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Method selection for demand forecasting

Master of Science Thesis

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Examiner: Professor Janne Huiskonen
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ABSTRACT

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The purpose of this master's thesis was to find a systematic way for choosing the optimal forecasting scheme and to use this method to increase accuracy of material level demand forecasts in Konecranes.

This thesis is based on literature and earlier research of the topic which is used to determine a forecast method selection framework. The framework is then used to find out the optimal forecasting scheme for demand forecasting in two manufacturing plants. Actual demand data was pulled from SAP and Microsoft Excel, R and RStudio were the tools used to generate forecasts and calculate forecast accuracies.

The accuracy of proposed forecasting scheme is also compared to currently used processes and steps to implement it in ERP are presented.

TIIVISTELMÄ

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Hakusanat: toimitusketju, ennustaminen, ennustemallit, metodin valinta, kvantitatiivinen ennustaminen

Tämän diplomityön tavoitteena oli löytää systemaattinen tapa optimaalisen ennustemallin tai -mallien valintaan ja soveltaa tätä materiaalitason kysyntäennusteiden tarkkuuden parantamiseen Konecranesillä.

Työ pohjautuu kirjallisuuteen ja aihealueen aiempiin tutkimuksiin, joiden pohjalta valitun ennustemallin valintametodin avulla kehitettiin optimaalinen ennustemallien yhdistelmä kahden tuotantolaitoksen kysynnän ennustamiseen. Kysyntädata kerättiin SAP:sta ja työkaluina ennusteiden generoinnissa ja ennustetarkkuuksien laskennassa olivat Microsoft Excel, R ja RStudio.

Lopulta luotua ennustemallien yhdistelmää verrattiin yrityksen nykyisin käyttämiin malleihin ja esitettiin miten se olisi mahdollista ottaa käyttöön ERP-järjestelmässä.

PREFACE

It has been a long journey to this point in my life, when I am finally about to graduate. Writing this master's thesis (as well as my studies as a whole with the mechanical engineering detour) have taken longer than probably anyone anticipated.

I wish to thank Konecranes for giving me this opportunity to write my thesis about an interesting topic and everyone who has contributed to or supported this work in any way. Especially I want to express my sincere gratitude to Virpi Tikkala and professor Janne Huiskonen for your invaluable advice and comments while working on this project as well as all the nudges to keep me writing when I needed them.

I also want to thank my family and friends for all the support over the years. Couldn't have done this without you.

Samuli Vaskinen
Hyvinkää 2017

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ABBREVIATIONS AND SYMBOLS

Abbreviations

AME	Americas. One of three Konecranes' geographical regions.
APAC	Asia-Pacific. One of three Konecranes' geographical regions.
BOM	Bill of materials
DSB	Demand supply balancing
EBIT	Earnings before interest and taxes
EMEA	Europe, Middle East and Africa. One of three Konecranes' geographical regions.
ERP	Enterprise resource planning system which integrates many business functions into one software solution
GMAE	Geometric mean absolute error
GMRAE	Geometric mean relative absolute error
HML	Hämeenlinna
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MASE	Mean absolute scaled error
MdRAE	Median relative absolute error
MSE	Mean square error
SAP	Enterprise resource planning system which integrates majority of operations into one IT solution.
SCM	Supply chain management
SES	Single exponential smoothing
SMA	Simple moving average
sMAPE	Symmetric mean absolute percentage error
SKU	Stock keeping unit
SPR	Springfield
UoM	Unit of measure

Roman symbols

b	Trend component
e	Forecast error
e^*	Benchmark method's forecast error
F	Forecasted demand
l	Level component
m	Count of periods in a season
n	Count of observations
p	Percentage error
q	Scaled error
r	Relative error
s	Seasonality component
t	Time period
Y	Observed demand

Greek symbols

α	Smoothing constant
β	Smoothing constant for trend
γ	Smoothing constant for seasonality

1 INTRODUCTION

Forecasting has been used to help decision making for almost as long as there have been businesses. In short it means creating an estimate of future events that are at least partially independent of the decisions the company makes. In the beginning forecasting was mainly used as a managerial tool for budgeting and other high level decisions but since then more and more detailed forecasts have been the focus of research. Future demand is not usually known in advance and as a result production planning and inventory management have to rely on forecasts to be able to fulfill demand competitively.

1.1 Background

Globalization and other competition increasing developments in the markets during the last decades has created a need to be able to offer goods to customers with shorter lead times and with greater customization than before which has increased the pressure to make operative decisions based on forecasts instead of waiting for customer orders to start procurement of materials. Increasing forecast accuracy naturally increases the quality of decisions which base on that forecast and creates competitive advantage as it enables better utilization of resources and higher customer satisfaction.

Even though forecasting offers many benefits it does not come without its limitations. There is always some uncertainty in the future and it is impossible to predict all events that will occur and affect future demand. When the time horizon a forecast is created for is increased the accuracy of said forecast usually goes down. Same can be said about the detail level of a forecast. For example, forecasting demand on daily level is less accurate than on weekly level or forecasting demand of material group is usually more accurate than forecasting demand of single material.

Traditionally forecasting research has focused on development of forecasting techniques especially on time series methods (Fildes & Goodwin, 2007). Time series techniques aim to predict future demand based on actual past demand using a set algorithm to statistically extrapolate the data set. Other methods which have been studied include judgmental reviews of experts, market tests and surveys. Even with multitude of sophisticated forecasting methods available surveys show that simple methods are the most often utilized ones in real world scenarios (Tokle & Krumwiede, 2006).

Fulfilling upcoming demand in an optimal manner which keeps inventory levels as low as possible without causing stock outs increases the operational performance in multiple ways. Higher inventory turnover rates lower the capital tied to inventories and allows it to be utilized in a more profitable manner. Lower inventories also mean lower inventory carrying costs which directly affects company's profits and with accurate forecasts the amount of stocked materials becoming obsolete due to declining demand can be reduced. Naturally the effects of these potential benefits become stronger with more accurate forecasts which should make forecasting one of the cornerstones of inventory optimization processes.

If forecasts are utilized to their fullest extent they do not benefit just the company generating them but can also improve performance of whole supply chains. The company which sells the final goods to end customers has the most information available to forecast upcoming demand so they should be the one generating forecasts and sharing their data with the rest of the supply chain. This way the forecasts are based on real demand data instead of some form of consolidated demand i.e. orders of bigger batches from component vendors some of which go to inventories to wait for upcoming end customer needs.

1.2 Research objective and scope

This thesis aims to improve Konecranes' forecasting process with the target of increasing forecast accuracy in a cost-effective manner. Because the process should be easily scalable to cover a wide scope of materials, quantitative methods which are based on available past demand data are the main focus of the research as they are less labor intensive than qualitative methods which rely on input from personnel.

Demand forecasts are already used in Konecranes for two purposes. Internally they are used to determine when material replenishments should be ordered. In practice this means that reorder points are dynamic results of calculations based on safety stock values, known upcoming consumption and forecasted demand over material lead time and thus change as new forecasts are generated.

Information generated by forecasting future demand is also shared with some key suppliers. By sharing material needs with vendors Konecranes allows them to optimize their material flows by having better visibility to what Konecranes will be ordering from them and when. In addition to being able to optimize material flows the vendors can also utilize the information in their production planning, once again improving performance. As more and more vendors are given access to the forecast data it becomes even more valuable to improve forecasting accuracy as much as possible.

As accurate forecasts offer multiple benefits and aforementioned methods to utilize forecasts have already been developed and are being actively utilized, the main objective of this research is on optimizing forecasting accuracy. This is achieved through answering the following research questions:

- Could another quantitative forecasting method generate more accurate forecasts than currently used model?
- How should a forecasting scheme be chosen?

1.3 Research methods and structure

Research done in this thesis can be divided into three phases. The first phase consists of literature review about general forecasting theory and benefits, methods and their classification as well as metrics used for measuring forecast accuracy. Information in this phase has been gathered from scientific peer reviewed articles and books which present best practices.

The second phase contains a case study in which multiple forecasts are generated with the most potential methods. After generating the forecasts their accuracy is measured to determine the most suitable forecasting scheme. Software solutions utilized in this study were Microsoft Excel, R and RStudio.

Consumption used for this study is actual usage of materials as it has been saved into company's enterprise resource planning system, SAP. Data from 2015 was used to generate forecast for 2016 consumption. Accuracy of this forecast is then compared to actual consumption which happened in 2016. This phase also offers suggestions on which system should be used in the future to have as accurate forecasts as possible. Also, parameters which affect the outcome of forecasting models available are considered and optimization possibilities are identified.

Phase three consists of comparison of accuracy between the new forecasting scheme and current forecasting methods and presents the steps needed to take the new scheme into use. Also conclusions and some further study possibilities are considered.

2 FORECASTING IN SUPPLY CHAIN MANAGEMENT

There is not just one definition of supply chain but instead multiple descriptions can be found in the literature with slightly different defining factors. Arnold, Chapman and Clive (2008) define supply chain as all the processes and actions that are needed in the production of goods and the delivery of said goods to the end customer. According to their research, inclusion of recycling or disposal of goods at the end of their life cycle is also becoming more common as part of the idea of supply chain (Arnold et al., 2008). Christopher (2005) on the other hand sees supply chains as networks of organizations which are linked together by either supplier or customer relationship. All of these organizations are important in creating additional value to the end customer through refining the end product or offering some service thus impacting the success of produced goods (Christopher, 2005).

In the end, all of the definitions contain a group of companies, organizations or units which cooperate to produce goods and bring them available to end customers and in some cases even recycle or dispose of the goods when they are no longer needed by the customer. Even a simple supply chain usually contains multiple raw material suppliers, production facilities, distribution centers, retailers, customers and logistics service providers. Usually large, globally operating companies have very complex supply chains which might contain hundreds of organizations.

Members of supply chain can be either internal of external. For example, a company that manufactures subassemblies in multiple production facilities and assembles end products in some other facility sees the subassembly supplier as an internal vendor when looking at the supply chain from the assembling units point of view.

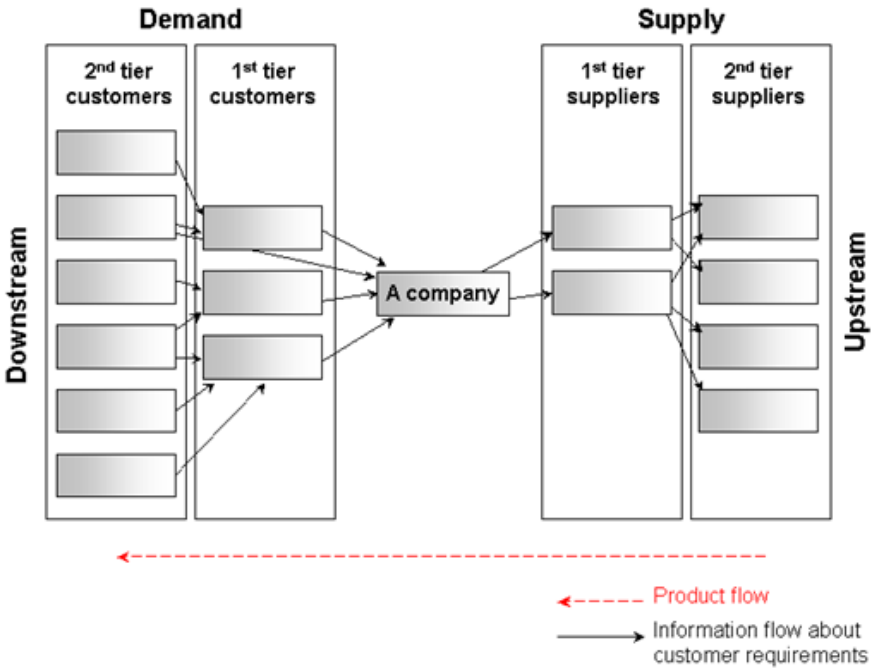

Figure 1. A supply chain from one company's point of view. (Kangas, 2008, Adapted from Slack, Chambers & Johnston, 2001)

In figure 1 a supply chain is presented from one company's point of view. All supply chain members have their own customers and usually there are multiple levels or tiers of suppliers and customers. (Slack et al., 2001) In this research focus is on crane factories which for example purchase hoists from internal supplier which would be considered first tier supplier. This internal supplier in turn purchases a motor from external supplier which would be considered second tier supplier from the crane factory's point of view.

Supply chain management (SCM) is relatively new branch of science which emerged in the 1950's. Until that time companies and scientific research had focused solely on a single entity and its competitive factors. Of course, suppliers and customers had been observed also before that but the connections to potential competitive advantages had not been identified nor pursued. With the advent of supply chain management, the focus has partially shifted to the performance of whole supply chains and how they can create advantages in competition against other supply chains. (Fredenhall & Hill, 2001)

In practice optimizing the whole supply chain is a difficult task because individual organizations often try to locally optimize their operations instead of taking the whole supply chain into account. This leads to suboptimal supply chain performance and uncoordinated actions which in turn the end customer sees as late deliveries and increased prices as the cost structure used to produce goods is not as good as it could be. In the long run, such problems often cause lost customers and missed sales opportunities which negatively affect all the members of the supply chain. (Yu, Yan & Cheng, 2001)

2.1 Push and pull methods in supply chain management

There are two approaches to initiating action in a supply chain, push and pull. The traditional way to manage supply chains was the push method in which goods are produced (or any other action starts) before an actual customer order has been received. On markets with scarce competition and steady demand this method yielded good results as it was able to keep goods available and fulfill customers' demand for goods which were not customizable. (Christopher, 2007)

The other approach to handle demand in a supply chain is the pull method. The actions happen reactively after the order has been received and the initial signal to start production comes from the customer. The emphasis is on the customer and their need of certain goods. As the competition on many industries has become fiercer in the last decades and as a result products have become more customizable and the risk of them becoming obsolete has risen, the pull method has become more popular and widely applied. (Christopher, 2007)

In reality supply chains usually contain some processes which use the push method and some processes which utilize the pull method. This combination is used to counter the negative effects of pull method. In purely pull driven supply chain delivery times to the customer would often be too long for company to remain competitive so some of the most time consuming processes, which often have to do with procurement or part of the production process, are push driven. Because the

actual demand is not known when the push processes are executed, they are based on anticipated customer needs also known as forecasted demand. As the decisions made in the push processes set constraints to the demand that can be fulfilled without deviating from designed ways of working, it is valuable for companies to have accurate forecasts. (Chopra & Meindl, 2007)

2.2 Benefits of forecasting

Forecasting is done on multiple levels in a typical large enterprise. Vollmann et al. (2005) classify forecasts into strategic business planning, sales and operations planning and master production scheduling and control based on their level of detail. Strategic business planning provides data on a rough level to support strategic decision making. Usually such forecast is done by judgmental methods for example, expert opinions are used to determine how markets are going to develop, although it is not unheard of to utilize economic growth models. Output of strategic business planning is a forecast of total sales on an annual or quarter level with a horizon of multiple years. The main use of these forecasts is to help management in making better strategic decisions in high impact matters such as investing into new production facilities to increase capacity or to enter or withdraw from certain markets.

