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Master's Programme in Supply Management

MASTER'S THESIS

Demand forecasting of spare parts – case study from automotive industry

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ABSTRACT

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The purpose of this thesis is to find suitable methods in forecasting the intermittent demand for spare parts and in an automotive company. Four existing methods, from simple to exclusively developed for forecasting intermittent demand items, were tested to determine the best-performing method. The optimal method was chosen on the basis of which model provides the lowest level of error against the actual demand.

Demand pattern was classified into 4 types of demand pattern, namely erratic, lumpy, smooth and intermittent, by the degree of intermittence and degree of erraticness. Dataset extracted from sales data of 5 operating markets in the period 2013-2018, on monthly aggregation level. Demand was forecasted using forecasting methods such as Moving Average, Exponential Smoothing, Croston's method, and Syntetos-Boylan Approximation.

The study's result proved that the simple Moving Average is not a good approach in forecasting items with intermittent demand. On the other hand, Syntetos-Boylan Approximation and Exponential are the 2 methods that provided the best accuracy, depending on demand patterns and markets. The findings also proposed a forecasting framework to the case of the company.

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Espoo, May 23, 2019

Nguyen Huynh

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LIST OF SYMBOLS AND ABBREVIATIONS

ρ	degree of intermittence
CV^2	degree of erraticness
MA	moving average
ES	exponential smoothing
CR	Croston's method
SBA	Syntetos-Boylan Approximation
Ft	forecast demand for period t
Dt	demand for period t
N	number of period
α	smoothing constant
Pt	forecast interval between transaction for period t
Q	interval from latest period with positive demand
Ct	forecast mean demand for period t
MAD	Mean Absolute Deviation
MSE	Mean Squared Error
SMAPE	Symmetric Mean Absolute Percentage Error

1. INTRODUCTION

The aftermarket of spare parts and service business is indeed an important and inseparable sector of the automotive industry. In fact, it is considered as one of the most profitable sectors as the global aftermarket generated around USD 760 billion (20%) of total automotive revenues in 2015. Separately, the spare parts market has accounted for approximately 55% of the aftermarket revenues while the service business contributed the rest 45%. Moreover, the global part product market has been growing gradually with positive signs and is expected to grow at an average rate of 3% annually until 2030, with Europe at 1.5% to reach the total revenue at USD 295 billion (from USD 237 billion in 2015). (Breitschwerdt et al., 2017). With such a crucial role, automotive company is paying more attention to the performance of aftersales to maintain customer satisfaction level, thus, various car manufacturers have made aftersales one of the focuses in their strategies. As a result, it is essential for a company to maintain an efficient management system for their aftersales business, including activities such as demand forecasting, warehousing, part distributing or service coordinating with other stakeholders in the aftersales supply chain. As the service business is also depending on spare parts, a company is required to ensure spare part stock availability in order to reduce delivery time to customer, as well as to avoid potential extra cost incurred due to long lead time in order to maintain a satisfactory level of customer retention.

1.1. Background of the study

The demand for spare parts has always been volatile. In fact, most of the time the reason is the bullwhip effect in the supply chain. Specifically, it reflects the uncertainty and variation as the demand varies significantly as it goes upstream in the supply chain, for example, inconsistency in the market of end-users, i.e. automobile owners, or due to price fluctuations that cause batch ordering from manufacturer’s direct customers. (Lee, Padmanabhan and Whang, 1997). There are various terminologies to determine demand pattern, and besides items with regular demand, consumable spare parts are categorized into 2 common patterns, namely intermittent demand and slow-moving demand, on the basis of transaction frequency and demand size. Specifically, if the transaction of an item is frequent and its demand size varies significantly, it is classified as intermittent demand, or erratic demand, while on the other hand, if transaction is frequent, yet demand size is small, it is classified as slow-moving demand, and regular demand pattern is simply used to categorize items with smooth and continuous demand. (Eaves and Kingsman, 2004; Williams, 1984).

In theory, forecasting provides advantages in managing its business in several terms, e.g. being able to plan production, procurement or inventory ahead and therefore being able to save resources and eventually save costs. However, forecasting demand poses a challenging task due to the uncertainty of upcoming events that affect the demand. More specifically, irregular and intermittent demand of spare parts is always presented when the demand usually does not remain smooth and continuous in a long period, thus, resulting in significant errors and inaccuracy in forecast results. (Kerkkänen, 2010).

1.2. Research problems

The problem motivating this research is that in an automotive manufacturing company, forecasting demand for spare parts is conducted based on one single employee's own experience and expertise. Hence, end results are heavily dependent on the analyst's knowledge and understanding of the model and the business of the company, which sometimes leads to a shortage of various items, high amount of backorders and consequently leads to unnecessary costs and lower retention level. Although there is a variety of spare parts demand forecasting methods, the current method being applied in the current context of the company is the naive forecasting method. Therefore, this research is aimed to address the gap between forecasting literature and empirical use, where there is no reliable forecasting method is used in the case company. The research would solve such problems in the company by answering the questions below:

Q1: What are the suitable methods to forecast the intermittent demand of automotive spare parts in the company's case?

SQ1: What is the level of accuracy of the current method, Moving average, in the case company's forecast approach?

Q2: How can the selected forecasting methods be implemented in the company's case?

1.3. Research methodology

In order to answer the research questions, the study is designed so that the research methodology is a quantitative method in a single case study. In detail, the study employs a single case-oriented approach in data collection focusing on the case of the company. Then, the analysis phase aims at the extensive data set that covers several observations across multiple geographical markets.

As a matter of fact, the quantitative approach is the method that is aimed to solve business problems in practice by helping the study and the researcher to deliver unbiased findings, validating proposed hypotheses using empirical and factual evidence with the assistance of statistical and mathematical models, theories and hypotheses. In general, scholars have classified quantitative research type into 2 categories, namely, descriptive research and normative research. The former approach focuses on developing a model that addresses the relationship between practical situations and theoretical concepts. On the other hand, the latter applies a practical approach that aims to tackle the current business problem based on already developed theories, concepts, and models existing in the literature. (Kotzab et al., 2005). Law and Kelton (2000) also proposed a framework several phases that helps explain how normative quantitative research is an appropriate answer to real-life business problems. The process starts from defining the business issue and plan the study, then, data is collected for the modeling stage and continuing with making example runs, analyzing data output and finalizing with describing and applying the results into practice. Similarly, Dubois and Araujo (2007) and Glesne (2011) agreed that a quantitative research generally consists of several phases, e.g. theory and hypothesis developing, method experimenting, data collecting, data modelling and analyzing. Therefore, it is necessary to conduct this study in a quantitative method. In a quantitative research method, there are several common ways to collect data, such as primary data, secondary data, historical stored data, observation, questionnaire or interview (Wynstra, 2010). Data used in quantitative research is in numerical form, which is historical sales data in this paper.

On the other hand, a single case study approach is also applicable in this case, due to the fact that it is a distinctive approach in addressing a specific empirical situation (Saunders, Lewis and Thornhill, 2009). Moreover, according to Voss, Tsikriktsis and Frohlich (2002) and Kähkönen (2014), when the research is about examining existing developed concept and model in a unique situation, it is suggested to be conducted in a single case approach as it able to provide a comprehensive answer to the business issue. However, it should be noted that a single case study also faces several disadvantages, when researchers easily gets into generalization of the case's result since it is not able to extrapolate to a bigger sample (Voss, Tsikriktsis and Frohlich, 2002; Kähkönen, 2014).

1.4. Theoretical and research framework

The theoretical framework on which this research is based is described in the below figure. According to Dubois and Araujo (2007), a theoretical framework acts as a bridge connecting the empirical and the conceptual perspective of the study. In this study, it involves the relationships between the variables in the dataset. The framework which was developed by Syntetos et al. (2016) demonstrates a four-dimension design on which a supply forecasting process is recommended to be established.

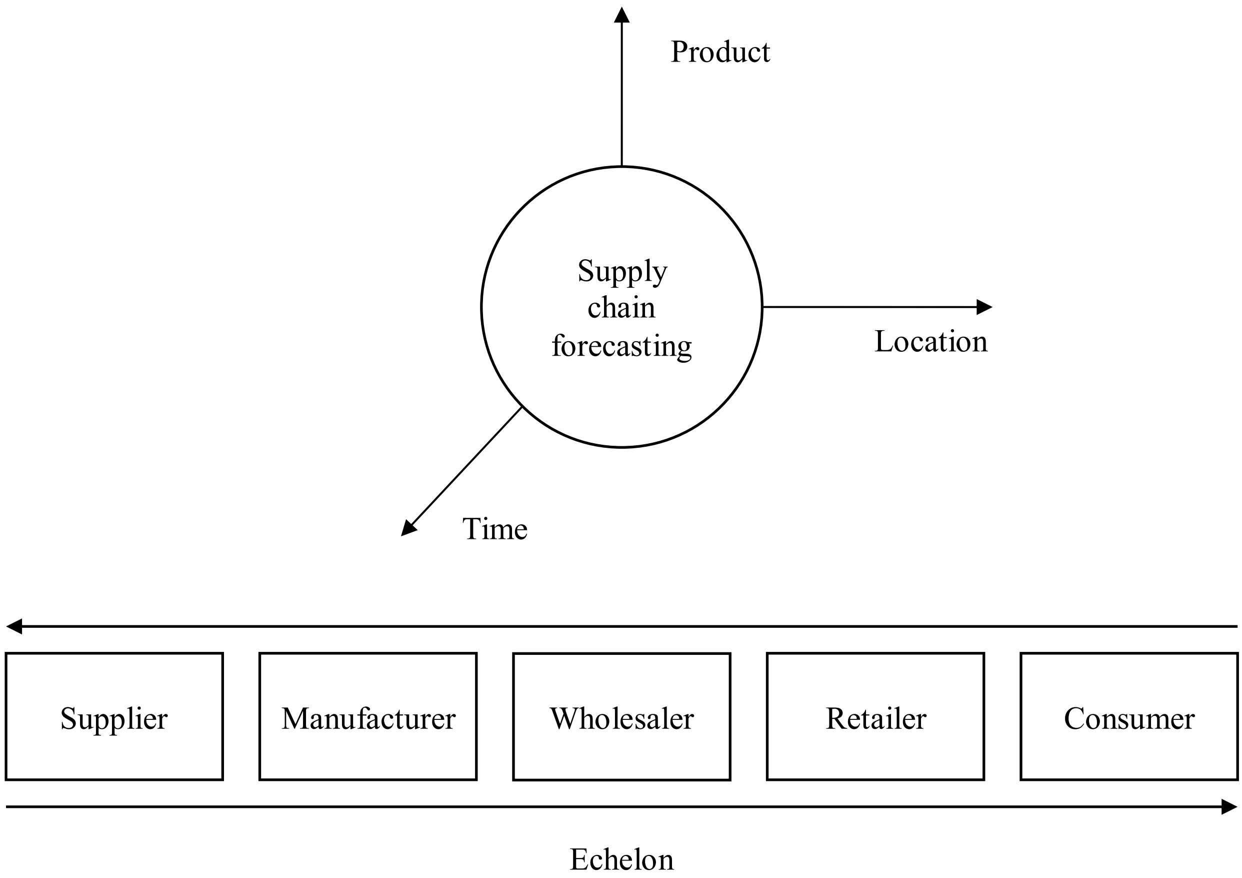

Figure 1. Supply chain forecasting framework (Syntetos et al., 2016)

Firstly, the product dimension is related to the level of aggregation of the inventory and depends on the organizational decisions to be made, whether it is all items or simply some line items for different customer groups that need to be forecasted. While forecasting across the whole inventory providing insights at a strategic level, for example, annual budgeting or performance establishing, grouping items with similar characteristics would help the organization at lower, operational level tasks such as inventory control, transport planning or warehouse planning. In this study, the product dimension is at the demand type level of aggregation, which means, items in the spare parts inventory are grouped into different categories based on their demand type. Secondly, the location dimension defines the level of aggregation of the location, in other words, since different locations have different sales or demand pattern, it is necessary to choose an appropriate approach in selecting the suitable locations to include in the forecast models. In this study, since the company operates on 5 different markets, it is essential to aggregate data on a country level, instead of a warehouse-based level, which would lead to a fragmented dataset and results. Thirdly, the time dimension of the forecasting framework affects all forecasting issues rather than only the supply chain. The dimension includes elements that help to decide the forecast approach and strategy, such as time bucket in which the data is collected, forecasting horizon which is determined based on the forecast purpose, demand characteristic which is the level of intermittence of the demand between periods. It is worth mentioning that, forecasting accuracy is also dependant on the time dimension of the forecast (Kerkkänen, 2010). The time dimension in this research is on monthly aggregation level, time bucket spanning from the last 6 calendar years and the forecasting horizon is one period ahead. Lastly, the fourth dimension in the forecasting framework is the echelon level. That is, the higher the number stakeholders involving in a supply chain, the more the difficulty increases in demand forecasting. Specifically, due to the bullwhip effect, demand is uncertain as it travels upward the supply chain and thus increasing forecast inaccuracy. Also, since information is not always shared along the supply chain, it is unable for upstream players to forecast the demand from other players down the chain as they are dependant on the orders. (Syntetos et al., 2016). In this study, the echelon dimension is focused on the wholesaler, as the company is operating in the regional business unit as an organization that distributes spare parts to its dealerships and does not own manufacturing sites.

The aim of this research is to determine the optimal methods for forecasting the demand for spare parts for the case company. To begin with, studies in relevant literature of spare part inventory management, continuing with demand classification were reviewed. For a spare part item to be selected as intermittent, it is required to have inter-demand interval or average demand interval (ρ) larger than 1.25 (Croston, 1972; Johnston and Boylan, 1996). Items with average demand interval values larger than 12 mean that there is no demand in the last 12 period and are either not for sale or for old models and considered obsolete in the inventory, therefore excluded from the model calculation. Then, it is classified into either 4 types of demand pattern using 2 cut-off values that demonstrate the degree of erraticness (CV^2) and degree of intermittence (ρ). Next, literature in demand forecasting and forecasting methods and their selection process were also discussed. For instance, four forecasting models selected are: Moving Average, Exponential Smoothing, Croston's original method and Syntetos-Boylan Approximation are applied to the 4 categorized demand patterns from the previous step. Next, forecast accuracy is calculated using three error measurement techniques, MAD, MSE and SMAPE and then compared against each other in order to determine the best-performing methods. The measurement accuracies are the averaged statistics across all selected items. Finally, methods with the highest accuracy for each demand pattern are selected so that each demand pattern group would have one best-performing forecasting method. Specifically, the total number of times each method is ranked first in each accuracy measurement is counted and summed. As a result, a combination of selected forecasts for all demand patterns would be able to apply to the company case. A summary of the research framework is demonstrated in the below figure.

