IMPROVING TRANSPARENCY IN SUPPLY CHAIN FOR BETTER BRAND PERFORMANCE: A STATISTICAL APPROACH

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DECLARATION

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ABSTRACT

The competition of the economic environment is increasing rapidly and it has been a prevailing issue in many businesses to achieve the balance between the supply and demand. This issue is further increased when there is a lack of transparency in the supply chain both internally and externally. Proper analysis on how to mitigate the gap of lack of transparency would lead to better performance of the business. Various time series forecasting analyses with the soft computing of neural networks can be utilized to hinder the gap of supply chain transparency. Further, application of queuing theory for the complete process enables to mitigate the issues created due to lack of transparency in the supply chain process.

In this study, the focus was to improve the transparency by in depth study of produced and sold garments of a particular style in a global brand. The quantities of produced and sold were taken from a leading manufacturing company in Sri Lanka. The study was carried out with both time series analysis and queuing theory. For time series analysis, decomposition method, ARIMA method, VAR method have been applied. The VAR model was statistically adequate where models were derived for manufactured and sold quantities. Application of queuing theory has been carried out to understand the finished good quantity that would be stored in the warehouse before selling it to the consumer. Apart from that, a mathematical model has been carried out to identify the extensive stocks that were stored in the warehouse with a percentage reduction. This mathematical model could reduce further stock amount and thereby lead to better financial performance as well. The final short-term solution of stock reduction model is helpful to reduce the stock that will be stored in the warehouses and also opens for more holistic queueing modelling in future.

Key words: Forecasting, Queuing, supply chain

DEDICATION

This Thesis is dedicated to all those who helped me, encouraged me in numerous ways!

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I would like to take this opportunity to thank my supervisor Senior Lecturer in Mathematics and Statistics, Division of Interdisciplinary Studies, Institute of Technology, University of Moratuwa, Dr. Samanthi Mathugama.

Also my family and friends who have been always with me!

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1 INTRODUCTION

1.1 Overview

This study was focused on a leading Apparel Brand in the world. It was based on how this apparel brand would lead to better performance in terms of market conditions, financial performance as well as operational performance. Queuing modeling and time series analysis were used to focus in-depth analysis to understand the facts on improving the brand performance.

1.1.1 Global Apparel Industry

The global apparel industry is an inclusion of clothing textiles, footwear and luxury goods. This plays a major role in global economy in terms of investment, trade, employment, and revenue. Apparel industry have reached approximately US$596,520 million in 2021(Sri Lanka Export Development Board , 2022).

The rivalry within the industry is at a mediocre level where the global apparel industry continues to grow at a healthy rate. The sector has become grand and magnificent due to the fact of globalization. Vast product differentiation, short product life cycles are inherited characteristics in this industry.

In the new world, irrespective of the size of your business, they need to be agile and have more digital advancements in order to be successful in this competition. Busines should look into more innovative methods to re-build their identity while being transparent and incorporating sustainable methods. There are predictions that the fashion industry will have a massive growth in the upcoming years and players in the industry have to encounter challenges within the industry and be competitive in the market.

1.1.2 Sri Lankan Apparel Industry

For ethical and sustainable manufacturing, most of the top ranked brands trust the Sri Lankan manufactured garments and the apparel industry for producing the best quality products. Sri Lankan garment industry is developing rapidly with more technological advancements being introduced and new techniques are being introduced too. With these technologies are coming up and smart apparels are being created from Sri Lanka, it has become a regional hub for textile and apparel. There are many brands that Sri Lankan apparel companies are having partnerships with and hence created a connection with those brands. For the Sri Lankan economy, Apparel sector plays a vital role and massive contribution to uplift the economy.

According to Sri Lanka's Export Development Board (EDB) apparel industry accounts to 40% of primary foreign exchange of the total exports and 52% of industrial product exports. It states that apparel sector in Sri Lanka contribute to 15% from the total working population. Further from the South Asia region, Sri Lanka tops the highest apparel exports per capita. Production of top quality ethical fashion apparel is the success behind Sri Lankan apparel manufacturers & suppliers which is reputed and trusted by iconic global fashion brands.
The success of the Sri Lankan apparel sector has been deemed due to the facts such as firm adherence to International Labour Standards, incorporating ethical production of "Garment without guilt" and high excellence workforces.

1.2 Importance Of Robust Supply Chain To The Apparel Sector

Apparel supply chains are often geographically widely distributed, due to strong outsourcing of fashion manufacturing to low labour cost regions. Also there are circumstances where the raw materials are produced in one location and the manufacturing will be on a different location. Hence there should be a robust integration in the supply chain system to ensure the streamline manufacturing process.

To minimize the cost, it is necessary to place the movement where the resources should be at the exact right place on the tight time with the satisfactory quantity and quality. In order to have a streamline process it is necessary to have a transparency in the supply chain process.

1.3 Problem Statement

Although, in Sri Lanka, apparel sector has had a significant growth and robust relationships between the global apparel brands, the transparency about the end consumer behaviour to the manufacturing companies in Sri Lanka is limited. Since the manufacturing companies do not have the visibility towards the behaviour of the consumer, throughout the supply chain starting from raw materials to the finished goods they keep excess stocks which creates unnecessary cost for each operation. This cost gets accumulated to the final consumer also making the products more expensive for the end consumers. On the other hand, it is harmful for the environment, and it impacts for the sustainability of the nation. As at now the environmental sustainability is a major concern for all users and hence this creates a negative reputational impact for such brands. This clearly shows that due to the lack of transparency in the supply chain there has been numerous issues.

1.4 Significance Of The Study

There are many ways that the brand performance could be improved by having a complete transparency in the supply chain. However, the complexity of the fashion industry is a major concern to have a visibility in the supply chain.

It is common to see that most of the brands work with many factories at a given time and these factories may operate in different part of the world making sure the finished garments are transfer across the world quite often.
Most of the time, when a product is ready to launch to the end consumer, a brand may place an order with one supplier, who generally sub contracts the work to other factories. This happens regularly across the industry and it leads to a great challenge

and many manufacturing delays for the end consumers. To look this scenario in a more statistic manner, In USA out of the clothing sold, 97% of were mostly from other developing countries (Reidy, 2019). One of the solution for these problems is to have a complete visibility and the transparency in the fashion supply chain. The visibility in the supply chain can help companies to proactively and sensibly react to unplanned events, ensures the continuous supply of needed raw materials and avoids unethical practices within the factories.

With the current trends the fashion industry is improving rapidly and due to that, fashion industry is striving to "fashion on demand" and geared for speed to market it is a necessary factor to have the complete transparency in the Supply chain from the beginning to the end.

Further with such incredibly rapid growth expected for the industry it is important that the main brands should understand the challenges in the supply chain and understand the importance to be more transparent to be more competitive in the market. The understanding and the outcomes of this report would be beneficial for both manufacturing company and the brand which will lead to better customer service for the end consumer.

1.5 Objectives

Main objective:

The key objective of this study is to suggest a mechanism to minimize the production that is been stocked and hence to reduce the inventory cost.

Sub objectives:

- To carve out a better business model to improve the operational excellence and thereby reduce the financial impact with statistical model building.

1.6 Data Usage

For this study, data was obtained by a reputed apparel company in Sri Lanka for a particular brand. The number of manufactured goods and sold goods were obtained over the five years for this study.

1.7 Outline Of The Thesis

This study consist with six chapters and chapter outlines are as follows.
The literature review section under the chapter 2, outlines the previous studies related to this study. It has been sub categorised to understand the studies conducted under time series analysis and queuing theory to improve the supply chain transparency.

Chapter 3, Methodology, consists of detailed description about how the study was conducted, apparel industry supply chain process and the statistical methods used for the study.

Chapter 4, Data analysis chapter consists of the descriptive statistical methods along with the time series decomposition method.

Chapter 5, Advanced statistical analysis chapter consists of the multivariate time series analysis, application of queuing theory and stock reduction method.

Chapter 6, consists of the conclusions, recommendations and opportunities for the future studies.

2 LITERATURE REVIEW

This section is devoted to analyzing past research and literature related to the research problem.

2.1 Supply Chain Transparency

The transparency of Supply chain is a paramount aspect in global business. According to the study by Deloitte Touche Tohmatsu Limited, it depicts the supply chain transparency with more of a practical aspect of describing, understanding, and creating the transparency in economy around the globe. Through the study they reveal how it became vital component in the global economy. As per the study, by Upton Sinclair has spent quite some time in one of the village understanding about the meat-packing industry which lead to imposing new laws for the United States for food and drug act and meat inspection act, which could be considered as one of the first step in supply chain transparency (Linich, 2014).

In order to manager risks more effectively, companies would like to take actions bases on the insights gained by a higher visibility in transparency. The four steps that are identified by the study for forming transparency are: Identifying and prioritizing risks, visualizing risks, using transparency levers to close information gaps and Managing and monitoring (Linich, 2014).

Harvard Business Review emphasize that although that the supply chain transparency has been known for more than 2 decades that it has become vital aspect now and more concerns are being coming from many stakeholders and cost of failing to meet the reputational implications could be high. The article has defined that the Supply chain transparency is where companies get to know what is happening at the consumer end and cascading the knowledge to both internal and external parties (Bonanni, 2019).

It states that "Early adopters such as Nike maps their manufacturing plants and offer insights into individual factories, while UK retail chain Marks & Spencer provides an interactive mapping of its food and apparel manufacturers." Further, this article states that blockchain and other techniques have been signaled as the solution to supply chain, it should be a combination of both technology as well as the involvement of other stakeholders to capture, translate and disseminate useful data and support appropriate decision making (Bonanni, 2019).

As per the article on How to create more transparency in Supply Chains it states that although that there are many options and methods drive on how to improve the supply chain transparency it is unlikely that they will be able to continue doing business per the status quo (Apple Rubber, 2017).

As per the study by Alicke, McKinsey and Company (2016), it states that big data and supply chain goes hand in hand where the supply chain creates big data and big supply chain analytics will help to turn the data into meaningful insights.

As per the study, cross section of the supply chain design could be segregated as per the below table 2.1.

Table 2-1: McKinsey & Company source document: The landscape of supply chain analytics opportunities

Product design

Supply chain design

A. Sales, inventory, and operations planning

- Supplier risk management and incoming goods projection
- Inventory projection and scenario planning
- Forecasting accuracy evaluation and optimization

B. Sourcing	C. Production	D. Warehousing	E. Transportation	F. Point-of-sale	G. Consumer
• Cost modeling to identify cost drivers • Quantification of benefits from spend pooling • Automatic analysis of contract compliance • Aggregate demand/supply balancing	• Scheduling of energy-intensive production • Statistical quality control and tolerance optimization capabilities • Lot sizing and scheduling considering cost, inventories, and capacities	• Picking zone/ warehouse space allocation • Worker to picking zone allocation based on efficiency • Automatic stock relocation in high bay storage areas • Cleansheet cost modeling • Workload optimization	• Real-time routing and ramp allocation at warehouses • Delivery scheduling in line with consumer patterns • Cleansheet cost modeling • Dynamic routing	• Out-of-stock detection and prevention • Shelf space optimization • Channel/store allocation of goods maximizing service • Retail employee scheduling	• Credit rating to define payment terms offered • Return projection to calculate outstanding inventory • Product recommendations based on purchase history • Fraud detection

McKinsey&Company | Source: KLU research report "Supply Chain Analytics—Gaining value from data-based decision making"

Under the supply chain design, sales, inventory and operations planning are the key aspects where most of them are data driven process. Clear visibility on the sales, inventory data and production volumes and analysing them on timely manner would improve better performance for the brand. There are many methodologies that have been developed that have improved the forecasting accuracy and hence used by retailers around the globe (Alicke, 2016).

Based on the above studies in order to be improve the supply chain transparency, it is important to have a better forecasting for the quantity that need to be produced and understanding about the quantity that will be sold on particular month. This will be beneficial to understand the stock quantity that can be reduced too. Hence in depth literature understanding about how statistical techniques would be used are discussed as follows.

2.2 Time Series Forecasting To Improve Production And Sales

For forecasting, the most commonly used forecasting approach would be a univariate time series model. However, there are some limitations when it comes to univariate time series. The biggest assumption is where that all other factors will affect the revenue the same way. Nevertheless, that assumption often breaks when the factors affecting product demand changes. Hence for this complex behaviour requires multivariate time series analysis (Alam, Multivariate time series forecasting, 2020).

Forecasting is an important aspect in many industries. For better forecasting in shale reservoirs, has been challenging due to various aspects and hence, has come up with two methods for forecasting. One aspect under the study is time series to make sure the analysis is accurate it need to understand the trend, rate of decline, correlation and change in value. Other study was data mining techniques such as and self-organizing maps (SOM) and neural networks (NN), genetic algorithms (GA). Based on the models produced accuracy of the forecasting has been improved (Gupta, Fuehrer, & Jeyachandra, 2014).

As per the study conducted to study forecasting women's apparel sales using mathematical modelling it states that traditional statistical time series methods like moving average, auto regression or combination of these are used. However, the prediction would occur only based on the previous sales and hence other influencing factors like exogenous variables such as , climatic data, size, prize, effect of media are not been taking into consideration. However, a linear regression model will be able to take some factors into account which would have the limitation that the forecasting would be restricted to be linear. Hence it is recommended that soft computing such as fuzzy logic, artificial neural networks (ANNs) and generic algorithms offer an alternative taking into account both endogenous and exogenous variables. Hence, data would learned directly from the data itself for better forecasting and modelling using ANNs (Frank, 2003).

As per the study in a glove industry to understand the production fault simulation and forecasting from time series data with machine, it highlights that although we are in the Industry 4.0 and there are developments integrated into textile sector there has been some restriction and data sharing related to production process due to various commercial concerns and confidentiality. For the study, they have prepared simulation for the annual production plan. Using data set various machine learning algorithms have been trained, in order to verify the hypothesis that the errors may forecast (Coşkun, 2019).

A study has been carried out to understand the forecasting method formulation for global supply chain of fuel and lubricants additive models. It depicts that the supply chain using both optimization and simulations techniques along with the actual demand data. Under the optimization, to minimize the total supply chain cost, it forecasts to improve a production, inventory and transportation plan.
From the time series perspective, customer service and trade off curves are used to match exponential smoothing methods (Yavuzacar, 2012).

In a two stage supply chain with ARIMA(0,1,1) forecasting it states that model has been widely used due to theoretical properties and empirical evidences. A study has been carried out to analyse the relationship between the forecasting accuracy and inventory performance and benefits has been shared with both retailer and manufacturer (Babai, 2013).

