ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF MANAGEMENT

DEMAND FORECASTING OF SPARE PARTS: IN THE CASE OF MOENCO

A THESIS SUBMITTED TO A SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF BUSINESS ADMINSTRATION

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Certification

This is to certify that Belay Gebremariam has carried out this thesis work on the topic entitled “Demand Forecasting for Spare Parts Inventory Management” under my supervision. This is his original work and has not been presented to any other University for similar degree award and it can be submitted for the partial fulfillment of the requirements for the award of Masters of Business Administration.

Advisor: ________________

Signature: ________________

Declaration

I, Belay Gebremariam, declare that this thesis work is my own original work on the topic entitled “Demand Forecasting for Spare Parts Inventory Management” and that it has not been presented to any other University for similar or any other degree award. To this end, I acknowledged all sources of information that I used to produce the study appropriately and I would say perfectly.

Signature: ________________

Date: _________________

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List of tables

Table 1: Initial data collected from source ……………………………………………35

Table 2: Forecasted demand, error and MAPE value………………………………...41

Table 3: Safety stock value………………………………………………………...46

Table 4: Service rate, and inventory amount……………………………………....50

Table 5: Findings…………………………………………………………………...55

List of Figures

Figure 1: Needs for marketing forecast ……………………………………………9

Definitions of key terms and Abbreviation

After Sales: Services provided to the customers after products have been delivered.

Auto Correlation: A statistical measure that indicates the degree of correlation of random variable with itself.

Back Order: Customer demand cannot be met from stock, but the customer waits for the item to come into stock.

Binning: Placing parts in its particular location assigned.

CKD: Completely Knocked Down.

Customer Satisfaction: customer fulfilment response

OEM: Original Equipment Manufacturer.

Service Level: A measure of the proportion of customer demand met from stock.

SKD: Semi Knocked Down

SKU: Stock Keeping Units

Spare Part: Components, assemblies, and equipment that are completely interchangeable with like items installed or in use, which are used, or can be used, to replace items removed during maintenance and overhaul.

Table of Contents

1. Introduction …… 2
   1.1. Problem Statement …… 3
   1.2. Purpose of the study …… 5
   1.3. Research question …… 5
   1.4. Research objective …… 6
   1.5. Existing inventory system …… 6
2. Literature review …… 9
   2.1. Theoretical review …… 9
      2.1.1. Forecasting methods …… 10
         2.1.1.1 Methods based on judgment …… 10
            2.1.1.1.1. Unaided judgment …… 10
            2.1.1.1.2. Delphi …… 10
            2.1.1.1.3. Structured analogies …… 11
            2.1.1.1.4. Game theory …… 12
            2.1.1.1.5. Judgment decomposition …… 12
            2.1.1.1.6. Judgment bootstrapping …… 12
            2.1.1.1.7. Expert system …… 14
            2.1.1.1.8. Simulated interaction …… 14
            2.1.1.1.9. Intentions and expectation survey …… 15
            2.1.1.1.10. Conjoint analysis …… 17
         2.1.1.2 Methods requiring quantitative data …… 18
            2.1.1.2.1. Extrapolation …… 18
            2.1.1.2.2. Quantitative analogies …… 19
            2.1.1.2.3. Rule base forecasting …… 19
            2.1.1.2.4. Neural nets …… 20
            2.1.1.2.5. Data mining …… 20
            2.1.1.2.6. Casual method …… 21
            2.1.1.2.7. Segmentation …… 22
      2.1.2. Empirical review …… 23
         2.1.2.1 Intermittent demand forecasting …… 23
         2.1.2.2 Probability distribution of demand …… 26
3. Method …… 29
   3.1. Approximation demand forecasting method …… 29
   3.2. Research setting …… 31
   3.3. Sample selection …… 32
   3.4. Data analysis procedure …… 33
   3.5. Problems and limitations of the study …… 34
4. Finding …… 35
5. Discussion …… 56
6. Conclusion …… 58
7. References …… 61
8. Appendix I …… 70

Abstract

Holding optimum inventory and satisfying customers demand with sufficient service level is a challenging task. To keep a good balance between inventory level and sufficient service level implementing appropriate demand forecasting model plays important role in inventory management system of spare parts. The purpose of this thesis study is to recommend a better demand forecasting approach for spare parts inventory management of MOENCO from models suggested in literatures that provides a better solution in keeping a good balance between stock holding amount and service level. Companies who implement appropriate demand forecasting model will have less tied up capital, reduce operational & overhead costs, and lower wastage of wealth due to obsolescence & scraping while satisfying customers demand with sufficient service level that helps to sustain in business with good profit. A model suggested in literatures called approximation demand forecasting model selected to simulate sample spare parts data obtained from MOENCO database. With 2 weeks aggregated demand, and 4 months lead time period optimum values of smoothing constant of demand size (α_z), smoothing constant transaction interval (α_i), and forecasted demand identified by simulation with Microsoft Excel, that provide the least average MAPE. Then, the stock amount and service level calculated, and compared with the existing inventory model to prove its effectiveness. It is observed that approximation model can be considered as a good managerial tool for automotive parts inventory management system of MOENCO to have optimum stock holding position with sufficient service level so that, it reduces capital tied up, enhances efficient cost management, and efficient utilization of forex with acceptable service level, and hence maximizes the profitability of the business. This thesis work can be more enhanced by testing spare parts inventory data of other similar companies using approximation method that include different demand patterns.

1. Introduction

Holding optimum inventory and satisfying customers demand with sufficient service level is a challenging task; it is the so called dilemma of inventory management (Becker et. al, 2013; Wanke, 2004).

Original equipment manufacturers (OEM's) and their distributors need to supply parts to keep the equipment's, and machineries of their customer's operational (Hopp et al, 1997). Therefore, companies need to keep spare parts in warehouses and supply whenever demand rises (Flowers and O'Neill II, 1978). But holding high amount of inventories have also negative consequences like capital tied up, cost for the care of the stored material, spoilage, obsolescence…etc. To hold optimal inventory, appropriate demand forecasting is of vital importance in inventory management of spare parts (Hua et al, 2007;Wagner and Lindeman, 2008).

For efficient utilization of vehicles a good after sales service i.e., provision of spare parts and quality services are critical (Öner et al, 2010). After Sales service is a service provided after a product is sold (Confente and Russo, 2015). The service is very essential to customers to use products efficiently during the life time (Cohen et al, 1990; Confente and Russo, 2015). Therefore, if customers are satisfied with the performance of after sales service, the possibility of repeat purchase is very high (Cohen, 2005). Now day's companies are giving more emphasis on after sales service to differentiate themselves from the competition in order to maintain and expand their market share (Seluck et al, 2013; Kranenburg and Houtu, 2007). Therefore, Companies needs to hold and supply spare parts to customers whenever demand arises. But the type and quantity of spare parts companies need to order and keep in their stock should be based on appropriate demand forecasting model (Hua et al, 2007).

1.1 Problem Statement

Inefficient demand forecasting have a lot of consequences that follow it. One of the major problem is excess stocking. Excess stocking is holding an inventory more than the market or demand requires (Wagner and Lindemann, 2008). It should not be confused that having excess stock means satisfying all the customers demand. An inventory which have excess stock in many of the parts may fail to hold or carry less than the demand requires in some parts. But, when we say excess stock it reflects the balance is to excess stocking than stock out. Its negative consequences is high if the overstocked parts are large in size and high in unit cost (Baluch, 2013).

When inventory is overstocked it tied up capital that can be invested to bring more profit (Aronis et al., 2004). Insurance cost is proportional to the cost of the inventory, which leads to high insurance premiums. According to Angane et al. (2014) it requires additional machineries and people to handle and take care of the parts, carries additional space and requires to build more shelves or will force to pay more for rental. All of these forced companies to unwanted additional investments and maximize the operational and overhead costs that will erode the profit of the company that can be obtained from the business (Relph and Milner, 2015).

Due to the continuous and fast technological advances in automotive industry parts of successive models may not be the same and overstocked parts will be subjected to obsolescence (Caggiano et al, 2007).

When parts stays for long on the shelf scraping is inevitable. The only reason that scrapping can be considered at all is that the holding costs of the items from now till their eventual use in the distant future may exceed the loss associated with scrapping and repurchase (Stulman, 1989).

In Ethiopia there is no automotive company that designs and manufactures its own brand. Although there are few companies that assemble CKD (completely knock down) and SKD (semi knock down) automotive components, overall all the origins of vehicles, components, and spare parts are from abroad (Desta, 2007). Therefore, using effectively the scarce forex is the responsibility of each and every company involved in the industry. When companies' inventory is overstocked they are accumulating forex which can be used somewhere in the country to solve critical problems. When the stocked parts get obsolete or scraped it is a total loss of the forex consumed by the parts.

The second problem associated with inefficient demand forecasting is related to service level. It is a measure of the proportion of customer demand met from stock or the percentage of the total demands served punctually (Becker et. al, 2013; Hopp et al, 1997).If companies cannot meet sufficient service level due to stock out they will lose their reliability and customer's starts to look other possibilities to meet their demand (Aronis et al, 2004). Customers lose confidence on the supplier and may not purchase the product again (Caggiano et al, 2007). This will leads loss of market share, creates poor image in the minds of customers, unable to attract new customers & to retain existing ones, and finally it leads to bankruptcy (Wagner and Lindemann, 2008;Relph and Milner, 2015).

Therefore, the importance of demand forecasting is very crucial to hold optimal inventory while keeping sufficient service level to meet customers' demand (Baluch, 2013; Stanford and Martin, 2007). It helps to keep the right balance between excess stocks and stock out which in turn contributes greatly to cost efficiencies, and meeting customer's satisfaction with sufficient service level which are a milestones for sustainable and profitable business (Hopp, 1997; Chen et al, 2007; Wagner and Lindemann, 2008; Zea, 2013).

The problems associated due to inefficient demand forecasting are observed in the inventory management system of MOENCO. Some parts of the inventory are overstocked while some parts are stock out, and back orders & lost sales are frequent. All in all the inventory management system needs improvement to run with optimal costs and sufficient service level by implementing appropriate demand forecasting model .

1.2 Purpose of the study

The purpose of this thesis study is to recommend a better demand forecasting approach for spare parts inventory management of MOENCO from models suggested in literatures. A test will be conducted to check the effectiveness of the selected forecasting model and the results i.e. inventory amount and service level are compared with the existing inventory management system. The selected model needs to provide a managerial solution to determine optimal inventory with sufficient service level. Hua et al., 2007 state that the principal objective of any inventory management system is to achieve sufficient service level with minimum inventory investment and administrative costs.

1.3 Research question

The research questions that will be answered by this thesis work are:

- How the selected model improves the balance between stock level and service level?
- What are the contributions of selected model to optimize costs of inventory?
- What benefits of the selected model brings to the company by providing sufficient service level?

1.4 Research objective

The objective of this thesis is to provide managerial solution for efficient demand forecasting model for spare parts inventory management, such that:

- Optimal inventory holding with sufficient service level will be achieved.
- Costs of inventory and its management will be reduced.
- Sufficient service level will be achieved.

1.5 Existing inventory system

The existing inventory system of the company uses the formula below to determine the suggested order size of spare parts. All the parameters are controlled on part number basis. Max-Max program run every fortnight as the order cycle is twice per month (i.e. 0.5 months). The periodical stock order and replenishment is mainly based on demand although lead time and safety stock are also considered. The average lead time period is 4 months.

SOQ = MAD x (OC + LT + SS for LT + SS for Demand) - (OH + OO) + BO

MIP = MAD x (OC + LT + SS for LT + SS for Demand)

Where:

SOQ is suggested order quantity. Ordering official runs Max-Max on the computer software to get Suggested order quantity (*SOQ*).After the *SOQ* value obtained the official analyzes and make subjective judgment and prepares the final order.

