Aalto University
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Developing an Optimal Selective Procurement Matrix for Resale Business - Case Studiotec Oy

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ABSTRACT

OBJECTIVES OF THE STUDY

The foundation of this study is to understand the procurement challenges that the case company Studiotec Oy and its sister company Soundtools Oy are currently confronted with. Moreover, this study aims to develop procurement directions in order to increase inventory turnover and improve customer satisfaction whilst releasing working capital.

Academic literature is filled with recommendations on how to profile inventories into classes, on forecast approaches and with inventory control policies. However, a clear link between classes and different forecast systems and replenishment systems does not exist yet. Therefore, the aim of this study is to develop a practical SKU classification framework that guides the inventory decision and aids in the selection of the most appropriate combination of forecast approach and replenishment system. This study furthermore tries to assist the responsible purchasing employees to reconsider customary purchasing manners and enables management to think of the fresh ways of inventory management.

ACADEMIC BACKGROUND AND METHODOLOGY

In order to classify items and to test the designed framework, the sales and order data from the beginning of 2010 until September 2012 were analyzed. The empirical recommendations are based on heuristics and cost comparisons that were carried out for 90 items. Company's top management, product managers and the logistics manager who are responsible for making the purchase decisions were interviewed in order to get a better overall understanding about the situation, including the entity being evaluated and the circumstances. The inventory management literature was thoroughly reviewed as to select the best classification factors is the first step, followed by determining the most suitable forecasting methods and inventory control policies for the different classes.

FINDINGS AND CONCLUSIONS

The pivotal reason for increased inventory lies on demand intermittence and erratic. In addition, product managers unjustifiable large order quantities played a big role. By way of the new framework, items were categorized into six classes based on their contribution to net sales and demand frequency. Based on academic research, an optimal forecasting method and an inventory replenishment system were addressed for each class. Empirically optimal procurement tool differed from theoretical suggestion. The study suggests that the case company should abolish stocking items sold less frequently than every three months. This way, the case company could decrease its inventory value by 20 % and dramatically deplete the risk of obsolescence. Moreover, the new procurement tool embedded in product life cycle directs on overall procurement decisions.

KEYWORDS

Inventory categorization; forecasting, intermittent demand, inventory control, resale business

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ABSTRAKTI

TUTKIMUKSEN TAVOITTEET

Tutkimuksen lähtökohtana oli case-yritys Studiotec Oy:n ja sen sisaryritys Soundtools Oy:n varaston kasvuun liittyvien syiden selvittäminen ja uuden ostotoimintamallin kehittäminen siten, että tuotteiden kiertonopeus ja asiakaspalvelutaso paranisi ja yrityksen käyttöpääomaa vapautuisi.

Kirjallisuudesta ei löytynyt selkeätä luokittelumallia, joka yhdistäisi tuotteen ominaisuudet ennuste- ja varastohallintamenetelmään. Näin ollen tutkimuksen tavoitteena oli rakentaa erilaisille tuotteille käytännöllinen luokittelumalli, joka ohjaisi varastointipäätökseen ja sopivan ennuste- ja varastohallintamenetelmä valintaan. Tutkimuksen tavoitteena myös oli edesauttaa tuotepäälliköitä irtautumaan perinteisistä ajattelutottumuksista ja antaa johdolle uusia aineksia ajattelulle kuinka varastoa voisi johtaa.

KIRJALLISUUSKATSAUS JA METODOLOGIA

Tuotteiden luokittelua ja viitekehyksen testaamista varten yrityksen osto- ja myyntidataa käytettiin vuoden 2010 alusta syyskuuhun 2012. Empiiriset suositukset perustuivat kustannusvertailuihin, jotka toteutettiin 90 nimikkeellä sekä heuristiseen päättelyyn. Tutkimuksessa haastateltiin yrityksen johtoa, logistiikkapäällikköä, tuotepäälliköitä, projektisihteeriä ja osastosihteeriä, jotka ovat vastuussa ostopäätöksistä, paremman yleiskuvan saamiseksi. Tutkimusta varten haastatteluja kertyi 23. Lähdekirjallisuus painottui tuotteiden luokitteluun, ennustemenetelmiin ja varastotäydennysmalleihin teoreettisen ostotoimintamallin rakentamiseksi.

TULOKSET JA PÄÄTELMÄT AVAINSANAT

Keskeinen syy varaston kasvulle juontuu kysynnän epäsäännöllisyydestä ja epätasaisuudesta. Myös tuotepäälliköiden perusteettoman suuret ostotilaukset ovat olleet merkittävä varastokasvun syy. Uuden viitekehyksen avulla tuotteet kategorisoitiin kuuteen luokkaan liikevaihdon ja kysyntäfrekvenssin perusteella. Kirjallisuuden perusteella kullekin luokalle määriteltiin ennuste- ja varastohallintamenetelmäsuositus. Tutkimuksessa havaittiin, että teoreettinen ostotoimintamalli erosi empiirisestä. Tutkimus ehdottaa, että harvemmin kuin kolmen kuukauden välein myytäviä tuotteita ei enää varastoitaisi. Näin varastoarvo laskisi noin 20 % ja varaston vanhenemisriski pienenisi merkittävästi. Lisäksi, uusi ostotoimintaohjeistus ohjaa kokonaisvaltaisesti ostopäätöksenteossa kun tuotteen elinkaarimalli otetaan huomioon.

AVAINSANAT

Varastoluokittelu, ennustaminen, epäsäännöllinen kysyntä, varastohallinta, jälleenmyynti

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1 INTRODUCTION

1.1 MOTIVATION

Holding an inventory is a risky business these days. Stocking seldom adds value to a product and the swift pace of technological development may change product demand dramatically overnight. Customers' rising expectations of faster deliveries and broader product portfolio offered by the vendor complicate the situation furthermore. In addition, the emerged e-businesses have set new price completion in many industries due to their low cost structures. All these facets have created fiercer competition among domestic and foreign companies to cut costs in their supply chains. Consequently, developing a suitable inventory management system is more important than ever before.

Numerous forces, of which some of them are internal and under company's control whereas some of them are external and not governable by the company, affect inventory decisions. As purchasing decision has to be done already months before delivery, and the current economy situation is worldwide unpredictable, purchasers are facing challenging times. As an example, China confronted mounting piles of unsold goods in autumn 2012 since the export sales and domestic consumption had stalled[1].

Inventory management is an intrinsic part of import and wholesale businesses. Making goods available for customers at the right time and at the right place is a pivotal principle of doing business. Accordingly, inventory decisions have a crucial influence on the firm's operational performance and on their competitiveness. The aim of developing inventory management is to cut holding costs while revamping product availability. As Chen et al. (2007) point out this goal is a like a double-edged sword, as a large variety of goods boosts the service level but simultaneously increases the costs. In order to minimize the costs, understanding the demand becomes critical in order to opt for the depth and breadth of range of the products to be stocked. Having a broad range of items but only a few pieces of each item would be as detrimental as investing a lot of stock only a few items from a customer point of view (Johnston et al., 2011;

[1] www.alsosprachanalyst.com/economy/hsbc-markit-china-manufacturing-pmi-flash-aug-2012.html

Silver et al., 1998). Hence, demand examination is critical part of succeeding in increasing inventory turnover and customer satisfaction whilst releasing working capital.

Even though inventory management as a discipline is not new, SMEs are struggling with problems in inventory control invariably. Boylan et al. (2008) explains this issue by stating that stocking and replenishment decisions are ultimately made for each individual item separately. Small and medium sized businesses, especially, do not have sufficient resources to establish teams dedicated to forecasting or stock optimization issues and thus often struggle to choose the most appropriate forecast and inventory control methods. To lessen the workload of managing items at an individual level, academic literature suggests classifying items into classes. Nevertheless, an efficient and straightforward taxonomy to select the most appropriate forecasting method, inventory control policy and replenishment system based on an item’s characteristics has not been covered yet. The challenge in building such a comprehensive framework lies in finding characteristics that determine the most suitable forecast and inventory replenishment methods effectively yet efficiently.

Developing such a framework in practice would require taking into account aspects that are more practical than theoretical. The size of the investment a company is willing to make, employees’ capabilities and the current limitations in IT software for instance need to be considered while developing a tool. However, the potential benefits of a new procurement framework are numerous. It can release working capital, increase inventory turnover, and decrease the risk of obsolescence. It would also aid purchasers to assimilate important determinants relating to replenishment decisions and facilitate them in the purchasing decision-making. Lastly, a formal procurement framework could reduce behavioral bias among purchasers and decrease total inventory costs.

1.2 THE RESEARCH PROBLEM AND AIMS OF THE STUDY

In this study, a medium-size Finnish family owned wholesale company Studiotec Oy, specialized in audio-visual solutions and products, has been facing a bulge in its inventories recently. As the company has not documented formal guidance on how purchasing decisions should be made, a study to improve present activities was initiated. The improvement target is on a single-location inventory system. Since the decisions on purchasing must be done at unit level, clustering items into categories can facilitate the decision-making process tremendously.

Academic literature is filled with recommendations on how to profile inventories into classes and with forecast approaches and inventory control policies. Yet, a clear link between classes and different forecast systems and replenishment systems does not exist. Especially, linking demand pattern to a suitable inventory control policy has not been examined in the academic context (Boylan et al., 2008). From a theoretical point of view, this study analyzes how stock keeping units (SKUs) can be classified and what different forecasting, inventory control policies and replenishment systems exist that would be suitable for the case company needs, in terms of its size, available resources, current procurement processes and IT software, employee capabilities, and negotiation power in the supply chain.

The theoretical research questions can be formulated as following:

- *Which criteria should be used in classifying items as to minimize the inventory costs and to improve the customer service level?*

This requires that the classification scheme is linked to the chosen forecast method and inventory policy. Hence, a question follows:

- *Which forecast approach, an inventory control method, and a replenishment system suit best for each class according to literature?*

Moreover, it is under the interest to see how well the framework applies in practice. The following questions are related to the case company as to satisfy managerial needs:

- *How well does the framework apply the case company's needs?*
- *What are the main reasons behind the increased inventory levels?*
- *How to determine the depth and breadth of items to be stocked?*

As Syntetos et al. (2010) notes, the academic literature about inventory management is rather extensive but very few papers examine solutions that are empirically implemented. In that sense, besides building a classification scheme based on existing theories on forecasting and inventory control methods, this study aims to fill the gap between theory and practice.

The objective of this study is to incorporate economically sound theories into a procurement framework, which counsel purchasers on which forecasting method and stock control policy to use for each class. The aim of the theoretical framework is to release working capital while ascertaining good customer service level. Moreover, the practical tool is to be developed for the case company's needs basing on the theoretical framework. The tool should be robust and easy to implement and run. This study furthermore aims to understand current purchasing and logistical problems in the case company.

1.3 RESEARCH METHODOLOGY

The purpose of this thesis is to solve a practical problem within a company and falls within the spectrum of applied research. The focus of this study is on a contemporary phenomenon. As (Lockett, 1981) stresses, understanding the underlying problem in-depth is critical since corporate strategy and behavioral courses can preclude a meaningful use of any mathematical model in inventory management. In that regard, a case study method that also copes with multiple other sources than just data points lends itself to this underlying study ideally. In addition, as the investigator has no control of events, a case study approach suits well (Yin, 2009).

The basis of empirical part will be built upon both sales and inventory data retrieved from case company's ERP system, and on interviews conducted with product managers, the logistics manager and project secretary who are responsible for purchasing decisions. The statistical analysis, in order to track potential trends and other attributes in demand pattern, will range from the year 2010 until the end of September 2012.

The literature review is based on academic publications mainly considering SKU classification and suitable forecast and inventory control policies. In the empirical part, a quantitative analysis in combination with interviews will be used in order to understand the reasons behind mounting inventories. Whereas sales segmentation and data analysis reveal were to sink one's teeth into, the interviews will reveal the opinions, attitudes, knowledge which influence purchasers' decision-making. Since the same personnel who are responsible for making the purchases are in response of sales, one-time interviews will be adequate. If this were not the case, both procurement personnel and sales personnel would have to interview in order not to investigate the settings from one angel only. After these examinations, one can opt for the most suitable inventory control policies and coax personnel to use them in practice.

1.4 LIMITATIONS

Supply Chain Management topics range from strategic decision making to tactical issues. Because of time and resource limitations, following issues are not taken into consideration: the implications of supplier selection and supplier relationship development, and negotiation tactics or quality. Enhancing forecasting and selecting an inventory replenishment system are only one part of logistics decisions. Especially, questions relating to the type of transportation, warehousing, outsourcing and information systems are considered as given and unchangeable.

The empirical part concentrates on audio-visual wholesale business and project business and thus recommendations may not be applicable to other industries. For instance, in respect with holding costs, inventories can be classified regarding to how they are inventoried or at which production stage there are. This study focuses purely on end-product inventory items due to the nature of the case company's SKUs.

Recommendations are naturally given on the present basis – meaning that changes in the inflation ratio or in economic situation are not taken into account when building the procurement tool. The case company is undergoing a process examination in tandem, but that review is excluded from this study.

1.5 STRUCTURE OF THE THESIS

The remainder of this study is structured as follows: in Section 2, relevant literature on inventory categorization is reviewed in conjunction with discussion on their suitability in practical implementation. In Section 3, general short-term forecast methods are contemplated following by inventory control and replenishment systems in Section 4. The theoretical procurement matrix is introduced in Section 5. In Section 6, the case company and reasons behind increased inventories are covered. Section 7 is dedicated to analysis of how theoretical matrix fits with real demand data. An optimal procurement matrix based on empirical findings is represented in Section 8. Conclusion and further research suggestions are given in Section 9.

2 INVENTORY CATEGORIZATION

Traditionally, the goal of inventory management has been to minimize the overall inventory holding and ordering costs while ensuring good product availability (Krajewski et Ritzman, 2002; Silver et al., 1998; Wild, 2002). Thanks to the e-procurement and IT software, the ordering costs have mitigated notably and the challenge has shifted more towards balancing between holding costs and customer service level. Logically thinking, in order to minimize holding costs, it is necessary to reduce inventory levels. Lowering inventory levels can, however, risk good product availability and weaken a customer service level. Consequently, a conflict exists when deciding how high inventory levels a firm should carry. Moreover, the question cumulates: how much should a firm carry each SKU? Opting for the depth and breadth of range of the products to be stocked is then the main question in inventory management and in order to answer the question all SKUs need to be understood. Namely, without understanding the characteristics of the item in the matter, selecting a suitable forecast procedure and stock control policy reminds more like a lottery.

Logistics as a business concept evolved in the 1960s[2] and since then has attracted numerous researchers. Logistics literature is filled with different forecast approaches and inventory management systems. Suitable forecasts and inventory control systems provide a way to satisfy customers with the right item in the right quantity at the right place at the right time while keeping holding costs acceptable low. In order to understand and opt for the best suitable forecast and inventory management systems, the decision maker must understand the underlying product attributes. The biggest challenge is to find a way to choose the most appropriate methods. Items that the firm sells can be categorized in many different ways depending on the purpose of the whole categorization, e.g. according to their cost, weight, volume, color, physical shape, sales, margin, criticality, functionality (i.e. are they parts for sale or spare parts), types of inventories, demand pattern, lead time, life cycle, and the risk of perishability and obsolescence. None of these criteria alone gives a sufficient guidance or insight how to manage different pools. Sales or margin gives the most valuable perspective where the biggest portion of capital is tied

[2] http://www.referenceforbusiness.com/encyclopedia/Bre-Cap/Business-Logistics.html#b

up and thus the biggest cost savings can be achieved. Nature of the demand, in turn, determines what kind of forecast method is the most suitable one. A product life cycle stage is also an important aspect that should not be left aside either. Product life cycle will be considered later in this study, and the next classification based on sales and demand patterns are to be looked more carefully at for.

2.1 CATEGORIZATION BASED ON ABC ANALYSIS

The increased competition among companies, the growing number of SKUs and ever-expanding customer needs has set companies to find ways to cut inventories on hand. Scholars and practitioners have paid a lot of attention how to categorize SKUs analytically (Stanford et Martin, 2007). One of the best-known inventory classification techniques is called ABC analysis, which is based on the assumption that inventories in organizations are not of equal value and coincide closely with the Pareto distribution. The Pareto distribution shows that very often 20 % of the subjects comprise 80 % of the observable phenomenon. The roots of this philosophy originally emanate from the allocation of wealth among individuals observed in Italy (Wold et Whittle, 1957). On the strength of ABC analysis, one can set service level targets for different classes (Chen, 2012; Teunter et al., 2010). More precisely, the idea is to segment SKUs into classes based on predetermined criteria and to reveal the most important items and address sufficient yet appropriate inventory control policy for each class.

Traditionally, items are categorized at least into three classes though six classes are not uncommon either, and in industrial wholesaling firms, it is not unprecedented that a firm utilizes up to 12 inventory classes (Graham, 1987). Silver et al. (1998, pp. 359) emphasize that it is not about the number of classes but how they are managed. In addition, the classes should be reviewed periodically since classification may change over time. Unfortunately, Silver et al. (ibid) do not imply how often the re-evaluation should be carried out.

Traditionally, ABC is based on solely one criterion but in practice, it has been noticed that several criteria are needed (Chen, 2012; Silver et al., 1998). Perhaps the most generic criterion is the value of annual consumption of inventory items in a year following by other popular criteria such as criticality, gross profits, usage frequency, scarcity and lead-time, value added per product unit, product's stage in product life cycle, a number of customer transactions, product's value adding potential, and size. The choice should be based on company's situation and needs (Johnson et Leenders, 2006; Hayes et Wheelwright, 1979).

The table below shows how different classes should have different stakes in terms of forecasting and controlling investments. The table portrays how SKUs should not be treated equally but addressed by their importance. According to Hill et Zhang (2010) everything else being equal, products with higher demand should have higher inventory turnover, which is attained by high investments on tight inventory control policy. A few words of warning are however worth noticing. When the ABC classification is made upon annual demand volume A items will tie up the most of the capital. Thus, those items burden company's balance sheet the most and entail the biggest risk of obsolescence. In this manner, the safety stock level should be at the minimal acceptable level and the expected turnover rate the highest among the classes. Alternatively, if the classification is based on criticality, where A class stands for the most critical items, the inventory turnover rate should not be emphasized. In this case, it can be dangerous to strive for a high turnover rate. Consequently, the recommendations in the table do not hold universally.