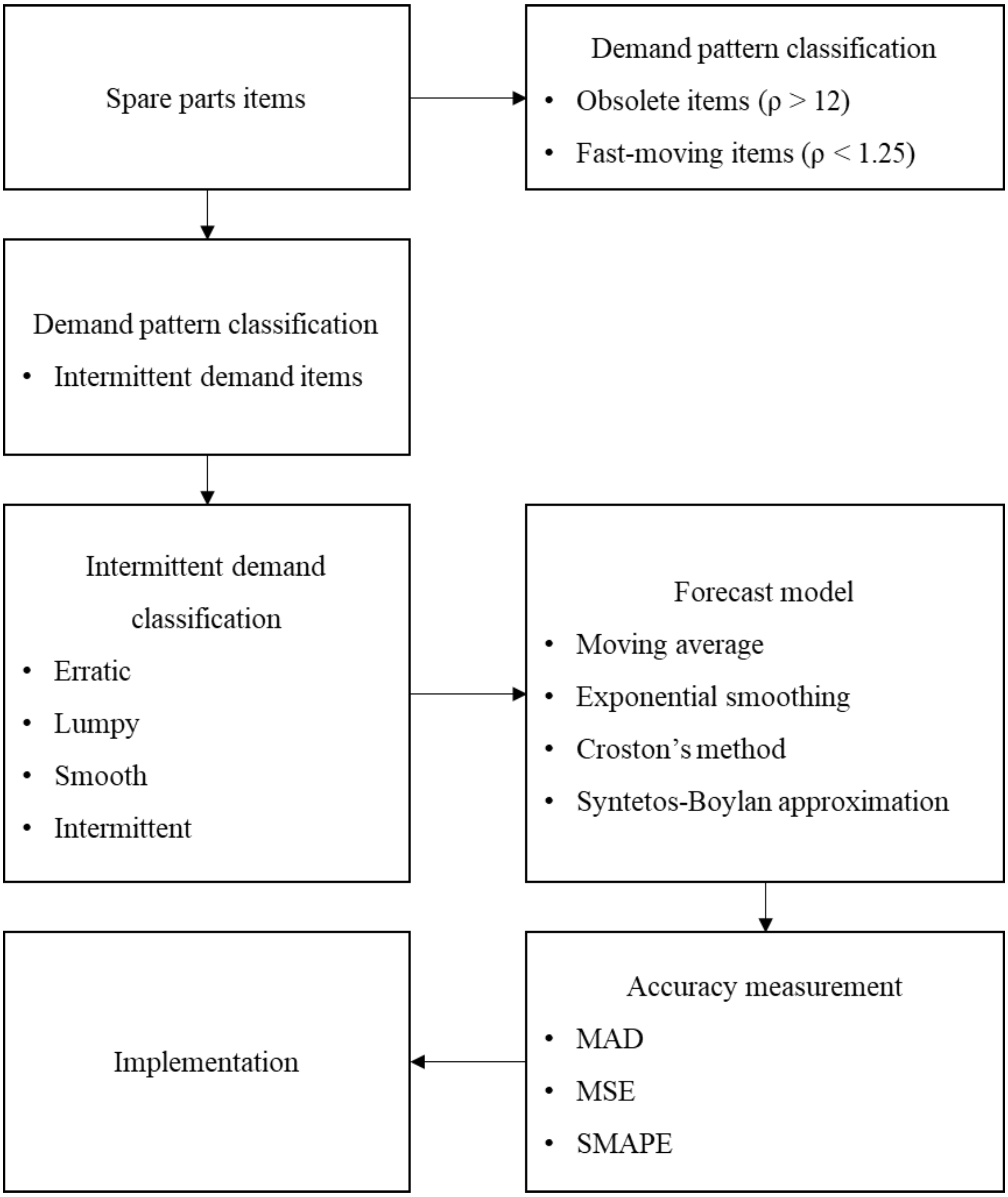

Figure 2. Research framework (Oguji, 2013)

1.5. Research scopes and limitations

The purpose of the study is to find a convenient, simple yet accurate technique to forecast the demand of automotive spare parts. It is important to mention that in the case company, there is no comprehensive approach for forecasting the demand for spare parts but the simple moving average method. It is reported that the current forecasting method used is simply based on the analyst's judgemental decision. The first limitation is data availability. To be specific, the research only uses empirical sales data to train forecast models, to project future data and to measure their accuracies. If more data such as lead time, amount of back order, amount of cancelled order were available, the study would have been able to measure the forecast results more extensively, for example, monitoring how the forecasts would affect fill-rate which further affects customer satisfaction. Due to time and resource constraint, the research focuses on finding the suitable forecast methods for the company, based on its own perspective and available historical data, instead of considering the demand at other levels in the supply chain. Moreover, the study did not consider forecasting demand as a process that involves other organizational factors, e.g. insights from management, cross-function information sharing.

1.6. Definitions of key concepts

Demand pattern classification: the demand of spare part items is not the same across the whole inventory, therefore it is essential to separate the inventory into groups in which items of a group would share similar characteristics with each other. For example, there are several types of demand, namely, sporadic, slow-moving and smooth (Williams, 1984) or smooth, irregular, slow-moving, erratic (Eaves and Kingsman, 2004). In theory, widely-used approaches to classify demand pattern are developed on the basis of either usage volume, moving rate or demand variability (Cavalieri et al., 2008).

Demand forecast: demand forecasting is defined as a managerial task being used to project and predict customer demand in order to assist in the decision making process. Typically, demand forecast for spare parts items, which are considered having intermittent demand pattern, is classified based on the types of data used, whether it is a quantitative method that utilizes historical in the estimation or a qualitative method that uses subjective inputs from forecaster. (Kerkkänen, 2010).

Accuracy measurement: demand forecast accuracy is a vital factor in forecasting management (Chopra and Meindl, 2001) that enables forecaster to conclude whether a forecasting method is accurate. Forecast accuracy is calculated on the basis of the error, in other words, the difference between forecast values and actual values (Hyndman and Koehler, 2006).

1.7. Structure of the thesis

The first chapter introduces the background of the thesis, following by research problems, research methodology, research framework, limitations and the definitions of the main concepts in this study. Next, the second chapter is about spare parts demand forecasting, in which existing literature of spare parts inventory management, demand classification, and demand forecasting are covered. In the third part, fundamental knowledge of 4 forecast methods is reviewed to deliver understandings of forecasting methodology, following by a subsection about accuracy measurement of each forecast results. The fourth chapter discusses the findings of the results as well as answers for the proposed research questions. Lastly, the fifth chapter concludes the study with managerial implications, limitations, and suggestions for future research. A summary of the structure of the thesis is in the following table.

Table 1. Thesis structure

Chapter	Content
1. Introduction	Research problems, methodology, framework, scopes and limitations, and definitions of key concepts
2. Spare parts demand forecasting	Literature of spare parts inventory management, demand classification of spare parts and demand forecasting
3. Forecasting methods	Literature of forecasting methods and accuracy measurement
4. Research findings	Discussions of research's results
5. Conclusion	Managerial implication, limitations, and suggestions for future research

2. SPARE PARTS DEMAND FORECASTING

This section reviews existing literature in spare parts inventory. Initially, the role of an inventory in a company is reviewed, then followed by a discussion about the needs of demand forecasting and finally the approaches in forecasting the demand for spare parts items.

2.1. Spare parts inventory

Basically, spare parts items are distinguished from regular manufacturing items in 2 aspects. Firstly, it is the function that differs from the two. For example, the purpose of other manufacturing inventories such as raw material, work-in-process item or buffer inventory is to keep production running without interruption while there are disruptions in supplier deliveries. Additionally, a company maintains sufficient level of finished goods inventory to be able to meet customer demand when there is variation or issue in distribution; or company also considers ordering an excessive amount of inventory to hedge against price fluctuation or just simply to take advantage of bulk ordering. On the other hand, the purpose of spare parts inventory is to keep the operation and manufacturing process running without any delay. In the automotive aftermarket, spare parts indicate the parts that keep automobile running, such as bumpers, windscreens, wipers, etc. Secondly, the difference between spare parts inventories and regular manufacturing inventories is in management policies. That is, the level of work-in-process or finished goods inventories is dependent on production rates, lead times, schedules, etc.; and changes as these factors change. (Kennedy, Patterson and Fredendall, 2002; Russell and Taylor, 2011). Moreover, the signature characteristics of automotive industry are that it consists of high amount of service parts, up to hundreds of thousand, high amount of customers, short response time but long lead time, multiple service centers, different stock policies for different items, and last but not least, the lumpiness demand pattern of the stock keeping units (de Souza et al., 2011).

Meanwhile, spare parts inventory is mainly determined based on the rates of how equipment, in the case of automotive industry, cars, is used and maintained. In fact, the bullwhip effect, in which demand significantly variates when travelling upwards the supply chain, causes companies to keep and maintain inventory. By keeping an inventory running, companies are partly protected against such variation in demand by timely fulfilling customer order with buffered stocks. Moreover, since lead time and order from customers are always presented, the necessary time for a company to replenish customer orders from an existing inventory comparing to the time when the company has to manufacture is apparently shorter. In other words, due to the fact that spare parts customer demand is uncertain, it is necessary for a company to hold an inventory. (Russell and Taylor, 2011).

In the review of spare parts inventory's literature, Kennedy, Patterson and Fredendall (2002) also summarized other unique characteristics of spare parts management. The first factor is the organization's maintenance policy, that is, whether to replace a broken part or to repair it, determines the usage level of spare parts inventory. However, in the automotive aftermarket, car parts are also dependent on customer usage. For example, careful drivers would have lower chances of getting an accident/close call than a reckless one, thus leading to lower needs of having a part repaired or replaced and eventually lower demand for spare parts. Secondly, the demand for spare parts is usually affected by cannibalism of different parts, units. For example, a new car model introduced to the market would decrease the market share of an older version, thus, resulting in a decrease in demand for the old version's spare parts. Next, part failures are often unpredictable. Nevertheless, it can be offset by assigning a supervisor to monitor the operation of the machine to prevent part failures, e.g. when car owner has their car checked and maintained more frequently, they might be able to prevent the car parts from malfunctioning. Therefore, the cost of car maintenance would be understandably higher than usual. The last characteristic that should be taken into account is the evolution of the inventory. That is, when there are machines and models that become obsolete, spare parts for such products will become obsolete as well. In the same example when a new model is introduced, the demand for older models would become obsolete. Therefore a company usually finds it difficult in determining the appropriate level of stock availability for older models.

Furthermore, one major phenomenon that creates considerable problems in managing spare parts inventory in practice is the bullwhip effect. Although being long recognized and studied by supply chain management scholars, the terminology was first introduced by Lee, Padmanabhan and Whang (1997) as a situation in a supply chain in which the variation of demand in a higher level is always remarkably larger than that of the lower level. The effect is presented as companies are always in need of controlling the supply chain. However, the uncertainties from the demand of other lower echelons have distorted the information of upstream stakeholders, resulting in a higher level of stocking in inventory as it moves through every level. In order to counter the impacts of the bullwhip effect, it is necessary to understand the root causes of the phenomenon. Several reasons that cause the bullwhip effect have been identified, in which there are 4 major factors (Lee, Padmanabhan and Whang, 1997). The first reason is demand handling. In other words, since companies always maintain a safety stock level policy in inventory management, it is common to forecast and plan for production, inventory control, material management, and other operational tasks. For example, when a customer places an order, the order is then used by the retailer as an indication to predict future demand. Next, that information is used to request orders from the manufacturer. Due to a long lead time, it is understandable that the retailer keeps a specific level of safety stock in its inventory. The situation is then repeated at other levels of the supply chain, thus resulting in greater fluctuation of the demand after a level. The second reason is due to order batching. Although demand at the lowest level occurs frequently, a company usually wait for the demand to accumulate before placing an order on a monthly, or quarterly basis instead of daily or weekly due to economies of scale, i.e. the time and cost in order handling, and the situation known as “hockey stick” phenomenon when sales personnel creates order to reach end of period sales target. The third reason that causes the bullwhip effect is variation in price. In practice, companies usually offer promotions and trade deals to their customers to push sales in order to take advantage of price fluctuation. As a result, customers then order more than what they actually need, resulting in the demand pattern is determined by promotion instead of actual demand. The last reason suggested by Lee, Padmanabhan and Whang (1997) is the rational gaming scheme between different levels of the supply chain. This is referred to the situation when customers exaggerate their order estimation to assure that they will receive a sufficient amount of goods in case there is a shortage in supply and production. Similarly to the previous cause, the demand a company received from customers does not accurately reflect the actual demand. As a result, Lee, Padmanabhan and Whang (1997) proposed the demand information sharing in inventory management as an approach in order to tackle the bullwhip effect.

Managing spare parts inventory in practice is similar to normal inventory management in terms of objective, that it is aimed to improve the service level at the lowest possible cost level. The difference from general inventory management is in the approach of how companies handle the erratic demand pattern of spare parts item. (de Souza et al., 2011). For example, Cavalieri et al. (2008) had proposed an approach that consists of step-by-step instruction for the empirical implementation of spare parts inventory management. Initially is the introduction of the spare parts coding system, a scheme, which consists of codes, to provide basic information of the part, e.g. purpose, supplier. Next, the organization continues with item classification: a system that puts parts into groups based on usage value or consumption (ABC classification), moving frequency (FSN classification), importance or criticality of the item (VED classification). Thirdly, demand forecasting, which is the phase when consumption of spare parts is estimated, should be put into usage by deciding whether forecasting is a reliability based, or a time-series based. Lastly, it is necessary for inventory controllers to apply and eventually review the organization's stock management policy and its test and validation: ranging from no-buffer stocking to common techniques such as on-demand or Economic Order Quantity.

Moreover, de Souza et al. (2011) also proposed a framework in managing spare parts items in the airline and automotive industry. The framework starts with setting the appropriate objectives and goals for customer's service level. In fact, response time for customer's requests and demands is considered vital in the aerospace and automotive industry. Specifically, the group of authors examined 3 levels of service in relating to the criticality of the part, the lead time of demand and the amount of cost incurred. In detail, a typical demand request can take up to 1 week in lead time to get the necessary spare part, with the least amount of cost. As the criticality increases, the customer might expect the unit to be delivered sooner, less than 1 week and up to within 1 day as costs are subjected to increase accordingly. When service levels are defined, the company is recommended to establish an exclusive aftersales supply chain from 4 distinctive units, such as part supplier, regional logistics center, country warehouse and lastly, dealer, in order to ensure that customer demands are handled in a timely and efficient manner. In this aftersales supply chain, there are 3 widely applied structures, that are, decentralized, centralized and hybrid. In a decentralized structure, parts are shipped from supplier to the regional warehouse before being distributed to local country warehouses. On the other hand, a centralized system has the company dropped the need of a local warehouse, but store all the necessary line items in the regional warehouse after purchasing them in small batches from the part supplier. After that, items will then be shipped straight to customers when demand order is placed. The key characteristic of this structure is that the central warehouse mainly keeps fast-moving items instead of all. The hybrid scheme is a combination of the 2 structures above when the regional logistics center acts as a hub of receiving bulk shipments from suppliers before distributing to country warehouses in smaller shipments and further dispatched to dealers. In the management framework, de Souza et al. (2011) also defined the efficiency enablers that consist of the suitable technology that supports management in warehouse inventory tracking, operation monitoring and report generating and the requirement that customer service level is measurable and benchmarked against best practice in the market, in order to raise the performance of the system. Subsequently, de Souza et al. (2011) suggested companies develop relevant processes to ensure logistics performance level, which might include activities such as inventory management, order fulfillment, distribution, transportation and reverse logistics. The decision to outsource or keep such activities in-house is a company-specific choice. Moreover, as all business processes are meaningless without proper people, it is of vital importance for a company to equip itself with personnel of high skills, sufficient level of knowledge, innovative mindset and continuously improved training procedure. Last but not least, external factors such as infrastructure, regulation, and incentive also play an important role in boosting the productivity of the framework. (de Souza et al., 2011).

In inventory management, the inventory is also monitored by a replenishment system. There are 2 major strategies in inventory control policy in literature, namely, continuous review system and periodic review system.

In the continuous review system, a company is recommended to define a reorder point (s) as an indicator for inventory level. Specifically, when the inventory is constantly monitored so that when the stock level drops below the predetermined reorder point, personnel is required to make restock to the inventory. Initially introduced by Harris (1913), the fundamental yet simple planning system (s, Q) suggested a company to replenish its inventory in the case the item’s quantity falls below the reorder point (s) with the amount of order of size Q. In detail, reorder point (s) is dependant on the average demand that occurred during lead time and safety stock level. Whereas, the model introduces Q as the economic order quantity (EOQ) which is determined by variables such as annual demand quantity, fixed cost per order and annual stock holding cost per unit. The EOQ allows a company to minimize its total cost by managing the ordering cost, holding cost as well as purchase or production cost. In 1990, Schultz further developed the planning system (S, s) to manage slow-moving items with a high value of usage. Specifically, Schultz (1990) also employed the reorder point (s) as in the case of Harris (1913), yet instead of restocking level with order size Q, the model considers a maximum level (S). In other words, when inventory level falls below reorder point, a new order with the amount of S less the current inventory level will be placed to refill the inventory back to higher than the reorder point (s). Additionally, a replenishment order is also created when the stock level drops below point $S - 1$. An order-up-to-level is able to be determined by multiple approaches. The first approach takes into account the relationship between ordered quantity and expected cost in relating to the holding cost, backorder cost and lead time demand (Oguji, 2013). For intermittent demand items, Teunter and Duncan (2009) utilized service level to calculate the order-up-to-level with the assumption that lead time follows a lognormal distribution. A simpler method was presented by Babai, Jemai and Dallery (2011) to optimize S with independent variables such as fill-rate, average lead time and backorder level. The second approach optimizes the order-up-to-level with the mean demand size across periods. It is favourable to the first approach due to its simplicity and convenience as it eliminates the need for deciding ordering costs frequently, and due to the fact that it takes into account the demand uncertainty factor. For example, an EOQ does not change because of its assumption of a constant demand size, however, in case of an intermittent item, a replenishment order quantity measures the probability of a stock-out scenario when demand variates as well as the fluctuation of demand size to modify the order quantity accordingly. (Oguji, 2013).

