process. the second figure ca be concluded as a stationary time series data, the value of first lag is far from one. The autocorrelation function is not only indicates the stationarity of time series data, but the autocorrelation function (ACF) graph can indicates the lag of seasonal. It can be seen that the result of autocorrelation test after 1st differencing shows the lag that exit from confidence interval are lag 12 and lag 24. It means that the data is seasonal with the number of lag is equal to 12. In conclusion, the stationary of data series's comparison after various differencing process are shown in Figure 4.6.



a) stationary after 1st differencing process



b) stationary after 12th (seasonal) differencing process



c) stationary after (1st,12th) differencing process

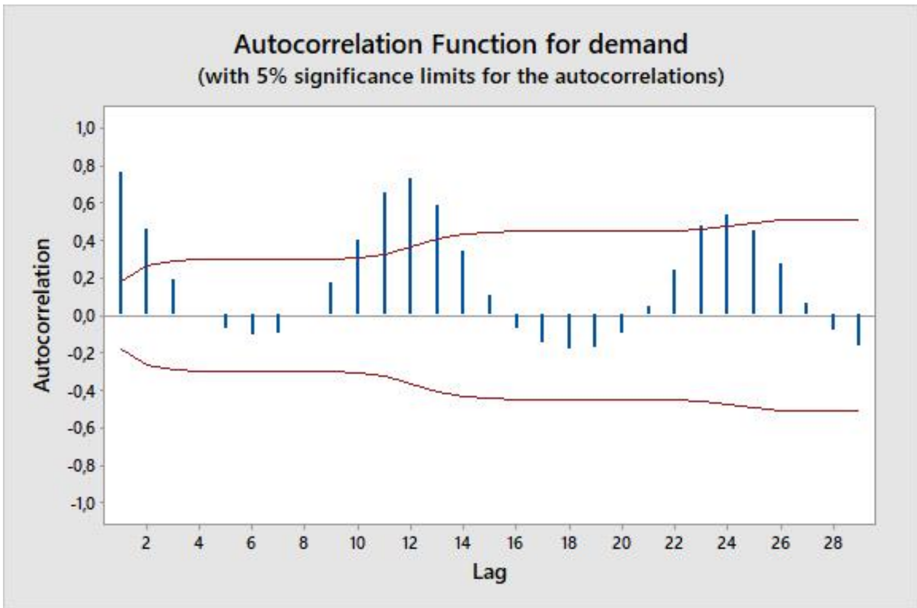
Figure 4.6 Time Series Data Plot After Various Differencing

The Figure 4.6 shows the time series data plot after various differencing process. Figure 4.6a is the first differenced data series from the demand data after the trasnformation process. the plot indicates that the data is not stationary yet, due to there are a lot of data plot which away from the zero values parallel to the x-axis. Figure 4.6b is the 12th differenced data series or the seasonal data which show a downward (negative) trend, then the data is not stationary enough to be proceed as ARIMA model. The last is Figure 4.6c which is the (1st,12th) differenced data or the data series that has been differenced after first and seasonal differencing process. The plot of the data appear to be sationary due to the plot is close from the zero values that parallel to the x-axis. Thus, the (1st,12th) differenced data is selected to be a stationarity in mean.

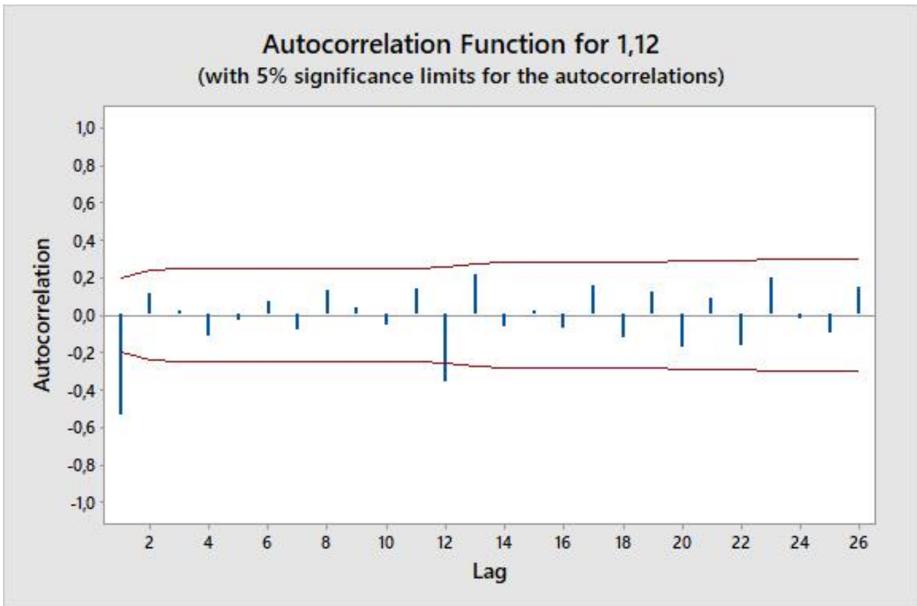
Order and Seasonality Identification

The next step is to identify the value of order for *p* and *q*, which are p value will be order for autocorrelation (AR) and q value will be order for moving average (MA). In ARIMA model, there also an order value for d (difference) which has been determined by the number of differencing process. The equation of fundamental

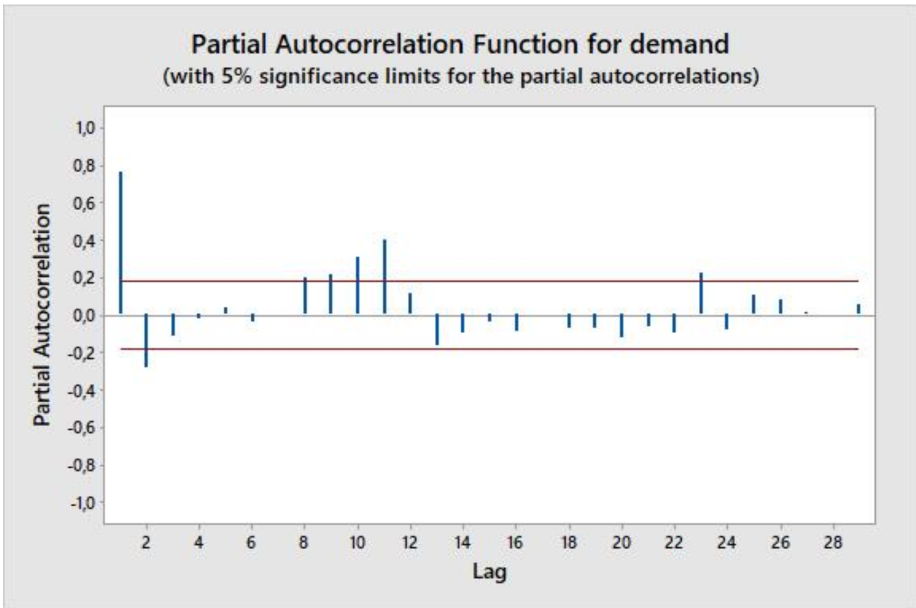
ARIMA model is (p,d,q), but if the data has detected as a seasonal trend, then the equation will be (p,d,q) x (P,D,Q)$_{\text{(lag number)}}$. The primary tools in analyzing the order value are the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The form of ACF and PACF with no differencing, with differenced data, and after first and twelfth seasonal differencing data series are shown in the Figure 4.7.



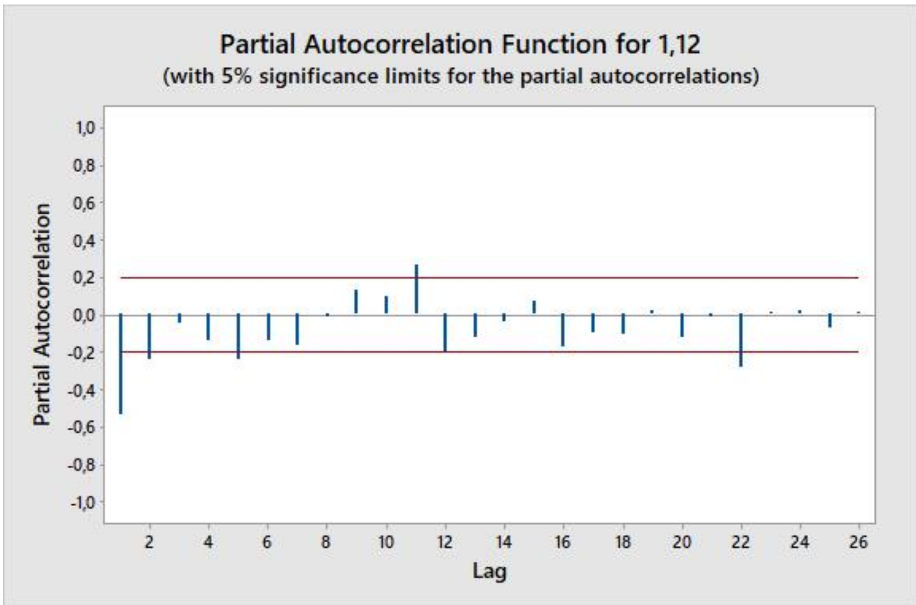
a) ACF with no differencing



b) ACF of differenced data



c) PACF with no differencing



d) PACF of differenced data

Figure 4.7 ACF and PACF of Differenced Demand Data

According to the Figure 4.7 above, it can be seen that the number of lag appears is automatically set by the minitab software, which is *n/4 = 117/4 =29 lag*. Not only that, but the autocorrelation test will show the value of correlation among the data series. If the T > $Z_{0.05}$ which is α = 5% and confidence level = 95% , then the data has a correlation. Besides that, the correlation value also can be seen through the plot of the lag.

the patterns of ACF and PACF is commonly decreasing exponentially. The order of p and q will be determine by differenced data. In Figure 4.7(b), it shows that the at the 1st lag, the data series is correlation each other, but after the 1st lag the correlation among the data is cut off by the confidence interval. Since the value of ACF indicates the order of moving average (q), then it can be estimated that the order of moving average is 1 or MA(1). Besides, the value of PACF indicates the order of autoregression (p), then it can be estimated that the order of autoregression is 2 or AR(2).

In order to select the best model for ARIMA, the order will be tested using estimated parameters. If the P-value of the order < 0.05, then it can be conclude that the order is significant and will be select to be the ARIMA model. The estimated values of parameters will be shown in Table 4.3.

Table 4.3 Estimated Value of ARIMA Model (2,1,1)x$(0,1,0)_{12}$ Parameters

Type	Coef	SE Coef	T	P
AR 1	0.2022	0.1	2.02	0.046
AR 2	0.1908	0.1001	1.91	0.060
MA 1	0.9859	0.0374	26.35	0
Constant	46.5	110.2	0.42	0.674

Based on the Table 4.3 above, the P-value of AR(2) is not significant to the α, which is 0.06 > 0.05. Thus, the value of order *p* that will be selected is 1 or AR(1).

Model Selection

In statistics, there is a goodness-of-fit which can be used to identify the best model. There are two kind of goodness-of-fit value that commonly used for model selection, which are Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC). Both of the those value are determined based on a likelihood function. Here is the alternative Seasonal ARIMA model (SARIMA) that testes corresponding to AIC and BIC values, listed on Table 4.4. the aim of this process is to select the model that provide the minimum value of AIC and BIC.

Table 4.4 SARIMA Model with Corresponding to AIC and BIC Values

SARIMA model **(p,d,q) x $(P,D,Q)_{12}$**	**AIC**	**BIC**
$(1,1,1)$ x $(1,1,1)_{12}$	2498.13	2516.64
$(1,1,0)$ x $(1,0,0)_{12}$	2902.92	2908.43
$(1,1,1)$ x $(0,1,0)_{12}$	2504.28	2512.22
$(1,0,1)$ x $(1,0,0)_{12}$	2928.97	2937.26
$(0,1,1)$ x $(1,1,0)_{12}$	2496.80	2504.70
$(0,1,1)$ x $(1,1,1)_{12}$	2500.10	2513.30
$(0,1,1)$ x $(0,1,0)_{12}$	2505.46	2510.63

The value of Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC) is getting from the goodness-of-fit statistics using XLStat in the microsoft excel. According to the Table 4.4 above, the Seasonal ARIMA model that have the lowest value of AIC and BIC is $(0,1,1)$ x $(1,1,0)_{12}$, which means that the model will be selected as the best model to do the forecasting.

4.2.1.2 Parameter's Estimation of Seasonal ARIMA Model

The purpose of this stage is to ensure the model that has been selected is fit to the data series. The parameters are estimated by using the maximum likelihood method. The result of the final estimates of parameters for model $(0,1,1)$ x $(1,1,0)_{12}$ are listed in the Table 4.5.

Table 4.5 Final Estimates of Parameters for Selected Model $(0,1,1)$x$(1,1,0)_{12}$

Type	**Coef**	**SE Coef**	**T**	**P**
SAR 12	-0.360	0.098	-3.660	0.000
MA 1	0.783	0.063	12.510	0.000
Constant	72.100	817.500	0.090	0.930

The table above shows the parameters that exist in the model are significant. The significant parameters can provide the best forecast result. Therefore, based on the Table 4.5, since that each parameters have a P-value is less than $\alpha = 0.05$

(significant value), then it can be conclude that there is no other parameters were presented in the model and the parameters that used in the selected model have a significant contribution. The final estimate value of the seasonal autoregressive (SAR 12) and moving average parameters (MA 1) are -0.36 and 0.783 respectively, and the coefficient of the parameters will including to the forecast formula based on seasonal ARIMA model.

4.2.1.3 Model Validation and Verification

The model verification process is concern to check wether the selected model contains any systematic pattern or not. The ARIMA model can be tested by verifying the probability plot of residual error that have to follow normal distribution. The Figure 4.8, shows the probability plot of residuals is spread near to the normal line. Therefore, it can be conclude that the selected model is fit to the time series data, and also can be used to do the demand forecast.

