LIABILITY REDUCTION
THROUGH
DEMAND FORECASTING IMPROVEMENT

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Preface

Dear reader,

With pleasure I present to you my master thesis 'Liability Reduction through Demand Forecasting Improvement'. This report is the result of a research conducted at Company X in order to fulfil the graduation requirements for the study Industrial Engineering and Management with the specialization Production and Logistic Management at the University of Twente.

When I started my summer job at Company X in July 2018, I was impressed by the open culture and positive working atmosphere of the company. To get the chance to also execute my graduation project here from November 2018 on was delighting. I would like to thank employee A and employee B for granting me this opportunity. My special thanks go to employee B, who acted as my external supervisor, for his expertise and valuable input, which has been really helpful during the whole project. Furthermore, I would like to thank all colleagues from the Sourcing department for the great time. Being part of this team was a real pleasure.

Moreover, I would like to thank my supervisors Petra Hoffmann and Engin Topan. With the guidance of Petra in which direction to go, I found the right path to finish this thesis. Engin really helped me structuring the report, which has made it way better readable. Also, there was a certain time pressure, and thanks to their clear feedback and willingness to help me, I was able to graduate within the time frame that I had set myself the goal.

Furthermore, I would like to thank my university colleagues, without whom I wouldn't have had such an amazing time as a master's student. In particular, I want to thank Nina and Suzan for making our exchange to Taiwan unforgettable. This semester was definitely the highlight of my study period and it wouldn't have been without you.

Last, but certainly not least, I would like to thank my family and loved ones for their unconditional support.

All that remains for me is to wish you an enjoyable read.

Marleen Roerink
May 2019

Management Summary

Company X is a manufacturer of smart technical applications. In 2016, the company worked on a new strategic multi-year plan (Company X, 2018). With this plan, Company X wants to accelerate the organizational development by focusing on its core business, which is software development. As a part of this plan, their supply chain has been reorganized by outsourcing the production activities to strategic partners, so-called EMSs (Electronics Manufacturing Services).

The EMSs send a monthly file to Company X containing data about the inventory of components and materials they have in stock on behalf of Company X. Company X has deduced from these liability files that there is a lot of excess inventory, which is defined as the inventory that has no expected demand for one year in advance. This excess inventory belongs to Company X' liability, since they have agreed with the EMSs to purchase it after there have been no call offs for twelve months. The Company X' business units that are included in the scope of this research are Business Unit A, Business Unit B and Business Unit C, because the other business units have relatively less hardware.

The goal of this research is to improve Company X' liability by reducing (and avoiding further creation of) excess inventory at the EMSs. The main causes contributing to the buildup of this excess inventory are: high Minimum Order Quantities (MOQs), demand forecasting errors, improper lifecycle management, and the leftover of the inventory buffer for the outsourcing process. An analysis after classification of the excess inventory to these causes using rules of thumb, showed that for Company X most excess inventory is assigned to the cause 'forecasting errors'. These results in combination with the relatively high influenceability of this cause by Company X, has led to the focus of this research being the improvement of Company X' demand forecasting performance. The cause Lifecycle Management was ranked at the second place, the cause High MOQs has given the lowest priority, and the cause 'Leftover of the outsourcing buffer' has been disregarded as core problem of this research.

In order to improve Company X' forecasting performance, a literature review after forecasting methods and different metrics for measuring the forecasting performance has been performed. What the most appropriate forecasting model for a certain product is, depends on its demand pattern. Demand patterns can be classified into four categories, based on two variables: the squared coefficient of variation (CV^2), representing the variability in demand size, and the average inter-demand interval (ADI). A smooth demand pattern indicates that the product is well forecastable and a lumpy demand pattern implies a poor forecastability, which is defined as the ability to statistically forecast a product's sales. The forecastability of the classes intermittent demand and erratic demand are in between, whereas intermittent demand has a relatively high ADI and erratic demand a relatively high CV^2.

Classification of Company X' products to demand patterns showed that there are no significant differences between the three business units. Most of Company X' products have an intermittent demand pattern and some products have a lumpy demand pattern. However, the bubble chart in Figure 1 shows that the products with the greatest value (purchase price multiplied by the demand in 2018) are closer to having a smooth demand pattern than the low value products. Since this implies that the ability of statistically forecasting these products is relatively high, improving the forecasting method by using a statistic model is expected to be effective.

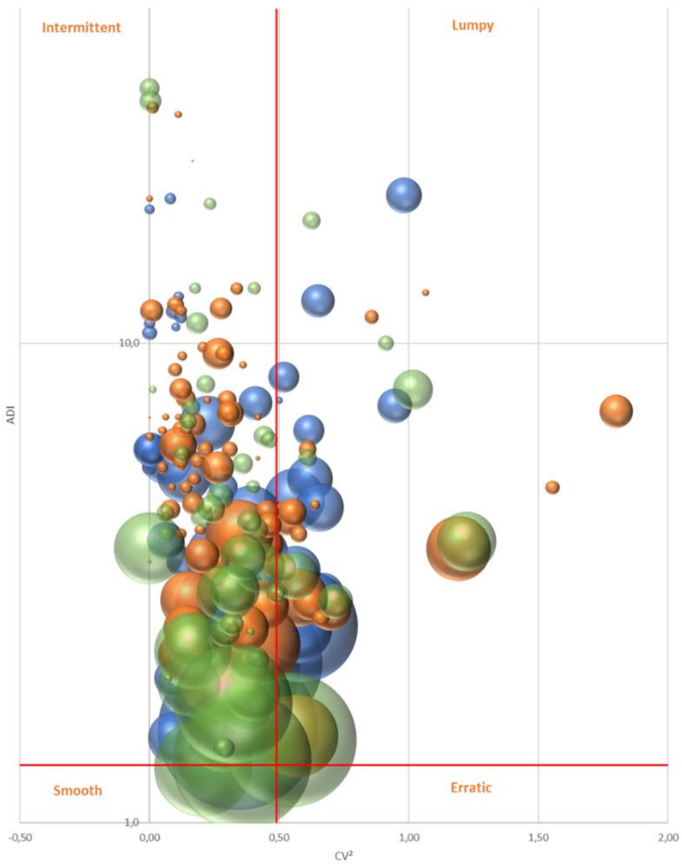


Figure 1: Bubble chart Company X' demand patterns

An analysis on assessing the current forecasting performance of Company X indicates that the forecasts are neither stable nor accurate. The forecasting performance is divided in assessing the forecasting accuracy by calculating the Adjusted Mean Absolute Scaled Error (aMASE) and determining its bias by calculation of the course of the Mean Error (ME) over the year 2018.

For all business units, the value of the aMASE is higher than 1, implying that generating forecasts using the simple Naïve method would result in a smaller forecasting error compared to the current forecasting method. In the Naïve method the most recent observation is used as a forecast (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). Hence, the values of the aMASE show us that there is certainly room for improvement of the demand forecasting accuracy of Company X.