MIP is maximum inventory position.

MAD is the monthly average demand. It is the moving average of the past six month's demands.

OC is order cycle. It is the period of times between stock replenishment orders and expressed in months.

LT is lead time. It is the average period of time in months between ordering and binning completion.

SSLT is the safety stock for lead time. It is the safety stock which is kept to cover fluctuations in lead time. If the lead time for parts delivery is longer than average, it is necessary to keep enough stock to handle customer demand until the parts do arrive. However, when looking back at lead time histories to determine safety stock for lead time, it is important to eliminate exceptionally long lead times from your calculations. To calculate the safety stock needed to cover fluctuations in the lead time, average lead time subtracted from the maximum lead time then divided by the average lead time.

SSD is safety stock for demand. It is a parameter which is used to cover fluctuations in customer demand. It is calculated by subtracting the monthly average demand from the maximum demand then dividing by the monthly average demand.

OH is on hand quantity

OO is on order quantity

BO is back order quantity

The next section is literature review that discusses theoretical framework, and different researches conducted on forecasting intermittent demand which is the most encountered type of demand in reality. With intermittent items the observed demand during many periods is zero interspersed by occasional periods with irregular nonzero demand. The probability distribution of demands also discussed to indicate the type of distribution that approximates the nature of uncertain demand.

The method section discusses the reasons why a particular model is selected, and detailed historical development of the model. It also discusses the procedures that will be used on the data simulation, data analysis procedure and the limitations of the study.

Following the method section findings, discussion, and conclusions presented respectively. On the finding one sample part selected for illustration and detailed steps used to get the results presented. The discussion part presents the analysis of the results in perspective of the research questions & objectives. The conclusion section summarizes points raised on the chapters of this thesis work. Also recommendation for future direction of the study is presented on conclusion section.

2. Literature review

2.1 Theoretical review

Armstrong & Green (2006) investigated in detail the importance of forecasting for marketing practitioners. Dalrymple (1987), in his survey of 134 US companies, found that 99% prepared formal forecasts when they developed written marketing plans. In Dalrymple (1975), 93% of the companies sampled indicated that sales forecasting was 'one of the most critical' aspects, or a 'very important' aspect of their company's success. Jobber, Hooley and Sanderson (1985), in a survey of 353 marketing directors from British textile firms, found that sales forecasting was the most common of nine activities on which they reported.

Forecasting needs and their relationships are illustrated in Figure 1.

FIGURE 1 Needs for marketing forecasts

2.1.1 Forecasting methods

In this section brief descriptions of forecasting methods and their application presented.

2.1.1.1 Methods based on judgment

2.1.1.1.1 *Unaided judgment*

It is common practice to ask experts what will happen. This is a good procedure to use when:

• Experts are unbiased
• Large changes are unlikely
• Relationships are well understood by experts (e.g., demand goes up when prices go down)
• Experts possess privileged information
• Experts receive accurate and well-summarized feedback about their forecasts.

Unfortunately, unaided judgement is often used when the above conditions do not hold.

2.1.1.1. 2 *Delphi*

The Delphi technique was developed at RAND Corporation in the 1950s to help capture the knowledge of diverse experts while avoiding the disadvantages of traditional group meetings. The latter include bullying and time-wasting.

To forecast with Delphi the administrator should recruit between five and twenty suitable experts and poll them for their forecasts and reasons. The administrator then provides the experts with anonymous summary statistics on the forecasts, and experts' reasons for their forecasts. The process is repeated until there is little change in forecasts between rounds – two or three rounds are usually sufficient. The Delphi forecast is the median or mode of the experts' final forecasts.

Rowe and Wright (2001) provide evidence on the accuracy of Delphi forecasts. The forecasts from Delphi groups are substantially more accurate than forecasts from unaided judgement and traditional groups, and are somewhat more accurate than combined forecasts from unaided judgement.

2.1.1.1.3 *Structured analogies*

The outcomes of similar situations from the past (analogies) may help a marketer to forecast the outcome of a new (target) situation. For example, the introduction of new products in US markets can provide analogies for the outcomes of the subsequent release of similar products in other countries.

People often use analogies to make forecasts, but they do not do so in a structured manner. For example, they might search for an analogy that suits their prior beliefs or they might stop searching when they identify one analogy. The structured-analogies method uses a formal process to overcome biased and inefficient use of information from analogous situations.

To use the structured analogies method, an administrator prepares a description of the target situation and selects experts who have knowledge of analogous situations; preferably direct experience. The experts identify and describe analogous situations, rate their similarity to the target situation, and match the outcomes of their analogies with potential outcomes in the target situation. The administrator then derives forecasts from the information the experts provided on their most similar analogies.

2.1.1.1. 4 *Game theory*

Game theory has been touted in textbooks and research papers as a way to obtain better forecasts in situations involving negotiations or other conflicts. Despite a vast research effort, there is no research that directly tests the forecasting ability of game theory. However, Green (2002, 2005) tested the ability of game theorists, who were urged to use game theory in predicting the outcome of eight real (but disguised) situations. In that study, game theorists were no more accurate than university students.

2.1.1.1.5 *Judgmental decomposition*

The basic idea behind judgmental decomposition is to divide the forecasting problem into parts that are easier to forecast than the whole. One then forecasts the parts individually, using methods appropriate to each part. Finally, the parts are combined to obtain a forecast.

One approach is to break the problem down into multiplicative components. For example, to forecast sales for a brand, one can forecast industry sales volume, market share, and selling price per unit. Then reassemble the problem by multiplying the components together. Empirical results indicate that, in general, forecasts from decomposition are more accurate than those from a global approach (MacGregor, 2001). In particular, decomposition is more accurate where there is much uncertainty about the aggregate forecast and where large numbers (over one million) are involved.

2.1.1.1.6 *Judgmental bootstrapping*

Judgmental bootstrapping converts subjective judgments into structured procedures. Experts are asked what information they use to make predictions about a class of situations. They are then asked to make predictions for diverse cases, which can be real or hypothetical. For example, they might forecast next year's sales for alternative designs for a new product. The resulting data are then converted to a model by estimating a regression equation relating the judgmental forecasts to the information used by the forecasters. The general proposition seems preposterous. It is that the model of the man will be more accurate than the man. The reason is that the model applies the man's rules more consistently.

Judgmental bootstrapping models are most useful for repetitive complex forecasting problems where data on the dependent variable are not available (e.g. demand for a new telecommunications device) or data does not vary sufficiently for the estimation of an econometric model.

Once developed, judgmental bootstrapping models provide a low-cost procedure for making forecasts. The review in Armstrong (2001a) found that judgmental bootstrapping was more accurate than unaided judgment (the normal method for these situations) in 8 of the 11 comparisons, with two tests showing no difference, and one showing a small loss. The typical error reduction was about 6%.

Judgmental bootstrapping also allows experts to see how they are weighting various factors. This knowledge can help to improve judgmental forecasting. For example, with respect to personnel selection, bootstrapping might reveal that some factors, such as height, weight or looks, are used, even though they are not relevant for the job. Bootstrapping also allows for estimating effects of changing key variables when historical data are not sufficient to allow for estimates.

2.1.1.1.7 *Expert systems*

As the name implies, expert systems are structured representations of the rules experts use to make predictions or diagnoses. For example, 'if local household incomes are in the bottom quartile, then do not supply premium brands'. The forecast is implicit in the foregoing conditional action statement: i.e., premium brands are unlikely to make an acceptable return in the locale. Rules are often created from protocols, whereby forecasters talk about what they are doing while making forecasts. Where empirical estimates of relationships from structured analysis such as econometric studies are available, expert systems should use that information. Expert opinion, conjoint analysis, and bootstrapping can also aid in the development of expert systems.

Expert systems forecasting involves identifying forecasting rules used by experts and rules learned from empirical research. One should aim for simplicity and completeness in the resulting system, and the system should explain forecasts to users.

Developing an expert system is expensive and so the method will only be of interest in situations where many forecasts of a similar kind are required. Expert systems are feasible where problems are sufficiently well- structured for rules to be identified.

Collopy, Adya, and Armstrong (2001), in their review, found that expert systems forecasts are more accurate than those from unaided judgement. This conclusion, however, was based on only a small number of studies.

2.1.1.1.8 *Simulated interaction*

Simulated interaction is a form of role playing for predicting decisions by people who are interacting with others. It is especially useful when the situation involves conflict. For example, one might wish to forecast how best to secure an exclusive distribution arrangement with a major supplier.

To use simulated interaction, an administrator prepares a description of the target situation, describes the main protagonists' roles, and provides a list of possible decisions. Role players adopt a role and read about the situation. They then improvise realistic interactions with the other role players until they reach a decision; for example to sign a trial one-year exclusive distribution agreement. The role players' decisions are used to make the forecast.

Using eight conflict situations, Green (2005) found that forecasts from simulated interactions were substantially more accurate than can be obtained from unaided judgement. Simulated interaction can also help to maintain secrecy.

2.1.1.1.9 *Intentions and expectations surveys*

With intentions surveys, people are asked how they intend to behave in specified situations. In a similar manner, an expectations survey asks people how they expect to behave. Expectations differ from intentions because people realize that unintended things happen. For example, if you were asked whether you intended to visit the dentist in the next six months you might say no. However, you realize that a problem might arise that would necessitate such a visit, so your expectations would be that the event had a probability greater than zero. This distinction was proposed and tested by Juster (1966) and its evidence on its importance was summarized by Morwitz (2001).

To forecast demand using a survey of potential consumers, the administrator should prepare an accurate and comprehensive description of the product and conditions of sale. He should select a representative sample of the population of interest and develop questions to elicit expectations from respondents. Bias in responses should be assessed if possible and the data adjusted accordingly. The behavior of the population is forecast by aggregating the survey responses.

Useful methods have been developed for selecting samples, obtaining high response rates, compensating for non-response bias, and reducing response error. Dillman (2000) provides advice for designing surveys. Response error (where respondent information is not accurately reported) is probably the largest component of total error for marketing problems.

Expectations are most likely to be useful in cases where survey respondents have previously indulged in the behavior of interest, for example visited a theme park. Other conditions favoring the use of expectations surveys are: (1) responses can be obtained; (2) the behavior is important to the respondent; (3) the behavior is planned; (4) the plan is reported correctly; (5) the respondent is able to fulfil the plan; (6) the plan is unlikely to change (Morwitz, 2001).

One popular type of survey, focus groups, violates five important principles and they should not, therefore, be used in forecasting. First, focus groups are seldom representative of the population of interest. Second, the responses of each participant are influenced by the expressed opinions of others in the group. Third, a focus group is a small sample – samples for intentions or expectations surveys typically include several hundred people whereas a focus group will consist of between six and ten individuals. Fourth, questions for the participants are generally not well structured. And fifth, summaries of focus groups responses are often subject to bias. There is no evidence to show that focus groups provide useful forecasts.

2.1.1.1.10 C*onjoint analysis*

By surveying consumers about their preferences for alternative product designs in a structured way, it is possible to infer how different features will influence demand. Potential customers might be presented with a series of perhaps 20 pairs of offerings. For example, various features of a personal digital assistant such as price, weight, battery life, screen clarity and memory could be varied substantially such that the features do not correlate with one another. The potential customer is thus forced to make trade-offs among various features by choosing one of each pair of offerings in a way that is representative of how they would choose in the marketplace. The resulting data can be analyzed by regressing respondents' choices against the product features. The method, which is similar to bootstrapping, is called 'conjoint analysis' because respondents consider the product features jointly.