In a periodic review system, instead of constantly monitoring the inventory, personnel reviews the stock level after a specific, predetermined time interval and consequently places orders to raise the inventory back to a safety level. This technique was first studied and named (S, T) control system by (Hadley and Thomson, 1963). (S, T) system's basic principles are deciding the length of a period before reviewing the inventory, and the size of the order to be made after a review interval. Due to demand variation of intermittent item, it is common to hold a high amount of safety stock to prevent supply shortage, therefore the holding cost of inventory is increased. On the other hand, if a company holds a low amount of safety stock, there are chances of lack of supply and subsequently shortage cost, backorder cost and loss of sales. Besides, there are also other inventory control systems such as (R, s, S) or (R, s, Q). The (R, s, S) and (R, s, Q) control schemes are similar to their equivalent systems in a continuous, when after a period of R, the inventory is reviewed, if stock level is under safety level s, it is brought up a specific level S, by issuing an order with the amount of S less the current level, or just simply placing an order Q regardless of the actual demand. Since it does not take into consideration the actual demand factor, a periodic review system is usually applicable in cases when it is costly to maintain a continuous inventory control system, or when it is not possible to constantly track the number of items in warehouse. (Oguji, 2013).

2.2. Demand classification of spare parts

In spare parts demand, due to the difference in characteristics of different spare parts items, it is important for company to classify spare parts into different classes or types of demand pattern, since each class requires a distinctive managing techniques and methods, all eventually to support the forecasting and inventory control decision-making process (Bacchetti and Saccani, 2012). As a result, there are generally 3 approaches to classify the demand patterns (Cavalieri et al., 2008).

The first and also the traditional approach is the classification of inventory based on quantitative techniques. The most widely used method in this approach is to categorize items based on usage volume and unit price, namely ABC classification (Bacchetti and Saccani, 2012). The technique uses item demand and unit price as criteria to organize the inventory into 3 classes, namely A: small percentage (5-10%) of inventory items that account for most of the total value of the inventory (50-70%); B: 10-30% of the inventory with 15-40% of the total value; C: largest percentage (60-85%) of items for 5-10% of the total value. With such variations, various authors agreed that inventory control policy for each class is also different, i.e. important items in class A are needed to receive a high level of attention in terms of order quantity, demand forecast, procurement to avoid high amount of backorders, while B and C items are less important items should receive less strict focus, respectively

(Russell and Taylor, 2011; Oguji, 2013; Teixeira et al., 2017). On the contrary, Teunter, Babai and Syntetos (2009) debated that because class C holds the highest proportion of the inventory, the cost of handling backorder and emergency shipments of such items would be significantly higher than the cost of keeping them in stock, therefore it is essential to receive the highest level of attention from management. Syntetos, Boylan and Teunter (2011) also argued that since class A is the most critical part, a high price item would generate a higher level of stocking cost due to higher stock level and eventually leading to cost-ineffectiveness.

Besides the fact that ABC classification is simple and convenient, it is also capable of effectively managing inventory costs and service level of an inventory with relatively similar and consistent characteristics (Russell and Taylor, 2011; Oguji, 2013; Teixeira et al., 2017). On the other hand, Huiskonen (2001) argued that since it solely employs simple criteria in classifying, ABC analysis is unable to comprehensively capture an inventory with various items in different and complex demand types.

Another single-criterion classification method that takes into account the element of demand while applying the Pareto principle is the FSN method, in which item demands are categorized into 3 patterns, namely fast-moving, slow-moving and non-moving. In this method, the demand of inventory items in a specific time period is analyzed to calculate the quartiles, acting as default cut-off values, in order to determine whether an item is fast-moving if total demand is larger than the third quartile, non-moving if total demand is smaller than the first quartile, and slow-moving if otherwise (Parekh and Lee, 2008). In practice, the FSN classification is preferable when the focus of the manager is on spare parts item's moving rate, as well as the ability to identify non-moving parts or items that became obsolete after a period (Cavalieri et al., 2008).

The second approach is a qualitative classification. In detail, these methods are based on the expertise and experience of those who manage the inventory. For example, the VED analysis decides items as Vital, Essential or Desirable based on the analyst's perception of the spare part's importance. Similar to the ABC analysis, VED classification is simple, however, the major disadvantage is that it is not straightforward due to the heavy dependency on the user's biased decision. Therefore, Gajpal, Ganesh and Rajendran (1994) proposed the use of the

Analytical Hierarchy Process (AHP) to assist in the criteria selection process prior to the classification stage. In fact, AHP itself is also considered as an effective method in handling a situation that involves the selection of multiple criteria (Teixeira et al., 2017). Moreover, AHP is favored because of its versatility and capability to deliver comprehensive results despite the tangible or intangible qualifying criteria and resulting in reducing subjective assessments of the decision maker (Ho, Dey and Lockström, 2011).

The third approach classifies demand as a forecast-based that takes into account the demand's variability, erraticness, and intermittence. Specifically, Williams (1984) first proposed to categorize demand into 3 groups, namely sporadic, slow-moving, and smooth demand base on the degree of lumpiness and intermittence. This classification approach takes into account the degree of intermittence and the degree of lumpiness of the demand. In the model, the intermittence level is represented by the amount of lead time between non-zero demand and the lumpiness level is demonstrated by the squared coefficient of variation as a proportion of mean inter-demand interval and mean lead time. Using cut-off values of the 2 variables, Williams (1984) specifically described sporadic demand items as those with very lumpy demand (high lumpiness level larger than 0.5 and high level of intermittence), in which there are also highly sporadic demand with a significantly high level of intermittence. Then, slow-moving demand items are those with a low level of intermittence, although the level of lumpiness might vary. Lastly, smooth demand items are those with a high level of intermittence and low level of lumpiness.

Arguing that the framework does not consider the element of lead time variability, Eaves and Kingsman (2004) thus suggested applying lead time variability to further divide the erratic demand into smaller categories, which are erratic demand and highly erratic demand items. Specifically, Eaves and Kingsman (2004) in their paper performed an analysis of lead time in which the lead time demand is made up from independent variables namely, transaction variability, represented by squared coefficient of variation for demand frequency as a proportion of lead time mean; demand size variability, represented by squared coefficient of variation as a proportion of average number of transaction and lead time demand; and lastly lead time variability represented by squared coefficient of variation of lead time. As a result, Eaves and Kingsman (2004) classified erratic demand items into 5 groups, which are, smooth, irregular, slow-moving, erratic and highly erratic. Smooth items are expected to have low transaction variability with frequent demand transaction. Irregular items are those with low transaction variability and high demand size variability. Consequently, stock keeping units with high transaction variability, low demand size variability are then termed as slow-moving items and characterized by infrequent and small-sized demand transaction. The difference between Eaves and Kingsman (2004) and Williams (1984) is in the last category erratic. Eaves and Kingsman (2004) divided it into erratic and highly erratic demand, which is both defined by high transaction variability and demand size variability, but different in terms of lead time variability, low for erratic and high for highly erratic items. However, instead of determining cut-off values for 3 variables, Eaves and Kingsman (2004) recommended that they should be taken as a management decision, implying that different organizations, different industries might implement different values between category boundaries. Figure 3. *Demand classification (Eaves and Kingsman, 2004)* illustrates the classification by Eaves and Kingsman (2004).

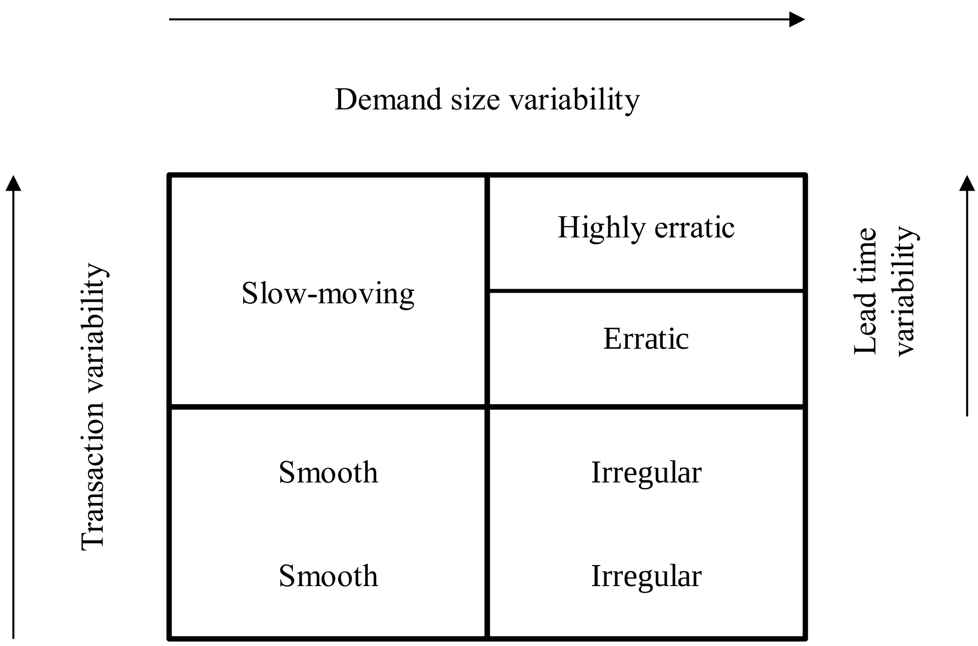

Figure 3. Demand classification (Eaves and Kingsman, 2004)

Adding further modification to the approach, Syntetos, Boylan and Croston (2005) classified demand based on their level of erraticness and intermittence. In their study, the degree of erraticness is measured by squared coefficient of variation while degree of intermittence is calculated by the average of inter-demand interval including the first period with non-zero demand. According to Syntetos, Boylan and Croston (2005), an item is said to have erratic demand pattern if it is high in the level of erraticness and low in the level of intermittence, meaning that the average gap between consecutive periods are relatively low, and the variation between demand sizes are large. Similarly, an item is defined as lumpy if its demand variation is high between demand periods and the amount of period with zero demand is also high, i.e. a high degree of erraticness and a high degree of intermittence. On the other hand, when the degree of erraticness is low, the authors argued that, although having the same low level of erraticness, it is possible that the level of intermittence is different amongst items. Therefore, a less erratic item is classified as either a smooth item, if there is low amount of zero demand period, or an intermittent item, if there is high amount of zero demand period. (Syntetos, Boylan and Croston, 2005).

Figure 4. *Demand classification (Syntetos, Boylan and Croston, 2005)* below shows how an inventory is suggested to be categorized, using two cut-off values of the aforementioned variables to determine whether an item has erratic, lumpy, smooth or intermittent demand pattern according to Syntetos, Boylan and Croston (2005).

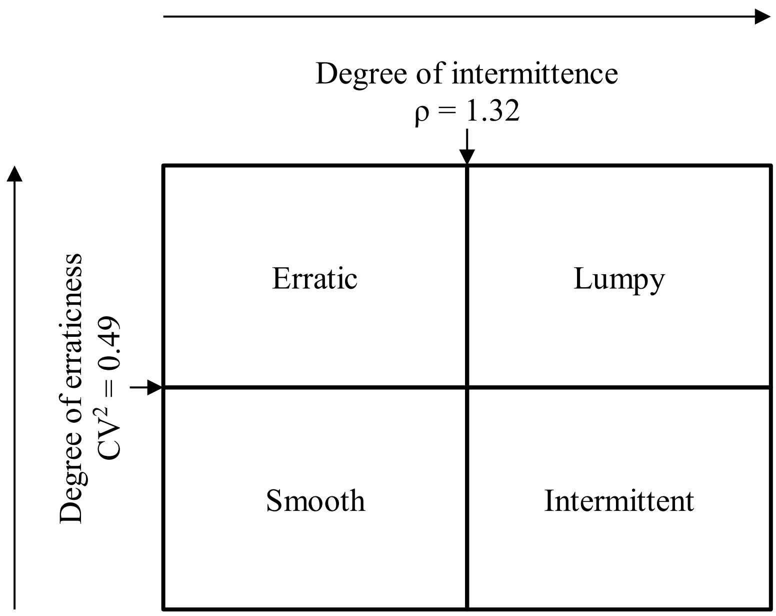

Figure 4. Demand classification (Syntetos, Boylan and Croston, 2005)

The next figure illustrates the difference between items belonging to 4 types of demand pattern categorized using the framework proposed by Syntetos, Boylan and Croston (2005). It is observed that, despite having the same level of erraticness, which is the variation in demand sizes between consecutive periods, an erratic item does not have the same intermittence comparing to that of a lumpy item. Likewise, a smooth item and an intermittent item are similar when it comes to the demand size discrepancy between periods, although their amounts of zero demand periods are not the same. In other words, an erratic item is expected to have large variations between demand sizes and short gaps between demand periods, while an intermittent item is an exact opposite with little differences between demand sizes and long distance between demand periods. On the other hand, an item in the lumpy is characterized by large variability in terms of size and also large gaps between demand periods. Its counterpart is a smooth item with little deviation across demand sizes and also a low number of zero demand periods.

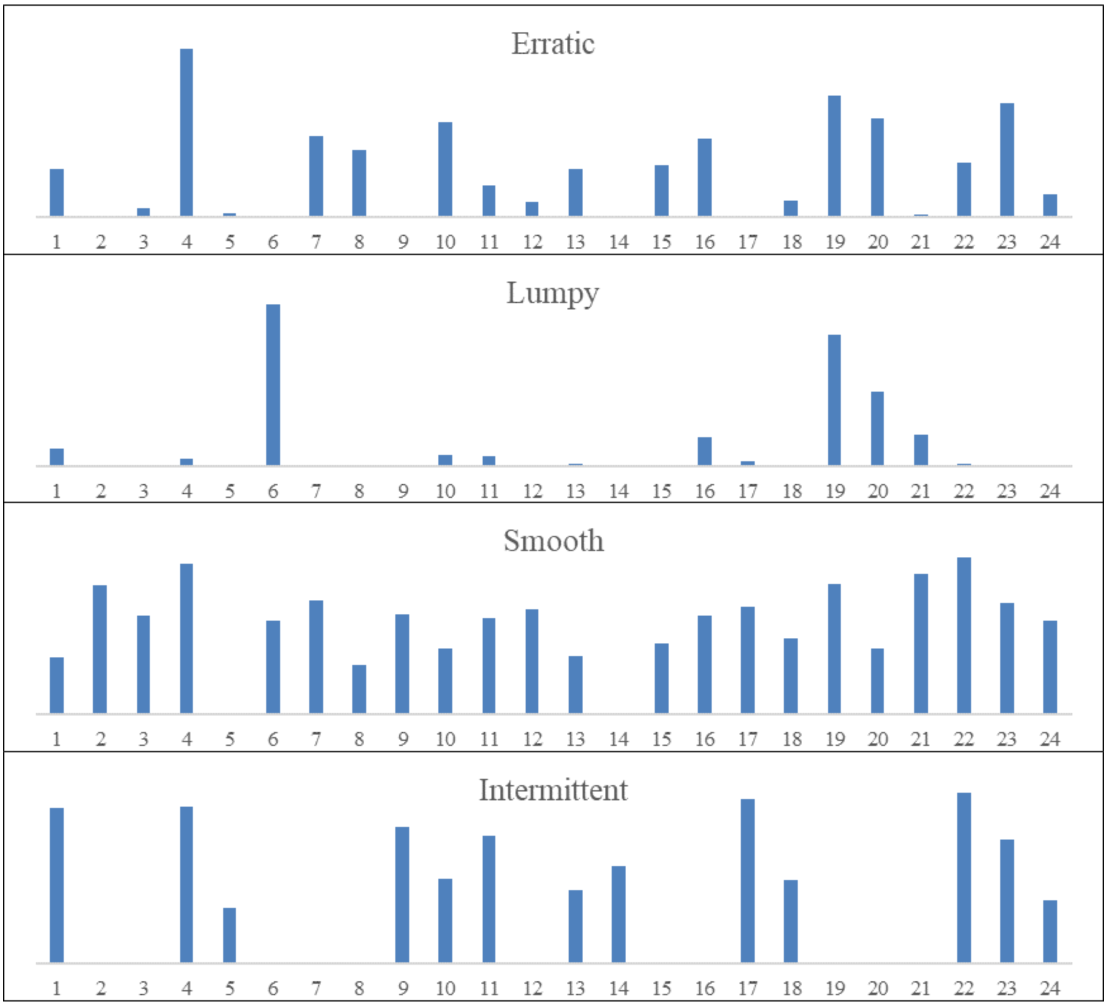

Figure 5. Visualization of 4 types of demand

2.3. Demand forecasting

In practice, the role of demand forecasting in a company is closely associated with the function of demand management. According to Cox, Blackstone and Spencer (1995), demand management is the managerial process that determines all potential demands of products and services from the market. Demand management includes operational tasks such as demand forecasting, order fulfilment, warehouse management, part servicing. A demand management procedure is considered efficient if only it is able to address resource planning and usage to achieve profitable business outcomes. (Cox, Blackstone and Spencer, 1995).