The trendline of the bias over the year 2018 of the different business units all showed a different slope. For Business Unit B the bias was positive over the whole year, but with a negative slope. This indicates that Business Unit B forecasts too low, which can be explained by the fact that they forecast most demand in the near future, resulting in the forecast running empty towards the end of the forecasting horizon. The bias of the forecasts of Business Unit A show a positive slope, crossing the x-axis in the middle of the year. This is the result of too high forecasts at the beginning of the year, which are compensated by lower forecasts towards the end of the year. The slope of the bias of Business Unit C is in between the graphs of Business Unit B and Business Unit A and is slightly negative with a negative slope. It has some (mostly negative) outliers, which indicates that the proportion forecasted demand to the actual demand is not stable. The negative outliers imply that there has been forecasted way too much, which results in excess inventories.

Demand forecasting at Company X is a decentralized process over the business units. We interviewed the employees who are responsible for these demand forecasting tasks in order to map the processes. All demand forecasting processes of the three different business units currently consist of many manual steps with judgmental input. This results in an inefficient and subjective forecasting process, since the forecasting task and its output are dependent of the person who executes it. This is not desirable in terms of flexibility and consistency.

We recommend applying statistical forecasting, in order to create less variability in the forecasted demand, to have a more efficient forecasting process and to have an increased forecasting accuracy by reducing the subjectivity in the forecasting process. For intermittent demand, Croston's method is the most frequently used method, since it can deal with the zero values in the data (Doszyn, 2018). The basic idea of Croston's method is to divide the forecasted demand into two parts, which are both calculated using exponential smoothing; one for the size of the demand and one for the inter-demand interval (Croston, 1972). Nevertheless, also some limitations of Croston's method have been addressed in literature, which have given rise to adjustments to Croston's method.

First, Syntetos, Boylan and Croston (2005) proposed to multiply the estimated demand with a certain factor in order to remove the bias that has been observed, resulting in the SBA method. This method has proven its performance for intermittent, erratic and lumpy demand patterns (Syntetos, Boylan, & Croston, 2005). Second, the TSB method by Teunter, Syntetos and Babai (2011) tackles the issue of Croston's method (and the SBA method) that it does not adjust the forecast downwards in case of periods with zero demand. This issue is overcome by updating the demand probability instead of the demand interval, and doing so in every period. Finally, the Modified SBA method combines the adjustment of the SBA method in order to reduce the bias, with the idea of the TSB method to update the forecast also after periods of zero demand in order to deal with inventory obsolescence (Babai, Dallery, Boubaker, & Kalai, 2019).

Since both these adjustments are relevant for Company X and the Modified SBA method has shown positive results (Babai, Dallery, Boubaker, & Kalai, 2019), we recommend Company X to implement the Modified SBA method, whose formulas are shown below.

Modified SBA method (Babai, Dallery, Boubaker, & Kalai, 2019):

$$D'_t = \left(1 - \frac{\beta}{2}\right) * \frac{Z'_t}{T'_t}$$

where

$$If\ D_t > 0\ then \begin{cases} Z'_t = Z'_{t-1} + \alpha * (Z_t - Z'_{t-1}) \\ T'_t = T'_{t-1} + \beta * (T_t - T'_{t-1}) \end{cases}$$

$$If\ D_t = 0\ then \begin{cases} Z'_t = Z'_{t-1} \\ T'_t = \begin{cases} T'_{t-1} + \beta * (T_t - T'_{t-1}) & if\ T_t > T'_{t-1} \\ T'_{t-1} & if\ T_t \leq T'_{t-1} \end{cases} \end{cases}$$

D_t : Demand for an item at time t

D'_t : Estimate of mean demand per period made at time t for period $t+1$

Z_t : Actual demand size at time t

Z'_t : Estimate of the demand size at time t

T_t : Actual demand interval at time t

T'_t : Estimate of the demand interval at time t

α, β: Smoothing parameters $(0 \leq \alpha \leq 1, 0 \leq \beta \leq 1)$

The demand forecasting processes of Company X are decentralized over the business units, so we provide a roadmap to an improved demand forecasting performance, which is described in section 5.1. This roadmap should be followed for each business unit individually. Each year, the forecasting model should be reset by the employee(s) who is responsible for the forecasting task, by executing step 5 for each product again. The steps of the roadmap are:

- Step 1. Project initiation: define people, goals, tools and scope.
- Step 2. Product segmentation: select which products should be forecasted statistically, which ones judgmentally and which ones should not be forecasted, based on their expected demand pattern.
- Step 3. Data exploration: analyze and preprocess the data. Perform a baseline measurement using the forecasting performance metrics aMASE for accuracy and ME for bias (has already been done in this research). Perform time series decomposition on the demand data if there is a chance that it contains seasonality or a trend. An example of time series decomposition has been elaborated in appendix XIII. Split the time series data in a training set for model fitting and a test set for model testing (80-20 ratio).
- Step 4. Model selection: choose the statistical model(s). As explained before, we propose to apply the modified SBA method. We recommend to also select a simple statistical forecasting method like the moving average method , in order to extent the framework of reference. Comparing the results of the Modified SBA method with both the zero measurement and the forecasting performance of a simple statistical method, provides insight in the results of applying statistical forecasting and the differences in forecasting performance of different statistical models.
- Step 5. Model fitting: estimate the model parameters. The modified SBA method contains smoothing parameters (α and β), which require setting of their optimal values. This implies iteratively setting different values of these parameters and calculating the performance metrics over the training set. The combination of values which results in the lowest aMASE and ME close to zero is labeled as optimal. An example of model fitting has been elaborated in appendix XIII.
- Step 6. Model testing: calculate the aMASE (and ME) over the test set and compare. Generate forecasts for the test set using each selected model (Modified SBA method and Moving average method). Calculate the aMASE and ME for these forecasts and compare these scores with the scores from the baseline measurement.
- Step 7. Process design: organize the forecasting task. The responsibilities concerning generating forecasts, but also maintaining the forecasting model, must be assigned. Maintaining the forecasting model implies updating the dataset, controlling its performance by monitoring the forecasting errors and reviewing the statistical model. Review of the statistical model should be performed each year for each product, in order to re-establish the optimal values of the smoothing parameters. In case of non-stationary demand data, also the seasonal component and trend component should be updated by applying time series decomposition and model fitting, subsequently.

Besides improving the forecasting performance, there are also other possibilities for avoiding further creation of excess inventory in the future. The first proactive approach to excess inventory reduction that we discuss is applying risk pooling to reduce the impact of MOQs and possibly purchase for better prices. In practical terms, risk pooling implies the aggregation of inventory on a certain location. Since this is a rather complex implementation, involving multiple parties, we suggest to perform further research after this possible improvement.

The recommended Modified SBA method deals with inventory obsolescence by adjusting the forecasted demand downwards after periods of zero demand. Notwithstanding, when a product reaches its end-of-life, this is not enough to avoid creation of excess inventory. Excess inventory due to the phasing-out of products should therefore be communicated proactively in a timely manner.

Furthermore, Company X should encourage its Product Development to use even more 'shared components', especially for products which production is accommodated at the same EMSs. The benefits of more shared components are both the purchase price and the relatively lower MOQs. Additionally, the risk that inventory becomes obsolete decreases when its demand is divided over multiple products.