Table 1: ABC-classification and its implications on inventory management

CLASS	Investments on forecasting	Inventory control	Expected inventory turnover
A	High	Very tight control and accurate records, Kept under High Value Storage/Asset Tracking / Access Control required	High
B	Moderate	Less tightly controlled and good records	Moderate
C	Low	Simplest controls possible and minimal records	Sufficient

Table derived from Silver et al. (1998) and Krajewski et Ritzman (2001)

Albeit ABC classification enjoys a widespread use among practitioners as it provides a good understanding about the distribution of items according to the classification method, it has also been questioned in the literature. Pearse (1985; from Silver et al., 1998) warns that manufacturers and distributors often have different perspectives on ABC classification, which may incur schism. More recently, Teunter et al. (2010) argue that the ABC-classification has not been developed from inventory cost perspective. The authors argue that determining which class should draw the highest customer service level remains vague when value multiplied by the volume is used as a ranking criterion. A class, which normally consists of the most valuable items, generates the biggest portion of the firm's profit and so should have the highest service level in order to prevent backlog orders. On the other hand, running to a situation where C items, comprising of the least valuable items, dry up from stock is not worth rush ordering due to the low gross margins they generate. Thus, there should always be an excess inventory on C items meaning that the service level should be high as well. As a cure, Teunter et al. (ibid.) provide a cost criterion were items are ranked in descending order based on item's criticality, demand volume, unit holding cost and order size:

$$bD/hQ,$$

Where:

b = the criticality measured by the shortage cost

D = the demand volume

h = the unit holding cost

Q = the order size

Although the cost criterion entails many important facets and is more comprehensive than a single criteria used in traditional ABC, it has some pitfalls why it can be difficult to implement in practice. Teunter et al. (ibid), you see, measures criticality by the shortage cost, which is measured as some percent of the value of the item. As holding cost is also a predetermined fixed amount of the value, the shortage cost and holding cost partly cancels their effect out. Otherwise, if an item were expensive and critical, its place in the ranking would fall. The biggest problem is that the cost criterion is not linked to any forecast or replenishment system directly. As the order size is tied up with the replenishment policy but the order size should be known before classifying to a class, this leads to a circle problem. Based on the issues Teunter's et al. (2010) cost criterion was waived from further consideration.

From time to time, a confronted inventory analysis framework combines item's value (ABC analysis), the criticality (VED analysis) and the usage frequency (FSN). Combining these three factors can give a good insight into item's attributes according to their placement in the three-dimensional matrix. Though appealing in theory, in practice the scheme is difficult to run because of its three dimensional nature and nine different block. In order to effective, all these blocks should be managed differently which would turn out to be rather complex and laborious. Therefore, the aspect of item's criticality is taken into account separately later in the study when inventories are segmented according to their sales (in Section 6.3). As ABC alone does not offer a tool, which forecast model or replenishment system to address for each group, the focus is next placed on the ways to analyze different demand patterns.

2.2 CATEGORIZATION BASED ON DEMAND PATTERNS

As pointed out earlier, there has been a considerable amount of studies on how to classify SKUs. Mainly, the classification has offered a guideline for managers on how much they should devote their time and resources to manage different classes. However, a link on how to combine a forecast method and a stock replenishment system to classes has lacked (Boylan et al., 2008).

In the past, demand categorization has attracted very limited academic interest (Boylan et al., 2008). The authors guess that the reason stems from the difficultness of managing erratic demand. Only recently, published case studies (Boylan et al., 2008; Nenes et al., 2010; Syntetos et al., 2010) have shown significant improvements in terms of decreasing inventory-holding costs while improving customer service level. The good results have been achieved once forecast and inventory replenishment systems have been chosen based on SKUs' demand pattern.

The following definitions of demand patterns are based on Syntetos et al (2005) classification (Figure 1). It is worth to note that the definitions in the literature are not always used unequivocally. In this study, the following definitions will be used through the study. Especially terms lumpy and irregular are used interchangeable even though irregular demand has a broader interpretation (Nenes et al., 2010).

Smooth demand as the name implies, means that the demand takes place frequently and the size of individual demand points varies only a little. A great part of academic literature on forecasting is focused on handling smooth demand. The most well-known methods are accounted in Chapter 3.1. Smooth demand is the easiest kind of demand to handle and only problem can incur if the lead times are long or fluctuate markedly.

Erratic demand means that the variation of demand sizes is high while the demand frequently occurs. This kind of demand can be managed by holding safety stocks if the lead time is long or in the case of short lead times also deploying rush orders is possible.

Intermittent demand stands for demand were the demand appears sporadically. Many periods can have no demand at all and when a demand arrives, the size tends to be higher than one unit. However, the variation of demand size is smaller than in the case of erratic or lumpy demand. Studies in the field of wholesaling, distributing and spare parts' contexts have found that demand is often intermittence by nature (Johnston et al., 2003; Nenes et al., 2010; Porras et Dekker, 2008; Syntetos et al., 2010; Teunter et al., 2010) Sometimes intermittent demand is mixed up with slow moving demand. There is however, a distinctive difference between these two definitions in that intermittent demand has infrequent transactions with variable demand sizes whereas products having slow-moving demand are transacted infrequently with low demands. Most common reasons for intermittent demand are small customers and a few large. Spare parts, as for, are a good example that comes under slow demand class. What is common for these two types of demand patterns is that generic forecasting methods do not apply well.

Lumpy demand is a mixture of erratic demand and intermittent demand. It is the most difficult category to manage since there can be a great number of intervals with zero-demand and a great variability in the quantity. Assessing a safety stock level for these kinds of items is extremely difficult since the estimates for the lead-time demand vary greatly. This also holds with intermittent and erratic demand but is accentuated within lumpy demand.

3 FORECASTING

Forecasting stands for a prediction of future events used for planning purposes (Krajewski et Ritzman 2001). It provides valuable guidance to various decisions ranging from human resource planning to running inventory controls or to managing cash flows (Fildes et Goodwin, 2007). On the other hand, when the forecast goes wrong, huge costs may incur. Apple Corporation, for instance, reported $388 million write-downs of inventories, which was largely due to poor order forecasting in the late 1990s (Hanssens, 1998).

Swift technological changes, actions taken by rivals, and changes in consumer preferences among others exert pressure on firm's capability to generate accurate forecasts. A good forecast is often a combination of different perspectives. Particularly, it should include three different pieces of information, namely, the state of the economy, demand by customers, and data collected from the specific market sector (Davies et Mentzer, 2007). Further, demand forecast methods are divided into four categories: subjective or judgmental methods, causal methods, time series methods, and scenario writing (Krajewski et Ritzman, 2002; Silver et al., 1998)

One of the key goals of this study was to develop a purchasing guidance for the case company needs. Therefore, the focus of the following sections lies on relatively simple demand forecasting methods designed for a short time horizon. As an academic justification for concentrating on rather simple methods only, Makridakis et al. (1982) compared numerous statistical forecast methods for individual items possessing smooth demand using 1001 time series. The findings showed that the simple methods most often outweighed statistically sophisticated methods. Forecast methods, designed for intermittent demand, are picked up the simplicity in mind. Later, widely encountered forecast error metrics are shortly reviewed, as they are needed when different forecast methods are to be tested in empirical part.

3.1 SHORT-TERM FORECASTING MODELS FOR SMOOTH DEMAND

Last decades have been a boom time for developing sophisticated quantitative forecasting (Danese et Kalchschmidt, 2010). Nonetheless, these newly developed and more complex techniques do not automatically offer more accurate results than simpler methods (Lawrence et al., 2000; Makridakis et al., 1982), and the most suitable method mostly depends on business conditions (Wright et al., 1986). Though the literature is full of different kinds of forecasting methods, the following ones have been found to be reasonable accurate and still inexpensive to use for short-term and for individual SKUs (Hyndman, 2010; Silver et al., 1998).

Naïve forecast

A naïve forecast is a technique that postulates the demand for the next period being equivalent to the demand for the current period. The naïve method is used in practice due to its simplicity and low cost (Krajewski et Ritzman, 2002). The method can be considered using when the horizontal, seasonal and trend patterns are rather stable and random variation remains low. It also provides a good benchmark how well techniques that are more sophisticated perform.

The Simple N-Period Moving Average

The simple moving average is an estimate for the average of the past demand time series. Typically, the time series included in the calculation ranges from 3 to 12. The method is suitable when demand has no pronounced trend or seasonal influence and when the underlying demand can be modeled as following:

$$X_t = a + \varepsilon_t$$

Where X_t stands for underlying demand pattern, a for level and ε_t for random noise.

The forecast for the next period (F_{t+1}) can then be calculated as:

$$F_{t+1} = \text{Sum of last } n \text{ demands} / n$$

The decision concerning how many periods of past demand to involve (i.e. the value of *n*) should be based on the demand pattern. If the demand shows to be stable, a large number of demand series should be used. By increasing the number of periods, the forecast becomes less susceptible to random variations but on the other hand lag behind changes if the underlying average in the series is changing. Accordingly, when the demand is susceptible to changes, shorter periods are recommended. Silver et al., (1998) remind a reader that simple moving average technique possesses two distinctive drawbacks. Firstly, the historical data must be stored for each SKU burdening the database. Secondly, an equal weight is given each period. Thanks to present-day IT, the first worry is valid no more. For the second concern, a weighted moving average comes into a picture.

Weighted Moving Average

Simply speaking, the weighted moving average method accounts for the Simple N-Period Moving Average method added with specific weights. Thus, demand periods (D_t) do no longer have the same weights. The weighted moving average is obtained by multiplying the weight constant with the value for that period and then summing up the products together. Mathematically:

$$F_{t+1} = w_1 D_t + w_2 D_{t-1} + w_3 D_{t-2}$$

Where the sum of weights *(w)* accounts for 1. The advance of weighted moving average is that the most recent demand can be emphasized and in this fashion, the forecast is more responsive to the changes of underlying average of demand series. Yet, this procedure also lags behind demand since it reflects the average of past demands, and due to higher responsiveness, the risk of adapting false signals increases (Black, 2013).

Simple Exponential Smoothing

Simple exponential smoothing (SES) is a sophisticated version of weighted moving average method, and probably the most widely used statistical method for short-term forecasting

(Krajewski et Ritzman, 2002; Silver et al., 1998). Its popularity is based on its simplicity and small amount of required data (Gardner, 1985). The underlying demand model is the same for SES than it is for the moving average method. As often is the case with weighted moving average, SES gives more weight to recent demands than earlier demands. To make the forecast, only last period's forecast (F_t), the same period demand (D_t) and a fixed smoothing parameter alpha (a) are needed. The forecast for the next period (F_{t+1}) equals the forecast of previous period plus a proportion of forecast error of the period. Specifically:

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

By changing the alpha, the emphasis of the most recent demand can be altered. Two requirements are worth addressing, i.e. how to initialize the first forecast, and which value to give for parameter alpha. Initialization can be made in two ways: either using the last period's demand as the initial forecast or calculating the average of several recent periods of the demand. The choice diminishes over time so the solution is not critical in a long run. Selecting the most appropriate smoothing constant is more troublesome because there is a basic trade-off since no one knows whether or when the underlying average of demand will change. In the stable conditions, small values of *alpha* are more preferred and in the fluctuating, condition a larger value. According to Silver et al. (1998) the likely range of alpha ranges from 0.1 to 0.3.The authors further state that if the smoothing constant is above value 0.3, it should raise a question of changing the whole forecast method.

When the underlying demand pattern involves a significant trend, a somewhat more complicated smoothing procedure is needed. The approach is called a trend-adjusted exponential smoothing. This approach estimates both an average and a trend. Compared with the SES, this approach requires two smoothing constants. Eilon et Elmaleh (1970) developed an approach, where the smoothing constant was able to change over time. However, several studies later showed that implementing an adaptive smoothing constant brings several problems along and is therefore seldom adapted in the practice (Ekern, 1981; Flowers, 1980; Gardner et Dannenbring, 1980). Due to disputed arguments around trend-adjusted exponential smoothing, only SES is about to be tested with case company's demand data.

Multiplicative trend-seasonal method

Seasonal patterns are regularly observed upward or downward movements in demand over a calendar year. An easy way to account for seasonal effect is to use methods above described i.e. using a naïve method but instead of taking the forecast from the previous period, it is taken from the previous season. This approach surely discards considerable information on past demand but can be accurate if the demand data does not involve trend. If the demand possesses trend, then a multiplicative seasonal method becomes worth consideration. In the four-step procedure, seasonal factors are multiplied by an estimate for average period demands (Krajewski et Ritzman, 2002).

3.2 SHORT-TERM FORECASTING MODELS FOR INTERMITTENT DEMAND

Intermittent demand as earlier was discussed, stands for situation where demand arrivals on a random basis and there can be several periods without demand. The sizes of demand do not vary significantly but are still big enough to be distinguished from the slow moving items. As many scholars have claimed and practitioners have experienced, most of the ‘simple’ methods do not work well since they are designed for smooth demand (Syntetos et Boylan, 2005; Teunter et Duncan, 2009). On the other hand, those theoretical models that have shown promising results have been perceived too complex to run and update among practitioners. In that sense, case studies provide models that are more appealing since they are easier to implement. Ghobbar et Friend (2003) conducted a survey where they compared 13 different forecasting methods for slow-moving items used in airline industry and deduced that weighted moving average and Croston’s model rouse above other methods including exponential smoothing and seasonal regression models.

More recently, Boylan et al. (2008) utilized a demand classification matrix built by Syntetos et al. (2005). In the matrix, items were classified based on demand frequencies and fluctuation of demand sizes. Boylan et al. (ibid.) studied almost 16 000 SKUs, classified them based on their demand structure and pointed out the most suitable forecast methods from the maximal customer service level point of view (Figure 1). They found out that the Syntetos-Boylan-Approximation

(SBA) overcame for erratic, lumpy and intermittent demands as Croston's method outperformed other methods if the demand was smooth. The biggest weakness of the study was that the authors compared only three forecast systems, namely SBA, Croston's method and SES. Nevertheless, the finding gives a signal that SBA overcomes Croston's method when the demand fluctuates.

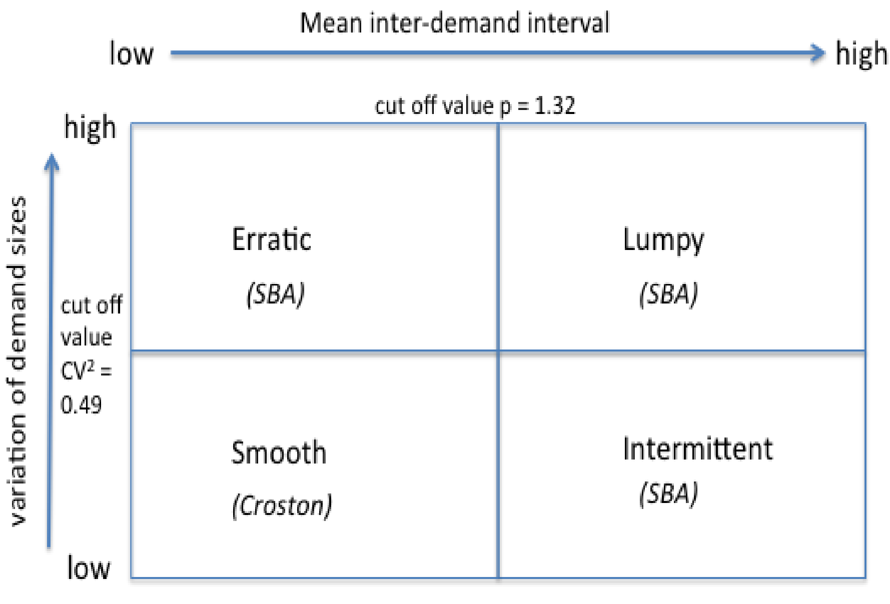

Figure 1: Demand based categorization and appropriate forecasting method (after Syntetos et al., 2005)

Croston's method

Croston's pioneering model from 1972 takes both demand size and inter-arrival time between demands into account and forecasts them separately. Moreover, the interval and size are updated only if a positive demand occurs, not after each period, as is the case with forecast methods introduced in the previous section. Albeit, the model is over forty years old, it has received comparatively scarcely attention among scholars until the recent days (Syntetos et al., 2010). The forecast is based on division of estimates of demand size and demand interval:

$$F_t = \check{Z}_t / \check{T}_t$$

Further, the estimated demand size ($\check{Z}_t$) and the estimated demand interval ($\check{T}_t$) are calculated by applying exponential smoothing:

$$\check{Z}_t = \check{Z}_{t-1} + \lambda(Z_t - \check{Z}_{t-1})$$

$$\check{T}_t = \check{T}_{t-1} + \delta(T_t - \check{T}_{t-1}) ,$$

Where:

$\check{Z}_{t-1}$ = estimated demand size at time t-1

Z_t = actual size of the demand at time t

$\check{T}_{t-1}$ = estimated value of time between consecutive positive demand transactions at time t-1

T_t = actual value of time between consecutive positive demand transactions at time t

λ and δ are smoothing constants and typically low values are recommended and typically used by practitioners.

Syntetos-Boylan-Approximation

In 2001, Syntetos et al. claimed that Croston's method was biased and four years later in 2005 introduced Syntetos-and-Boylan (SBA) approximation. SBA can be derived when Croston's model is multiplied by a factor (1-δ/2), where (δ) is smoothing factor. The smoothing factor, as the other smoothing factors in Croston's equation, is recommended to be low.

$$F_t = (1-\delta/2) * \check{Z}_t/\check{T}_t$$

Rather recent studies have shown that SBA outperforms Croston's method when the demand is intermittent (Boylan et al., 2008; Eaves et Kingsman, 2004; Gutierrez et al., 2008), albeit contrary findings have been found (Babai et al., 2012).

Temporal aggregation

Though Croston's and SBA offer a good optional way to forecast intermittent demand, Teunter et Duncan (2009) note that universally neither Croston nor SBA outperform the traditional methods in all settings. In addition, as in many industries, the demand tends to be intermittent; one option is to reduce the intermittence by increasing the time horizon rather than trying to implement sophisticated computation programs. Interestingly, temporal aggregation has been studied more in finance than in logistics, albeit the idea is intuitively appealing and simple (Babai et al., 2012).

By lengthen the time horizon the number of non-demand time-buckets would decrease while mitigating the intermittence. Nikolopoulos et al. (2011) studied how long the time bucket should be. They found out that time horizon that equals lead-time and one review period gave promising results and advocated of using that. Further Babai et al. (2012) showed that using temporal aggregation Croston or SBA does no more outperform SES significantly. Based on these findings, it was decided to examine case company's demand data on monthly level instead of weekly level.