As per the study done by Ria Gupta, it states that hierarchical time series predictions have a lot of uncertainties when it comes to forecasting for apparel sector. Hence there will not be a single model work well at all levels. Since the sales could be depending on various aspects models like ARIMA, LSTM (Long Short Term Memory) and Prophet models would fit at certain levels only. Prophet model is where additive or multiplicative models were used for non-linear trends for different time series periods. In some studies, prophet has performed better as it handles seasonality and trends (Gupta, 2020).

Na Liu, (2013) has studied many literature reviews and select a set of papers on fashion retail sales forecasting. The advantages and disadvantages of different analytical methods of fashion retail sales have been examined. Based on the different studies and years they have derived some studies shows pure statistical models while some shows pure Artificial Intelligence models while others studies have used Hybrid models. Based on the study most of the studies have used the hybrid models. To enhance the strengths of various models together to form a new model, Hybrid forecasting methods are build. Rather than using pure statistical model or only an AI model, these would be more efficient. Fuzzy model, ANN, and ELM(extreme learning machine)with other techniques such as statistical models, the grey model (GM), and so forth are usually combine for fashion forecasting.

As per the study in UAE, the apparel industry uses all the possible methods for forecasting. About 29% of companies use naïve, 29% use exponential, 29% use linear regression and balance use multiple regression. Further critical thinking reveals the need of consolidation and standardization in demand management in apparel industry (Supriya Kamath, 2008).

2.3 Queuing Theory Applications To Improve The Supply Chain Transparency

In a manufacturing point of view there would be various operational steps that are involved in converting the raw materials into the finished goods products. To ensure that the process is efficient and cost effective, analytical tools such as queuing theory has been used extensively by companies and they help to improve the total process including the performance analysis, design, planning and control of the manufacturing processes. Under this subtopic, previous studies on the application of the queuing theory on manufacturing process are discussed.

Based on the study carried out in Food industry, one of the studies have been done to understand the extensive studies done so far in the industry with the application of Queuing theory. Some of the key highlights of the study were that approximately 56%

of the studies out of last fifty years were carried out during the last decade which realized that now there is far more importance given to the Queuing theory more than before. Another aspect has been identifying that most of the queuing theory application has been done to study on the supermarkets or rather centres that individuals have daily customers. Hence there is a substantial gap on studying the application into other food centres like farms, Store units, distribution centres. Also most of the collected articles has focused on short term decision rather long term strategic decisions. Further there has not been much studies carried out to understand the idle time with the application of queuing theory. Hence under this study, it shows that there are many more research areas to study as there are these wider gap in studies (Motamedi, 2020).

Another study has carried out in order to understand the production line performance analysis and improve the manufacturing system with MTS (Mixing the Make-To-Stock) and MOT (Make to Order). A model has been developed to show the application of MTS and MTO. A two dimensional queuing model has been developed under this study for two different scenarios. Where one of the scenario is utilization of the customization station in a system that can only customize semi-finished products based on the customer order while other scenario is customized the semi- finished product based on the customer order along with the forecast. From this study, possible future research indicated applying Fuzzy theory to study the uncertain behaviour of customers and production line (Suer, 2018).

To understand the waiting time using Queuing theory in an Advanced manufacturing environment another study has been done in year 2020. This study has been carried out to implement a robot at the packing stage where mathematical models were used to different manufacturing scenarios and stages in the process. Newton-Raphson iteration formula has been implemented and simulation has been carried out to achieve optimal values that could yield efficient productivity. From this study, they have shown that queuing theory has been an effective analytical tool that can be used to solve a waiting line model. The M/M/S queue model has had its servers arranged in a parallel form where the service time at each station is identical following the same exponential law. To optimize the performance of each robot with its corresponding queue the average queuing time has been further differentiated. Further, the outcome has been further analysed using the Newton-Raphson iteration method (Salawu, 2020).

To understand about the application of queuing theory in production inventory optimization a study has been conducted and it presented a mathematical mode. In this model stochastic parameters have been defined for inventory control system, customers' demand and suppliers. This problem has been solved through queuing theory for single item which has extended for multi item inventory and further new heuristic algorithm has been developed. Further, sales lost shortage have been deemed as one of the drawback in their model. As a future study, they have suggested to increase this into the model while it would become more complex, but model would be more realistic (Rashid, 2015).

On a study which has been done on production process optimization based on Queuing theory, they have taken an enterprise as an example. Queuing theory has been used to compare and contrast the two optimization strategies in manufacturing industry where this has been used to solve the problems of, long service time, low efficiency and high costs. Study has showed how each strategy that was developed could be used by managers depending on how optimistic they are about the business. They have shown the figures of how much they could save from each strategy by showing calculations on the savings (Gongshan, 2020).

Cruz, (2014) has studied the generalized expansion method which is the act of the queuing networks that are evaluated using advanced network analyser. Further various model have been described and optimized in respect to key parameters in the network like server sizes and buffer. With the Powell heurisric, this has been solved.

This study has further suggested that for future studies that the queuing section would be consist with analysis and optimization of networks with cycles to model industrial systems that have loops or networks with independent arrivals and generally distributions (Cruz, 2014).

In a manufacturing environment, a study with the use of queuing model has been done for production line performance and production system is catered with size of the batch and throughput. The focus of the study has been the assembly operations in its production line in a manufacturing industry. The result that has been obtained under the study was when the batch size and throughput are increased is directly proportional to the utilization increment. Only when the capacity is not suffice to meet the demand requirement, bottleneck would occur. Under the study the model presented has shown how throughput and batch size affect the performance of a manufacturing system (Shafeek, 2013).

2.4 Summary Of Chapter 2

Many researchers identified the importance of supply chain transparency and how they could positively impact the performance of the brand in terms of internal as well as how it could positively impact for customer end. As per the statistical studies many researches shows time usage of time series analysis and it has been widely recommended to go ahead with hybrid model where soft computing is necessary. On the queuing modelling perspective for better production performance, many models have been derived depending on each scenario. Mostly, queuing theory has been used in many studies as a holistic view to improve the supply chain.

3 METHODOLOGY

3.1 Introduction

The Apparel Company selected for this research is catering to many brands in their factories and the brand that has been chosen is the most important brand for the apparel company as this brand would provide the products with the highest margin and hence would lead to a higher profitability. The process of how the orders are placed is discussed under this chapter along with the statistical approach to improve the supply chain transparency.

3.2 Order Placement

At the beginning of each year, from the Brands end they would give a rough forecast of the number of produced units that they require from the apparel company. Based on this the apparel company would do a capacity calculation and confirmation of the order capacity for each brand. This is illustrated under the figure 3-1.

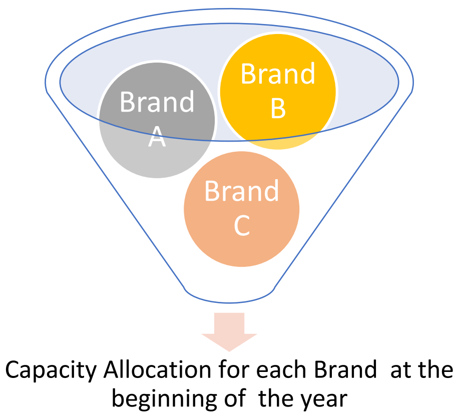

Figure 3-1: Forecasting capacity at the beginning of year

Then on each month there could be monthly reconciliation on the capacity point of view as well as considering the brands performance too. Based on this the apparel company would do the production as per the Brand's request and send the finished goods (Produced quantity) to the relevant ware house (Shipped out of the country). This is further illustrated under the figure 3-2.

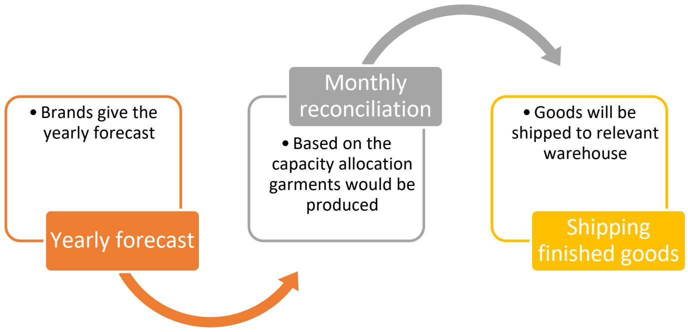

Figure 3-2: Capacity Allocation Process

Although, under this study capacity calculation and the capacity allocation is not studied into depth, basic understanding of them would be provided as follows.

3.2.1 Capacity Calculation

The capacity is calculating based on SMV (Standard Minute value) value and the no of forecast quantity under each brand. Therefore, to make an accurate forecast it is mandatory to make sure that the SMV value should be approximately accurate and the projection should be approximately approach which will lead to proper capacity allocation. The capacity is based on number of hours that will be required to stich the garment. The capacity calculation is illustrated under the equation 3-1.

$$\text{The Number of Hours } = \frac{\text{SMV Value} * \text{Number of pieces}}{\text{Efficiency}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3-1)}$$

3.2.2 SMV Value

SMV or SAM – The work you do for the content of a garment is measured under the Standard Allowed minutes. This is used for the valuing the cost of making a garment. The SMV value can be calculate base on two different scenarios. It can be done either based on using Synthetic Data where “pre-determined Time Standards”. Another method of calculating SMV is using Time Study (Sarkar, 2019).
Therefore, under each brand the required hours will be calculated where the total number hours will be calculated for each month.

3.2.3 Efficiency

Under each brand, each style they forecast efficiency would differ. Therefore, time allocation for each sample type will differ. This explain the variability of different sample type. Capacity of the factory evaluated according to the efficiency. Efficiency for each brand is calculated as per below equation. The efficiency calculation is illustrated under the equation 3-2.

$$\text{Efficiency} = \frac{\text{SMV} * \text{Quantity Produced}}{\text{Number of Operators} * \text{Number of Hours worked}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3-2)}$$

3.2.4 Number Of Pieces Submission

There will be number of prediction for each brand as explained earlier which is used to calculate the resource capacity for next year. From the Apparel Company's point of view, they would prefer Brands which are able to give the forecast more accurately at the beginning of the year and that there would be less changes on each month. The brand that is used for this study, has less variations against the initial forecast given at the beginning of the year.

3.2.5 Order Shipment

Once the garments are produced they are kept on a respective warehouse and one of the aspect of this study is, to reduce the number of days that the garments will be there on the warehouse in order to improve on the working capital. This is further illustrated under the figure 3-3.

Figure 3-3: Finished goods at warehouse

3.3 Data Sources

For the study of understanding the importance of having a complete transparency in the supply chain to improve the brand performance secondary data are used. The data were obtained by a leading manufacturing apparel company in Sri Lanka who are catering for a leading global brand. The secondary data consist with the number of finished goods produced by the manufacturing company along with the actual finished goods sold by the brand. These data were obtained at the current stage where there is no transparency in the supply chain.

Data for 5 years were obtained from secondary data sources to conduct the study.

3.3.1 Data Used

To study the relationship between the manufactured quantity and sold quantity on one of the product type, the secondary data of one style called "Mula" was taken from the leading apparel organization. Mula is a lingerie wear style which has been produced continuously for consecutive 5 years by the same manufacture and it is one of the basic styles where the brand has been continuing. Since this is a basic style, brand has not changed it much. This helps the manufacturer to get a competitive advantage to improve the efficiency when manufacturing too. From this study, the analysis was done comparing the production quantity and the sold quantity and how much it is been stocked.

The final objective of this study is to identify whether it is possible to minimize the production that is been stocked and hence to reduce the inventory cost and give this cross section transparency to both manufacturer and Brand who is selling, hence to come up with improvement on each end.

3.4 Descriptive Analysis

Descriptive statistics are the basic of data analysis that helps to understand and describe the data in summarized and meaningful way to understand the patterns and basic statistical interpretations. The descriptive statistics of measures of locations (mean, median, mode) and measures of dispersion (range, variance, standard deviation) are calculated.

To assess the degree of association in between two random variables the Pearson Correlation Coefficient ranges from 1 (strong positive correlation) to -1 (strong negative correlation) is calculated (Nettleton, 2014).

Put the formula for r and label it.

$$r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma((x_i - \bar{x})^2)((y_i - \bar{y})^2))}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3\text{-}3)$$

r= correlation coefficient

x_i =reperesents the values of the x-variable in a given sample

$\bar{x}$ = represents the value of the mean of the values of the x-variable in the given sample

y_i = represents the values of the y-variable in a given sample

$\bar{y}$ = represents the value of the mean of the values of the y-variable in the given sample

3.5 Multiple Regression Model

To forecast and predict the ultimate outcome of a response variable, multiple linear regression model uses several explanatory variables. The ultimate goal of the multiple linear regression is to model the linear relationship between the response (dependent) variable and explanatory(independent) variable and.

Multiple regression, models dependent variables or multiple responses with a single set of predictor variables.

In the multiple linear regression model, Y has normal distribution with mean and follows the below equation 3-4;

$$Y = \beta_0 + \beta_1 X_1 + \ldots\ldots \beta_\rho X_\rho + \in \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3\text{-}4)$$

β_0 = intercept

Y = dependent variable

$\beta_1,\ldots, \beta_\rho$ = regression coefficients

$\in$= model's error terms

Below are the assumptions of the multiple regression model is based on:

- The relationship between the independent variable and the dependent variable is linear
- The correlation between the independent variables are at aa minimal
- Observations are selected from the population randomly and independently
- Residuals have a mean 0 and variance σ normally distribution (Adam Hayes , 2021).

3.6 Time Series Analysis

As there were data of produced quantity (finished goods / Manufactured quantity) by the apparel company as well as the sold quantity, time series analysis was conducted to see whether it is possible to come up with a time series model that would be best fitted for the data.

Time Series Decomposition

From the time series decomposition, it is the process of simply decomposing or rather deconstructing a time series. Under Trend it gives the general movement over time, the individual seasonal periods are derived by the seasonal component while everything that is not captured under the trend and the seasonal components are captured under the residuals. There are two main decomposition models, namely additive and multiplicative model. However, in real life data, there could be issues with model selection, overfitting, and multicollinearity. The mean absolute percent error (MAPE), The mean absolute deviation (MAD) and The mean square deviation (MSD) are different types of error percentages that are calculated to measure the accuracy of the models (Minitab, 2018).

Based on the results, if the data does not fit the model well with additive or the multiplicative model, it was further carried out different time series models.