Sales and operations planning deals with more detailed questions than strategic business planning. Forecasting is carried out on product family scope and on weekly or monthly level and is used to balance sales with production capacity and in some cases to minimize the costs to fulfill upcoming demand by optimizing production planning and material replenishments. If the components of the end products are not too variable, i.e. product is not customizable, raw material needs can also be predicted based on the forecast generated for sales and operations planning and material management can be done optimally. (Vollmann et al. 2005)

Master production scheduling and control is the finest level of forecasting Vollmann et al. (2005) identify and it and it goes to daily or even hourly level. Main

usage of these forecasts is in production planning and controlling actual operations in a facility.

Having accurate forecasts of future material consumption on a raw material level allows organizations to better optimize their inventories. Naturally basing inventory parameter calculations on the upcoming demand gives a better chance to be able to cost-effectively fulfill that demand than basing calculations purely on what would have been needed to fulfill the past demand, especially in situations when there has been some shift in end customer's needs or when a certain product is being replaced by a new revision.

Even though some studies have questioned the tangible benefits gained from sharing information of actual demand and forecasts there have been individual success stories. The more information there is available between the supply chain members the better the whole chain can operate and the negative effects of material shortages or limitation in production capacity caused by bullwhip effect can be mitigated. (Holweg et al., 2005)

However, utilizing available information is not always an easy task and just sharing that information does not bring any benefits if it does not affect the operations in any way. In simulation models external collaboration has been shown as a powerful tool with multiple benefits, most notable of which are improved capacity utilization and inventory turnover. In practice it has proved to be a much more difficult to reach the improvements the shared demand visibility brings. The challenges in utilizing this data usually relate to lack of knowledge or expertise in the area, distrust into the shared data or contractual limitations. If there is no willingness to utilize the data on both parties, the benefits will not realize. (Holweg, 2005)

A common problem with forecasting processes is that multiple functions in a company need forecasts for their own needs and often generate those forecasts within that business function. This phenomenon known as "island of analysis" leads to unaligned forecasts and ultimately to unaligned plans between different

functions. This phenomenon can often be found in case studies and is caused by lack of communication between different units. (Mentzer & Moon, 2005)

2.3 Demand patterns

Sometimes there are clearly identifiable characteristics in the past demand. Multiple forecasting methods have been developed which take these characteristics into account and at least in theory they should provide more accurate forecasts than using simpler methods like simple moving average or single exponential smoothing. However, just because some pattern has repeated in the past, does not guarantee it to happen again in the future as situations in the market can change drastically or market might get saturated. Pattern recognition is also used in some approaches to forecast method selection, one of which is presented later in chapter 3.3.

Sometimes seasonal patterns can be identified in past demand as in figure 2 and it is possible to utilize a forecasting model that takes seasonal changes in demand into account to produce more accurate forecasts. For some products, seasonal changes can be extremely influential and forecasting demand by more traditional methods would not yield the wanted results. For example, ice cream consumption in Finland varies highly with seasons because of the weather and how it affects customer behavior.

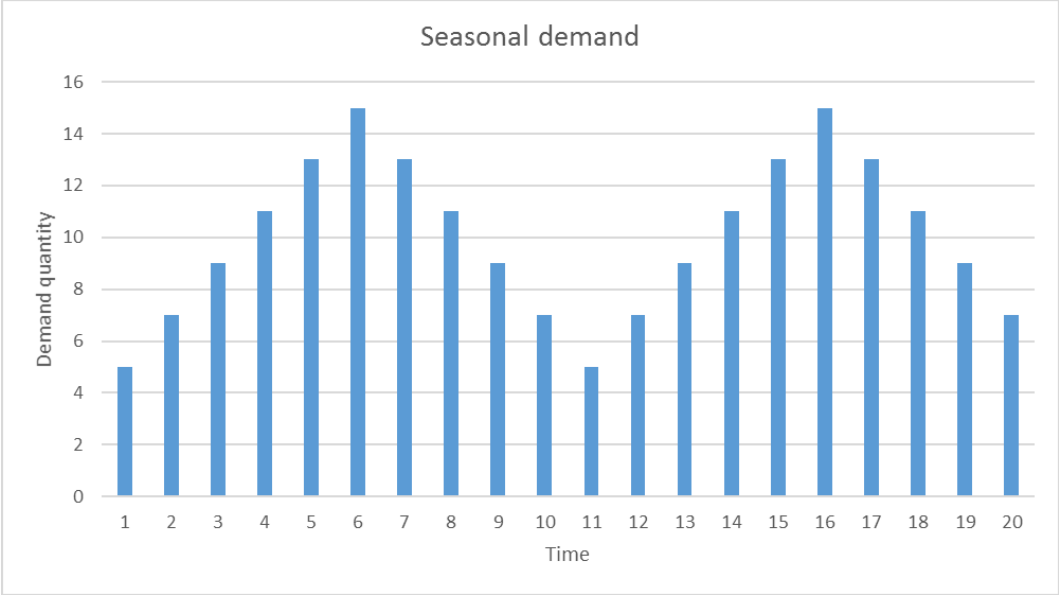

Figure 2. Seasonal demand example.

In practice, there are two ways seasonality can be accounted for in forecasts: additive and multiplicative. Which of these methods is more suitable is dependent upon the situation and should be decided case by case. In cases where the amplitude of seasonal increase or decrease is independent of the original level of demand additive method should be used. More often the seasonal fluctuation is proportional to the non-seasonal demand and multiplicative method leads to better results. (Winters, 1960)

As with seasonal patterns it is possible to identify trends in demand and utilize that information while generating forecasts. Constantly increasing demand (figure 3), for example during product ramp ups or with increasing market shares in times of superior product offering, assuming that the demand keeps increasing and modifying forecasts accordingly might increase forecast accuracy and reduce stock-outs. Also for trending demand the forecast model can take the trend into account in multiple ways. The decision on if the model should handle the trend as ratio, additive or linear have to be done case by case as one method is not universally better than the others. (Winters, 1960)

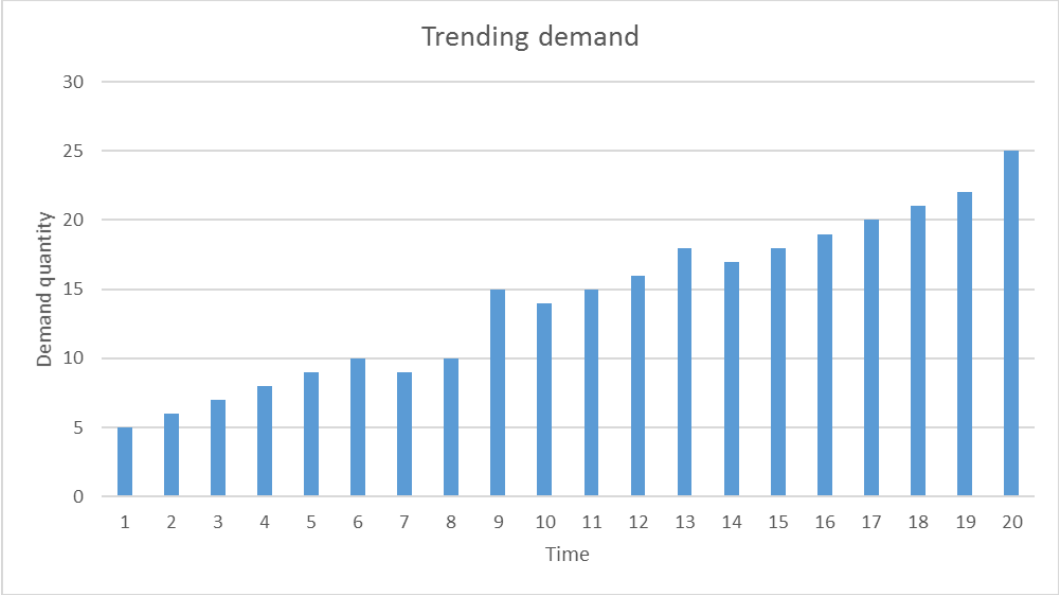

Figure 3. Trending demand example.

While utilizing trends in forecasts there are always risks to under or over forecast because of the assumption that the trend will hold true also in the future. Of course that is not always the case and it often leads to overstocking or stock-outs if the trend suppresses more quickly than anticipated by the model.

Demand is called intermittent when it appears sporadically at random intervals with periods of zero demand in between demand occurrences, as in figure 4. Another feature of intermittent demand is that occurring demand is not always of a constant size. As a result, the variance is great and predicting such demand is difficult. The errors in forecast might be especially costly because the risk of obsolescent stock or stock outs is high on materials with intermittent demand. (Syntetos & Boylan, 2005)

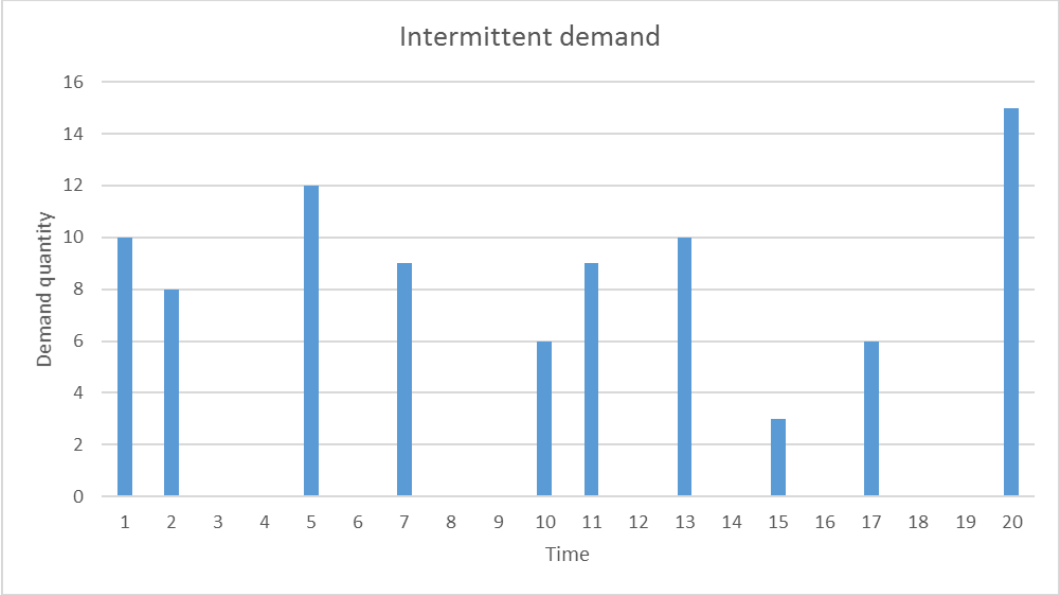

Figure 4. Intermittent demand example.

In practice, single exponential smoothing (SES) and simple moving average (SMA) are used to forecast intermittent demand but creating methods specifically for predicting such demand has been the focus of some research. Croston (1972) presented the current standard for forecasting intermittent demand which is known as Croston's method. (Syntetos & Boylan, 2005)

2.4 Dimensions of forecasting

A framework for visualizing supply chain and potential dimensions used in forecasting concept creation developed by Syntetos et al. (2016) is presented in figure 5. Their framework has three dimensions: product, time and location. In practice, all of these dimensions affect the detail level of generated forecasts and require decision to be made that are independent of forecasting method selection. Because these affect the detail level of forecasts, the values used for these dimensions should be chosen based on how the forecast is planned to be utilized.

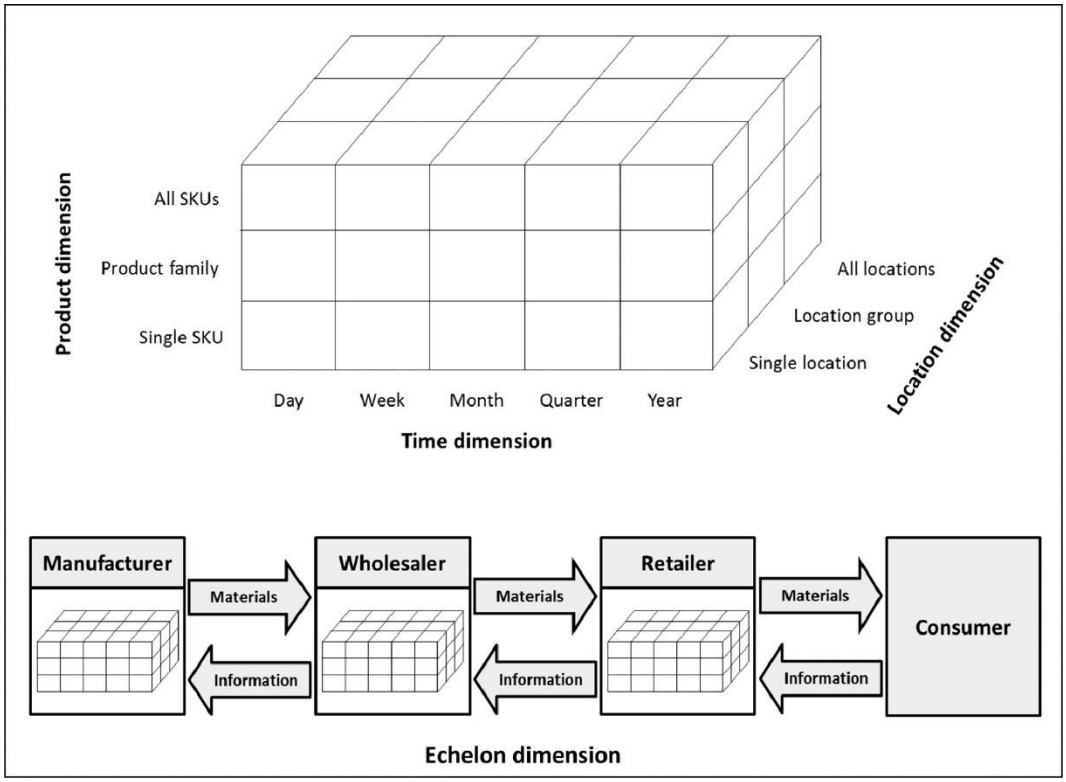

Figure 5. Supply chain structure: a framework. (Syntetos et al., 2016)

Actual demand is realized on order line level i.e. a customer or internal process requires a certain quantity of particular stock keeping unit (SKU) at a certain time. The data on this transactional level cannot be used for forecasting purposes and it must be aggregated before further processing. How this aggregation happens, is driven by the three dimensions. (Syntetos et al., 2016)

Product dimension determines if all SKUs are handled individually or if some of these get grouped together. The most used aggregation options regarding products are single SKUs, product families and all SKUs. As an example, single SKU forecasts are needed for inventory management while for budgeting it is enough or even preferable to have forecasts of all SKUs as a single value which contains everything. Product family detail level is often used for capacity planning as products from the same product family are often manufactured on the same production line. (Syntetos et al., 2016)

The second dimension, time, deals with the period of time for which the demand is aggregated into a single value. The usual options are day, week, month, quarter or year. Selecting period for time aggregation is not usually as straightforward decision as selecting product dimension. Even if the planned usage is clearly defined there might be multiple time periods that would be good choices and the optimal choice might even be one period for one SKU and another for some other SKU. Especially from inventory management point of view it might be optimal to forecast consumption of some SKUs on weekly level and some on monthly level depending on how high and stable their demand is. (Syntetos et al., 2016)

Location dimension is usually the easiest to define and is a clear decision once it is defined what the forecast will be used for. Once again budgeting or upper management might not be interested to know details of a single location and location group might be the correct level of detail. For inventory management though it is crucial to know in which location the demand is going to actualize. (Syntetos et al., 2016)

In forecasting and operational literature, it is commonly assumed that the aggregation level of the utilized data is the same as the needed forecasting output. However, the degree of aggregation of the source data and output does not have to match as there are multiple ways to manipulate data to reach the output needed and it should not be a limiting factor. Instead the level of output aggregation should be driven by the usage of said forecast. (Syntetos et al., 2016)

In the ideal world, the data used to generate forecasts would always be on the same detail level than the required output but in reality, that is rarely the case. Syntetos et al. (2016) identified three cases where the level of detail has to be modified:

- The level of detail needed in the forecast is lower in one or multiple dimensions than the level of detail in input data. Forecasts can either be generated on the level of input data and the results aggregated to the wanted level or the input data can be aggregated before producing forecasts.