In general, the accuracy of forecasts from conjoint analysis is likely to increase with increasing realism of the choices presented to respondents (Wittink and Bergesteun, 2001). The method is based on sound principles, such as using experimental design and soliciting independent intentions from a sample of potential customers. Unfortunately however, there do not appear to be studies that compare conjoint-analysis forecasts with forecasts from other reasonable methods.

2.1.1.2 Methods requiring quantitative data

2.1.1.2.1 *Extrapolation*

Extrapolation methods use historical data on that which one wishes to forecast. Exponential smoothing is the most popular and cost effective of the statistical extrapolation methods. It implements the principle that recent data should be weighted more heavily and 'smoothes' out cyclical fluctuations to forecast the trend. To use exponential smoothing to extrapolate, the administrator should first clean and deseasonalise the data, and select reasonable smoothing factors. The administrator then calculates an average and trend from the data and uses these to derive a forecast (Makridakis, Wheelwright & Hyndman, 1998).

Statistical extrapolations are cost effective when forecasts are needed for each of hundreds of inventory items. They are also useful where forecasters are biased or ignorant of the situation (Armstrong, 2001b).

Allow for seasonality when using quarterly, monthly, or daily data. Most firms do this (Dalrymple, 1987). Seasonality adjustments led to substantial gains in accuracy in the large-scale study of time series by Makridakis et al. (1984). They should be dampened because seasonal adjustment programs tend to over-adjust for seasonality (Miller and Williams, 2004); this follows the principle of being conservative in the face of uncertainty.

Retail scanner technology provides reliable and up-to-date data for extrapolating sales of existing products. As a result, forecast accuracy should improve, especially because error in assessing the current situation is reduced. Not knowing where you are starting from is often a major source of error in predicting future values.

2.1.1.2.2 *Quantitative analogies*

Experts can identify situations that are analogous to a given situation. These can be used to extrapolate the outcome of a target situation. For example, to assess the loss in sales when the patent protection for a drug is removed, one might examine the historical pattern of sales for analogous drugs.

To forecast using quantitative analogies, ask experts to identify situations that are analogous to the target situation and for which data are available. If the analogous data provides information about the future of the target situation, such as per capita ticket sales for a play that is touring from city to city, forecast by calculating averages. If not, construct one model using target situation data and another using analogous data. Combine the parameters of the models, and forecast with the combined model.

While Duncan et al. (2001) provide evidence that accuracy can be improved by using data from analogous time series no other evidence found on the relative accuracy of quantitative analogies forecasts.

2.1.1.2.3 *Rule-based forecasting*

Rule-based forecasting (RBF) is a type of expert system that allows one to integrate managers' knowledge about the domain with time-series data in a structured and inexpensive way. For example, in many cases a useful guideline is that trends should be extrapolated only when they agree with managers' prior expectations. When the causal forces are contrary to the trend in the historical series, forecast errors tend to be large (Armstrong and Collopy, 1993). Although such problems occur only in a small percentage of cases, their effects are serious.

To apply RBF, one must first identify features of the series using statistical analysis, inspection, and domain knowledge (including causal forces). The rules are then used to adjust data, and to estimate short- and long- range models. RBF forecasts are a blend of the short- and long-range model forecasts.

RBF is most useful when substantive domain knowledge is available, patterns are discernable in the series, trends are strong, and forecasts are needed for long horizons. Under such conditions, errors for rule-based forecasts are substantially less than those for combined forecasts (Armstrong, Adya, and Collopy, 2001). In cases where the conditions were not met, forecast accuracy is not harmed.

2.1.1.2.4 *Neural nets*

Neural networks are computer intensive methods that use decision processes analogous to those of the human brain. Like the brain, they have the capability of learning as patterns change and updating their parameter estimates. However, much data is needed in order to estimate neural network models and to reduce the risk of over-fitting the data (Adya and Collopy, 1998).

There is some evidence that neural network models can produce forecasts that are more accurate than those from other methods (Adya and Collopy, 1998). While this is encouraging, it is advisable to avoid neural networks because the method ignores prior knowledge and because the results are difficult to understand.

2.1.1.2.5 *Data mining*

Data mining uses sophisticated statistical analyses to identify relationships. It is a popular approach.

Data mining ignores theory and prior knowledge in a search for patterns. Despite ambitious claims and much research effort, evidence not found that mention data mining techniques provide benefits for forecasting. In their extensive search and reanalysis of data from published research, Keogh et al. (2002) found little evidence for that data mining is useful. A large part of this, they said, was due to the fact that few studies have used a proper design to assess data mining.

2.1.1.2.6 Causal models

Causal models are based on prior knowledge and theory. Time-series regression and cross-sectional regression are commonly used for estimating model parameters or coefficients. These models allow one to examine the effects of marketing activity, such as a change in price, as well as key aspects of the market, thus providing information for contingency planning.

To develop causal models, one needs to select causal variables by using theory and prior knowledge. The key is to identify important variables, the direction of their effects, and any constraints. One should aim for a relatively simple model and use all available data to estimate it (Allen and Fildes, 2001). Surprisingly, sophisticated statistical procedures have not led to more accurate forecasts. In fact, crude estimates are often sufficient to provide accurate forecasts when using cross-sectional data (Dawes and Corrigan, 1974)

Statisticians have developed sophisticated procedures for analyzing how well models fit historical data. Such procedures have, however, been on little value to forecasters. Measures of fit have little relationship with forecast accuracy and they should therefore be avoided. Instead, holdout data should be used to assess the predictive validity of a model. This conclusion is based on findings from many studies with time-series data (Armstrong, 2001c). Statistical fit does relate to forecast accuracy for cross-sectional data, although the relationship is tenuous.

Causal models are most useful when (1) strong causal relationships are expected, (2) the direction of the relationship is known, (3) causal relationships are known or they can be estimated, (4) large changes are expected to occur in the causal variables over the forecast horizon, and (5) changes in the causal variables can be accurately forecast or controlled, especially with respect to their direction.

2.1.1.2.7 Segmentation

Segmentation involves breaking a problem down into independent parts, using data for each part to make a forecast, and then combining the parts. For example, a company could forecast sales of wool carpet separately for each climatic region, and then add the forecasts.

To forecast using segmentation, one must first identify important causal variables that can be used to define the segments, and their priorities. For example, age and proximity to a beach are both likely to influence demand for surfboards, but the latter variable should have the higher priority; therefore, segment by proximity, then age. For each variable, cut-points are determined such that the stronger the relationship with dependent variable, the greater the non-linearity in the relationship, and the more data that are available the more cut-points should be used. Forecasts are made for the population of each segment and the behavior of the population within the segment using the best method or methods given the information available. Population and behavior forecasts are combined for each segment and the segment forecasts summed.

Where there is interaction between variables, the effect of variables on demand are non-linear, and the effects of some variables can dominate others, segmentation has advantages over regression analysis (Armstrong, 1985). Segmentation is most useful when there are benefits from compensating errors. This is likely to occur where the segments are independent and are of roughly equal importance, and when information on each segment is good.

Segmentation based on a priori selection of variables offers the possibility of improved accuracy at a low risk. Dangerfield and Morris (1992), for example, found that bottom-up forecasting, a simple application of segmentation, was more accurate than top-down forecasts for 74% of the 192 monthly time series tested.

In some situations changes in segments are dependent on changes in other segments. For example, liberalization of gambling laws in city-A might result in decreased gambling revenue in already liberal cities B, C, and D. Efforts at dependent segmentation have gone under the names of microsimulation, world dynamics, and system dynamics. While the simulation approach seems reasonable, the models are complex and hence there are many opportunities for judgmental errors and biases. Armstrong (1985) found no evidence that these simulation approaches provide valid forecasts.

2.2 Empirical Review

2.2.1 Intermittent demand forecasting

Most spare parts behave intermittent demand pattern, that is, occur at given moments followed by long and variable periods without demand. Intermittent demands are particularly difficult to predict and shortage may result in extremely high costs (Hua et al, 2007; Caggiano et al, 2007; Babi et al, 2010).

Besides a few publications on demand forecasting methods, researches on spare parts inventory has mostly focused on inventory modeling. Accurate forecasting of demand is important in inventory control, but there are three main difficulties in forecasting the demand of spare parts. First, demand of spare parts is often intermittent. Second, historical data of spare parts demand are usually very limited. Third, in some industries spare part inventory level is largely a function of how equipment is used and how it is maintained (Hua et al., 2007).

Researchers, who developed Intermittent demand forecasting methods usually compare the performance of their methods with ES (exponential smoothing), and Croston's method. (Eaves and Kingsman, 2004), (Hua et al., 2007)

Accurate demand forecasting is of vital importance in inventory management of spare parts in process industries .In process industries the service requirements are higher as the effect of stock out may be financially remarkable. Also demand of parts are extremely sporadic & difficult to forecast, and the number of part types are usually high. As a result, enterprises in process industries may keep a large spare parts inventory, while the annual turnover may be very low. Hua et al. (2007) developed a new approach for forecasting the intermittent demand of spare parts i.e. integrating forecasting method (IFM). IFM provides a mechanism to integrate the demand auto correlated process and the relationship between explanatory variables and the non-zero demand of spare parts during forecasting occurrences of nonzero demand over lead time. Experimental results show that IFM considerably improve forecasting accuracy in comparison with other methods such as Exponential Smoothening (ES), Croston method and Markov Bootstrapping (MB).The experiment conducted using 40 type of spare parts from petrochemical enterprise in China. The result of the experiment shows that: 1) IFM is significantly better than MB on forecasting occurrences of nonzero demand. 2) In comparison with ES, Croston’s method, and MB method, IFM is the leading approach in terms of accuracy of forecasted LTD, no matter LTD is zero or not. 3) Comparison of ES, Croston’s method, and MB method shows that they have no significant difference on forecasting LTD in their case study, though Croston's method can provide a more accurate estimate of the mean demand over lead time. 4) Lead time has no significant effect on the accuracy of forecasting results in the case study.

Eaves and Kingsman (2004) made a case study on RAF (Royal Air Force) to give a solution when RAF is under immense pressure in reduction of its resources. The large investment in consumable stocks, makes inventory management the primary candidate for perceived cost saving. The RAF has a large and diverse consumable inventory with some 685,000 line items and a total value in excess of £2 billion. A large proportion of the Inventory is described as having an intermittent or a slow moving demand patter, presenting particular problems as far as forecasting and inventory control. In their paper, they use extensive demand and replenishment lead-time data to assess the practical value of forecasting models put forward in the literature for addressing these problem. Forecasting models put forward as particularly suitable for intermittent demand (Approximation method, Exponential smoothening, Croston's method Moving average, and Prev. year average) are then compared using traditional measures of accuracy, such as MAD, RMSE and MAPE. With weaknesses identified in making comparisons by this means an alternative measure which compares the implied stock-holdings is developed. Forecasting performance is assessed using 18,750 randomly selected line items from RAF inventory. The result shows that, the best forecasting method for a spare parts inventory is deemed to be the approximation method. This method allows the lowest stock-holdings across all demand patterns including smooth, irregular, slow-moving and intermittent. Substantial savings can be achieved by using more accurate forecasting methods and cutting safety stock with no appreciable reduction in service.

Reliability of parts and inventory levels are major factors that determines the service level for the maintenance of machines provided by original equipment manufacturers. In general decisions on reliability and stock levels are made separately in practice, and academic literatures offers little guidance on how jointly make the two decisions. In order to fill in the gap in the literature and provide guidance to OEM's reliability and inventory problems jointly modeled by Selcuk and Agrah (2013).The reliability of the spare part affects the inventory level of the spare part. An increase in the reliability of the spare part directly increases its value and the unit holding cost of the spare part. Therefore, reliability and inventory decisions should be considered simultaneously. From a data obtained from an OEM company based in Europe on 200 spare parts the joint reliability and inventory problem model tested and the result compared with the model that reliability and inventory decision made sequentially. The result showed that cost savings from integrating the reliability and inventory decisions can be as high as 28.6% and that the choice of service level measure is an important factor that affects the reliability improvement efforts.