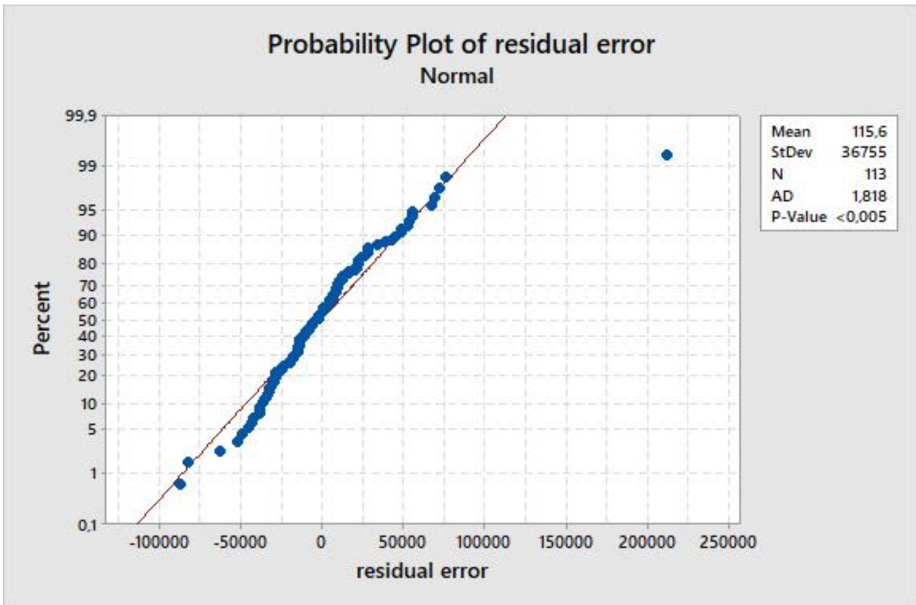


Figure 4.8 Normality Test of Residual Error

Another model validation method are verification test corresponding to moving range (MR) and tracking signal test. The detail calculation for model validation test will be listed in appendix A.

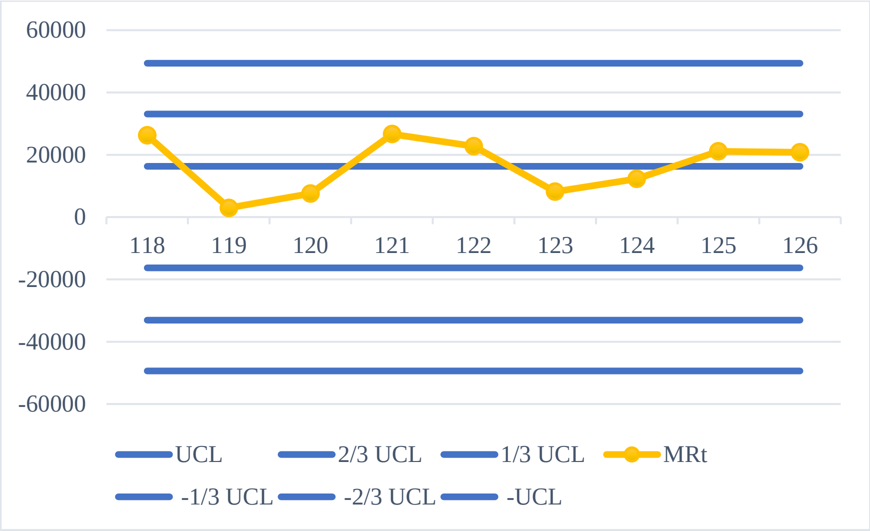


Figure 4.9 Verification Test of ARIMA Forecast Data

According to the chart of verification test above, there is no forecast data by using ARIMA model is out of the upper control limit and lower control limit. Thus, it can be conclude that the forecast data has verified to be applied for inventory planning.

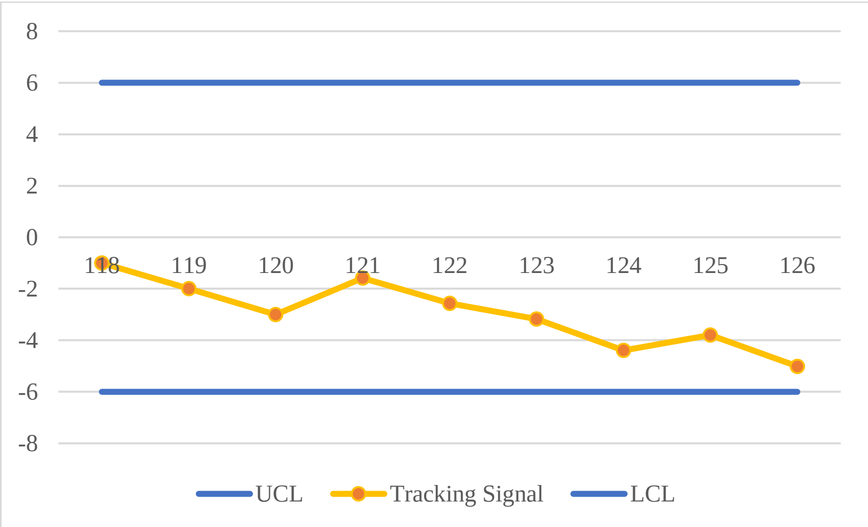


Figure 4.10 Tracking Signal Test of ARIMA Forecast Data

The figure of tracking signal above shows the plot of forecast data by using ARIMA model. According to the brown-check theory, the control limit value of signal in range ± 4 to ± 6. The control limit that has been choosen for this test is 6, and it shows there is no tracking signal value that out of the control limit. The positif tracking signal value shows that the actual demand is larger than the forecast data, while the negative tracking signal value shows that the actual demand is less than the forecast data. Therefore, it can be conclude that the data forecast is good to estimate the actual value of demand.

4.2.1.4 Forecast Result

The last stage of ARIMA model is to determine the forecast result of the time series data. The SARIMA model $(0,1,1) \times (1,1,0)_{12}$ that has been selected before will used to do the forecasting of the demand data. The forecast result by using minitab software will be proved by using the manual calculation.

The seasonal AR(1) or order P (1) polynomial is $= (1 - \emptyset B^{12})$
The non-seasonal difference d(1) is $= (1 - B)$
The seasonal difference D(1) is $= (1 - B^{12})$
The non-seasonal MA(1) or order q is $= (1 - \theta B)$
Then the Seasonal ARIMA model is

$$(1 - \emptyset B^{12})(1 - B)(1 - B^{12})y_t = (1 - \theta B)e_t + C$$

The purpose of this equation is to find the value of y_t , then it have to be transformed into :

$$y_t = \frac{(1 - \theta B)e_t + C}{(1 - \emptyset B^{12})(1 - B)(1 - B^{12})}$$

$$y_t = \frac{(1 - \theta B)e_t + C}{(1 - \emptyset B^{12})(1 - B - B^{12} + B^{13})}$$

$$y_t = \frac{(1 - \theta B)e_t + C}{(1 - B - B^{12} + B^{13} - \emptyset B^{12} + \emptyset B^{13} + \emptyset B^{24} - \emptyset B^{25})}$$

$$y_t - y_t(B + B^{12} - B^{13} + \emptyset B^{12} - \emptyset B^{13} - \emptyset B^{24} + \emptyset B^{25}) = (1 - \theta B)e_t + C$$

$$y_t = [y_t B + (1 + \emptyset)y_t B^{12} - (1 + \emptyset)y_t B^{13} - \emptyset y_t B^{24} + \emptyset y_t B^{25}] + e_t - \theta B e_t + C$$

Since the value of $y_t B = y_{t-1}$ and $y_{t-d} = y_t B^d$, then the equation can be simplify as :

$$y_t = y_{t-1} + (1+\emptyset)y_{t-12} - (1+\emptyset)y_{t-13} - \emptyset y_{t-24} + \emptyset y_{t-25} + e_t - \theta e_{t-1} + C$$

In order to do forecasting for the next one period which is period 118, then the equation that will be fit to the time series data is

$$y_{t+1} = y_t + (1+\emptyset)y_{t-11} - (1+\emptyset)y_{t-12} - \emptyset y_{t-23} + \emptyset y_{t-24} + e_{t+1} - \theta e_t + C$$

Since the term e_{t+1} which is the next residual or future random error between the forecast and demand data is unknown, then it may be assumed as zero.

$$y_{118} = 472{,}126 + (0.64)(563{,}417) - (0.64)(472{,}376) + (0.36)(564{,}176) - (0.36)(423{,}895) + (0.783)(35{,}477.451) + 72.1$$

$$y_{118} = 608{,}745$$

By using the equation above, the forecast data could be determined whether for the second period of forecast or the next three period ahead. However, according to (Arnold dan Chapman 2004), the most important principle of an effective forecasting result is forecasting data will be more accurate when applied for a short period of time. Therefore, the forecasting of the demand data will be projected for the next nine period ahead, which is 1st week of November 2017 until the end of the year (period 118-126).

Table 4.6 The Forecast Result by Using SARIMA (0,1,1)x(1,1,0)$_{12}$ Model

Period	Actual Demand	Forecast Demand	Lower (95%) Limits	Upper (95%) Limits
118	599,475	608,745	532,404	682,911
119	322,091	328,398	251,392	405,404
120	238,912	252,814	174,094	331,533
121	221,079	208,350	127,954	288,746
122	177,620	187,669	105,630	269,708
123	219,839	221,687	138,037	305,336
124	201,118	215,202	129,973	300,432
125	216,940	209,936	123,155	296,717
126	231,069	244,882	156,577	333,187

The table shows the forecast data and forecast error toward demand data of RFID after proposed improvement. The sum value of residual error for the proposed improvement is -62,937 pieces, it means that the material shortage could be controled during 126 periods if the company willing to buy the raw material based on the foreasting value. Based on the data result from the proposed improvement, the forecast error is about 15.29% which means the accuracy of the demand forecast is 84.71%. therefore, it can be conclude that the proposed improvement was successfully to reduce the forecast error, which is 23.50% from the current forecasting model.

4.3 Inventory Planning Analysis

The objectives are to determine the right time to place an order, minimize subcontract activity, and find the minimum expected inventory cost. The first step is to ensure the forecast data has a probabilistic demand data and follow the normal distribution before continue to the calculation process. the normality test for the forecast demand data was perfomed by using minitab. According to the result in Figure 4.11 the forecast data is normally distributed due to the data plot is near to the normal line and the *p*-value < 0.05.

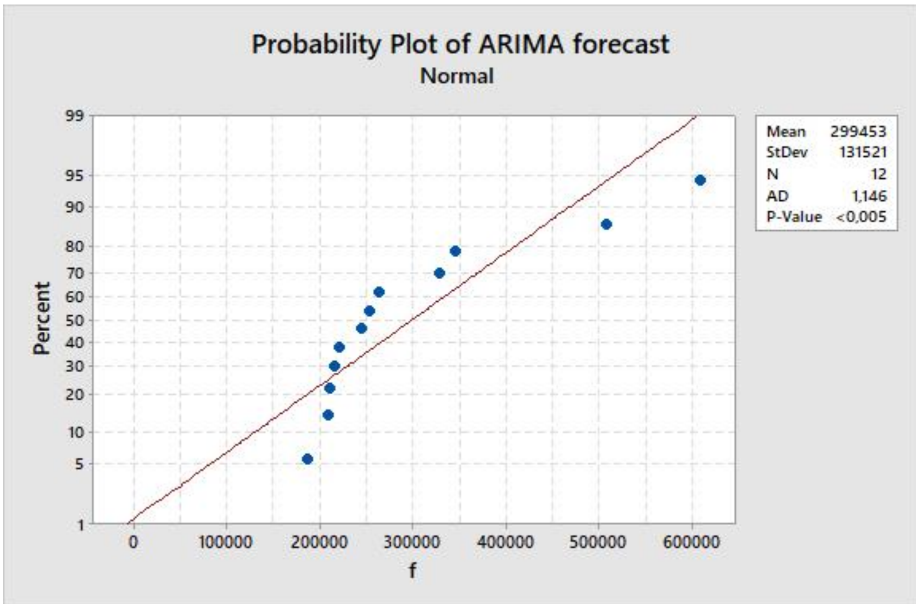


Figure 4.11 Normality Test of ARIMA Forecast Data for Last 12 periods

4.3.1 Safety Stock

Service Level Identification

Service level is one of the important aspect that should to be considered in manufacturing company. Essentially, every companies want to have the optimum amount of safety stocks, due to minimizing the inventory cost either caused by excess or stockout of raw material. The calculation of safety stock depends on the level of service that the company wants to give to the customers, by determining the value of safety factor first. Service level (probability) = 100% - α (confidence level), then the z_α or safety factor value can be seen in Z-table based on the service level (Appendix B).

Table 4.7 Safety Factor Based On the Various Service Level

Service Level	Safety Factor
50%	0
60%	0.2533
75%	0.6744
80%	0.8416
85%	1.0364
90%	1.2815
91%	1.3407
92%	1.4050
93%	1.4757
94%	1.5547
95%	1.6448
96%	1.7506
97%	1.8807
98%	2.0537
99%	2.3263

Safety Stock Calculation

Safety stock is one of the inventory component that can be useful to cope with demand fluctuation issue. In order to determine the number of safety stock that suitable with the company, the forecast error will be the one of important point to calculate and implement the right safety stock strategy. The forecast error method that will be used in safety stock calculation is Root Mean Square Error (RMSE). Based on the result of goodness-of-fit statistics from selected Seasonal ARIMA model for the last 12 periods, the forecast error value from the actual demand is

14,126 pieces. Therefore, by using the safety stock formula, the number of safety stock will be listed in Table 4.8 and Table 4.9.

Table 4.8 Safety Stock in Various Service Level Using Air Shipping Mode

service level		90%	92%	93%	94%	95%	96%	97%	98%
safety factor		1.28	1.4	1.48	1.55	1.64	1.75	1.88	2.05
lead time	weeks	1	1	1	1	1	1	1	1
forecast error	weekly	14,126	14,126	14,126	14,126	14,126	14,126	14,126	14,126
safety stock	pieces	18,081	19,776	20,906	21,895	23,167	24,721	26,557	28,958

Table 4.9 Safety Stock in Various Service Level Using Sea Shipping Mode

service level		90%	92%	93%	94%	95%	96%	97%	98%
safety factor		1.28	1.4	1.48	1.55	1.64	1.75	1.88	2.05
lead time	weeks	3	3	3	3	3	3	3	3
forecast error	weekly	14,126	14,126	14,126	14,126	14,126	14,126	14,126	14,126
safety stock	pieces	31,318	34,254	36,211	37,924	40,126	42,817	45,998	50,157

The Table 4.8 shows the result of safety stock calculation by using air freight or air shipping mode, from supplier to the company. While, Table 4.9 shows the result of safety stock calculation by using ocean freight or sea shipping mode. The differences is related to the value of lead time, which is 1 period and 3 periods for air and ocean freight respectively. For example,

$$SS\ (90\%)\ using\ ocean\ freight = 1.28(14{,}126)\left(\sqrt{3}\right) = 31{,}318$$

Thus, due to the lead time of ocean freight is longer than air freight, and the value of its safety stock also more than air freight.