3.3 MEASURES OF FORECAST ERRORS

Measuring the forecast errors offers several benefits. Firstly, it helps choosing the suitable forecast model. Secondly, it gives the feedback whether the whole forecast model or its parameters should be updated. The forecast errors can be classified to bias errors or random errors. Biased errors incur when the forecast method is not suitable for the demand, whereas the random error results from unpredictable factors. The goal is then to minimize the cumulative error (Krajewski et Ritzman, 2002). The accuracy of a forecast can be measured in several ways. However, none of these has been found to be universally best. Moreover, it is worth to notice that improved forecast accuracy does not automatically translate into better customer service or lower inventory holding costs.

The Cumulative Sum of Forecast Errors

The cumulative sum of forecast errors (CFE) or *the Bias* is probably the simplest way to assess forecast error. It measures the tendency of a forecast method to consistently over- or under the forecast. However, due to the simplicity of equation, CFE can be deceptive since positive errors can be offset by negative errors.

$$CFE = \sum (E_t) = \sum (D_t - F_t)$$

Where:

D_t = Actual demand for given period

F_t = Forecast for the given period

The Mean Absolute Deviation

The mean absolute deviation (MAD) measures the dispersion of forecast errors. It can be seen as a continuation of CFE but its biggest flaw has been fixed. Namely, positive and negative errors cancel each other out no more. Due to its computational simplicity and easiness to understand by managers, it was widely recommended among practitioners (Silver et al., 1998).

$$MAD = \sum |E_t| / n$$

Where $E_t = (D_t - F_t)$

The Mean Squared Error

The mean squared error (MSE) has the same advantage as MAD has over Bias. In addition, MSE penalizes large errors much more than MAD, since the errors are squared:

$$MSE = \sum E_t^2 / n$$

The Mean Absolute Percent Error

The mean absolute percent error (MAPE) is another intuitive measurement of demand dispersion but compared with MAD it shows the error related to the level of demand. Krajewski et Ritzman (2002) note that putting the error on the proper perspective gives useful insight for managers about the performance of the forecast method. However, Silver et al. (1998) warns that MAPE performs poorly when demand values are low.

$$MAPE = (\sum E_t / D_t) * 100\% / n$$

4 INVENTORY CONTROL AND REPLENISHMENT SYSTEMS

An inventory control system tells how often the inventory status should be determined, whereas a replenishment system answers when a next replenishment should be placed and how large a replenishment order should be. The means are very different depending whether the demand is deterministic or stochastic. Under the conditions of deterministic demand all the demand parameters and variables associated with an inventory are known or can be computed with certainty. Thus, the decision concerning inventory review frequency, timing an order and deciding the order size becomes much more straightforward. Firstly, the inventory status can be calculated at any time because the demand is known. Since the demand is known, the order size can be determined using economic order quantity size (EOQ) or a heuristics application depending on the demand size variation (Silver et al., 1998). The situation when demand is known for sure in advance becomes only into a question in Material Requirement Planning (MRP) context when the components of an item are already scheduled (Dixon et Silver, 1981) or in the case of projects if they are ordered in advance. Stochastic demand, in turn, possesses unpredictable demand. In real life, a stochastic demand occurs more often than deterministic but because of its more sophisticated formulas and computational requirements it has not been in practitioners' favor. Nevertheless, understanding the demand in question is important since different procedures are needed. Since the demand that the case company has experienced in the past reminds more stochastic than deterministic, the focus will be on inventory control systems assigned for stochastic demand. Over the next sections, different options for inventory control and replenishment systems introduced in the literature that would fit the company settings are represented. Later, a short review on cost components is discussed.

4.1 CONTINUOUS VERSUS PERIODIC REVIEW

The first issue to address as to inventory control policies concerns how often the inventory status should be determined. Two extremes are the *continuous review* where the stock status is known all the time and the *periodic review* where the stock level is not precisely known between two consecutive checking moments. Under continuous review, the order size is fixed but the order interval varies. In periodic review, the order size can vary but the order interval is fixed. Between those order interval moments there can be significant uncertainty as to the value of a stock (Silver et al., 1998).

Both review systems have their advantages and disadvantages. The decision comes under which one suits better for the underlying environment. The periodic review is especially appealing when the coordination of replenishments brings cost savings (e.g. purchases from the same supplier or combined shipments). It is also more convenient to administer and the workload is more predictable when periodic review is used. The biggest benefits that continuous review brings are the ascertained customer service level since the orders can be placed at any moment, and a lower safety stock required. On the other hand, continuous review is more expensive to administer and since the orders can be made at any time, the workload is more random (Silver et al., 1998).

The demand pattern has a great impact on what review system to employ. In the case fast moving items, the continuous system becomes expensive since the orders need to be places oftentimes (Silver et al., 1998). On the other hand, when the demand is intermittent, the periodic review is recommended (Altay et al., 2012; Nenes et al., 2010; Ritchie et Kingsman, 1985; Syntetos et al., 2010; Syntetos et Boylan, 2005). In many cases, employing a periodic review system is justified. Often the presently running IT software has a big influence and determines how inventory status is reviewed.

4.2 REPLENISHMENT SYSTEMS

The replenishment system addresses when to place an order and how much to order. These systems are run by control parameters. Common for all these parameters is the requisite to know the demand during the lead-time at least at some level. Since the lead-time demand varies greatly when the demand is intermittent, determining safety stock can be difficult. One option is then to reserve adequate amount at all times. This however burdens holding costs greatly.

Next, two forms of replenishment systems from both continuous and period review systems are shortly introduced following by discussion of their advantages and disadvantages.

Order-Point, Order-Quantity (s, Q) System

The (*s*, *Q*) system belongs to the group of continuous review systems. Every time when the inventory position drops below a reorder point (*s*), a fixed quantity (*Q*) is ordered. The inventory position is defined as the sum of the on-hand inventory and scheduled receipts minus backorders. The reorder point hedges against the unpredictable demand during the lead-time. In general, the reorder point is:

Reorder point (s) = Average demand during the lead time + Safety Stock

Obtaining the parameters of inventory policies requires reckoning the reorder point. As one can see from the equation, an estimation of the lead-time demand is essential in order to calculate it. The lead-time demand can, in turn, be plotted by using probability distribution e.g. the normal distribution, gamma distribution, and binomial distribution. Some authors instead advocate the use of model based forecast techniques like SES or average moving average.

The fixed order size (Q) can be determined by using Economic-Order-Size formula (EOQ):

$$Q^* = \sqrt{\frac{2DS}{H}}$$

Where, Q* stands for order quantity, *D* for annual demand, *S* for a fixed cost per order and *H* for annual holding costs.

In spite of EOQ's very strict assumptions (e.g. a steady demand rate, fixed lead-time, instantaneous replenishment), which are most often violated in the real life, it is widely used in business thanks to its robustness. It is summoned that using EOQ for determining order size is only 1/8 biased vis-à-vis optimal but much more complicated models when the demand is smooth (Silver et al., 1998). Thus, in this study EOQ will be also tested due to its simplicity. The (s, Q) system is rather simple to understand though its biggest pitfall is that it may not work well if large individual demand occurs.

Order-Point, Order-Up-to-Level (s, S) System

The (s, S) system comes under continuous review policy and likewise in the (s, Q) system the order is placed whenever the inventory position drops to the reorder point or lower. However, the order size varies as the stock position at the time of placing an order can be at the level of the reorder point or less. If the sales transactions are a unit sized, S can be plotted as:

$$S = s + Q$$

The best (s, S) system outperforms the best (s, Q) system. Yet, the computational efforts to find the best values for s and S can be substantial. Consequently, the values are often set arbitrarily in practice and on that account, (s, S) seldom overcomes (s, Q) markedly. In addition, from a supplier point of view, receiving fixed order sizes compared with variable ones are more likely preferred (Krajewski et Ritzman, 2002; Silver et al., 1998).

Periodic-Review, Order-Up-To-Level (R, S) System

As the name implies, in (R, S) system, the inventory position is checked periodically. The idea is to order enough at each R time units to raise the inventory position up to level S. The system is commonly encountered when the items are ordered from the same supplier overseas as to minimize transportation costs. The system also makes possible to update the order-up-to-level S if the demand has changed.

Unlike the continuous review system that requires a buffer stock only to cover the demand during the replenishment lead-time, a periodic system needs a buffer also for the time between the intervals. Hence, compared with continuous review systems, it invokes higher inventory levels and higher holding costs (Krajewski et Ritzman, 2002; Silver et al., 1998).

(R, s, S) System

In the (R, s, S) system, the inventory is also review at every R time unit. Further, an order is not placed unless the inventory position is at the level of reorder point s or below. In that sense, the (R, s, S) system combines features from both (s, S) system and (R, S) system. The best (R, s, S) incurs the lower total costs than all the other systems described earlier. This system is more complex to understand and requires more computational efforts.

Silver et al. (1998) recommends a rule of thumb how to select inventory replenishment systems based on ABC classes. In this context, A and B items are clustered based on their annual usage value. As A items are the most valuable, the biggest benefits can be achieved by addressing the best methods even if they are somewhat complex or costly. Therefore, systems assigned for A items can require more computational efforts. However, the time required to determine and update control parameters would not pay off in most cases of B items. C items are left out since Silver et al., (ibid.) advocates simpler routines to manage those items.

Table 2: Recommended inventory policies according to ABC classes (after Silver et al., 1998)

Class	Continuous review	Periodic review
A items	(s, S)	(R, s, S)
B items	(s, Q)	(R, S)

4.3 COST COMPONENTS

Before jumping into Inventory Procurement Matrix and empirical part it is good to review cost parameters, which affect decisions on order quantity and order frequency. Some of these cost parameters also come into question when deducing whether to stock an item at all. As Fisher (1997) notes, one should recognize two distinctive types of functions in supply chain management that incur different kinds of costs. Physical costs are those costs incurred by production, transportation and inventory holding. Market mediation costs relate to ensuring that the supply matched demand and so the costs incur when one of these recent parameters exceeds the other one engendering markdowns or lost sales.

Holding costs (often symbolized by h) and ordering costs (S) are perhaps the two most well-known cost parameters in the inventory management literature. Holding costs consist of opportunity costs, the relative riskiness of the SKUs, a cost of storage, special handling requirements, insurance and possible taxes of which the opportunity cost makes the lion's share. Since holding cost is difficult to measure precisely, both the academic world and practitioners have employed it as a policy maker. Holding costs can be tackled by decisions on the breadth of range of the assortment and the depth of SKUs. More precisely, the most efficient method of lowering holding costs is to increase SKUs inventory turns. Addressing appropriate forecast and a replenishment system or deciding not to stock, an item can achieve this.

Ordering cost is made up of cost of making the orders, telephone calls, receiving the orders and their inspection, follow-ups on unexpected situations and handling the vendor invoices (Silver et al., 1998). Normally the ordering costs are treated fixed in that they are not influenced by the order size. As nailing down the value of ordering cost is very cumbersome it is often times more beneficiary to improve the procurement process itself rather than gauging the value for S.

Backlog cost stems from rush orders. The time spent on rescheduling the order and potential additional freight costs are often the biggest shares of backlog costs. Likewise, in the case of ordering costs, instead of tracking the accurate value for backlog cost, one should focus on optimizing the backlog costs. Hence, sometimes the planned backlog costs may pay off instead of taking the risk of stocking.

5 THE THEORETICAL SELECTIVE PROCUREMENT MATRIX

In an ideal world, each SKU would be examined separately and the most suitable forecast and inventory management system would be addresses accordingly. In reality this seldom comes into question since the breadth of SKUs sold by the company can range up to thousands or even hundreds of thousands. Therefore, clustering SKUs into classes and managing them are called for. Interestingly, the academic literature does not offer a clear tool how to categorize inventories that would be linked into the most suitable forecast approach and to the inventory management system. In practice this is easy to understand since the industry, business environment, company size, IT systems, resources, SKUs life cycle and employees' capabilities and so for vary greatly, and thus building a ubiquitously workable tool would be extremely difficult. Nonetheless, in theory, this kind of tool should be possible to scheme. In this study, such a theoretical scheme is built for products in the context of resale business.

The fundamental purpose of inventory management is to minimize inventory costs while maintaining a good customer service level. As there are multifold interconnected factors relating to inventory management that have to be viewed simultaneously, decision-making becomes so complex that individual's capability to adapt and rationalize all the factors concurrently turns impossible (Silver et al., 1998, pp. 28). Simon (1957) invokes the help of models in order to round the individual's information processing bounds, the cognitive limitations of their minds, and the finite amount of time they have to make a decision. Models that simplify the reality and help to expand the bounds of rational thinking ease to understand the key factors. However, in order to meet these advantages, a model is most often forced to leave out some relevant factors. Hence, when building a framework one has to be careful which factors to incorporate and which ones to leave out. Silver et al. (ibid) further stress that inventory systems should be designed into the context of existing resources and managerial capabilities.

The Selective Procurement Matrix is built on the foundation of incorporating two distinctive parameters that alone cannot foretell what the other one will be alike. The first parameter is based on net sales using ABC classes as a template. Segmenting according to gross margin was also weighted up. Both offer a great tool to cluster items into classes and to fix a target service level per a class. The net sales were decided to use as a ranking criterion since it is better linked with cost factors relating to inventories. An item's net sales only addresses where firm should focus but does not imply anything about how the item should be managed. To counsel on this, it is essential to understand item's demand pattern. Syntetos et al. (2005, see Figure 1) demand categorization offers a great tool but was discovered too complex to apply. Implementing it as such would be too burdensome to run in practice. Along these lines, the average demand interval parameter, which signals of demand frequency, was deployed. Syntetos et al. (2005) suggested the cut-off value 1.32 for detecting intermittence (see Figure 1). This value was used as a tentative criterion. The value will be reconsidered whether is suits for the case company in the empirical part.

As accurate forecasts are costly to make, a company should consider how accurately it wants forecasts to be. Thus, the decision maker needs to compare the benefits of accurate forecasts with costs incurred by carrying them out. According to Silver et al. (1998) items belonging to A class should be examined by managers, as some form of statistical forecast model would aid in the purchase decision. Several studies show that combining different forecast techniques lead to more accurate forecasts than using only one (e.g. Clemen, 1989; Sanders et Ritzman, 2001). Silver et al. (ibid) further suggest that for B items, one should count on statistical forecasting and a manual overrating would be exceptional. For C items, the authors do not recommend statistical forecasting at all. These days, when the computational costs have decreased, it is probably worth to forecast C items using simple statistical methods.

The suggested forecast, inventory control and replenishment systems are based on earlier literature and recommendations found in the case studies. Simple exponential smoothing (SES) is broadly acknowledged by practitioners and is widely used in many companies when the demand is smooth. In the case of intermittent demand, the decision becomes more complex. Babiloni et al. (2010) studied earlier literature on forecasting intermittent demand and found out that there is a lot of disagreement how intermittent demand should be forecasted and that universally best approach is still undisclosed. Syntetos-Boylan-Approximation (SBA) has, though, shown good results in numerous case studies recently when the demand has been intermittent. These suggestions in mind, single exponential smoothing (SES) and (SBA) are proposed the main forecast methods for A and B items. In the case of A class items also human judgment is recommended to involve the decision making. Since (SBA) requires more computational efforts than SES does, it is recommended to apply *moving average* for C items having intermittent demand. Moving average has shown to outperform SES when the demand intermittent.

The decision does not only concern selecting the most appropriate forecast method according to ABC classes and demand pattern but also the inventory control and replenishment systems. As it turned out earlier, systems that are more accurate can decrease holding costs but increase both administrative costs and computational costs. Academic literature is not anomalous on whether the review policy should be continuous or periodic since both methods have their strength and weaknesses (Babiloni et al., 2010; Silver et al., 1998). However, in the context of intermittent demand, several scholars offer supportive theoretical arguments to use periodic review (Porras et Dekker, 2008; Silver et al., 1998; Syntetos et Boylan, 2005). Further, many case studies have chosen the periodical review for intermittent items (see e.g. Ritchie et Kingsman, 1985; Syntetos et al., 2010). In the case of frequent demand items, the tentative suggestion is to apply continuous review policy. In the empirical part, both review policies will be tested.

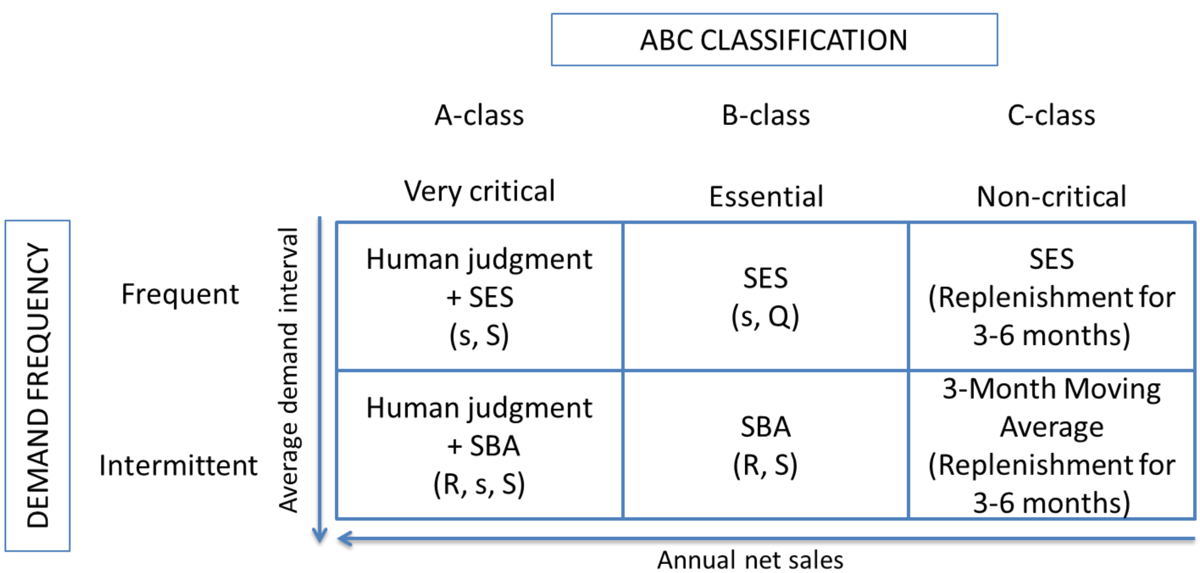

Figure 2: The Selective Procurement Matrix

From an empirical point of view, the interest lies in whether the framework is applicable in practice. Hence, in the empirical part, the framework will be road tested. Earlier introduced forecast methods and different replenishment systems tried out and the framework will be molded based on findings.