3.6.1 Box Jenkins Methodology

by George Box and Gwilym Jenkins came up with the Box-Jenkins method of systematic time series modelling with integrated autoregressive, moving average (ARIMA). There are two main categories under each, where deterministic is covered if the future value can be determined by a mathematical formula. Stochastic process is where the values are determined on probability distribution (NCSS, 2020).
The flow diagram of Box Jenkins methodology is presented under the figure 3-4 (Brownlee, 2020).

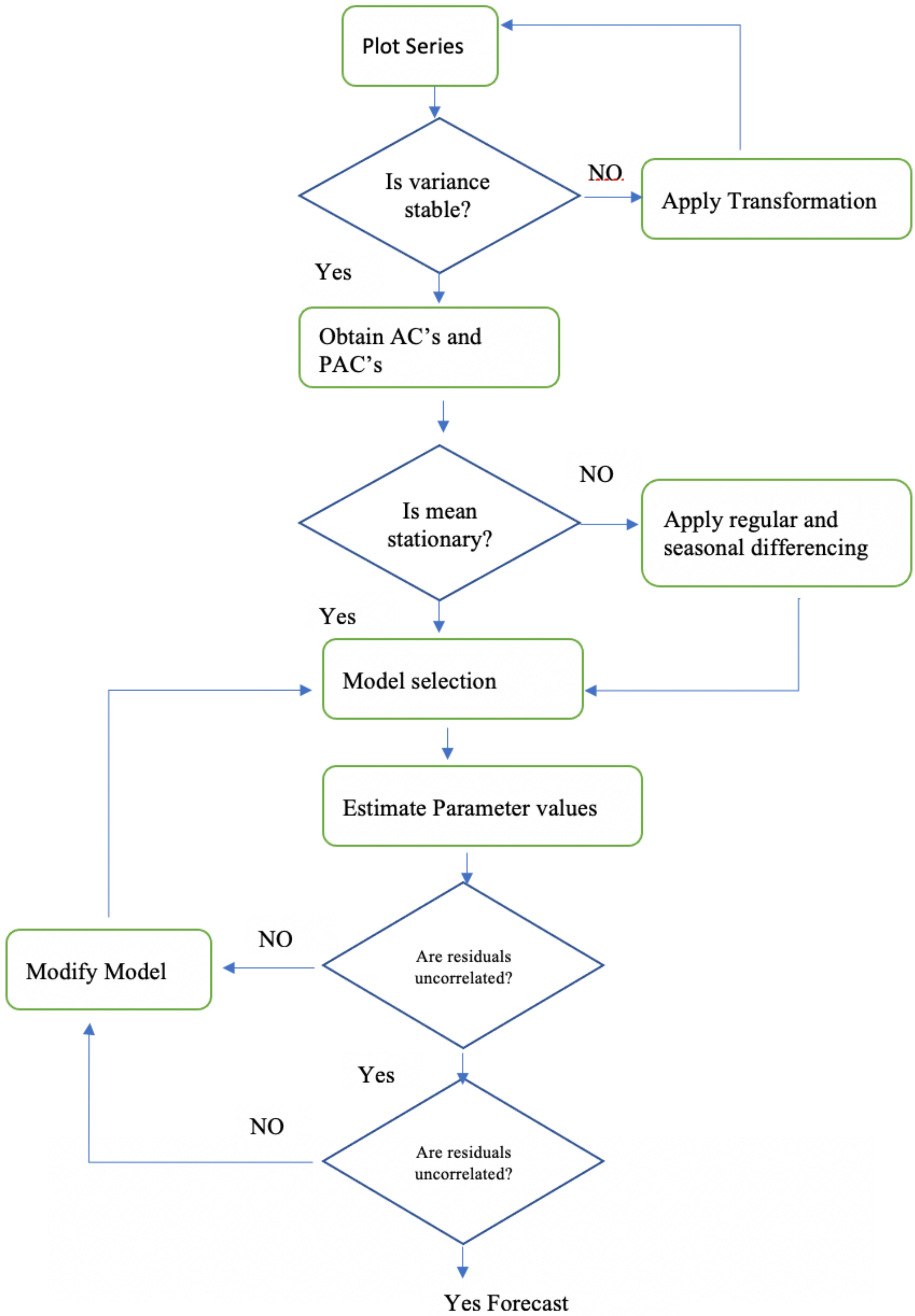

Figure 3-4: Box Jenkins methodology

The test statistics of the Ljung Box Statistic is as follows ,

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j} \ldots\ldots (3\text{-}5)$$

N= number of usable data points after any differencing operations

r_j = accumulated sample autocorrelations
m= up to any specified time lag

Further studies about ARIMA model building will be discussed as follows.

3.6.2 Autoregressive Integrated Moving Average Model

The Autoregressive Integrated Moving Average Model (ARIMA) explains a given time series on different areas where it explains based on its past values, its own lags and the lagged forecast errors.

When stationary is not an issue, the autoregressive integrated moving average model can be define under equation 3-6;

$$Y_t = \sum_{i=1}^{p} \emptyset_i Y_{t-1} + a_t - \sum_{j=1}^{q} \theta_j a_{t-j} \ldots\ldots (3\text{-}6)$$

Autoregressive parameters that are needed to be estimated are $\emptyset_i .. \emptyset_p$ while moving average parameters would be under $\theta_1 \ldots..\theta_j$ and series of unknown random errors which follow a normal distribution lies with $a_1 \ldots a_t$.

Definitions of the parameters of the ARIMA(p,d,q) model would be as follows:

- **p**: Lag order. This defines the number of lag observations
- **d**: Degree of differenced. This depicts the number of times that the raw observations are differenced.

- **q**: Order of moving average. This defines the size of the moving average (Prabhakaran, 2021).

Once the model is fitted for a data set, it is necessary that the assumptions of the model, model in the raw observations and in the residual errors of the forecast from the model need to be validated (Brownlee, Machine Learning Mastery , 2017).

3.6.3 Stationarity Of The Time Series

When a time series has mean, variance and autocorrelation constant over time, it is known to be a stationary time series. An important part of the process of fitting an ARIMA model is differencing a time series model to make it stationary.

Augmented Dickey Fuller Test

Augmented Dickey Fuller test (ADF Test) is used to check the unit root nonstationary of the series.

$H_0 : \gamma = 0$ vs. $H_1 : \gamma < 0$

$$DF = \frac{\hat{\gamma}}{SE\ (\hat{\gamma})}$$

To compare with the relevant critical value for the Dickey-fuller test, value for the test statistics need to be computed.

$$Y(t) = c + \beta_t + \alpha y_{t-1} + \phi \Delta y_{t-1} + e_t \quad \text{(3-7)}$$

where,

- y(t-1) = Time series lag 1
- delta Y(t-1) = This depicts the first difference of the series at time (t-1)

The coefficient of Y(t-1) is 1, implies the presence of a unit root. The series is taken to be non-stationary if not rejected. This means, the p-value < level (0.05) leads to rejection of the null hypothesis. Thereby inferring that the series is stationary (Otext, 2020).

3.6.4 Multivariate Time Series Analysis

When time dependent variables are more than one, multivariate time series are used. It is considered that each variable depends both on the previous values as well as it has some dependency on other variables as well. For forecasting this dependency will be considered.

For multivariate time series, Vector Auto Regression (VAR) commonly used.

The VAR model consist with the linear function of past values of itself as well as the past values of the other variables.

Let Y_t = ($y_{1t,}$ $y_{2t,}$ ....y_{nt}) depicts an (n*1) of time series variable vector. The basic p-lag vector autoregressive (VAR(p)) model under the equation 3-8.

$$Y_t = c + + \prod_1 Y_{t-1} + \prod_2 Y_{t-2} + \ldots\ldots \prod_p Y_{t-p} + \epsilon_t, \quad t=1 \ldots T \quad \ldots\ldots\ldots\ldots \text{(3-8)}$$

The (n×n) coefficient matrices are denoted by Πi and $\epsilon_{t,}$ is an (n × 1), invariant covariance matrix which denotes serially uncorrelated or independent, unobservable zero mean white noise vector process.

This can be explained in a simple mathematical equation as follows,

For calculating $y_1(t)$, previous values of y_1 and y_2 are used and similarly to calculate $y_2(t)$ previous values of y_2 and y_1 are being used. Mathematical way of presenting this combination is given below:

$$y_1(t) = a_1 + w_1 11 * y_1(t-1) + w_1 12 * y_2(t-1) + e_1(t-1)$$

$$y_2(t) = a_2 + w_1 21 * y_1(t-1) + w_1 22 * y_2(t-1) + e_2(t-1) \quad \ldots\ldots\ldots\ldots \text{(3-9)}$$

Here,

- The constant terms are a_1 and a_2,
- w_{11}, w_{12}, w_{21}, and w_{22} are the coefficients,
- Error terms are e_1 and e_2,

These equations are similar to the equation of an AR process.

Multivariate vector white noise is represented by the term ε_t in the equation. ε_t should be a continuous random vector. Following conditions should be satisfied too:

1. $E(\varepsilon_t) = 0$
2. Expected value for the error vector is 0
3. $E(\varepsilon_{t1},\varepsilon_{t2}') = \sigma_{12}$

Expected value of ε_t and ε_t' is the standard deviation of the series (Singh, 2018).

Steps of building a VAR model in R.

1. Packages like urca, vars, sandwich, lmtest, mFilters, tseries, forecast and tidyverse need to be installed.
2. It would be ideal to have a stationary variable in a VAR model. However, even without the stationarity of the time series, we still can build the VAR model (Smith, 2017).
3. To formally estimate our VAR, variables were bind together and some lag order was determined.
4. The lag order based on the multivariate iterations of the AIC, SBIC, HQIC and the FPE, will generate automatically. These are different kind of criteria to determine the lag order (Christoph Hanck, 2020).
5. Then the model will be estimated using the VAR function in R.
6. For model diagnostics in VAR series of steps will be taken. It was necessary to check whether the residuals are non-autocorrelated, presence of heteroscedasticity, Normality distribution of the residuals and stability test.

7. Policy Simulation in VAR model is done under 3 categories namely, Granger causality, impulse response and forecast error variance.
8. Then finally a forecast could be based on the model developed which is validating diagnostic tests as well (Alam, towards data Science , 2020).

3.7 Queuing Theory Application

In this study basic concepts were accomplished in accordance with the objective of the study.

Following steps were conducted under the study.

1. Considered the production average as the service rate and the selling quantity average as the arrival rate.
2. Analyse the arriving and leaving data by Chi-Squared Goodness Test to determine its variable distribution. This is to ensure that the queuing theory can be applied for exponential or poison distributions.
3. Conduct performance measures and measured the utilization factor (**ρ**).
4. Conduct the calculation based on number of parts in the system, number of parts in the queue, waiting time spend in the queue.
5. Equation to calculate each of the above would be as follows.

$$\rho = \frac{\lambda}{\mu} \qquad \text{(3-10)}$$

From λ it derives the average number of garments (finished goods) arriving in to the system at one unit of time. μ define the average number of garments (finished goods) servicing out of the system at one unit of time.

Percentage of idle work would be: (1- ρ)100%

Number of parts in the system, L_s would be define as follows, under equation 3-11

$$L_{s} = \frac{\lambda}{\mu - \lambda} \qquad \text{(3-11)}$$

Another important aspect to be considered was L_q , number of parts in the queue, which can be shown under the equation 3-12.

$$L_q = \frac{\lambda^2}{\mu(\mu-\lambda)} \quad \text{......(3- 12)}$$

Waiting time spent in the queue was W_q , the equation for the waiting time spent in the queue would be as follows, under the equation 3-13.

$$W_q = \frac{L_q}{\lambda} \quad \text{...... (3-13)}$$

Waiting time spent in the system would be derived under W_s , the equation for that would be, under the equation 3-14.

$$W_s = W_q + \frac{1}{\mu} \quad \text{......(3-14)}$$

Based on the above equations, certain calculations were derived and general guidelines were derived which will be discussed in the next chapter (Muhammad Marsudi, 2014). Queuing Model could be derived as follows,

$$(a\ /\ b\ /\ c): (d\ /\ e\ /\ f)$$

a = Denotes the distribution of the arrival

b = Denotes the departures (service time) distribution

c = Indicates the number of parallel servers $(1,2, \ldots \infty)$

d = Indicates queue discipline

e = Indicates the maximum number (finite or infinite) allowed in the system (in-queue plus in-service)

f = Size of the calling source (finite or infinite)

3.8 Stock Percentage Reduction Approach

Further analysis of data lead to the step by step approach is suggested to come up with reduction of order quantity that need to be produced. This approach may be looked upon on yearly basis and then cascade down it to quarterly basis.
The three main parameters that we are considering would be, produced quantity, Sold quantity and the remaining quantity.

Remaining quantity was always the cumulative figure, which is rather the total of the remaining quantity which was carried forward from the previous month. Hence to occupy the demand on a particular month, the produced quantity of that month along with the remaining quantity from the previous month would be considered. Further, at the end of each year it is assumed that only 50% of the remaining quantity will be brought forward for the next year. This was considered, as the brand does not wants to sell the finished goods which were produced over a year ago and hence the cut off was taken at the end of each year.

The tabular illustration of how the finished goods distribute would be as follows: Table 3-1: Finished good quantity distribution

Year	Produced Qty	Remaining Qty	Qty available to sell	Sold Qty	Remaining Qty at the store
Y1 Jan	100		100	75	25
Y1 Feb	200	25	200+25 = 225	210	225-210 = 15
Y1 Mar	150	15	150+15 = 165	100	165-100 = 65
Y1 Dec	100	25	100+25 = 125	100	125-100 = 25
Y2 Jan	250	25*50% = 12	250+12 = 262	100	262-100 = 162

Based on the above table 3-1, finished good distribution, to reduce the stock count the approach that would be suggested can be cascade down into 2 segments.
Segment 1 with yearly approach and the segment 2 would be quarterly approach.

Yearly approach would be to consider the least number of stock remaining month and then come up with a logical approach that quantity could be removed from the beginning of the year. To keep some space for any sudden demand fluctuations, it was necessary to come up with a plan of reducing only a percentage of quantity.
Likewise, this could be repeated over the years to understand the percentage reduction that could be suggested for the brand as well as the producing company.
Similarly, this same plan could be cascade down for quarterly basis which would lead to the final objective to improve the supply chain transparency.

The yearly approach of reducing the production quantity is shown in tabular approach format as bellow, under the table 3-2.