- The level of detail needed in the forecast is higher than is available in demand data. In this case forecasts can either be generated on the level of input data and disaggregated from the result or the input data can be disaggregated and forecasting carried out on the required detail level.

- The level of detail is higher on some dimension and lower on some dimension than the source data. This typically requires more finesse in data manipulation.

(Syntetos et al., 2016)

3 FORECASTING METHODS AND METHOD SELECTION

There are many forecasting methods presented in literature. Usually they are categorized into qualitative and quantitative methods according to what they use as inputs. One method has not been proved to perform better than others and decision on what kind of forecasting process and methods should be used has to be done a case by case basis. The patterns in demand, resources and available data usually determine what kind of forecasting method is chosen. (Mentzer & Moon, 2005)

3.1 Qualitative forecasting methods

Qualitative methods base their projections on judgment and intuition of key people who are experts in the area being forecasted. As they are based on opinions they are prone to being subjective and biased. Even though all forecasting can be considered judgmental in the sense that method and model selection and parameter definition is done judgmentally, only methods which wholly rely on judgment as input are considered to be qualitative. (Wright & Goodwin, 1998)

In cases where no demand history is available for a product (for example during a new product launch) or when the demand history is considered irrelevant for predicting future demand, qualitative forecasting is the preferred way to generate forecasts. But in addition to this qualitative forecasting is widely used on high level to evaluate budgets. Most used qualitative method is using expert opinions of either internal experts or external. In practice this means for example asking opinions of sales department or carrying out a survey for companies in the same industry. (Armstrong, 2001)

3.2 Quantitative forecasting methods

Quantitative methods are also known as extrapolation methods and that describes their inner workings quite well. They use purely historical data as input and extrapolate future demand based on historical figures. Companies usually have

historical data available, especially nowadays when enterprise resource planning (ERP) systems are being utilized by even small companies. Time-series methods assume that what has happened in the past will happen again in the future and use a mathematical formula to forecast future demand. More sophisticated systems even analyze demand history and use an algorithm to select a mathematical model from multiple options based on that analysis. (Arnold et al. 2008)

Over 70 time-series methods have been developed by researchers and they vary from extremely simple to rather complicated. The simplest one is to just take last period's demand and extrapolate that number as future demand. Other simple but more widely used methods include simple moving average and single exponential smoothing. More complex ones analyze past demand and take possible trend or seasonality into account when generating the forecast. (Mentzer & Moon, 2005)

3.2.1 Naïve forecasting

The simplest forecasting method is called naïve forecasting. In naïve forecasting method the generated forecast is equal to the last period's actual demand. If a forecast is needed for more than one period beyond the current period, it receives the same value as the previous forecast. Naïve forecast has the potential to change without limits between periods and it is not widely applied in practice as the values that change widely every period don't really support real world operations. However, forecasts generated by naïve forecasting are often used as a benchmark in studies that compare different forecasting methods with each other. (Mentzer & Moon, 2005)

As can be seen in the formula below the mathematical basis in naïve forecasting is very simple and the method does not have any additional parameters which could be used to optimize its behavior. Forecasted demand F is equal to the actual demand Y of the previous period while t denotes time.

$$F_t = Y_{t-1} \tag{1}$$

3.2.2 Simple moving average

In simple moving average (SMA) the forecast is the arithmetic mean of predefined amount of past demand observations. New forecast is generated on every period change and in that process the oldest observation is dropped out and newest observation is added to the sample. The results from M1 competition, which pits different forecasting methods against each other, have shown that simple moving average is not the most accurate forecasting method. However, due to its simplicity and familiarity, it has ranked as the most used method in practice. (Ali & Boylan, 2012)

The formula below presents the calculation of simple moving average. In addition to selecting the method SMA requires a decision to be made on the period based on which the forecast is generated i.e. how many past observations *n* should affect the forecast value. All the observations used for the calculation have the same weight.

$$F_t = \frac{Y_{t-1} + Y_{t-2} + \cdots + Y_{t-n}}{n} \tag{2}$$

3.2.3 Single exponential smoothing

Single exponential smoothing (SES) also known as simple exponential smoothing is an old statistical method first applied to inventory control and demand forecasting by Brown (1959). The demand observations are weighted and their weight decreases with age. Single exponential smoothing has an important parameter, smoothing constant α, which defines how influential older values are compared to new ones. Low smoothing constant puts more weight to older demand observations and is slow to react to systematic changes whereas high smoothing constant reacts faster but is also sensitive to random changes. SES was originally widely adopted because of its low computational requirements but it has proved to be a robust method and it still available in most software packages that offer time series based forecasting functionalities. (Wallström & Segerstedt, 2010)

Even though computationally and from data storage point of view SES is not requiring, in mathematical form, presented below, it is more complex than previous models. Basically, the forecast generated in the previous period is modified by observed forecast error in previous period times smoothing constant α.

$$F_t = F_{t-1} + \alpha(Y_{t-1} - F_{t-1}) \tag{3}$$

3.2.4 Holt-Winters

Holt-Winters method (Holt, 1957) is much more complicated model than the previously mentioned forecasting methods. It does not just smooth or average past demand but also attempts to take trends and seasonality into account in the forecast. In practice Holt-Winters forecast consists of three components: level, trend and seasonal. Level is the base value of the forecast which in practice is calculated similarly to single exponential smoothing. Trend is also a result of exponential smoothing i.e. also this component has different weights to different demand observations in the past and its behavior can be manipulated by smoothing constant. Seasonal factor is a multiplier derived from seasonal demand patterns in past demand. (Winters, 1960)

The three components used in Holt-Winters method can be expressed mathematically by smoothing equations below, where:

- l = level component
- b = trend component
- s = seasonality component
- α = smoothing constant for level
- β = smoothing constant for trend
- γ =smoothing constant for seasonality
- Y = observed demand
- m = periods of the seasonality i.e. number of periods in a season, for example 12 if periods are months and seasonality is considered to happen yearly

$$l_{t-1} = \alpha(Y_{t-1} - s_{t-m}) + (1-\alpha)(l_{t-2} + b_{t-2}) \tag{4}$$

$$b_{t-1} = \beta(l_{t-1} - l_{t-2}) + (1-\beta)b_{t-2} \tag{5}$$

$$s_{t-1} = \gamma(Y_{t-1} - l_{t-2} - b_{t-2}) + (1-\gamma)s_{t-m} \tag{6}$$

Once the smoothing constants have been chosen, which is usually done automatically by statistics software, and components have been calculated there are two options when using Holt-Winters method. Seasonality can be accounted for either multiplicatively or additively depending on the situation. Forecast formula for multiplicative method in (7) and additive in (8).

$$F_t = (l_{t-1} + b_{t-1}) * s_{t-m} \tag{7}$$

$$F_t = l_{t-1} + b_{t-1} + s_{t-m} \tag{8}$$

3.2.5 Box-Jenkins

Box-Jenkins method is an iterative multistep approach to applying autoregressive moving average or autoregressive integrated moving average to find the best fitting model to past values. The first step is to analyze the available data and select a sub-class of the model that is the most suitable one for the given time series. After a sub-class of the model has been selected an estimation of optimal parameters is carried out by utilizing numerical methods to minimize errors. Finally, the selected model and parameters are evaluated in an attempt to identify areas where the model could be improved to better fit the available time series. (Box & Jenkins, 1970)

In reality the mathematics behind Box-Jenkins is complex and is usually only applied in computer software. Fortunately, practically all recent statistical software packages include Box-Jenkins method in their model selection which allows it to be used more widely. (Makridakis, Wheelwright & Hyndman, 1998)

3.2.6 Croston's method

Croston (1972) presented a method specifically designed for forecasting materials with intermittent demand in his paper: Forecasting and Stock Control for Intermittent Demands. This method derives two-time series from the original data, one for non-zero demands and another one for inter-demand intervals. Then both of these new series are independently forecasted using exponential smoothing. Only one smoothing parameter α is defined and it is used to smooth both series. (Kourentzes, 2014)

The actual equation used for forecasting in Croston method is presented below. Forecasted consumption F_t is equal to exponentially smoothed size of non-zero demands divided by exponentially smoothed inter-demand intervals. The forecast is updated only when occurs so after periods with zero demand the forecast is equal to the previous period's forecast.

$$F_t = \frac{z_t}{p_t} \tag{9}$$

Since its inception Croston's method has been the focus of multiple studies (for example Willemain et al. 1994, Johnston & Boylan, 1996) and has been widely applied in practice as it is available in several forecasting software packages. Case studies have shown the method leading to good forecasting accuracy and inventory performance (for example Willemain at al., 1994, Johnston & Boylan, 1996).

However, Croston's method has been criticized for its theoretical grounding (Snyder, 2002, Shenstone & Hyndman, 2005) and for its assumption that inter-demand intervals and demand volumes are independent (Willemain et al. 1994).

3.2.7 Boylan-Syntetos

In 2001 Syntetos and Boylan proved the bias of Croston's method and proposed a new model with a correction to the problem which showed improved accuracy.

They used Croston's method as a basis and approached the accuracy problem from a mathematical point of view and found two problems. Firstly, Syntetos and Boylan identified a mistake in the mathematical derivation used to calculate expected estimate of demand. Secondly, they found a source of bias in Croston's model and developed a modification that theoretically should eliminate it. Simulations presented in their 2001 paper showed this modified model to reach higher forecast accuracy than original Croston's method. (Syntetos & Boylan, 2001)

3.3 Forecasting method selection framework

As noted before there are numerous possibilities for generating forecasts and selecting a method that best suits the needs is not always an easy task. Testing all available methods is rarely feasible and instead some criteria to select a smaller subset of them to be tested should be applied. Earlier studies have presented frameworks for choosing the most potential forecasting methods based on available data and observed deviation in demand. One of those frameworks, presented as a decision tree in figure 6, has been created by Sepúlveda-Rojas et al. (2015).

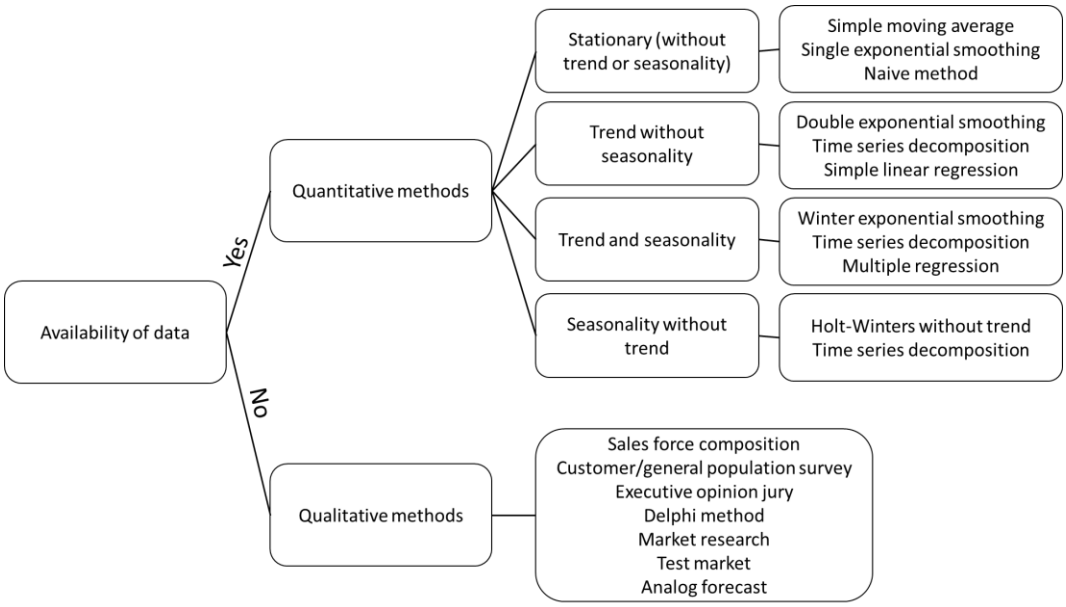

Figure 6. Forecast method decision (Adapted from Sepúlveda-Rojas et al., 2015)

The first selection criteria in this framework is availability of data. Formulas used in quantitative methods require historical consumption data as input so they cannot be used new materials. Another situation where required data might not be available is if the company is not keeping records of past consumption.

In the situations where not enough data is available only qualitative methods can be used. For these cases Sepúlveda-Rojas et al. (2015) suggest the following methods as options:

- Sales force composition
- Customer and general population survey
- Executive opinion jury
- Delphi method
- Market research
- Test market
- Analog forecast

Aforementioned methods rely more or less on intuition and are subject to biases of the one generating the forecast (Sepúlveda-Rojas et al., 2015). The main focus of this thesis is in improving the case company's automated forecasting process which has access to past consumption data so these qualitative methods will not be discussed further.

In cases where data is available Sepúlveda-Rojas et al. (2015) suggest identification of trends and seasonality as the next step. Depending on if these demand patterns can be found in the historical data an appropriate model is chosen. This approach requires setting arbitrary cut-off values on what is considered trending or seasonal and periodically reanalyzing the data to make sure that the demand has remained within those limits. If it is identified that a material should be forecasted by a different method according to the decision tree in figure 6, it has to get reinitialized. (Sepúlveda-Rojas et al., 2015)

3.4 Categorization of demand

All forecasting methods have their own strengths and are best suited for materials with certain characteristics in the demand. The usual approach to categorization of demand in software packages that generate forecasts is to arbitrarily categorize materials based on their demand patterns and base forecast method selection on this categorization, similarly to the decision tree presented in chapter 6. For example, cutoff values for number of demand occurrences in a year, standard deviation of the demand sizes or confidence levels for trend identification may be required as an input in the system which then categorizes materials into slow movers, intermittent, lumpy, trending etc. based on the demand history and selected values. (Syntetos, Boylan, & Croston, 2005)

Syntetos, Boylan and Croston (2005) presented an alternative approach to categorization which should lead to better forecasting accuracy at the cost of being more labor or computational intensive. They argue that it is more meaningful to generate forecasts for all materials by using multiple forecasting methods and comparing the achieved accuracy to find regions of superior performance. Then categorization of demand would be done based on these results.