Furthermore, there are also several reactive approaches to excess inventory reduction. Logically, the longer excess inventory is retained, the more money it costs and the less valuable it becomes. Inventory of components whereof Company X expects to have demand in the (near) future can be retained. The other excess inventory should be either disposed (sold or scrapped) or transferred to an EMSs that can use this inventory. The excess inventory can already be reduced by more than €XX, by applying these so-called lateral transshipments between the four biggest EMSs of Company X.

Contents

List of Tables and Figures

List of Abbreviations

Abbreviation	Definition
ADI	Average inter-Demand Interval
AIC	Akaike's Information Criterion
ANOVA	Analysis Of Variance
BIC	Bayesian Information Criterion
BU	Business Unit
CC	Computational Complexity
CM	Croston's Method
CoV/CV	Coefficient of Variation
CRM	Customer Relationship Management
EMS	Electronics Manufacturing Service
EOL	End Of Life
EOQ	Economic Order Quantity
ES	Exponential Smoothing
FC	Forecast
GMAE	Geometric Mean Absolute Error
GMRAE	Geometric Mean Relative Absolute Error
IOS	Inactive, Obsolete, Surplus
LLI	Long Leadtime Item
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
(s)MAPE	(Symmetric) Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MdRAE	Median Relative Absolute Error
ME	Mean Error
MOQ	Minimum Order Quantity
MPE	Mean Percentage Error
MRO	Maintenance, Repair and Operating
(R)MSE	(Root) Mean Squared Error
MTO	Make To Order
MTS	Make To Stock
PCB	Printed Circuit Board
Production Facility X	Company X' production facility
RCA	Root Cause Analysis
SEATS	Seasonal Extraction in ARIMA Time Series
SKU	Stock Keeping Unit
SLA	Service Level Agreement
VBA	Visual Basic for Applications
WMA	Weighted Moving Average

1. Introduction

This Master thesis project is performed on behalf of Company X. In section 1.1, Company X as a company is introduced. Section 0 provides some background information about the research assignment at Company X. Section 1.3 presents information from literature about the concerned topics. In section 1.4, the problem is discussed. This is followed by an explanation of the research design and the scope of the research in section 1.5 and 1.6, respectively.

1.1. Company X

Company X consists of multiple business units, since different problems require a different field of expertise. Each one of these business units has deep insight into their particular market, resulting in innovative technological systems that focus on relevant issues for now and in the future. The Company X business units and their core products are:

- Business Unit A: loss prevention and stock management systems.
- Business Unit B: systems for monitoring and caring using individual animal identification.
- Business Unit C: light management systems for the industry.
- *Enumeration of the other business units*

Together, these Company X' business units account for approximately XX million euros of profit (excluding one-off items, which are expenses or revenues from non-recurring activities, so outside a company's usual business operations), see Figure 2.

Figure 2: Profit of Company X from 2014 to 2017

Since its founding, Company X has been manufacturing smart technical applications. In 2016, the company worked on a new strategic multi-year plan (Company X, 2018). With this plan, Company X wants to focus on accelerating the organizational development by focusing on its core business, which is software development. For example, their product range will be reduced from approximately 1000 to 400 technological solutions. These products can consist of only software or a combination of both software and hardware.

As another part of this plan, their supply chain is reorganized by outsourcing the production activities to strategic partners and closing Company X' production location. To manage this process the department Sourcing, which overarches the business units, was brought into being.

1.2. Research motivation

The research assignment is performed on behalf of the Sourcing department. Company X has outsourced its production activities to so-called Electronics Manufacturing Services, hereafter called EMSs. In the contracts with the EMSs, Company X agreed on an open cost price calculation model. Hereby, Company X has insight in the prices the EMSs pay for the different components. The general supply chain of the products of all Company X' business units is visualized in Figure 3: Supply chain.

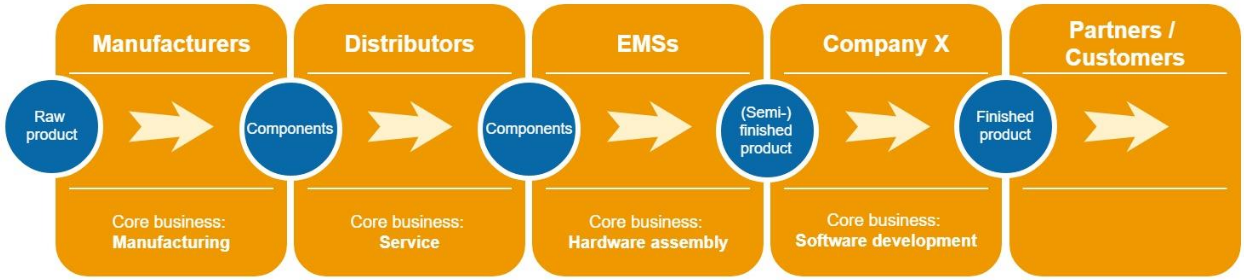


Figure 3: Supply chain

Company X has contracts with about six EMSs. This number is dynamic, since some projects are shifted from one EMS to another. Per project, which is one or a bundle of Company X products, Company X has Service Level Agreements with the EMS. The Company X business units specify which manufacturer supplies which component of the product they are developing. The Sourcing department of Company X selects in consultation with the concerned Business Unit the EMS per project. Most manufacturers sell their components through distributors and not directly to EMSs. Therefore, the EMS can select their own suppliers (distributors), as long as they purchase the components from the manufacturer specified by the Company X Business Units.

Some components are fabricated based on Company X specifications, further referred to as 'Company X specific components'. These components are directly distributed from the manufacturer to the EMS. Generally, the manufacturers require high Minimum Order Quantities (MOQs) on these components, which might results in excessive inventory levels.

Each EMS is responsible for managing their own inventory of components and materials for Company X. The Company X Business Units send weekly forecasts with their expected demand for one year in advance to the EMSs. The EMSs produce to Company X orders, but have to manage their inventories of components based on these demand forecasts of Company X. The four biggest EMSs, based on the value of Company X' demand, provide monthly data of their inventory in a so-called liability overview.

The Sourcing department of Company X has deduced from these data that the EMSs have a lot of excess inventory. This poses a financial risk for both the EMSs and Company X. The financial risk for Company X regarding the excess inventory at the EMSs and its causes are explained in more detail in the problem description in section 1.4. The size of the problem is indicated by quantifying the financial risk for Company X in section 0. We define 'financial risk' as any measurable risk that can have financial consequences. 'Excess inventory' is the part of the inventory of components for which no Company X demand (order or forecast) is known. The goal of this research is to improve Company X' liability by reducing the excess inventory of the EMSs.

Company X' liability concerning the excess inventory at the EMSs constitutes a discrepancy between the norm and reality for Company X. Hence, we can conclude that the problem of Company X regarding the excess inventory is an action problem, according to the definition of Heerkens and Van Winden (2012). The Management Problem Solving Method (MPSM) is a framework for solving an action problem (Heerkens & Van Winden, 2012). This method consists of seven phases, which are elaborated in the chapters and sections mentioned per phase:

1. Problem identification: section 1.4 Problem identification
2. Solution planning: section 1.5 Research design
3. Problem analysis: chapter 2 Problem analysis
4. Solution generation: chapter 3 Literature review
5. Solution choice: chapter 5 Improvements
6. Solution implementation: chapter 5 Improvements
7. Solution evaluation: chapter 5 Improvements

Chapter 4 is not explicitly part of one of the phases of the MPSM, but contains a description of the current situation. Herewith we provide the baseline measurement for the validation of design of phase 7 and a starting point for the description of the solution of phase 5 and 6.