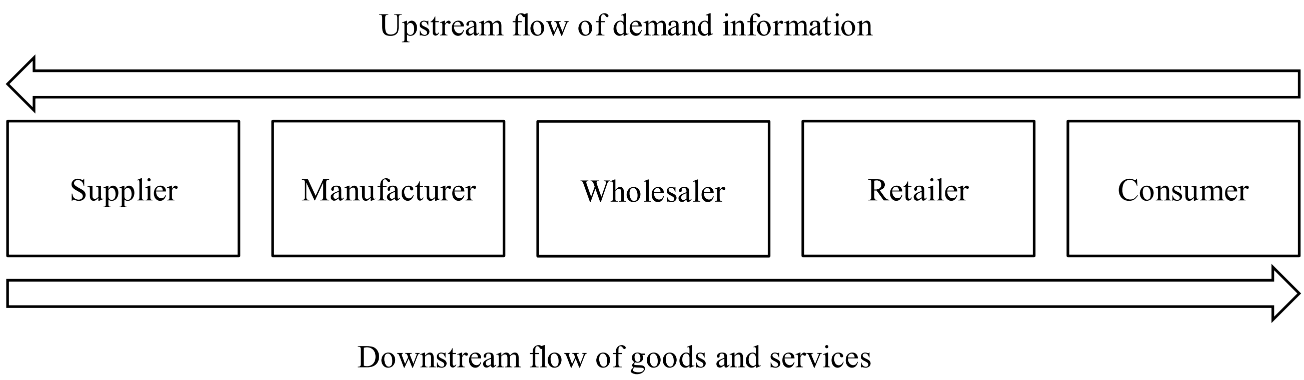

Figure 6. Supply chain information and goods flow (Metters, 1997)

Due to the distinctive inventory characteristics, which are the volatility of spare parts demand and the presence of bullwhip effect in a supply chain, a company performs forecasting in order to match with real-time information flow from demand from customers downstream. In a supply chain with an upstream flow of information and a downstream of flow of goods (demonstrated in Figure 6. *Supply chain information and goods flow (Metters, 1997)*), the bullwhip effect is one of the major causes of demand variations. (Lee, Padmanabhan and Whang, 1997). For example, when a wholesaler receives an order with irregular high amount of goods from its retailer, without information sharing they would assume that the demand had increased, thus ordering higher amount from the manufacturer to ensure they are able to meet its customer resulting in the manufacturer increases production to keep up with the increase in order. As a result, the demand from one end of the supply chain has increased significantly from its actual original demand. In other words, as demand moves upward the supply chain, it has the tendency to variate since each stakeholder is uncertain regarding the demand of their related counterparts. If a company is unable to capture the final demand of customers, there is a high chance that the bullwhip effect would inflict significant problems, for example, excessive stocking, to the company's inventory which in turn causes an unnecessarily high level of costs.

Besides, Eaves (2002) after reviewing several existing studies in intermittent demand had summarized multiple factors that lead to an item's intermittent demand pattern. Firstly, it is apparent that there are customers with different business sizes in a company's business network, in which the number of small clients is usually larger than that of clients of considerable size. Therefore, when small-sized clients create order, demand would be small and smooth, while large clients at one time may request larger orders thus generating demands with significant size. Secondly, as mentioned above, the bullwhip effect transforms demand from one echelon to be significantly variated in inventory management at higher echelons. Thus, a distributing company may experience an erratic demand pattern from its customer, while in fact the demand is just magnified from a smooth pattern from the end-consumer. (Silver, 1970). Thirdly, when taking into account the factor of the high number of potential customer and the period between customer demand, the frequency of demand from customer is negatively related to the lumpiness of demand. For example, when there are various customers making requests, the frequency of order increases, thus resulting in a lower level of lumpiness. Fourthly, there is a possibility that the lumpiness between customer demand is positively correlated with each other. In such cases, the level of erraticness between customer orders still increases regardless of the high amount of customers in a company's network. (Bartezzaghi, Verganti and Zotteri, 1999). Fifthly, for some spare part items, the time from a manufacturer to a repairing garage consists of several phases that lengthen the lead time. Therefore, in large-scaled maintenance facilities, it is common to perform maintenance after a long period instead of frequent check-up to reduce costs from long lead time. (Foote, 1995). Sixthly, large order demand size happens from potential failure inspection. That is, when a car goes under maintenance, one part is inspected as malfunctioning thus similar parts of other cars of the same model year would then be inspected and repaired in advance and as a result, increasing the demand for that specific part. (Beckmann, 1964). Lastly, the approach in which a researcher determines the level of aggregation also affects the level of erraticness and intermittence of an item. In detail, it is possible for a stock keeping unit to have different types of demand pattern at different levels of aggregation. For example, an item with smooth demand at a quarterly level of aggregation likely to have an intermittent and erratic demand pattern at a monthly aggregation. (Eaves, 2002).

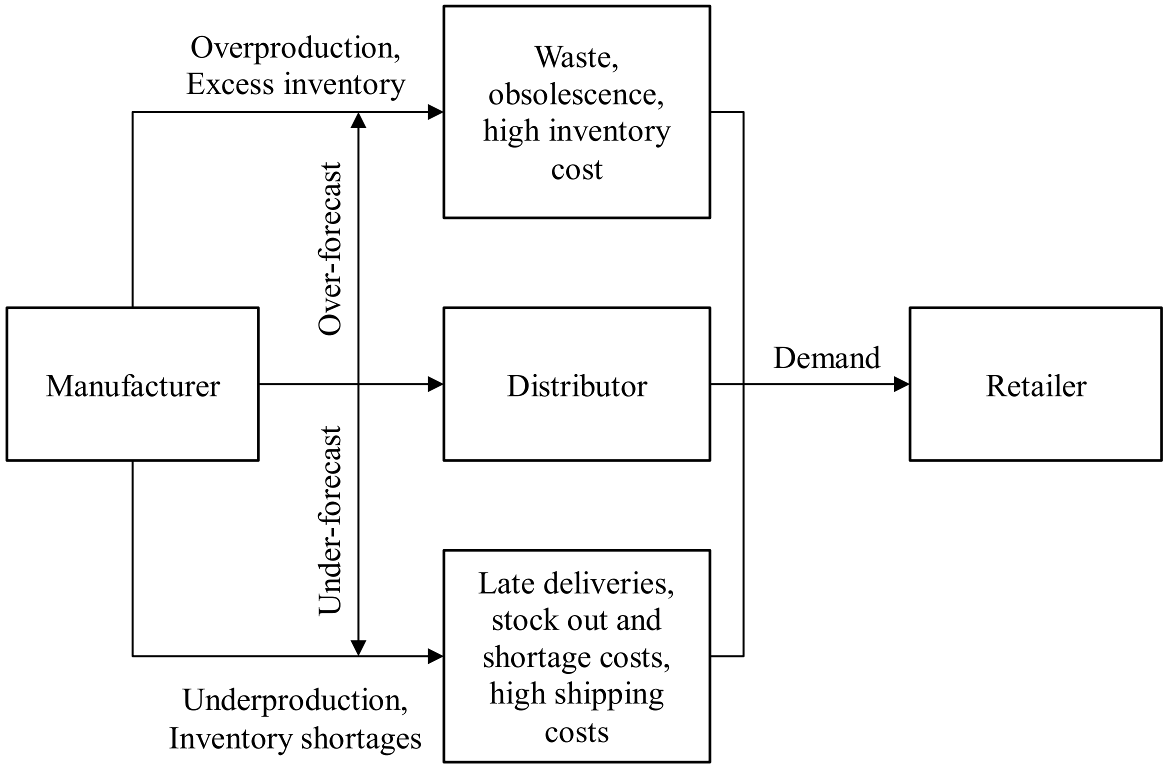

Figure 7. The effect of inaccurate forecasting (Russell and Taylor, 2011)

As a matter of fact, demand forecasting is the action when a company tries to match consumer's need with the sufficient level of inventory, the level of production, and the level of procurement. Then, the results would be used for logistics, warehousing to be delivered in time. Figure 7. *The effect of inaccurate forecasting (Russell and Taylor, 2011)* demonstrates the relationship between forecast and demand in a supply chain in practice. In a case when a forecast delivers inaccurate results comparing to actual demand, it will lead to overstocking since an excessive amount of inventory must be kept at every stage in the supply chain in order to offset the uncertain demand. Thus, under-forecast leads to shortages in inventory and later, backorders and late shipping costs are also inevitable. On the other hand, an over-forecast would result in overproduction and high inventory cost. All those circumstances are critical factors in inventory and demand management procedures. (Russell and Taylor, 2011).

Moreover, Wright and Yuan (2008) when studying the bullwhip effect had concluded that inventory ordering policies and forecasting methods are able to alleviate the negative impact of the phenomenon on the supply chain. Specifically, Wright and Yuan (2008) in a simulated analysis investigated the relationship between the 2 latter factors and the bullwhip effect by comparing different forecasting methods, such as simple moving average, Holt's forecast, and Brown's forecast. Using the forecast results, orders are then placed in accordance with an appropriate stock level and supply chain length. As a result, combining the implementation of a suitable ordering policy and accurate forecast methods, the forecasters were able to reduce the variability of demand by 55% on overall, thus minimizing uncertainty risk and resulting in a supply chain with more stability.

As a result, it is vital that company forecasts to protect themselves against variability and uncertainty in demand. Therefore, it is possible that an accurate demand forecasting is helpful to business planning, production planning. (Kerkkänen, 2010).

In demand forecasting, there are various methods being studied in literature and implemented to practice, yet, they are categorized into 2 major groups: qualitative and quantitative. The former does not require the use of historical data to project into the future, therefore, they are preferred when historical data is unavailable, e.g. forecasting the future demand of a new product. Commonly used qualitative techniques utilize expertise, knowledge, and experience from executives or salesperson, or results from teamwork, market research. On the other hand, quantitative forecasting methods apply calculation based on existing historical data and are categorized into 2 types: causal methods, in which forecast is made based on external factors for the planning of business and production in general; and time series methods, in which historical data already available in the company is used to forecast. (Armstrong, 2001; Kerkkänen, 2010).

In time series forecasting methods, the assumption is that the future will repeat itself, meaning the same demand pattern will appear again. Based on the hypothesis, the most basic and straightforward method is naive forecast when historical data of previous periods is used to estimate the next period's demand, without including other factors to the formula. Other notable methods are simple Moving Average (MA) and simple Exponential Smoothing (ES). In practice, simple time series forecasting techniques such as are preferred to other complex methods (Syntetos et al., 2016). As a matter of fact, MA and ES are two of the quantitative forecasting methods that are favored in the literature (Kerkkänen, 2010).

However, regarding the intermittent pattern of spare parts demand when there are periods with zero demand occurring in between several irregular non-zero periods, Croston (1972) believed that ES is unable to capture the underlying inconsistency of the demand pattern. As a result, Croston (1972) proposed a new method to address the issue and later corrected by Rao (1973), that estimates the mean demand per period only after a period with positive demand, otherwise, the method just increases the count of periods towards the last period when demand occurred and calculates based on that last period's demand. Croston's method (CR) is considered similar to traditional ES when demand is regular, i.e. there is demand for every period (Eaves and Kingsman, 2004).

Similarly taking into account the factor of interspersed zero interval, Syntetos and Boylan (2001) suggested an improvement to Croston's original method by providing a deflation factor to Croston's method. The proposed technique is named after the two researchers, Syntetos-Boylan Approximation (SBA) and is discussed later in the research.

In order to select an appropriate forecasting method, Armstrong (2001) discussed 6 principles for analyst to consider, i.e., convenience: whether the method is easy to use; market popularity: whether the method is popular amongst the literature; structured judgment: whether the method is able to fit predetermined criteria; statistical criteria: whether the method fit the statistical requirements; relative track records: the comparison of the performances of various methods; and guidelines from prior research: whether the method is used in other similar cases. In other words, Armstrong (2001) suggested analysts prioritize structured methods, using a quantitative method instead of judgemental when data is available, avoiding naive methods when there are significant changes in business, and using simple methods unless complexity is presented. In conclusion, the author (Armstrong, 2001) proposed a decision-making tree to help with selecting the forecasting methods described in the below figure. It is noted that although the tree does help the decision maker, it does not provide a direct answer to the question of what the best forecasting method is (Kerkkänen, 2010).