6 EMPIRICAL PART – CASE STUDIOTEC OY

6.1 THE CASE COMPANY – STUDIOTEC OY

Studiotec Oy is a Finnish distributor and a solution provider of audio-visual supplies. The company was founded in 1980 and locates in Espoo. Studiotec is sole proprietorship employing nowadays around 50 full-time workers. The company has met a rapid growth in last few years and in 2011, it reached sales revenue up to €15M of which half came from project business and the other half from sales to retailers, universities, government funded bodies, professional end-users and companies among others. What is characteristic of project business is that the customer's orders often involve highly complex solutions that Studiotec sources from various suppliers. In terms of running the resale business i.e. offering a wide range of items available, Studiotec's supply base is broad including over 100 suppliers, mainly from Europe, the U.S and Japan. The contracts vary between suppliers, as do the lead times. An entry of a German e-commerce company to Finland has set strict price pressures. The business requirements and challenges incurring by different businesses are gathered to the table below.

Table 3: Business requirements and challenges from logistics' point of view that three businesses carry on

Business	Business requirements	Challenge from logistics' point of view
Import	Bringing goods closer to customer	Long and variable lead times
Wholesale	Stocking goods closer to end customer	Balancing between inventory holding costs and quantity discounts Setting safety stock levels
Project	Providing tailor-made solutions for customers	Unpredictable demand, where delivery in time is crucial. Placing orders on time

Studiotec awoke to its current inventory issue when its premises became too small. It had increased its sales revenues steadily as of the year 2008, and in 2011, it managed to grow up its revenues nearly by 50% compared with the year 2010. As the top management calls, due to growing pains, management did not have enough time to pay attention to inventory and purchasing issues. Further, the company has not established a formal documented procedure how purchasing activities should be run. The figure below shows how net sales to average inventory value have developed as of 2010. The revenue to average inventory value -ratio has climbed by 18 % since 2011.

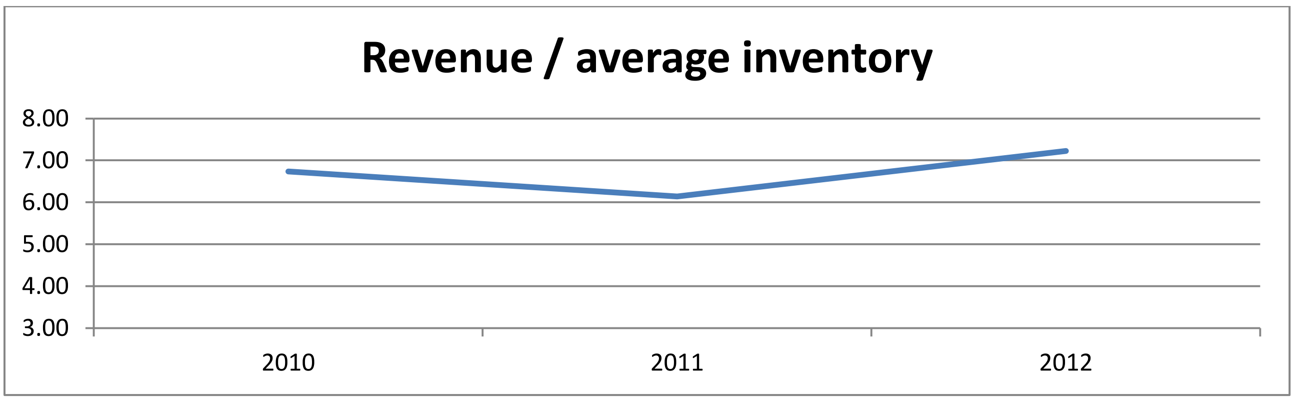

Figure 3: Development of revenue to average inventory

6.2 REASONS BEHIND INCREASED INVENTORIES

In order to reveal the root-causes behind increased inventories, it was decided to use both qualitative and quantitative methods. At first, product managers in charge of placing orders were queried about why their inventories have mounted up. Later, quantitative analyses were conducted to find out whether managers' perceptions were supported by the historic data.

One-to-one interviews were conducted at company's premises in order to understand the case company's business, their customer expectations, relationships to suppliers, and product attributes. Each product manager in charge of making purchases plus the logistics manager and two secretaries were interviewed. Interviews took from 25 minutes to 60 minutes per respondent.

Open questions were decided to use as the main interview method since they offer a good way of revealing what is important from respondents' point of view, reveal the strength of their emotions and motivations (Hirsjärvi et al., 1997). Also Yin (2009) advocates that interviews should resemble more guided conversations rather than structured queries. The interview questions were not handed to interviewees before the interview took place in order to expose respondents' behavior, knowledge, attitudes, opinions and notions relating to procurement decisions.

During the interviews, the respondents were asked to select the three most relevant reasons behind increased inventories. Demand intermittence and lumpiness were perceived by far the biggest challenges following by mistrust on suppliers' delivery reliability. Significant variations in the lead-time analysis justified their concern. Also the lack of retrieving the past demand data easily on individual SKU level showed out to be the clear issue. The present software does not provide a swiftly accessible wrap up on historic demand on SKU level and therefore the purchasing decisions have been made based on experience and guess in the past. Over the interviews, also errors in dispatching turned up. The lacks of inventory space, fixed shelf positions, and bar code readers were also claimed to be clear root causes for increased inventory levels.

Table 4: Distribution of reasons behind increased inventories perceived by product managers

Cause	Distribution of answers
Demand intermittence or lumpiness	30 %
Distrust on suppliers delivery reliability	19 %
Overestimated demand	15 %
Order decision made without suffifcient consideration	11 %
Holding safety stock	9 %
Obsolescence / increased inventory of demo-items	7 %
Flaws in the inventory data	6 %
Customer cancellations	2 %
Typing errors when making an order or errors occured when supplier dispatching the request SKU	1 %
	100 %

Tackling the lead-time uncertainties would be a challenging task due to several reasons. Firstly, the case company does not have the required purchasing power to force suppliers to reform. As a solution for this kind of problem, the literature suggests a re-evaluation of current suppliers, reducing the number of suppliers and forming a deeper relationship with remaining ones. Since the import is the case company's core business and a great array of suppliers can be counted as strength, this aspect becomes strategic. Consequently tackling the lead-times was decided to leave out this study. The focus of empirical part was to find ways to resolve problems relating to managing intermittent demand, establishing formal procedures in order to prevent expensive SKUs to being left on the shelf, and determining sufficient safety stock levels for items to be stocked.

Next, the focus was settled down to purchasing behavior issues. Figure 4 expresses how the possession of inventory value is divided over product managers in euro. The differences are smoothed out in previous years stemming from the fact that the company runs aggressive write-offs and the FIFO accounting system is in use. Therefore, differences of inventory value possessions mainly exist among product managers only in 2011 and 2012. It is evident that purchasing behavior has influence on inventory levels since the possessions of inventory values vary so significantly. Besides different purchasing behaviors, another reason is that suppliers are assigned to product managers and therefore the product lines differ. Hence, some suppliers have longer lead times compared with others and items differ from each other in value and demand wise.

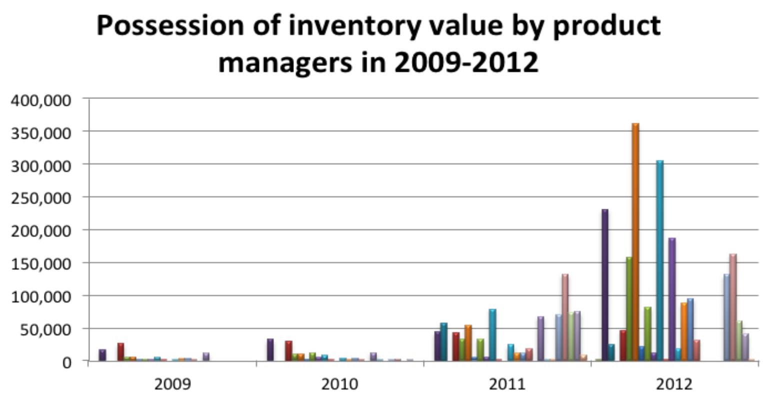

Figure 4: Possession of inventory value by product managers on September 30, 2012

Actually, the most common reasons behind excess inventories; errors associated with replenishments or overestimating the demand rate, often result from purchasing behavior. Demand and order analysis showed that product managers have placed too big orders in the past. When the top 20 items burdening inventory levels were analyzed, large and unjustified orders popped most often up. Whether a purchaser has overestimated the future demand or has not examined the past demand (Figure 5), or the order quantities were reckoned for too long periods (Figure 6). Figure 5 demonstrates how significantly unjustified purchasing decisions can increase inventories. The historic data do not support the decision on making large purchasing orders. Especially, the decisions of placing orders after week 36 in 2011 are not reasonable.

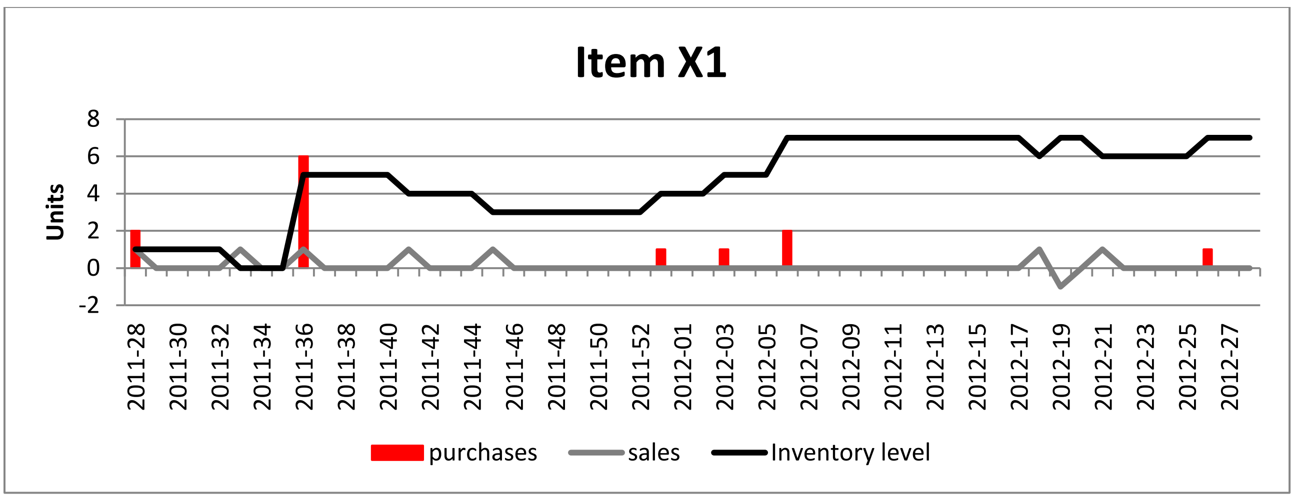

Figure 5: Example of past purchasing behavior with item X1

According to the Logistics Manager and Project Secretary who are working in the supplier interface believed that the reason why inventories had enlarged stemmed from purchasers' aims to minimize the unit price. As the figure below illustrates, the next order after 27/2011 needed to be placed almost 11 months after. This burdens inventory holding costs, stagnates inventory turnover, increases the risk of obsolescence, and reserves a lot of space on the inventory floor. Crystalizing product managers all the cost components that inventory carries, and introducing a forecast method and replenishment protocol while improving the reporting system would avoid these kinds of mistakes in the future.

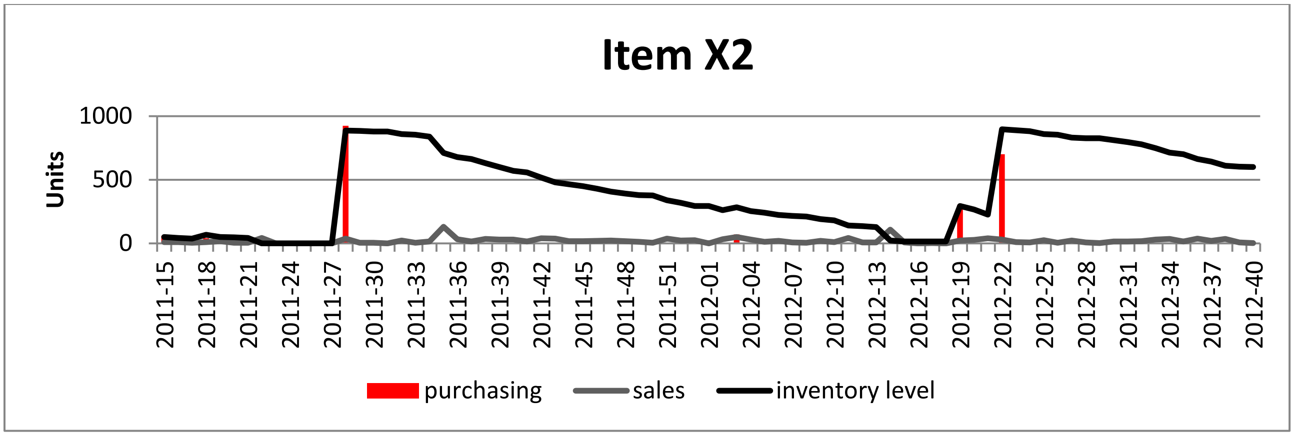

Figure 6: Example of past purchasing behavior with item X2

6.3 INVENTORY AND DEMAND ANALYSIS

Over the interviews, it turned out that many items had seasonal demand. Therefore, it was reasonable to address one-year data when running ABC classification. Year 2011 was selected the primary classification year, as all-year data was available.

6.3.1 Distribution of inventory value based on sales

In order to tackle the increased inventory problem that seemed to have miscellaneous reasons according to interviewees, the inventory needed to be segmented. The segmentation was decided to conduct on the strength of sales, more specifically, according to sales to projects, sales to projects & resale and sales to the retailers or end customers (see Figure 7). Items, which were purely sold to projects, represented only 4.4 % of total inventory value on September 30, 2012. This makes sense since projects are often times known in advance and no extra inventory is required. The 4.4 % of total inventory value stands for items that were ordered in advance for upcoming projects, or products from previous projects that need to be stored in order to ascertain a prompt customer service if an item breaks down. In this research study, the focus is addressed to the two biggest segments: resale and project & resale. These segments account for over 95 %

of total inventory value, and stand for the area were the biggest savings are achievable. The resale segment accounts for almost two thirds of the whole inventory and includes items sold solely to retailers or end customers.

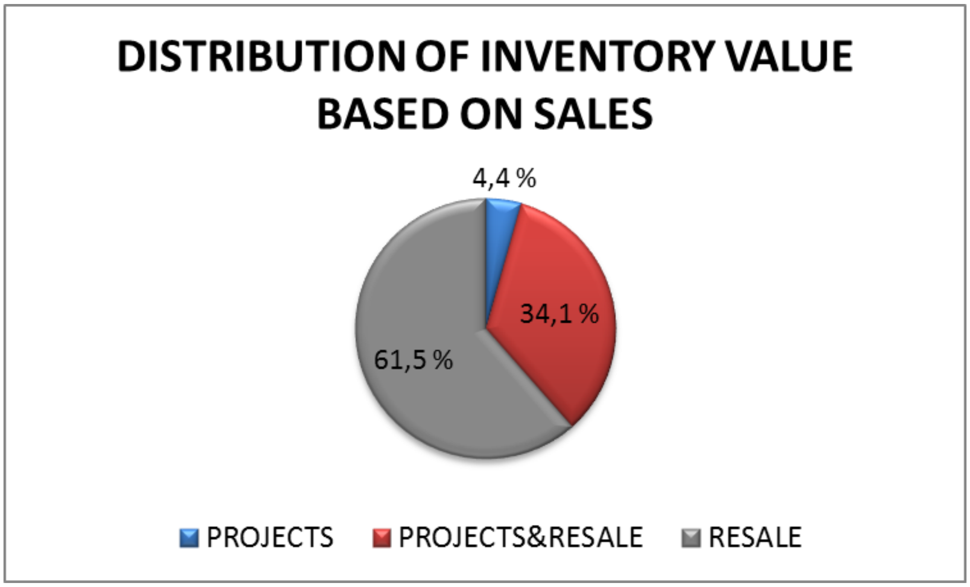

Figure 7: Distribution of total inventory value based on sales on September 30, 2012

Items belonging to the project & resale segment have been sold to both projects and resale in the past, and accounts for one third of total inventory value. Managing items on this segment requires a good internal communication between resale and project departments. Currently, one person is responsible for coordinating purchases for projects and is in contact with product managers in the case of items belonging under the surveillance of the resale segment.

Next, an ABC analysis was conducted for resale and project & resale segments. The project segment was deducted from a further ABC investigation. Besides that, fact that project segment does not burden the total inventory value, all the items needed for projects are critical. Accordingly, the stock-outs at the time of project delivery are not acceptable. Therefore, adapting inventory policy according to ABC analysis might bring severe setbacks. A timely ordering is instead, is the solution for project items. Consequently, from now on, the study, analysis and recommendations are assigned for resale and project and resale segments.

6.3.2 ABC analysis within resale and project & resale segments

A traditional ABC analysis was conducted for items that were sold to the resale segment or the project & resale segment. Besides Studiotec's sales data, sales data of its sister company Soundtools Oy was also incorporated in. Figure 8 illustrates how the lion's share of total net sales was generated from small portion of the total number of SKUs.