1.3. Theoretical background

In this section the background information about excess inventory and its causes according to literature is explained. In order to better understand what kind of inventory Company X' problem is about, the relevant theory behind inventory classification is described in section 1.3.1. Also the definitions of different kinds of inventory and especially of excess inventory are discussed in this section. To clarify what inventories exactly belong to the excess, approaches for determining the excess inventory levels are explained in the section 1.3.2. Subsequently, the possible causes of excess inventory according to literature are explained in section 1.3.3. This theory serves as input for the problem cluster.

1.3.1. Inventory classification and definition

Generally, inventory can be classified in two types based on whether it effectively serves a function or not. The inventory that does not effectively serve a function is excess.

"Inventory is a current asset that should more than earn its keep; if inventory incurs more costs than benefits, it is really a liability. Excess inventory is clearly an operational liability." (Toelle & Tersine, 1989).

In literature, excess inventory is defined in several ways. Nnamdi (2018) defines excess inventories as the Stock Keeping Units (SKU's) that have a significant amount of inventories on-hand compared to average annual consumption. Crandall and Crandall (2003) state that "in essence, inventory is not excess when it is in the right quantity of the right goods at the right place at the right time". As stated by Rosenfield (1989) is inventory excess when "the potential value of excess stock, less the expected storage costs, fails to match the salvage value". According to Toelle and Tersine (1989), excess inventory is any item that not effectively serves one of the following functions:

- **Working stock** (cycle or lot size stock). Inventory that is held so that ordering and production can be done using an economical lot size instead of on an as-needed basis.
- **Safety stock** (buffer or fluctuation stock). A buffer of inventory which protects against the consequences of uncertainties in supply and demand.
- **Anticipation stock** (seasonal or stabilization stock). Inventory which is held to deal with peak seasonal demand and unusual requirements as strikes or vacations.
- **Pipeline stock** (transit or work-in-process stock). Inventory that is being processed or transported within or between facilities.
- **Decoupling stock**. Inventory within a production or distribution process so that one stage of the process does not slow down other parts of the process.

These definitions of excess inventory have all in common that inventory belongs to the excess, when it will not be used within a certain timeframe and can therefore be labelled as inefficient.

Next to the division of inventory in whether it is excess or not, it can also be classified based on several other factors. A classification based on the purpose of holding the inventory is already mentioned in the definition of excess inventory by Toelle and Tersine (1989) mentioned above. In a manufacturing organization, the most common classification is based on the value addition or stage of completion. In general, a distinction between three main types of inventory is made. Next to these three categories, there is a category 'Other', which consists of inventories to support the manufacturing- and administration operation, such as packing material and MRO supplies (Maintenance, Repair and Operating suppliers).

- **Materials/components**. This type of inventory includes all materials/components to be used as input in the manufacturing process.
- **Work-In-Progress**. This includes the inventory of any unfinished goods (semi-finished goods) that have been made by the company.
- **Finished goods**. This type of inventory includes any finished goods produced that are ready for sale.

As will be motivated in section 1.6, this research is scoped to the inventory type 'materials/components' only. In turn, the excess inventory of this type can be categorized in different types. Toelle and Tersine (1989) distinguish three operational types of excess inventory:

- **Dead stock**. This is the inventory which has not been used for a specific length of time, so the inventory that does not turn over (anymore).
- **Degraded stock**. This stock consists of items which do not meet the quality requirements (any longer). These items can for example be spoiled, damaged or deteriorated.
- **Slow-moving stock**. These are the items of stock on hand which retain their full utility and which have a continuing demand, but which have a higher amount on stock than can be justified by the anticipated rate of future demand (Toelle & Tersine, 1989).

A different classification of excess inventory is made by Bragg (2011). He states that IOS inventory (Inactive, Obsolete, Surplus) consists of the following parts:

- **Inactive**. These are the parts on stock that have no forecasted usage.
- **Obsolete**. These parts are no longer incorporated in any current product.
- **Surplus**. The inventory levels of these parts exceed the forecasted usage.

In section 2.2.1 we use the definitions of these two different classifications for determining what belongs to the excess inventory according to Company X.

1.3.2. Determination of excess inventory levels

There are also multiple ways of determining the excess inventory levels. From simple models in which time value corrections are ignored to more complicated models which consider the inflations and time values through a present value correction (Tersine & Toelle, 1984). The method of determining the excess inventory levels also depends on the used definition of excess inventory and which corresponding operational types are taken into account. For determination of the excess inventory levels of slow-moving-items Toelle and Tersine (1989) state three possible approaches, which are explained in the following paragraphs.

One approach is to set a certain time supply as the tolerable time supply of stock on hand. A 12-months' supply is often used as a benchmark, because inventory that will not be used within this time interval is not really a "current asset" (Toelle & Tersine, 1989).

Another approach of determining the excess inventory levels is to refer to previously established inventory policies, like the EOQ. In that case, the excess inventory is defined as the difference between the actual inventory levels and the sum of the lot size and safety stock (Toelle & Tersine, 1989). In case of inventory control by using for example a min-max system, every item that exceeds the maximum inventory level belongs to the excess inventory. When a company has the objective to have at least four inventory turns per year, the (potential) excess inventory would consist of every item that is not needed for a three-months' supply (Toelle & Tersine, 1989).

In the third approach mentioned by Toelle and Tersine (1989) the excess inventory is determined by calculating for what part of the inventory the liquidation would be economically justifiable. This approach defines what part of the slow-moving items should be liquidated in order to minimize relevant costs. Herewith this decision-oriented approach serves as a guide to action once the excess inventory levels have been established (Toelle & Tersine, 1989).

1.3.3. Causes of excess inventory

There are numerous reasons for a surplus or obsolete inventory mentioned in literature. No author states to have an exhaustive list of possible causes of excess inventory, because these causes differ from organization, industry, situation, and so on. The reasons may vary from (Tersine & Toelle, 1984): a change in methods of production, new technological innovations to an over-zealous purchasing practice. Some examples of potential causes mentioned by Willoughby (n.d.) are: price increases, customer cancellations, the introduction of a new (competing) product or changing business conditions.

A distinction in the possible causes can be made based on the kind of inventory. For example, a part of the possible causes are particularly for the excess inventory of spare parts, like a change in maintenance policy or the use of alternative spare parts. Some frequent general causes of excess inventory stated by Toelle and Tersine (1989) are:

- **Forecasting errors**. Negative differences between the predicted and actual demand and the failure to anticipate on it usually result in excess inventory levels.
- **Inventory record inaccuracies**. Errors in for example disbursements, stock levels, part identification numbers, etc. often manifest in excess inventory.
- **Inadequate planning and execution systems**. The use of decent planning methods, correct and accurate purchase or work orders, and an adequate production scheduling and control system are part of the basis for proper inventory control.
- **Long or variable lead times**. Long production times result in a build-up of work-in-process stock and variable production lead times generally ask for higher safety stocks.
- **Obsolescence**. Whenever a product reaches its end-of-life, the demand will drop down. Engineering change activities such as product redesign or product termination should therefore be planned and coordinated very well.
- **Master schedule smoothing**. The planned rate of supply may not exactly match the (expected) rate of demand in order to achieve manufacturing efficiencies, which can cause an accumulation of stocks.
- **Distribution channel adjustments**. When stocking and shipping policies change within a distribution channel, it can appear to the source as real increases in customer demand. If the production activities of the source are increased in response to this, excess inventory arises.
- **Changes in inventory holding costs**. A sudden increase in inventory holding costs can make inventory reductions imperative. Although the number of units which are physically on stock remain the same, the accepted inventory levels might change, which causes an excess of inventory.