4.3.2 Total Inventory Cost of Period 115 until 126 (year 2017)

4.3.2.1 Inventory Cost by Using Current Forecast Method

The detail calculation as listed in Table 4.10 below:

Table 4.10 Total Inventory Cost at Current Inventory Planning

Cost Incurred	Cost per Unit	Total Unit	Total Cost
Purchasing Cost	IDR 2,000	2,670,200	IDR 5,340,400,000
Ordering Cost	IDR 10,000,000	23	IDR 230,000,000
Holding Cost	IDR 100	139,291	IDR 13,929,100
Route Cost	IDR 4,000	797,251	IDR 3,189,004,000
Average delivery cost per route	IDR 2,000,000	10	IDR 20,000,000
Total Inventory Cost for 12 periods			**IDR 8,793,333,100**

Based on the Table 4.10 above, the total cost is the multiplication between cost per unit and total unit that corresponding to Table 4.2. For example,

$$total\ holding\ cost\ at\ current = IDR\ 10{,}000{,}000\ \times 23 = IDR\ 230{,}000{,}000$$

Therefore, it can be concluded that the total inventory cost for 12 periods at the current condition is IDR 8,793,333,100. This occur due to high number of item that routed or transfer to PT. X Vietnam, which is the route cost is 36.44% from the total cost. Not only that, but also there are 23 times for ordering the RFID material to the supplier. The number of ordering cycle is also influence by the the inaccuracy of demand forecast at the current condition. The company tend to separate the ordering quantity in order to minimize the total loses that caused either by holding cost or unuseful materials in the future.

4.3.2.2 Inventory Cost by Using ARIMA Forecast Method

After do data analysis by using ARIMA model, the forecast result will be use in executing the inventory planning for period 115 until period 126. The detail of iventory planning will be listed in Table 4.11.

Table 4.11 Inventory Planning by Using SARIMA Forecast Data for Period 115-126 (Year 2017)

Period	Forecast	Orders				Inventory			
		Total Order Received at the end of week (pcs)	Total Complete Order (pcs)	Total Incomplete Order On Hand (pcs)	Total Order Route to PT. X Vietnam	Inventory Balance	Safety Stock (90%)	Open PO at Supplier (optional)	
								Monday	Thursday
114						**52,500**	18,081	**229,043**	**-**
115	263,462	264,434	264,434	-	-	17,109	18,081	362,774	**-**
116	344,692	355,248	355,248	-	-	7,526	18,081	525,685	**-**
117	507,603	472,126	472,126	-	-	53,559	18,081	626,826	**-**
118	608,745	599,475	599,475	-	-	27,351	18,081	346,480	**-**
119	328,398	322,091	322,091	-	-	24,389	18,081	270,895	**-**
120	252,814	238,912	238,912	-	-	31,983	18,081	226,431	**-**
121	208,350	221,079	221,079	-	-	5,352	18,081	205,750	**-**
122	187,669	177,620	177,620	-	-	28,130	18,081	239,768	**-**
123	221,687	219,839	219,839	-	-	19,929	18,081	233,284	**-**
124	215,202	201,118	201,118	-	-	32,166	18,081	228,017	**-**
125	209,936	216,940	216,940	-	-	11,077	18,081	262,963	**-**
126	244,882	231,069	231,069	-	-	31,894	-		
Total	**3,593,441**	**3,519,951**	**3,519,951**			**342,965**		**3,757,916**	

The Table 4.11 shows the inventory planning for period 115 until period 126 in 2017 by using seasonal ARIMA forecast result as reference. In order to check whether the ARIMA has a better result or not, the order will be place once a week. Also there will be safety stock with 90% service level applied to the inventory planning in order minimize the company experience material shortage. Based on the Table 4.11 above, by implementing ARIMA and safety stock with 90% service level, the company successful to overcome from stockout problem. Not only that, but also it can minimize the order frequency which will affecting the ordering cost. in contrast, the number of inventory balance is increasing due to safety stock is applied. In conclusion, the total cost required by using ARIMA forecast data corresponding to the cost incurred for each activity will be listed in Table 4.12.

Table 4.12 Calculation of Inventory Cost by Using ARIMA Model for Year 2017

Cost Incurred	Cost per Unit	Variable	Total
Purchasing Cost	IDR 2,000	3,757,916	IDR 7,515,832,356
Ordering Cost	IDR 10,000,000	12	IDR 120,000,000
Holding Cost	IDR 100	342,965	IDR 34,296,518
Route Cost	IDR 4,000	-	IDR -
Average delivery cost per route	IDR 2,000,000	-	IDR -
Total Inventory Cost for 12 periods			**IDR 7,670,128,874**

The table above shows the calculation of inventory cost by using ARIMA for year 2017 which corresponding to Table 4.11. The value of total is come from the multiplication between cost per unit and variable. For example,

$$ordering\ cost = IDR\ 10{,}000{,}000\ \times 12 = IDR\ 120{,}000{,}000$$

Based on the sum of the calculation in Table 4.12, it can be conclude that the total cost incurred by using ARIMA forecast data is equal to IDR 7,670,128,874 with the total purchase cost is IDR 7,515,832,356, total ordering cost is IDR 120,000,000, total holding cost is IDR 34,296,518, and zero route cost.

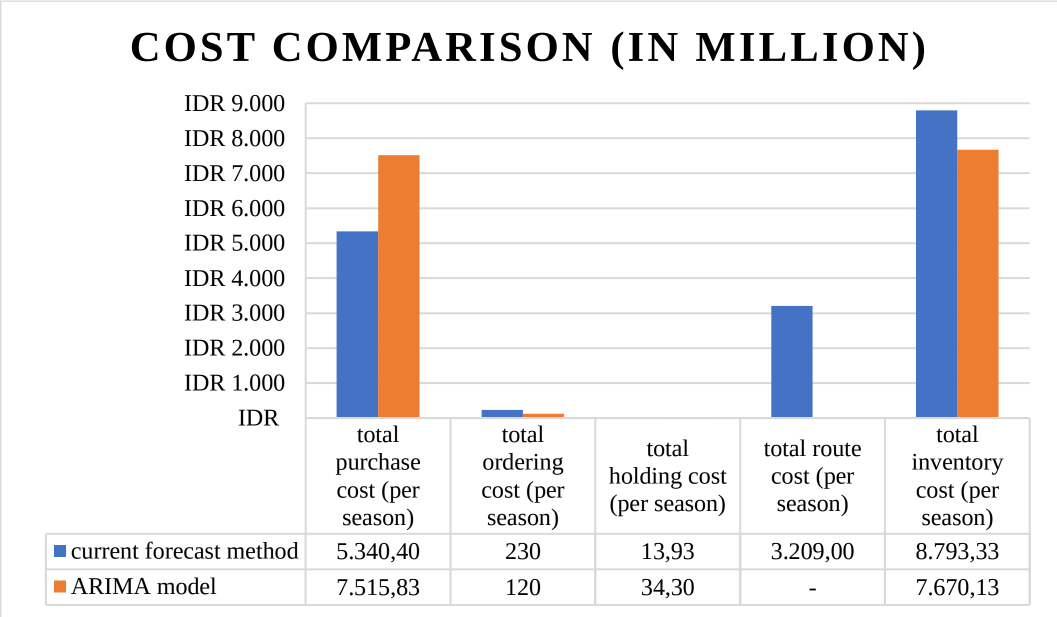
4.3.2.3 Comparison Between Current and Proposed Forecast Method

From the previous calculation related to the inventory planning, the result between current inventory planning and proposed inventory planning by implementing ARIMA model will be compared. The purpose is to determine the best forecast method that fit and suitable with the characteristics of RFID demand data. The comparison between current and proposed forecast method toward inventory planning will be summarized in Table 4.13.

Table 4.13 Comparison of total cost for each inventory planning for period 115 - 126

Comparison Aspect	Current Forecast Method		Arima Model	
Total forecast (pcs per season)		2,738,905		3,593,441
Total order (pcs per season)		3,519,951		3,519,951
Total complete order (pcs per season)		2,722,700		3,593,441
Total incomplete order (pcs per season)		797,251		-
Safety stock (in pcs per period)		-		18,081
Ending inventory balance		-		31,894
Total order frequency		23		12
Total purchase cost (per season)	IDR	5,340,400,000	IDR	7,515,832,356
Total ordering cost (per season)	IDR	230,000,000	IDR	120,000,000
Total holding cost (per season)	IDR	13,929,100	IDR	34,296,518
Total route cost (per season)	IDR	3,209,004,000	IDR	-
Total cost (per season)	IDR	8,793,333,100	IDR	7,670,128,874

Based on the Table 4.13 above, it can be conclude that the order frequency is decreasing from 23 to 12 times. Also by using ARIMA model, it can reduce the total incomplete order from 797,251 to 0, which means that successfully reducing the total route cost from IDR 3,209,004,000 to 0. Therefore, the inventory planning that implementing the ARIMA model is better than the current forecast method by using total cost as the parameter. The total cost by using ARIMA model less than the current forecast data. It successfully reduce the total cost from IDR 8,793,333,100 to IDR 7,670,128,874 or by 12.8%.



	total purchase cost (per season)	total ordering cost (per season)	total holding cost (per season)	total route cost (per season)	total inventory cost (per season)
current forecast method	5.340,40	230	13,93	3.209,00	8.793,33
ARIMA model	7.515,83	120	34,30	-	7.670,13

Figure 4.12 Cost Comparison Between Current Forecast Method and ARIMA

The Figure 4.12 shows the comparison of cost between current forecast method and ARIMA forecast. The values are express in million IDR and it shows the difference for both of the method. The value of ARIMA model is less than the value of current forecast method. Thus, it can be conclude that the ARIMA model is reasonable fit to the RFID demand data.

4.3.3 Proposed Inventory Planning for 2018

In this part, the inventory model for forecast data from selected ARIMA model will be reviewed by using two kinds of inventory review, which are continuous review and periodic review. Both of model will use the EOQ principle in calculating the value of optimal order quantity (Q) and reorder point (R). The difference between the deterministic EOQ model and the stochastic EOQ model is in calculating the value of reorder point (R), which includes the safety stock (Sipper and Bulfin, Jr. 1997). In order to perform the EOQ model, the details of price will be listed in the Table 4.14.

Table 4.14 Details of Prices Incurred

Type Of Price	Value		Description
Average Ordering Cost (A) by air	IDR	10,000,000	Per Order
Average Ordering Cost (A) by sea	IDR	5,000,000	Per Order
Interest (i)		5%	Per Season
Unit Price (c)	IDR	2,000	Per Pieces
Holding Cost (h)	IDR	100	Per Pieces Per Season
Shortage Cost (π)	IDR	150	Per Pieces

4.3.3.1 Demand Forecast

According to the previous calculation and analysis, the ARIMA Model has proven to be the better method to do forecasting for RFID product which is HM-RT01. The demand forecast for the next season in 2018 will be listed in Table 4.15.

Table 4.15 Demand Forecast for next season in 2018

Period	Forecast Demand	Lower 95% Limits	Upper 95% Limits
127	290,163	217,814	362,512
128	374,629	300,617	448,640
129	511,657	436,020	587,295
130	625,889	548,659	703,118
131	363,147	284,358	441,936
132	270,810	190,492	351,129
133	242,263	160,443	324,083
134	205,227	121,934	288,521
135	251,932	167,190	336,673
136	234,794	148,629	320,959
137	243,425	155,859	330,991
138	267,261	178,316	356,206

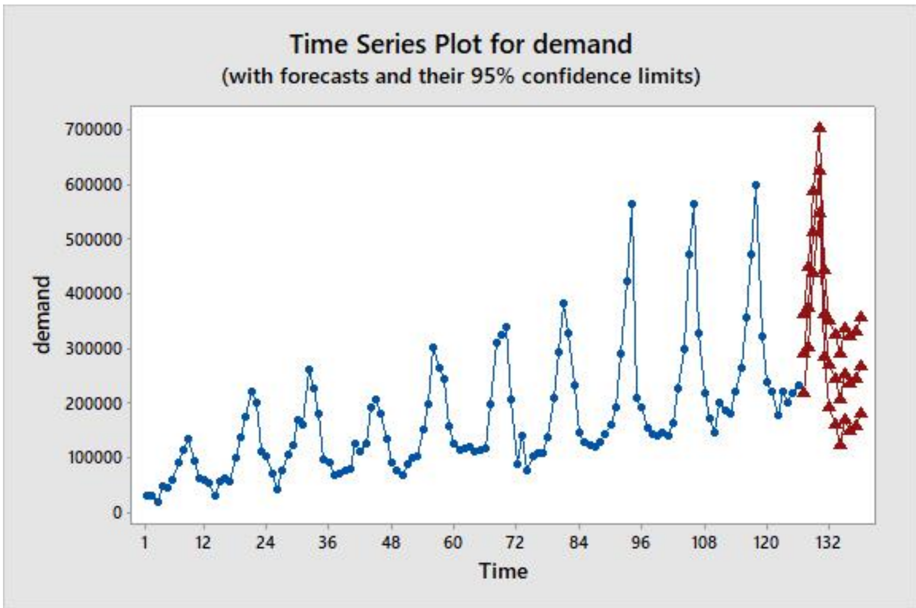


Figure 4.13 Time Series Plot for Demand Forecast 2018

4.3.3.2 (Q,R) model (continuous review)

Continuous review or fixed order quantity policy is one of the inventory system that permits a real-time updates of product's stock level, which calculate each time the product is moves in or moves out from the storage. This kind of review will triggers to place an order for more stock when the inventory leve falls below a particular reorder point (R) or $X_t \leq R$. There are two approaches that can be used in continuous review: management approach and optimization approach. In order to find the value of safety stock, the management approach will use the service level policy that has been set by the company, besides the optimization approach will considering the shortage cost (π) to set the service level.

The management approach calculation

The company set the service level is equal to 95%, thus the order quantity (Q) and reorder point (R) can be calculate as below.

$$Q = \sqrt{\frac{2A\overline{D}}{h}} = \sqrt{\frac{2(10{,}000{,}000)(3{,}881{,}198)}{100}} = 881{,}045\ pcs$$

$$R = \overline{D}_\tau L + z\sigma_\tau\sqrt{L} = 323{,}433(1) + (1.64)(14{,}126)(1) = 346{,}599\ pcs$$

The order frequency :

$$n = \frac{D}{Q} = \frac{3{,}881{,}198}{881{,}045} = 4.405 \approx 5 \; times\ of\ order$$

The calculation above is the value of order quantity, re-order point, and order frequency for ordering the material by using air shipping mode. The value of D is the sum of demand forecast for period 127 until period 138 (three months ahead in year 2018) which is 3,881,198 pieces. The result is the order quantity, re-order point, and order frequency by using sea shipping mode are 622,993 pcs, 1,010,377 pcs, and 7 times respectively.