Table 3-2: Quantity that can be reduced on yearly basis

Year	Produced Qty	New Qty to produced	Remaining Qty	Qty available to sell	Sold Qty	Remaining Qty at the store
Y1 Jan	100	=100-15=85		85	75	10
Y1 Feb	200		10	200+10 = 210	210	210-210 = 0
Y1 Mar	150		0	150+0 = 150	100	125-100 = 25
Y1 Dec	100	25	100+25 = 125	100	125-100 = 25	125-100 = 25
Y2 Jan	250		25*50% = 12	250+12 = 262	100	262-100 = 162

Table 3-3: Quantity distribution after the reduction of initial quantity

Year	Produced Qty	Remaining Qty	Qty available to sell	Sold Qty	Remaining Qty at the store
Y1 Jan	100		100	75	25
Y1 Feb	200	25	200+25 = 225	210	225-210 = 15
Y1 Mar	150	15	150+15 = 125	100	125-100 = 25
Y1 Dec	150	15	150+15 = 125	100	125-100 = 25
Y2 Jan	250	25*50% = 12	250+12 = 262	100	262-100 = 162

As shown in above table 3-3, the same could be applied to actual data and further on quarterly basis.

4 DATA ANALYSIS

From this chapter, the data analysis is carried out to build a suitable model for a better prediction of the quantity that company may produce and reduce the stocked quantity leading to minimize the working capital.

4.1 Data Analysis Methodology Steps

1. Conduct Time Series analysis of "Mula" product, produced quantity and "Mula" product sold units.
2. Apply queuing theory techniques to improve the operational excellence.
3. Determine the stock quantity against the production and sold quantity.
4. Construct confidence Interval of the stock quantity.

4.2 Descriptive Statistics

Data are summarized using descriptive statistics as per table 4-1.

Table 4-1: Average and Standard Deviation of manufactured and sold quantities

Year	Annual Average Quantity		Annual Standard Deviation	
	Manufactured	Sold	Manufactured	Sold
2015	28,518	25,764	14,990	14,147
2016	30,209	26,709	15,749	15,511
2017	30,777	28,274	15,982	16,427
2018	31,256	29,169	19,608	19,035
2019	31,509	30,113	21,678	17,916

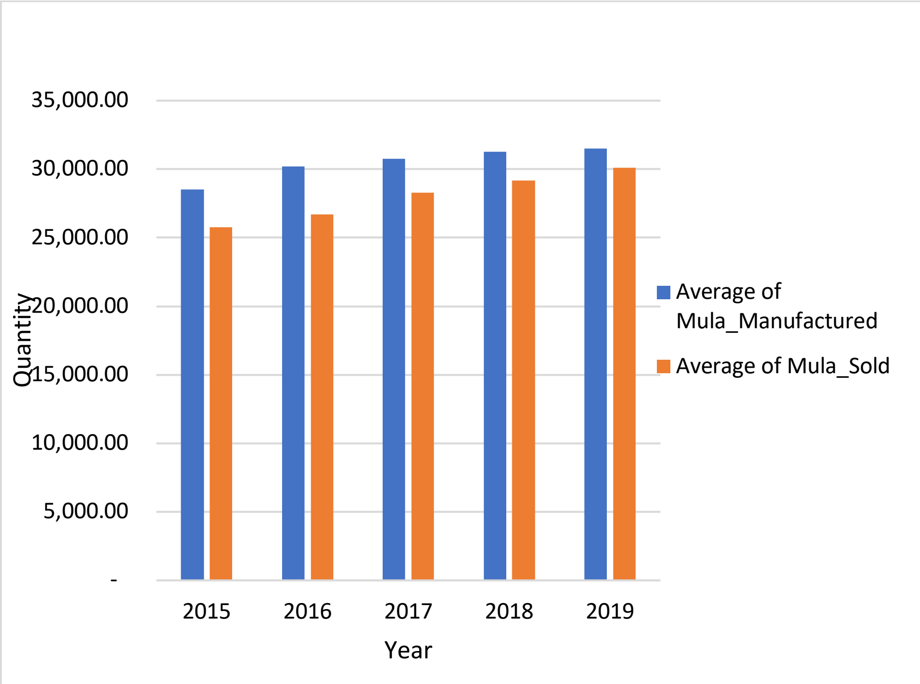

Figure 4-1: Graph of average quantity - produced and sold

From the above table 4-1 and figure 4-1, it shows how the average of the manufactured and sold quantity has been varied. It shows a continuous growth over the years. It clearly shows that the average sold quantity is lower than the average manufactured quantity in each year.

Further over the five years there is a higher standard deviation on each year which explains how far each value varies from the mean. As per the figures it depicts that the data set is more variable.

It is important to understand the correlation of the manufactured and sold quantities as well and Pearson correlation coefficient was produced along with the scatter plot in figure 4.2.

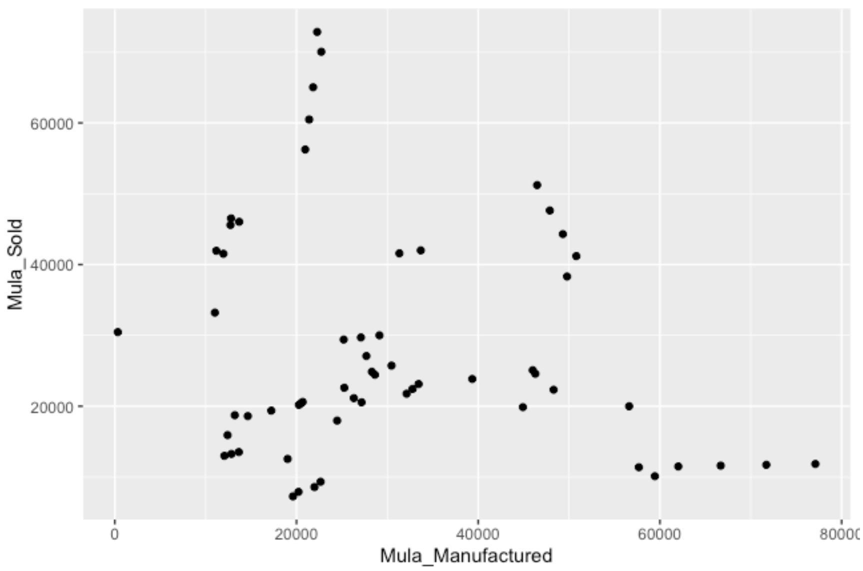

Figure 4-2: Scatter plot for Mula _ manufactured and Mula_sold

From the above scatter plot, under the figure 4-2, of Manufactured and Sold quantity it depicts that there isn't much of a relationship between these two variables as the data points has been scattered all over. This is statistically depicted with the Pearson correlation where the p-value of the test is 0.1532 >significance level alpha=0.05, where we can conclude that the manufacturing and sold quantity are not significantly correlated. The correlation coefficient is also -0.18, which is a very less value.

As the correlation is very low, a multiple linear regression model will not be adequate. A model was tried out, however the R squared was very low implying the model was not adequate. The results obtained was 0.01821(= 2%) for adjusted R squared with the p-value of 0.1532 which indicated that the regression model was not adequate.

4.3 Time Series Decomposition Analysis

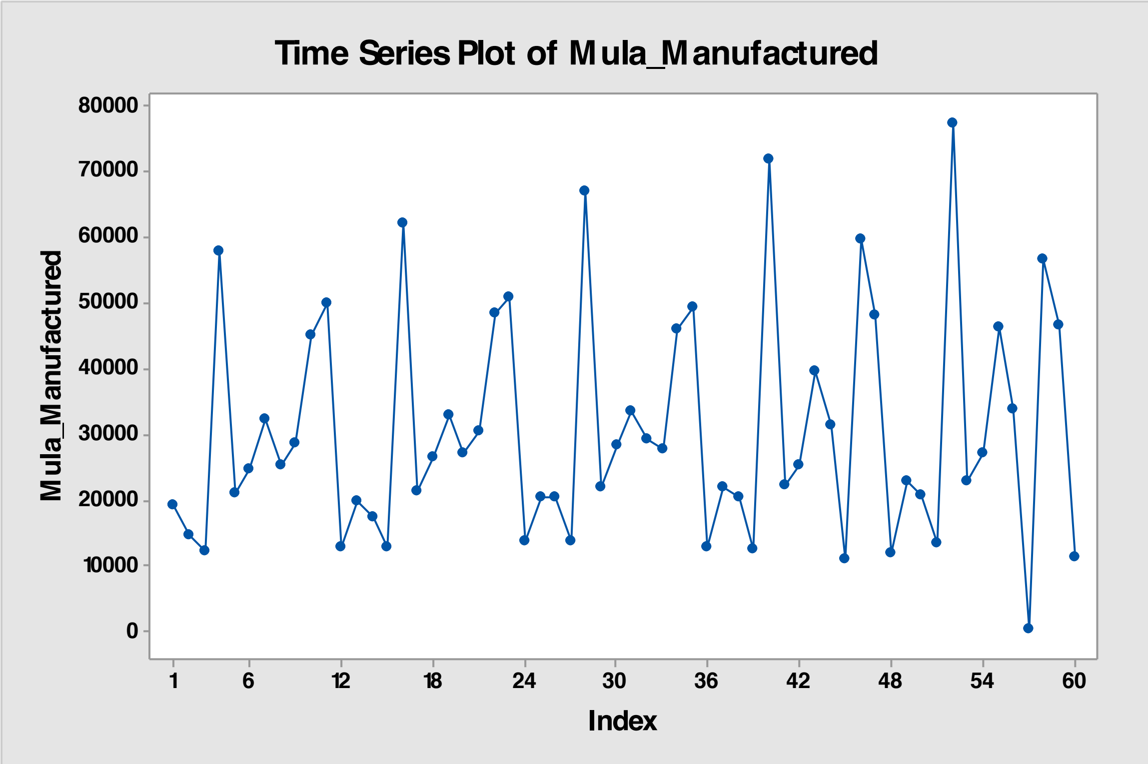

Figure 4-3: Time Series Plot of “Mula” manufactured

The above figure 4-3, has been drawn for the past 5 years of data with the actual produced quantity from the apparel company. The number of product units are initially predicted by the Brand. This will be given to the manufacturing company for them to produce.

From the above graph it shows that there seems to be a seasonal variation on the time series plot for the Mula manufactured goods graph. This further indicates with the spikes shown in certain months. This seasonal behaviour indicated that the brand is forecasting a massive sale amounts in every year towards the where these high production has been catered on mainly in September month. Also it shows that there is a middle year sales potential where there has been high produced quantity in March and April months.

Further towards the end of the time period considered, specifically during the time series of 54-60 there seems to be a decrement in the manufacture goods for this style. The main reason for this could have been a lower demand requested by client.
Based on the time series pattern it seems that the time series have an additive model and this will be statistically tested on below and further validate with the multiplicative model as well.

4.3.1 Time Series Additive Model Decomposition For Produced Quantity

To fixed a trend line and fix seasonal indices decomposition can be used. Therefore when the both trend and seasonal indices are fixed is the ideal scenario to use the decomposition. When the trend and the seasonality are consistent, we could use the decomposition to forecast. From various graphs, adequacy of the decomposition method will be studied.

Under the decomposition, we need to study the component analysis for the data set of “Mula” produced quantity. The graphical illustration of Component Analysis of Mula Manufactured quantity would be as follows.

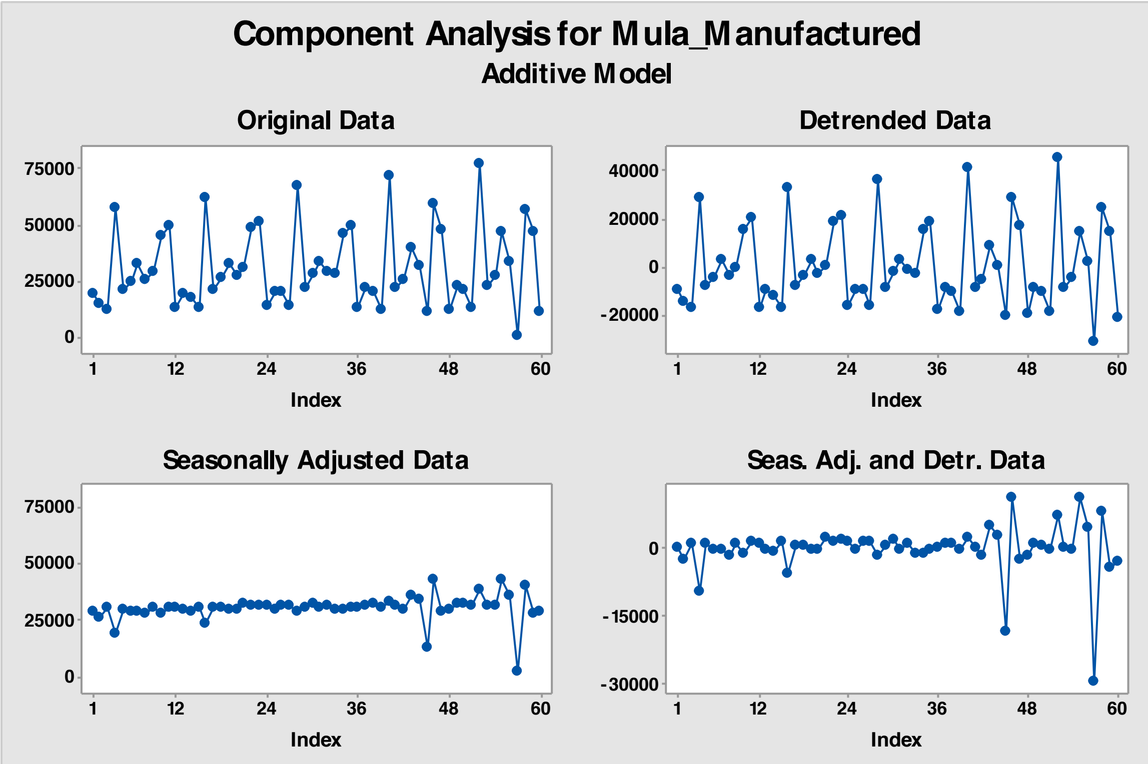

Figure 4-4: Component analysis of Mula manufactured

From the above figure 4-4, it shows that detrended data is the is the difference between the observed value and the trend value. The pattern of the detrended data clearly shows that it is similar to the original data pattern hence depicts that there is no trend component exit in the data. it further shows that the seasonally adjusted data look different from the original observations. Hence it can be concluded that a seasonal component exist in the data.