2.1.2 Probability distribution of demand

In practice mostly demand is uncertain. We assume that demand is unknown, but that the probability distribution of demand is known.

(Eaves, 2002) mentioned that, many inventory models rely upon the probability distribution of lead-time demand (LTD). LTD distribution requires taking the distributions of both the demand per unit time and the lead-time into account .There are Empirical evidences that the normal distribution does not provide a reasonable model for LTD for erratic demand items. Often compound distributions are chosen as they allow the total demand over a lead-time to be considered as the sum of a random number of transactions, each generating a random demand. The compound Poisson distribution has frequently found favor. Under this distribution, the transactions arrive in accordance with a stationary Poisson process and to adequately represent demand, the distribution for demand size will depend on the variability in the historical data.

Although the uncertainty of the lead-time in practical settings is well documented, the scarcity of lead-time data often restricts the modelling to constant lead-times. In any case, realistic constant lead-time models can be obtained from both a constant-Poisson distribution and a stuttering poisson (sp) distribution. The constant-poisson distribution models the situation where each demand has a fixed quantity and the number of transactions arriving within any interval of time follows a Poisson distribution. Alternatively, under the stuttering Poisson, or geometric-Poisson distribution, when a transaction occurs, the request is for one or more units of the item, with the quantity given by the geometric distribution (Eaves, 2002).

On their article on the demand distribution of spare parts Synthetic, Babi, and Altay (2012) address demand distributional assumptions for spare part management. On the article they discussed that parametric approaches to stock control rely upon a lead-time demand distributional assumption and the employment of an appropriate forecasting procedure for estimating the moments of such a distribution (typically mean and variance). For the case of fast demand items the Normality assumption is typically sufficient. However, Stock Keeping Units (SKUs) often exhibit intermittent or irregular demand patterns that may not be represented by the Normal distribution. This is almost invariably the case for service/spare parts. Intermittent demand patterns are characterized by infrequent demands, often of variable size, occurring at irregular intervals. Consequently, it is preferable to model demand from constituent elements, i.e. the demand size and inter-demand interval. Therefore, compound theoretical distributions (that explicitly take into account the size-interval combination) are typically used in such contexts of application

Syntetos et al. (2012) further discussed that, if time is treated as a discrete (whole number) variable, demand may be generated based on a Bernoulli process, resulting in a geometric distribution of the inter-demand intervals. When time is treated as a continuous variable, the poisson demand generation process results in negative exponentially distributed inter-arrival intervals. They indicated that there is sound theory in support of both geometric and exponential distribution for representing the time interval between successive demands, and also there are empirical evidences in support of both distributions (e.g. Dunsmuir and Snyder, 1989; Kwan, 1991; Willemain et al., 1994; Janssen, 1998; Eaves, 2002).With Poisson arrivals of demands and an arbitrary distribution of demand sizes, the resulting distribution of total demand over a fixed lead time is compound Poisson. Inter-demand intervals following the geometric distribution in conjunction with an arbitrary distribution for the sizes, results in a compound binomial distribution. Regarding the compound Poisson distributions, the stuttering poisson, which is a combination of a poisson distribution for demand occurrence and a geometric distribution for demand size, has received the attention of many researchers. Particularly for lumpy demands, the demand size distribution is heavily skewed to the right, rendering the normality assumption far from appropriate. They cited works of Quenouille (1949) that a Poisson-Logarithmic process yields a negative binomial distribution (NBD). When event arrivals are assumed to be Poisson distributed and the order size is not fixed but follows a logarithmic distribution, total demand is then negative binomially distributed over time.

The conclusion of the experiment conducted by Syntetos et al. (2011) is made for demand per period and lead time demand. The discrete distributions, i.e. Poisson, NBD and Stuttering Poisson provide, overall, a better fit than the continuous ones, i.e. Normal and Gamma. More precisely, and with regards to ‘Strong Fit’, the Stuttering Poisson distribution performs best in all three datasets considered in the research. This is followed by the NBD and then by the Poisson distribution. On the other hand, the Normal distribution is judged to be far from appropriate for intermittent demand items. For lead time demand the results indicate that NBD performs, overall, best showing a strong fit, and Stuttering Poisson comes in a close second. Both the NBD and Stuttering Poisson are compound in nature, meaning that they account explicitly for a demand arrival process (Poisson) and a different distribution for the transaction sizes (Log series and Geometric for the NBD and Stuttering Poisson respectively).

3. Method

3.1 Approximation demand forecasting method

Researchers have been developing different methods for forecasting demand in different assumption conditions.

ES (exponential smoothing) is not appropriate when demand is intermittent (Eaves and Kingsman, 2004). With intermittent items the observed demand during many periods is zero interspersed by occasional periods with irregular nonzero demand. ES places most weight on the more recent data, giving estimates that are highest just after a demand and lowest just before a demand. With the replenishment level broken by a demand occurrence, the replenishment quantity is determined by biased estimates that immediately follow the demand as a consequence. This tends to lead to unnecessarily high stocks.

An alternative method developed by Croston separately applies exponential smoothing to the interval between demands and the size of the demands. Updating only occurs in periods with positive demand; if a period has no demand, the method simply increments the count of time periods since the last demand.

Let y_t be the demand for an item at time t, p_t Croston's estimate of mean interval between transactions, z_t Croston's estimate of mean demand size, $\hat{y}_t$ Croston's estimate of mean demand per period, q the time interval since the last demand, as, α_s, α_i the smoothing parameters between 0 and 1 for size and interval, respectively.

If $y_{t} = 0$

$p_t = p_{t-1}$

$z_t = z_{t-1}$

$q = q+1$

Else,

$P_t = P_{t-1} + \alpha_i (q - p_{t-1})$

$z_t = z_{t-1} + \alpha_s (y_t - z_{t-1})$

$q = 1$

Combining the estimates of size and interval provides an estimate of the mean demand per period $\hat{y}_t = z_t / p_t$ when demand occurs every period, Croston's method is identical to conventional ES.

The modification that was found to perform the best in research undertaken by (Eaves, 2002) was the heuristic that incorporates a simplification of the forecast bias, referred to as the approximation method by Syentetos and Boylan. The method, derived from a Taylor series expansion, uses a deflator based on the interval smoothing constant to remove the bias:

$$\hat{y}_t = \left(1 - \frac{\alpha}{2}\right)\frac{z_t}{p_t}$$

(Eaves and Kingsman, 2004, p 2-3)

According to Syntetos et al. (2011) if demand is intermittent and calculates demand per period, the most likely probability distribution is stuttering poisson.

3.2 Research Setting

For this thesis data taken from The Motor and Engineering Company of Ethiopia (MOENCO) simulated using approximation model proposed by Syntetos and Boylan (2005) to test its effectiveness in the context of MOENCO in search of managerial solution for spare parts inventory management.

Approximation demand forecasting method is selected because it outperforms other commonly used forecasting methods (Exponential smoothing, Croston's, Moving average, Previous year average) in different lead time demand patterns (smooth, irregular, slow moving, mildly intermittent, and highly intermittent) and demand aggregations (quarterly, monthly, and weekly).The performance of the forecasting models is measured using MAPE (mean absolute percentage error). Approximation model provides also the lowest stock holding in the vast majority of the cases (Eaves and Kingsman, 2004; Syntetos et al, 2009)).

It is assumed that a single echelon multi item setting such that, the distributor place order to the OEM and sells the parts to customers.

Lead time demand with average lead time of 4 months (8 fortnights), and demand aggregation of 2 weeks (1 fortnight) are considered. The forecast for p_t Croston's estimate of mean interval between transactions, and z_t Croston's estimate of mean demand size will be calculated only when a demand occurs, if the demand is zero p_t and z_t will take the previous result i.e. p_{t-1} and z_{t-1}. This particular setting is chosen because the existing inventory system actual average lead time is 4 months and order is prepared every fortnight, so that the results of the approximation method and the existing inventory can be compared based on the same ground.

Demand, transaction interval & stock level data for spares retrieved from 2013 to 2016. During this period availability of forex was relatively stable and orders arrived in 4 months lead time. Aggregated demand & transaction interval for each fortnight from 2013 to 2016 and the stock level at the beginning of each fortnight identified. The average of 2013 data used to generate the initial parameters value of p_t and $z_{t,}$ and data from 2014 to 2016 used to generate a forecast. It is diachronic study due to the fact that the forecasted demand of sample spare parts are observed each fortnight from 2013-2016.

3.3 Sample Selection

30 part numbers selected from fast moving and slow moving parts based on experience. Fast moving parts are turned out to behave like irregular demand pattern, which show low in transaction variability and high in demand size variability while slow moving parts behave like slow moving demand pattern which show high in transaction variability and low in demand size variability(Eaves and Kingsman,2004). Out of the 30 parts selected due to data filtering 28 part numbers left 12 of which behave irregular demand pattern and the remaining 16 behave slow moving demand pattern. The number of samples determined based on judgement, since it is very time consuming to aggregate demand every fortnight and i.e. filtering, and determining the stock level at the beginning of each fortnight since there are frequent movement of stock like new stocks in, parts sales, and sales returns. Demand patterns limited to two types, because unable to find simple mechanism to identify the lead time demand in to different demand patterns.

3.4 Data analysis procedure

The data analysis procedure presented as follows:

- Initial parameters of p_t and, z_t determined using 2013 data.
- p_t , z_t and $\hat{y}_t$ values are simulated at different values of α_s, and α_i between 0 and 1for each sample spare part for each fortnight from 2014 to 2016.
- Calculate MAPE and select the combination of α_s, and α_i as the optimum smoothing constant which gives the lowest average MAPE value. Optimum value of $\hat{y}_t$ is also the forecast at the lowest MAPE value.
- Calculate safety stock for the forecasted demand.
- Calculate (forecast + safety stock- actual average lead time demand) for approximation method and (Inventory-Actual demand) for the existing system. If the result is ≥ 0, then multiply the results with unit cost of the spare parts to find the excess inventory. In this case the service rate is 100%.If the result is < 0, then calculate the stock out.
- Calculate the average excess stock or stock out amount for existing inventory and approximation method.
- Calculate the service level as a ratio of supplied/requested for both options. Which is the ratio of the smaller of demand and inventory level to demand.
- Take the average of the results for excess/shortage of inventory amount and service rate for both approximation forecast method and the existing inventory.
- Compare the average values of (inventory amount, service level) of the two methods.

3.5 Problems and limitations of the study

Some of the problems and limitations of the thesis are:

- During stock out the demand data obtained have zero values because back order and lost sales are not registered properly.
- The stock movement data for some fast moving parts is not displayed in full from 2013-2016 due to large data size. The data base provides only partial data.
- Very time consuming to aggregate demand, filtering, and determining the stock level at the beginning of each fortnight for four years.
- Simulated data includes limited type of demand patterns.
- Data source from other companies is not presented for comparison and generalization

4. Finding

28 spare parts data simulated in Micro Soft Excel. The initial data gathered are aggregated demand of every fortnight, stock quantity at the beginning of each fortnight, and the transaction interval between demands from January 2013- December 2016. The average lead time period is taken 4 months from order preparation until the spare parts are ready for sale.

Since the aggregated demand is for one fortnight the unit of analysis to calculate the lead time demand and average lead time demand is fortnight i.e. the lead time demand is the sum of 8 fortnights and the average lead time demand is the lead time demand divided by 8.

The inventory system of the distributor is considered as a single echelon multi item setting such that, the distributor place order to the OEM and sells the parts to customers.

There are 104 total fortnights from 2013 to 2016.To illustrate the findings the analysis of on sample spare part presented in this section.