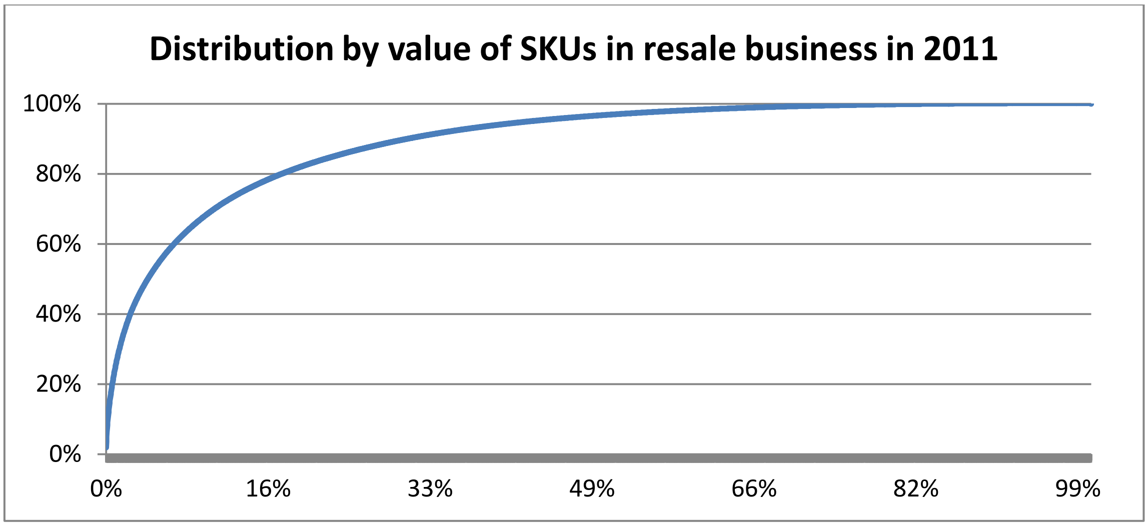

Figure 8: Distribution of 3954 active parts' net sales per se SKUs within resale segment in 2011

The breakdown of ABC-classes was chosen in concert with the top management in a following way:

- A items – 80 % of annual net sales
- B items – 15 % of annual net sales
- C items – 5 % of annual net sales

It is noteworthy that in academic literature other breakdown of classes can be seen frequently (see e.g. Werner, 2002; Wild, 2002). The best threshold depends on objectives and criteria used, and on that account, there is not a widespread acceptance on one overcoming breakdown for different kinds of inventories.

Next, inventory levels were reckoned based on appointed classes to each SKU using 2011 sales data. The table below shows that A class binds approximately two thirds of the total inventory value, whereas class B 20 % and class C 15 %, respectively. The total inventory value based on ABC classes "ABC total" differs from total inventory value at the time, which is represented in the last column called "Difference". Hence, at the end of 2011, half a million euro worth of items were lying on the shelves that were assigned for projects or did not have any sale transactions during 2011.

Table 5: Inventory value (€) as per ABC classes

	Class					
Date	A	B	C	ABC total	Total inventory value	Difference
31.12.2011	805 076,90	207 650,89	200 136,35	1 212 864,12	1,7M	0,5M

6.3.3 Demand analysis based on demand frequency

As Silver et al. (1998) notes, the biggest savings are most often generated from the decisions whether to stock or not. The decision can be made based on heuristic methods or on mathematical models. In the mathematical models, following variables are often encountered*: a unit variable cost, an ordering cost, a holding cost of an item, a demand forecast, an expected interval between demand transactions,* and *an expected size of demand transactions in units*. Due to the vast amount of SKUs, that the case company is selling and required computational efforts, stock versus not to stock decision is suggested to make on the heuristic basis, more specifically based by the nature of demand.

The data generated from the case company's ERP system comprised of inventory and the demand histories of approximately 8 000 SKUs, of which approximately half had transactions in the last two years. In 2011, 3955 different items were sold to resale or resale & project segments. Items, which were returned from customers, were excluded from the data.

As the figure below shows, most of SKUs possessed intermittent demand as 74 % of SKUs sold in 2011 had over 3 months' average demand intervals.

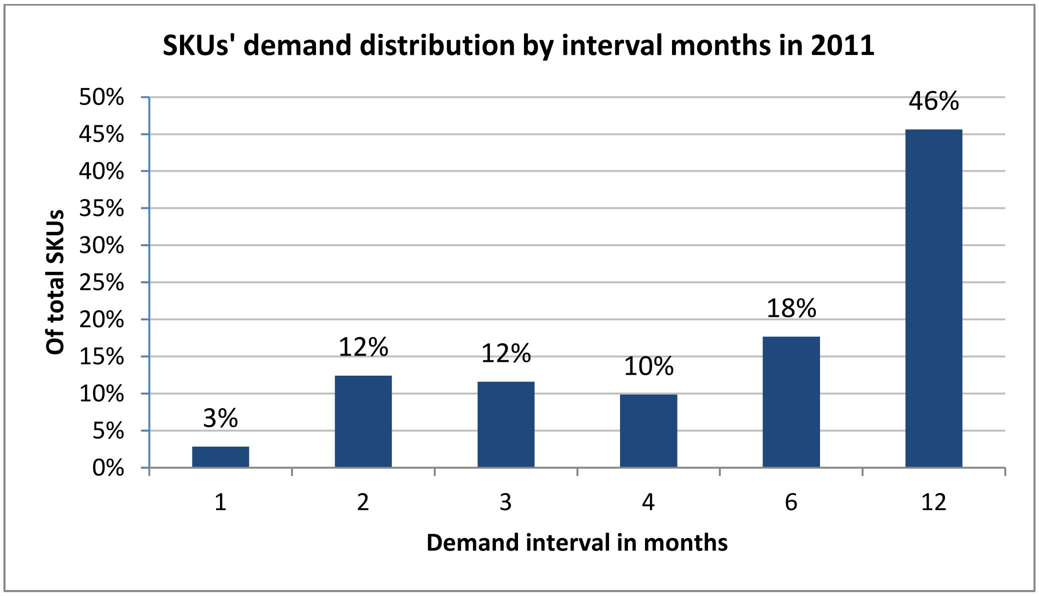

Figure 9: Demand distribution of items in interval months in 2011

A further examination showed that items, which were sold less frequently than every three months, comprised only 31 % of the total volume and 38 % of total net sales (Figures 10 and 11). Items, that had only one sale transaction in 2011, comprised only 9 % of total volume but accounted for 19 % of total net sales. This indicates these products could be expensive. Thus, holding costs and the risk of obsolescence if stoked are also higher for these kinds of items.

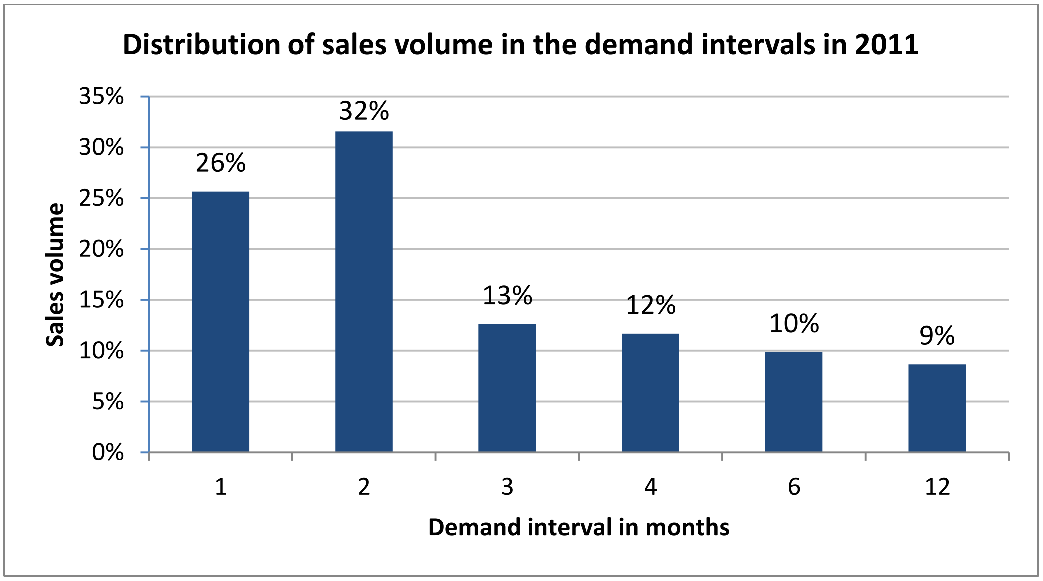

Figure 10: Distribution of sales (units) in interval months in 2011

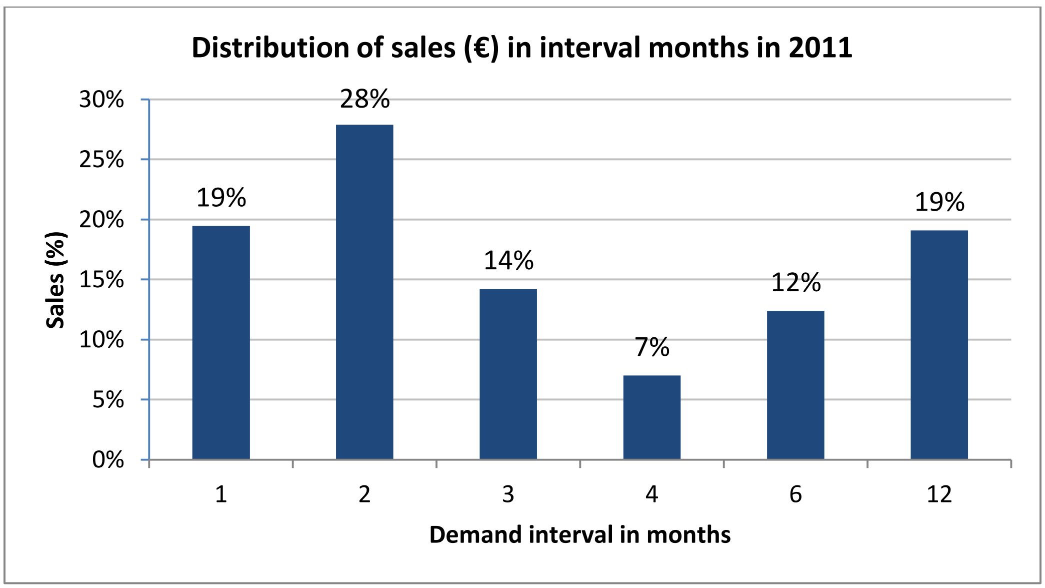

Figure 11: Distribution of sales (€) in interval months in 2011

As earlier mentioned in section 6.2, the company has suffered from errors in dispatching. The root cause for this has been the lack of inventory space, lack of fixed shelf positions, and lack of bar code readers. By reducing the number of SKUs in the inventory at a time, it would help in these matters. Almost half of the SKUs that were sold in 2011 had only one sale transaction. Stocking these items does not only strain the inventory floor, but also impose a risk of outdating. This raise a question that should items a kind of that be stocked at the first place? For the case company, a heuristic decision tool based on expected (or average) interval between demand transactions is recommended. If the average interval between sale transactions is higher than three months, an item should not be stocked but purchased to order. In order to measure the effects of this proposition, ABC analyses in conjunction with demand frequency are next conducted.

6.3.4 ABC analysis combined with demand frequency

Items were further analyzed by incorporating ABC analysis to demand patterns. Again, items sold only to projects were deducted from the investigation. The breakeven point between frequent and intermittent demand was based on a number of sale transactions in 2011. Together with the top management, it was concluded that if SKU's average demand interval was longer than three months, it was defined as an intermittent item. The break-even point was decided subjectively in concert with top management since it supports firm's overall goal to ascertain inventory turnover at least up to three.

The table below illustrates how the demand was spread over ABC classes in 2011. Over half of total SKUs sold in 2011, were intermittent by nature. This finding matches with Syntetos et al. study (2005) where the authors claimed that the most of the items in the wholesale business are sold infrequently. Moreover, a closer look reveals that there are significant differences between classes in terms of demand nature. While the majority of A items possess frequent demand and in the B class the demand among items is divided evenly, most of the C items have intermittent demand. Nenes et al. (2010) encountered the findings of the same kind relating to the distribution of demand among different ABC classes.

Table 6: Spread of demand categorization over ABC classes in 2011

	Class			
# of SKUs	A	B	C	total
Frequent	509	509	620	1638
Intermittent	196	485	1636	2317
Total	705	994	2256	3955

Next, items on the inventory at the end of 2011 were divided into corresponding classes.

Table 7: Spread of inventory value over ABC classes on December 31, 2012

	Class			
Nature of demand	**A**	**B**	**C**	**total**
Frequent	51 %	12 %	7 %	69 %
Intermittent	16 %	5 %	10 %	31 %
total	66 %	17 %	17 %	100 %

Table 8: Distribution of gross margin on December 31, 2012

	Class			
Nature of demand	**A**	**B**	**C**	**total**
Frequent	62 %	10 %	4 %	76 %
Intermittent	14 %	6 %	3 %	24 %
total	76 %	16 %	8 %	100 %

Comparison between tables 7 and 8 reveals that A class ties up 66 % of total inventory value but generates 76 % of total gross margin, B class 17 % and 16 %, and C class 17 % and 8 %, respectively. The C class turns out to be the least cost-effective. Besides it ties up as much of working capital as the class B, it contributes only half as much gross margin. Items having intermittent demand (in total 2 317 SKUs) contributed only 24 % of total gross margin. In addition, since the demand for most of the items was found to be lumpy, safety stocks should be vast in order to guarantee high customer service level. As in chapter discussed, assessing safety stock levels for lumpy demand items is extremely difficult and burdensome. Rendering demand distributions and plotting suitable safety stocks for highly intermittent and lumpy items would be a nightmare. Consequently, the recommendation so far, is not to stock those intermittent items at all. Exception plays spare parts needed in projects and items having depending demand. Next A and C classes will be examined more closely.

Most often, the technological development is the most rapid among expensive items. Therefore, those items possess a higher risk of outdating. Besides, holding those items is also costly. During the interviews, it became clear that in the case of more expensive items, a potential customer contacts a salesperson in advance asking question relating to specification, price, and expected lead-time among other things. Hence, the initiative implication of a potential sale is often times perceived in advance and required actions can be put in place. Besides, customers are more understanding to wait for expensive items. Ergo, expensive items having intermittent demand should be purchased only to order (PTO).

Analyses reveal that the product managers have been cautious when buying expensive products with erratic demand but more audacious with less expensive items. This kind of action, cumulated by over dozens of purchasers has skyrocketed the inventory value of C class items possessing intermittent demand. The corresponding segment ties up to 10 % of total inventory value but generates only 3 % of total gross margin. Therefore, from the cost-efficiency point of view, a company should try to get rid of these kinds of items. In addition, less expensive items, which are sold on infrequent basis, burden the current inventory floor capacity. As the company is struggling with the lack of inventory space, waiving of over 1'600 SKUs would give a lot of space and easy the material handling.

As a general recommendation for the case company, intermittent items should not be stocked at all but purchase-to-order (PTO). Naturally, some exception are welcome, for instance, if the item has dependent demand. In addition, if the lead times are long, especially in the case of C items, acquisitions from domestic competitors are also worth consideration.

In the case of frequent demand, the goal is to deplete the inventory level while improving customer service. In the next section, the theoretical procurement matrix and other forecasting and inventory policy methods for smooth demand items will be tested.

7 DEMAND AND INVENTORY ANALYSIS

7.1 AGGREGATE MEDIUM-RANGE DEMAND ANALYSIS

The aim of examining the overall demand in a medium-term run was to reveal a possible trend and seasonal factors, and to find out whether a regression model should be further tested at the level of single items. During the interviews, it turned out that most of the interviewees had experienced causality in their sales. Regression analysis was carried out for both resale and project businesses separately to justify their observations. This time the segment “project et resale” was neglected due difficulties of extracting that segment from the data.

A regression model assumes that the demand is a linear function of time:

$$x = a + bt + e$$

Where a stands for level, bt for trend and e irregularity. R^2, the coefficient of determination, shows how well independent variable x accounts for dependent variable y. The value of R^2 can range between [0,1], and the bigger the value is, the better the model fits the data. Simply speaking, the coefficient of determination provides a measure of how well future outcomes are likely to be predicted by the model.

Linear regression analysis was carried out first for the resale segment. The sales were examined at a unit level, not in euro since possible price changes wanted to be cut out. As the figure below shows, the sales tend to go up as the season moves on though faces a slight drop during June and July. The same pattern was observed in 2010 (see appendices 1 and 2). The demand fluctuates over time and therefore R^2 remains fairly low (0.50). Since strong seasonality was observed among some SKUs, and during the interviews was often times pointed out, the tentative suggestion is that the case company could update the classes annually. This way seasonality could be taken into account but still the workload would not become too high.

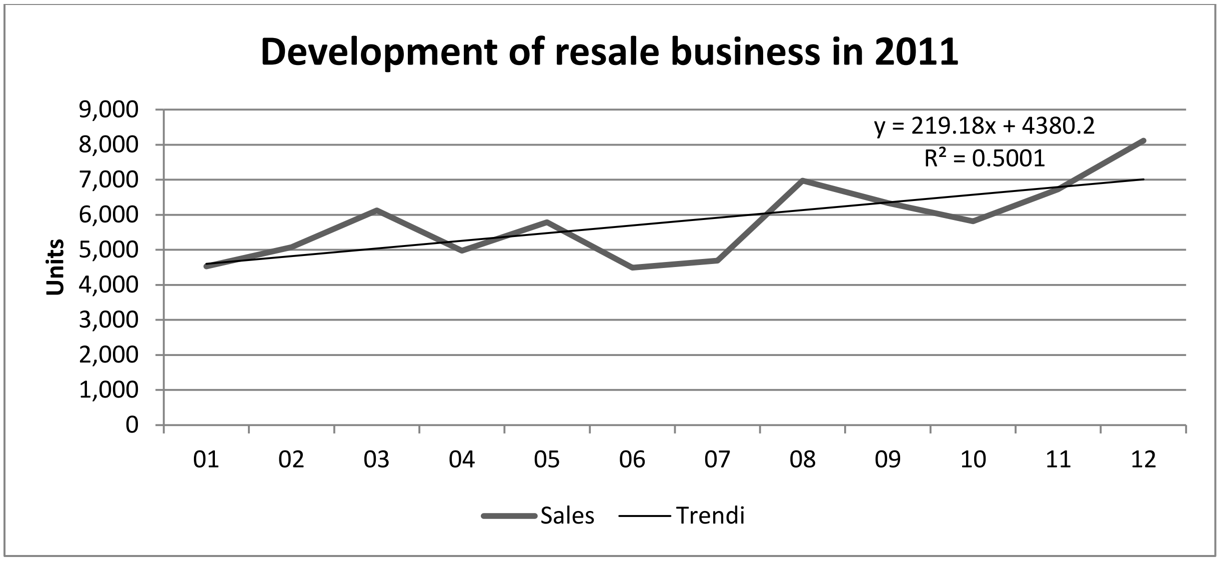

Figure 12: Development of sales to resellers in 2011

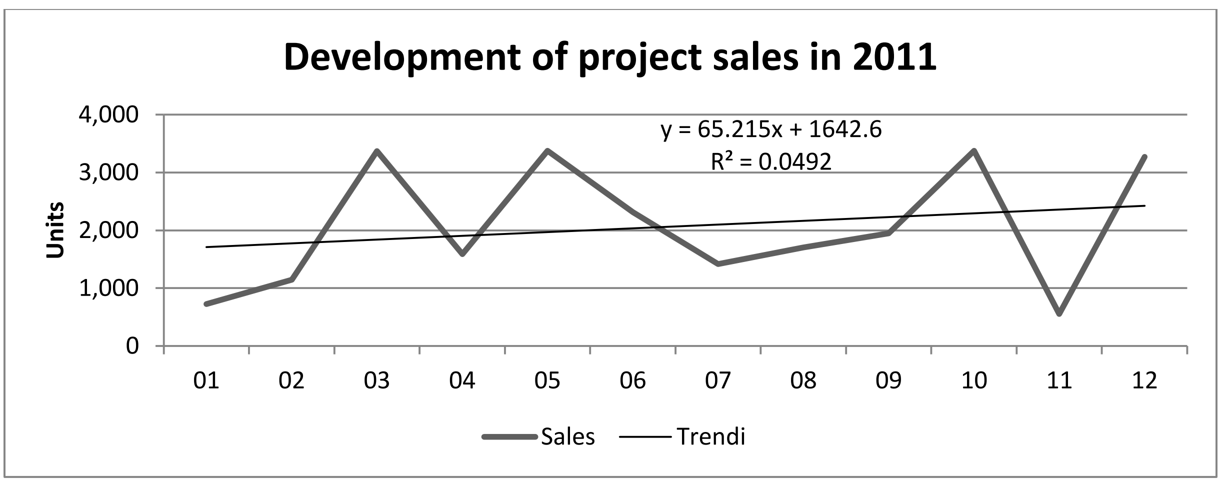

Figure 13: Development of project sales in 2011

As the curve in Figure 13 exhibits, causality was not observed in the project business. A slight trend was though observed during 2011 but was clearly smaller than on the resale side. Even an aggregate forecasting for project business would be difficult due to the significant fluctuations of demand. Fortunately, as it has become evident in earlier parts of this study, the demand for projects is in most cases known in advance and can be responded to within the given time. Thus, forecasting demand for project business is not required.