When categorizing materials and finding regions of superior performance there are almost unlimited number or potential criteria. It is not feasible to try to find some defining characteristic that could be used for categorization. Instead of testing all possible characteristics Syntetos et al. (2005) argue that the most meaningful characterizing variables are coefficient of variation and inter-demand interval and finding regions of superior performance based on these should be sufficient for forecasting method selection. (Syntetos, Boylan & Croston, 2005)

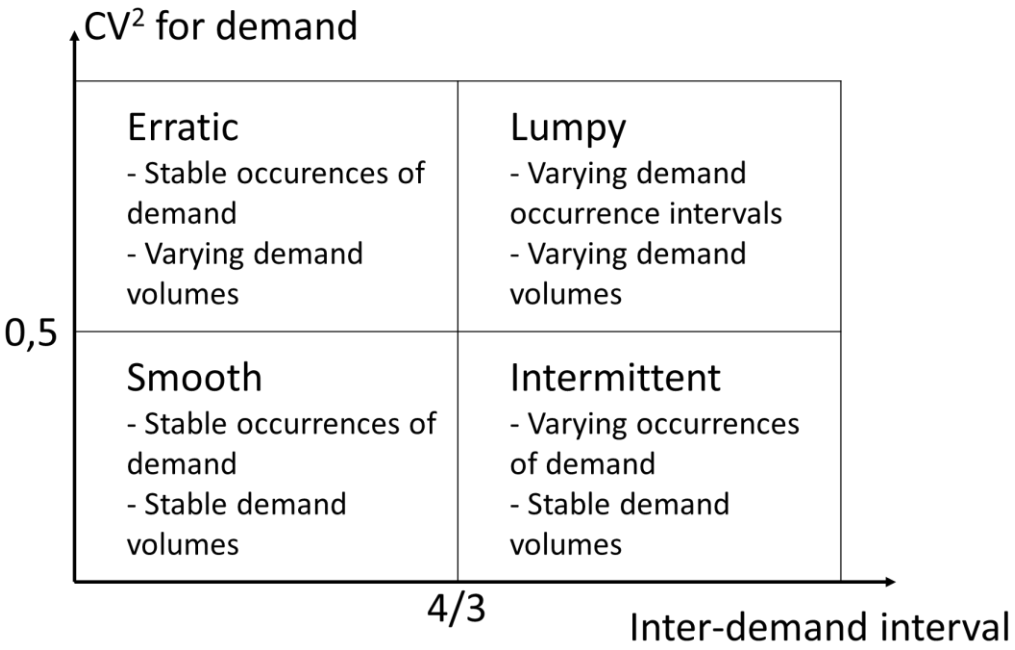

Figure 7. Demand categorization according to Syntetos et al. (2005): (Adapted from Syntetos et al. 2005)

Syntetos et al. (2005) categorize demand into four different categories, presented in figure 6, depending on how often demand occurs and how varying demand volumes are on those occurrences. In their model presented in the paper the deciding factors on which category a certain material belongs to are its squared coefficient of variation and inter-demand intervals found in the series. (Syntetos, Boylan & Croston, 2005)

Squared coefficient of variation is used to describe how varying the demand volumes are and inter-demand interval presents if there is demand during all or nearly all periods. This categorization is pretty intuitive and the logic behind is easy to understand. It also gives an idea of how easy the material is to accurately forecast as the more variance there is in the demand the harder forecasting becomes.

The easiest category to handle from material management point of view is the smooth category. The materials have rather stable demand volumes occurring on

practically all periods. As the demand is stable by all metrics SES or even SMA usually leads to satisfactory forecasting accuracy.

When demand is occurring constantly but with varying volumes Syntetos et al. (2005) categorize it as erratic. As the demand volumes, might vary significantly the forecasting difficulty and potential accuracy within this category is not necessarily good or bad, for some materials forecasted demand might be very close to actual demand whereas for some materials it might differ significantly.

Usually the metric used to identify intermittent demand is high amount of inter-demand intervals (for example Croston, 1972) but in this categorization approach intermittent category requires the material to have stable demand volumes when demand occurs in addition to having high amount of inter-demand intervals to be categorized into this box. If also the demand volumes have high variance, then the material is identified as lumpy. In principle, both of these categories are hard to forecast and traditional methods such as SMA or SES might not work adequately.

In the practical part of this thesis, all of the quantitative methods except for naïve method are utilized to find the optimal solution for future forecasting needs. The categorization of materials based on squared coefficient of variation and inter-demand interval will be to find the optimal forecasting scheme. In addition to this the categorization is used to better describe the demand data in chapter 7.1.

4 MEASURING FORECAST ACCURACY

Over the years since the advent of forecasting, numerous metrics have been developed for measuring accuracy of said forecasts. Hyndman and Koehler (2006) categorizes metrics into four categories based on the logic they are calculated.

4.1 Scale-dependent error metrics

The forecast error *e* used in scale-dependent error metrics is presented below (10) as a function of actual demand quantity *Y* and forecasted demand quantity *F*.

$$e_t = Y_t - F_t \tag{10}$$

Usually focus is on a longer time horizon so using a forecast error *e* of a single period is not feasible and instead errors from multiple periods are combined as mean or geometric mean. Most used of these are presented in formulas (11), (12) and (13) below. (Hyndman & Koehler, 2006)

$$Mean\ Absolute\ Error\ (MAE) = mean(|e_t|) \tag{11}$$

$$Geometric\ Mean\ Absolute\ Error\ (GMAE) = gmean(|e_t|) \tag{12}$$

$$Mean\ Square\ Error\ (MSE) = mean(e_t^2) \tag{13}$$

MAE, GMAE and MSE are suitable for measuring accuracy of a single series but because of their scale dependency they cannot be use for comparing multiple series. Differences in demand quantities are not accounted for which means in practice results become extremely skewed if one series contains for example screws with demand quantities in thousands and another one contains demand of motors with demand of dozen pieces. (Syntetos & Boylan, 2005)

4.2 Percentage error metrics

Several percentage error metrics have been developed to measure forecast accuracy and they are often the intuitive choice. Main advantages percentage error metrics have over scale-dependent error metrics are scale independence which allows multiple data series to be compared and if the error is for example 20 % it is easy to understand by just that number how accurate the forecast is without needing any additional information. The most used percentage based metric is mean absolute percentage error which is defined by below formulas. (Hyndman & Koehler, 2006)

$$Percentage\ error\ (p_t) = 100e_t/Y_t \tag{14}$$

$$Mean\ absolute\ percentage\ error\ (MAPE) = mean(|p_t|) \tag{15}$$

Percentage error metrics have couple notable disadvantages. They cannot be used for series that contain zero demand periods as that would involve division by zero. Percentage based error metrics can also lead to extremely skewed view of forecast accuracy if actual demand is close to zero. MAPE also has the disadvantage of putting heavier emphasis on positive errors than on negative. Symmetric MAPE (sMAPE) has been developed as an alternative to MAPE and it solves some problems MAPE faces. (Makridakis & Hibon, 2000)

$$Symmetric\ MAPE\ (sMAPE) = mean(200|Y_t - F_t|\ /\ (Y_t + F_t)) \tag{16}$$

However, even sMAPE cannot be used both the forecast and actual demand series contain zeros. sMAPE might also have both positive and negative values which is not ideal when interpreting the results (Makridakis & Hibon, 2000)

4.3 Relative error metrics

One of the alternatives to scale-independent metrics are relative error metrics which directly compare forecast errors obtained by using the method to be tested and some

benchmark method. After absolute errors have been calculated for both methods relative errors can be calculated by below formula where e_t^* is the benchmark method's forecast error.

$$Relative\ error\ (r_t) = e_t\ /\ e_t^* \tag{17}$$

The most used benchmark method is the naïve method i.e. the observed demand is used as the forecast for the period coming after it. Median relative absolute error and geometric mean relative absolute error presented below have been suggested by Fildes (1992) and by Armstrong and Collopy (1992) to be used for comparing forecast accuracy of different methods over multiple series.

$$Median\ relative\ absolute\ error\ (MdRAE) = median(|r_t|) \tag{18}$$

$$Geometric\ mean\ relative\ absolute\ error\ (GMRAE) = gmean(|r_t|) \tag{19}$$

However, Hyndman and Koehler (2006) note that relative errors cannot be used for all demand series. If the errors are small as is often the case with intermittent demand and naïve forecasting as the benchmark method calculating relative error is impossible because it would once again lead to division by zero.

4.4 Scale-free error metrics

Mean absolute scaled error (MASE) has been proposed as an option which can be used universally to measure forecast accuracy for all demand series. In MASE the error is scaled based on in-sample MAE of naïve forecast. Naïve forecast is generated as one period ahead for all periods in the sample and scaled error q is calculated according to below formula (5). (Hyndman & Koehler, 2006)

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|} \tag{20}$$

If scaled error is less than one the forecast being measured is more accurate than naïve forecast generated from previous month's demand and greater than one if the forecast is worse than said naïve forecast. As with other measurements error of one period is not that useful and mean of multiple periods is better for performance comparison of different forecast methods. Mean absolute scaled error can be calculated with below formula (6). (Hyndman & Koehler, 2006)

$$Mean\ absolute\ scaled\ error\ (MASE) = mean(|q_t|) \tag{21}$$

Mean absolute scaled error will be used in the practical part of this thesis as it is the only forecast accuracy measure mentioned which can be both calculated for nearly all materials and compared between different materials. Measuring forecast accuracy is not as easy as could be assumed but to be able to compare performance of different forecasting methods a universally applicable metric is needed. Based on current literature MASE is the closest available.

5 CASE COMPANY

Konecranes Plc is a global company focused on designing, manufacturing and marketing material handling solutions and offering related services. The company is headquartered in Finland but had sales and service locations in 50 countries in 2016. During the same year reached net sales of over 2 100 million euros and had 11 000 employees. In the beginning of 2017 Konecranes acquired material handling and port solution businesses of Terex Corporation and as a result key figures are expected to change significantly in 2017. (Konecranes, 2017)

5.1 Business areas of Konecranes

Konecranes consists of two main business areas: Equipment and Service. Business area Equipment offers world leading material handling solutions for a wide range of customers including for example process industries, nuclear sector, container handling and shipyards. Konecranes markets its product under multiple brands and in addition to products sold under Konecranes brand their technology can be found in SWF Krantechnik, Verlinde, R&M, Morris Crane Systems and SANMA Hoists & Cranes. (Konecranes, 2017)

Konecranes' product range comprises industrial cranes, workstation lifting systems and components for these such as wire rope hoists and electric chain hoists. In addition, Konecranes offers more specialized solutions to certain industries which have highly characterized needs to their material handling. These include but are not limited to nuclear cranes, container and bulk handling equipment, shipyard cranes and lift trucks. The company produces thousands of industrial cranes and tens of thousands of wire rope hoists, trolleys and electric chain hoists. (Konecranes, 2017)

As shown in Figure 5, over half of Konecranes' profits are generated by business area Service which offers a global service network with specialized maintenance and modernization capabilities. The extensive services include inspections,

preventive maintenance programs, remote and on-call service, repairs, spare parts, modernizations and consultation for all lifting equipment even for products originally purchased from competitors. According to current megatrends Konecranes has been investing into its proprietary internet of things platform called TRUCONNECT which gathers usage data and abnormal usage alerts and sends those over the internet to be processed. This data enables Service to identify maintenance and performance issues preemptively before they cause loss of productivity or affect safety. (Konecranes, 2017)

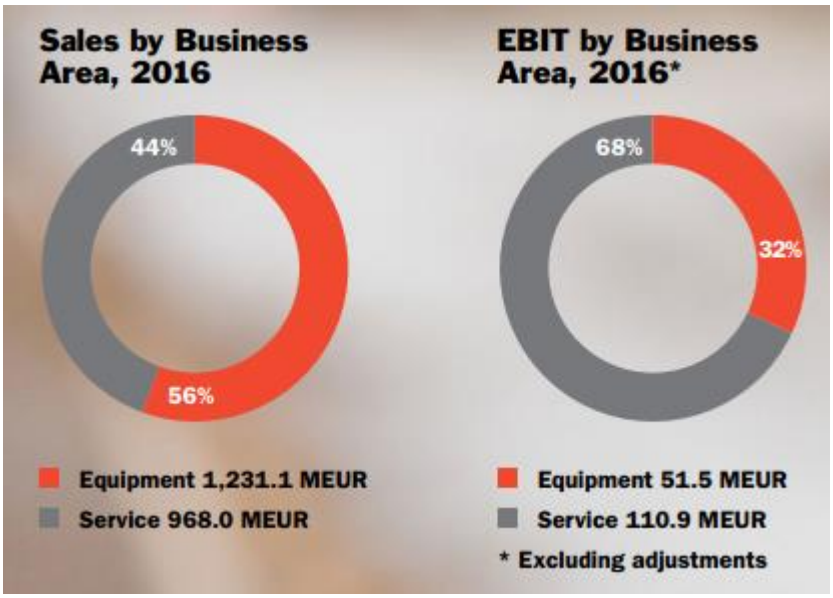

Figure 8. Sales and Earnings before interest and taxes (EBIT) in 2016 by business area. (Konecranes, 2017)

5.2 Mission, vision and values of Konecranes

According to mission statement Konecranes is not just lifting things, but entire businesses. This means that the company is not just selling and maintaining cranes and other lifting equipment but offers deeper cooperation to its customers. Konecranes helps customers in defining their needs and offers them the best solution to increase the customer’s productivity and profitability. (Konecranes, 2017)

The vision of Konecranes is to “know in real time how millions of lifting devices perform”. Gathering that information allows them to analyze the data around the clock and make their customers’ operations safer and more productive. This data of how the cranes are actually used also allows the company in product development and offering even more suitable replacements when the current equipment reaches the end of its lifecycle. (Konecranes, 2017)

Values of Konecranes are defined as Trust in People, Total Service Commitment and Sustained Profitability. Trust in people means that the company wants to be known for its great people. Responsibilities and career opportunities are also offered openly to those who have shown they are ready for that. (Konecranes, 2017)

Total service commitment is in the company values to represent that Konecranes wants to be known for always keeping its promises and servicing customers as well as possible. On the other hand, Sustained Profitability means that that customer satisfaction is not chased at the expense of profitability but instead a solution that benefits both parties is found. (Konecranes, 2017)

Strategy of Konecranes revolves around real time visibility to customer’s equipment, end to end profitability and shared & harmonized processes. Business area Service aims to utilize its global service network to service all types and makes of hoists no matter who manufactured them originally. TRUCONNECT and the visibility it offers allows them to offer real time care over the whole lifecycle of a crane and improves safety and productivity of customers’ operations. In business area Equipment Konecranes sees need based customer offering as key in reaching high customer satisfaction and profitability. Equipment is offered through direct and indirect channels to customers utilizing a multi-brand strategy. (Konecranes, 2017)

5.3 Markets in which Konecranes operates

Konecranes operates globally and has presence all over the world as can be seen in figure 7. Service units exist on all main continents and even production plants can be found on all continents except for South America and Australia in which subcontracting is used when needed.