Table 1. Initial data collected from source.

1	2	3	4	5	6
No of fortnights	2 weeks Aggregated demand, (y_t)	Lead time Demand (4months lead time)	Average Lead time Demand	Interval	Stock level
1	96	765	96	1	1,480
2	69	748	94	1	1,386
3	95	770	97	1	1,316
4	60	757	95	1	1,222
5	164	790	99	1	1,162
6	69	719	90	1	998

7	104	745	94	1	1,132
8	108	799	100	1	1,027
9	79	788	99	1	920
10	91	809	102	1	1,041
11	82	794	100	1	951
12	93	836	105	1	869
13	93	841	106	1	1,079
14	95	864	108	1	986
15	158	859	108	1	891
16	97	801	101	1	734
17	100	808	101	1	637
18	76	858	108	1	537
19	124	869	109	1	461
20	98	856	107	1	737
21	116	850	107	1	639
22	90	853	107	1	863
23	100	890	112	1	779
24	104	939	118	1	951
25	150	955	120	1	1,227
26	87	903	113	1	1,077
27	111	920	115	1	1,196
28	92	983	123	1	1,085
29	119	985	124	1	1,461
30	127	977	123	1	1,362
31	149	961	121	1	1,626
32	120	929	117	1	1,803
33	98	906	114	1	1,684
34	104	887	111	1	1,587
35	174	898	113	1	1,483

36	94	841	106	1	1,311
37	111	840	105	1	1,216
38	111	825	104	1	1,106
39	117	808	101	1	1,115
40	97	801	101	1	1,078
41	79	810	102	1	1,217
42	115	842	106	1	1,438
43	117	888	111	1	1,323
44	93	961	121	1	1,207
45	96	991	124	1	1,114
46	94	1042	131	1	1,019
47	110	1031	129	1	926
48	106	1034	130	1	816
49	111	1134	142	1	711
50	161	1115	140	1	800
51	190	1091	137	1	1,053
52	123	1015	127	1	862
53	147	1001	126	1	740
54	83	1020	128	1	636
55	113	1037	130	1	554
56	206	1052	132	1	441
57	92	938	118	1	528
58	137	1007	126	1	636
59	114	985	124	1	499
60	109	987	124	1	585
61	166	1033	130	1	476
62	100	1064	133	1	609
63	128	1047	131	1	910
64	92	1021	128	1	782

65	161	1099	138	1	890
66	115	1078	135	1	1,128
67	116	1153	145	1	1,014
68	155	1229	154	1	1,198
69	197	1230	154	1	1,043
70	83	1165	146	1	846
71	102	1357	170	1	764
72	170	1360	170	1	1,093
73	140	1327	166	1	1,524
74	190	1371	172	1	1,384
75	192	1289	162	1	1,316
76	156	1239	155	1	1,245
77	132	1189	149	1	1,139
78	275	1187	149	1	1,007
79	105	1057	133	1	1,030
80	137	1140	143	1	1,131
81	184	1150	144	1	1,563
82	108	1136	142	1	1,730
83	142	1112	139	1	1,623
84	106	1183	148	1	1,481
85	130	1149	144	1	1,377
86	145	1158	145	1	1,447
87	188	1125	141	1	1,302
88	147	1124	141	1	1,114
89	170	1078	135	1	967
90	84	1054	132	1	798
91	213	1064	133	1	1,113
92	72	972	122	1	901
93	139	1005	126	1	799

94	112	972	122	1	783
95	187	1043	131	1	1,071
96	101	1036	130	1	893
97	146	1043	131	1	1,093
98	94			1	948
99	121			1	853
100	105			1	1,332
101	106			1	1,267
102	183			1	1,632
103	180			1	1,628
104	108			1	1,448

The first column shows the number of fortnights from January 2013 to December 2016.In column 2 aggregated demand for each fortnight presented. Because lost sales and back orders were not captured, when the demand data is very low or zero due of stock out of spare parts the average demand of the past two month (4 fortnights) is taken as a demand. All branch transfers are considered as a sales, even though the branches may not sold all the parts received from CPD (central parts depot) .In column 3 the lead time demand in 4 months' time is summed up (i.e. 8 fortnights). In column 4 average lead-time demand is calculated by dividing column 3 by 8.In column 5 number of transaction between intervals is presented. Since the selected spare part for illustration is fast moving there is transaction every fortnight and the number of interval between transactions is 1 in all cases. In column 6 the stock quantity at the banging of each fortnight is presented. The stock quantity is the sum of stock end at the end of the previous fortnight, new stock received and stock returned in the fortnight under consideration.

Croston's estimate of mean interval between transactions(p_t), Croston's estimate of mean demand size z_t, can be calculated using Croston's equations for interval & demand respectively, and estimate of the mean demand per period ($\hat{y}_t$) calculated by approximation method.

If $y_t = 0$

$p_t = p_{t-1}$

$z_t = z_{t-1}$

$q = q+1$

Else,

$P_t = P_{t-1} + \alpha_i (q - p_{t-1})$

$z_t = z_{t-1} + \alpha_s (y_t - z_{t-1})$

$q = 1$

$$\hat{y}_t = \left(1 - \frac{\alpha}{2}\right)\frac{z_t}{p_t}$$

The results of z_t, p_t and $\hat{y}_t$ are dependent on the selection of α_s ,and α_i . Therefore, first the values of the coefficients (α_s, α_i) needs to be determined that will give optimum values of z_t,p_t and $\hat{y}_t$.

(Eaves, 2002) mentioned that trough an analysis of the widely available time series data, the forecasting performance of smoothing methods is dependent on how the smoothing parameters are estimated. Rather than using fixed arbitrary values, improvements in performance can be obtained by using information drawn from the time series themselves.

Using the selected 28 line items, average MAPE (mean absolute percentage error) across all line items for a range of smoothing constants α_z between (0.01- 1) and α_i between (0.01-1) with incremental of 0.01 is computed. The smoothing constant pair in which the average MAPE is at a minimum is taken as the optimal pair value of smoothing constants.

(MAPE) relates the size of the error to the actual observation on a proportional basis:

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{y_t} \times 100}{n}$$

The startup parameters for z_t and, p_t are calculated from 2013 data. By simulating for every value of α_s between 0.01 -1 with values of α_i between 0.01- 1 using Microsoft Excel the optimum values that gives minimum MAPE occur at α_z =0.41 and α_i =0.01.

Table 2 below shows the values of forecast demand, error and MAPE values for the selected part number to illustrate.

Table 2. Forecast demand, error and MAPE values

1	2	3	4	5	6	7	8	9
No of fortnights	2 weeks Aggregated demand (y_t)	Average Lead time Demand	Interval	z_t	p_t	$\hat{y}_t$	error	MAPE
1	96	96	1					
2	69	94	1					
3	95	97	1					
4	60	95	1					
5	164	99	1					
6	69	90	1					
7	104	94	1					
8	108	100	1					
9	79	99	1					
10	91	102	1					
11	82	100	1					

12	93	105	1					
13	93	106	1					
14	95	108	1					
15	158	108	1					
16	97	101	1					
17	100	101	1					
18	76	108	1					
19	124	109	1					
20	98	107	1					
21	116	107	1					
22	90	107	1					
23	100	112	1					
24	104	118	1					
25	150	120	1					
26	87	113	1					
27	111	115	1	100.33	1			
28	92	123	1	96.92	1	96.43	26.57	22%
29	119	124	1	105.97	1	105.44	18.56	15%
30	127	123	1	114.59	1	114.02	8.98	7%
31	149	121	1	128.7	1	128.06	7.06	6%
32	120	117	1	125.13	1	124.51	7.51	6%
33	98	114	1	114.01	1	113.44	0.56	0%
34	104	111	1	109.9	1	109.36	1.64	1%
35	174	113	1	136.18	1	135.5	22.5	20%
36	94	106	1	118.89	1	118.29	12.29	12%
37	111	105	1	115.65	1	115.08	10.08	10%
38	111	104	1	113.75	1	113.18	9.18	9%
39	117	101	1	115.08	1	114.5	13.5	13%
40	97	101	1	107.67	1	107.13	6.13	6%
41	79	102	1	95.91	1	95.43	6.57	6%
42	115	106	1	103.74	1	103.22	2.78	3%
43	117	111	1	109.18	1	108.63	2.37	2%
44	93	121	1	102.54	1	102.03	18.97	16%
45	96	124	1	99.86	1	99.36	24.64	20%
46	94	131	1	97.46	1	96.97	34.03	26%
47	110	129	1	102.6	1	102.09	26.91	21%
48	106	130	1	103.99	1	103.47	26.53	20%

49	111	142	1	106.87	1	106.33	35.67	25%
50	161	140	1	129.06	1	128.42	11.58	8%
51	190	137	1	154.05	1	153.28	16.28	12%
52	123	127	1	141.32	1	140.61	13.61	11%
53	147	126	1	143.65	1	142.93	16.93	13%
54	83	128	1	118.78	1	118.19	9.81	8%
55	113	130	1	116.41	1	115.83	14.17	11%
56	206	132	1	153.14	1	152.38	20.38	15%
57	92	118	1	128.07	1	127.43	9.43	8%
58	137	126	1	131.73	1	131.08	5.08	4%
59	114	124	1	124.46	1	123.84	0.16	0%
60	109	124	1	118.12	1	117.53	6.47	5%
61	166	130	1	137.75	1	137.06	7.06	5%
62	100	133	1	122.27	1	121.66	11.34	9%
63	128	131	1	124.62	1	124	7	5%
64	92	128	1	111.25	1	110.69	17.31	14%
65	161	138	1	131.65	1	130.99	7.01	5%
66	115	135	1	124.82	1	124.2	10.8	8%
67	116	145	1	121.2	1	120.6	24.4	17%
68	155	154	1	135.06	1	134.39	19.61	13%
69	197	154	1	160.46	1	159.65	5.65	4%
70	83	146	1	128.7	1	128.06	17.94	12%
71	102	170	1	117.75	1	117.16	52.84	31%
72	170	170	1	139.17	1	138.48	31.52	19%
73	140	166	1	139.51	1	138.82	27.18	16%
74	190	172	1	160.21	1	159.41	12.59	7%
75	192	162	1	173.25	1	172.38	10.38	6%
76	156	155	1	166.17	1	165.34	10.34	7%
77	132	149	1	152.16	1	151.4	2.4	2%
78	275	149	1	202.53	1	201.51	52.51	35%
79	105	133	1	162.54	1	161.73	28.73	22%
80	137	143	1	152.07	1	151.31	8.31	6%
81	184	144	1	165.16	1	164.33	20.33	14%
82	108	142	1	141.72	1	141.02	0.98	1%
83	142	139	1	141.84	1	141.13	2.13	2%
84	106	148	1	127.14	1	126.51	21.49	15%
85	130	144	1	128.32	1	127.67	16.33	11%

86	145	145	1	135.16	1	134.48	10.52	7%
87	188	141	1	156.82	1	156.04	15.04	11%
88	147	141	1	152.8	1	152.03	11.03	8%
89	170	135	1	159.85	1	159.05	24.05	18%
90	84	132	1	128.75	1	128.11	3.89	3%
91	213	133	1	163.29	1	162.48	29.48	22%
92	72	122	1	125.86	1	125.23	3.23	3%
93	139	126	1	131.25	1	130.59	4.59	4%
94	112	122	1	123.36	1	122.74	0.74	1%
95	187	131	1	149.45	1	148.7	17.7	14%
96	101	130	1	129.59	1	128.94	1.06	1%
97	146	131	1	136.32	1	135.63	4.63	4%
98	94		1					
99	121		1					
100	105		1					
101	106		1					
102	183		1					
103	180		1					
104	108		1					
								11%

2013 ends at fortnight 27 and the startup parameters for z_t and p_t which are Croston's estimate of mean demand size (average of column 2 from the 1st fortnight to the 27th) and Croston's estimate of mean interval between transaction (average of column 4 from the 1st fortnight to the 27th) equals 100.33 and 1 respectively.