The regression model as a forecasting model was decided to test further with items belonging to the resale segment. Although the value of R^2 was somewhat low, it came out during the interviews and discussions with the top management, that the trend and causality were experienced in the past and wanted to be tested.

7.2 COMPARISON BETWEEN SHORT-TERM FORECAST METHODS

Small and medium size companies seldom have capabilities, willingness or resources to establish forecasting teams to estimate upcoming sales. Besides it is costly, forecasting is always more or less wrong as Silver et al. (1998) point out. To make forecasting even more difficult Krajewski et Ritzman (2002) remind that the best forecast technique to explain the past data does not necessarily mean to be the best to predict the future demand. Moreover, as Syntetos et Boylan (2005) stress improved forecasting accuracy is not automatically translated to better customer service level or lower inventory costs. Nonetheless, assessing an upcoming demand is a necessity when building procurement guidance. One object for the study was to find the most appropriate forecasting method for different demand patterns. As the earlier suggestion was that intermittent items should not be stocked at all but purchase-to-order, the focus is on frequent demand items purely.

Forecasting a trend and seasonality requires data at least from two periods according to Silver et al. (1998). As the earliest accessible sales data exists from the beginning of 2010, in many cases there were not enough data to examine a trend or seasonal patterns. Thus, in this study, the focus was put on short-run forecasting. The demand was reviewed on a monthly basis instead of a weekly, as to utilize temporal aggregation. The following seven methods were tested: naïve, 3-month moving average, 12-month moving average, 3-month weighted moving average with 0,5; 0,3 and 0,2 coefficients, single exponential smoothing (SES), Croston's method and Syntetos-Boylan-Approximation (SBA). Silver et al. (1998) suggest a compromise value of 0.1 for alpha as a smoothing constant for all SKUs when using SES. This value was decided to use for all the tested SKUs. The initialization value for the first forecast was calculated by using the average of first three available demand observations. Five first forecasting methods were opted for based on their simplicity, and a frequent demonstration in the academic literature. The latter two ones

(Croston and SBA) are designed for intermittent demand and were decided to be tested based on promising results in numerous case studies recently.

The top 25 items sold by Pro-Audio department in 2011 was decided to use as a test data. Pro-Audio forms the biggest portion of sales in the resale segment and sells items to the resale segment and the project & resale segment. The number of items was determined to ascertain the reliability and validity of the results. As earlier stated, items possessing intermittent demand should be purchased only to order (PTO). Therefore, the items having frequent demand were only tested. The following table shows how different forecast systems performed with items having max three months' demand intervals.

Table 9: A comparison between forecast methods with 25 frequent demand items

SMOOTH DEMAND	BIAS	MAD	MSE	MAPE
SBA	-3,01	17,38	1269,08	158 %
Croston	-3,77	17,38	1269,63	168 %
12-Month Moving Average	-1,49	17,13	1309,99	160 %
SES	-1,85	18,00	1376,73	168 %
Weighted 3-Mo Average	-1,88	17,72	1395,45	159 %
3-Month Moving Average	-1,89	18,85	1590,77	167 %
Naïve	-2,99	2057,49	2057,49	8001 %

Forecasting methods are listed in descending order based on the average of items' MSE. MSE was decided to use as the main criterion since it is used often times in theoretical articles. Mean, likewise, eases the comparison. Interestingly, SBA and Croston's methods rose above other forecasting methods even though these methods are primarily designed for erratic demand. A further investigation revealed that 17 out of 25 items' standard deviation of order sizes (CV^2) was over 0.49 and would be categorized erratic items if Syntetos et al. (2005) categorization was applied. Thus, it seems that SBA and Croston work still well because the demand sizes vary between months.

Since *Croston* and *SBA* methods are costly to maintain when using Microsoft Excel and would require high computational efforts, the attempt to smooth the demand and to leave out Croston's method and SBA becomes tempting. As a solution, Nikopoulos et al. (2011) advocate for expanding a time horizon in order to diminish zero demand occasions, and remind that seasonality and trend are very difficult to assess with intermittent items. Babai et al. (2011) found out that by temporal aggregation Croston's method do not outperform SES anymore. Based on these findings, the decision was to lengthen the time horizon from one month to three months and omit Croston and SBA methods from further analysis. In the next chapter, *multiplicative seasonal, SES and 12-Month Moving Average* were tested with the new time horizon. In addition, *linear regression* and *naïve* were tested using *order-up-to-level (s, S)* and *order-point, order quantity (s, Q)* replenishment models.

7.3 TESTING THE SELECTIVE PROCUREMENT MATRIX

Based on findings and conclusions on ABC and demand frequency analyses, it came evident that highly intermittent items should not be stocked at all. One of the main interest of this study was to then to find out whether the theoretical Selective Procurement Matrix for frequently sold items would work with real demand data or would some other approaches outperform the suggested ones? Noteworthy, demand size variation was not filtered out so some items could still have very variable demand. For that purpose, 90 items possessing frequent demand were tested applying different forecast and inventory control policies. Moreover, thirty SKUs possessing smooth demand were arbitrarily picked up from each class. The tests were carried out with a real demand data instead of using simulations. The historical data was divided into two sets. The first set ranging from 2010 until the end 2011 was used for fitting purposes (i.e. tracking the seasonality, trend, safety stock levels and initiating the inventory policies). The second set ranging from January 1, 2012 until September 30, 2012 was used for cost comparison purposes. ABC categorization was made with 2011 data and was not updated during 2012. This way it wanted to be tested how well an ABC analysis worked with the new demand data. Possible quantity discounts or freights were not taken into account.

On the following table are listed the forecast methods and replenishment policies that were tested. Continuous inventory review was used for (s, S) and (s, Q) methods while periodic review was used for multiplicative seasonal, SES and 12-Month moving average methods. Short-term forecasting using (s, Q) model would require continuous updating of reorder points. Thus, for practical reasons, naïve approach was decided to deploy as the forecast method so that updating the reorder points would not need to be done recurrently. On the other hand, using SES, for instance, but having a year as the time horizon would not come into question as there were not enough years in the past. In addition, SES is traditionally recommended to use only for short term forecasting.

As the case company acts as a wholesaler and importer in Finland, it has promised to hold 3 months' inventories. Hence, the scheme for making the orders for the next three months was based on contractual agreements that the case company has made with its suppliers. It is also company's new policy to strive for limiting the shelf life of the commodity to three months due to the storage capacity limitations.

Table 10: Tested forecast methods and replenishment policies

Inventory control	Forecast method	Replenishment policy
Continuous	Linear regression vs. Naïve	Order-point, Order-up-to-level (s, S)
Continuous	Naïve	Order-point, order quantity (s, Q)
Periodic	Multiplicative Trend-Seasonal	Replenishment for the next 3 months
Periodic	Single Exponential Smoothing (SES)	Replenishment for the next 3 months
Periodic	12-Month Moving Average	Replenishment for the next 3 months
Transactional basis	The present-day practise	The present-day practise

Since the aim was to find the optimal inventory policy, all three cost components were taken into account – holding costs, ordering costs and backlog costs. Holding costs were decided to account for 10 % of item's purchasing price and was agreed to mirror the opportunity cost and a risk of obsolescence. The fixed ordering cost was set up to €10.00 based on time consumption required to make an order, receive the dispatch, and handle an invoice. The backlog cost was decided to account for 5 % of an item's purchasing price.

An item-level lead-time analysis was conducted in order to incorporate lead times to the simulations. A product's average lead times were used and the standard deviation of lead times was left out from the simulation. If a stock-out was detected let say in January, the earliest replenishment was delivered to the case firm not earlier than in February. On the other hand, if the lead-time was two months, it would be delivered not earlier than March, and so on. This decision was made since the demand was made on monthly basis and an exact date of the demand was not known. In reality, some of the demand would have been supplied during January. Therefore, the estimate for a backlog cost was slightly over-emphasized.

In order to optimize safety stock level, accurate estimates for stock-out and backlog costs are necessitated. Lost sales due to stock-out occurrence are, still, a very difficult task to assess since company's reputation and goodwill may diminish along with lost gross margin. Besides, companies seldom keep a track record on lost sales. Due to these difficulties, the top management is often called on for setting a service level for inventories in order to determine the safety stock levels (Silver et al., 1998). Safety stocks were calculated using 95 % safety stock factor. The safety factor was derived from the normal distribution because of its easiness to understand and practicality when using excel. Other considerable options were Poisson distribution that has been perceived as an adaptable one for intermittent context for a long time (Shale et al., 2008) and more recently suggested Gamma distribution (Syntetos et Boylan, 2005). Table 6 portrays that within A class over 70% of items possessed a smooth demand. Based on that finding and for the sake of simplicity, the demand during the safety stock is retrieved from the normal distribution when demand during lead-time demands was assessed.

In the periodic inventory control, the scheme was to make purchases every three months if the inventory level was under the reorder point. Reorder points were used in order to prevent excess stock from cumulating. If a stock-out was emerged during that period, the amount of required to raise inventory level positive was ordered. Again, the average lead times of the item were taken into account. In Appendix 3 is represented the simulation carried out for one B-class item.

7.3.2 Cost comparison within frequently sold A items

First, linear regression was compared with a naïve forecast method using order-up-to-level (s, S) inventory replenishment policy (see tables 11 and 12). The trend was derived from monthly data in 2011. Albeit, in overall demand analysis for resale products the linear trend line described the demand quite well (Figure 12), linear regression does not suit well at an individual SKU level. The forecast error using linear regression was actually so strong that it was decided to leave out B and C-class analyses.

Table 11: The cost comparison within 30 A items using linear regression

	Linear regression				
	Total				
Method	**Holding Costs**	**Ordering Costs**	**Backlog Costs**	**Total Cost**	**Inventory turnover**
Order-up-to-level (s,S)	19 740,96 €	1 410,00 €	6 550,63 €	27 701,59 €	5,0

Table 12: The cost comparison within 30 A items using a naïve forecast method

	Naïve forecast				
	Total				
Method	**Holding Costs**	**Ordering Costs**	**Backlog Costs**	**Total Cost**	**Inventory turnover**
Order-up-to-level (s,S)	14 443,24 €	1 460,00 €	7 928,84 €	23 832,08 €	7,8

Next, order-point, order quantity (s, Q) replenishment method using naïve forecast, and replenishment for upcoming 3-month using multiplicative trend-seasonal, SES and 12-Month moving average forecasting methods were compared with (s, S) method.

Table 13: Cost comparison within 30 A items possessing frequent demand

Forecast and replenishment method	Total				
	Holding Costs	Ordering Costs	Backlog Costs	Total Cost	Inventory turnover
Naïve, (s, Q)	8 878,77 €	2 020,00 €	11 477,85 €	22 376,61 €	29,3
Naïve, (s, S)	14 443,24 €	1 460,00 €	7 928,84 €	23 832,08 €	7,8
12-Month Moving Av (R for 3 Months)	14 800,18 €	730,00 €	11 417,79 €	26 947,97 €	6,36
Multiplicative Seasonal Method (R for 3 Months)	11 086,64 €	920,00 €	15 182,68 €	27 189,33 €	9,3
SES (R for 3 Months)	9 280,93 €	970,00 €	18 400,29 €	28 651,22 €	22,43
Present-day method	12 211,14 €	1 480,00 €	8 374,69 €	22 065,84 €	6,9

The results are in the line with the theory showing that continuous inventory review brings the highest cost savings. The order-up-to-level ascertains low backlog costs but at the same time keeps holding costs high. Order-point, order quantity (s,Q) has the lowest holding cost, the highest inventory turnover rate, and has the second lowest total costs, right after the present-day method. The present-day method reminds how valuable human judgment can be in decision-making. By looking at the data alone, one cannot predict upcoming product launches, or customer queries that can derive to new a deal. Ergo, in the case of A items, incorporating product managers' subjective judgment to (s, Q) method would most probably outperform the present-day-method.

7.3.3 Cost comparison within frequently sold B items

Since continuous inventory control policies are expensive to run, (s, S) method was omitted from the following simulations totally. The order-point, order quantity (s, Q) replenishment method was reckoned mainly for illustrative purposes and applying it to the practice was not considered.

Table 14: Cost comparison within 30 B items possessing frequent demand

Forecast and replenishment method	Total				Inventory turnover
	Holding Costs	Ordering Costs	Backlog Costs	Total Cost	
Naïve, (s, Q)	6 353,70 €	1 230,00 €	5 528,90 €	13 112,60 €	4,6
12-Month Moving Av (R for 3Mo)	5 091,87 €	530,00 €	5 911,13 €	11 533,01 €	4,27
Multiplicative Seasonal Method (R for 3Mo)	3 495,00 €	630,00 €	7 315,04 €	11 440,04 €	12,4
SES (R for 3Mo)	4 398,03 €	630,00 €	6 755,94 €	11 783,98 €	6,66
Status quo	3 551,73 €	780,00 €	8 843,61 €	13 175,34 €	3,4

Comparison of different methods reveals something very interesting. Order-point, order quantity (s, Q) method and the present-day method stay behind periodic methods. The difference among periodic review methods in total costs is fractional and the differences come from holding costs and the backlog costs. Among periodic review systems, the 12-Month moving average with 3-month replenishment scheme has the lowest backlog costs and achieves the firm's goal of inventory turnover rate. The reason why 12-Month moving average is recommended over SES stems also from the previous finding when different forecast methods were tested (in Section 7.2). If the demand shows to be more erratic in the future i.e. the demand sizes fluctuate though demand frequency remains high, the 12-Month moving average will rise above SES. On the other hand, Silver et al. (1998) do not recommend incorporating seasonal factors for B items as the computational efforts may easily overcome the benefits attained from forecasts that are more accurate.

7.3.4 Cost comparison within frequently sold C items

Again, the order-point, order quantity (s, Q) method fall behind periodic review systems from the total costs point of view. If the aim were to maximize customer service level, (s, Q) method would be recommended. (s, Q) method's significantly high holding costs indicate that the safety stock levels should be high. A further examination revealed that demand for C class items was very erratic. 12-Month moving average is the most cost effective and balances backlog cost and holding costs most evenly. The average inventory turnover rate is also above 4, which was wished by the company. Interestingly, 12-Month moving average requires fewer orders than SES does, and still its backlog costs are lower. This means that the demand from month to other changes a lot since SES does not work. The difference with regard to the present-day method remains low.

Table 15: Cost comparison within 30 C items possessing frequent demand

Forecast and replenishment method	Total				Inventory turnover
	Holding Costs	Ordering Costs	Backlog Costs	Total Cost	
Naïve, (s, Q)	1 916,53 €	850,00 €	303,59 €	3 070,13 €	3,1
12-Month Moving Av (R for 3Mo)	764,28 €	580,00 €	1 038,91 €	2 383,19 €	4,43
Multiplicative Seasonal Method (R for 3Mo)	774,77 €	570,00 €	1 431,30 €	2 776,07 €	7,9
SES (R for 3Mo)	628,60 €	710,00 €	1 534,06 €	2 872,66 €	11,25
Present-day method	952,85 €	740,00 €	780,24 €	2 473,09 €	7,1

8 REVISED SELECTIVE PROCUREMENT MATRIX

The theoretical model (Figure 2) suggested three different kinds of forecasting methods and five replenishment systems. In practice, running such a scheme on a daily basis would require a full-time forecast person and a full-time buyer. In addition, the computational requirements would increase significantly. Based on findings from ABC analysis combined with demand frequency and cost comparisons (Sections 6.3 and 7.2) a revised decision matrix is suggested for items belonging to resale and project & resale segments. All the items for projects are critical if they are missing. Accordingly, the matrix does not concern those items. Heuristics replenishment systems are recommended to items sold solely to projects.

Next, the Optimal Selective Procurement Matrix for the case company is represented following by more detailed descriptions how these recommendations were deduced. Further suggestions and discussion about product life cycle are also covered.