Crandall and Crandall (2003) also came up with some potential causes of excess inventory. The variation in demand and supply are both external forces and the remaining causes are due to internal variation. The causes due to internal variation are broken down to different parts of the organization.

- Demand variation. Product proliferation and shorter product cycles contribute to more uncertainty in the demand, which makes it harder to make an accurate demand forecast. When a company does not properly track the life-cycle stages of a product, an excess inventory is a possible consequence. Not only the product cycles, but also economic cycles contribute to the forecasting problem, since it seems that companies fail to act proactively to an economic slowdown or upturn.

  In addition to that, the demand variability increases as one moves up the supply chain (Chen, Drezner, Ryan, & Simchi-Levi, 2000). This phenomenon in supply chain management is known as the *bullwhip effect*. The five main causes of this effect are: the use of demand forecasting, supply shortages, lead times, order batching, and price fluctuations (Chen, Drezner, Ryan, & Simchi-Levi, 2000). More information about this phenomenon is provided in section 3.3.

- Supply variation. Excess inventory can arise when for example a supplier does not have sufficient capacity or no consistency in their delivery times. Also volume discounts can be a trigger to purchase more than needed.

- Internal variation:
  - Sales and Marketing: they sometimes want to have excess inventory available for a fast response to customer demand.
  - Engineering: when the product design is improved, engineers are mostly impatient to see the effect. New product designs require additional inventories and cause that existing inventories become obsolete.
  - Production Planning and Purchasing: to avoid fluctuations in the workforce, production planners prefer producing at a balanced workload. In combination with a fluctuating demand, this can cause an excess in the finished goods inventory.
  - Accounting/Finance: sometimes it seems to be attractive to buildup inventory, because of the performance measures a company uses. For example, when more focus is on the income statement rather than on the balance sheet, since the level of inventory does not affect the income. This is also the case when managers use income, instead of cash flow, as performance measure. In addition to that, excess inventory can also cause hidden costs, like the diversion of management time.

1.4. Problem identification

The problem assignment provided by Company X is that their liability is too high, due to excess inventory at the EMSs. Several causes contribute to this problem. The first phase of the MPSM concerns the problem identification resulting in a problem statement (Heerkens & Van Winden, 2012). We elaborate this phase of the MPSM in this section.

The consequences of the excess inventory are explained in section 1.4.1, followed by an explanation of its causes in section 1.4.2. Both the consequences and causes have been assigned to a color, which refers to the color of these blocks in the problem cluster. The causes have been identified by having conversations with Company X employees and using the information about possible causes according to literature. Finally, in section 1.4.3 the causes and consequences are schematically presented in a problem cluster and the core problem is explained.

1.4.1. Consequences

Each month the biggest EMSs of Company X send an overview of the actual inventory they have on behalf of Company X, so Company X is proactively informed about (potential) excess inventory. The inventory consists of components that the EMSs need for manufacturing of Company X' products. Most of this inventory is allocated to a certain demand, which is a Company X order or a demand forecast provided by Company X. For the remaining part of the inventory there is no demand. This is what Company X and the EMS call 'excess inventory'.

Aging of components: This excess of inventory poses a financial risk, since when Company X does not expect to have any demand for a certain component in the future, this component becomes waste to Company X. Moreover, some components have a certain shelf life, so are perishable. In some cases, it is worth the effort to sell such inventory. Nevertheless, the value of the components deceases by time, which implies that they will never yield the same as they have cost. Therefore, there is always a financial loss on aged components that will not be used by Company X anymore.

Company X specific components: There are also components that can never be sold, since they are fabricated based on Company X' specifications. No other company uses them. Hence, this is waste of material and therefore a financial loss.

Contracts: Company X has agreed with their EMSs that they will repurchase the inventory after it has not been used in twelve months. Therefore Company X foots the bill of the financial risk that goes along with the excess inventory.

1.4.2. Causes

According to the theoretical background in section 1.3.3., there are several possible causes of excess inventory. Some of these causes are only relevant for excess inventory in finished goods, like 'insufficient production capacity'. Since this research is scoped to inventory of materials and components, these possible causes are eliminated. Other possible causes according to literature simply do not apply to the situation of Company X, like handling financial performance measures that make buildup of inventory attractive.

Remainder inventory from outsourcing buffer of Production Facility X: When Company X announced the outsourcing of the production activities from Production Facility X (Company X' production plant), they started creating an inventory buffer in order to ensure the order fulfillment during the outsourcing process. After the outsourcing process, there was still a big part of this buffer left, so Company X requested their EMSs to take over this inventory from Production Facility X. Therefore, some of the current excess inventory at the EMSs could be leftovers from the inventory buffer of Production Facility X.

Lack of incentives to purchase efficiently: Company X has contractually agreed that the EMSs are allowed to purchase based on Company X forecast, Minimum Order Quantities (MOQs) and lead times of components. However, these agreements have not always been defined quantitatively. Also, the consequences of excessive inventory levels at the EMSs are mostly the risk of Company X, since Company X has to repurchase it after twelve months. These agreements result in that currently the EMSs have no additional incentives to optimize their inventory levels, except for the holding costs and the physical space they have available. According to literature, also wrong performance measures can result in the EMSs holding too much inventory.

Unreliable and long lead times: The EMSs can have several reasons to order more than the demand is. For some components, the lead time is long and unreliable due to the current market's scarcity. Therefore, the EMSs order more than needed to ensure the order fulfilment and therewith create a buffer of components.

Inventory record inaccuracies: Errors in actual inventory levels might result in unnecessary purchase orders of components. This in turn results in excess inventories.

High MOQs: Another cause for higher order quantities of the EMS than needed to fulfil Company X' demand, is the MOQs of the EMSs' suppliers. Generally, a higher MOQ results in a lower price per component and the other way around. Also, a part of the components in the Company X products are fabricated based on Company X' specifications, the so-called 'Company X specific components'. This implies that these components are not generic and therefore the manufacturer requires high MOQs. The MOQs are a problem to the EMSs of Company X, because Company X has products with mostly high variety and low volumes. This might causes that the MOQs of the suppliers of the EMS are too high for the demand of Company X.

Demand forecasting errors of Company X: Every week, the EMSs receive a demand forecast of the Company X business units. Generally, they forecast one year in advance but some of the business units might deviate from this. Each business unit forecasts on their own manner. There might be some uniformity in the forecasting formats of some business units, but the expected demand levels are determined in different ways. Also, the Sales department of the business units do not have an incentive to provide accurate demand information, since they will not be called to account for the accuracy of their forecast information. The interests of Sales are in general not totally similar to the interests of Operations, because Sales focuses more on delivery performance instead of efficiency. Therefore, their sales forecasts are often too high, which results in an excess inventory at the EMSs.