Optimization Approach

According to Sipper and Bulfin,Jr. (1997), the stochastic version of the deterministic EOQ (Economic Order Quantity) for the continuous review is the optimization approach, which is the Reorder point as a decision variable. Besides, the service level will be determine by using shortage cost as the consideration.

$$Q_0 = \sqrt{\frac{2A\bar{D}}{h}} = \sqrt{\frac{2(10{,}000{,}000)(3{,}881{,}198)}{100}} = 881{,}045 \; pcs$$

The next step is to find the corresponding R_0 by using the standardized normal distribution in order to find the value of $F(z)$.

$$1 - F(z) = \frac{hQ}{\pi\bar{D}} = \frac{(100)(881{,}045)}{(150)(3{,}881{,}198)} = 0.1513$$

The value of $F(z)$ = 0.8486 and the safety factor can be determine by refers to normal distribution table (Appendix B) , which is z = 1.03 and

$$R_0 = 323{,}433\ (1) + (1.03)(14{,}126)(1) = 337{,}982 \; pcs$$

The next is calculating the maximum backorder level, from the table of unit normal linear loss integral (Appendix B),the value of L(1.03) = 0.0787

$$\bar{b}(R_0) = \sigma_\tau L(z) = (14{,}126)(0.0787) = 1{,}111.7$$

Then, the new order quantity (1st iteration) is

$$Q_1 = \sqrt{\frac{2\bar{D}\left(A + \pi\bar{b}(R_0)\right)}{h}}$$

$$Q_1 = \sqrt{\frac{(2)(3{,}881{,}198)(10{,}000{,}000 + 150(1{,}111.7))}{100}} = 888{,}360\ pcs$$

By using the value of Q_1, the value of R_1 also can be determine as below:

$$1 - F(z) = \frac{hQ}{\pi\bar{D}} = \frac{(100)(888{,}360)}{(150)(3{,}881{,}198)} = 0.1525$$

Thus, the value of F(z) = 0.8474 and the safety factor (z) = 1.02, and the reorder point corresponding to Q_1 is

$$R_1 = 323{,}433\ (1) + (1.02)(14{,}126)(1) = 337{,}842\ pcs$$

Since the second iteration value is quite the same to the first iteration, then it can be conclude that the Q_1 = 883,360 pieces and R_1 = 337,842 pieces is the optimum value for this model. The order frequency is

$$n = \frac{\bar{D}}{Q_1} = \frac{3{,}881{,}198}{883{,}360} = 4.39\ \approx 5\ times\ of\ order$$

The detail calculation for sea shipping mode will be listed in appendix B, the summary are Q_1 = 629,784 pieces and R_1 = 1,000,602 pieces is the optimum value for this model. The order frequency is

$$n = \frac{\bar{D}}{Q_1} = \frac{3{,}881{,}198}{629{,}784} = 6.16\ \approx 7\ times\ of\ order$$

4.3.3.3 (S,T) model (Periodic Review)

The other model for inventory management is periodic review (S,T) model. This review will counting and do documenting of inventory at specified times. the difference between continuous and periodic review is the timing for decision making, either to place an order or not. The inventory will be reviewed every T periods, if the value of stock $(X_t > R)$, the procurement will not place an order, but if the value of stock ($X_t \leq R$), the company will order up to the inventory target level (S). Here is the calculation for study case at PT. X Indonesia for RFID product:

Service level calculation for periodic review

For the periodic review model, the service level will be calculate by considering the possibility of shortage happened during the period. This application is corresponding to the dissertation of Mohammad Anwar in 2008, which the problem is quite similar to this research. The shortage might be occur when the actual demand is greater than the forecast data ($Y_t > D_t$). Assume that each unit of good sold by w Rupiah, which is w > c (selling price is greater than the unit purchasing cost). Besides, the average ordering cost per period will be given as $\frac{A}{D_t}$, the company revenue per period will be $(w - c)D_t$, and the average number of inventory per period will be $h(\frac{(D_t - Y_t)}{2})$. The equation derivative will be listed in appendix B.

Then, the value of $F(z)$ is

$$F(z) = 1 - \frac{h_t L}{2\pi} = 1 - \frac{8.33(1)}{2(150)} = 0.97$$

Based on the calculation above, the service level for periodic review is 97% with the probability of stockout is 3%. Then, optimum re-order point is

$$T = \sqrt{\frac{2A}{h\bar{D}}} = \sqrt{\frac{2(10{,}000{,}000)}{100(3{,}881{,}198)}} = 0.227 \approx 1\, week$$

$$S = \bar{D}(T + t) + z_\alpha \sigma_d \sqrt{T + t}$$

$$S = 323{,}433(1 + 1) + (1.88)(14{,}126)\left(\sqrt{2}\right) = 684{,}423\, pieces$$

Based on the calculation above, the inventory will be reviewed every 1 week (1 period) with the quantity decision up to S is equal to 684,423 pieces. Meanwhile, by using sea shipping mode, the inventory will be reviewed every 1 week (1 period) with the quantity decision up to S is equal to 1,346,846 pieces.

4.3.3.4 Inventory Cost Comparison Among Inventory Model

Corresponding to result of the calculation, the comparison of the inventory cost can be obtained. The purpose is to identify the minimum inventory cost between two inventory model (continuous review; management approach and optimization approach, and periodic review) and two difference ship mode (air freight and ocean freight). The result of calculation data will be listed in Table 4.16. In order to simplify the decision making, the comparison of re-order point, safety stock, and total cost will be summarize in Figure 4.14.

Table 4.16 Comparison of Inventory Cost among Proposed Inventory Model for Next Season in 2018

Inventory Model	Service Level	Q*	R* or S	Safety Stock	Total Cost
Air Shipping Mode					
(Q,R): Management Approach	95%	881,045	346,599	23,167	IDR 7,852,817,161
(Q,R): Optimization Approach	85%	883,360	337,842	14,048	IDR 7,851,905,564
(S,T) model air shipping mode	97%	S-I	684,423	37,180	IDR 7,854,218,461
Sea Shipping Mode					
(Q,R): Management Approach	95%	622,993	1,010,377	40,078	IDR 7,828,703,062
(Q,R): Optimization Approach	85%	629,784	1,000,602	30,059	IDR 7,827,704,823
(S,T) model sea shipping mode	97%	S-I	1,346,846	53,114	IDR 7,830,006,984

Table 4.16 shows the summary of economic order quantity (Q*), re-order point (R*), maximum inventory level (S), and safety stock calculation for both inventory model (continuous review and periodic review). The total cost is come from the calculation by using equation **Error! Reference source not found.**. For example,

$total\ cost\ (Q,R) Management\ approach\ by\ air\ freight$

$$= (3{,}881{,}198 \times 2000) + \left(\frac{3{,}881{,}198}{881{,}045} \times 10{,}000{,}000\right)$$

$$+ \left(100\left(\frac{881{,}045}{2} + 23{,}167\right)\right)$$

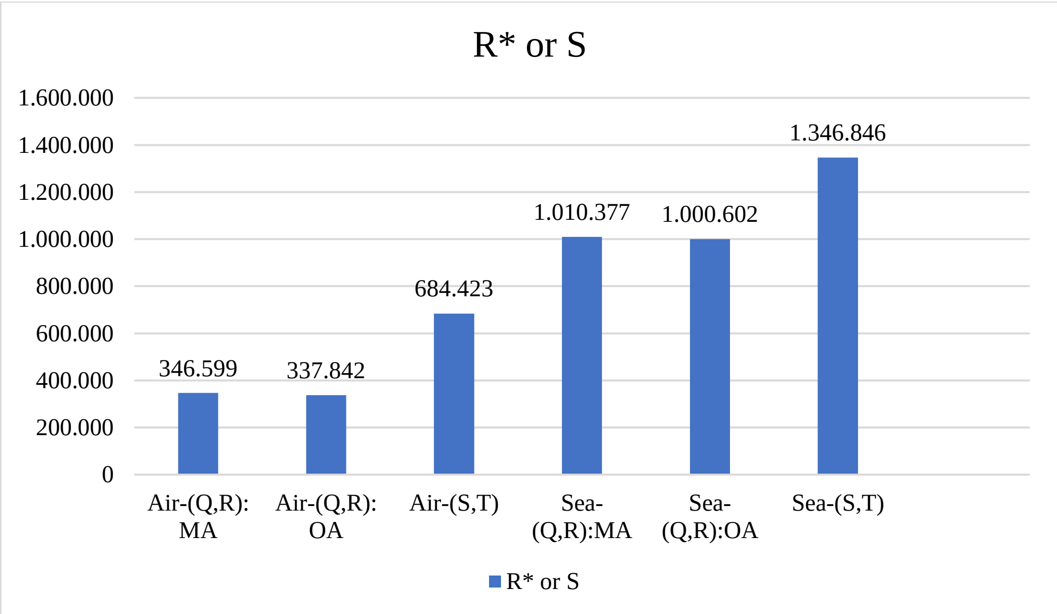
$$= IDR\ 7{,}852{,}817{,}161$$

$total\ cost\ (S,T)\ by\ ocean\ freight$

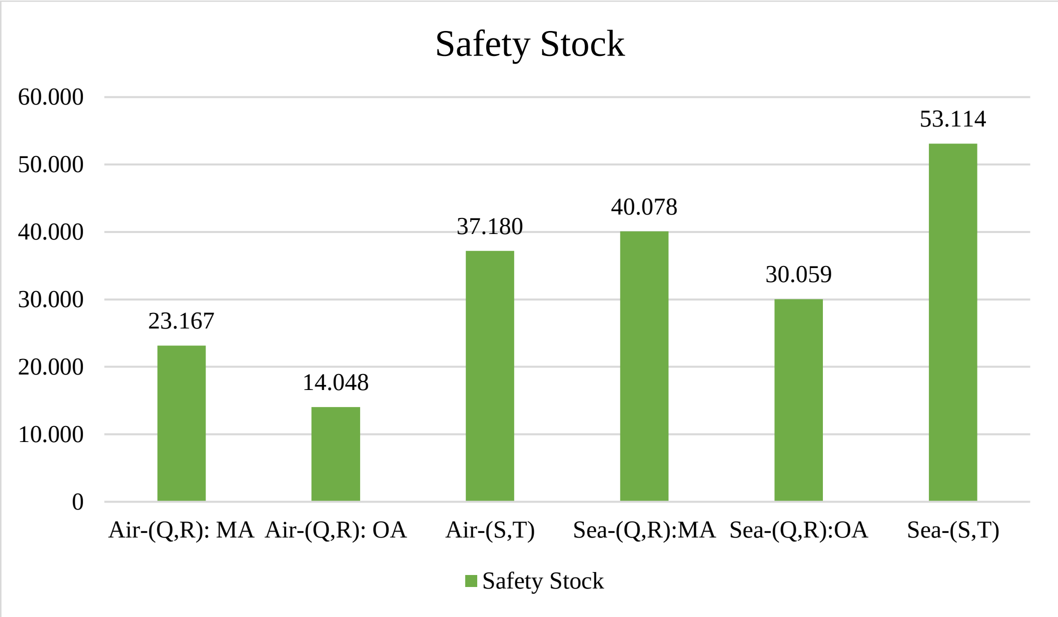
$$= (3{,}881{,}198 \times 2000) + \left(\frac{1}{0.16} \times 5{,}000{,}000\right)$$

$$+ \left(100\left(\frac{3{,}881{,}198 \times 0.16}{2} + 53{,}114\right)\right)$$

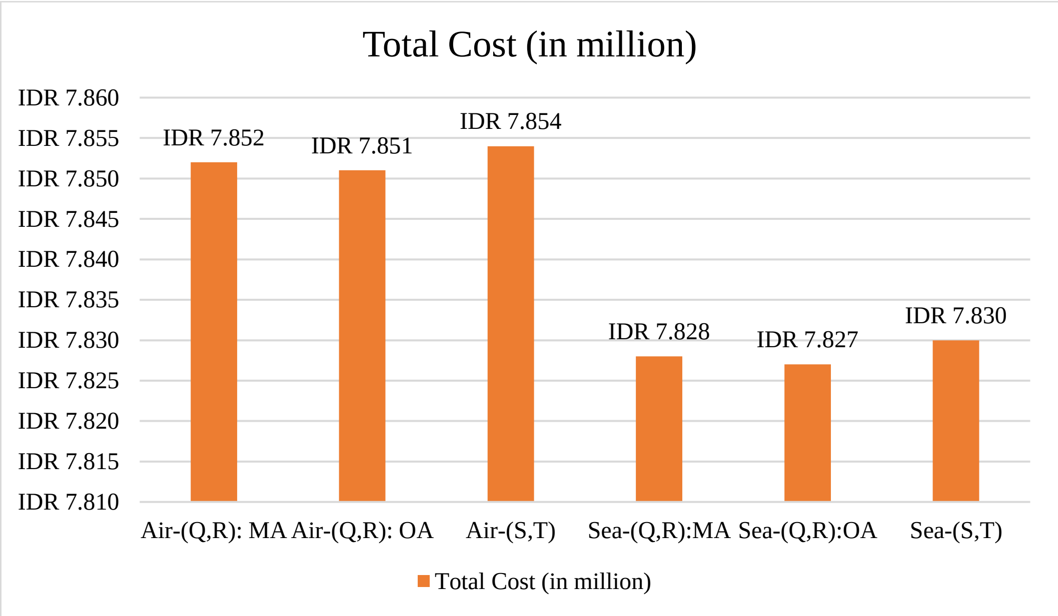
$$= IDR\ 7{,}830{,}006{,}984$$



a) Comparison of Optimum Re-Order Point or S Among several model



b) Comparison of Safety Stock Value Among Several Model



a) Comparison of Total Cost Value Among Several Model

Figure 4.14 Comparison of ROP, SS, and Total Cost Among Several Model

The Figure 4.14 above shows the comparison of re-order point, safety stock, and total cost among several inventory model that has been discuss in the previous sub-chapter. In Figure 4.14(a), the lowest value of re-order point is given by continuous review (Q,R): optimization approach by using air freight which is 337,842 pieces. While, the highest value is given periodic review for ocean freight which is

1,346,846 pieces. These value are influenced by the value of service level, which is higher service level will give higher value re-order point. Also, the longest lead time will increase the re-order point due to the multiplication process. The Figure 4.14(b) shows the comparison of safety stock among several model. Similar to re-order point, the value of safety stock is influenced by the value of service level and lead time. The last is comparison of total cost that listed in Figure 4.14(c), it can be conclude that the lowest total cost is given by (Q,R) model with optimization approach by using sea Shipping mode, which is IDR 7,827,704,823. This value was getting from the purchase cost, ordering cost and holding cost that cover 12 periods. Since all of model above are using the EOQ approach (stockout are not allowed), then the PT. X Indonesia can implement the (Q,R) model with optimization approach for RFID product.