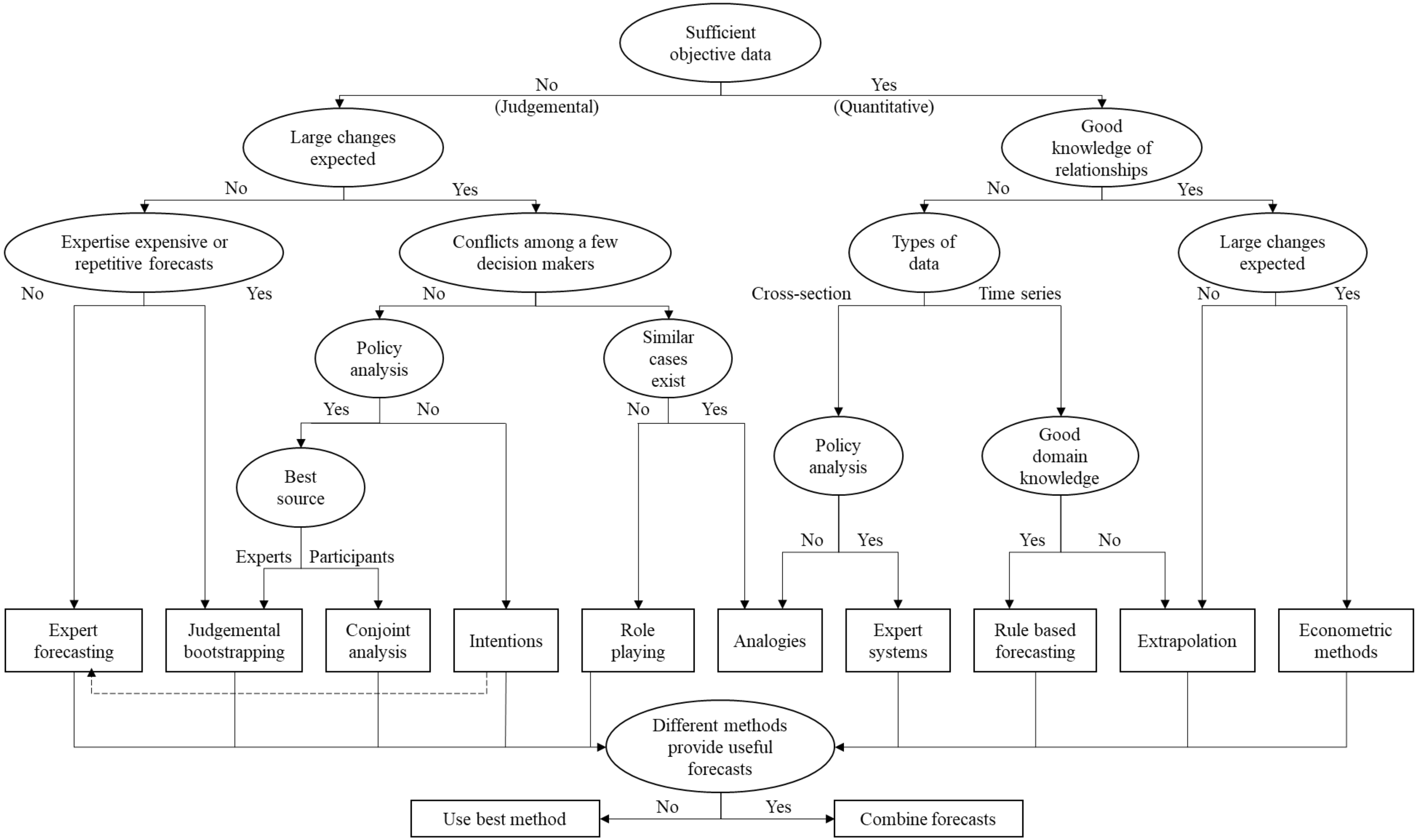

Figure 8. Decision making tree for forecasting method selection (Armstrong, 2001)

3. FORECASTING INTERMITTENT DEMAND

Being considered as two of the most preferred methods in forecasting time series data (Syntetos and Boylan, 2005), MA and ES were selected in this study for comparison against other the two methods for forecasting intermittent and erratic demand, CR and SBA. This section begins with the definition of intermittent demand, then the four methods will be reviewed and finally followed by a subsection of how forecast accuracy is measured.

3.1. Intermittent demand

Intermittent demand pattern is defined when an item is experiencing variability in terms of the frequency of customer's orders. In other words, an item is said to have intermittent demand when there are several periods with zero demand. Scholars had suggested several approaches to examine the degree of intermittence of an item. For example, Brown (1977) in his work proposed that an item is classified as intermittent, or erratic when its standard deviation generated from the best-performing forecast model is larger than that of the original series. Willemain et al. (1994) also presented a statistical test that consists of 3 elements to identify an intermittent item. Firstly, the average interval between demand periods is calculated to determine the level of intermittence. Secondly, the coefficient of variation, denoted by standard deviation as a proportion of the mean to show the variation of demand in terms of order size. Lastly, autocorrelations and cross-correlations are calculated to assess the level of independence between demand size and demand frequency. A simpler approach was developed by Croston (1972), supported by Syntetos, Boylan and Croston (2005) showed that an item is classified as intermittent if the average demand interval is greater than 1.25. The following example will discuss how to calculate the degree of erraticness and degree of intermittence.

Table 2. Example of Intermittence Demand

Demand period	1	2	3	4	5	6	7	8	9	10	11	12
Item A	37	50	0	0	84	42	0	0	0	87	63	32

The degree of erraticness, denoted by square coefficient of variation, is measured by calculating the variance of non-zero demand item as a proportion of average of non-zero demand period. In this case, it is determined by: var(37, 50, 84, 42, 87, 63, 32)/[(37 + 50 + 84 + 42 + 87 + 63 +32)/7]^2 = 493.62/3184.34 = 0.156

The degree of intermittence, denoted by average demand interval, or mean inter-demand interval is calculated by simply counting the interval between demand period and then taking the mean value. In this example, it is equal to [(2 – 1) + (5 – 2) + (6 – 5) + (10 – 6) + (11 – 10) + (12 – 11)]/6 = 1.83 (period).

3.2. Moving average

MA method calculates the next period demand value based on actual demand of previous periods. In other words, it is an average of demand values of periods in prior to the forecasted period. Formula to calculate MA is

$$F_{t+1} = \frac{D_t + D_{t-1} + D_{t-2} + \dots + D_{t-N+1}}{N}$$

In which: F_{t+1} = forecast demand for period t+1

D_t = demand for period t

N = number of period

The method is preferred when there is no significant variation or seasonality in recent demands. Therefore, when a trend appears in the selected time bucket, there will be a deviation between forecasted value and actual value. However, one major disadvantage is to determine the periods to use in the forecast. As a matter of fact, a long period has the tendency to flatten the variation in actual data, on the other hand, a short period is able to demonstrate demand changes in recent periods. Hence, a too long period moving average is slower in capturing the variability in demand, while a too short period is simply identical to naive forecasting. Nevertheless, MA method does have the advantages, which are simplicity, economical and the ability to produce satisfactory forecast result in short period. (Russell and Taylor, 2011).

3.3. Exponential smoothing

Originally, ES is developed to address the main drawback of MA, i.e. the inability to reflect changes in recent data. Since ES only requires a minimal amount of historical data, the method is favored in management practice and used widely in companies as a reliable technique of forecasting (Russell and Taylor, 2011). In detail, ES calculates the weighted average of forecasted and actual demand value in previous periods, placing adjusting parameters on the two values depending on the weights given to recent demand data. Formula to calculate ES is

$$F_{t+1} = F_t + \alpha(D_t - F_t)$$

In which: F_{t+1} = forecast demand for period t+1

D_t = demand for period t

α = weighting parameter smoothing constant, $0 < \alpha < 1$

Generally, smoothing constant α is judgementally determined based on the production itself and managerial decision (Russell and Taylor, 2011). For example, a forecast for steady-growth products would implement a relatively low value of α as the gap between forecasted value and actual value is small. On the other hand, if actual demand is increasing (or decreasing), a larger value of α is preferred to respond quickly to variation in demand. However, as α moves closer towards zero the forecast would take more period to adjust to the actual demand movement while being closer towards 1 would convert the formula to a naive forecast. In fact, statistical techniques are often employed to calculate the most accurate value of α based on trial-and-error analysis, so that the best value of α would result in the lowest value of error in the formula, e.g. lowest mean absolute deviation (MAD) value.

One problem of traditional ES pointed out by Croston (1972) is that the method does not take into account previous periods with zero demand, thus, estimated demand is biased by a series of zero demand, whether they are in sequence or interrupted. Croston (1972) stated that because in ES, most recent would have the highest weight, demand is highly affected by the demand of the last period whether it is a zero or non-zero demand period. Specifically, if a demand occurs in a period, the next period will have more tendency to encounter an even higher demand, also when there are consecutive periods with zero demand, the estimate will be at lowest just right before a demand occurring in the next period (Eaves and Kingsman, 2004).

3.4. Croston's method

According to Johnston (1980) and Croston (1972), the inefficiency of ES is that when there are more than two consecutive periods with zero demand, the method is unable to provide an accurate estimate of demand. As a result, it is common that the forecast should treat the demand process as two separate elements, namely mean interval between transactions and mean demand size and subsequently, mean demand per period is calculated by dividing mean demand size by mean transaction interval. Therefore, originally introduced by Croston (1972) and later corrected by (Rao, 1973), Croston's method focuses the mean demand of period by implementing exponential smoothing separately to demand intervals and demand sizes. As mentioned before, Croston's method is similar to traditional ES when demand is steady (Eaves and Kingsman, 2004). The difference is that in Croston's method, forecasting is made only when demand is positive, otherwise, the method increases period count until demand is no longer zero.

Initially, Croston's method calculates the average interval between demand periods (denoted P) and average size of demand (denoted F), specifically,

When $D_t = 0$,

$$F_{t+1} = F_t$$

$$P_{t+1} = P_t$$

$$Q = Q + 1$$

Else,

$$F_{t+1} = F_t + \alpha(D_t - F_t)$$

$P_{t+1} = P_t + \alpha(Q - P_t)$

$Q = 1$

Subsequently, forecasted mean demand per period is calculated by dividing mean demand size by mean demand interval, that is,

$$C_{t+1} = \frac{F_{t+1}}{P_{t+1}}$$

In which: D_t = demand for period t

F_{t+1} = forecast demand for period t+1

P_{t+1} = forecast interval between transaction for period t+1

Q = interval from latest period with positive demand

C_{t+1} = forecast mean demand for period t+1

α = smoothing parameter for forecast intervals, $0 < \alpha < 1$

In a research in 1994, Willemain et al. agreed that although Croston's method provides evident advantages to tackle the scattered zero demand periods, i.e. decomposing mean demand to demand size and demand interval, the method when applying to empirical case study was not able to deliver an outcome as robust as those performed in theory. Moreover, Syntetos and Boylan (2001, 2005) proved that the forecasted demand value of both methods is biased, being more critical in ES, by conducting a comparison between ES and Croston's method. As a result, the authors concluded that although the components of the forecast, mean demand size and mean demand interval, are calculated with no error, the combined element of mean demand per period is inaccurately calculated. Specifically, the error is that demand forecasted by Croston's method is considerably higher or lower than actual demand and increasing as the smoothing parameter α approaches 1 (Syntetos and Boylan, 2001; Wallström and Segerstedt, 2010).

3.5. Syntetos-Boylan Approximation

Stating that Croston's method is biased by the considerably high difference between forecasted and demand, therefore, Syntetos and Boylan (2001) suggested a modification to the method by adding a deflating factor to the estimate of mean demand per period based on the smoothing parameter for demand interval α. Syntetos and Boylan (2001) argued that a CR is only accurate in the case when the smoothing parameter is smaller than 0.15. For example, when smoothing constant α is equal to 1, the bias error of CR is 64.75% in the forecasted value of the average demand period.

In particular, given the forecast demand and forecast interval between transaction are the same as those being calculated in the original method, modification to Croston's method is

$$C_{t+1} = (1 -)\frac{F_{t+1}}{P_{t+1}}$$

In which: F_{t+1} = forecast demand for period t+1

P_{t+1} = forecast interval between transaction for period t+1

C_{t+1} = forecast mean demand for period t+1

α = smoothing parameter for forecast intervals, $0 < \alpha < 1$

3.6. Forecast accuracy measurement

Apparently, the result of each employed forecasting method needs to be quantified to select the best-performing method in order to put into practice. Specifically, in practice, the measurement can be used for deciding if the selected method provides accurate results, or to develop a backup plan in case the method delivers erroneous results (Chopra and Meindl, 2001).

The fundamental of statistical measurement of forecast result is based on the assessment of error, that is, Error = Forecast value – Actual value

Commonly used estimates for forecasting errors are Mean Absolute Deviation (MAD) and Mean Squared Error (MSE). MAD is calculated as the average of the difference between the actual and forecast demand. Due to its simplicity and convenience, MAD is considered a common method in the literature (Stadtler, Kilger and Meyr, 2015). It should be noted that using one MAD result is incapable of providing good insights, but better being compared with that of other methods. Similarly, MSE is also used in calculating the mean difference from actual value as an estimate of variance. However, due to its square function, large error deviation is amplified more comparing to smaller ones. In other words, MSE is sensitive to errors and outliers.

Another type of measurement is scale-independent based measures in which the preferred estimator is Mean Absolute Percentage Error (MAPE) that calculates the error in terms of the percentage of actual demand. However, since the denominator of MAPE calculation is actual demand, which can be zero for intermittent demand items, the measure becomes undefined, therefore, resulting in undefined errors in periods with zero demand. As a result, Symmetric Mean Absolute Percentage Error (SMAPE) is used instead. Proposed by Makridakis and Hibon (2000), SMAPE is advantageous to MAPE because of two reasons. Firstly, SMAPE is not affected by the scale of the demand as demand approaches zero. Secondly, due to its symmetry of error function, SMAPE is independent of the difference in demand and forecast size, i.e. the error measure value does not change whether forecast value is significantly larger than actual demand or vice versa (Wallström and Segerstedt, 2010).

Calculation formulae of mentioned error estimators are as below

$$MAD = \frac{\sum | F_t - D_t |}{N}$$

$$MSE = \frac{\sum (F_t - D_t)^2}{N}$$

$$SMAPE = \frac{100}{N} \sum \frac{|F_t - D_t|}{(F_t + D_t)/2}$$

In which: F_t = forecast demand for period t

D_t = actual demand for period t

N = number of period

Besides, there are other widely used approaches in measuring the forecast accuracy, namely, Relative Geometric Root Mean Square Error (RGRMSE), Percentage Better (PB), Percentage Best (PBt), Average Percentage Regret (APR), Cumulative Forecast Error (CFE), Period in stock (PIS), Number of shortages (NOS), Median Absolute Percentage Error (MdAPE). The below table is a summary of related existing studies in the literature that used different approaches in evaluating the accuracy and the performance of proposed forecasting methods.

Table 3. Existing studies and results

Authors	Forecast methods	Accuracy measurements	Best methods
Willemain et al. (1994)	ES, CR	MAPE, MdAPE, MAD, MSE	CR
Eaves and Kingsman (2004)	MA, ES, CR, SBA	MAD, RMSE, MAPE, cost-based	SBA
Syntetos and Boylan (2005)	MA, ES, CR, SBA	RGRMSE, PB, PBt	SBA
Syntetos and Boylan (2006)	MA, ES, CR, SBA	ME, PBt, APR	SBA
Boylan and Syntetos (2007)	ES, CR, ModCR	MSE	CR
Teunter and Duncan (2009)	MA, ES, CR, SBA, bootstrapping	MAD, MSE, RGRMSE	CR, SBA, bootstrapping
Wallström and Segerstedt (2010)	ES, CR, SBA, ModCR	MAD, MSE, SMAPE, CFE, PIS, NOS	ES, SBA

Initially, Willemain et al. (1994) were able to conclude that CR evidently performs better than ES by simply comparing the 2 methods on a simulated dataset, using 4 accuracy measurements of MAPE, MdAPE, MAD, MSE. Motivated by a practical business issue in a computer wholesale company with 75% of the item's demand were intermittent, Willemain et al. (1994) conducted a simulation with multiple scenarios, experimented with several types of demand interval and pattern, covered various demand order sizes to forecast at different time horizons at different values of smoothing constant. In the end, the group of authors confirmed that CR showed superiority in terms of performance when the intermittence level of demand is larger than 1.25 periods. Furthermore, as the degree of intermittence of an item increases, the performance of CR also increases accordingly.

Further expanding the literature, Eaves and Kingsman (2004), Syntetos and Boylan (2005) and Syntetos and Boylan (2006) similarly compared CR and its improved version SBA with 2 fundamental forecast methods MA and ES. In detail, Eaves and Kingsman (2004) studied the relationship between forecast results and stock holding costs of a military airline inventory. Before that, the 2 authors analyzed lead time demand and demand size variability to classify 5 different demand patterns. Meanwhile, Syntetos and Boylan (2005) utilized an actual sample in the automotive industry, that consisted of 3,000 items in a 2 year period, average demand interval from 1.04 to 2 months, average demand size from 1 to 194 items and smoothing parameters from 0.05 to 0.20 with steps of 0.05. Syntetos and Boylan (2006) also used the same set of data yet with the attention at the capability to control inventory. Although applying different techniques to measure the accuracy, 3 separated studies on 2 different datasets had delivered the same findings that SBA shows superiority in forecasting intermittent demand in relating with other methods. Despite Syntetos and Boylan (2005) stating that even when a method is assessed as the best-performing method, it does not necessarily translate to better service level or better cost saving in inventory management, Eaves and Kingsman (2004) was able to prove that SBA is capable of reducing the level of stock-holding to the lowest level, when in the study it eventually saved £285 million of the total inventory value when comparing with ES.