8.1 THE OPTIMAL SELECTIVE PROCUREMENT MATRIX FOR STUDIOTEC

The choice of general type of the forecast model to use for the class depends very much on cost considerations and the business type. Nevertheless, as a general recommendation can be stated that the inventory management for products having smooth demand (A1-C1) should be designed to be physically as efficient as possible as the market response strategy should be addressed for products having intermittent demand pattern (A2-C2). More specifically:

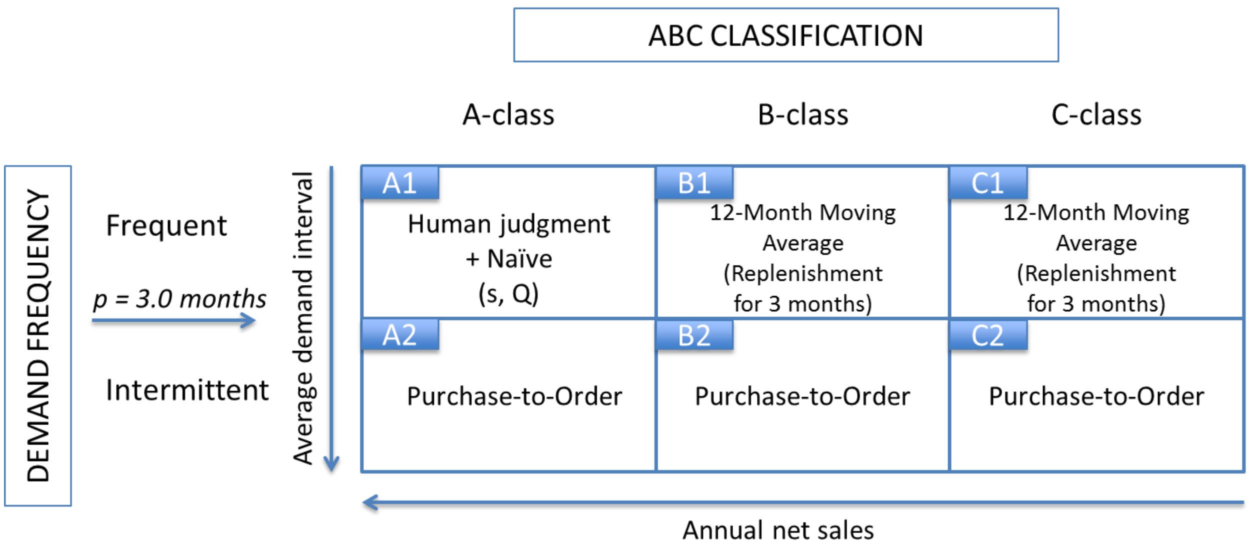

Figure 14: The Optimal Selective Procurement Matrix

A1: A1 items comprised 62 % of overall gross margin in 2011 and some 500 items belonged to this group. This group is the most important one and the best possible inventory management systems should be addressed. The costs of addressing systems that are even more complex can pay off. Based on cost comparison a (s, Q) replenishment method in concert with the naïve forecast is recommended. Product managers own judgment should also be incorporated since the present-day method actually overcame (s,Q) method. (s,Q) together with product managers own judgment would certainly lower the present total inventory costs. In order to maximize the benefits of human judgment and preventing stocks from increasing, product managers could be asked to offer explicit reasons if they overwrite statistical forecast. Fildes et al. (2009) found out in their study that expert-adjusted forecasts have a tendency to be over-optimistic. As a solution, Fildes et Goodwin (2007) suggest that purchasers should be asked to justify their judgments by writing them down. The authors found out this procedure reduced the number of unnecessary manipulation to statistical forecasts from 85 to 35 percent. This dramatic decline was probably because of purchasers felt more accountable; documentation requires more effort and can force people into learning.

Incorporating a trend to the forecast led to huge forecast errors. This is because the demand is still very lumpy even within the frequent demand segment. In addition, the SES method was waived since does not fit when the demand is lumpy or intermittent. As earlier discussed the (s, Q) replenishment system outperforms (s, S) system when the loss of sales is not crucial.

A2: Based on literature, the SBA system should be applied. Yet, for the case company's purposes it is too burdensome to run manually. Due to swift technological development among expensive items, also the risk of outdating is relevant. In addition, since the demand for most of the items was found to be lumpy, safety stocks should be vast in order to guarantee customer service. As customers are more willing and understanding to wait for items that are more expensive, recommendation is that product managers should implement purchase-to-order policy.

B1: The cost comparison shows that periodic review works better than continuous because of high ordering costs. Based on simulations, 12-month moving average and replenishment for the next three months are recommended. Opting for 12-months' moving average over SES was based on simplicity. With "C1" items, the 12-month moving average work out better and therefore same forecast method over two different ones is recommended. The multiplicative seasonal forecast also gave rather accurate forecasts. On the other hand, Silver et al. (1998, pp. 82) are skeptical when it comes to introducing seasonal and trend components for B items because the benefits are often overrun by incurred costs to run forecast. Thus, 12-month moving average were opted for.

B2: Recommendations for forecast and replenishment policies for "B2" items are in line with "A2 and C2" classes. See closer justifications from "A2 and C2".

C1: Giving the lowest total inventory costs, the 12-month moving average and replenishment for following three months is recommended. In addition, methods are easy to run and fit the case company's present IT software. Since the categorization did not take into account demand size variation but only demand intermittence, SES forecasting method does not react to changes fast enough. Estimating the upcoming demand showed to be very challenging even within frequently sold items since many items possess fluctuating order sizes. Among simulated items over 80% had lumpy demand, which was surprisingly high since the company's policy does not support offering quantity discounts to their customers.

C2: Giving recommendations for C2 class was the most difficult one. From the traditional logistics point of view, C items should be always reserved enough since the backlog costs can overrun the gross margins. Product managers shared the opinion that customers are more likely ready to wait for expensive products than inexpensive, which they often times require immediately. From these aspects, receiving sufficient amount of C2 items would be justified. As ABC and demand frequency analyses revealed, this segment comprises over 1'600 different SKUs, tying up 10 % of total inventory value but generating only 3 % of total gross margin. Moreover, as the company has been suffering from lack of inventory space, it is recommended that the company would consider purchasing these items only to order, maybe even from the Nordic competitors.

Some practitioners could argue that the pitfall of the matrix lies behind the fact that SKUs ordered from the very same supplier should belong to same group. Surely, the suggested process will not be as streamlined or standardized as it could be if items sourced from the very same supplier were handled in the very same way. On the other hand, if all SKUs ordered from the same supplier were managed in the same way, the optimization of inventories would become very difficult. In addition, one could argue that the number of months of supply should differ among ranges of annual dollar usage i.e. adjusting shorter shelf life for B items than for C items. This, in general, is very true. Nonetheless, in the study where the lack of inventory space and increased inventory levels were the main issue, the study does not advocate of lengthening the supply time for C items or reducing the supply time for B items due to the mistrust on suppliers' delivery reliability. Also due to the simplicity and agreements made between the case company and its suppliers, 3 months' supply was set for all classes

8.2 Embedding the Selective Procurement Matrix in Product Life Cycle

Maybe the biggest shortcoming of the Selective Procurement Matrix is that it works only if there is enough data available. At the introduction stage, there is not enough data available to conduct quantitative forecasts reliably. On the other hand, when an item's demand is declining, 12-month moving average neither naïve forecast methods react swiftly enough to changes in the underlying average. Thus, the Selective Procurement Matrix does not work always and supportive tools are called for. In the following figure, the Selective Procurement Matrix is embedded in product life cycle context.

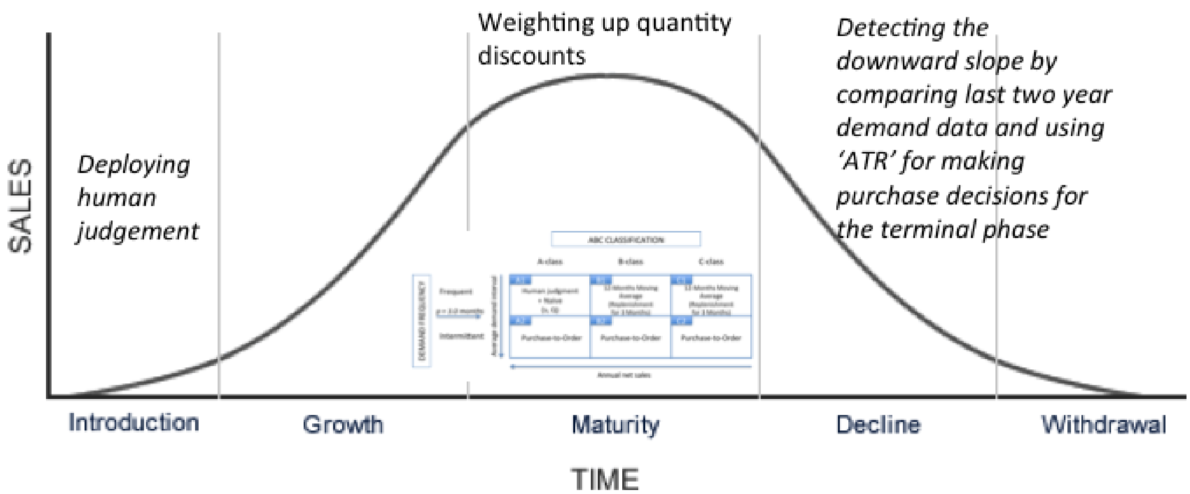

Figure 15: The Selective Procurement Matrix in a product life cycle and supportive decision tools

Introduction stage

At the introduction stage, product managers' subjective judgment is invaluable. However, as it is often encountered, human judgment tends to be overoptimistic. Requiring written documents and establishing formal procedures where a product manager does not need to make the decision alone, would reduce overoptimistic demand estimations. Depending on the value of an item in question different subjective procedures are recommended. For expensive items or expensive orders, a *Delphi method* is recommended as it has shown promising results in practice. Another option is to query from each product manager how much he or she believes that is are going to sell the very item him or herself. Then the product manager could conduct based on the answers the first order. For less expensive items, practices that are more straightforward are suggested.

When the demand is about to be evaluated, especially following aspects should be taken into account:

External factors.

1. Economic situation
2. Competitors' recent actions and new product launches
3. Threat of other substitute products
4. Customer preferences
5. Season

Internal factors

6. The product from the customers point of view:
    a. If it is a substitute, is it going to inherit the demand from the existing item?
    b. If it is novel, is it going to be stocked item or purchase-to-order?
7. Price changes
8. Promotions
9. Upcoming marketing initiatives

If the product is totally novel and assessed to belong to stocking items (enough demand transactions) it is recommended to order an amount that stands for max 3-month estimated demand. As a new item has enough demand data, it is recommended to transfer from subjective forecasting to Selective Procurement Matrix and forecast items accordingly. Also in terms of learning, it would be valuable to track and evaluate how well product managers' subjective judgment has succeeded.

Declining phase

In order to detect when an item is nearing the end of its lifecycle, last 12-month demand data and the demand data two years ago could be compared. The linear demand comparison of last two years does not react fast enough to the changes. On the other hand comparing e.g. average last 3-month data with last 12-month data can severely mislead as many items were found to have seasonality. Especially in early autumn, after low demand summer months this kind of tracking signal would imply that an item is turning to the end of its life cycle. Fortuin (1980) found that the demand tends to decrease geometrically rather than linearly at later stages of life cycle of an item. One can calculate the overall all-time-requirements for an item. Mathematically:

$$ATR = x_0 * f / (1-f)$$

Where,

ATR = an estimate of all time requirements, in units

x_0 = An overall demand of an item at first examined year

f = illustrates how the demand has decreased over the examined period

Further, the value for *f* can be measured by taking logarithms:

$$ln\ (x_t) = t\ ln\ (f) + ln\ (x_0)$$

Where,

x_t = An overall demand of an item at year *t*

t = Time in years between consecutive comparison time sets.

For the case company's needs, it is recommended to track an item's moving along its life cycle by tracking value for *f*. This would take place so that last 24-month demand data would be compared with last 12-month demand. If the value of f drops below 0.75, product managers should be more causes when placing new orders. ATR value gives an idea of the overall future demand if nothing else changes. However, as competitors' actions and entrance of new substitutes are not taken into account, ATR should not be fully trusted.

Quantity discounts

Quantity discounts are often an important part of order decisions. Although, at the cost comparison part (Section 7.3) bulk discounts were neglected, in reality they can make a significant contribution to generated gross margins. The decision concerning should a discount be utilized cumulates to the estimated demand. When the order size would extend the pre-determined 3-month supply, it is recommended that product managers should justify why they are placing such a big order and make a tentative marketing plan how they are going to sell those items. Another option is to set a time limit and within those constraints product managers are allowed to utilize quantity discounts without asking permission from departmental manager. Product managers, for instance, would be allowed to enlarge the order size to last in the inventory for 4 months with the present demand forecast. Naturally, quantity discounts would not be allowed to utilize in the case of PTO items.

9 CONCLUSIONS

9.1 THEORETICAL IMPLICATIONS

While stocking and replenishment decision are seen as operational level practices, the importance of inventory management cannot be overrated. Namely, inventory management is acknowledged as one of the most important functions and has a great impact on overall performance (Nenes et al., 2010). Many SMEs businesses are struggling with inventory decisions since the decisions ultimately need to be done at the level of individual SKUs. In that case, inventory management can become a very exhaustive task unless operational guidelines are built. Classification items can guide how much time and attention should be devoted to the different items. Nevertheless, the literature does not offer a clear link between categorization SKUs and different forecast approaches and replenishment systems.

One of the main goals of this study was to find practical taxonomic rules for different items in order to minimize the inventory investments subject to constraints on determined service levels. Different approaches about how to segment items were analyzed and two criteria emerged above others due to their simplicity and direct linkage to forecast and inventory systems. The net sales and demand frequency were decided to use as the classification criteria. While the net sales guides on how much time and attention should be devoted to the different items, the demand frequency counsels on choosing a suitable forecast and inventory replenishment system. Based on these two parameters, items were segmented into six classes and appropriate forecast and replenishment methods were addressed. The frames of Selective Procurement Matrix were then built on these two parameters. Recommendations about suitable forecast methods and replenishment systems were then opted for. The selection was based on recommendations found in academic literature and case studies. Three different quantitative forecast methods and five different replenishment systems were suggested in total.

The theoretical Selective Procurement Matrix can be expanded beyond company borders. The decision concerning the most suitable forecast and replenishment methods can be decided on a company level, based on important factors; e.g. IT system, resources, and capabilities. It also offers a powerful analysis tool to examine company's products and inventories; how SKUs are divided by their value among classes, what is a class's contribution to overall gross margin and where the inventory burdens the firm's cost structure the most.

Noteworthy, demand size variation was not taking into account when the suggestions of forecast methods for each class were made. Ergo, the framework needed to be tested with real demand data in order to justify or change the suggested models and methods. Lastly, the framework was embedded in the product life cycle concept. As the Selective Procurement Matrix is highly dependent on data, other tools are needed during item's introduction phase and terminal phase. Recommendations were discussed more closely in the empirical part.

9.2 MANAGERIAL IMPLICATIONS

Even though the Selective Procurement Matrix is built on rather 'basic' inventory control solutions, the savings can be significant. Suggested actions, when implemented correctly, can decrease the annual inventory costs approximately by 20 %. Thanks to the reduced number of SKUs on the self at a time, required inventory premises will also decrease. In addition, the risk of obsolescence will deplete when the holding inventory levels will be limited and items having intermittent demand will not be stocked. For the items that will be stocked, assigned forecast and inventory replenishment propositions will increase items inventory turnover, improve customer service level while maintaining holding costs under control. Lastly, a formal procurement framework will reduce behavioral bias among purchasers.

The practical goal of this study was to understand the reasons behind increased inventories and to guide and streamline procurement by giving comprehensive directions on how to make order decisions. Inventory analysis based on sales showed that the project sales reserved only 4 % of the total inventory value at the end of 2011. Thus, the rest of the study was dedicated to the resale side where the biggest potential improvements were achievable. Based on interviews, buffering against intermittent and lumpy demand was perceived as the biggest reason behind increased inventories. In addition, the mistrust to suppliers' ability to deliver orders on time and unjustified orders made by product managers were considered as the biggest concerns. Demand analysis showed that product managers have placed too big orders in the past. When the top 20 items burdening inventory levels were analyzed, large and unjustified orders popped most often up. Product managers' goal to minimize unit price was one permanent reason for increased inventories. The procurement data also revealed that the product managers have been more cautious when buying expensive products having intermittent demand but more audacious with less expensive items having the same demand pattern. This behavior has led to the situation where less expensive and infrequently sold products reserve 10 % of the total inventory value in the resale side while contributing only 3 % of the gross margin.

Forecast and replenishments methods assigned for intermittent demand items in the theoretical framework were abolished from the empirical investigations since the aim was to develop an easy-to-use yet effective tool for the company. As is often the case in business, complex situations call for simple solutions. Like Silver et al. (1998) note, very often the biggest savings in inventory management come from decision regarding to whether to stock or not. Studiotec's demand was found to be highly intermittent and lumpy and new product introductions appear frequently. This study recommends the firm to invest in building and running the SKUs categorization based on sales and demand frequency, as to enhance its responsiveness. Responsiveness means that fewer items are carried in the inventory and more purchases are done only for customer orders. The study suggests, based on findings, that items having intermittent demand should not be stocked but purchase-to-order (PTO). In the study, items were considered having infrequent demand if they had max 4 sales transactions in 2011. In addition, since the demand for most of the items was found to be lumpy, safety stocks should be vast in order to guarantee good customer service if these items were decided to be stocked.

The depth of items to be stocked is determined by on which class they fall under. Interestingly, theoretical suggestions were not supported by empirical findings and the recommendations for each segment differed from theoretical ones. For items having frequent demand, simulations were run and most appropriate methods were assigned. For A items naïve forecast in concert with product managers subjective input was recommended as the primarily forecast method. Cost comparisons showed that product managers subjective judgment is invaluable and should be incorporated in making replenishment decisions. Since the demand was lumpy 12-month moving average was found to be the most suitable forecast approach for B and C classes The replenishment system (s, Q) system would fit best for A class whereas a more simplistic 3-month supply replenishment would fit better for B and C classes. In addition, in order to mitigate the occurrence of intermittence, extending the time horizon from a week to a month deployed temporal aggregation.

The Selective Procurement Matrix does not take into account quantity discounts, as it would be difficult to incorporate to the matrix. A major reason leaving the quantity discounts aside from the matrix was that the case company seldom confronts discounts. Because the purpose of this study was to deplete the inventory level, it is recommended that each time when the quantity discount would be higher than the 3-months' supply, the permission should be asked from a departmental manager.