CHAPTER V
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The objectives of this research is to find the optimal solution that can be implement in PT. X Indonesia, especially for RFID product. According to the data calculation and analysis that has been done in the previous chapter, it can be conclude that the objectives of this research has been achieved. The final conclusion that could be obtained based on the analysis result are:

- The cause of material shortage is due to the lack of forecast data and inventory planning for RFID product. Also the company did not have safety stock and replenishment schedule.
- The accuracy of demand forecast for RFID product is successfully improved by using Seasonal ARIMA (SARIMA) model. This approach was selected because of this model suitable with the characteristics of RFID product which are seasonal and non-stationary. The equation to do forecasting as below:

  $$y_{t+1} = y_t + (1+\emptyset)y_{t-11} - (1+\emptyset)y_{t-12} - \emptyset y_{t-23} + \emptyset y_{t-24} + e_{t+1} - \theta e_t + C$$

  Based on MAPE (Mean Absolute Percentage Error) calculation, the selected ARIMA model (0,1,1) x $(1,1,0)_{12}$ increase the accurcy of demand forecast by 23.5%, from 61.21% to 84.71%. While, the ARIMA approach also reduce the ME (Mean Error) from 53,374 pieces to 104 pieces.
- By using ARIMA model, the company can reduce the total inventory cost at the current condition by IDR 1,123,204,226 or 12.8%.
- The inventory management calculation for next season in 2018 comes up with the lowest total inventory cost which offered by (Q,R) model with optimization approach, which is IDR 7,827,704,823 by using sea shipping mode compared to the other model. Also by using service level equal to 85%, the order quantity

is 629,784 pieces, re-order point is 1,000,602 pieces, and safety stock is equal to 30,059 pieces will help the company to avoid the stockout of RFID material and able to maximize the profit.

5.2 Recommendation

In order to do continuous improvement related to inventory control problem, the recommendation are made for further research as bellow:

1. Do future research by considering the other connstraints that related to the inventory management, such as company inventory turnover and limitation of budget and storage space.
2. To perform a research for product with fluctuating demands especially for new product, by considering other important sources of uncertainty.

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APPENDICES

7.1 APPENDIX A

Weekly Demand Data of RFID period Aug 2015 – Oct 2017

No.	Year	Month	Week	Demand
1	2015	August	2015-31	30,035
2		August	2015-32	28,855
3		August	2015-33	18,226
4		August	2015-34	47,618
5		August	2015-35	43,698
6		September	2015-36	57,861
7		September	2015-37	90,580
8		September	2015-38	113,998
9		September	2015-39	132,567
10		October	2015-40	93,025
11		October	2015-41	61,690
12		October	2015-42	56,823
13		October	2015-43	51,470
14		November	2015-44	30,359
15		November	2015-45	55,744
16		November	2015-46	60,002
17		November	2015-47	55,793
18		December	2015-48	98,139
19		December	2015-49	136,690
20		December	2015-50	172,973
21		December	2015-51	220,674
22		December	2015-52	198,903
23	2016	January	2016-1	110,528
24		January	2016-2	100,647
25		January	2016-3	70,130
26		January	2016-4	40,660
27		January	2016-5	74,996
28		February	2016-6	105,259
29		February	2016-7	122,613
30		February	2016-8	168,417
31		February	2016-9	159,282
32		March	2016-10	259,705
33		March	2016-11	226,288
34		March	2016-12	179,422

Weekly Demand Data of RFID period Aug 2015 – Oct 2017 (cont)

35		March	2016-13	96,891
36		April	2016-14	90,781
37		April	2016-15	67,104
38		April	2016-16	69,105
39		April	2016-17	75,224
40		April	2016-18	78,892
41		May	2016-19	124,301
42		May	2016-20	109,233
43		May	2016-21	124,946
44		May	2016-22	191,877
45		June	2016-23	206,649
46		June	2016-24	180,616
47		June	2016-25	134,132
48		June	2016-26	90,805
49		July	2016-27	74,301
50		July	2016-28	67,209
51		July	2016-29	87,158
52		July	2016-30	100,012
53		August	2016-31	101,178
54		August	2016-32	150,498
55		August	2016-33	197,004
56		August	2016-34	300,895
57		August	2016-35	264,456
58		September	2016-36	243,576
59		September	2016-37	156,412
60		September	2016-38	124,974
61		September	2016-39	113,267
62		October	2016-40	115,712
63		October	2016-41	119,398
64		October	2016-42	110,542
65		October	2016-43	114,301
66		November	2016-44	117,073
67		November	2016-45	195,949
68		November	2016-46	310,715
69		November	2016-47	325,693
70		December	2016-48	337,532
71		December	2016-49	206,267
72		December	2016-50	88,237
73		December	2016-51	139,954

Weekly Demand Data of RFID period Aug 2015 – Oct 2017 (cont)

74		December	2016-52	75,066
75	2017	January	2017-1	102,791
76		January	2017-2	106,887
77		January	2017-3	107,243
78		January	2017-4	134,977
79		January	2017-5	208,560
80		February	2017-6	291,722
81		February	2017-7	382,085
82		February	2017-8	326,011
83		February	2017-9	231,312
84		March	2017-10	146,012
85		March	2017-11	128,348
86		March	2017-12	122,533
87		March	2017-13	119,259
88		April	2017-14	128,098
89		April	2017-15	141,457
90		April	2017-16	158,236
91		April	2017-17	191,794
92		April	2017-18	289,491
93		May	2017-19	423,895
94		May	2017-20	564,176
95		May	2017-21	209,543
96		May	2017-22	192,357
97		June	2017-23	153,089
98		June	2017-24	141,249
99		June	2017-25	138,548
100		June	2017-26	145,944
101		July	2017-27	138,416
102		July	2017-28	162,582
103		July	2017-29	226,657
104		July	2017-30	299,869
105		August	2017-31	472,376
106		August	2017-32	563,417
107		August	2017-33	326,440
108		August	2017-34	217,896
109		August	2017-35	170,397
110		September	2017-36	144,631
111		September	2017-37	199,189
112		September	2017-38	184,785

Weekly Demand Data of RFID period Aug 2015 – Oct 2017 (cont)

113		September	2017-39	180,678
114		October	2017-40	221,575
115		October	2017-41	264,434
116		October	2017-42	355,248
117		October	2017-43	472,126

Current Forecast Data and Forecast Error of RFID

period	demand	forecast	residual error	abs. Error	% error
1	30,035	11,250	18,785	18,785	63
2	28,855	48,348	- 19,493	19,493	68
3	18,226	41,917	- 23,691	23,691	130
4	47,618	39,809	7,809	7,809	16
5	43,698	26,887	16,811	16,811	38
6	57,861	36,400	21,461	21,461	37
7	90,580	42,388	48,192	48,192	53
8	113,998	65,723	48,275	48,275	42
9	132,567	77,000	55,567	55,567	42
10	93,025	71,344	21,681	21,681	23
11	61,690	71,344	- 9,654	9,654	16
12	56,823	71,344	- 14,521	14,521	26
13	51,470	34,119	17,351	17,351	34
14	30,359	81,524	- 51,165	51,165	169
15	55,744	76,538	- 20,794	20,794	37
16	60,002	29,900	30,102	30,102	50
17	55,793	23,823	31,970	31,970	57
18	98,139	40,400	57,739	57,739	59
19	136,690	45,200	91,490	91,490	67
20	172,973	45,200	127,773	127,773	74
21	220,674	45,200	175,474	175,474	80
22	198,903	90,400	108,503	108,503	55
23	110,528	90,400	20,128	20,128	18
24	100,647	90,400	10,247	10,247	10
25	70,130	45,200	24,930	24,930	36
26	40,660	45,200	- 4,540	4,540	11
27	74,996	45,200	29,796	29,796	40
28	105,259	21,200	84,059	84,059	80
29	122,613	24,624	97,989	97,989	80
30	168,417	51,455	116,962	116,962	69
31	159,282	84,272	75,010	75,010	47

Current Forecast Data and Forecast Error of RFID (cont)

32	259,705	91,524	168,181	168,181	65
33	226,288	106,538	119,750	119,750	53
34	179,422	119,900	59,522	59,522	33
35	96,891	46,200	50,691	50,691	52
36	90,781	46,200	44,581	44,581	49
37	67,104	55,672	11,432	11,432	17
38	69,105	55,789	13,316	13,316	19
39	75,224	100,800	- 25,576	25,576	34
40	78,892	57,600	21,292	21,292	27
41	124,301	50,400	73,901	73,901	59
42	109,233	88,800	20,433	20,433	19
43	124,946	100,800	24,146	24,146	19
44	191,877	107,600	84,277	84,277	44
45	206,649	140,380	66,269	66,269	32
46	180,616	147,833	32,783	32,783	18
47	134,132	104,200	29,932	29,932	22
48	90,805	105,433	- 14,628	14,628	16
49	74,301	50,852	23,449	23,449	32
50	67,209	52,117	15,092	15,092	22
51	87,158	52,117	35,041	35,041	40
52	100,012	77,650	22,362	22,362	22
53	101,178	81,322	19,856	19,856	20
54	150,498	102,381	48,117	48,117	32
55	197,004	142,180	54,824	54,824	28
56	300,895	200,340	100,555	100,555	33
57	264,456	213,023	51,433	51,433	19
58	243,576	330,000	- 86,424	86,424	35
59	156,412	102,000	54,412	54,412	35
60	124,974	109,534	15,440	15,440	12
61	113,267	120,000	- 6,733	6,733	6
62	115,712	132,319	- 16,607	16,607	14
63	119,398	71,926	47,472	47,472	40
64	110,542	75,000	35,542	35,542	32
65	114,301	86,000	28,301	28,301	25
66	117,073	105,000	12,073	12,073	10
67	195,949	230,000	- 34,051	34,051	17
68	310,715	150,000	160,715	160,715	52
69	325,693	70,000	255,693	255,693	79
70	337,532	350,000	- 12,468	12,468	4

Current Forecast Data and Forecast Error of RFID (cont)

71	206,267	172,500	33,767	33,767	16
72	88,237	110,000	- 21,763	21,763	25
73	139,954	73,099	66,855	66,855	48
74	75,066	90,600	- 15,534	15,534	21
75	102,791	96,890	5,901	5,901	6
76	106,887	117,510	- 10,623	10,623	10
77	107,243	99,536	7,707	7,707	7
78	134,977	108,253	26,724	26,724	20
79	208,560	128,253	80,307	80,307	39
80	291,722	152,989	138,733	138,733	48
81	382,085	223,541	158,544	158,544	41
82	326,011	219,528	106,483	106,483	33
83	231,312	291,072	- 59,760	59,760	26
84	146,012	104,339	41,673	41,673	29
85	128,348	101,250	27,098	27,098	21
86	122,533	101,250	21,283	21,283	17
87	119,259	135,000	- 15,741	15,741	13
88	128,098	135,000	- 6,902	6,902	5
89	141,457	70,000	71,457	71,457	51
90	158,236	45,600	112,636	112,636	71
91	191,794	275,000	- 83,206	83,206	43
92	289,491	70,000	219,491	219,491	76
93	423,895	45,600	378,295	378,295	89
94	564,176	275,000	289,176	289,176	51
95	209,543	70,000	139,543	139,543	67
96	192,357	45,600	146,757	146,757	76
97	153,089	83,352	69,737	69,737	46
98	141,249	108,218	33,031	33,031	23
99	138,548	127,335	11,213	11,213	8
100	145,944	181,176	- 35,232	35,232	24
101	138,416	64,336	74,080	74,080	54
102	162,582	30,380	132,202	132,202	81
103	226,657	55,789	170,868	170,868	75
104	299,869	100,388	199,481	199,481	67
105	472,376	202,887	269,489	269,489	57
106	563,417	241,000	322,417	322,417	57
107	326,440	269,500	56,940	56,940	17
108	217,896	341,000	- 123,104	123,104	56
109	170,397	255,000	- 84,603	84,603	50

Current Forecast Data and Forecast Error of RFID (cont)

110	144,631	255,000	- 110,369	110,369	76
111	199,189	144,600	54,589	54,589	27
112	184,785	144,600	40,185	40,185	22
113	180,678	92,200	88,478	88,478	49
114	221,575	104,400	117,175	117,175	53
115	264,434	158,000	106,434	106,434	40
116	355,248	204,800	150,448	150,448	42
117	472,126	349,060	123,066	123,066	26
118	599,475	496,085	103,390	103,390	17
119	322,091	347,320	- 25,229	25,229	8
120	238,912	149,078	89,834	89,834	38
121	221,079	166,950	54,129	54,129	24
122	177,620	150,030	27,590	27,590	16
123	219,839	189,431	30,408	30,408	14
124	201,118	188,506	12,612	12,612	6
125	216,940	142,105	74,835	74,835	34
126	231,069	197,540	33,529	33,529	15
	Sum		6,725,167	8,589,988	4,887
	average		53,374.34	68,174.51	38.79
			ME	**MAD**	**MAPE**

The Calculation of Forecast Error by Using SARIMA (0,1,1)x(1,1,0)$_{12}$

Period	Demand	ARIMA Forecast	Residual Error	Abs. Error	%Error
1	30,035	30,035	-	-	-
2	28,855	28,855	-	-	-
3	18,226	18,226	-	-	-
4	47,618	47,618	-	-	-
5	43,698	43,698	-	-	-
6	57,861	57,861	-	-	-
7	90,580	90,580	-	-	-
8	113,998	113,998	-	-	-
9	132,567	132,567	-	-	-
10	93,025	93,025	-	-	-
11	61,690	61,690	-	-	-
12	56,823	56,823	-	-	-
13	51,470	51,470	-	-	-
14	30,359	45,395	- 15,036	15,036	50
15	55,744	33,006	22,738	22,738	41
16	60,002	67,731	- 7,729	7,729	13