To serve the customers better and identify local characteristics in the market a division to three regional areas has been done. The largest region, Europe, Middle East and Africa (EMEA), accounts for over half the work force and nearly half of the sales is generated by this region. The second largest region is Americas (AME) with around 2700 employees and 800 million euros in sales. The region with the lowest amount in sales is Asia-Pacific (APAC) which accounts only for 15 percent of sales. Smaller local brands are strong in APAC and they have a high portion of market share. (Konecranes, 2017)

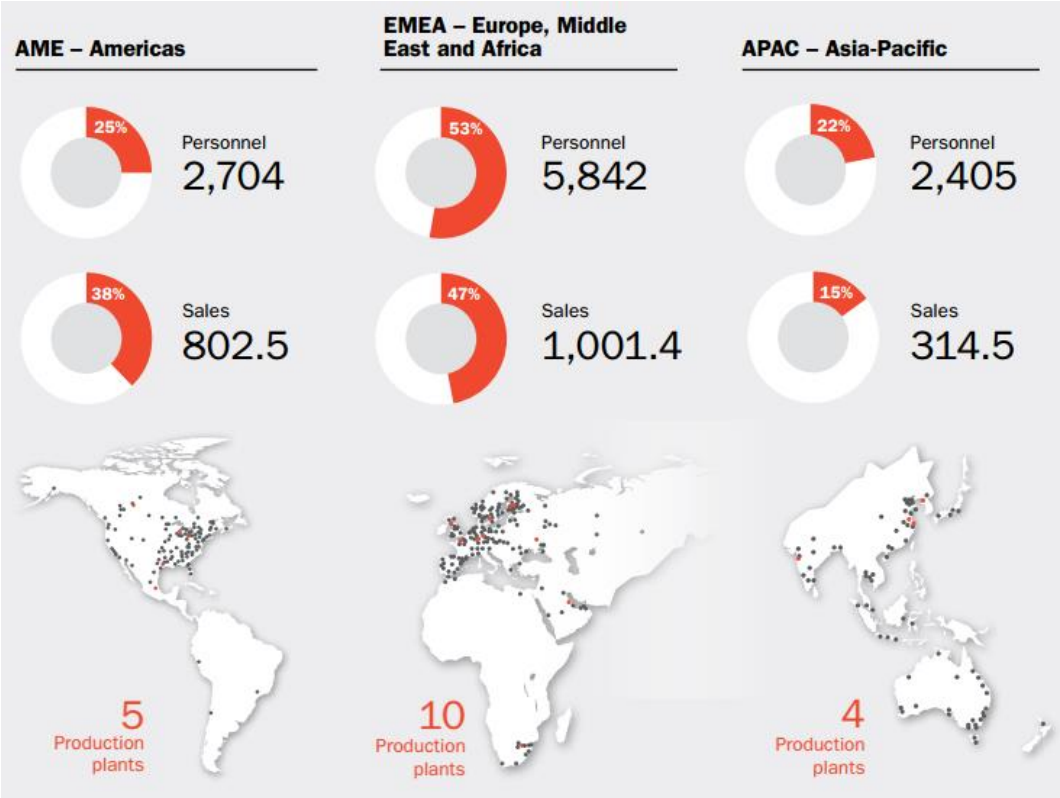

Figure 9. Regional view of Konecranes' operations. (Konecranes, 2017)

5.4 Products of Konecranes

Konecranes offers a wide variety of products for material handling. Most important of these products are presented in figure 8. Since there is rarely need for this kind of products in consumer markets, practically all Konecranes' business is conducted in business to business environment.

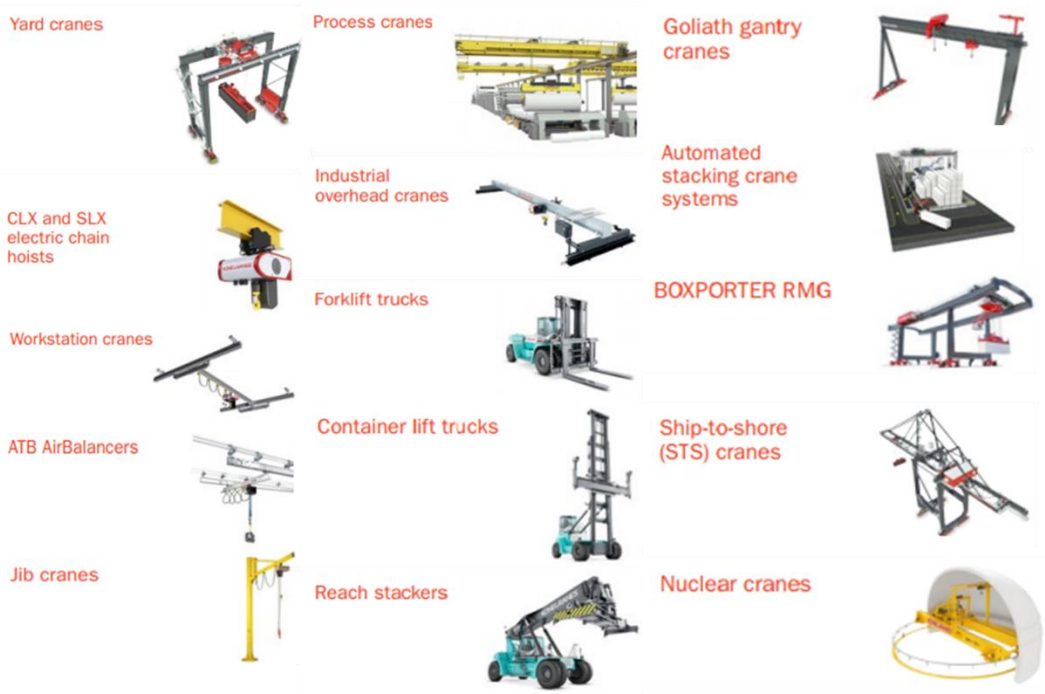

Figure 10. Main products of Konecranes (adapted from Konecranes, 2017)

There are very few standardized products in Konecranes' offering and most of them have to be customized to better suit customers' needs. Especially the parts of the crane which define range of movement usually have to be customized so they match with the customer's facilities. Another feature that is crucial to get right and changes widely between customers is the lifting capacity.

Some products require so heavy modifications that they even have to be engineered to fulfill customer needs. These are typically larger projects involving multiple people and can span timeframes of several years.

Because of all these customizations are needed it is not possible to define one bill of materials (BOM) for the products. This presents demand forecasting with the challenge that even if end product demand was known exactly it is not possible to calculate which materials are needed to fulfill that demand unless all the characteristics of the final products were known. In reality that is not a realistic expectation since there is almost an unlimited amount of possible product variations. Instead historical demand of components is used to extrapolate future demand on per material basis.

6 CURRENT FORECASTING PROCESSES IN KONECRANES

In the past as Konecranes was using multiple ERP systems there was no defined forecasting process. The historical consumption data required for material level forecasting was so fragmented into multiple systems which saved it in different formats made a global forecasting process not feasible to implement. With SAP implementation project, a better visibility to all actions going on in the company was received which has increased potential benefits and attractiveness of forecasting.

With this new visibility two forecasting processes were implemented. More labor-intensive demand supply balancing which considers hot offers and expert opinions from sales function is used for some key products. Because of the resources it requires there are no plans to get all materials into its scope. To generate forecasts also for other materials a totally automatic process is needed.

Currently all materials for which demand is forecasted have the forecast data is generated on weekly level. This level of detail is needed because of the way material management is set up in SAP. Forecasting materials with high demand volumes on a monthly level would lead to higher inventories than needed and thus increase working capital. Reduction of working capital has been one of the main targets for material management organization for the past years so switching forecasting setup to a monthly level is not desirable, at least not for all materials.

The horizon for which demand is forecasted is 12 months. Forecasts are not used only for optimizing the next purchases but for selected materials the forecasted demand is also shared with the suppliers so they can improve their inventory management and capacity utilization. Suppliers usually prefer to have forecasts for as long into the future as possible as long as their accuracy does not decrease significantly. These longer forecast horizons also give the option for better

optimization of order quantities so inventory carrying costs and procurement costs can be minimized by utilizing methods like economic order quantity.

6.1 Demand-supply balancing

Demand-supply balancing (DSB) process, presented in figure 11, is a judgmental forecasting process used by Konecranes to estimate future demand for some of its product families. As the process is judgmental and thus requires input from personnel it is not feasible to expand its scope to cover all products.

	DEMAND PLANNING	DEMAND CLOSING	SUPPLY PLANNING	DEMAND-SUPPLY BALANCING
WHEN	**WEEK 1**	**WEEK 2**	**WEEK 3**	**WEEK 4**
WHO	E.g. sales person, country sales manager	E.g. vice presidents of regions and business units	E.g. vice president of supply, director of supply unit	E.g. vice presidents of business area and supply
INPUTS	Sales funnels, orders,hot orders and opportunities	Consolidated volume demand plans, sales targets	Sales volume plan proposal	Supply plan proposal
OUTPUTS	Consolidated demand view on country and area level	Unconstrained sales volume plan	Supply plan proposal	One balanced plan
SYSTEM	E.g. ProCom and Excel	E.g. Excel	E.g. Excel and SAP	E.g. Excel and PowerPoint

Figure 11. Konecranes' demand-supply balancing monthly process. (Pakarinen, 2011)

This monthly process is initiated by country sales manager who gathers information about sales funnel, orders and potential opportunities from sales person and consolidates that data. After this the consolidated data is reviewed by the country

sales manager after which it is delivered to the competence center which is responsible for consolidating the data further and generating sales plan for the region.

During week two this consolidated sales plan is delivered to the vice president of regions who links it to monetary sales forecasts. Adjustment proposals might also be raised at this phase if those are deemed necessary. Finally, this plan is matched to the sales target volumes and brought to the demand closing meeting in which an unconstrained sales volume plan is generated.

This unconstrained sales volume plan is then used as an input for supply planning phase in which it is checked if the factories have the capacity and have materials available to fulfill the planned sales. In case constraints are found in the supply chain which prevent fulfillment of the sales plan a modified supply plan proposal with allocations is generated. This plan is then used in the final stage, demand-supply balancing. In this final meeting between vice president of the business area, vice president of supply, chief procurement officer and finance the goal is to reach a consensus, one balanced plan.

As inventory management requires forecasts on SKU level this balanced plan is not on a detailed enough and some additional data manipulation is needed to disaggregate it. Many Konecranes products, even the ones in the scope of DSB, do not have a fixed bill of materials which could be directly used to calculate material requirements if end products are known. Instead historical data for the end products is analyzed and the probabilities of usage for certain material in the selected end product is calculated and this is used to disaggregate the end product data to component level.

6.2 Statistical forecast

Currently Konecranes utilizes SAP to generate SKU level forecasts via statistical method. The model used for all materials has been simple moving average using

historical data of the past 13 weeks. Main reason for this choice has been its simplicity which allows users to easily and quickly understand why it outputs a certain number. This forecasting process is carried out once a month. However, the accuracy of this forecasting method has not been measured actively before this thesis and there have been some discussions about its suitability to this use case and especially as a blanket solution for all materials.

7 COMPARISON OF TIME SERIES MODELS

The current forecasting process used is not as accurate as the company would like so possibilities for parameter optimization and other models were studied. Selection criteria for candidates as potential new model was mainly based on the following characteristics:

- Easily deployable
- Can be automatically run for a wide variety of materials
- Based on best practices presented in literature
- Can be run on a commercially available, actively developed software solution

7.1 Sample data

Data used for testing different forecasting methods consists of two data sets. One contains demand data from Hämeenlinna plant and the other from a plant located in Springfield. As the goal is to find models that can be applied to a wide range of materials the only scope restriction for materials was annual consumption which was given minimum value of 3. Main reason for this restriction was to reach a systematic way to clearing major outliers in accuracy measures. Such small volumes of demand cannot be reliably forecasted so including them in the data was not practical from that point of view either.

All the data was obtained from the company's ERP system, SAP, aggregated on weekly level; sample of the source data can be seen in appendix I. SAP is relatively new system in Konecranes and its deployment schedule played a major part in plant scope selection. Deployments are ongoing and these two plants were among the first ones to take SAP into use so they had demand data available from 2015 and 2016 which allowed generation of forecasts based on 2015 data and comparing that to actual demand that happened in 2016.

However, this limited history data available also affected the possibility to analyze if some demand patterns can be identified, namely seasonality, which would require demand data from multiple years. As the company operates mostly in business to business markets and mostly serves industrial customers seasonal changes in demand are practically non-existent and seasonality is not seen as a big factor from demand forecasting point of view. Based on these reasons, seasonality was not considered in this study.

The demand data contains materials with varying degrees of demand variance and inter-demand intervals. Some descriptive statistics for the items are presented in tables 1 and 2 below.

Table 1. Statistical characteristics of demand in Hämeenlinna.

	Mean demand volume/occurrence [UoM]	Standard deviation of demand volume/occurrence [UoM]	Coefficient of variation	Mean inter-demand interval [Week]
Max	233640	73771	499	52
Median	9,5	5	1,6	1,6
Min	1	0	0	1

The data used in this study contains 2277 materials from Hämeenlinna with varying degrees of demand. Demand volumes per demand occurrence have values ranging from 1 to 233640 in the material's base unit of measure (UoM) which is based on the type of said material. For example, motors have piece as base unit of measure while cables might be measured in millimeters. Usually the base unit of measure is the same as in which the material is purchased and consumed with some notable exceptions especially in cases where the material is purchased from a supplier located in the United States who often use feet and inches. In these cases, the ERP system converts those amounts into base unit of measure and does calculations based on that. Because of these automatic conversions the consumption data

available in SAP is in base unit of measure and it is the most feasible approach to handle the data in these base UoMs.

Deviation in these occurrences has high variance as well as can be seen from Standard deviation of demand volume/occurrence and coefficient of variation columns. Mean inter-demand intervals, meaning the time between demand occurrences, also vary widely between different materials. Some materials have inter-demand intervals of 1, i.e. there has been demand for these materials every week, while some materials have only been needed once a year and have inter-demand interval of 52.

Table 2. Statistical characteristics of demand in Springfield.

	Mean demand volume/occurrence	Standard deviation of demand volume/occurrence	Coefficient of variation	Mean inter-demand interval
Max	16205	5981	40639	52
Median	4,2	2	1,6	3,5
Min	1	0	0	1

The second set of data gathered from Springfield contains 2507 materials and also has high variance in demand behavior between materials. The maximum mean demand volume/occurrence is lower than in Hämeenlinna as is standard deviation of demand/occurrence. However, maximum coefficient of variation is higher than in Hämeenlinna which means that there are materials with higher levels of variation when the variation is considered in proportion to demand volume instead of looking at absolute values of variation.

Presenting the characteristics of the data at hand by some way of consolidation, like tables 1 and 2, is the most common way to showcase what kind of demand is used in the research. In cases where the data contains highly variable sets, like this study, presenting these statistical characteristics does not really tell much more than that

there are materials with very different demand patterns. Based on these tables it is impossible to say how easily or accurately the demand could be forecasted.

To better describe and categorize the demand the categorization scheme presented by Syntetos et al. (2005) has been utilized with the cut-off values defined by Kostenko and Hyndman (2006). in their paper. items are divided into four different categories and presented in a matrix which later had its categorization threshold values modified by Kostenko and Hyndman (2006). These categorizations containing the sample sets of this study are presented in figures 11 and 12 below.