Lifecycle management: When products reach their end-of-life and this is not well-managed and communicated with the suppliers, they do not take action on time. Later on, it is hard to get rid of the components on stock for these products which have no demand anymore. Furthermore, not only whole products of Company X might be replaced by newer versions. Also the individual components are updated sometimes. This 'revision' of a component, results in obsolescence of previous versions of this component.

1.4.3. Problem cluster

The problem cluster is a method for structuring the problem context by mapping the different problems and their interrelationships (Heerkens & Van Winden, 2012). The problem of Company X concerning the inventory at the EMSs is schematically represented in Figure 4.

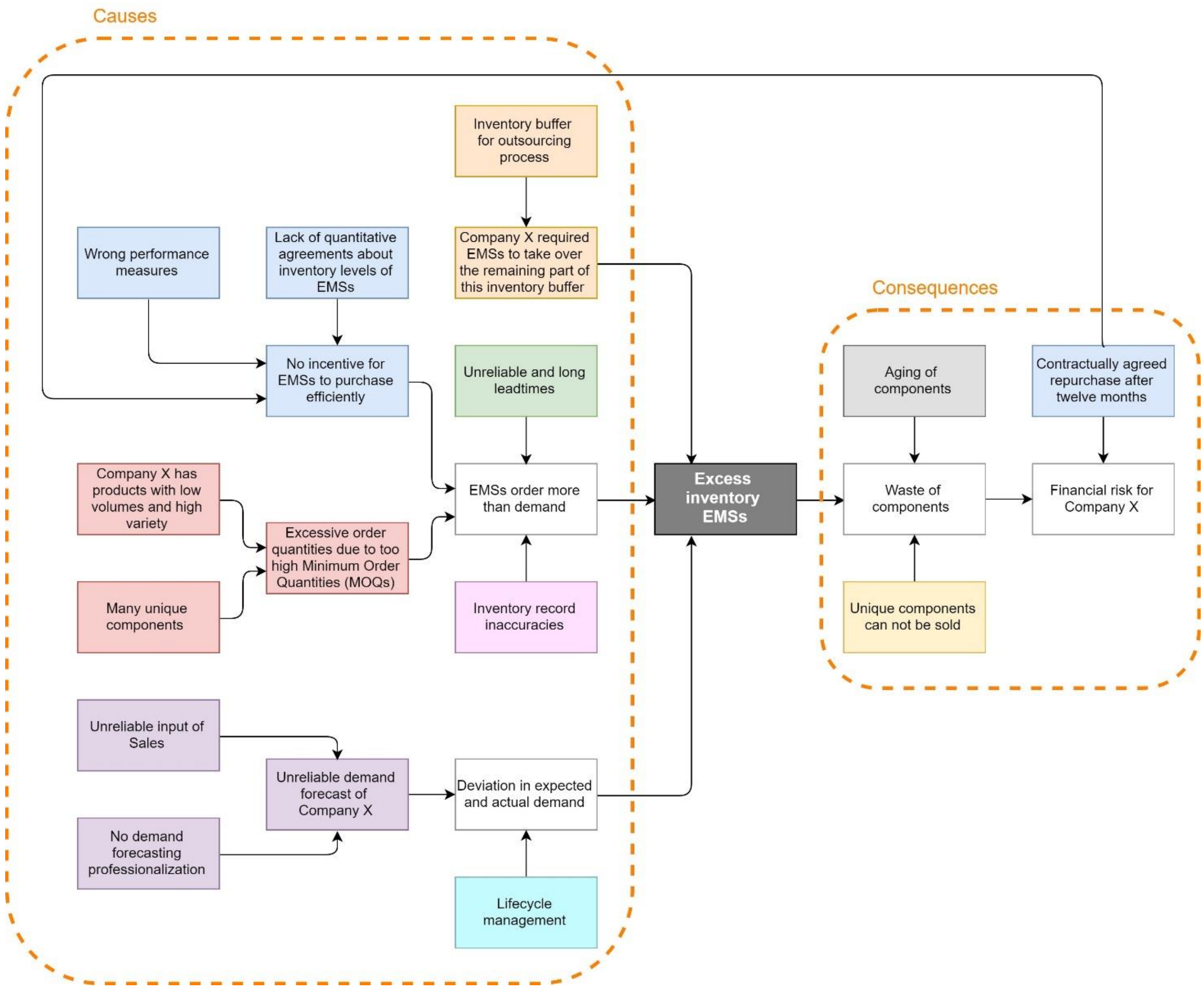


Figure 4: Problem Cluster

Heerkens and Van Winden (2012) state that the core problem must be influenceable, has no other causes and is the problem which has the greatest effect in case of multiple problems (Heerkens & Van Winden, 2012).

The causes that qualify for being the core problem of this research are selected from the problem cluster. Causes that are not really influenceable by Company X are therefore omitted. Hence, the cause 'Unreliable and long lead times' is eliminated. Also the cause 'Remainder inventory buffer from Production Facility X' is not influenceable anymore, since this was a one-time event from the past. The cause 'inventory record inaccuracies' refers to the inventory management process of the EMSs. By the time the EMSs were selected, Company X performed audits regarding their inventory control systems. Company X also performs structural quality and logistic audits at the EMSs. Since inventory management belongs to the responsibility of the EMSs, the cause 'inventory record inaccuracies' does not qualify for being the core problem.

There are multiple remaining causes that qualify for being the core problem. These causes are:

- **High MOQs**. The MOQs are too high for Company X' demand, this is partly caused by using many Company X specific components, which have generally higher MOQs compared to generic components.
- **Lack of incentives to purchase efficiently**. Due to the lack of qualitative agreements, for example about allowed inventory levels, or due to wrong performance measures, for example delivery performance, the EMSs are not triggered to optimize their inventory levels.
- **Demand forecasting errors of Company X**. A lower actual demand compared to what was forecasted results in an excess inventory of components that already have been ordered to fulfil the forecasted demand.
- **Lifecycle management**: No proper keeping track and communication about the life-cycle stages of a product might result in excess inventories when a product is phased out.

To be able to determine and motivate what the core problem of the excess inventory is, more research after the causes and their effect on the inventory levels is required. Hence, we first have a knowledge problem we have to solve, before we can continue with solving the action problem regarding the excess inventory.

The analysis after identification of the core problem is elaborated in chapter 2. The problem statement of the knowledge problem is: A lack of insight in the causes of the excess inventory to be able to identify the core problem of this research. This leaves us with a rather general problem statement for the action problem for now: Company X' liability is too high, due to excess inventory at the EMSs.

1.5. Research design (knowledge problem)

The problem where the Sourcing department of Company X took note of is described in the previous section. We explained in section 1.4.3 that we first have to solve a knowledge problem, namely identifying the core problem of excess inventory at the EMSs. This section presents the research plan for solving this knowledge problem. Herewith we elaborate phase 2 of the MPSM: solution planning (Heerkens & Van Winden, 2012).