The Calculation of Forecast Error by Using SARIMA $(0,1,1)x(1,1,0)_{12}$ (cont)

17	55,793	61,521	- 5,728	5,728	10
18	98,139	75,990	22,149	22,149	23
19	136,690	114,726	21,964	21,964	16
20	172,973	144,329	28,644	28,644	17
21	220,674	171,487	49,187	49,187	22
22	198,903	144,802	54,101	54,101	27
23	110,528	123,481	- 12,953	12,953	12
24	100,647	115,243	- 14,596	14,596	15
25	70,130	107,821	- 37,691	37,691	54
26	40,660	82,556	- 41,896	41,896	103
27	74,996	85,876	- 10,880	10,880	15
28	105,259	95,504	9,755	9,755	9
29	122,613	93,841	28,772	28,772	23
30	168,417	134,220	34,197	34,197	20
31	159,282	179,110	- 19,828	19,828	12
32	259,705	206,581	53,124	53,124	20
33	226,288	257,720	- 31,432	31,432	14
34	179,422	222,773	- 43,351	43,351	24
35	96,891	142,171	- 45,280	45,280	47
36	90,781	123,063	- 32,282	32,282	36
37	67,104	92,835	- 25,731	25,731	38
38	69,105	59,876	9,229	9,229	13
39	75,224	93,570	- 18,346	18,346	24
40	78,892	111,180	- 32,288	32,288	41
41	124,301	113,964	10,337	10,337	8
42	109,233	161,137	- 51,904	51,904	48
43	124,946	154,769	- 29,823	29,823	24
44	191,877	227,670	- 35,793	35,793	19
45	206,649	211,500	- 4,851	4,851	2
46	180,616	171,456	9,160	9,160	5
47	134,132	89,255	44,877	44,877	33
48	90,805	92,665	- 1,860	1,860	2
49	74,301	66,369	7,932	7,932	11
50	67,209	60,256	6,953	6,953	10
51	87,158	77,009	10,149	10,149	12
52	100,012	91,559	8,453	8,453	8
53	101,178	130,065	- 28,887	28,887	29
54	150,498	127,455	23,043	23,043	15
55	197,004	140,771	56,233	56,233	29

The Calculation of Forecast Error by Using SARIMA (0,1,1)x(1,1,0)$_{12}$ (cont)

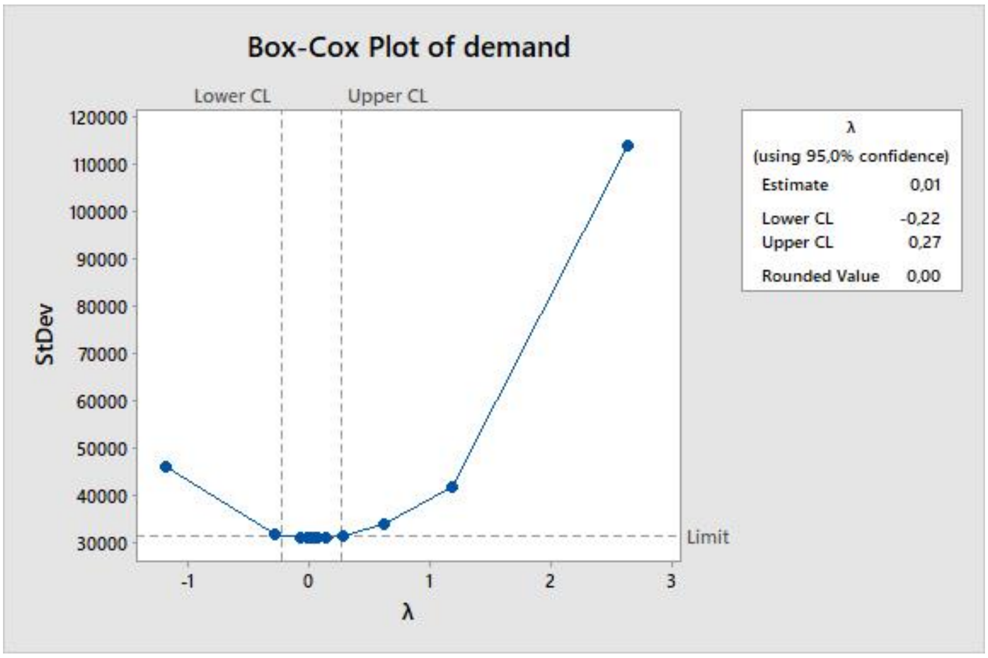
56	300,895	231,785	69,110	69,110	23
57	264,456	247,740	16,716	16,716	6
58	243,576	219,075	24,501	24,501	10
59	156,412	166,980	-10,568	10,568	7
60	124,974	132,964	-7,990	7,990	6
61	113,267	112,271	996	996	1
62	115,712	108,308	7,404	7,404	6
63	119,398	125,628	-6,230	6,230	5
64	110,542	134,072	-23,530	23,530	21
65	114,301	143,688	-29,387	29,387	26
66	117,073	165,512	-48,439	48,439	41
67	195,949	190,654	5,295	5,295	3
68	310,715	284,056	26,659	26,659	9
69	325,693	270,271	55,422	55,422	17
70	337,532	260,991	76,541	76,541	23
71	206,267	205,047	1,220	1,220	1
72	88,237	170,120	-81,883	81,883	93
73	139,954	137,328	2,626	2,626	2
74	75,066	137,367	-62,301	62,301	83
75	102,791	131,343	-28,552	28,552	28
76	106,887	122,571	-15,684	15,684	15
77	107,243	121,759	-14,516	14,516	14
78	134,977	135,867	-890	890	1
79	208,560	204,236	4,324	4,324	2
80	291,722	316,576	-24,854	24,854	9
81	382,085	309,266	72,819	72,819	19
82	326,011	328,094	-2,083	2,083	1
83	231,312	210,356	20,956	20,956	9
84	146,012	124,870	21,142	21,142	14
85	128,348	161,467	-33,119	33,119	26
86	122,533	110,081	12,452	12,452	10
87	119,259	133,136	-13,877	13,877	12
88	128,098	129,798	-1,700	1,700	1
89	141,457	130,830	10,627	10,627	8
90	158,236	153,164	5,072	5,072	3
91	191,794	229,642	-37,848	37,848	20
92	289,491	313,814	-24,323	24,323	8
93	423,895	374,393	49,502	49,502	12
94	564,176	351,741	212,435	212,435	38

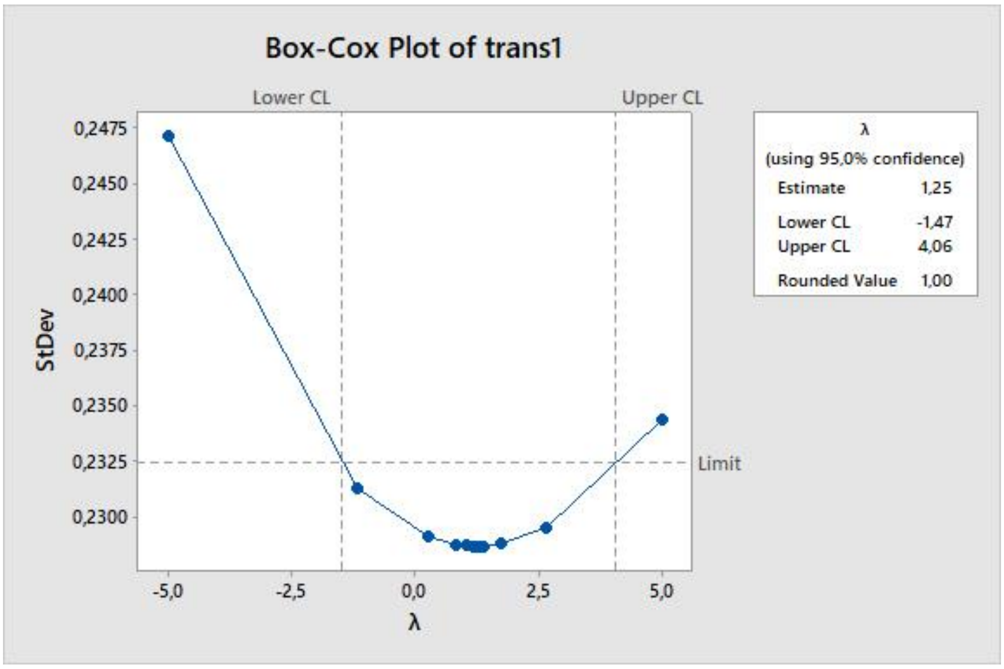
The Calculation of Forecast Error by Using SARIMA $(0,1,1)x(1,1,0)_{12}$ (cont)

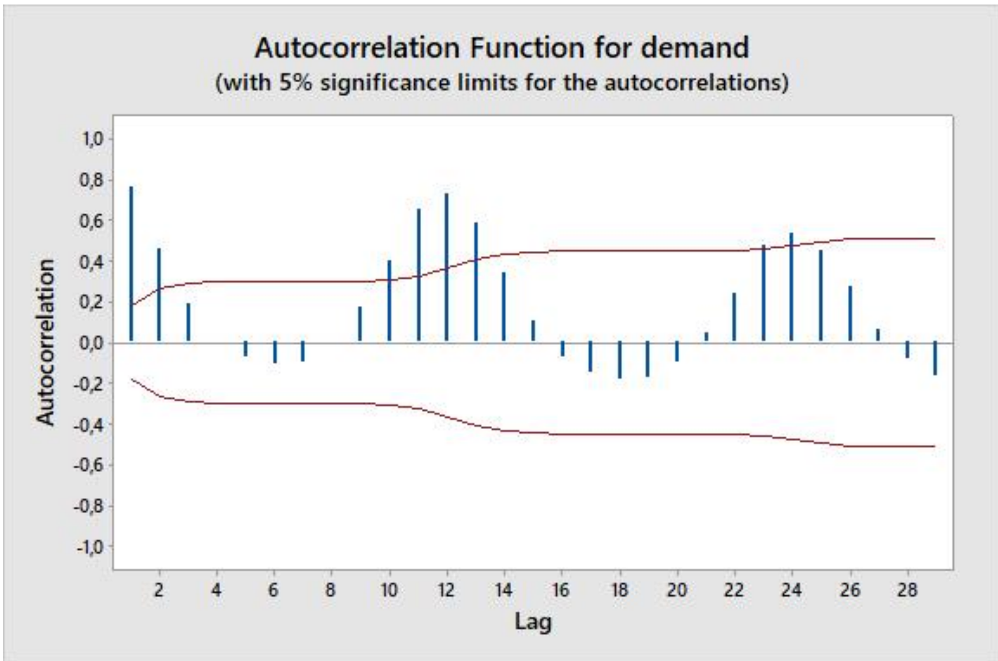
95	209,543	296,158	- 86,615	86,615	41
96	192,357	179,759	12,598	12,598	7
97	153,089	187,169	- 34,080	34,080	22
98	141,249	154,427	- 13,178	13,178	9
99	138,548	157,863	- 19,315	19,315	14
100	145,944	160,580	- 14,636	14,636	10
101	138,416	166,308	- 27,892	27,892	20
102	162,582	179,908	- 17,326	17,326	11
103	226,657	222,056	4,601	4,601	2
104	299,869	316,230	- 16,361	16,361	5
105	472,376	432,720	39,656	39,656	8
106	563,417	520,029	43,388	43,388	8
107	326,440	258,424	68,016	68,016	21
108	217,896	235,823	- 17,927	17,927	8
109	170,397	199,144	- 28,747	28,747	17
110	144,631	182,353	- 37,722	37,722	26
111	199,189	170,459	28,730	28,730	14
112	184,785	185,177	- 392	392	0
113	180,678	184,198	- 3,520	3,520	2
114	221,575	205,174	16,401	16,401	7
115	264,434	263,462	972	972	0
116	355,248	344,692	10,556	10,556	3
117	472,126	507,603	- 35,477	35,477	8
118	599,475	608,745	- 9,270	9,270	2
119	322,091	328,398	- 6,307	6,307	2
120	238,912	252,814	- 13,902	13,902	6
121	221,079	208,350	12,729	12,729	6
122	177,620	187,669	- 10,049	10,049	6
123	219,839	221,687	- 1,848	1,848	1
124	201,118	215,202	- 14,084	14,084	7
125	216,940	209,936	7,004	7,004	3
126	231,069	244,882	- 13,813	13,813	6
	sum		13,063	2,889,866	1,926
	average		104	22,935	15.29
			ME	**MAD**	**MAPE**