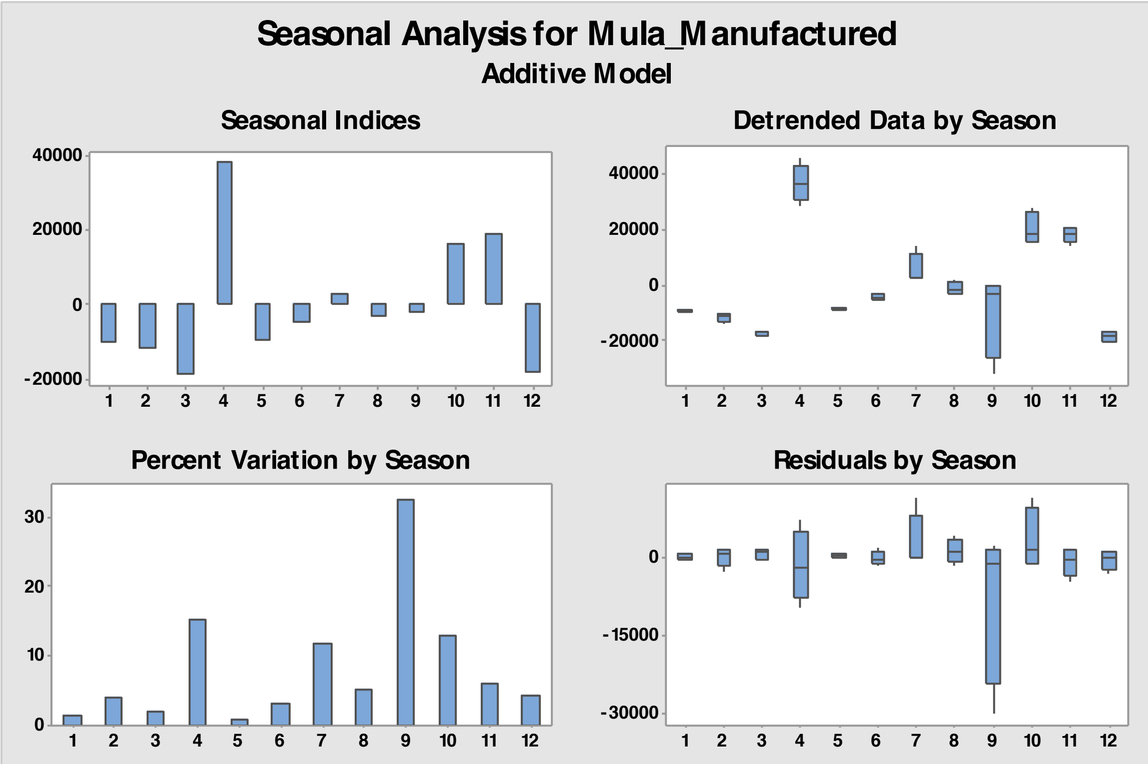

Figure 4-5: Seasonal analysis for Mula manufactured

From the above figure 4-5, it shows separate plots for the detrended data, the seasonally adjusted data, the seasonally adjusted and detrended data (the residuals). From the above plot it is indicated that there is a diminishing movement in the seasonal indices in the first 3 months and upwards movements in the 10 and 11 months. There seems to be not much of a pattern within 5 to 9 months. There is a sudden upward spike on the 4th month and spike on the 12th month as well. Least variation in the month of 1 depicts in the chart of percent variation by season and the 4th month shows the most variation. Having a spike on the 4th month on season indices and a comparatively higher variation on the percent variance it indicates that although there is a spike on the season indices the variation would be much higher.

The months where the seasonal effect is smaller, it is depicted in the boxplots of the detrended data by season. It clearly shows that the seasonal indices is smallest on the 9th month and hence it has the largest variation on the detrended data.

The difference between the observed values and the predicted values are determined by the residuals. Seasonal effect on the residuals could be determined by the plot. From the graph the residuals by season plot shows the highest variation on the 9^{th} month indices.

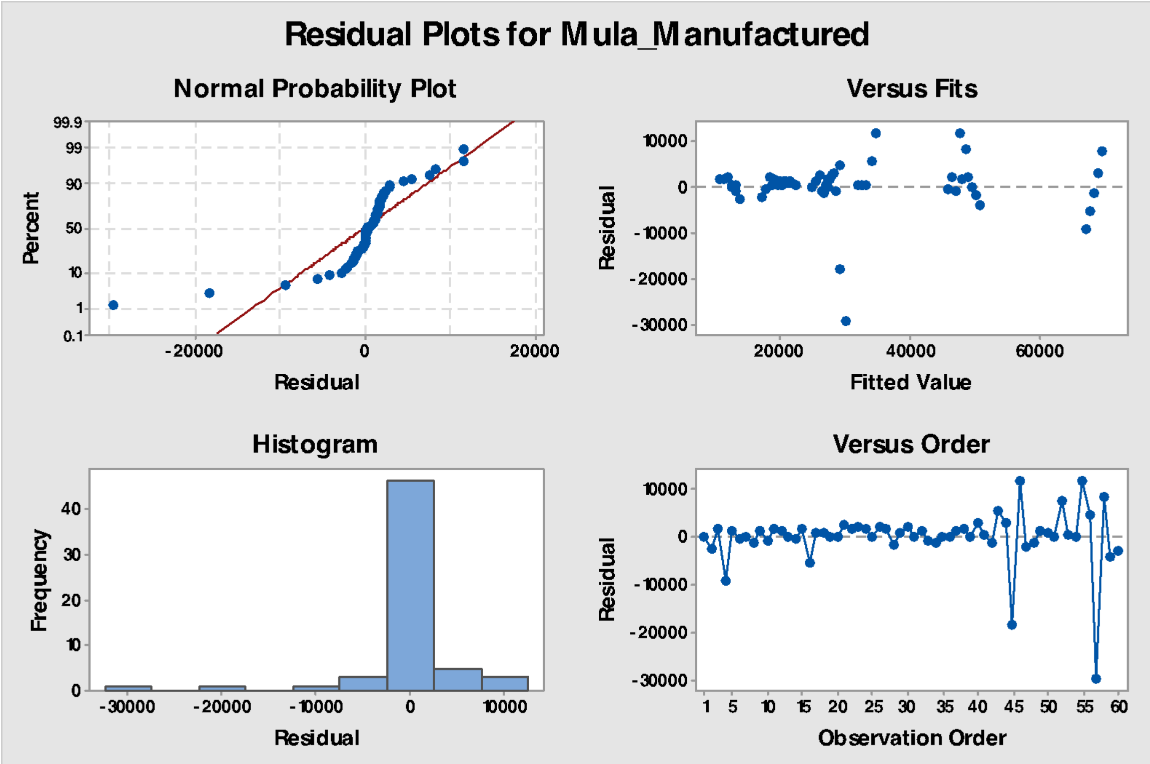

Figure 4-6: Residual Plots for Mula Manufactured - Additive Model

From the figure 4-6, it shows that under the histogram residuals shows the distribution is random around the mean of zero where it is approximately symmetric around zero.

However, from the normal Probability plot it shows that the residuals are not exactly on a straight line, but it’s approximately on either side of the probability plot, which is slightly close to a normal distribution.

The unbiasedness as well as the constant variance property of the residuals are determined by the residuals versus fits plot. To satisfy this property, there should not be any pattern in the point distribution in the graph where it should fall on both sides from zero in a random manner. From the above figure it shows that this plot satisfies this condition where data points are distributed without a proper pattern. From the above figure it shows that under the residuals versus order plot shows a pattern in the points. As there seems to be a pattern in the points it depicts that the model does not fit the data accordingly.

Based on above steps, time series plot with the fits were developed as follows,

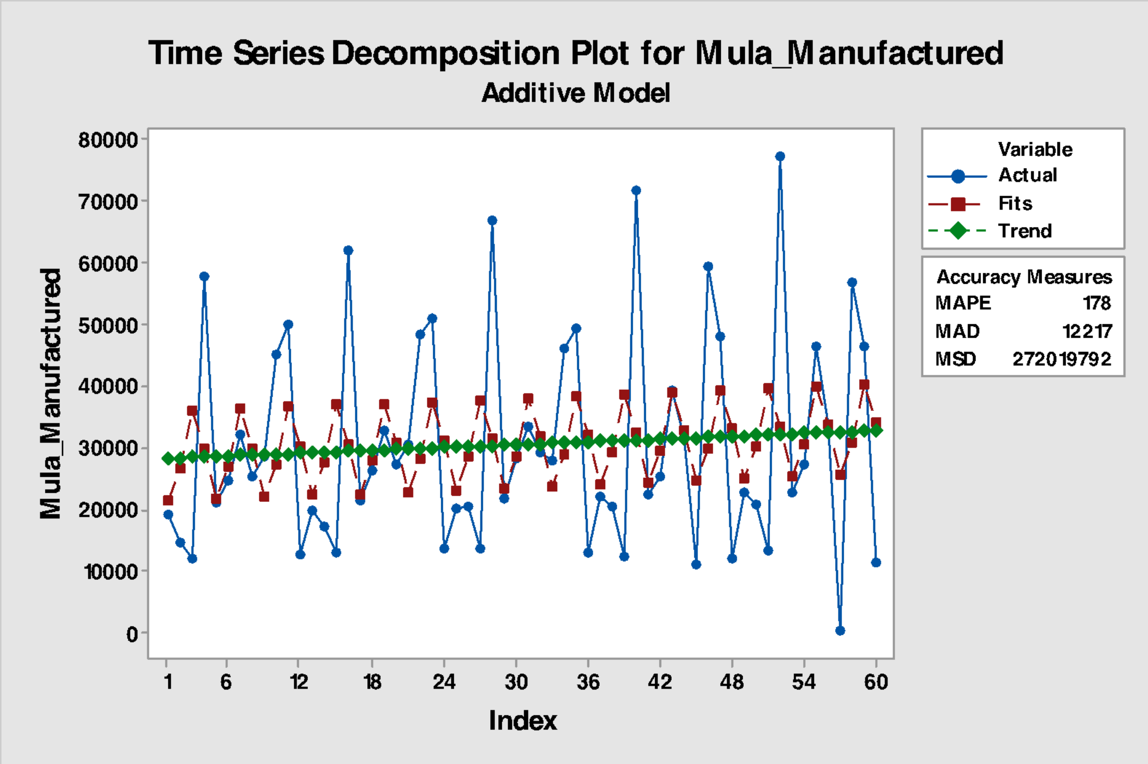

Figure 4-7: Time Series Plot of Decomposition of Additive model

From the above figure 4-7, it shows that the trend and seasonality are not fixed nor consistent where it depicts well with the error percentages also.

From the below tables also it shows the additive model equation which was derived with a constant linear trend. The equation given under the model is:

Forecast = 28787 + 54.7×Time (Equation given for the trend.)

It is necessary to identify that the fits match the actual values at the end of a time series, in case if there is less match with the seasonal pattern or tern, we may try other model fitting options. As per the fits on the graph it shows that fits are not aligning much with the actual figures. Further, based on the output figures derived, it shows that there are very higher figures for accuracy measures. From the model that has been fitted it depicts that the additive model is not a good fit for the produced quantity units of the Mula Brand.

However, there could be a chance that one or two outliers would lead to higher error component. Hence percentage error would be calculated. Based on the average percentage error it is only 0.07% against the forecast, which may suggest that the additive model would be suffice too.

To further analyze and check upon the multiplicative model adequacy for the Mula produced quantity, the same steps were followed as above. From the output derived it shows that the multiplicative model that was fitted for the data set was : Forecast $= 29230 + 33.6 \times t$.

However, when we compare the percentage errors on the model which is under Appendix 1 it shows how the percentage error has been varied over each month and the average percentage error for each model. By looking at the error distribution, it's difficult to see any pattern or come up with any conclusions.

The same process of decomposition will be conducted for Mula sold quantity as follows.

4.3.2 Time Series Multiplicative Model For Sold Quantity

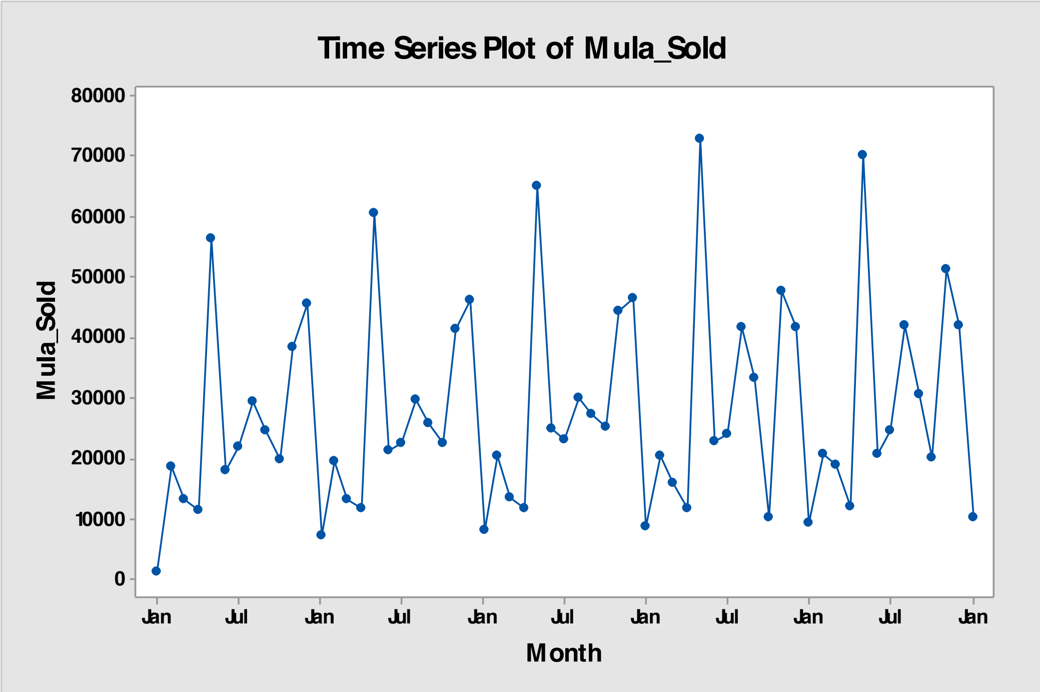

Figure 4-8: Time Series plot for Mula sold quantity

The Sold quantity of the data was given by the Brand end, where they take the count of number of sold quantity on each month. From the graph under the figure 4-9, it shows that the data set has a seasonal pattern for the data set and based on the data structure it shows that this has a multiplicative model. The same steps were carried out as per the manufactured quantity decomposition and the time series for Mula Sold quantity with the fits were derived as follows.