9.3 FURTHER RECOMMENDATIONS

Krajewski et Ritzman (2002) remind that besides trying to plot the optimal safety stock level, companies should try to reduce the deviation of demand during the lead-time by sharing data and form closer coordination with major customers.

In short, changing '*the givens'* which are tightly relating to the limitations that were set at the beginning of this study, is not possible. Therefore optimizing the status quo can be achieved by deploying the Selective Procurement Matrix and other tools represented in pursuance of product life cycle. In a long run, influencing the givens becomes prospective. As the analysis showed, for most of the items the order demand was either intermittent, erratic or both. This can be partly justified by relative narrow and small markets in Finland. Another reason for that is the placement in the supply chain. As Parkany (1961) explains, the orders placed by an immediate downstream partner (in this case the retailer) will reflect the "rhythm" of the ordering entity more than the "rhythm" of consumer demand. As the "rhythm" of a retailer does not only consist of consumer demand but changes in retailer's inventory position, changes in the forecast and changes in forecast error. Hence, the demand frequency and size perceived by the case company are biased. This symptom of this behavior is better known as the Bullwhip Effect (Coppini et al., 2010). The case company could consider sharing data with its biggest retailers in order to understand the consumer demand. By understanding the real consumer demand, the uncertainty throughout the whole supply chain would reduce. Therefore, the case company could consider of building closer relationships with its biggest retailers and sharing data. Even the suppliers would benefit since the orders made by Studiotec would most probably level off. Adapting Just-In-Time purchasing would not be possible, i.e. changing the "push" method to "pull" method because the initiative should be taken by the one who has the greatest negotiation power. The literature claims that JIT requires that the one who has the power in the supply chain take the initiative. The case company is not able by geographically and by its size to initiate these kinds of vast changes with their suppliers but nurturing collaboration with their retailers could be possible.

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Ari Hilden, Product Manager, Studiotec Oy, Espoo, 25.10.2012

Arto Puranen, Product Manager, Studiotec Oy, Espoo, 26.10.2012

Auli Arminen, Porject Secretary, Studiotec Oy, Espoo, 26.10.2012

Esa Horttanainen, Product Manager, Studiotec Oy, Espoo, 16.10.2012

Hannu Huhtamo, Sales Rep., Soundtools, Helsinki, 30.10.2012

Johanna Lodewijks, Product Manager, Studiotec Oy, Espoo, 26.10.2012

Juha Kiuru, Product Manager, Studiotec Oy, Espoo, 16.10.2012

Juhani Vitikka, CEO, Soundtools, Helsinki, 30.10.2012

Marko Koskimies, Product Manager, Studiotec Oy, Espoo, 25.10.2012

Olavi Barck, Marketing Manager, Studiotec Oy, Espoo 17.10.2012

Oskar Krogell, Technical Support

Pekka Lintuluoto, Product Manager, Studiotec Oy, Espoo, 25.10.2012

Perttu Siren, Product Manager, Studiotec Oy, Espoo, 22.10.2012

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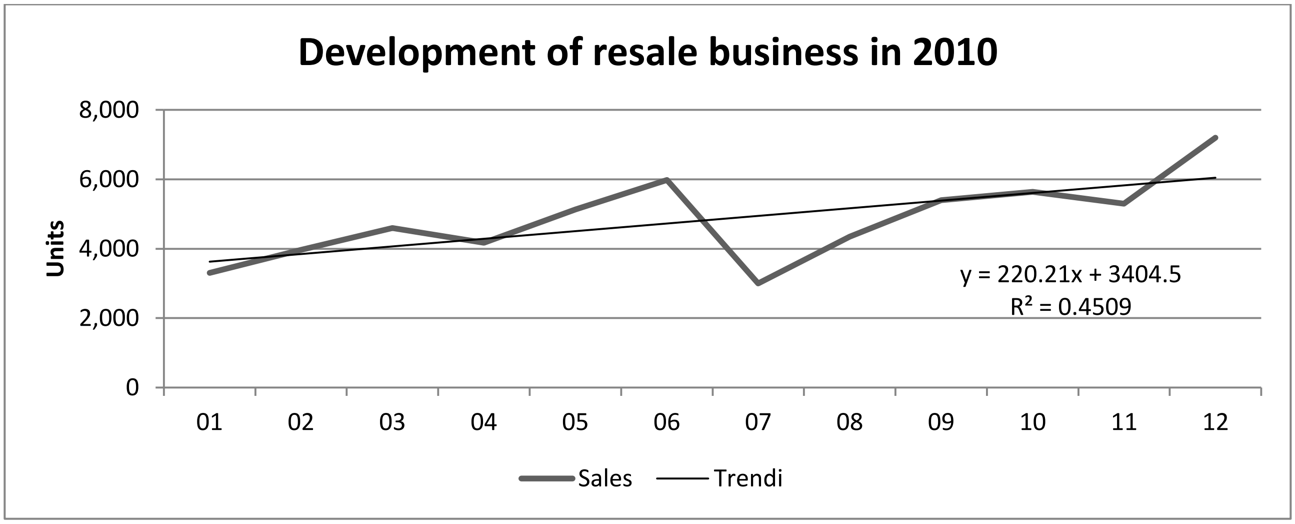
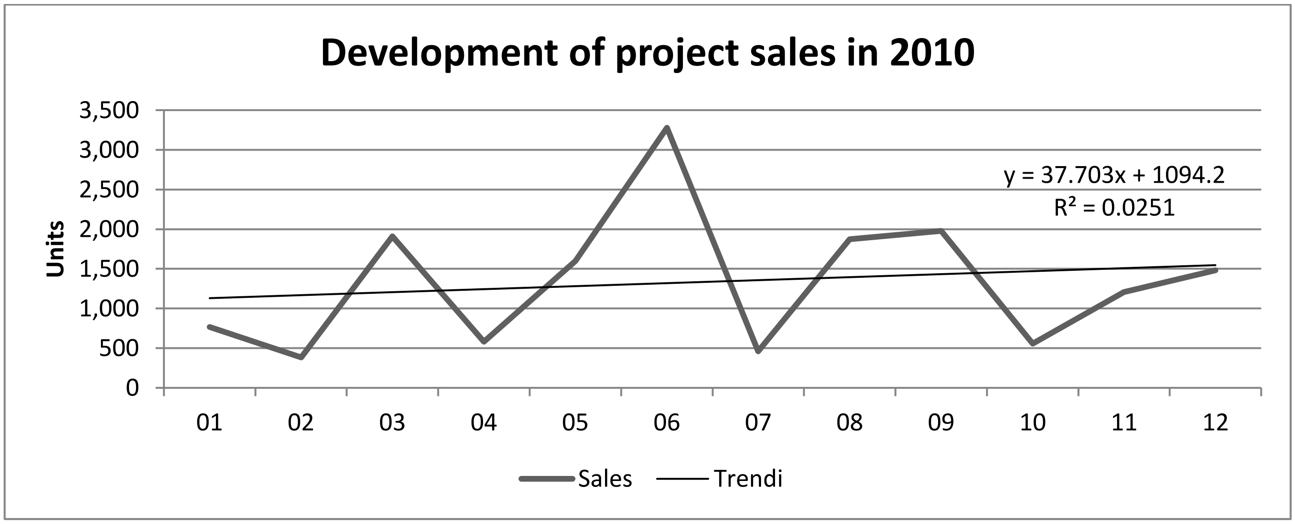
11 APPENDICES

Appendix 1: Development of resale business in 2010



Appendix 2: Development of project business in 2010



Appendix 3: Example of computing parameters for a B-item

VARIABLE	VALUE	SYMBOL
Purchasing price	183,94 €	v
Ordering cost	10,00 €	A
Holding cost, in a year	18,39 €	r
Demand forecast, in a year (units)	40	D
Average lead time (months)	1,5	l
Expected demand during the lead time (units)	5	x(l)
Standard deviation of demand, in a month	2	σ(t)
Standard deviation of demand during the lead ti	2,8	σ(L) = σ(t)*(L)^0,5
Service level	95 %	k

ECONOMIC ORDER QUANTITY	ARVO	KAAVA
Order quantity (units)	**7**	((2*A*D)/(r))^0,5
Number of orders, in a year	**6**	D/EOQ
Safetystock (units)	**5**	kσ(l)
Reorder point (units)	**10**	kσ(l) + x(l)

Appendix 4: An example of realized procurement for an individual B-item possessing frequent demand

Total Costs using current method			
73,58 €	**50,00 €**	**- €**	**123,58 €**

A Present-Day Method

Year	Month	Received	Demand	Ending Inventory	Holding Cost	Order Cost	Shortage Cost	Total Cost
2011	01	4	-5	-1	0,00	10,00	9,20	19,20
	02	1	-5	-5	0,00	10,00	45,98	55,98
	03	6	-3	-2	0,00	10,00	18,39	28,39
	04	8	-3	3	4,60	10,00	0,00	14,60
	05	4	-7	0	0,00	10,00	0,00	10,00
	06	8	0	8	12,26	10,00	0,00	22,26
	07	0	-4	4	6,13	0,00	0,00	6,13
	08	4	-2	6	9,20	10,00	0,00	19,20
	09	0	-2	4	6,13	0,00	0,00	6,13
	10	0	-1	3	4,60	0,00	0,00	4,60
	11	4	-1	6	9,20	10,00	0,00	19,20
	12	3	-7	7	10,73	10,00	0,00	20,73
2012	01	0	-6	1	1,53	0,00	0,00	1,53
	02	8	-2	7	10,73	10,00	0,00	20,73
	03	0	-2	5	7,66	0,00	0,00	7,66
	04	4	-5	4	6,13	10,00	0,00	16,13
	05	8	-5	7	10,73	10,00	0,00	20,73
	06	4	-3	8	12,26	10,00	0,00	22,26
	07	0	0	8	12,26	0,00	0,00	12,26
	08	5	-6	7	10,73	10,00	0,00	20,73
	09	0	-6	1	1,53	0,00	0,00	1,53

Inventory turnover	6,56

Appendix 5: Cost comparison applying (s,Q) replenishment system for the very same individual B-item

Reorder Point, Fixed Order Quantity

Total Costs in 2012			
353,40 €	**70,00 €**	**0,00 €**	**423,40 €**

Year/Month	Beginning Inventory Position	Beginning Inventory	Order Rec'd	Units Rec'd	Demand	End Inv	Lost Sales	Order Placed?	Ending Inv Pos	Lead time	Hold Cost	Order Cost	Short Cost	Total Cost
2011/1	16	16		0	5	11	0	NO	11		$ 17,24	$ -	$ -	$ 17
2	11	11		0	5	6	0	YES	6	1,5	$ 9,58	$ 10	$ -	$ 20
3	6	6		0	3	3	0	YES	10	1,5	$ 4,98	$ 10	$ -	$ 15
4	10	3	YES	7	3	7	0	YES	13	1,5	$ 10,49	$ 10	$ -	$ 20
5	13	7	YES	7	7	6	0	YES	13	1,5	$ 9,87	$ 10	$ -	$ 20
6	13	6	YES	7	0	13	0	NO	13		$ 19,98	$ -	$ -	$ 20
7	13	13	YES	7	4	16	0	YES	9	1,5	$ 23,95	$ 10	$ -	$ 34
8	9	16		0	2	14	0	YES	14	1,5	$ 20,89	$ 10	$ -	$ 31
9	14	14	YES	7	2	18	0	NO	12		$ 27,93	$ -	$ -	$ 28
10	12	18	YES	7	1	24	0	NO	11		$ 36,51	$ -	$ -	$ 37
11	11	24		0	1	23	0	YES	10	1,5	$ 34,97	$ 10	$ -	$ 45
12	10	23		0	7	16	0	YES	9	1,5	$ 24,24	$ 10	$ -	$ 34
2012/1	9	16	YES	7	6	16	0	YES	10	1,5	$ 25,16	$ 10	$ -	$ 35
2	10	16	YES	7	2	21	0	YES	14	1,5	$ 32,20	$ 10	$ -	$ 42
3	14	21	YES	7	2	26	0	NO	12		$ 39,24	$ -	$ -	$ 39
4	12	26	YES	7	5	27	0	YES	7	1,5	$ 41,69	$ 10	$ -	$ 52
5	7	27		0	5	22	0	YES	9	1,5	$ 34,02	$ 10	$ -	$ 44
6	9	22	YES	7	3	26	0	YES	13	1,5	$ 39,53	$ 10	$ -	$ 50
7	13	26	YES	7	0	32	0	NO	13		$ 49,64	$ -	$ -	$ 50
8	13	32	YES	7	6	33	0	YES	7	1,5	$ 50,55	$ 10	$ -	$ 61
9	7	33		0	6	27	0	YES	1	1,5	$ 41,36	$ 10	$ -	$ 51

Inventory turnover	1,4

Appendix 6: Cost comparison applying the SES forecasting and 3-month replenishment policy for the very same individual B-item

SES and 3-month replenishment policy

Total Costs in 2012			
71,49 €	20,00 €	84,43 €	175,92 €

Year	Month	Received	Demand	Ending Inventory	Holding Cost	Order Cost	Shortage Cost	Total Cost
2011	01	4	-5	-1	0,00	10,00	9,20	19,20
	02	1	-5	-5	0,00	10,00	45,98	55,98
	03	6	-3	-2	0,00	10,00	18,39	28,39
	04	8	-3	3	4,60	10,00	0,00	14,60
	05	4	-7	0	0,00	10,00	0,00	10,00
	06	8	0	8	12,26	10,00	0,00	22,26
	07	0	-4	4	6,13	0,00	0,00	6,13
	08	4	-2	6	9,20	10,00	0,00	19,20
	09	0	-2	4	6,13	0,00	0,00	6,13
	10	0	-1	3	4,60	0,00	0,00	4,60
	11	4	-1	6	9,20	10,00	0,00	19,20
	12	3	-7	7	10,73	10,00	0,00	20,73
2012	01	11	-6	12	19,14	10,00	0,00	29,14
	02	0	-2	10	16,07	0,00	0,00	16,07
	03	0	-2	8	13,00	0,00	0,00	13,00
	04	0	-5	3	5,34	0,00	0,00	5,34
	05	0	-5	-2	0,00	0,00	13,94	13,94
	06	0	-3	-5	0,00	0,00	41,53	41,53
	07	13	0	9	13,57	10,00	0,00	23,57
	08	0	-6	3	4,37	0,00	0,00	4,37
	09	0	-6	-3	0,00	0,00	28,95	28,95

Inventory turnover	6,75

Appendix 7: Cost comparison applying the multiplicative seasonal trend forecast and 3-month replenishment policy for the very same individual B-item

Multiplicative Seasonal Method

Total Costs using in 2012			
38,83 €	**30,00 €**	**100,82 €**	**169,65 €**

Year	Month	Receive	Deman	Ending Inventory	Holding Cost	Order Cost	Shortage Cost	Total Cost
2011	01	4	-5	-1	0,00	10,00	9,20	19,20
	02	1	-5	-5	0,00	10,00	45,98	55,98
	03	6	-3	-2	0,00	10,00	18,39	28,39
	04	8	-3	3	4,60	10,00	0,00	14,60
	05	4	-7	0	0,00	10,00	0,00	10,00
	06	8	0	8	12,26	10,00	0,00	22,26
	07	0	-4	4	6,13	0,00	0,00	6,13
	08	4	-2	6	9,20	10,00	0,00	19,20
	09	0	-2	4	6,13	0,00	0,00	6,13
	10	0	-1	3	4,60	0,00	0,00	4,60
	11	4	-1	6	9,20	10,00	0,00	19,20
	12	3	-7	7	10,73	10,00	0,00	20,73
2012	01	5	-6	6	9,40	10,00	0,00	19,40
	02	0	-2	4	6,34	0,00	0,00	6,34
	03	0	-2	2	3,27	0,00	0,00	3,27
	04	6	-5	3	4,67	10,00	0,00	14,67
	05	0	-5	-2	0,00	0,00	17,95	17,95
	06	0	-3	-5	0,00	0,00	45,54	45,54
	07	13	0	8	12,17	10,00	0,00	22,17
	08	0	-6	2	2,97	0,00	0,00	2,97
	09	0	-6	-4	0,00	0,00	37,33	37,33

Inventory turnover	12,43

Seasonal indices

Quarter	year 2010	2011	Avera	2012
1	0,194	0,833	0,51	5,134
2	0,516	0,667	0,591	5,914
3	1,355	0,833	1,094	10,941
4	1,935	1,667	1,801	18,011

Expected total demand in 2012	**40**
Expected demand in quarter in 2012	**10**

Appendix 8: Cost comparison applying the 4Q-moving average forecast and 3-month replenishment policy for the very same individual B-item

4Q moving average and 3Mo replenishment

Total Costs using in 2012			
168,61 €	20,00 €	- €	188,61 €

Year	Month	Received	Demand	Ending Inventory	Holding Cost	Order Cost	Shortage Cost	Total Cost
2011	01	4	-5	-1	0,00	10,00	9,20	19,20
	02	1	-5	-5	0,00	10,00	45,98	55,98
	03	6	-3	-2	0,00	10,00	18,39	28,39
	04	8	-3	3	4,60	10,00	0,00	14,60
	05	4	-7	0	0,00	10,00	0,00	10,00
	06	8	0	8	12,26	10,00	0,00	22,26
	07	0	-4	4	6,13	0,00	0,00	6,13
	08	4	-2	6	9,20	10,00	0,00	19,20
	09	0	-2	4	6,13	0,00	0,00	6,13
	10	0	-1	3	4,60	0,00	0,00	4,60
	11	4	-1	6	9,20	10,00	0,00	19,20
	12	3	-7	7	10,73	10,00	0,00	20,73
2012	01	18	-6	19	29,12	10,00	0,00	39,12
	02	0	-2	17	26,06	0,00	0,00	26,06
	03	0	-2	15	22,99	0,00	0,00	22,99
	04	0	-5	10	15,33	0,00	0,00	15,33
	05	0	-5	5	7,66	0,00	0,00	7,66
	06	0	-3	2	3,07	0,00	0,00	3,07
	07	18	0	20	30,66	10,00	0,00	40,66
	08	0	-6	14	21,46	0,00	0,00	21,46
	09	0	-6	8	12,26	0,00	0,00	12,26

Inventory turnover	2,86

Demand in quarters

Quarter	year 2010	2011	2012
1	3	15	15
2	8	12	12
3	21	15	14
4	30	30	
Average units sold in Q:	16	18	14