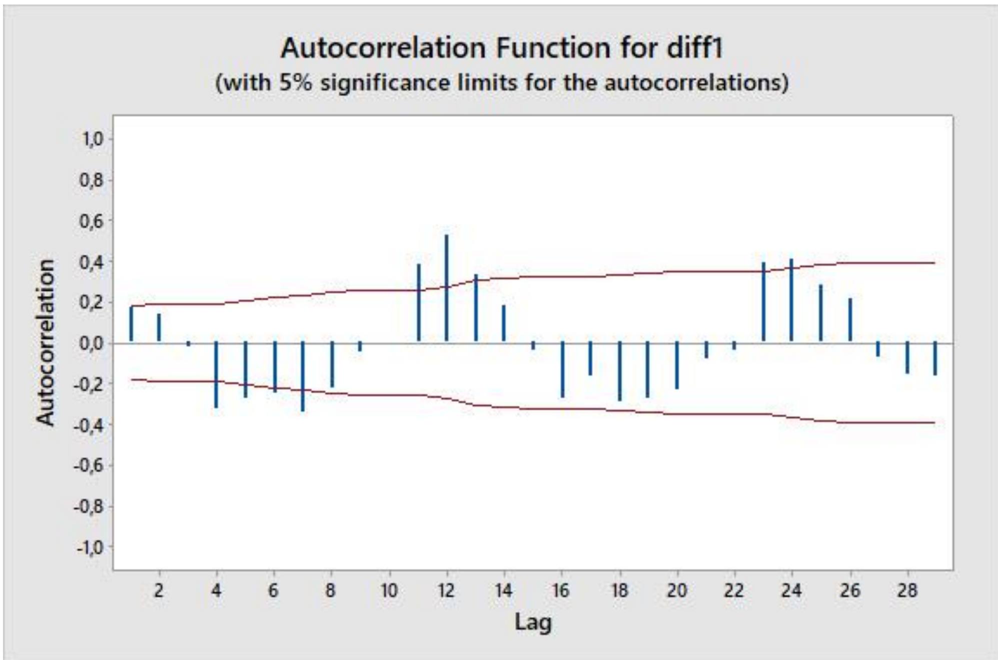
ARIMA model

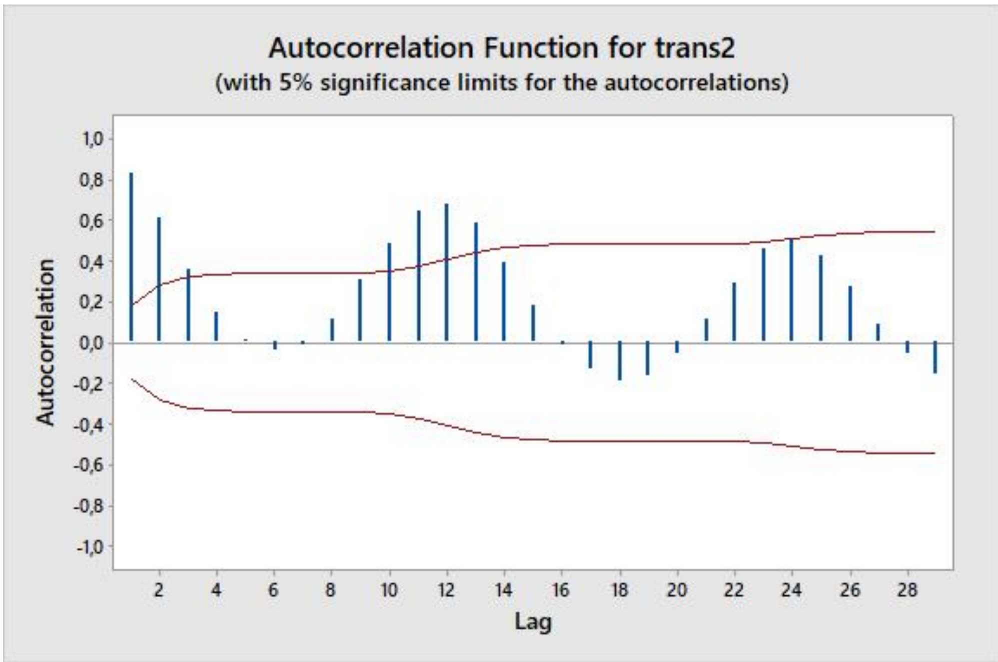
Stationarity process






Autocorrelation Function for demand
(with 5% significance limits for the autocorrelations)
Autocorrelation
Lag
1,0
0,8
0,6
0,4
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
2 4 6 8 10 12 14 16 18 20 22 24 26 28


Autocorrelation Function for diff1
(with 5% significance limits for the autocorrelations)
Autocorrelation
Lag
1,0
0,8
0,6
0,4
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
2 4 6 8 10 12 14 16 18 20 22 24 26 28


Autocorrelation Function for trans2
(with 5% significance limits for the autocorrelations)
Autocorrelation
Lag
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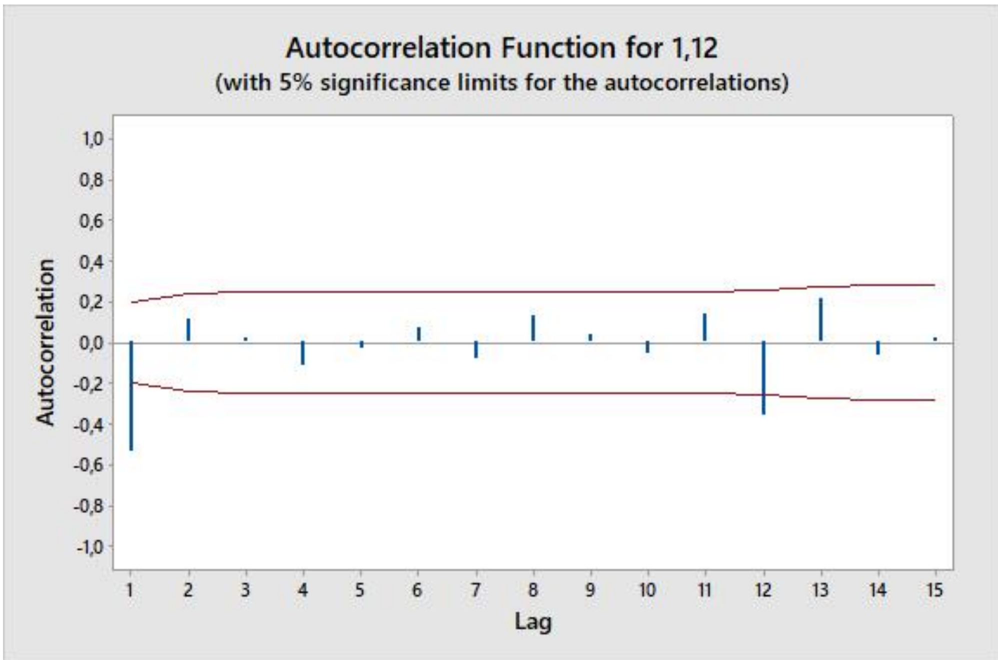
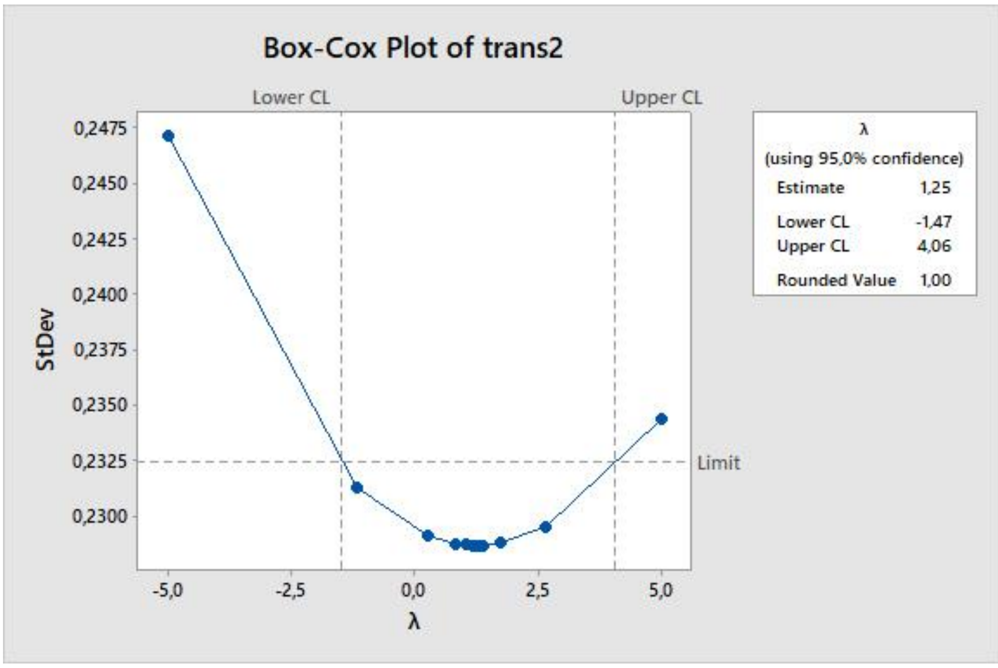
0,8
0,6
0,4
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
2 4 6 8 10 12 14 16 18 20 22 24 26 28


Autocorrelation Function for 1,12
(with 5% significance limits for the autocorrelations)
Autocorrelation
Lag
1,0
0,8
0,6
0,4
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15



Goodness of fit

Goodness of fit statistics (111)x(010)12:

Observations	104
DF	101
SSE	1.58467E+11
MSE	1523724599
RMSE	39034.91513
WN Variance	1523724599
MAPE(Diff)	144.2573775
MAPE	16.39397843
-2Log(Like.)	2498.28362
FPE	1553311484
AIC	2504.28362
AICC	2504.52362
SBC	2512.216792
Iterations	130

Goodness of fit statistics (011)x(110)12:

Observations	104
DF	101
SSE	1.50278E+11
MSE	1444985459
RMSE	38012.96435
WN Variance	1444985459
MAPE(Diff)	198.9465574
MAPE	16.14231593
-2Log(Like.)	2490.810432
FPE	1821938187
AIC	2496.810432
AICC	2497.050432
SBC	2504.743604
Iterations	37

Goodness of fit statistics
(011)x(010)12:

Observations	104
DF	102
SSE	1.68229E+11
MSE	1617586600
RMSE	40219.23172
WN Variance	1617586600
MAPE(Diff)	195.19958
MAPE	17.27630716
-2Log(Like.)	2501.340872
FPE	1617586600
AIC	2505.340872
AICC	2505.459684
SBC	2510.629653
Iterations	28

Goodness of fit statistics
(101)x(100)12:

Observations	117
DF	114
SSE	4.74483E+11
MSE	4055407875
RMSE	63682.08441
WN Variance	4055407875
MAPE(Diff)	25.36066784
MAPE	25.36066784
-2Log(Like.)	2922.973123
FPE	4125328701
AIC	2928.973123
AICC	2929.185512
SBC	2937.259644
Iterations	122

Goodness of fit statistics
(011)x(111)12:

Observations	104
DF	99
SSE	1.48965E+11
MSE	1432356209
RMSE	37846.48212
WN Variance	1432356209
MAPE(Diff)	195.3051933
MAPE	16.27056365
-2Log(Like.)	2490.058292
FPE	1806014350
AIC	2500.058292
AICC	2500.670537
SBC	2513.280246
Iterations	500

Goodness of fit statistics
(111)x(111)12:

Observations	104
DF	97
SSE	1.35375E+11
MSE	1301679641
RMSE	36078.79766
WN Variance	1301679641
MAPE(Diff)	144.7917533
MAPE	15.2339863
-2Log(Like.)	2484.126925
FPE	1673588110
AIC	2498.126925
AICC	2499.293592
SBC	2516.637661
Iterations	1000

Goodness of fit statistics
(110)x(100)12:

Observations	116
DF	114
SSE	4.84279E+11
MSE	4174818998
RMSE	64612.83927
WN Variance	4174818998
MAPE(Diff)	99.0602887
MAPE	24.89453765
-2Log(Like.)	2898.921402
FPE	4247424546
AIC	2902.921402
AICC	2903.027596
SBC	2908.428582
Iterations	24

Goodness of fit statistics
(211)(010)12:

Observations	104
DF	100
SSE	1.52423E+11
MSE	1465607126
RMSE	38283.24864
WN Variance	1465607126
MAPE(Diff)	151.2473123
MAPE	15.79680572
-2Log(Like.)	2493.872021
FPE	1523081916
AIC	2501.872021
AICC	2502.276062
SBC	2512.449585
Iterations	921

Calculation of model verification

period	Demand (dt)	Forecast Demand (dt')	Error	Abs Error	Sq Error	% Error	Abs % Error	MRt	RSFE Cumm.	Abs Error Cumm.	MAD	Tracking Signal
	472,126	507,603										
118	599,475	608,745	- 9,270	9,270	85,932,900	-2%	2%	26,207	- 9,270	9,270	9,270.00	- 1.00
119	322,091	328,398	- 6,307	6,307	39,781,741	-2%	2%	2,963	- 15,577	15,577	7,788.64	- 2.00
120	238,912	252,814	- 13,902	13,902	193,259,091	-6%	6%	7,594	- 29,479	29,479	9,826.35	- 3.00
121	221,079	208,350	12,729	12,729	162,031,228	6%	6%	26,631	- 16,750	42,208	10,552.05	- 1.59
122	177,620	187,669	- 10,049	10,049	100,983,336	-6%	6%	22,778	- 26,799	52,257	10,451.45	- 2.56
123	219,839	221,687	- 1,848	1,848	3,414,251	-1%	1%	8,201	- 28,647	54,105	9,017.50	- 3.18
124	201,118	215,202	- 14,084	14,084	198,372,572	-7%	7%	12,237	- 42,731	68,189	9,741.36	- 4.39
125	216,940	209,936	7,004	7,004	49,055,598	3%	3%	21,088	- 35,727	75,193	9,399.18	- 3.80
126	231,069	244,882	- 13,813	13,813	190,804,237	-6%	6%	20,817	- 49,540	89,007	9,889.63	- 5.01