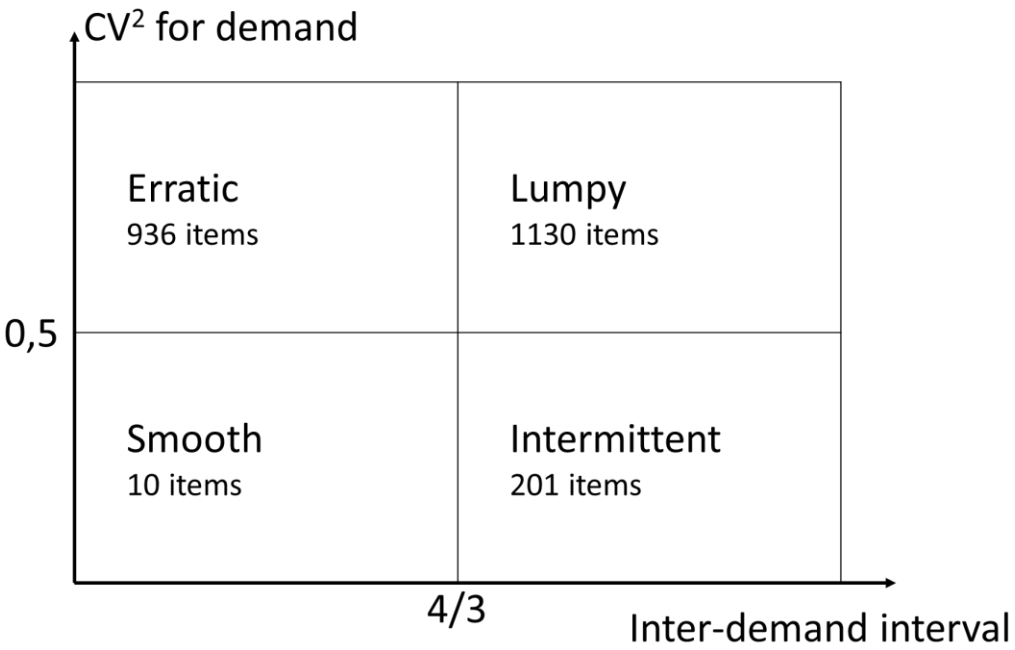

Figure 12. Demand categorization of sample materials from Hämeenlinna.

Very small portion, less than 1 percent, of materials used in Hämeenlinna belong to the smooth category which has traditionally been considered the easiest to forecast and achieve acceptable accuracy on. Majority of the materials get located to the top portion of the matrix meaning they have varying demand volumes. Some of these have demand occurring rather continuously and some have demand occurring only occasionally.

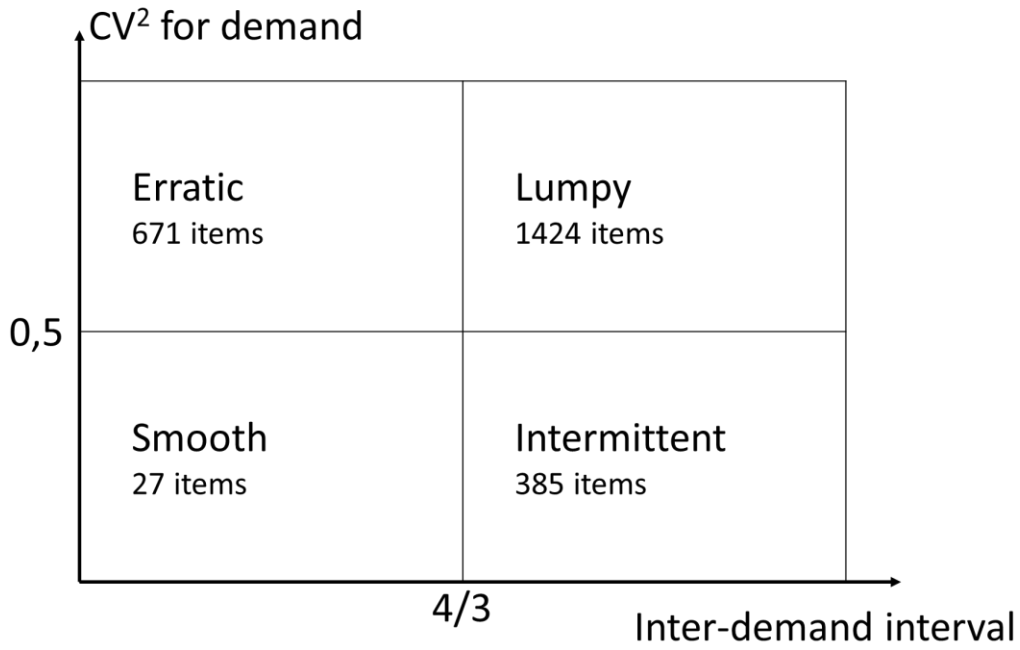

Figure 13. Demand categorization of sample materials from Springfield.

In Springfield the situation is rather similar to Hämeenlinna according to this categorization. The biggest difference is that higher portion of materials are focused on the right side of the matrix meaning periods with no demand are more common. Also in this set the focus is on the top part so demand intervals aren't the only varying parameter in demand patterns but also demand volumes when demand occurs vary pretty much.

As a whole it could be said that based on this analysis most of the materials behave in a way that is hard to forecast. Both inter-demand intervals and demand volumes when demand occurs change which introduces two variables with highly changing features.

7.2 Forecast accuracy metric selection

As the data, presented in chapter 10.1, has multiple materials with intermittent demand i.e. intervals with zero demand, the most intuitive accuracy metrics, which are percentage error metrics, cannot be used. Calculating for example MAPE for

intermittent demand leads to division by zero and thus is not suitable for the sample used in this research.

Calculating scale-dependent error metrics would be possible for all materials but because the sample contains materials with very varying demand quantities combining output of scale-dependent metrics would skew the data. Materials with high demand quantities, for example bearings, would receive much higher weight than materials with low quantities. In reality the materials with lower demand quantities are often more expensive components and accurate forecasts for these might be even more critical than forecasts for high moving parts.

Relative error metrics have been recommended by Armstrong and Collopy (1992) for measuring accuracy of multiple series. The preferred forecasting method used as a benchmark in these metrics has been naïve forecasting. However, calculating relative errors based on naïve forecasting might become impossible when errors are small, which is likely with intermittent demand, as that would lead to division by zero. (Hyndman and Koehler, 2006)

Eliminating the previously mentioned metrics from the pool of metrics presented in chapter 6 leaves only scale-free error metrics as a possibility. Hyndman and Koehler (2006) suggest mean absolute scaled error, MASE, to be used and it was chosen for this study because of its universal applicability.

7.3 Finding the most suitable forecasting methods

The approach used to find the optimal forecasting solution for the available data was a combination of the decision tree presented in chapter 6 and the approach of generating forecasts first and trying to find regions of superior performance presented in chapter 7. The initial selection of forecasting methods to be tested and further analyzed followed loosely the decision tree and as a result forecasts were generated with the following 6 methods:

- Boylan-Syntetos
- Box-Jenkins
- Croston's method
- Holt-Winters
- Single exponential smoothing
- Simple moving average

Because many of these methods have parameters that affect their outcome a total of 31 forecasts were generated per data set. As the source data was available from two different supply units this meant 62 forecasts in total.

For simple moving average, which is mathematically the easiest, forecasting method the forecasts were generated using Microsoft Excel's basic functions. The parameter available to change the behavior of SMA is the time periods used in the calculation and these were tested from 4 to 52 weeks in 4 week intervals i.e. 4 weeks, 8 weeks, 12 weeks etc.

The other selected forecasting methods, Boylan-Syntetos, Box-Jenkins, Croston's method, Holt-Winters and single exponential smoothing, were tested utilizing R software environment, RStudio and the freely available packages "forecast" and "tsintermittent" developed by Rob Hyndman and Nikolaos Kourentzes respectively. For Croston's method and single exponential smoothing the tested smoothing parameters ranged from 0,1 to 0,4 with 0,05 intervals. Boylan-Syntetos, Box-Jenkins and Holt-Winters had their parameters optimized automatically.

As it is not feasible to compare 31 different forecasts at once to try to find regions of superior performance, the number of forecasts was first limited to one or two forecasts per forecasting method i.e. the best performing parameters were identified and selected for further studying. This was done by a four step process. First mean absolute scaled error was calculated per material for all generated forecasts on 3-, 6- and 12-month forecasting horizons. After this average, median and 99th percentile were formulated from the MASE values per forecast and forecasting

horizon. To get a better idea if certain parameters performed better with some coefficient of variation regions and/or inter-demand interval regions tables similar to table 3 below were generated. Count of materials that had the lowest error is presented in this example. The values on top are the upper cut-off values of coefficient of variation used to define regions.

Table 3. Material count of best performing Croston's method parameters by coefficient of variation regions with Hämeenlinna data.

	Coefficient of variation											
Method	**0**	**0,5**	**1**	**1,5**	**2**	**2,5**	**3**	**3,5**	**4**	**4,5**	**5**	**>5**
Croston 0.1	85	4	57	237	317	169	104	62	33	24	2	16
Croston 0.4	72	12	59	172	176	57	44	15	7	2	0	20
Croston 0.35	3	0	8	16	30	8	2	1	1	1	0	1
Croston 0.2	2	0	3	28	28	10	10	7	2	3	0	0
Croston 0.3	1	0	10	37	24	11	6	2	0	1	1	0
Croston 0.25	4	1	10	32	55	15	4	4	4	1	0	2
Croston 0.15	1	0	11	41	49	17	14	9	0	0	0	0

Finally, all these factors were taken into account while choosing the method-parameter-combinations that had the highest potential for being a part of the optimal forecasting solution. Surprisingly, there was not a single forecasting method for which one parameter would've performed significantly better in one region and another on some other region but instead there was either one clearly superior or two similarly performing parameters in all regions. As a result of this elimination, the following seven forecasting method-parameter-combinations were left:

- Boylan-Syntetos
- Box-Jenkins
- Croston's method
- Holt-Winters
- Single exponential smoothing (0,1)
- Single exponential smoothing (0,4)
- Simple moving average (8 weeks)

The performance metrics used for the final selection were the same ones that were used for eliminating some method-parameter combinations previously. As table 5 shows, the average MASE over all materials varied widely between different forecasting methods. However, the 99th percentile values are much closer to each other which tells us that Croston's method's Boylan-Syntetos' poor average is caused by a handful of materials for which the error has been considerably worse than with other methods.

Table 4. Statistics of MASE calculated per material for 12 month horizon in Springfield.

	SMA 8w	SES 0,1	SES 0,4	Croston 0,1	Boylan-Syntetos	Box-Jenkins	Holt-Winters
Average	1,72	2,16	1,61	187,36	12,07	1,98	3,24
Median	0,81	0,86	0,81	0,95	0,95	0,88	0,90
99th Percentile	20,89	24,47	16,60	37,98	32,95	23,74	30,41

While looking for regions of superior performance by coefficient of variation, no clear regions where one method performed better than others could be found as can be seen in table 5. This is only an example of how one of these tables looked like, in practice similar ones were both of the demand series and for all forecasting time horizons that the company is interested about.

Table 5. Count of materials for which the forecasting method was most accurate by coefficient of variation, Springfield 12 month horizon.

	Coefficient of variation											
	0	**0,5**	**1**	**1,5**	**2**	**2,5**	**3**	**3,5**	**4**	**4,5**	**5**	**>5**
SMA 8w	70	12	54	173	172	86	123	18	16	2	7	10
SES 0.1		3	4	30	59	20	31	26	9	7	4	14
SES 0.4	52	21	59	169	210	52	68	17	4	2	1	7
Box-Jenkins	16	2	17	44	70	30	50	11	5	3	5	5
Boylan-Syntetos	13	5	19	47	68	32	48	11	6	1	5	8
Croston 0.1	14	2	18	66	66	27	25	2	3			

Looking for regions of superior performance by inter-demand interval shows more actionable intel. According to the information in table 6 it can be seen that for materials which have inter-demand interval of 1 single exponential smoothing seems to be the clear winner in performance. While inter-demand interval increases there is a clear decrease in SES 0,1 performance. For materials with inter-demand interval 2, simple moving average of 8 weeks and single exponential smoothing with smoothing constant 0,4 seem to be pretty close to each other but SES 0,4 pulls ahead when inter-demand interval is between 3 and 5 and remaining rather close to SMA 8w until inter-demand interval reaches values greater than 10.

Table 6. Count of materials for which the forecasting method was most accurate by inter-demand interval, Springfield 12 month horizon.

	Inter-demand interval									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**>10**
SMA 8w	42	167	41	59	31	36	22	20	35	441
SES 0.1	115	77	1	1	3	4		1	2	3
SES 0.4	42	146	107	81	37	28	22	29	21	149
Box-Jenkins	67	78	9	14	6	11	5	4	9	55
Boylan-Syntetos	57	89	19	14	7	3	13	13	10	38
Croston 0.1	7	75	27	25	10	18	6	13	9	33

For Hämeenlinna factory the data looks very similar and same pattern can be found while analyzing forecast accuracy by inter-demand interval. This was to be expected as these factories serve a similar purpose in the supply chains and product mixes or typical demands are not totally different. It can be concluded as a result that similar forecasting scheme will work for both of these units.

Based on the data presented above a new forecasting process is proposed in which forecasting method is simple exponential smoothing for all materials but smoothing constant is chosen based on inter-demand interval calculated from past demand. Materials for which inter-demand interval is less than 2 should be forecasted with smoothing constant 0,1 and rest of the materials with 0,4. One more set of forecasts

were generated with this new approach and it showed better or similar performance to all single methods' results in all metrics presented in table 7, where it is denoted as "New".

Table 7. Statistics of MASE calculated per material for 12 month horizon in Springfield.

	SMA 8w	SES 0,1	SES 0,4	Croston 0,1	Boylan-Syntetos	Box-Jenkins	Holt-Winters	New
Average	1,72	2,16	1,61	187,36	12,07	1,98	3,24	1,57
Median	0,81	0,86	0,81	0,95	0,95	0,88	0,90	0,79
99th Percentile	20,89	24,47	16,60	37,98	32,95	23,74	30,41	16,60

Also this test was carried out for both plants and all forecasting horizons and in every case an improvement or at least similar performance was achieved to what would have been possible while utilizing only one method-parameter-combination.

7.4 Accuracy of new scheme compared to current quantitative method

When considering changes to business processes it is important to compare the new way of working to the old approach and weigh the pros and cons the change would cause. Even simple changes usually require some work to be done, at least training, and thus incur expenses which the improved performance of the new solution has to cover for the change to be profitable. In case of forecast accuracy, quantifying the monetary benefit of improvements is not an easy task as forecasts affect multiple areas of business. In practice this would require detailed simulations and is out of the scope of this thesis.

However, the consensus is that improved forecast accuracy enables the whole supply chain to perform more efficiently if the information is utilized properly. Being able to show that the new process is objectively better also reduces resistance to the change. To prove that the new forecasting scheme performs better than

current methods, average, median and 99th percentile of mean absolute scaled errors (MASE) of materials were calculated.