First developed by Levén and Segerstedt (2004) on the basis of the work of Segerstedt (2000), the Modified CR was claimed by the 2 authors that it is an improvement of the original CR in terms of performance, simplicity and practicality. Stating that the ModCR was unable to deliver unbiased results, Boylan and Syntetos (2007) compared the 3 methods by measuring the forecast accuracy between ES, CR and a Modified CR method using MSE estimator. The research focused on demand intervals from 1.1 to 10 periods at smoothing constants of 0.1 and 0.2. In the end, is was proved that CR method consistently generates forecast results with better accuracy than ES and the Modified CR at all levels of smoothing parameters and at different points of demand occurrence.

Later, Teunter and Duncan (2009) also comparing 4 aforementioned forecasting methods, MA, ES, CR, SBA and bootstrapping method against a zero forecast technique on an empirical data set in the airline industry. The paper examined a spare part inventory of 5,000 items of 6 years, average demand intervals were 0.5-3 years, average demand sizes were 1-1330 and smoothing constant ranging from 0.10 to 0.20. Research's findings showed that CR, SBA and bootstrapping method provided superiority in achieving favourable service level and stock-holding level. Furthermore, the authors stated that the accuracy of such methods can also be increased by considering the time an order occurs in a demand period.

Lastly, Wallström and Segerstedt (2010) when examining multiple intermittent demand forecasting methods concluded that it is not sufficient using one single measure to evaluate the performance of a method. Specifically, Wallström and Segerstedt (2010)'s paper compared the performance of ES, CR, SBA and ModCR using both conventional, i.e. MAD, MSE, SMAPE and other newly developed performance measurement approaches such as PIS, NOS, CFE. The research concluded that it is wise to apply several error measurement approaches before concluding a method is capable of providing accurate results. Furthermore, Wallström and Segerstedt (2010) also said that ES and SBA are generally better forecasting techniques.

4. EMPIRICAL RESULTS

In this chapter, descriptive statistics of the dataset is first presented, followed by detailed accuracy measurements of each forecasting methods for all markets. Then it is concluded with discussions in which the study's findings are compared against existing researches in the literature.

4.1. Data collection and method selection

Data set is collected from the company's own data, that is, sales data of ordered spare parts in inventory during the period 2013-2018. In detail, data is collected on a monthly aggregation level, including item codes, item descriptions, ordered/shipped quantities. The target of this study is the 5 markets or the whole regional business unit in which the case company operates, namely, Baltics (consisting of Estonia, Lithuania, Latvia), Denmark, Finland, Norway, and Sweden. All items are then sorted into groups of different demand patterns based on their inter-demand interval and degrees of erraticness and intermittence.

Forecasting methods are Moving average, Exponential smoothing, Croston's original method, and Syntetos-Boylan approximation. A small sample of line items is used for determining smoothing parameters to be used in 4 forecasting models based on trial-and-error experimentation. Specifically, Mean Absolute Deviation (MAD) is calculated with a range of smoothing parameters against the sample data across all line items, for each forecasting method which parameter values provide the lowest MAD error were selected. Moreover, it is recommended that low value smoothing parameters ranging in between 0.05-0.2 are considered appropriate for items with intermittent demand (Croston, 1972; Willemain et al., 1994; Johnston and Boylan, 1996; Syntetos and Boylan, 2005). Furthermore, in moving average method, when performing forecast using data at monthly aggregation level, it is suggested that the widely accepted amount of period for an optimal result is up to 12 months (Syntetos and Boylan, 2005). It is worth mentioning that the selection of forecasting parameters helps to improve the performance of forecast (Fildes et al., 1998), thus, this study aims to estimate the parameter from the same data set, instead of using suggested values in forecasting literature.

Consequently, selected method's accuracy is measured using statistical error measurement, i.e. historical data is used to calculated Mean Squared Error, Mean Absolute Deviation and Symmetric Mean Absolute Percentage Error values and then these results are benchmarked against each other to identify the best-performing method to apply to the case of the company. In fact, the study ensures its reliability by using the methodological triangulation, that is, the involvement of different methods in measuring the accuracy of each forecast (Denzin, 2006). Similarly to Wallström and Segerstedt (2010) and Oguji (2013), triangulation in this study is maintained by counting the number of occasions in which a method is ranked the first place in terms of accuracy.

4.2. Descriptive analysis

Data of all items during the period 2013-2018 was collected from the database. First, items were filtered into different types of demand, simply based on the historical sales record in the selected period and also their degree of intermittence in the period 2017-2018.

Table 4. Types of demand

Category	Definition
Deadstock	items with zero demand in 2017-2018
No history	items with zero demand in 2013-2015
Fast-moving	items with no zero demand period in 2017-2018 and intermittence level $0 < \rho < 1.25$
Obsolete	items with $\rho \geq 12$
Intermittent	items with no zero demand period in 2017-2018 and intermittence level $1.25 \leq \rho < 12$

The above table provides brief definitions of different types of demand pattern in the case company's inventory. The Deadstock category is made up of items with zero demand in period 2017-2018, it is essential to exclude this category out of the forecasting models because these items belong to old models which are out of circulation and no longer being sold to customers, therefore it is not necessary to perform forecast on non-moving stock keeping units. The second group is termed No history, consisting of items recently introduced into the market. As a result, they do not have sufficient sales records to execute necessary forecasting steps and therefore excluded from the forecast. The third category is Fast-moving item, which is classified by filtering items with the degree of intermittence ranging from 0 to 1.25. It should be noted that for forecasting items with intermittence level in this range, ES forecasting method is an appropriate approach to deliver accurate results, since CR and other modified versions would simply become ES due to the fact that there is no zero demand period in the forecast time bucket (Johnston and Boylan, 1996; Boylan and Syntetos, 2007). The next group of items is those with obsolescence risk. Items with intermittence level of larger than 12, in other words, having more than 12 months with no sales, will no longer be held in inventory when their stocks reach zero. It means that when a customer orders these items, they would be sold and coordinated directly from supplier to customer, without keeping stock in inventory.

Then, the level of intermittence and the level of erraticness of each item were determined by the average inter-demand interval (or average demand interval) and squared coefficient of variation, respectively. In detail, the two variables are calculated based on sales data during the last 24 months, i.e. from January 2017 to December 2018. Subsequently, intermittence items were filtered based on their average demand interval in the last 2 years. Specifically, the distribution of all items is in

Table 5.

Country		Deadstock	No history	Fast-moving	Intermittent	Obsolete	Total
Baltics	Quantity	11,831	3,474	611	4,984	5,581	26,481
	%	44.68%	13.12%	2.31%	18.82%	21.08%	
Denmark	Quantity	16,974	4,934	1,314	9,117	7,589	39,928
	%	42.51%	12.36%	3.29%	22.83%	19.01%	
Finland	Quantity	23,250	4,107	1,254	9,135	9,928	47,674
	%	48.77%	8.61%	2.63%	19.16%	20.82%	
Norway	Quantity	19,932	5,000	1,977	11,690	8,418	47,017
	%	42.39%	10.63%	4.20%	24.86%	17.90%	
Sweden	Quantity	18,700	5,554	1,742	11,249	8,674	45,919
	%	40.72%	12.10%	3.79%	24.50%	18.89%	

Table 5. Demand pattern classification

As seen from the table, nearly half of the inventory falls into the category Deadstock. The second group following is Intermittent item with one-fourth of the total stock. Obsolete items are in third place of approximately 20% of all categories. The last 2 classes are No history and Fast-moving items with 8-14% and less than 4%, respectively.

Overall, the majority of the inventory are items with no consumption in the selected analysis periods, which are Deadstock and No history items accounting for more than half of the total inventory. Meanwhile, Fast-moving items are considered easy to be managed, thus being left out of the calculation model, whereas items with more than 12 months with no consumption are slow-moving items with obsolescence risk and therefore also being excluded from the model. The reason is that, obsolete items lack sufficient historical sales records to provide the estimation of a valid input. Moreover, slow-moving items are generally either held less than 2 parts per item or directly ordered from suppliers to sell to customers hence it is unnecessary for stocking or to analyze. (Eaves and Kingsman, 2004). Lastly, Intermittent items account for about a quarter of all inventory across all markets.

Next, items with intermittent demand are classified based on the degree of intermittence, denominated by average demand interval, and the degree of erraticness, denominated by squared coefficient of variations, into 4 groups of different types of demand pattern, namely Erratic, Lumpy, Smooth and Intermittent by using 2 cut-off values, 0.49 and 1.32, respectively. Consequently, the detail statistics of 4 groups of demand pattern are shown in Figure 9.

The statistics show that on average, most of the items fall into the intermittent category. Erratic items, on the contrary, only account for the lowest percentage in this category for approximately 0.5%. Lumpy items are the second most item for less than 10%, followed by Smooth items for around 2% of the whole category.

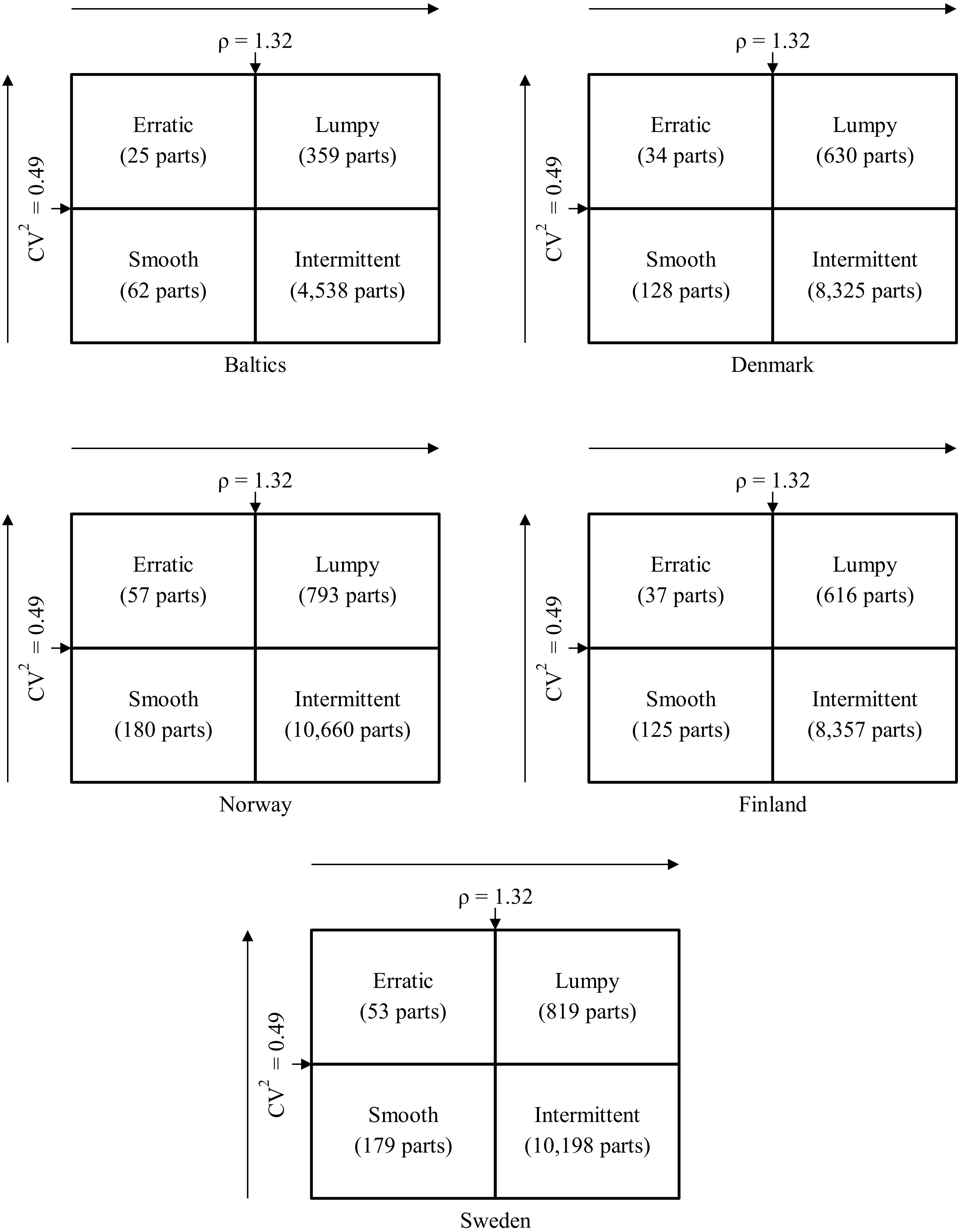

Figure 9. Demand pattern classification of 5 markets

After all demand patterns were grouped, a hold-out sample of historical data during period 2013-2015 was used to estimate the optimal smoothing parameters for each forecasting methods, that is, a trial-and-error experimentation of smoothing constant ranging from 0.1 to 0.9 to find the parameter that provides the lowest MAD error estimation of the result of each model. At this stage, MAD values are simply temporary and will be estimated again in the forecasting phase.

Table 6. Optimal parameters for each method

Parameters (α)	MA	ES	CR	SBA
Baltics	12	0.5	0.3	0.3
Denmark	12	0.6	0.3	0.3
Finland	12	0.6	0.3	0.3
Norway	12	0.5	0.3	0.3
Sweden	12	0.5	0.3	0.3

After smoothing constants for each method were determined, the forecast was conducted using data from 2016 to 2018 with the initial values defined as the average value of all previous periods. It is worth mentioning that, since the forecast is an estimation of data of all previous periods, a smoothing constant has a relatively considerable impact on the result of the forecast due to its relationship with recent data (Fildes et al., 1998; Eaves, 2002). In other words, a small value of α puts less weight on recent historical observations, thus slightly impacting the value of the forecast values. On the contrary, a large value of smoothing constant weights recent demand period more heavily, therefore having more impact on the estimated results. Moreover, smoothing parameters also affect the forecast with its impact on the initial values used in the model (Eaves, 2002). For example, an α value that is close to one would lessen the impact of the initial value on the forecast process, resulting in making the initial value less significant after some periods. Nevertheless, a smoothing parameter closer to zero would enhance the weight of the initial value even after several periods. In this study, ES method has average smoothing constants, therefore the forecast does not have the tendency to increase nor decrease the weight of the initial value and of recent data. For CR and SBA forecasts, smoothing constants are closer to zero, therefore it would put less weight on recent periods. This could be explained that in CR and SBA, periods with zero demand are considered while ES simply overlooks the zero demands.

The descriptive analysis of the average demand interval and squared coefficient of variation of intermittent demand items is presented in the following table.

Table 7. Descriptive statistics of degree of intermittence (ρ) and erraticness (CV^2)

		Mean	SD	Min	Max
Baltics	ρ	3.76	1.92	1.25	11.50
	CV^2	0.16	0.28	0.00	5.18
Denmark	ρ	3.85	2.01	1.25	11.50
	CV^2	0.16	2.01	0.00	5.36
Finland	ρ	4.61	2.72	1.25	11.50
	CV^2	0.17	0.26	0.00	5.19
Norway	ρ	3.70	1.95	1.25	11.50
	CV^2	0.16	0.25	0.00	5.93
Sweden	ρ	3.72	1.98	1.25	11.50
	CV^2	0.17	0.28	0.00	5.63

Again, it should be noted that the degree of intermittence represents the frequency of demand between periods, meaning that a low value of degree of intermittence signifies a relatively frequent demand with a small number of period experiencing zero demand order. It is seen from the statistics that, on average, the values of average demand interval ranging from 3.70 to 4.61 means that there are approximately 3 to 4 periods with zero demand in the forecast time bucket with deviation of around 1 to 2 periods, except for Finland, where there are 4 to 5 periods with deviation of 2 to 3 period. On the other hand, the degree of erraticness demonstrates the variability of an item in terms of demand size. In other words, an item is said to be erratic. In this case, the mean values of the squared coefficient of variation of 0.16-

0.17, which are considerably smaller than the minimum and maximum value of CV^2, imply that the demands did not variate significantly across all markets.