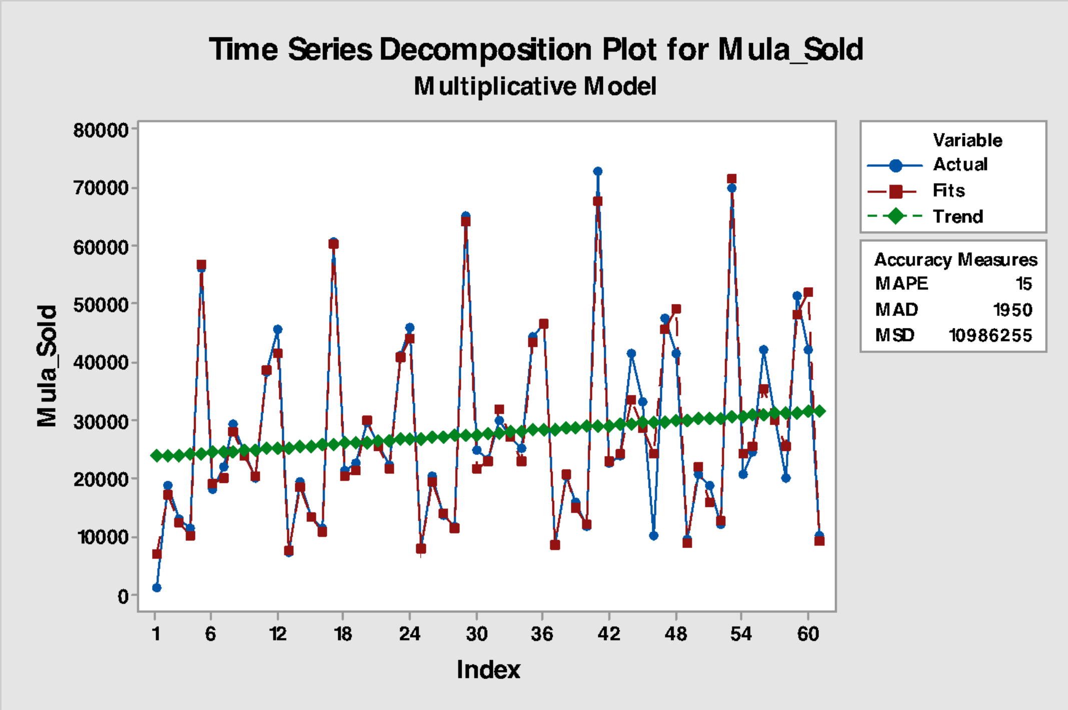

Figure 4-9: Time Series Decomposition plot for Mula sold quantity - Multiplicative model

From the above figure 4-10, it shows that on most of the months fits closely follow with the original data which indicates that that model fits the data. However, the accuracy measures taking a higher value question the model adequacy. Based on the data, multiplicative model that was fitted for the trend is: $Yt = 23565 + 131.4 \times t$

From the above graph and table with the equation given for the data although there depict a seasonal pattern, the accuracy measures are very low and hence the model adequacy is statistically questionable.

Further to statistically test the best model for the Sold Quantity as well ARIMA models were tried out too.

4.4 Summary of Chapter 4

From this chapter, it was analysed the basic descriptive statistics of the data set along with the time series decomposition method. From the basic statistics, it was derived that there has been a positive increment in the number of produced and sold quantity within the five years. There wasn't any relationship between the produced and sold quantity over the years and hence linear regression model was not adequate.

The forecast and the percentage accuracy under each decomposition method for next 5 years are as follows under table 4-3.

Table 4-2: Summary of the forecast decomposition method

			Produced Qty Models				Sold Qty Models	
Yr-Month	**Mula_Manufactured**	**Mula_Sold**	**Additive Model : Yt = 28787 + 54.7×t**	**Additive Model Percentage Error**	**Multiplicative Model : 29230 + 33.6×t**	**Multiplicative Model Percentage Error**	**Multiplicative Model : Yt = 23565 + 131.4×t for Season**	**Multiplicative Model Percentage Error**
2019 Jul	46288	24589	31795.5	46%	31078	49%	30792	-20%
2019 Aug	33678	42005	31850.2	6%	31111.6	8%	30923.4	36%
2019 Sep	330	30470	31904.9	-99%	31145.2	-99%	31054.8	-2%
2019 Oct	56612	20000	31959.6	77%	31178.8	82%	31186.2	-36%
2019 Nov	46486	51222	32014.3	45%	31212.4	49%	31317.6	64%
2019 Dec	11176	41948	32069	-65%	31246	-64%	31449	33%

From the above table it shows that the percentage error on both additive and multiplicative model has been varied in the last 6 months and overall months one will be shared in the Appendix 1. This depicts that the decomposition method error percentage may also vary and question about the adequacy of the model.

5 ADVANCED STATISTICAL ANALYSIS

This chapter has been devoted to time series model building, which are ARIMA modelling and multivariate forecasting for manufactured and sold combination along with the queuing theory application which leads to short term decision making too.

5.1 Time Series ARIMA Model For Produced Quantity

As Additive and multiplicative models may not be the ideal method of forecasting and hence Box-Genkins approach to find the suitable ARIMA models were tried out.
ACF plots and the PACFs plots were derived for non-differentiated time series.

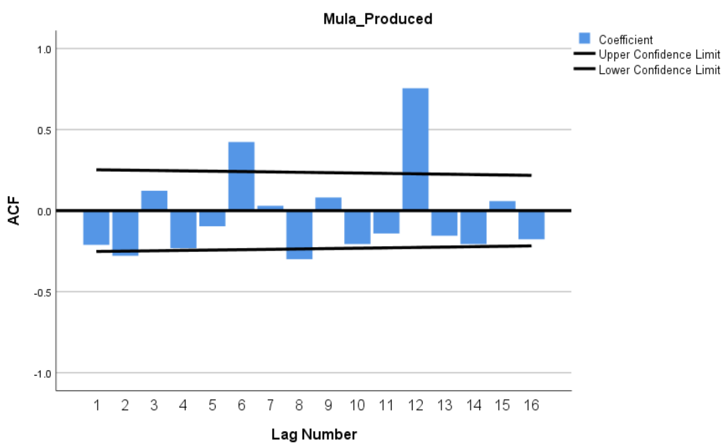

Figure 5-1: ACF plot for Mula produced qty

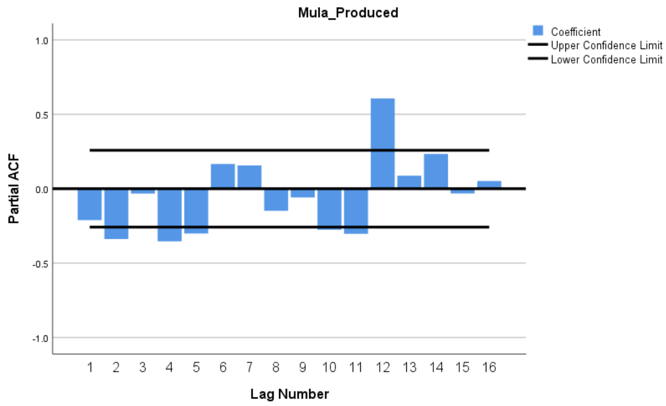

Figure 5-2: PACF plot got Mula produced quantity

From the above ACF and PACF graphs under figure 5-1 and figure 5-2, it doesn't show a clear indication on which ARIMA model would be useful. Further to understand whether the time series is stationary, Augmented Dickey Fuller test was conducted.

Table 5-1: Augmented Dickey Fuller test results

Augmented Dickey-Fuller Test		
Dickey-Fuller	Lag order	p-value
-6.7737	3	0.01
alternative hypothesis: stationary		

As depicted in the above table 5-1, since the p-value is less than .05, we reject the null hypothesis, which indicated that the time series is stationary.

By using the "auto.arima" command in R, a model was fitted for the manufactured goods, which would derive the best model possible by the software itself.

The model that was fitted was as below under the table 5-2,

Table 5-2: ARIMA model results

Model	ARIMA(0,0,1)(1,1,0)[12]	
Coefficients:	ma1	sar1
	-0.2332	0.3586
Standard Error	0.1308	0.1404
sigma^2 estimated as : 15136803		Log likelihood=-464.72
AIC=935.45	AICc=935.99	BIC=941.06

From the above table it shows that the model that has been best fitted for the data has not been differentiated, nor has the AR component, but has 1 moving average lags. However, it has 1 seasonal auto regressive lag along with the 1 seasonal differentiated lag. To further understand the model adequacy or the fit of the model, residuals were analysed as follows, under table 5-3,

Table 5-3: Ljung Box test results

Ljung_Box Test		
Data retrieved :	ARIMA (0,0,1)(1,1,0)[12]	
Q* = 6.3233	df=10	p value =0.7874

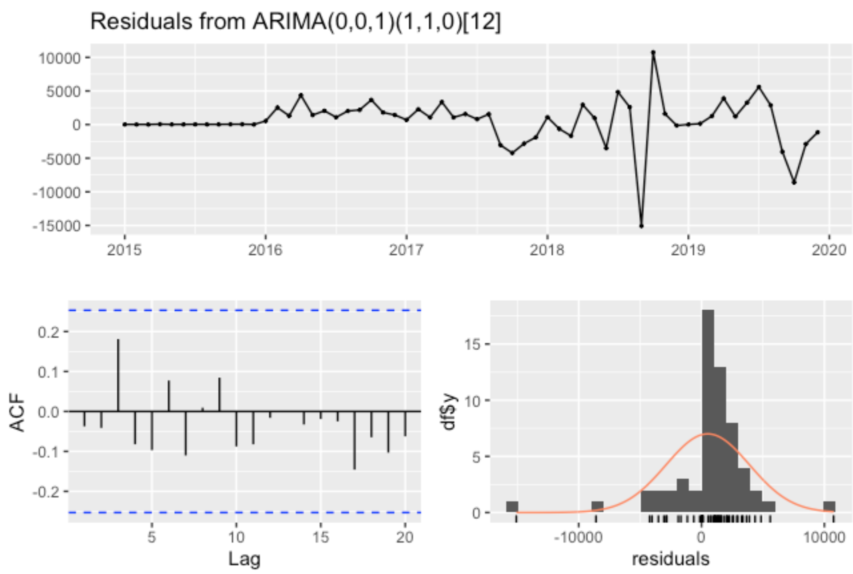

Figure 5-3: Residual of the ARIMA model

From the above table 5-3 and graph (figure 5-3) it shows that the residuals of the model follow a white noise where there aren't any lags which have gone beyond the ACF plot. Further from the normality plot it shows that the residuals follow a normal distribution. The Ljung-Box Model statistically test whether the residuals follow a white noise and it shows that p value is 0.7874, which implies not to reject the null hypothesis if that errors are white noise. Variation of the residuals shows under the time plot of the residuals seems to have few outliers as per the graph and hence constant variance is questionable.

Based on the model parameters, forecast for the next 6 months were derived.

Forecast method: ARIMA(0,0,1)(1,1,0)[12]

Table 5-4: Forecast for manufactured quantity with confidence limits

Month	**Forecast**	**Lo 95**	**Hi 95**
Jan-20	23,170.05	15,544.60	30,795.49
Feb-20	20,751.23	12,921.18	28,581.28
Mar-20	13,489.01	5,658.96	21,319.05
Apr-20	79,046.69	71,216.65	86,876.74
May-20	22,890.16	15,060.11	30,720.21
Jun-20	27,843.69	20,013.64	35,673.74

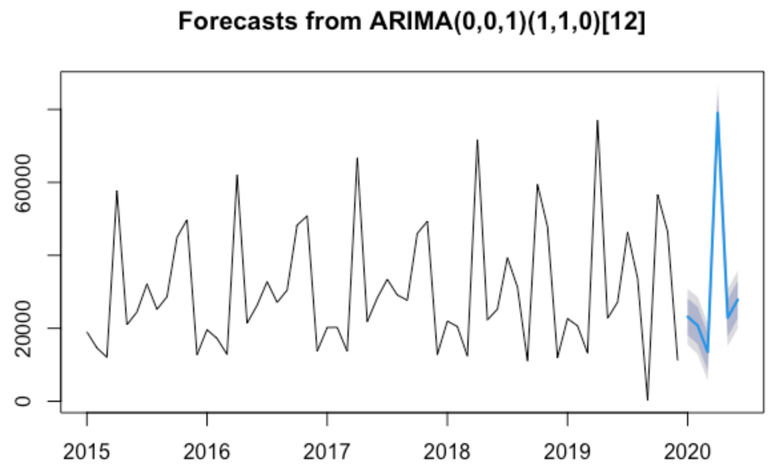

Figure 5-4: The graph of Forecast from ARIMA(0,0,1)(1,1,0)

From the table 5-4 it shows the estimated figures for the next 6 months with the upper and lower limits too. It depicts, that the forecast value derived from the model is near to the average value of observed data and further the upper confidence and the lower confidence limits are too broad.

Hence the model adequacy would be questionable for this model.

5.2 Time Series ARIMA Model For Sold Quantity

To understand whether an ARIMA model would be a better fit for the data set, ACF and PACFs plots were derived.

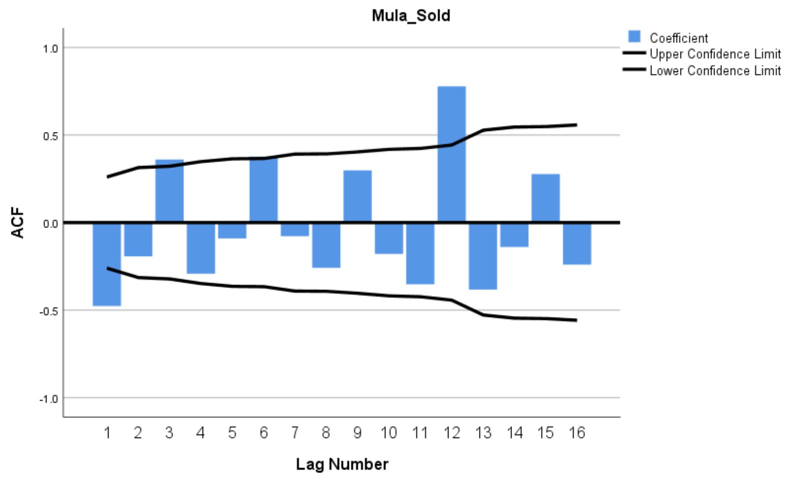

Figure 5-5: Mula sold quantity ACF plot

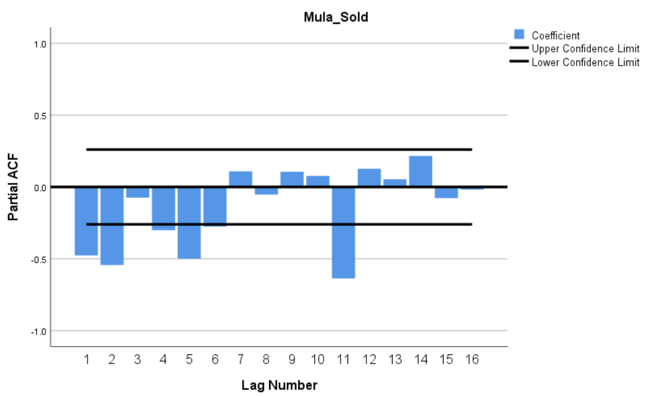

Figure 5-6: Mula sold quantity PACF plot

By looking at above 2 plots, under the figure 5-5 and figure 5-6 it is difficult to understand the exact model to be fitted and further, it was statistically tested whether the data set is stationary.