First MASE was determined per material and average of these error values across all materials was calculated. These averages are presented in figure 14 in 3, 6 and 12 month forecasting horizons. Two leftmost columns in every time horizon present average MASE in Springfield and two rightmost columns present same values in Hämeenlinna. As can be seen in the figure below, the average MASE in Hämeenlinna decreases to less than half of current values with the new forecasting scheme in all forecasting horizons. In Springfield the improvement is not as drastic but clearly noticeable at 18 percent.

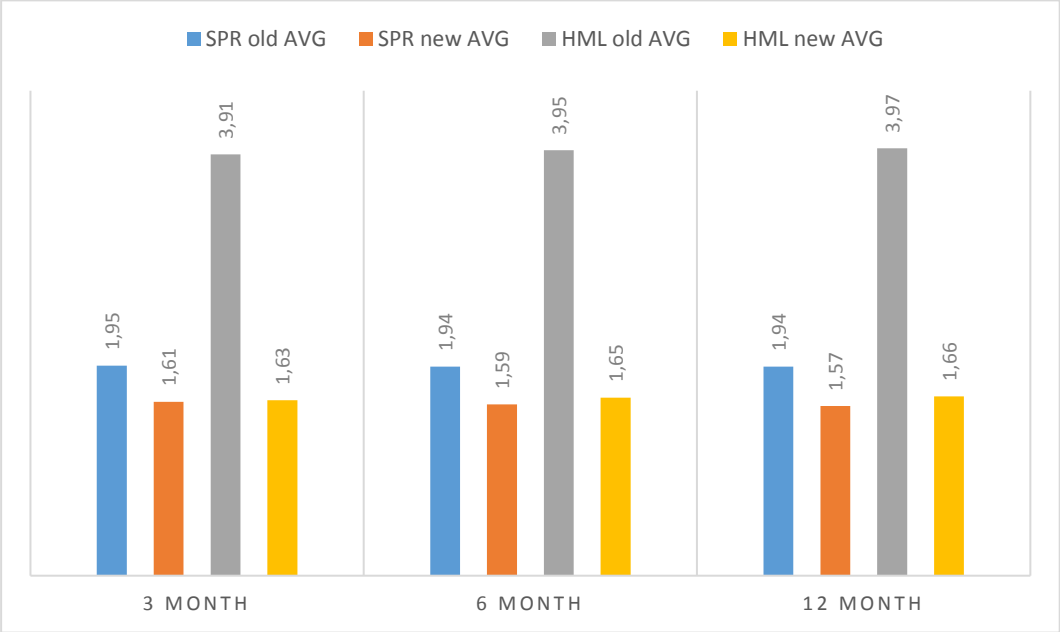

Figure 14. Average MASE with old and new quantitative methods.

Similarly calculated median of mean absolute scaled error values across all materials can be seen in figure 15. While looking at medians, the performance of new scheme and current method are much closer to each other. However, this statistic also shows the new scheme to achieve higher accuracy in both these plants at all forecasting horizons.

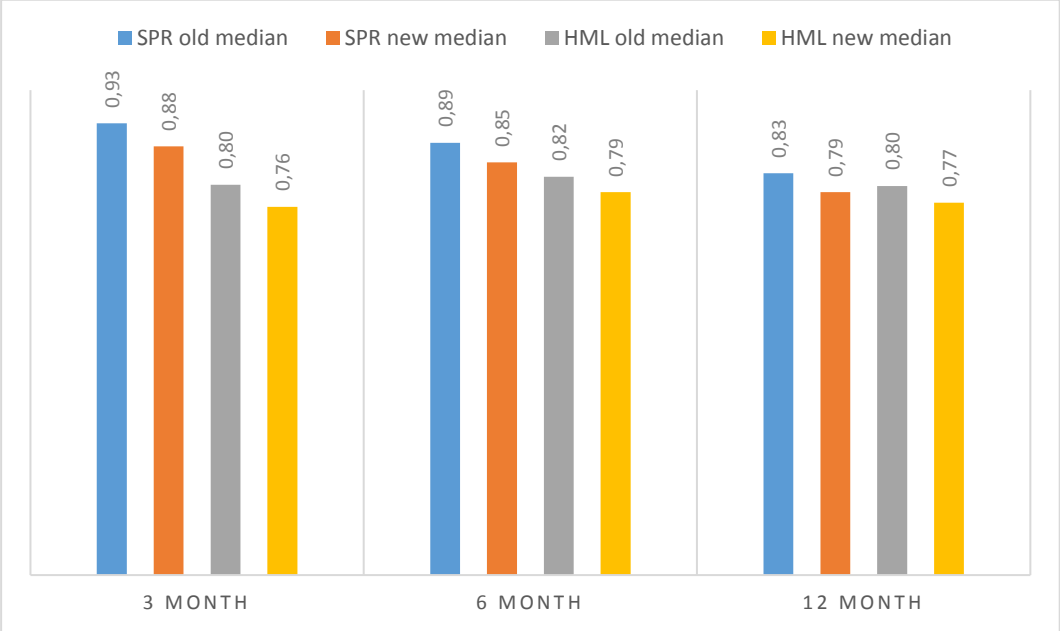

Figure 15. Median MASE with old and new quantitative methods.

While looking at worst case scenarios of forecast accuracy i.e. 99th percentile MASEs, there is a clear improvement in accuracy. With this metric, presented in figure 16, even the new scheme has high levels of error for some materials but compared to current solution its error is clearly lower.

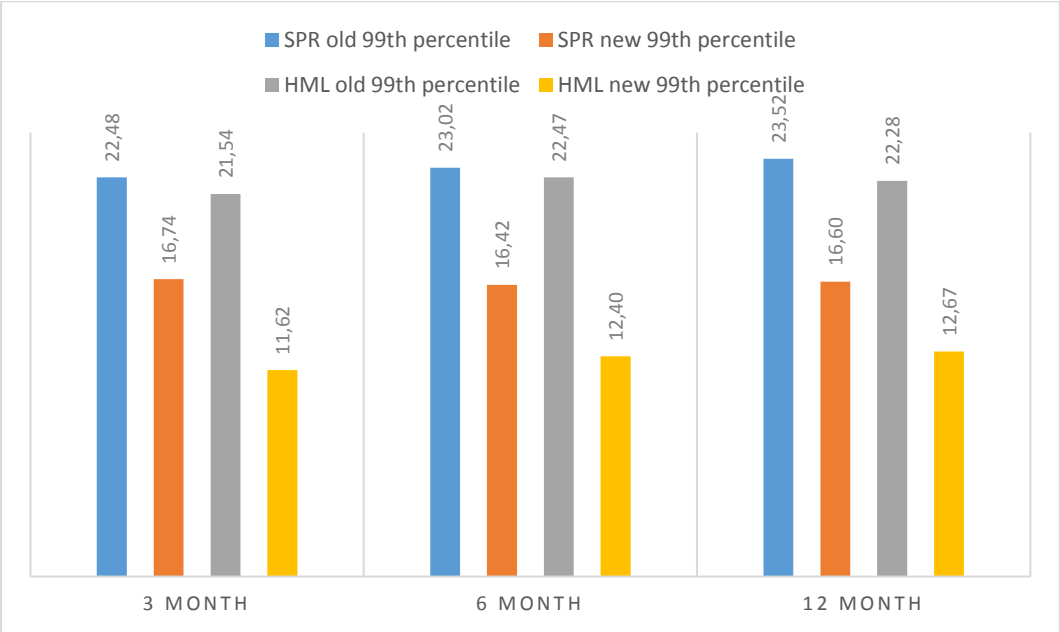

Figure 16. 99th percentile MASE with old and new quantitative methods.

7.5 Accuracy of new scheme compared to DSB process

Because it is nearly impossible to replicate or recreate the conditions for qualitative forecasting from the past, the sample size for comparing how the new model performs when pitted against the DSB model is smaller. Historical forecasts that had been active in the beginning of 2016 were pulled from SAP and this was compared to what the forecasting errors for these materials would have been with the new forecasting scheme. For Springfield data the sample size is 834 materials and for Hämeenlinna 94 materials.

Same approach as for quantitative method comparison was used for comparing DSB to the proposed forecasting scheme and similar graphs can be found below. Figure 17 shows the new scheme outperforming the much more labor intensive DSB process in Springfield by a noticeable margin. In Hämeenlinna the difference in averages between the two methods is low and the quantitative model is losing only slightly to DSB process.

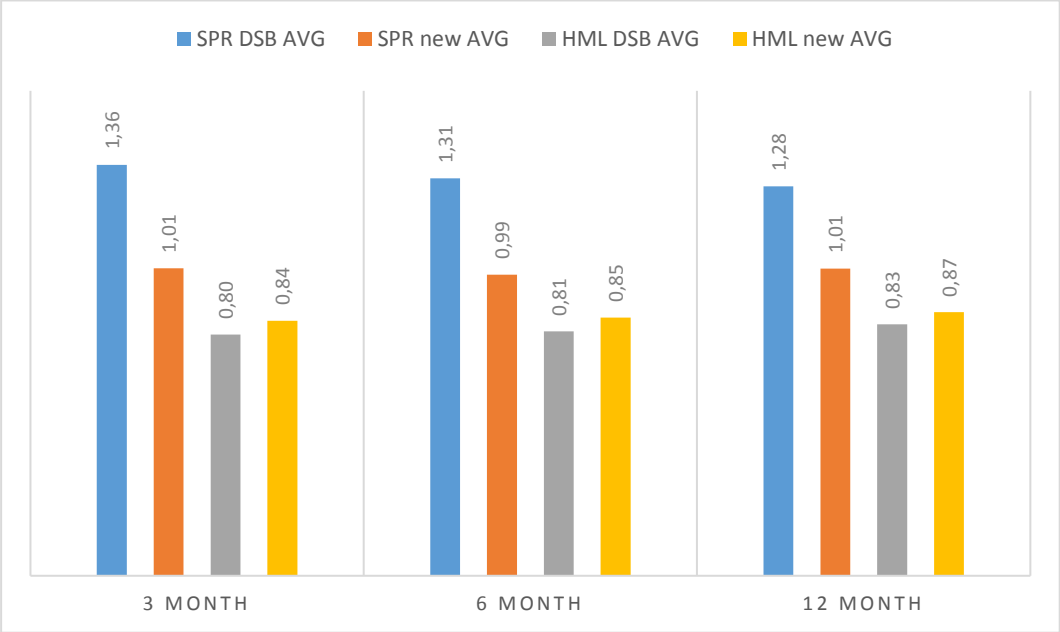

Figure 17. Average MASE with DSB and new quantitative methods.

Figure 18 shows the median across the materials. From this point of view the picture is very similar to averages. In Springfield the new scheme leads to lower errors than DSB process and in Hämeenlinna its error is only slightly higher. All forecasting horizons show similar differences in performance.

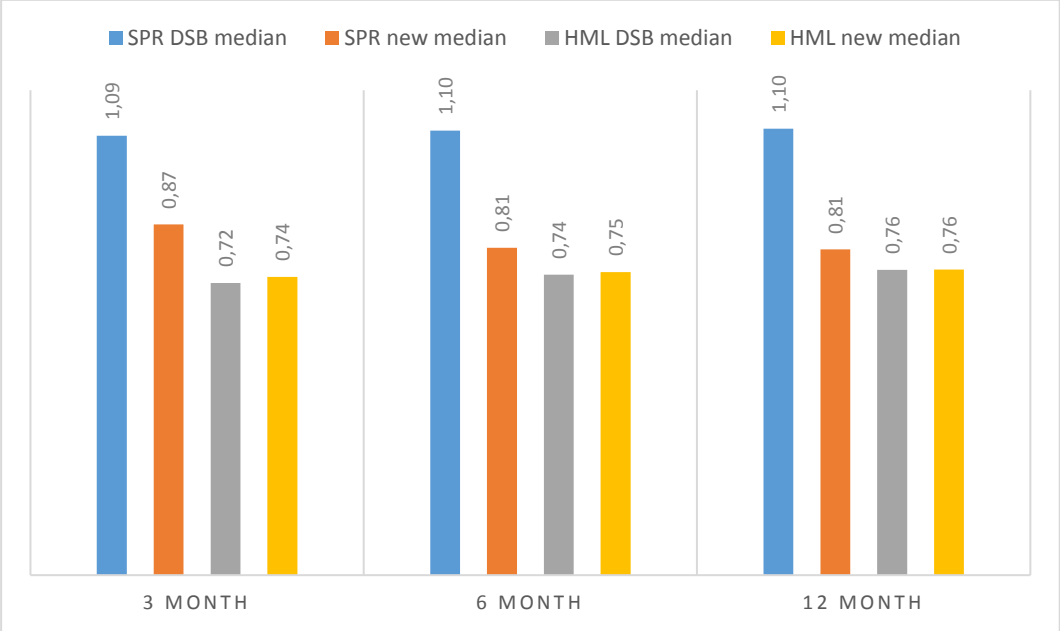

Figure 18. Median MASE with DSB and new quantitative methods.

While looking at the worst case scenarios of mean absolute scaled errors in figure 19, the story stays the same. Proposed new forecasting scheme outperforms DSB at all time horizons in Springfield and only loses slightly in Hämeenlinna. Based on these results it would be justifiable to question the benefits of DSB process and if the very slight accuracy improvement it generates in Hämeenlinna is worth all the additional resources required by the process especially when it is taken into account that the quantitative method can be totally automated.

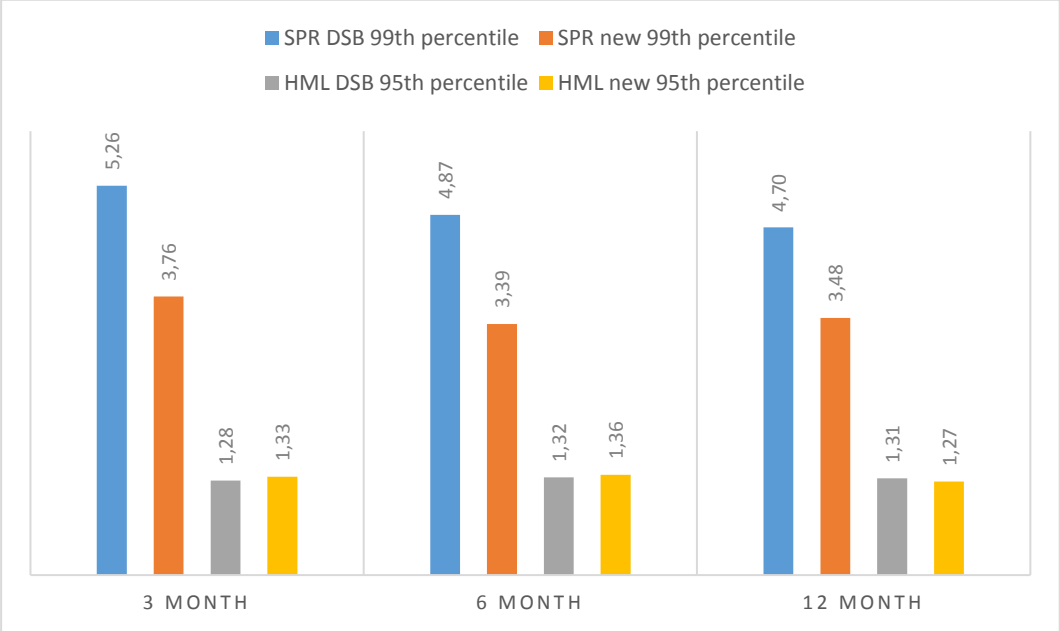

Figure 19. SPR 99th percentile, HML 95th percentile MASE with DSB and new quantitative methods.