4.3. Measurement of intermittent demand forecast accuracy

The accuracy of all forecasting methods was measured using 3 error estimators and the results of the best-performing method in each scenario are summarized in below subsections. In relating to the first research question, besides comparing the results to find the best accurate forecasting method, the finding section also looks at the performance of MA as it is the current forecasting approach in the company's case.

4.3.1. Baltics

For Eratic items, ES was ranked the best method twice with MAD and MSE, while SBA is ranked first amongst SMAPE. Similarly for Lumpy items, ES performed better in terms of MAD and MSE, while CR is better in terms of SMAPE. For Smooth items, SBA was the optimal method when its errors are the lowest when using MSE and SMAPE, although ES surpassed SBA in MAD, the difference is small with 1.15 compared to 1.19, respectively. For Intermittent items, there was no method overperformed others, however, ES' result was on par with SBA in terms of MAD, 0.60 and 0.59. Therefore it was concluded that ES performed better than other methods for Intermittent demand group. Moreover, the error estimates of MA are frequently the highest, sometimes second highest, value across all demand types, implying the low performance of this forecasting method.

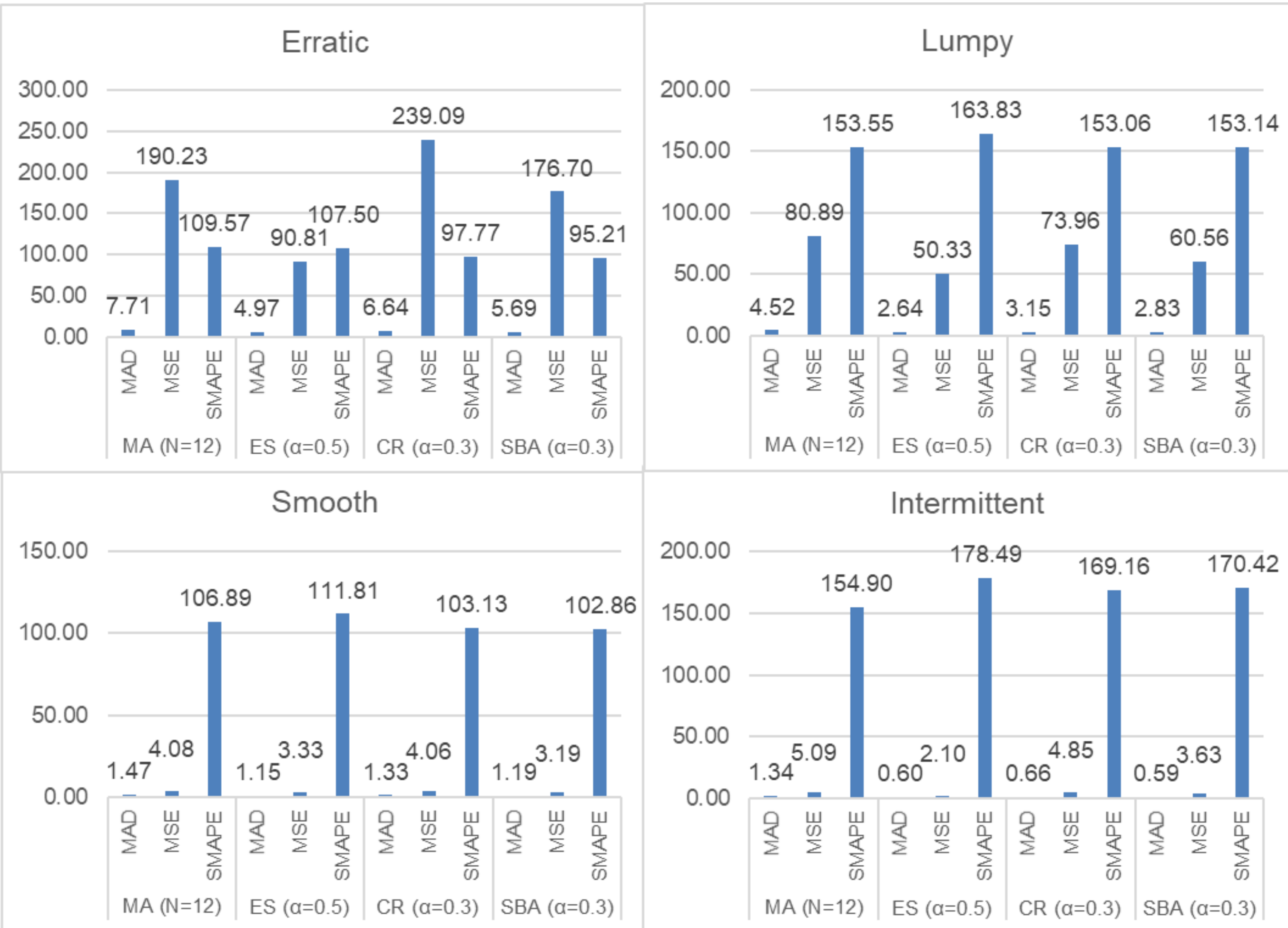

Figure 10. Forecasting method accuracy comparision for Baltic countries

4.3.2. Denmark

For Erratic demand items, SBA performed better than ES with lower error in all 3 estimators. Whereas, Lumpy items showed that ES errors were lower than others using MAD and MSE, despite the fact that its error was the highest amongst all. For Smooth items, SBA again outperformed other methods in terms of all 3, MAD, MSE and SMAPE, measurements. For the last pattern, Intermittent, SBA also had preferable results in MAD and MSE although its SMAPE error was higher than the other. Similarly to the case of Baltic countries, the error values of MA are higher than those of other forecasting methods.

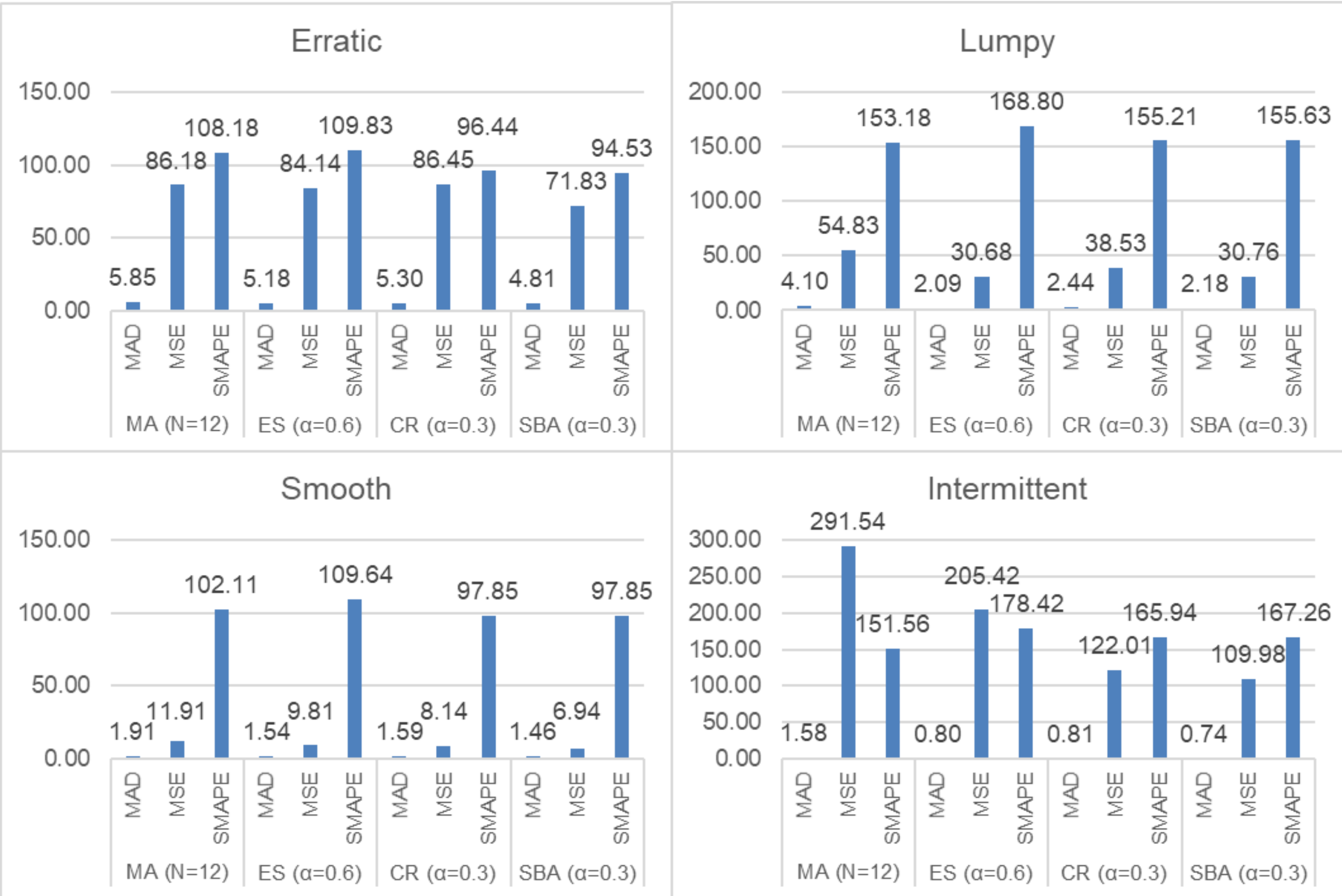

Figure 11. Forecasting method accuracy comparison for Denmark

4.3.3. Finland

In Finland, there was no method that outperformed others in the Erratic category. However, since MA's error when using MAD was not significantly higher than that of CR (4.51 against 4.40) while its MSE was remarkably lower than others, therefore MA was selected as the best-performing method in this category. For Smooth items, SBA performed better in terms of MAD and MSE, while CR was better in terms of SMAPE, yet the gap was relatively low. In the Lumpy category, the situation is similar to that of the Erratic category. Specifically, SMAPE results of CR and SBA were fairly equal (136.32 and 136.46), thus SBA was considered as a better method for Lumpy items. In the Intermittent category, ES contributed a good level of error in MAD and MSE, consequently, a better method. Additionally, MA again delivered relatively high error estimator values, which are frequently in the top comparing to other results.

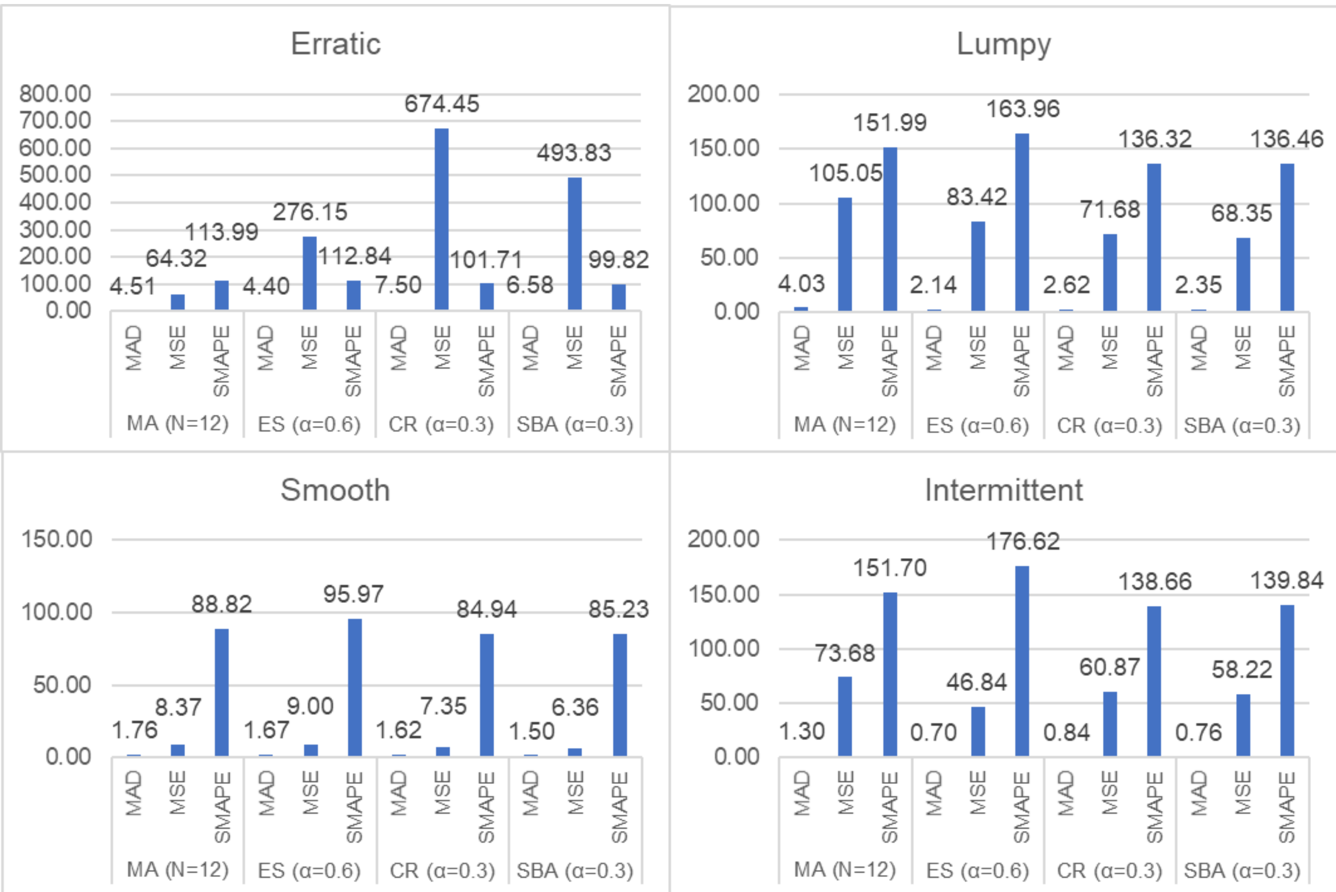

Figure 12. Forecasting method accuracy comparison for Finland

4.3.4. Norway

In the first category Erratic, ES surpassed other methods when using MAD and MSE measurements in spite of being in second place behind SBA in SMAPE. In the Lumpy category, SBA also achieved lower error results in MSE and SMAPE although it was only ranked second in MAD estimator. Similarly for Smooth items, SBA was able to yield a sufficiently lower error than other methods in MAD and MSE, although SMAPE point was ranked second, the gap was not remarkable. Despite the error values are relatively high in other markets, in the last category Intermittent, MA was the best-performing method in Norway when it overtook other methods in MSE and SMAPE estimators.