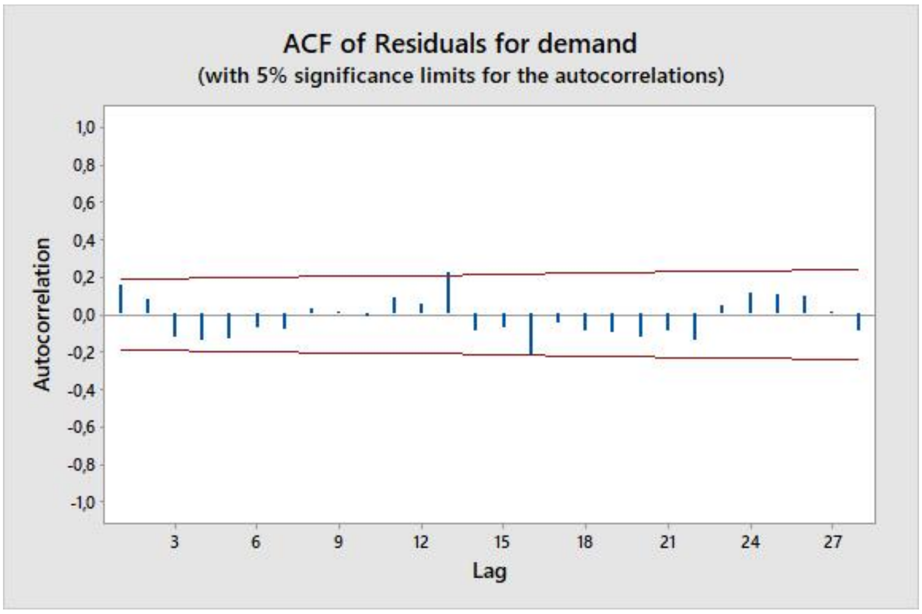
7.2 APPENDIX B

INVENTORY PLANNING FOR 2018

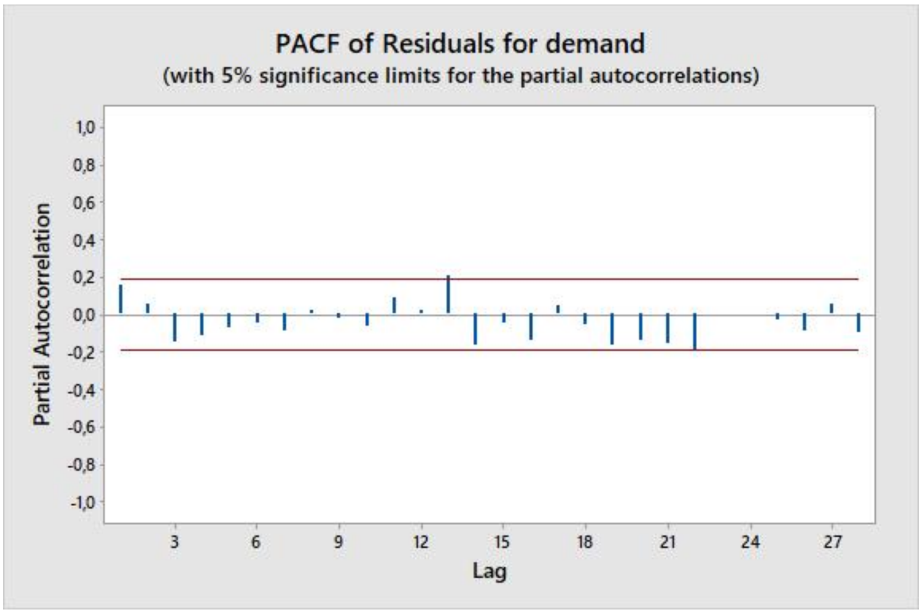
Demand Forecast for Next Season in 2018

```
Final Estimates of Parameters

Type          Coef  SE Coef       T      P
SAR  12    -0,3619   0,0906  -3,99  0,000
MA   1      0,7844   0,0597  13,14  0,000
Constant      20,8    748,8    0,03  0,978


Differencing: 1 regular, 1 seasonal of order 12
Number of observations:  Original series 126, after
differencing 113
Residuals:    SS =  149820580131 (backforecasts excluded)
              MS =  1362005274  DF = 110


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag             12      24      36      48
Chi-Square    12,8    38,8    46,4    64,9
DF               9      21      33      45
P-Value      0,172   0,010   0,061   0,028


Forecasts from period 126

                      95% Limits
Period  Forecast   Lower   Upper  Actual
   127    290163  217814  362512
   128    374629  300617  448640
   129    511657  436020  587295
   130    625889  548659  703118
   131    363147  284358  441936
   132    270810  190492  351129
   133    242263  160443  324083
   134    205227  121934  288521
   135    251932  167190  336673
   136    234794  148629  320959
   137    243425  155859  330991
   138    267261  178316  356206
```

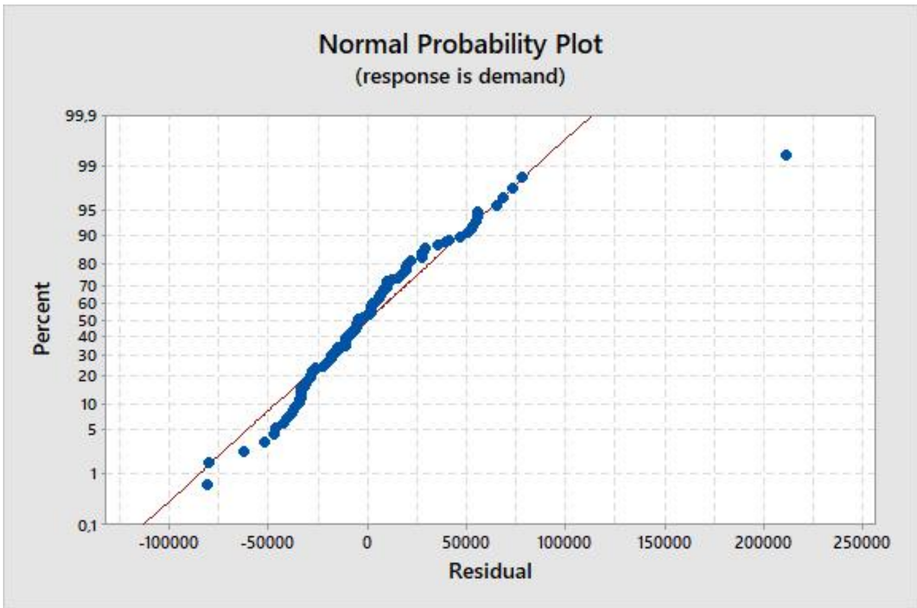
ACF of Residuals for demand



PACF of Residuals for demand



Normplot of Residuals for demand



The management approach calculation for sea shipping mode

$$Q = \sqrt{\frac{2A\bar{D}}{h}} = \sqrt{\frac{2(5{,}000{,}000)(3{,}881{,}198)}{100}} = 622{,}993\ pcs$$

$$R = \bar{D}_\tau L + z\sigma_\tau\sqrt{L} = 323{,}433(3) + (1.64)(14{,}126)(1.73) = 1{,}010{,}377\ pcs$$

The order frequency :

$$n = \frac{D}{Q} = \frac{3{,}881{,}198}{622{,}993} = 6.229 \approx 7\ times\ of\ order$$

Second iteration of optimization approach for air shipping mode

The next step is to find the corresponding R_1 by using the standardized normal distribution in order to find the value of $F(z)$.

$$1 - F(z) = \frac{hQ}{\pi\bar{D}} = \frac{(100)(883{,}360)}{(150)(3{,}881{,}198)} = 0.1517$$

The value of $F(z)$ = 0.8482 and the safety factor can be determine by refers to normal distribution table, which is z = 1.03 and

$$R_1 = 323{,}433\ (1) + (1.03)(14{,}126)(1) = 337{,}982\ pcs$$

The next is calculating the maximum backorder level, from the table of unit normal linear loss integral,the value of $L(1.03)$ = 0.0787

$$\bar{b}(R_1) = \sigma_\tau L(z) = (14{,}126)(0.0787) = 1{,}111.7$$

Then, the new order quantity (2nd iteration) is

$$Q_2 = \sqrt{\frac{2\bar{D}\left(A + \pi\bar{b}(R_0)\right)}{h}}$$

$$Q_2 = \sqrt{\frac{(2)(3{,}881{,}198)(10{,}000{,}000 + 150(1{,}111.7))}{100}} = 888{,}360\ pcs$$

By using the value of Q_2, the value of R_2 also can be determine as below:

$$1 - F(z) = \frac{hQ}{\pi\bar{D}} = \frac{(100)(888{,}360)}{(150)(3{,}881{,}198)} = 0.1525$$

Thus, the value of F(z) = 0.8474 and the safety factor (z) = 1.03, and the reorder point corresponding to Q_1 is

$$R_2 = 323{,}433\ (1) + (1.02)(14{,}126)(1) = 337{,}842\ pcs$$

Optimization approach for sea shipping mode

$$Q_0 = \sqrt{\frac{2A\bar{D}}{h}} = \sqrt{\frac{2(5{,}000{,}000)(3{,}881{,}198)}{100}} = 622{,}993\ pcs$$

The next step is to find the corresponding R_0 by using the standardized normal distribution in order to find the value of $F(z)$.

$$1 - F(z) = \frac{hQ}{\pi \bar{D}} = \frac{(100)(622{,}993)}{(150)(3{,}881{,}198)} = 0.107$$

The value of $F(z)$ = 0.893 and the safety factor can be determine by refers to normal distribution table, which is z = 1.24 and

$$R_0 = 323{,}433\ (3) + (1.24)(14{,}126)(1.73) = 1{,}000{,}602\ pcs$$

The next is calculating the maximum backorder level, from the table of unit normal linear loss integral,the value of $L(1.24)$ = 0.0517

$$\bar{b}(R_0) = \sigma_\tau L(z) = (14{,}126)(0.0517) = 730.3$$

Then, the new order quantity (1st iteration) is

$$Q_1 = \sqrt{\frac{2\bar{D}\left(A + \pi \bar{b}(R_0)\right)}{h}}$$

$$Q_1 = \sqrt{\frac{(2)(3{,}881{,}198)(5{,}000{,}000 + 150(730.3))}{100}} = 629{,}784\ pcs$$

By using the value of Q_1, the value of R_1 also can be determine as below:

$$1 - F(z) = \frac{hQ}{\pi \bar{D}} = \frac{(100)(629{,}784)}{(150)(3{,}881{,}198)} = 0.108$$

Thus, the value of F(z) = 0.891 and the safety factor (z) = 1.23, and the reorder point corresponding to Q_1 is

$$R_1 = 323{,}433\ (3) + (1.23)(14{,}126)(1.73) = 1{,}000{,}602\ pcs$$

It can be conclude that the Q_1 = 629,784 pieces and R_1 = 1,000,602 pieces is the optimum value for this model.

Service level calculation for periodic review

$$\max z = (w-c)yt - \frac{h}{2}(yt - xt) - \frac{A}{yt} - \frac{\pi}{L}S(yt, L)$$

$$\frac{dz}{dyt} = -\frac{h}{2} - \frac{\pi}{L} \times \frac{d}{dyt}S(yt, L) = 0$$

Then the final equation is:

$$F(yt) = 1 - \frac{hL}{2\pi}$$

Inventory periodic review for sea shipping mode

$$T = \sqrt{\frac{2A}{h\bar{D}}} = \sqrt{\frac{2(5{,}000{,}000)}{100(3{,}881{,}198)}} = 0.16 \approx 1\ week$$

$$S = \bar{D}(T+t) + z_{\alpha}\sigma_d\sqrt{T+t}$$

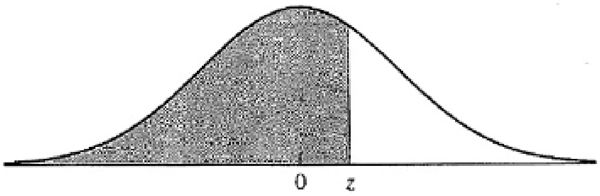
$$S = 323{,}433(1+3) + (1.88)(14{,}126)(\sqrt{4}) = 1{,}346{,}846\ pieces$$

Calculation of Total Cost Planning for New Season in 2018

	(Q,R) 1 by air	(Q,R) 2 by air	(S,T) by air	(Q,R) 1 by sea	(Q,R) 2 by sea	(S,T) by sea
purchase cost	7,762,396,000	7,762,396,000	7,762,396,000	7,762,396,000	7,762,396,000	7,762,396,000
ordering cost	44,052,211	43,936,764	44,052,863	31,149,612	30,813,723	31,250,000
holding cost	46,368,950	45,572,800	47,769,597	35,157,450	34,495,100	36,360,984
Total	7,852,817,161	7,851,905,564	7,854,218,461	7,828,703,062	7,827,704,823	7,830,006,984

Z-Table

TABLE A.2 Cumulative normal distribution (continued)



z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998
3.5	.9998	.9998	.9998	.9998	.9998	.9998	.9998	.9998	.9998	.9998
3.6	.9998	.9998	.9999	.9999	.9999	.9999	.9999	.9999	.9999	.9999

TABLE A-2

Unit normal linear loss integral: $L(z) = \int_z^\infty (t - z)\,\phi(t)\,dt$

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.3989	.3940	.3890	.3841	.3793	.3744	.3697	.3649	.3602	.3556
0.1	.3509	.3464	.3418	.3373	.3328	.3284	.3240	.3197	.3154	.3111
0.2	.3069	.3027	.2986	.2944	.2904	.2863	.2824	.2784	.2745	.2706
0.3	.2668	.2630	.2592	.2555	.2518	.2481	.2445	.2409	.2374	.2339
0.4	.2304	.2270	.2236	.2203	.2169	.2137	.2104	.2072	.2040	.2009
0.5	.1978	.1947	.1917	.1887	.1857	.1828	.1799	.1771	.1742	.1714
0.6	.1687	.1659	.1633	.1606	.1580	.1554	.1528	.1503	.1478	.1453
0.7	.1429	.1405	.1381	.1358	.1334	.1312	.1289	.1267	.1245	.1223
0.8	.1202	.1181	.1160	.1140	.1120	.1100	.1080	.1061	.1042	.1023
0.9	.1004	.0986	.0968	.0950	.0933	.0916	.0899	.0882	.0865	.0849
1.0	.0833	.0817	.0802	.0787	.0772	.0757	.0742	.0728	.0714	.0700
1.1	.0686	.0673	.0659	.0646	.0634	.0621	.0609	.0596	.0584	.0573
1.2	.0561	.0550	.0538	.0527	.0517	.0506	.0495	.0485	.0475	.0465
1.3	.0455	.0446	.0436	.0427	.0418	.0409	.0400	.0392	.0383	.0375
1.4	.0367	.0359	.0351	.0343	.0336	.0328	.0321	.0314	.0307	.0300
1.5	.0293	.0286	.0280	.0274	.0267	.0261	.0255	.0249	.0244	.0238
1.6	.0232	.0227	.0222	.0216	.0211	.0206	.0201	.0197	.0192	.0187
1.7	.0183	.0178	.0174	.0170	.0166	.0162	.0158	.0154	.0150	.0146
1.8	.0143	.0139	.0136	.0132	.0129	.0126	.0123	.0119	.0116	.0113
1.9	.0111	.0108	.0105	.0102	.0100	.0097	.0094	.0092	.0090	.0087
2.0	.0085	.0083	.0080	.0078	.0076	.0074	.0072	.0070	.0068	.0066
2.1	.0065	.0063	.0061	.0060	.0058	.0056	.0055	.0053	.0052	.0050
2.2	.0049	.0047	.0046	.0045	.0044	.0042	.0041	.0040	.0039	.0038
2.3	.0037	.0036	.0035	.0034	.0033	.0032	.0031	.0030	.0029	.0028
2.4	.0027	.0026	.0026	.0025	.0024	.0023	.0023	.0022	.0021	.0021
2.5	.0020	.0019	.0019	.0018	.0018	.0017	.0017	.0016	.0016	.0015
2.6	.0015	.0014	.0014	.0013	.0013	.0012	.0012	.0012	.0011	.0011
2.7	.0011	.0010	.0010	.0010	.0009	.0009	.0009	.0008	.0008	.0008
2.8	.0008	.0007	.0007	.0007	.0007	.0006	.0006	.0006	.0006	.0006
2.9	.0005	.0005	.0005	.0005	.0005	.0005	.0004	.0004	.0004	.0004
3.0	.0004	.0004	.0004	.0003	.0003	.0003	.0003	.0003	.0003	.0003