The procedure of solving a knowledge problem is the research cycle, which consists of eight phases (Heerkens & Van Winden, 2012):

1. Research aim
2. Problem statement
3. Research questions
4. Research design
5. Operationalization
6. Measuring
7. Analysis
8. Conclusions

The research aim of this knowledge problem is to identify the core problem and the problem statement is the lack of insight in the causes of excess inventory at the EMSs that qualify for being the core problem.

Phase 3 and 4 are included in this section. In section 0 and 2.3, both phase 5 and 6 are elaborated in by quantifying the size of the problem and the extent to which the causes contribute to the problem. In section 2.4 the results of this classification are analysed, by which phase 7 is completed. Finally, in section 2.5 we draw some conclusions about the identification of the core problem. Herewith we execute phase 8 of the research cycle and provide the answer the knowledge problem.

To be able to solve the knowledge problem, the following sub questions will be answered by the approach mentioned per question.

RQ: What is the core problem regarding excess inventory at the EMSs for Company X?

The research question will be answered by first determining the size of the problem in sub question 1 and thereafter prioritizing the causes in sub question 2.

SQ1: How big is the financial risk for Company X that goes along with the excess inventory?

This sub question is answered in section 0. The answer to this sub question provides an indication of the size of the problem for Company X. First, by analysing what Company X and the EMSs have agreed about the inventory levels and the corresponding responsibilities, the link between the excess inventory and why this poses a financial risk for Company X is clarified in section 2.1. The contractual agreements between Company X and the EMSs are examined for determining what part of the inventory at the EMSs belongs to the liability of Company X. In section 0, the consequences described in the problem cluster are quantified by analysing the liability files which are sent by the EMSs to Company X monthly.

SQ2: What causes the excess inventory for Company X and how are these causes prioritized?

This sub question is already partly answered by the problem cluster in section 1.4.3, because the problem cluster shows the possible causes of excess inventory. In section 2.3 the causes derived from the problem cluster that qualify for being the core problem are further analysed.

Quantification of these causes is required for determining how much a certain cause contributes to the problem. For this, the liability files of the different EMS are analysed. The liability files contain data that the EMSs derive from their ERP-system. This is the only information available for Company X regarding their liability due to excess inventories at the EMSs. The excess inventory is classified per cause by assigning the excess inventory per component to a certain cause. This classification is based on rules of thumb, since the data consists of too many rows (different components) to analyse them one by one. As a result of this analysis, the causes are given a priority in section 2.4.

The rules of thumb do not provide a 100% accuracy of the classification and the results therefore only provide an indication of the proportion of the causes. However, using the rules of thumb was the only possibility to quantify the causes, because otherwise each row of excess inventory should be considered individually. Since we are talking about approximately 5000 rows in total, this is not workable.

1.6. Scope

Company X and the EMSs define excess inventory as the inventory on stock and on order for which no demand (order or forecast) is known, because this inventory actually poses a financial risk to Company X. This inventory can consist of finished goods, as well as it can consist of components and materials. The finished goods are out of the scope of this research, since this inventory is not stored at the EMSs and is therefore not included in the liability files, from which Company X derived that there is too much excess inventory. Moreover, excess inventory of finished goods might require a different approach since it is possibly caused by a different core problem. Hence, this research is scoped to the EMSs' excess inventory of 'components and materials' (hereafter referred to as components) on behalf of Company X.

Figure 5 shows which EMS accounts for which part of the annual demand of Company X. The demand of Company X for 2018 is based on the known figures of the first half year of 2018 and an estimation of the figures for the second half year of 2018.

Figure 5: EMSs related to Company X' demand

The three biggest EMSs account together for 82% of Company X' demand in 2017 and for 81% of Company X' demand in 2018. The remaining three EMSs are currently in a transition to producing a bigger or smaller part of Company X' demand, so they have limited historic data about inventories for Company X. Therefore, this research is scoped to the three biggest EMSs of Company X, which are EMS 1, EMS 2 and EMS 3.

Company X still has an own production facility, called Production Facility X, in which some of the Company X products are produced or assembled. Some of the EMSs are suppliers of Production Facility X, so Production Facility X can be considered as both a Company X Business Unit and a supplier. Because of this, there could be some overlap in the inventory data of Production Facility X and the EMS. Since we cannot ensure the reliability of the data, Production Facility X is not considered as one of the EMSs, so left out of scope of this research.

The three selected EMSs produce for mostly three of the Company X Business Units. The other Business Units of Company X have relatively less hardware. The Business Units that are the main customers of these three EMSs are: Business Unit B, Business Unit A and Business Unit C. The remaining part of the inventory at the EMS, which cannot be assigned to one of these Business Units, will be accommodated in the group 'Other'.

2. Problem analysis

This chapter contains the problem analysis concerning the excess inventory at the EMSs and provides the answer to the knowledge problem. Hereby, phase 3 of the MPSM of Heerkens and Van Winden (2012) has been carried out.

Section 2.1 describes what Company X contractually agreed about allowed inventory levels of components and the performance measures they will assess the EMSs on. Section 0 provides an indication of the size of the problem for Company X regarding the excess inventory by quantification of the financial risk. Subsequently, section 2.3 contains an analysis to determine which causes contribute most to the excess inventory. This analysis is based on classifying the excess inventory from the liability files that the EMSs sent to Company X monthly. In section 2.4 the identified causes are prioritized. Herewith the research question of the knowledge problem is answered. Based on this, the research design for the action problem has been drawn up in section 2.6.

2.1. Contractual agreements

The problem cluster shows that the contractual agreements between Company X and the EMSs are both a cause of excess inventories and a reason the excess inventories pose a financial risk to Company X.

Company X has purchase agreements with each one of the EMSs. In addition to these agreements, per project (a bundle of Company X products) additional SLAs are drawn up. These SLAs have different themes, for example Quality, Tooling or Logistics. Both the SLA Logistics and Purchase Agreement are relevant for this research, since they contain agreements regarding the purchasing of components and the allowed inventory levels. We derived the information which is relevant for this research from these contracts. These agreements are listed in appendix I.

The qualitative agreements from the purchase agreements and SLAs between Company X and the EMSs are mostly similar over the EMSs. Only the quantitative agreements in the Logistic SLAs are rather different since they concern a specific project. Company X has agreed with the EMSs that the following parameters will be set per product and should be reviewed every 6 months:

- Purchase price per product per piece;
- Production batch size;
- Production lead time;
- Single package quantity;
- Safety stock for components;
- Safety stock for semi-finished products;
- Safety stock for finished products.

The contract also says that additional parameter settings, amongst others, component lead times, MOQs of components, safety stock levels per component etc. will be agreed in the SLA. Nevertheless, these parameters are mostly not defined quantitatively in the SLAs. Moreover, only agreements about on which factors the inventory levels should be based on and not how they should be determined are included. Due to this, it is not possible to determine what part of the excess inventory at the EMSs actually falls within the contracts and is therefore the liability of Company X. Hence, we are not able to assign a value to what currently the financial risk of Company X is according to the contracts. Figure 6 visualizes the inventory of the EMSs and the financial risk of Company X regarding this inventory.