7.6 Implementing new forecast solution

In SAP forecasting behavior is managed per material by values input into material master data. There are multiple fields which affect forecast generation, these are shown in figure 20. Most important of these values is forecast model which defines what method is used for the calculation. SAP offers only a limited amount of options for this but single exponential smoothing, which is the only one needed for the proposed forecasting scheme, is one of them.

Due to single exponential smoothing's availability in SAP without any additional work or modules needed, it is easy to implement the new forecasting scheme. As the new scheme requires utilizing two different smoothing constants, a mass update for all the materials cannot be done. Instead inter-demand intervals should be calculated for the materials and based on those results either 0,1 or 0,4 should be chosen as smoothing constant, or alpha factor as it is known in SAP.

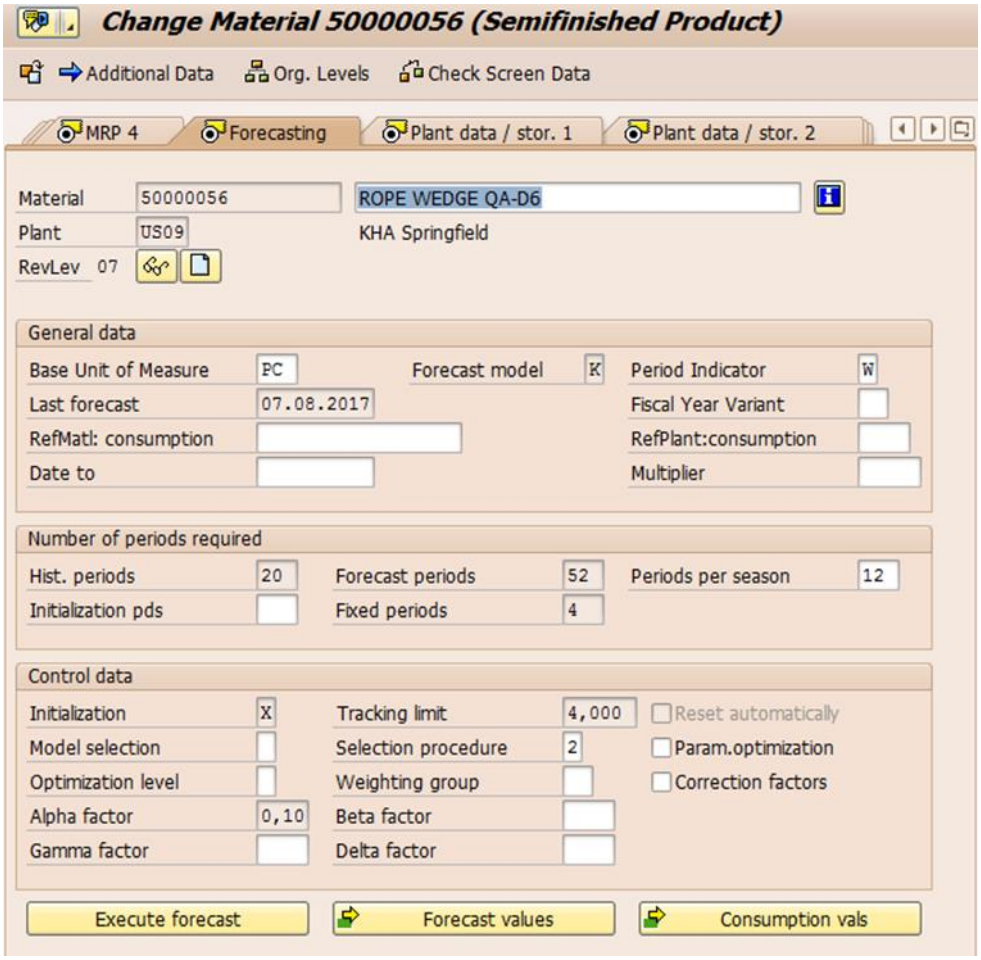

Figure 20. Forecasting tab of material master data in SAP.

SAP also offers the possibility to utilize forecasting profiles, creation screen for these is presented in figure 21. In practice this means creating a set of variables similar to the ones available in material master data which can then easily be applied for material. These profiles make it much easier to change or update forecasting method as only one value has to be changed per material instead of multiple ones. Two of these profiles should be created for the proposed forecasting scheme, one for single exponential smoothing with smoothing constant 0,1 and another one for single exponential smoothing with smoothing constant 0,4.

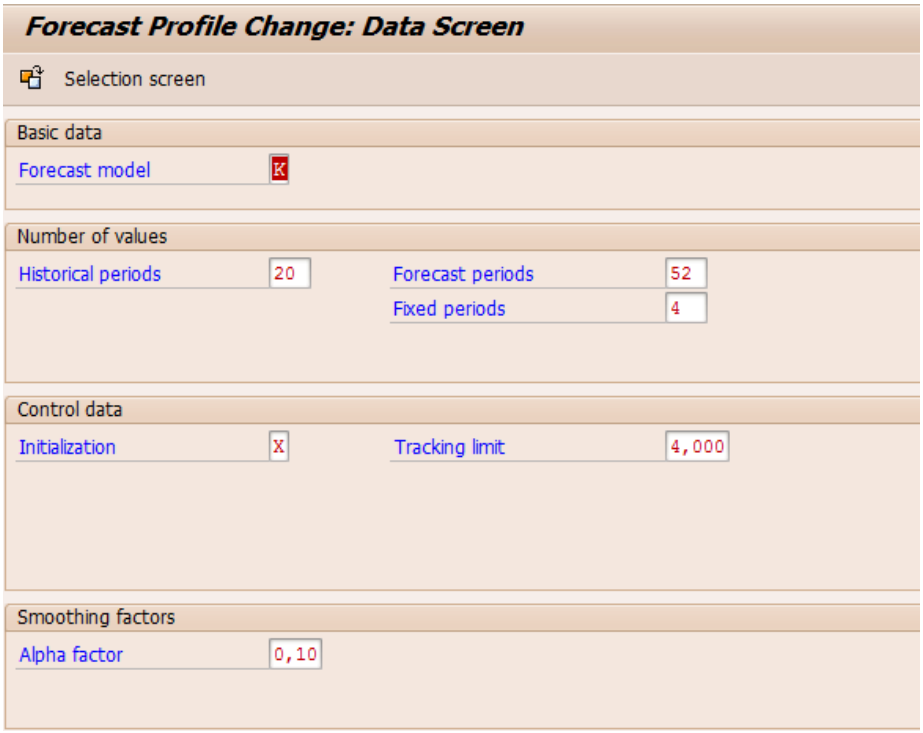

Figure 21. Forecast profile creation screen in SAP.

Even though the initial implementation of this solution is easy, choosing the correct parameters once is not enough. Demand of materials changes over time and naturally their inter-demand interval does not remain constant either. There should be periodic recalculations of inter-demand intervals and updates of forecast profiles when necessary, for example once a quarter.

8 CONCLUSIONS

The main purpose of this thesis was to find out the forecasting methods which would produce the most accurate demand forecasts without needing much resources. This meant looking into quantitative forecasting methods and what criteria or process should be used to choose the ones that yield the best results. Based on literature over 70 different quantitative methods have been developed over the years and which of these performs the best is dependent on how the demand behaves.

Usually materials' past demand is analyzed first and the materials are categorized to some predefined number of subsets which are then assigned to be forecast by a certain method. This categorization is based on manually input cutoff values of characterizing parameters like inter-demand interval or coefficient of variation. However, with this approach forecast accuracy is not necessarily as good as it could be. Instead, the approach used in this thesis relies on generating forecasts with multiple methods, calculating their accuracies and trying to find regions of superiority i.e. some characteristics in demand for which a certain forecasting method has the best performance.

Based on all the generated forecasts and analyzing them, a forecasting scheme consisting of single exponential smoothing with smoothing constant 0,1 for materials with inter-demand interval of two or less and smoothing constant 0,4 for rest of the materials is proposed as the optimal solution. This result contradicts with typical literature where Croston's method, or lately Boylan-Syntetos method, has been proposed as best practice to forecast intermittent demand. However, both of those methods were part of the study and the proposed solution had better accuracy with this demand data.

The proposed solution was also shown to outperform current quantitative method utilized by Konecranes while also being easy to implement in SAP. The most surprising result of the thesis was the new scheme's better or just slightly worse

performance against the DSB process depending on plant and metric used. DSB process is much more labor intensive and has already been the topic of other master's theses. Based on this it would be reasonable to consider if it is worth it to keep utilizing it or if it can be improved further.

For future research the optimal level of detail on which forecasts are being generated should be studied. Closer collaboration with suppliers and understanding what level of detail would be best for optimizing their production and material management could also yield positive results. Of course machine learning and artificial intelligence with the ever increasing amount of data are likely to have drastic effects in this field and research regarding their application to optimize forecasts would be warranted.

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APPENDICES

APPENDIX 1. Example of consumption data (MVER table from SAP)

Material	Plant	Fiscal Year	Period Indicator	Follow-on records	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption	Total consumption
Material 1	FI05	2015	W	1	73,000	43,000	35,000	41,000	46,000	26,000	39,000	34,000	23,000	39,000	25,000	46,000	48,000
Material 1	FI05	2015	W	2	36,000	27,000	52,000	56,000	33,000	38,000	41,000	47,000	31,000	49,000	35,000	23,000	57,000
Material 1	FI05	2015	W	3	41,000	45,000	31,000	52,000	71,000	34,000	38,000	32,000	58,000	46,000	23,000	41,000	56,000
Material 1	FI05	2015	W	4	56,000	47,000	35,000	65,000	38,000	58,000	84,000	49,000	33,000	38,000	52,000	39,000	28,000
Material 1	FI05	2015	W	5	18,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Material 2	FI05	2015	W	1	23,000	85,000	65,000	61,000	103,000	71,000	49,000	44,000	30,000	70,000	92,000	63,000	61,000
Material 2	FI05	2015	W	2	66,000	49,000	71,000	91,000	56,000	75,000	47,000	63,000	79,000	68,000	84,000	65,000	98,000
Material 2	FI05	2015	W	3	117,000	73,000	91,000	74,000	60,000	53,000	63,000	58,000	88,000	80,000	72,000	53,000	53,000
Material 2	FI05	2015	W	4	55,000	58,000	81,000	69,000	100,000	48,000	61,000	76,000	86,000	120,000	49,000	64,000	34,000
Material 2	FI05	2015	W	5	41,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Material 3	FI05	2015	W	4	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	200,000	0,000	0,000
Material 4	FI05	2015	W	1	125,000	446,000	176,000	194,000	179,000	130,000	220,000	327,000	148,000	175,000	547,000	50,000	188,000
Material 4	FI05	2015	W	2	185,000	198,000	210,000	129,000	360,000	394,000	472,000	459,000	239,000	87,000	457,000	148,000	392,000
Material 4	FI05	2015	W	3	92,000	263,000	420,000	140,000	163,000	111,000	90,000	108,000	169,000	408,000	198,000	137,000	206,000
Material 4	FI05	2015	W	4	199,000	130,000	134,000	133,000	161,000	201,000	437,000	153,000	107,000	122,000	128,000	215,000	406,000
Material 4	FI05	2015	W	5	160,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Material 5	FI05	2015	W	1	95,000	107,000	226,000	56,000	115,000	81,000	183,000	131,000	214,000	80,000	74,000	73,000	67,000
Material 5	FI05	2015	W	2	77,000	237,000	225,000	104,000	74,000	146,000	93,000	20,000	201,000	110,000	69,000	46,000	69,000
Material 5	FI05	2015	W	3	53,000	55,000	172,000	223,000	83,000	164,000	29,000	57,000	97,000	114,000	48,000	194,000	305,000
Material 5	FI05	2015	W	4	59,000	187,000	63,000	118,000	57,000	106,000	54,000	129,000	28,000	317,000	119,000	75,000	111,000
Material 5	FI05	2015	W	5	69,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Material 6	FI05	2015	W	1	5,000	7,000	12,000	49,000	2,000	8,000	28,000	27,000	3,000	4,000	14,000	41,000	12,000
Material 6	FI05	2015	W	2	26,000	16,000	8,000	21,000	12,000	46,000	10,000	19,000	18,000	0,000	24,000	0,000	4,000
Material 6	FI05	2015	W	3	0,000	0,000	14,000	3,000	13,000	10,000	0,000	7,000	6,000	0,000	10,000	18,000	0,000
Material 6	FI05	2015	W	4	0,000	17,000	0,000	16,000	14,000	3,000	37,000	0,000	0,000	12,000	4,000	0,000	2,000
Material 7	FI05	2015	W	1	16,000	67,000	80,000	59,000	49,000	43,000	74,000	55,000	76,000	87,000	65,000	78,000	43,000
Material 7	FI05	2015	W	2	46,000	43,000	58,000	58,000	66,000	78,000	58,000	54,000	79,000	64,000	61,000	65,000	72,000
Material 7	FI05	2015	W	3	74,000	73,000	94,000	38,000	52,000	113,000	57,000	59,000	60,000	65,000	58,000	70,000	58,000
Material 7	FI05	2015	W	4	80,000	100,000	74,000	59,000	55,000	61,000	71,000	66,000	76,000	73,000	69,000	64,000	29,000
Material 7	FI05	2015	W	5	44,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Material 8	FI05	2015	W	1	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	100,000	0,000	0,000	0,000	0,000
Material 8	FI05	2015	W	4	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	100,000	0,000	0,000	0,000
Material 9	FI05	2015	W	1	8,000	0,000	2,000	0,000	1,000	0,000	5,000	16,000	11,000	2,000	2,000	0,000	0,000
Material 9	FI05	2015	W	2	1,000	0,000	1,000	0,000	0,000	13,000	0,000	0,000	3,000	1,000	12,000	1,000	0,000
Material 9	FI05	2015	W	3	0,000	2,000	0,000	0,000	1,000	3,000	2,000	1,000	0,000	0,000	0,000	7,000	2,000
Material 9	FI05	2015	W	4	0,000	2,000	1,000	3,000	2,000	4,000	0,000	4,000	2,000	5,000	22,000	0,000	2,000
Material 10	FI05	2015	W	1	0,000	100,000	81,000	96,000	108,000	0,000	136,000	121,000	60,000	92,000	72,000	64,000	120,000
Material 10	FI05	2015	W	2	74,000	80,000	0,000	80,000	25,000	101,000	51,000	49,000	0,000	31,000	113,000	20,000	128,000
Material 10	FI05	2015	W	3	168,000	129,000	159,000	180,000	80,000	86,000	80,000	74,000	120,000	83,000	80,000	42,000	98,000
Material 10	FI05	2015	W	4	130,000	40,000	44,000	44,000	96,000	108,000	188,000	220,000	140,000	192,000	175,000	143,000	80,000
Material 10	FI05	2015	W	5	122,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000