Using the formulae mentioned above it is possible to calculate the values of p_t, z_t and $\hat{y}_t$ in column 5, 6 and 7 respectively. In calculating estimated demand for slow-moving parts, if the demand starts with zero at the beginning of January, 2013 it will be adjusted to one to simplify counting of transaction intervals. The error e in column 8 is the absolute value of the difference between column 3 and 7. Column 9 is MAPE (mean absolute percentage error) it is 11% for the spare part under illustration, but the average value for the 28 sample parts equals 27 % (The lease MAPE result of the simulation).

For calculation of safety stock, Syntetos AA and Teunter RH (2014) recommended the formula below.

$$\sqrt{1+\frac{(L-1)Var(Y')/Var(Y)}{1+Var(Y')/Var(Y)}}$$

Where:

L- Lead time

Y' -Demand forecast

Y- The actual demand

Var (Y) - per period demand variance

Var (Y') – per period forecast variance

Further the safety stock is adjusted using a correction factor shown below. Where α is Croston's estimate of mean demand size (α_s) which is 0.41 in this case.

$$\sqrt{1+\frac{(L-1)\alpha}{2}}$$

Table 3 below shows the value of safety stock calculated using a formula suggested by (Syntetos and Teunter, 2014).

Table 3. Safety stock value

1	2	3	4	5	6	7	8	9	10	11
No of fortnights	Average Lead time Demand	$\hat{y}_t$	Mean of average lead time demand	Mean of $\hat{y}_t$	per period demand variance-Var (Y)	per period forecast variance-Var (Y’)	Lead time	Safety stock	Correction factor	Corrected safety stock
28	123.00	96.43	132.00	129.96	81.00	1,124.41	8.00	2.31	1.56	4
29	124.00	105.44			64.00	601.40				
30	123.00	114.02			81.00	254.23				
31	121.00	128.06			121.00	3.64				
32	117.00	124.51			225.00	29.78				
33	114.00	113.44			324.00	273.11				
34	111.00	109.36			441.00	424.73				
35	113.00	135.50			361.00	30.68				
36	106.00	118.29			676.00	136.20				
37	105.00	115.08			729.00	221.66				
38	104.00	113.18			784.00	281.81				
39	101.00	114.50			961.00	239.00				
40	101.00	107.13			961.00	521.46				
41	102.00	95.43			900.00	1,192.34				
42	106.00	103.22			676.00	715.24				
43	111.00	108.63			441.00	455.15				
44	121.00	102.03			121.00	780.26				
45	124.00	99.36			64.00	936.53				
46	131.00	96.97			1.00	1,088.59				
47	129.00	102.09			9.00	777.14				

48	130.00	103.47			4.00	701.73				
49	142.00	106.33			100.00	558.48				
50	140.00	128.42			64.00	2.40				
51	137.00	153.28			25.00	543.43				
52	127.00	140.61			25.00	113.34				
53	126.00	142.93			36.00	168.08				
54	128.00	118.19			16.00	138.68				
55	130.00	115.83			4.00	199.80				
56	132.00	152.38			-	502.32				
57	118.00	127.43			196.00	6.40				
58	126.00	131.08			36.00	1.23				
59	124.00	123.84			64.00	37.50				
60	124.00	117.53			64.00	154.55				
61	130.00	137.06			4.00	50.40				
62	133.00	121.66			1.00	68.92				
63	131.00	124.00			1.00	35.59				
64	128.00	110.69			16.00	371.48				
65	138.00	130.99			36.00	1.05				
66	135.00	124.20			9.00	33.26				
67	145.00	120.60			169.00	87.72				
68	154.00	134.39			484.00	19.54				
69	154.00	159.65			484.00	881.44				
70	146.00	128.06			196.00	3.64				

71	170.00	117.16			1,444.00	163.86				
72	170.00	138.48			1,444.00	72.48				
73	166.00	138.82			1,156.00	78.33				
74	172.00	159.41			1,600.00	867.13				
75	162.00	172.38			900.00	1,799.01				
76	155.00	165.34			529.00	1,251.71				
77	149.00	151.40			289.00	459.59				
78	149.00	201.51			289.00	5,119.29				
79	133.00	161.73			1.00	1,008.92				
80	143.00	151.31			121.00	455.57				
81	144.00	164.33			144.00	1,181.33				
82	142.00	141.02			100.00	122.14				
83	139.00	141.13			49.00	124.64				
84	148.00	126.51			256.00	11.94				
85	144.00	127.67			144.00	5.25				
86	145.00	134.48			169.00	20.39				
87	141.00	156.04			81.00	679.83				
88	141.00	152.03			81.00	486.94				
89	135.00	159.05			9.00	845.96				
90	132.00	128.11			-	3.45				
91	133.00	162.48			1.00	1,057.05				
92	122.00	125.23			100.00	22.38				
93	126.00	130.59			36.00	0.40				

94	122.00	122.74			100.00	52.19				
95	131.00	148.70			1.00	351.15				
96	130.00	128.94			4.00	1.05				
97	131.00	135.63			1.00	32.15				
98										
99										
100										
101										
102										
103										
104										
Mean					272.91	443.46				

For calculating the variances first the actual demand and, the forecast demand average value needs to be determined. Mean of average lead time demand and forecast demand are 132 and 129.96 respectively calculated using the demand data's from fortnight 28 to 97.Then the variances are calculated for each fortnight and finally the means of the variances determined, and used for calculating the safety stock. The mean of the variances for the average lead time demand, and forecast demand are 272.91 and 443.46 respectively found at the end of column 6 and 7.The lead time is taken as 8 fortnights (4 months) .Results of the safety stock, safety stock correction factor, and the corrected safety stock are presented column 9, 10 and 11 respectively. This procedure is also performed for the remaining 27 sample line items.

Now it is possible to measure the KPI's i.e. service rate and excess stock/out of stock amount. Service rate is the ratio of parts supplied to demand in percentage. Simply it tells how much percentage of parts requested is immediately supplied. When the stock quantity is greater than the requested part quantity, the supplied quantity equals the requested and the service level equals 100%. But, when the stock quantity is less than the requested quantity, the supplied part equals the stock quantity and the service level is less than 100%.

The excess stock or stock out amount is calculated as a product of unit cost of the material with excess/shortage stock quantity. For the existing inventory system the excess/shortage is calculated as (*Stock qty – actual demand*), while for approximation method the excess/shortage calculated as (*Forecasted demand + safety stock – average lead time demand.)*

Table 4. Service rate and inventory amount

1	2	3	4	5	6	7	8	9	10	11	12
					Service level			Overage/shortage Qty		Overage/shortage Amount ETB	
No. of fortnights	2 weeks Aggregated demand (y_t)	Average lead time demand	Actual Stock Quantity	$\hat{y}_t$ plus safety stock	Existing inventory system	Approx.	Unit cost	Existing inventory system	Approx.	Existing inventory system	Approx.
28	92	123	1,085	101	100%	82%	209.03	993.00	(22.00)	207,566.79	(4,598.66)
29	119	124	1,461	110	100%	89%		1,342.00	(14.00)	280,518.26	(2,926.42)
30	127	123	1,362	119	100%	97%		1,235.00	(4.00)	258,152.05	(836.12)
31	149	121	1,626	133	100%	100%		1,477.00	12.00	308,737.31	2,508.36
32	120	117	1,803	129	100%	100%		1,683.00	12.00	351,797.49	2,508.36
33	98	114	1,684	118	100%	100%		1,586.00	4.00	331,521.58	836.12
34	104	111	1,587	114	100%	100%		1,483.00	3.00	309,991.49	627.09
35	174	113	1,483	140	100%	100%		1,309.00	27.00	273,620.27	5,643.81

36	94	106	1,311	123	100%	100%		1,217.00	17.00	254,389.51	3,553.51
37	111	105	1,216	120	100%	100%		1,105.00	15.00	230,978.15	3,135.45
38	111	104	1,106	118	100%	100%		995.00	14.00	207,984.85	2,926.42
39	117	101	1,115	119	100%	100%		998.00	18.00	208,611.94	3,762.54
40	97	101	1,078	112	100%	100%		981.00	11.00	205,058.43	2,299.33
41	79	102	1,217	100	100%	98%		1,138.00	(2.00)	237,876.14	(418.06)
42	115	106	1,438	108	100%	100%		1,323.00	2.00	276,546.69	418.06
43	117	111	1,323	113	100%	100%		1,206.00	2.00	252,090.18	418.06
44	93	121	1,207	107	100%	88%		1,114.00	(14.00)	232,859.42	(2,926.42)
45	96	124	1,114	104	100%	84%		1,018.00	(20.00)	212,792.54	(4,180.60)
46	94	131	1,019	101	100%	77%		925.00	(30.00)	193,352.75	(6,270.90)
47	110	129	926	107	100%	83%		816.00	(22.00)	170,568.48	(4,598.66)
48	106	130	816	108	100%	83%		710.00	(22.00)	148,411.30	(4,598.66)
49	111	142	711	111	100%	78%		600.00	(31.00)	125,418.00	(6,479.93)
50	161	140	800	133	100%	95%		639.00	(7.00)	133,570.17	(1,463.21)
51	190	137	1,053	158	100%	100%		863.00	21.00	180,392.89	4,389.63
52	123	127	862	145	100%	100%		739.00	18.00	154,473.17	3,762.54

53	147	126	740	147	100%	100%		593.00	21.00	123,954.79	4,389.63
54	83	128	636	123	100%	96%		553.00	(5.00)	115,593.59	(1,045.15)
55	113	130	554	120	100%	92%		441.00	(10.00)	92,182.23	(2,090.30)
56	206	132	441	157	100%	100%		235.00	25.00	49,122.05	5,225.75
57	92	118	528	132	100%	100%		436.00	14.00	91,137.08	2,926.42
58	137	126	636	136	100%	100%		499.00	10.00	104,305.97	2,090.30
59	114	124	499	128	100%	100%		385.00	4.00	80,476.55	836.12
60	109	124	585	122	100%	98%		476.00	(2.00)	99,498.28	(418.06)
61	166	130	476	142	100%	100%		310.00	12.00	64,799.30	2,508.36
62	100	133	609	126	100%	95%		509.00	(7.00)	106,396.27	(1,463.21)
63	128	131	910	128	100%	98%		782.00	(3.00)	163,461.46	(627.09)
64	92	128	782	115	100%	90%		690.00	(13.00)	144,230.70	(2,717.39)
65	161	138	890	135	100%	98%		729.00	(3.00)	152,382.87	(627.09)
66	115	135	1,128	129	100%	96%		1,013.00	(6.00)	211,747.39	(1,254.18)
67	116	145	1,014	125	100%	86%		898.00	(20.00)	187,708.94	(4,180.60)
68	155	154	1,198	139	100%	90%		1,043.00	(15.00)	218,018.29	(3,135.45)
69	197	154	1,043	164	100%	100%		846.00	10.00	176,839.38	2,090.30