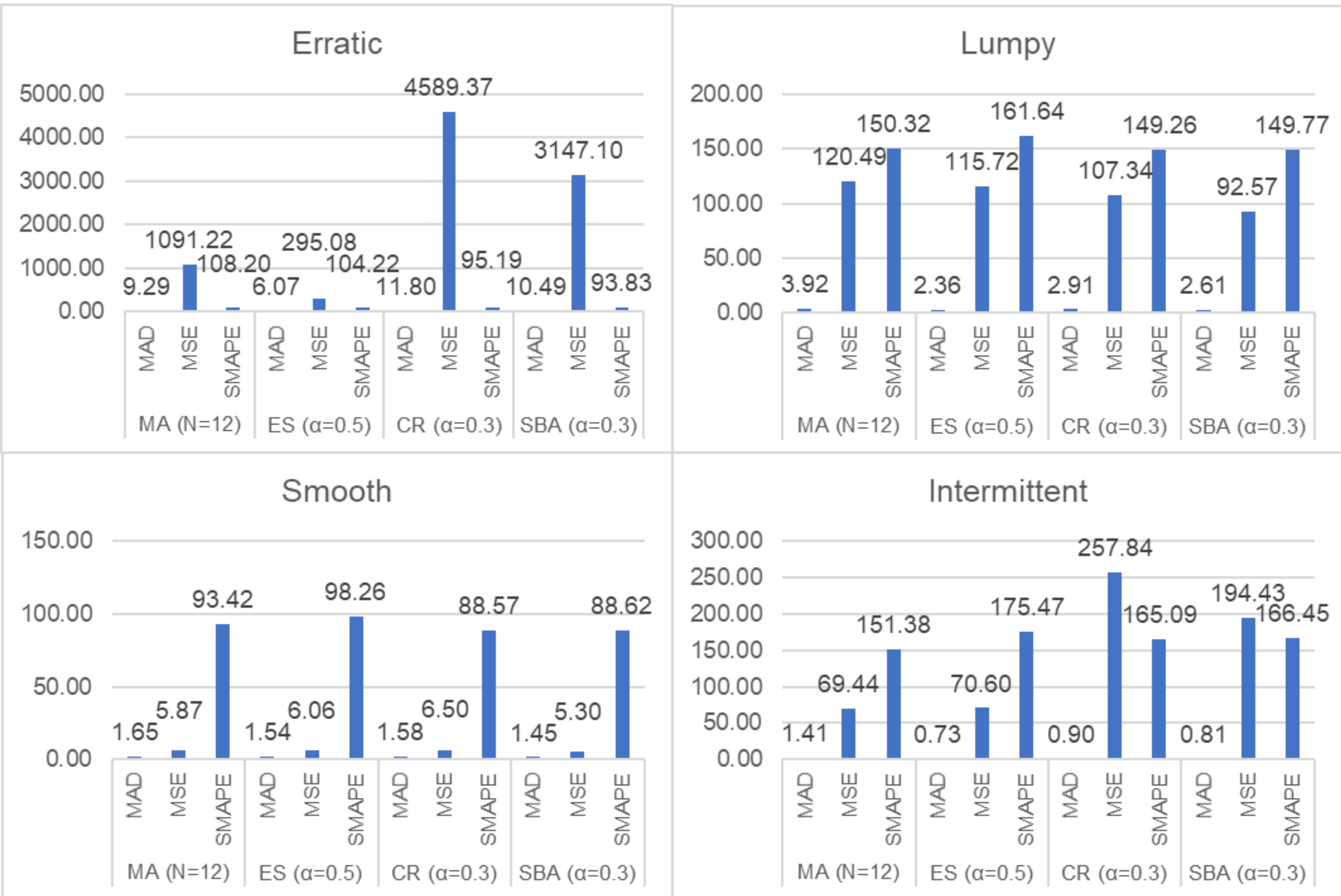

Figure 13. Forecasting method accuracy comparison for Norway

4.3.5. Sweden

In Sweden, SBA provided a reliable method for forecasting Erratic items with the lowest errors amongst all 3 estimators. Similarly, SBA showed the best results when applying to Smooth items across 3 measurement techniques. In the Lumpy category, ES performed well in MAD and MSE, although it was ranked last in terms of SMAPE. The outcome in the Intermittent group was also comparable to that of Lumpy's, when SBA was ranked first in MAD and MSE but SMAPE. Similarly to other markets, MA was also underperforming as its errors are in the top highest ranking of all demand patterns.

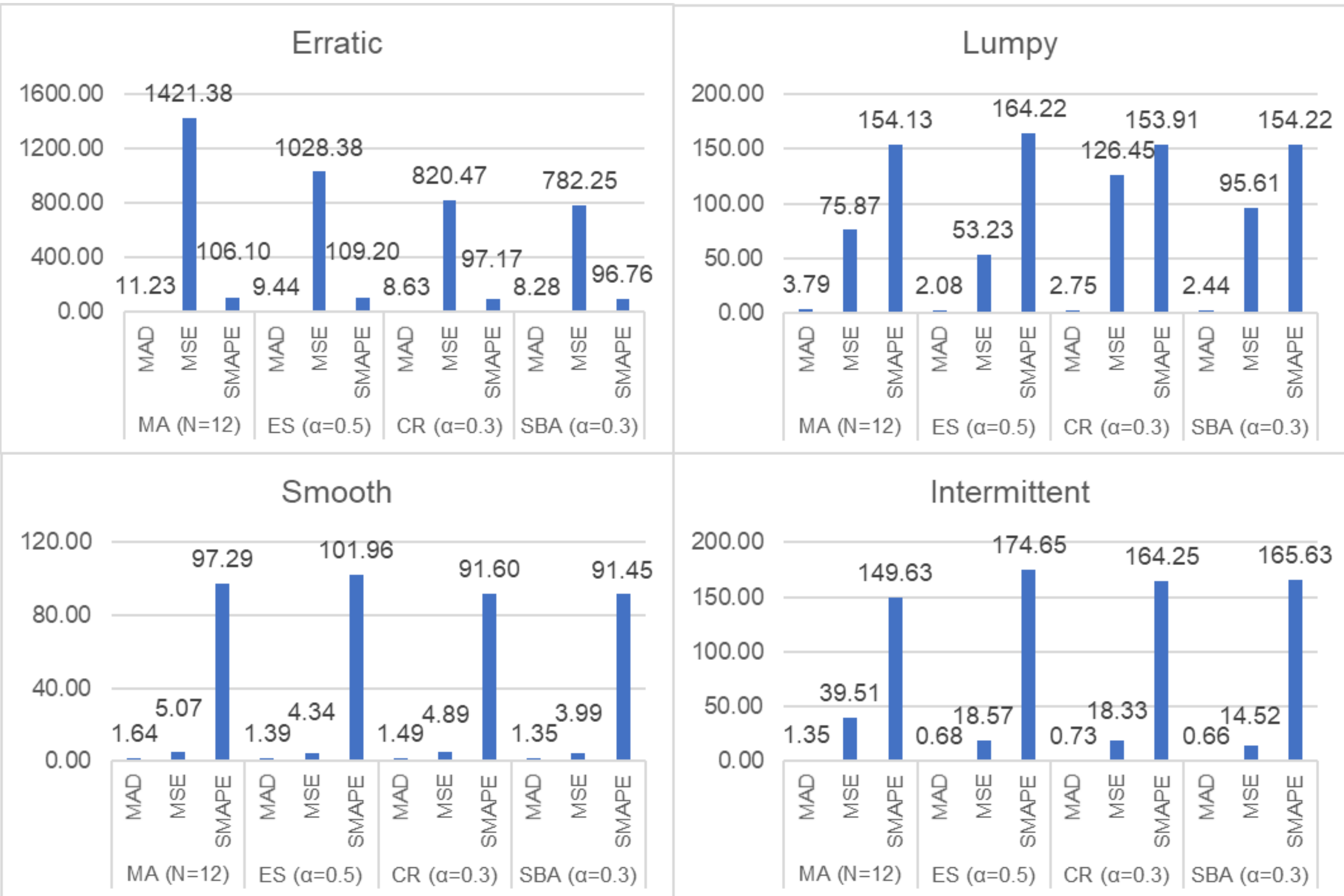

Figure 14. Forecasting method accuracy comparison for Sweden

4.4. Discussion

For the Erratic category, there are considerably high MSE values in specific markets, e.g. 674.45 for CR in Finland, or 1,421.38 for MA in Sweden. This is because of 2 reasons. Firstly, it is due to the erratic nature of the category when most of the items have relatively high varation in terms of demand size. Secondly, since this category has a relatively small sample size across all markets, therefore when there is one item with highly variated demand, it is possible to significantly increase the error estimator values of the whole group.

Table 8. Summary of best-performing methods

Demand pattern	Erratic	Lumpy	Smooth	Intermittent
Baltics	ES	ES	SBA	ES
Denmark	SBA	ES	SBA	SBA
Finland	MA	SBA	SBA	ES
Norway	ES	SBA	SBA	MA
Sweden	SBA	ES	SBA	SBA

Regarding the first research question: ***“What are the suitable methods to forecast the intermittent demand of automotive spare parts in the company’s case?”***, as seen from the table, there are only 2 cases when MA acts as the most accurate forecasting method. Hence, it is concluded that in the case of the company, MA is not a reliable approach in forecasting the demand of spare parts items as its error estimator results are frequently ranked in the highest or second highest place across all demand types and also across all markets except for Norway.

For the majority of the scenario, SBA acts as the best-performing method for more than half of the time, and ES is accountable for the rest of the case. The fact that CR has no appearance in the result shows a consistency with the results of other authors in the literature when SBA is an improvement of CR, that is, being able to reduce the error in CR’s forecast and cannot be used when forecasting erratic or lumpy demand items (Oguji, 2013). According to Wallström and Segerstedt (2010), ES performs better when the average demand interval is high, thus it is understandable that ES was selected for Intermittent category in Finland and Baltics as these market’s demand interval are amongst the highest of 5 markets. As a result, it is able to conclude that, in the case of the company, ES and SBA are suitable methods for forecasting, depending on the market and demand type.

This result is also aligned to other studies in the literature when ES and SBA are the two methods that generally perform better than other methods (Eaves and Kingsman, 2004; Syntetos and Boylan, 2005; Syntetos, Boylan and Croston, 2005; Wallström and Segerstedt, 2010). Particularly, from existing researches in the literature, SBA was proven to be one of the most efficient methods in several studies although the forecasting results were assessed against different error measurements (see Table 3. *Existing studies and results*).

For example, Eaves and Kingsman (2004) in their study about military airline industry’s inventory had compared the results of 4 forecasting methods MA, ES, CR, SBA using 3 conventional error estimators presented in the above section, combining with an additional implied stock-holding policy in order to achieve a specific service level. As a result, it was able to conclude that, SBA is the best-performing method for all demand patterns and also proven effective in reducing the level of excessive stocking. Similarly, Syntetos and Boylan (2005, 2006) also assessed the performance of the aforementioned forecasting methods in the relationship with inventory control in a sample of actual datasets from the automotive industry. The studies used both traditional and extensive accuracy measurement approaches (mean error, mean squared error versus percentage better, percentage best). In the end, it was confirmed that SBA is the favourable method as it is able to provide the least erroneous forecast result comparing to other methods. Another study conducted by Teunter and Duncan (2009). The authors applied 4 similar methods to forecast intermittent demand items in the UK’s Royal Air Force inventory and eventually found that Croston type methods (original method, CR and modified version, SBA) were able to show superiority in terms of accurate forecast outcomes. The same conclusion in which SBA is the best-performing method was also achieved in the paper by Wallström and Segerstedt (2010). In detail, the scholars examined intermittent demand using ES, CR and its 2 modification on a real data sample.

Besides using traditional error measurements, for example, MAD and MSE, the paper also assessed forecast accuracy with other estimators such as Periods In Stock (PIS) and Number Of Shortages (NOS). In other words, the result that SBA performs better than other forecasting methods is well aligned with other studies in the literature.

Additionally, since different demand pattern shows different results of the best-performing forecasting methods, that is, no method was able to show its superiority in all error measurement across all demand patterns, hence proving that it is necessary to categorize the whole intermittent demand group into 4 smaller demand patterns.

Regarding the second research question: ***"How can the selected forecasting methods be implemented in the company's case?"***, the implementation process is similar to the research framework of the study. Initially, the degree of intermittence (ρ) would be calculated to classify all inventory based on their demand data in order to identify intermittent items so that appropriate actions could be applied to each demand category. Specifically, if an item has the degree of intermittence higher than 12, or having no demand in specific periods, it falls into Deadstock, No history and Obsolete categories. Despite having been accounted for a high proportion of the inventory (approximately 75%), it is not necessary to apply forecasting method for stocking strategy for such item since there is no significant demand in the selected period as it can be ordered and shipped directly to customers upon request. When the degree of intermittence is calculated, if ρ is smaller than 1.25, meaning it is a Fast-moving item, since there is no zero demand in recent periods, it is recommended to use the forecasting method that the case company is employing, or conventional forecasting method, for example Moving average or Exponential smoothing, whichever method fits the trial-and-error experimentation. For example, Johnston and Boylan (1996) in a comparison study of ES and CR had concluded that when it comes to items with average demand intervals less than 1.25, i.e. Fast-moving item, ES is a more favourable method in forecasting. Next, all the remaining intermittent demand would be further classified into 4 groups using cut-off values from the degree of intermittence and degree of erraticness, each employs a different forecasting method specifically mentioned in the above section. Although it is recommended that the boundaries between different demand pattern should be selected carefully in order to provide a comprehensive look of all categories (Eaves, 2002), it is not necessary to do so since the accuracy of the forecast does not heavily depend on cut-off values (Boylan and

Syntetos, 2009). The selected intermittent items are then applied into forecasting models, ES and SBA to estimate the demand for the next period. Since there is more than 1 forecast method, it is recommended that the final forecasted value is an average of the 2 methods' results. Eventually, in order to ensure the accuracy of the forecast, it is suggested that the smoothing parameters used in models should be reassessed after one period of the forecast process (Rego and Mesquita, 2015).

5. CONCLUSION

The thesis's findings have contributed to the intermittent demand forecasting literature by reconfirming the suitability of SBA in forecasting intermittent demand. Secondly, it also proved that although being in the same intermittent category, different stock keeping units have different demand patterns, therefore requiring different forecast approaches.

With the result of this study, managerial personnels of the company have one more tool to improve business performance. The first and foremost benefit from the study is the fact that the current forecasting method (Moving Average) was proven to be an inaccurate approach in forecasting the demand for spare parts. Moreover, the study's result acts as a framework to apply forecasting into the company's case. Also, when using the forecast results it is possible that the inventory level would be optimized, reducing unfavourable situations such as overstocking and understocking. Moreover, being able to forecast the demand of intermittent items, managers are easier to focus to increase customer satisfaction and retention level by supplying them with sufficient product in reasonable lead time, while also improving product fill-rate and backorder due to accurate inventory stocking and positioning. On the other hand, logistics and warehouse tasks are also simplified since demands from direct customers are now clearer, resulting in efficient logistics planning and inventory balancing across the company's own warehouse network. On a strategic level, product management would also be improved since the management board would now be able to gain a better look on product life cycles, new launch or discontinuation of old models to provide support accordingly. Lastly, since demand forecasting is also related other organizational business functions such as Sales, Purchasing, Finance, it could support management in long term business planning, therefore being able to improve the efficiency of the company. (Kerkkänen, 2010).

Furthermore, the limitations of the study are from, firstly, the characteristics of the research. Due to the limitation in data availability, the research was unable to employ a more extensive forecasting method that uses a comprehensive approach to measure the forecast accuracy analysis, for example, unavailability in lead time data, backorder data during forecasting period or the number of cancelled orders. Secondly, since the study is aimed to find the appropriate technique to forecast the demand for its spare parts inventory, it is limited to not covering the demand from other echelons in the whole supply chain. In other words, the research is limited to a single-echelon level, that is the case company itself and did not including demands from other echelons up and down the supply network such as part manufacturers or end consumers. Thirdly, since the study applied forecasting models to the data sample on a monthly aggregation level, the forecasting task should be done once every month. Considering the hectic environment in the case company, the task would be seen as time-consuming by employee who is responsible for handling the forecasting task. Therefore, it is recommended that in practice the forecast should take into account a higher level of data aggregation, e.g. quarterly, yearly. However, one factor should be kept in mind that as the time frame scales up, forecast accuracy is also affected (Kerkkänen, 2010).

Although the research provided practical answers to the research problems, it is possible to extend further the research scope and therefore broaden the research questions. Specifically, the accuracy of the forecasting models could be improved by using a more comprehensive approach in measuring the effect between forecast result, inventory stocking and cost-saving activities. Moreover, instead of classifying the demand pattern solely based on demand volume, it is possible to category the inventory on the basis of lead time analysis to better reflect the relationship of transaction variability, demand size variability, lead time variability and demand pattern. Furthermore, in this study there is only 1 parameter used in modelling, thus future researches could add more smoothing parameters into the forecast formulas so that models would react easier to changes in demand in recent periods and therefore, improving the accuracy of the forecast. Additionally, it is beneficial to define more smoothing parameters for different demand patterns and also, for different line items. Finally, despite the fact that this study used a small sample of data to decide the smoothing constant with MAD trial-and-error experimentation, it could also be determined by using other error estimators.

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