Table 5-5: Dickey Fuller test results for sold quantity

Dickey Fuller Test		
Test Statistics	Lag Order	p-value
-7.0866	3	0.01
Alternative hypothesis: stationary		

From the above table 5-5, it was derived that the data set is stationary, as the p-value is less than 0.05, and indicates that the data set is stationary.

To better understand the model to be fitted, "auto. Arima" function was used in R, and the results are as follows.

Table 5-6: ARIMA sold quantity results

Model	ARIMA(0,0,0)(0,1,1)[12]	
	sma1	drift
Coefficients	-0.2235	91.7458
Standard Error	0.1445	37.8036
sigma^2 estimated as 14638146		
log likelihood=-463.37		
AIC	AICc	BIC
932.75	933.29	938.36

From the above table 5-6, it shows that the model that has been best fit is where there is a seasonal lag on differentiated component along the moving average component. The model adequacy will be studied by studying residual components.

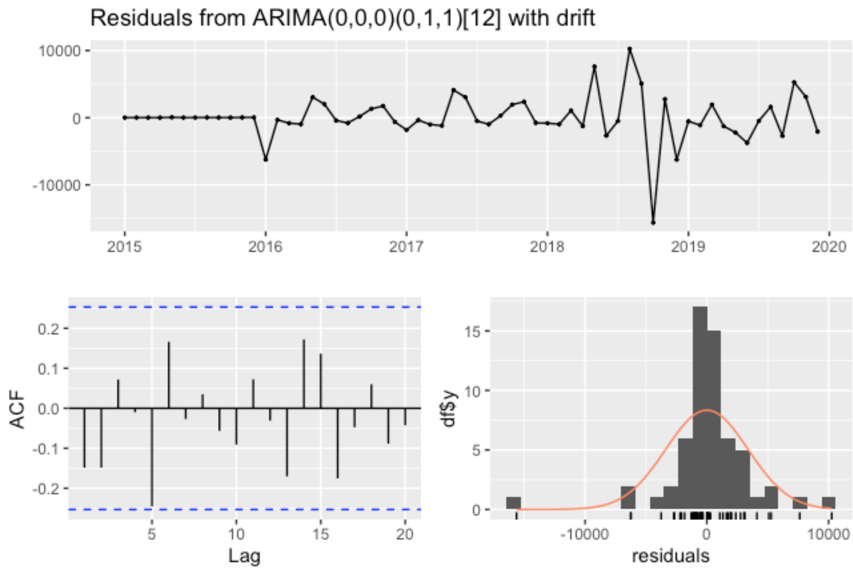

Figure 5-7: Graphs of Residuals from ARIMA(0,0,0)(0,1,1) model

Table 5-7: Ljung-Box test results for sold quantity

Ljung-Box test		
Data	Residuals from ARIMA(0,0,0)(0,1,1)[12] with drift	
Test Statistics (Q*)	df	p-value
10.583	10	0.3909
Model df : 2	Total lags used: 12	

From the above table 5-7 and graph (figure 5-7) it shows that the residuals of the model follow a white noise where there aren't any lags which have gone beyond the ACF plot. Further from the normality plot it shows that normality distribution is depicted by the residuals. The Ljung-Box Model statistically test whether the residuals follow a white noise and it shows that p value is 0.3909, which do not reject the null hypothesis if that errors are white noise.

However as same with the produced quantity, the variation of the residuals depict under the time plot of residuals and hence the constant variance is questionable.

Based on the model, next 6 months' forecast was derived.

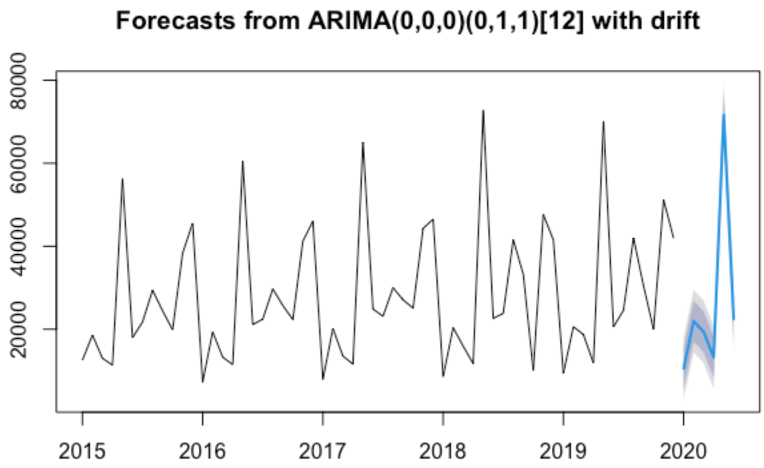

Figure 5-8: The graph of the forecast from ARIMA model for sold quantity

Table 5-8: Forecast figures from the ARIMA model for sold quantity

Month	**Forecast**	**Lo 95**	**Hi 95**
Jan-20	10,563.01	3,064.22	18,061.80
Feb-20	21,949.77	14,450.98	29,448.56
Mar-20	19,399.92	11,901.13	26,898.71
Apr-20	13,232.05	5,733.26	20,730.84
May-20	71,634.30	64,135.51	79,133.09
Jun-20	22,493.93	14,995.14	29,992.72

From the above graph (figure 5-8) and table 5-8 also it shows that the forecast is too wide for the model with upper and lower confidence levels.

To further understand and analyse better, as the models were fitted for individual data set, a multivariate time series will be derived combining both produced and sold quantity series.

5.3 Multivariate Time Series Analysis – VAR Model

Since the data has been checked for the stationarity, and it already confirmed that the data is stationary even without differencing that creates an ideal situation to carry out the VAR model.

Based on below output which was derived to identify the number of lags which need to be used for the model building. Since it has equal chance of selecting the model with 10 lags and 1 lag, the model with the lag 1 was chosen as it was derived by 2 of the multivariate iterations as well as to reduce the complexity of the equation. The equations for both manufactured and sold quantities are depicted under below table.

Table 5-9: Estimation results for manufactured and sold quantity

Statistics	Estimation equation for Manufactured quantity	Estimation equation for Sold quantity
	Manufactured = Manufactured.l1 + Sold.l1 + constant	Sold = Manufactured.l1 + Sold.l1 + constant.
Multiple R-Squared	0.1363	0.9457
Adjusted R-squared	0.1054	0.9438
F-statistic	4.418	487.9
DF	56	56
p-value	0.01653	< 2.2e-16

From the above tables, it depicts that the roots are below 1, which indicates they are within the unit root, which is necessary indicator for adequate VAR models. Also, although we do not typically interpret the coefficient of the VARs, it shows that each equation represents an equation in the VAR system.

The R squared adjusted value also shows the strong relationship of the model which is 59.6% for manufactured equation and 95.16% for the sold equation. Also the F statistic is very high where the p value is less than alpha (0.05) to reject H0. This indicate that this model is adequate.

Further model adequacy is checked by diagnostic tests.

Table 5-10: Model adequacy diagnostic test

Portmanteau Test (asymptotic)		
Data: Residuals of VAR object Model		
Chi-squared Test Statistics	df	p-value
55.447	8	3.61E-09

For model adequacy one of the assumptions is to check whether residual is non – auto correlated. From the above table 5-13, it shows that this was tested under "asymptotic" test and the p-value which is less than 0.05 indicates to reject H0, which implies residuals are not non- autocorrelated.

Another method to consider the model adequacy is to check the presence of heteroscedasticity. This was tested as follows.

Table 5-11: Model adequacy diagnostic test - ARCH

ARCH (multivariate)		
Data: Residuals of VAR object Model		
Chi-squared Test Statistics	df	p-value
111.81	108	3.82E-01

From the above table 5-14, it shows that the P value greater than 0.05, which lead not to reject null hypothesis, implies that the model does not have the heteroscedasticity effects. This identifies and clustered the volatility areas in a time series.

Another aspect to validate the model adequacy is to understands the normality of distribution of residuals. The residuals test in R, brings the following outputs under 3 tests, Jarque-Bera test, the Kurtosis Test, and the Skewness test.

Table 5-12: Model adequacy tests

Statistics	Data: Residuals of VAR object Model		
	JB-Test (multivariate)	$Skewness	$Kurtosis
Chi-squared Test Statistics	15.834	6.6666	9.1676
df	4	2	2
p-value	0.00325	0.03568	0.01022

However, based on all the three results, shown under the table 5-15, as the p-value is less that alpha (0.05), indicates to reject HO and therefore it insist that the residuals of this particular model are not normally distributed. Since it implies only a one aspect, we would further test for the stability of the model.

The presence of structural breaks are denoted by the stability tests. It is important to have structural breaks in order to have a robust estimation.

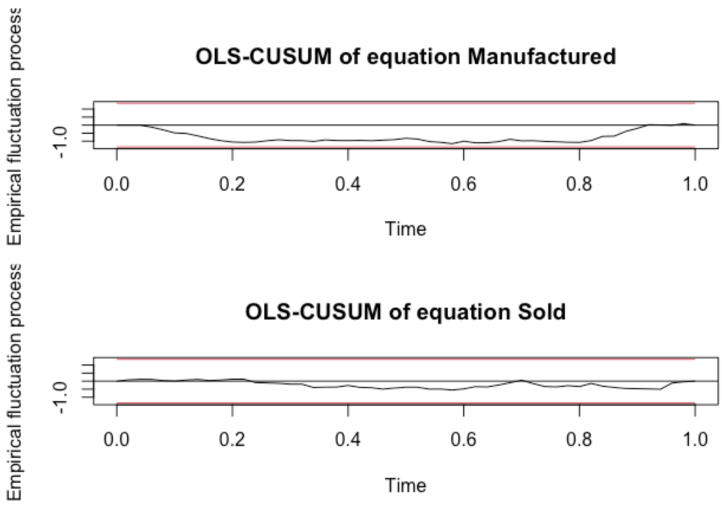

Figure 5-9: Model stability graphs

From the above graph under figure 5-9, it shows that respective confidence does not appear to be break and hence there seems no evident structural breaks which aligns that the model passes the particular test.

An overall Granger causality will be tested with each variable to understand whether there is a unidirectional, bidirectional or no causality relationships between variables (ScienceDirect, 2015).

Table 5-13: Policy simulations results

Data: VAR object Model			
$Granger	Granger causality H0: Sold do not Granger-cause Manufactured		
F-Test	df1	df2	p-value
2.7019	10	58	0.008623
$Instant	H0: No instantaneous causality between: Sold and Manufactured		
	Chi-squared	df	p-value
	0.019818	1	0.888

From the above table 5-16, we can conclude that the CPI granger causes the other variables and further there is no causality between the sold and manufactured quantities.

Next would be to understand the forecast error variance decomposition. This can be traced by understanding the shocks in our system to explain the forecast error variance of all the variables in the system.

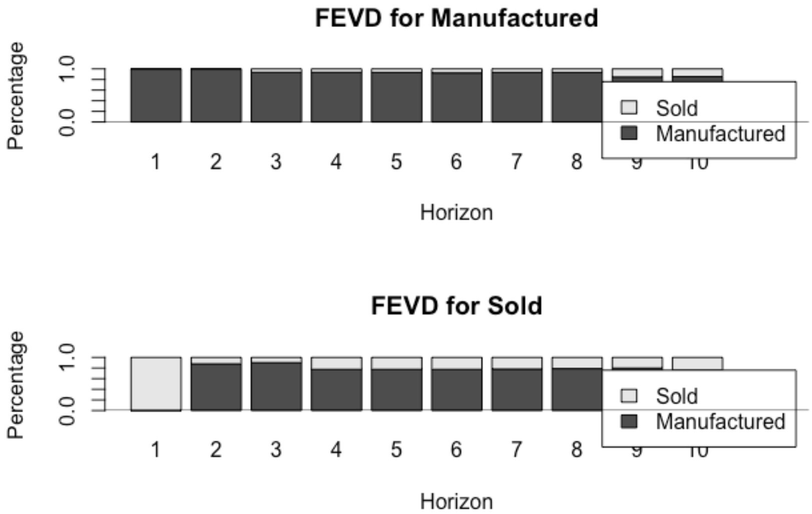

Figure 5-10: Error variance decomposition graphs

Based on the graphs under figure 5-10, it shows that the manufactured will not be impact much with the sold quantity in future, rather the manufactured itself.
However, for sold quantity, it shows that the first few forecasts will be impacted by the manufactured quantity, but rather it will decrease in future.

Finally, with the model creation the following forecast values have been derived.