70	83	146	846	133	100%	91%		763.00	(13.00)	159,489.89	(2,717.39)
71	102	170	764	122	100%	72%		662.00	(48.00)	138,377.86	(10,033.44)
72	170	170	1,093	143	100%	84%		923.00	(27.00)	192,934.69	(5,643.81)
73	140	166	1,524	143	100%	86%		1,384.00	(23.00)	289,297.52	(4,807.69)
74	190	172	1,384	164	100%	95%		1,194.00	(8.00)	249,581.82	(1,672.24)
75	192	162	1,316	177	100%	100%		1,124.00	15.00	234,949.72	3,135.45
76	156	155	1,245	170	100%	100%		1,089.00	15.00	227,633.67	3,135.45
77	132	149	1,139	156	100%	100%		1,007.00	7.00	210,493.21	1,463.21
78	275	149	1,007	206	100%	100%		732.00	57.00	153,009.96	11,914.71
79	105	133	1,030	166	100%	100%		925.00	33.00	193,352.75	6,897.99
80	137	143	1,131	156	100%	100%		994.00	13.00	207,775.82	2,717.39
81	184	144	1,563	169	100%	100%		1,379.00	25.00	288,252.37	5,225.75
82	108	142	1,730	146	100%	100%		1,622.00	4.00	339,046.66	836.12
83	142	139	1,623	146	100%	100%		1,481.00	7.00	309,573.43	1,463.21
84	106	148	1,481	131	100%	89%		1,375.00	(17.00)	287,416.25	(3,553.51)
85	130	144	1,377	132	100%	92%		1,247.00	(12.00)	260,660.41	(2,508.36)
86	145	145	1,447	139	100%	96%		1,302.00	(6.00)	272,157.06	(1,254.18)

87	188	141	1,302	161	100%	100%		1,114.00	20.00	232,859.42	4,180.60
88	147	141	1,114	157	100%	100%		967.00	16.00	202,132.01	3,344.48
89	170	135	967	164	100%	100%		797.00	29.00	166,596.91	6,061.87
90	84	132	798	133	100%	100%		714.00	1.00	149,247.42	209.03
91	213	133	1,113	167	100%	100%		900.00	34.00	188,127.00	7,107.02
92	72	122	901	130	100%	100%		829.00	8.00	173,285.87	1,672.24
93	139	126	799	135	100%	100%		660.00	9.00	137,959.80	1,881.27
94	112	122	783	127	100%	100%		671.00	5.00	140,259.13	1,045.15
95	187	131	1,071	153	100%	100%		884.00	22.00	184,782.52	4,598.66
96	101	130	893	133	100%	100%		792.00	3.00	165,551.76	627.09
97	146	131	1,093	140	100%	100%		947.00	9.00	197,951.41	1,881.27
98	94		948								
99	121		853								
100	105		1,332								
101	106		1,267								
102	183		1,632								
103	180		1,628								
104	108		1,448								
				Mean	100%	96%				198,312.73	531.53

Column 1 shows the No. of fortnights that forecasting started. Column 2 and 3 shows the actual 2 weeks aggregated demand and average lead time demand respectively. Column 4 shows the actual stock quantity at the beginning of each fortnight while column 5 shows the forecasted demand plus safety stock. Column 6 & 7 presented the service level for the existing inventory system, and approximation method respectively. In column 8 the unit cost of the part taken at the end of 2016 considered. In column 9 the overage/shortage quantity for the existing system calculated as *stock quantity – aggregated demand* , while in column 10 the overage /shortage for approximation method calculated as *forecasted demand + safety stock– average lead time demand*. In column 11 and 12 the overage/shortage in monetary value calculated by multiplying the quantity in column 9 and 10 by unit cost of the part in column 8.

The average service level for the selected spare part for illustration is 100% for the existing inventory system and 96% for approximation method. Regarding stock amount the average excess stock of ETB 198,312 is observed for the existing inventory system and excess stock amount ETB 531 for approximation method.

The findings of service level and overage/shortage for the 28 sample spare parts are presented in the table 5 below.

Table 5. Findings

No	Forecasting Method	Service level	Overage/shortage stock amount, ETB
1	Existing inventory	99.9%	245,852.00
2	Approximation	96.2 %	5,837.27

5. Discussion

The challenging task of inventory management is keeping the balance between stock amount and service level. To achieve the optimum balance appropriate forecasting demand and holding stock based on the forecast result is crucial.

On the existing inventory system the service level is 99.9 % with additional excess stock amount of ETB 245,825 for the 28 sample parts which includes irregular, and slow moving demand patterns. The result indicates that the effort to keep the balance between service level and stock amount is poor. Beyond satisfying the demand fully the inventory carry more excess stock than the demand requires.

Approximation method gives service level of 96.2 % with excess of stock amount of ETB 5,837.The result shows that there is an effort to keep a good balance between service level, and optimum inventory level. The service level of 96.2 % is quite a good result in the spare parts inventory management with few capital tied up. The required amount of Service level usually agreed between parties (Song et al, 2009; Seluck et al, 2013; Kranenburg and Houtu, 2007). Toyota expects a service level of 97% from its distributors on the monthly KPI & CMI report.

Existing system holds capital that can be invested to generate additional profits. In other words the opportunity cost is high. But, approximation method forecasted the demand by average with 96.2% likelihood and with less tied up capital so that the relived capital can be invested to generate more profit to the business entity.

Spare parts are imported using a scarce forex. When we import, & put spare parts on shelf for long time, it is abusing the fair distribution of forex that can be used to solve other critical problems of the country. Forecasting the demand with good certainty, like approximation demand forecasting method maximizes efficient utilization of forex.

Besides tied up of capital keeping excess inventory have also other consequence, it holds more spaces, requires additional shelfs, machines and labor to handle, and care the excess inventory that leads to unnecessary investment on fixed capital, and also maximizes operating expenses which increase the holding cost of spares. When the parts matured to dead stock a provision is allocated by finance that will be deducted from the profit. All these situations leads to a reduction on the profit that can be obtained from the business. By using good demand forecasting methods, and ordering the parts accordingly helps to minimizes greatly unnecessary costs and maximizes the profitability of the business.

Even though acceptable range of service level differs in different industries and countries, 96.2 % service level is a very good result in parts inventory management that usually manages more than 20,000 line items, and the type of spare part (line items) it holds increases from time to time due to inclusion of new models each time, and fastest technological changes (Thonemann et al, 2002).

Therefore, using approximation method greatly helps in maximizing the reliability & profitability of the company, meets customer's satisfaction and helps to capture considerable market share of the business.

6. Conclusion

Maintaining optimized inventory level without appreciable reduction in service rate is a challenging task. To keep the balance between the two parameters i.e. inventory level and service level, appropriate forecasting of demand is critical. But, there are three main difficulties in forecasting the demand of spare parts. First, demand of spare part is often intermittent. Second, historical data of spare part demand are usually very limited. Third, in some industries spare part inventory level largely a function of how equipment is used and how it is maintained.

Automotive industry exhibits fastest technological changes, introduce new model from year to year, the number of vehicles on the road are continually increasing, the type of spare parts line items are very large, and number and behavior of customers that needs the aftersales support are diverse and many. All these factors and others makes very challenging to manage the inventory of automotive spare parts.

This thesis work investigated the applicability of approximation demand forecasting method in the context of MOENCO as a better managerial solution for demand forecasting in parts inventory system. The model works successfully in providing optimum inventory with sufficient service level.

After processing and filtering the data, 28 parts are ready to be tested, out of which 12 of the parts have irregular demand pattern, while the remaining 16 have slow moving demand pattern.) Because of that fast moving parts are less in number than slow moving parts. The time between Jan.2013 –Dec, 2016 is selected because during this time the availability of forex is relatively in good condition, so that the Letter of Credit (L/C) approved regularly and orders received consistently by average every four months.

The demand aggregation of 2 Weeks (1 fortnight) is used in the analysis since the existing inventory management system places order in each fortnight, so that the comparison will be like for like. And also lead time demand is taken as 8 fortnights (4 months) due to the fact that the average lead time is 4 months.

Croston's estimate of mean interval between transactions (p_t), and Croston's estimate of mean demand size (z_t) startup parameters are calculated using as an average of 2013 data. The coefficients of z_t and p_t i.e. α_s & α_i selected in such a way that the average MAPE (mean absolute percentage error) for the selected 28 sample parts is sets at the minimum.

Using coefficients of α_z=0.41 and α_i=0.01 derived from the system itself, estimated demand calculated from 2014 to 2016. The forecasted demands rounded up for any forecast less than zero, but to the nearest for a forecast greater than one. The safety stock is calculated using the method suggested by Syntetos AA and Teunter RH and added to the estimated demand to get the final stock level.

Finally a comparison is made between the two systems by calculating and comparing service level and inventory amount from actual aggregated demand data and stock quantity as one set and average lead time demand and forecasted demand by approximation method plus safety stock as the second set. The result drawn from the approximation method proves that it significantly optimized the inventory level with very good service level result.

The method provides a multi-dimensional benefits for the business. It significantly minimizes tied up of capital so that companies can invest their money to generate more profits. It reduces the operating, overhead, and disposal costs which further enhances the profitability of the businesses.

As a corporate citizen companies play their responsibilities in using the scarce forex rationally, effectively and efficiently.

Companies maximize their profit with very good service level which leads to high customer satisfaction, large market share, and high reliability image. All these build a sustainable, and profitable business foundation for long term.

This thesis work can be more enhanced by simulating spare parts inventory data from other automotive companies that include different demand pattern types. It can also be tested in different industries other than automotive to experience informed decisions on ordering, and stockholding of spare parts.

References

Adya, M. and Collopy, F. (1998).How effective are neural nets at forecasting and prediction? A review and evaluation. *Journal of Forecasting*, 17, 451-461.

Allen, P. G. and Fildes, R. (ED.). (2001). *Econometric forecasting*. Norwell, MA: Kluwer Academic Publishers, pp. 303-362.

Angane, V. R., and Kachare, A. (2014). Inventory Management and Control using 'Probability Distribution Function'. *SAE International Journal of Materials and Manufacturing*, 7(1), 173-183.

Armstrong, J. S. (ED.). (1985). *Long-term Forecasting: From Crystal Ball to Computer (2nd ed.*). New York: John Wiley.

Armstrong, J. S. (Ed.) (2001), *Principles of Forecasting*. Norwell, MA: Kluwer Academic Publishers.

Armstrong, J. S. (ED.). (2001b). *Extrapolation of time-series and cross-sectional data*. Norwell, MA: Kluwer Academic Publishers, pp. 217-243.

Armstrong, J. S. (ED.). (2001c). evaluating forecasting methods. Norwell, MA: Kluwer Academic Publishers, pp. 365-382.

Armstrong, J. S. and Collopy, F. (1993).Causal forces: Structuring knowledge for time series extrapolation. *Journal of Forecasting*, 12, 103-115.

Armstrong, J. S., Adya, M. and Collopy, F. (ED.). (2001).*Rule-based forecasting: Using judgment in time-series extrapolation*. Norwell, MA: Kluwer Academic Publishers, pp. 259-282.

Armstrong, J.C., and Green, K.C. (ED.). (2006). *Strategic Marketing Management: A Business Process Approach.*USA: nd.

Aronis, K. P., Magou, I., Dekker, R., and Tagaras, G., and Kachare, A. (2004). Inventory Control of Spare Parts Using a Bayesian Approach: A Case Study. Econometric Institute Report EI-9950/A.

Babi, M. Z., Jemai, Z., and Dallery, Y. (2010, May). Analysis of Order-up-to-level Inventory Systems. Evaluation and Optimization of Innovative Production Systems of Goods and Services, Hammamet, Tunisia: International Conference of Modeling and Simulation.

Baluch, N., Abdullah, C. H, and Mohtar, S. (2013). Evaluating Effective Spare-parts Inventory Management for Equipment Reliability in Manufacturing Industries. *European Journal of Business and Management*, 5(6), 69-75.

Becker, J., Hartmann, W., Bertsch, S., Nywlt, J., and Schmidt, M. (2013). Dynamic Safety-Stock Calculation. *International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering*, 7(10).

Caggiano, K. E., Jackson, P.L., Muckstadt, J.A., and Rappold, J.A. (2007). Optimizing Service Parts Inventory in a Multiechelon, Multi-Item Supply Chain with Time-Based Customer Service-Level Agreements. *Operations Research*, 55(2), 303-318.

Chen, X., Sim, M., Simchi-Levi, D., and Peng, S. (2007). Risk Aversion in Inventory Management. *Operations Research*, 55(5), 828-842.

Cohen, M., Kamesam, P.V., Kleindorfer, P., Lee, H., and Tekerian, A. (1990). Optimizer: IBM's Multi-Echelon Inventory System for Managing Service Logistics. Interfaces, 20(1), 65-82.

Cohen, M.A. (2005). Tapping the Service Supply Chain. Line 56. Retrieved from: http://www.line56. com/print/default.asp?ArticleID ¼6615

Collopy, F., Adya, M. and Armstrong, J. S. (ED.). (2001).*Expert systems for forecasting* Norwell, MA: Kluwer Academic Publishers, pp. 285-300.

Confente, I., and Russo, I. (2015). After-Sales Service as a Driver for Word-of- Mouth and Customer Satisfaction: Insights from the Automotive Industry. *International Journal of Management Cases*, 17(4), 59-72.

Dalrymple, D. J. (1987).Sales forecasting practices: Results from a U.S. survey. *International Journal of Forecasting*, 3, 379-391.

Dangerfield, B. J. and Morris, J. S. (1992).Top-down or bottom-up: Aggregate versus disaggregate extrapolations. *International Journal of Forecasting*, 8, 233-241.

Dawes, R. M. & Corrigan, B. (1974).Linear models in decision making. *Psychological Bulletin*, 81, 95- 106.

Desta, E. (2007).*The Automotive Industry and Trend Analysis* (Unpublished master's thesis).Addis Ababa University, Addis Ababa.

Duncan, G., Gorr, W. and Szczypula, J. (ED.). (2001). *Forecasting analogous time series.* Norwell, MA: Kluwer Academic Publishers, pp. 195-213.

Eaves, A. H. C., (2002). *Forecasting for the ordering and stock-holding of spare parts* (Unpublished doctoral dissertation). University of Lancaster, Lancaster, UK.

Eaves, A. H. C., and Kingsman, B. G. (2004). Forecasting for the ordering and stock-holding of spare parts. *The Journal of the Operational Research Society, 55*(4), 431-437.

Flowers, A. D., and O'Neill II, J.B. (1978). An Application of Classical Inventory Analysis to a Spare Parts Inventory. *Interfaces*, 8(2), 76-79.

Green, K. C. (2005), Game theory, simulated interaction, and unaided judgment for forecasting decisions in conflicts: Further evidence. *International Journal of Forecasting*, 21, 463-472.

Green, K. C. (2002), Forecasting decisions in conflict situations: A comparison of game theory, role-playing, and unaided judgement. *International Journal of Forecasting*, 18, 321-344.

Gu, J. (2013). Proactive and Efficient Spare Parts Inventory Management Policies Considering Reliability Issues (Unpublished master's Thesis). University of Windsor, Ontario, CA.

Hopp, W. J., Spearman, M.L., and Zhang, R.Q. (1997). Easily Implementable Inventory Control Policies. *Operations Research*, 45(3), 327-340.

Hausman, W. H., and Thomas, L.J. (1972). Inventory Control with Probabilistic Demand and Periodic Withdrawals. *Management Science*, 18(5), 265-275.

Hausman, H. H., and Erkip, N.K. (1994). Multi- echelon vs. Single – echelon Inventory Control Policies for Low – demanded items. *Management Science*, 40(5), 597-602.

Hua, Z. S., Zhang, B., Yang, J., and Tan, D.S. (2007). A new approach of forecasting intermittent demand for spare parts inventories in the process industry. *The Journal of the Operational Research Society, 58*(1), 52-61.

Hua, Z., Yang J., Huang F., and Xu, X. (2009). A Static-Dynamic Strategy for Spare Part Inventory Systems with Nonstationary Stochastic Demand. *The Journal of the Operational Research Society*, 60(9), 1254-1263.

Juster, T. (1966), Consumer buying intentions and purchase probability: An experiment in survey design. *Journal of the American Statistical Association*, 61, 658-696.

Kelle, P., and Miller, P. A., (2001). Stock out risk and order splitting. International Journal of Production Economics, 71, 407-415.

Keogh, Eamonn, & Kasetty, S. (2002).On the need for time series data mining benchmarks: A survey and empirical demonstration. Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

Kranenburg, A. A., and Van Houtum, G. J. (2008). Service Differentiation in Spare Parts Inventory Management. *The Journal of the Operational Research Society*, 59(7), 946-955.

MacGregor, D. (ED.). (2001). *Decomposition for judgmental forecasting and estimation.* Norwell, MA: Kluwer Academic Publishers, pp. 107-123.

Makridakis, S., Wheelwright, S. C., and Hyndman, R. J. (1998). *Forecasting Methods for Management, Third edition*. New York: John Wiley.

Makridakis, S., Andersen, A., Carbone, R., Fildes, R., Hibon, M., Lewandowski, R., Newton, J., Parzen, E. and Winkler, R. (1984). *The Forecasting Accuracy of Major Times-Series Method*s. Chichester: John Wiley.

Miller, Don M. & Dan Williams (2004). Shrinkage estimators for damping X12-ARIMA seasonals. *International Journal of Forecasting*, 20, 529-549.

Morwitz, V. (ED.). (2001). *Methods for forecasting from intentions data*, *in J. S. Armstrong (Ed.) Principles of Forecasting*. Norwell, MA: Kluwer Academic Publishers, pp. 33-56.

Öner, .K .B. Kiesmüller, G. P. and Van Houtum, G. J. (2010). Optimization of Component Reliability in the Design Phase of Capital Goods. *European Journal of Operational Research* 205(3): 615-624.

Petkovic, R., Petkovic, D. (2009). Multicriteria ranking of inventory replenishment policies in the Presence of uncertainty in customer demand. International Journal of Production Economics, 71, 439-446.

Rego, J. R., & Mesquita, M.A. (2011). Spare parts inventory control: a literature review. Produção, 21(4), 656-666.

Relph, G., & Milner, C. (2015). *Advanced methods for managing inventory within business systems.* Nd: The Institute of Operation Management.

Rowe, G. and Wright, G. (ED.). (2001).Expert opinions in forecasting role of the Delphi technique. Norwell, MA: Kluwer Academic Publishers, pp. 125-144.

Schultz, C. R. (1987). Forecasting and Inventory Control for Sporadic Demand under Periodic Review. *The Journal of the Operational Research Society*, 38(5), 453-458.

Selcuk, A., and Agrali, S. (2013). Joint spare parts inventory and reliability decisions under a service constraint. *The Journal of the Operational Research Society, 64*(3), 446-458.

Silver, Edward A. (1991). A Graphical Implementation Aid for Inventory Management of Slow-Moving Items. The Journal of the Operational Research Society, 42(7), 605-608.

Song, H., Song, YF. (2009). Impact of Inventory Management Flexibility on Service Flexibility and Performance. *Transportation Journal*, 48(3), 7-19.

Stanford, R. E., and Martin, W., (2007). Towards a Normative Model for Inventory Cost Management in a Generalized ABC Classification System. *The Journal of the Operational Research Society*, 58(7), 922-928.

Strijbosch, L. W. G., Heuts, R. M. J. and Van der Schoot, E. H. M. (2000). A Combined Forecast-Inventory Control Procedure for Spare Parts. *The Journal of the Operational Research Society*, 51(10), 1184-1192.

Stulman, A., (1989). Excess inventory with stochastic demand: continuous reporting model. *The Journal of the Operational Research Society, 40*(11), 1041-1047.

Syntetos, A. A., Babi, M. Z. Altay, N. (2012). On the demand distribution of spare parts. *The International Journal of Production Research, 50*(8), 2101-2117.

Syntetos, A. A., Babi, M. Z., Dallery, Y., and Teunter, R. (2009). Periodic Control of Intermittent Demand Items: Theory and Empirical Analysis. *The Journal of the Operational Research Society*, 60(5), 611-618.

Syntetos, A. A., Teunter, R. H. (2014). *On the calculation of safety stocks.* (SOM Research Reports; Vol. 14003-OPERA). Groningen: University of Groningen, SOM research school.

Thonemann, U. W., Brown, A.O., and Hausman, W.H. (2002). Easy Quantification of Improved Spare Parts Inventory Policies. *Management Science*, 48(9), 1213-1225.

Topan, E., and Bayindir, ZP. (2012). Multi-item two-echelon spare parts inventory control problem with batch ordering in the central warehouse under compound Poisson demand. *The Journal of the Operational Research Society,* 63(8), 1143-1152.

Wang, Y., Cohen, M. A., Zheng, Yu-Sheng. (2000). A Two-Echelon Repairable Inventory System with Stocking-Center-Dependent Depot Replenishment Lead Times. *The Journal of the Operational Research Society*, 46(11), 1441-1453.

Wanger, S.M., and Lindemann, E. (2008). A Case Study-Based Analysis of Spare Parts Management in the Engineering Industry. *Production Planning and Control*, 19(4), 397-407.

Wanke, P. (2014). A Conceptual Framework for Inventory Management: Focusing on Low-Consumption Items. *Production and Inventory Management Journal*, 49(10), 6-23.

Wittink, D. R, and Bergestuen, T. (ED.). (2001), "Forecasting with conjoint analysis.

Principles of Forecasting, Norwell MA: Kluwer Academic Publishers, pp. 147-167.

Zea, O.S. (2013, December 02). Single echelon inventory strategies in spare parts supply chains. Retrieved from http://ingenieria.ute.edu.ec/enfoqueute/.

Zotteri, G., and Verganti, R. (2001). Multi-level approaches to demand management in complex environments: An analytical model. The International Journal of Production Economics, 71, 221-233.

Appendix 1

Results of stock amount and service level for the 28 sample spare parts

Item No	Stock amount ETB		Service level	
	Existing Inventory	Approximation	Existing Inventory	Approximation
1	198,312.73	531.53	100.00%	95.68%
2	1,256,258.40	(2,341.14)	100.00%	91.78%
3	447,524.02	(9,536.07)	100.00%	91.03%
4	103,273.21	855.63	98.69%	94.38%
5	171,929.62	1,689.11	100.00%	97.07%
6	405,141.79	(5,861.24)	98.64%	90.95%
7	807,779.85	(605.00)	100.00%	90.29%
8	1,194,582.98	1,075.52	100.00%	93.69%
9	155,882.29	(1,001.30)	100.00%	88.30%
10	1,918,788.12	385.83	100.00%	96.51%
11	76,648.66	(1,580.70)	100.00%	89.34%
12	62,624.32	172.18	100.00%	91.17%
13	2,252.66	26,457.66	100.00%	100.00%
14	3,710.26	16,475.30	100.00%	100.00%
15	7,818.04	7,906.38	100.00%	100.00%
16	5,477.04	11,086.60	100.00%	100.00%
17	5,653.30	14,204.51	100.00%	100.00%
18	4,394.42	23,482.67	100.00%	100.00%
19	1,483.27	844.94	100.00%	96.00%
20	221.97	335.79	100.00%	100.00%
21	3,887.21	6,321.83	100.00%	100.00%
22	1,067.61	1,533.34	100.00%	100.00%
23	26,474.02	37,667.74	100.00%	100.00%
24	8,747.17	12,199.32	100.00%	100.00%
25	1,186.32	1,283.49	100.00%	100.00%
26	5,441.19	6,778.69	100.00%	100.00%
27	3,497.18	6,009.23	100.00%	100.00%
28	3,798.49	7,071.65	100.00%	100.00%

Average	245,852.00	5,837.27	99.90%	96.20%