Manufactured Quantity Forecast

Table 5-14: Forecast for the manufactured quantity

Month	Forecast	lower	upper	CI
Jan-20	31,323.89	(731.96)	63,379.74	32,055.85
Feb-20	36,174.85	2,857.62	69,492.09	33,317.24
Mar-20	28,887.55	(5,206.78)	62,981.88	34,094.33
Apr-20	29,385.46	(5,011.98)	63,782.90	34,397.44
May-20	31,421.16	(2,990.82)	65,833.14	34,411.98

Sold Quantity Forecast

Table 5-15: Forecast for the sold quantity

Month	Forecast	lower	upper	CI
Jan-20	10,300.55	2,767.79	17,833.31	7,532.76
Feb-20	28,714.40	(1,682.32)	59,111.13	30,396.73
Mar-20	33,225.73	1,727.47	64,723.99	31,498.26
Apr-20	26,544.87	(5,652.25)	58,742.00	32,197.13
May-20	26,982.28	(5,483.26)	59,447.82	32,465.54

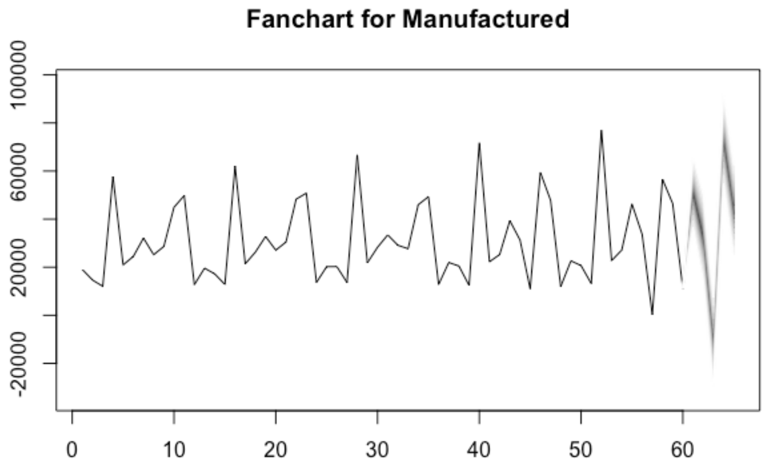

Figure 5-11: Graph of forecast for manufactured quantity

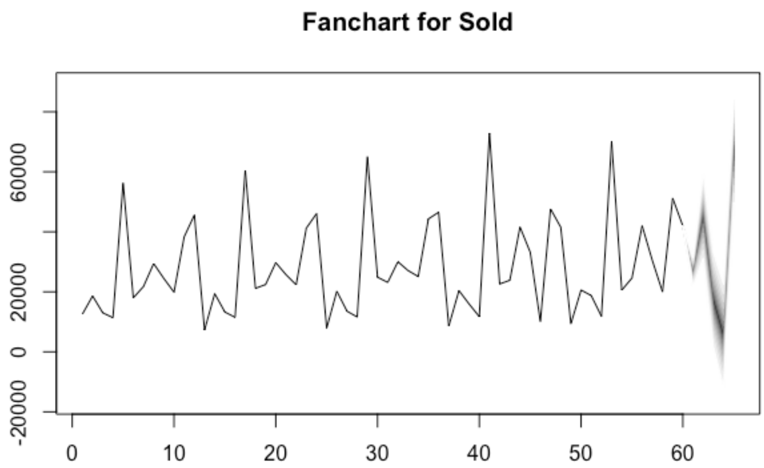

Figure 5-12 : Graph of the forecast of sold quantity

From the above the tables 5-17 and 5-18 and graphs 5-11 and 5-12, it depicts the forecasted figures along with the Upper and lower confidence figure with 95% Confidence interval. These data could be used to get a better understanding for the future predictions.

Nevertheless, it is necessary to understand that these models will not be 100% applicable with the practical data, however we would be able to derive a better forecasting method to improve the supply chain visibility.

5.4 Distribution of the Queuing Theory

Queuing theory application to this scenario was limited with the data availability and statistically it was difficult to come up with a queuing model that would best fit to improve the supply chain transparency, whereby to reduce the number of days' stocks last at the warehouse.

However, below steps were derived to understand about the scenario. Based on the data availability, following were derived.

For queuing model building, it is necessary to identify the arrival rate (λ) and the service rate (μ).

λ= Average number of units sold (Arrival rate) = 28005 per month.

(This was taken as the simple average of the number of sold units over the 5 years)

μ = Average number of units producing per month (Service rate) = 30453 per month

(This was taken as the simple average of the number of produced units over the 5 years)

Hence, we were able to see that service rate(μ) is greater than the arrival rate (λ). This depicts that there will be stock that will be stored in the storage.

In order to apply the queuing model, the data set need to have a poison or exponential distribution and this was calculated with the Chi- Square test.

Table 5-16: Chi Squared test results

Pearson's Chi-squared test		
X- squared Test Statistics	df	p-value
3540	3481	0.2385

Based on the above table 5-19, it shows that the p-value is greater than the alpha value (0.05) indicating that the chi-squared test is not significant. Hence this imply that the data may not have a proper poison or exponential distribution.
However, with the assumption that both arrival and service rate may have a poison distribution, following values were derived with the equations based on Queuing theory.

where, ρ is utilization factor, λ is average number of parts arriving in one unit of time, and μ is service rate to parts in one unit of time.

$\rho = \frac{\lambda}{\mu}$ ρ = 28005 / 30453 = 0.9196

Hence, it depicts that when one unit of produced garment is stored in the storage, only 0.91 unit will be sold.
For the number of parts in the system, following were derived. $L_{s=}\ \frac{\lambda}{\mu-\lambda}$
Ls = Number of parts in the system = 28005 / (30453 - 28005) = 11.44
This depicts at a point, number of units within the system. System includes the arrival units as well as the selling units.

To understand number of parts in the queue only, the following will be derived. $L_{q=}\ \frac{\lambda^2}{\mu(\mu-\lambda)}$
Lq = number of parts in queue = λ ^ 2 / (μ (μ- λ) = (28005^2)/ (30453(30453 – 28005)) = 10.52
From the above two equations it depicts that the number of parts in the system which is 11.44, the major portion is for the number of parts in the queue, which is 10.52.

The next important aspect to be studied was to understand the waiting time spent in the queue W_q, the equation for the waiting time spent in the queue would be as follows. $W_q = \frac{L_q}{\lambda}$
Wq = waiting time spent in queue = Lq/λ = 10.52/ 28005 =16.22 minutes

From this calculation it shows that the waiting time on the queue is very low, but when it comes to the mathematical calculation of the stock, it shows that there has been a lot of stock remaining. Due to limitations of the time period of data availability, other queuing models were not tried out and as per literature survey, more wholistic approach of queuing system could be used.

For this study, following short term method was derived too.

5.5 Reduction Of Working Capital By Reducing Production Quantity

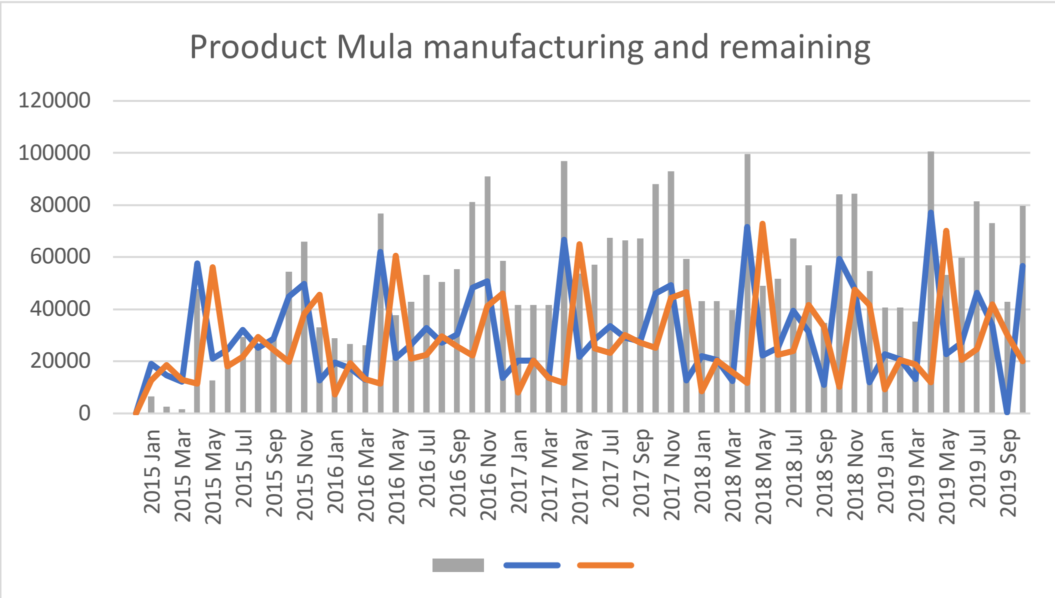

Figure 5-13: Manufactured, Sold and remaining Quantities on each month

Based on the above graph under figure 5-13, it shows that there are remaining production on each month, which is a wastage.

Hence it would be better if we can reduce this wastage, which will improve the worrking capital when the storage is less utilized and further prodcution cost can be reduced too.

Table 5-17: Remaining Quantity calculation on month wise

Yr-Month	Manufactured Qty	Sold Qty	Remaining		New_Manufactued	Sold	Remaining	Wastage
2015 Jan	19024	12560	6464		17929	12560	5369	1095
2015 Feb	14641	18607	2498		14641	18607	1403	1095
2015 Mar	12065	12999	1564		12065	12999	469	1095
2015 Apr	57682	11383	47863		57682	11383	46768	1095
2015 May	20962	56248	12577		20962	56248	11482	1095
2015 Jun	24470	17969	19078		24470	17969	17983	1095
2015 Jul	32119	21768	29429		32119	21768	28334	1095
2015 Aug	25194	29415	25208		25194	29415	24113	1095
2015 Sep	28631	24448	29391		28631	24448	28296	1095
2015 Oct	44919	19871	54439		44919	19871	53344	1095
2015 Nov	49781	38316	65904		49781	38316	64809	1095
2015 Dec	12733	45587	33050		12733	45587	31955	1095

Based on the above table 5-20, it shows that if we reduced the lowest remaining quantity from the first month of the production then we could reduce the remaining capacity from each month.

Yearly produced quantity reduction and thereby remaining quantity reduction is as follows. Hence this could be further developed to come up with a percentage of reduction in the production quantity against the original plan.

Table 5-18: Percentage reduction of the quantity on each year

Year	Produced Qty Reduction at the beginning of year	% of produced Qty reduction at the beginning of year	Stocked as per normal scenario	Stocked qty as per reduction of produced qty	Difference of stocked qty	% of reduced qty from the stock
2015	1,095	6%	327,465	314,325	13,140	4%
2016	18,394	94%	629,082	401,790	227,292	36%
2017	20,219	100%	773,851	417,583	356,268	46%
2018	21,977	100%	707,695	265,843	441,852	62%
2019	16,797	74%	726,150	303,666	422,484	58%

Hence based on this, which is illustrated under the table 5-12, it is clear that there is an opportunity to reduce the produced quantity at the beginning of each year. Hence the proposed would be to analyse this on quarterly basis and come up with the reduction of quantity to be produced at the beginning of each quarter.

With the percentage drops shown in above table, approximately 50% could be reduced on each year.

So this could be further developed on the percentage reduction on each year or quarterly reduction of produced quantity, which will further develop to reduce the production quantity as well.

5.6 Summary Of Chapter 5

From this chapter, it was analysed the produced quantity and sold quantity in time series ARIMA model as well as the VAR model. For the produced quantity ARIMA model that was built was ARIMA(0,0,1)(1,1,0)[12] where as per the residual analysis, model was adequate. For the Sold quantity, the ARIMA model that was developed was ARIMA(0,0,0)(0,1,1). A VAR model was developed too and as per the analysis it was derived that the model was adequate too.

The Queuing theory application was not much of a success to the data set, however it was identified the number of days (time) that the quantity was in stock as well as the system. The data set not been under the poison distribution, makes it questionable the usage of queuing theory for the data set.

Further, the last logical approach of understanding the initial quantity to be reduced at the beginning of the year, will be more appropriate option which can be further improved for the quarterly basis. It was identified that there is an opportunity to reduce the produced quantity and thereby to reduce the stocked quantity as well.

6 DISCUSSION, CONCLUSION, RECOMMENDATIONS AND FUTURE WORK

6.1 Discussion and Conclusion

The supply chain transparency is a vital aspect for any business entities improvement and this could be categorized into internal and external aspects. Externally, the end consumer would be interest in knowing the transparency of how the garments were produced. As the ethical and sustainable business is one of the key component consumers are looking at, external transparency would add value to any brand.

This study was focused for the internal supply chain visibility where the objective was to improve the visibility between the production company and the Brand or rather retail owner. The study was conducted using one style from a particular global brand. Monthly data was obtained for five years of produced (manufactured) goods and sold goods of that style to conduct this study.

This study was cascade down into few sections, initially a descriptive study was conducted to understand the overall behavior of the data set along with the time series decomposition for produced quantity as well as the sold quantity. Time series decomposition models were carried out for both of these series. As decomposition method was not the best to conclude with, ARIMA models were carried out separately for produced and sold quantity data series. However, the accuracy of these models was questionable when analyzing the error percentages of each model. Then, multiplicative model of VAR model was built upon, which was done by combining the both produced and sold quantity data series. Based on results obtained, as there was a higher variation in upper and lower confidence on the forecasted figures, it was necessary to carry out the other methods as well.

Queuing theory was applied to understand the queue waiting time of the finished goods which were stored inside the store room, before selling them. Looking at the queue time of the finished goods, it derived at a lower value, which was concerning when we look at the real figures of the finished good stored in the storage. This lead to come up with a mathematical calculation of reducing the wastage by producing lesser goods after evaluating the stock in previous years. Under this approach it was calculated to understand the previous year stock and hence come up with a percentage reduction of the quantity that we have to produce. This could be further improved to analyze on quarterly basis and thereby reduce the stock quantity on each quarter.

The short-term mathematical solution of reducing stock quantity will lead to operational and financial improvements in the company. Operations wise the wastage would be mitigated, because then the production will be done based on the requirement only. When the operations are improved, it directly impacts the financial gain too. Where this will help to improve the working capital of the organization as well as the day today financial gain. Therefore, until the data modeling would be appropriate after collecting more data, it would be best to concentrate for the short-term approach.

6.2 Recommendations

The extensive literature study conducted for this study shows that there have been appropriate statistical methods which have been carried out to forecast better with the time series models along with the soft computing like neural networks.

Also, in terms of queuing methodology, it has been carried out studies in a holistic manner for the entire system. However, with the limitations of this study carried out,

it is recommended to further look into the storage quantity, as there is substantial quantity that is stored. Further, if more data would be gathered, there could be a possibility to come up with a better forecasting method with the time series modeling.

6.3 Future Studies

Apparel industry is one of the main income generating industry in Sri Lanka and critically looking into these gaps would help to improve the business further. Hence following improvement points can be suggested.

- To further study the data points in future and look into the possibility of coming up with adequate time series modeling
- For model building, there could be various other factors that may affect for sales or production. Hence it would be appropriate to incorporate them to the model as well. Especially when coming up with multivariate time series, these components could be included into the time series and it would give a better model which speaks the data better.
- For time series model building, it was mostly suggested that soft computing is required where, AI model building along with the statistical models are required come up with better forecasting, especially for apparel industry. Hence for future studies it would be appropriate to come up with forecasting method which is a hybrid model with AI and statistical tools.
- To come up with queuing model building with simulations, which were mostly suggested by many literate review too. However, for this it is necessary to understand the system as a whole and then come up with a better simulation model.
- Some of the models for queuing theory that could be tried out are Markovian or poisson arrival or departures distribution or constant deterministic time queuing model

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