Company X has agreed to purchase the inventory of the EMSs after there have been no call offs after one year, see agreement eleven of appendix I. All inventory that has no demand is either already they liability of Company X or poses the risk to become the liability of Company X in the near future. Therefore, we include all inventory that is excess for determination of the financial risk of Company X. In Figure 6 this part of the inventory is represented by ‘has no demand, so is excess’.

Figure 6: Visualization of Company X’ financial risk regarding inventory

The proportions of the inventory in Figure 6 are not representative. Hence, Figure 6 only shows how the inventories can be broken up, but not in which proportions they are related.

The Key Performance Indicators (KPIs) where Company X and the EMSs contractually agreed upon regard only the logistical performance of the EMSs. These agreements are included in appendix I. Since only logistical KPIs have been defined, it seems that the EMSs are strictly assessed on their delivery performance. However, how these performance measures are defined indicate that this is not the case. Only target levels have been defined and no consequences are associated with non-performance. After inquire at the logistics auditor of Company X, we can conclude that the EMSs are assessed mildly on their delivery performance. He also states that the EMS desire to have low inventory levels as well. In the end, they foot the bill for the holding costs regarding these excess inventories. Hence, we eliminate ‘lack of incentives to purchase efficiently’ as one of the main causes of excess inventory.

2.2. Quantification of financial risk for Company X

In this section, the size of the problem is indicated by quantifying its consequences. This analysis is performed in order to determine whether the problem is actually worth investigating. As shown in the problem cluster of Figure 4, the excess inventories at the EMSs result in a financial risk. First we agree about what part of the inventory can be considered as excess inventory in section 2.2.1. In the subsequent sections, we quantify the main consequences of excess inventory, namely repurchasing and waste, respectively.

2.2.1. Excess inventory determination

Company X' definition of excess inventory is: inventory on stock and on order that has no demand (order or forecast). The demarcation of excess inventory according to literature is broader than what belongs to excess inventory in Company X' perception. See section 1.3.1 for what is stated in literature about defining excess inventory.

Obviously, the categories 'dead stock', 'degraded stock', 'obsolete', and 'inactive' are also excess inventory according to Company X' definition. This is less clear for the category 'slow-moving stock', because this includes the inventory which does have enough demand, but which is inefficient to have on stock already (the stock cannot be justified by the anticipated rate of future demand). Since this part of the inventory does not directly pose a financial risk to Company X, we decided to exclude it from our definition of 'excess inventory'.

The inventory that is considered as excess inventory in this research is therefore a part of the inventory that is excess according to literature. The scope of excess inventory that is maintained in this research is shown in figure 7.

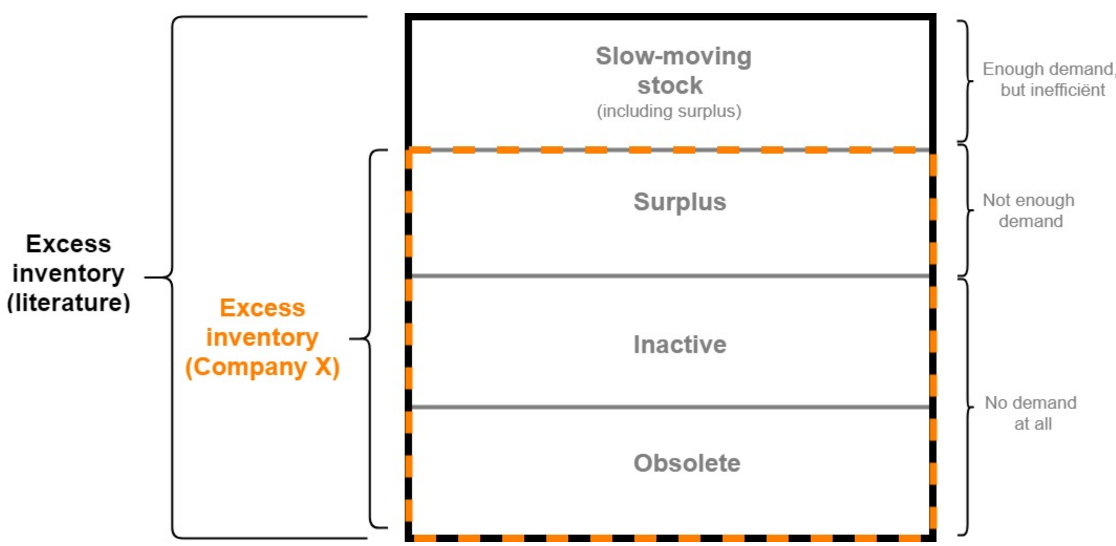


Figure 7: Excess inventory classification

Every item on stock or on order (future stock) which cannot be assigned to a certain demand is excess inventory. Therefore, the formula for determining the excess inventory levels is:

$$Excess\ inventory = \ on\ stock + on\ order - demand\ (orders + forecast)$$

2.2.2. Repurchase

Company X has agreed with their EMSs that if there has been no call off within one year for certain inventory, Company X will purchase it from the EMSs. The column 'financial risk' in Table 1 shows the total value of the excess inventory that had no call offs for twelve months or longer at the three biggest EMSs of Company X. This analysis is performed in November 2018 with actual data, so all excess inventory with a last-usage date in the 3rd quartile of 2017 or earlier is included. The column 'Near future risk' shows the part of the excess inventory which has a last-usage date in the 4th quartile of 2017, so which poses a financial risk in the near future.

Table 1: Inventory older than twelve months

EMS 2 does not provide information about the value in combination with the age of the inventory. The current financial risk due to the agreement of takeover of the inventory is therefore at least €XX. Moreover, the excess inventory covers XX% of the total inventory.

Some components from this excess inventory have no demand at all. Figure 7 classifies this inventory as 'inactive' or 'obsolete'. The total value of the excess inventory with zero demand is for the three EMSs €XX, which accounts for XX% of their total excess inventory. Table 2 shows the distribution of this excess inventory over the EMSs. EMS 2 has zero excess inventory that has no demand at all, since they produce the Company X products with a continuing demand.

Table 2: Inventory with zero demand (inactive and obsolete)

2.2.3. Waste

There are several reasons why components might no longer be usable. For example, a change in rules and legislations can cause that a component no longer meets the requirements. As shown in the problem cluster in Figure 4, there are two reasons that are significant and relevant for Company X' situation, namely the shelf life of components and whether they are Company X specific or generic.

Shelf life

Some components have an expiry date, since the quality cannot be guaranteed anymore after a certain amount of time. There is no information provided by the EMSs about the expiry dates of the components they have in stock. Based on experience, Company X made a selection of components that have a certain shelf life. In broad terms, this selection consists of PCBs (Printed Circuit Boards), coatings, glues and pottings. Figure 8 shows which part of the inventory that is needed for the already known future demand consists of products with a certain shelf life. This analysis only provides an indication of the size of this problem. The future demand of Company X that is already known represents approximately one year of demand.

Figure 8: Part of spend that has a shelf life

The pie chart in figure 8 shows that from all components and materials that are needed to fulfil Company X' demand, approximately X% has a certain shelf life. Table 3 shows that this percentage is XX% if we only consider the excess inventory. Company X requires the EMSs to properly manage the inventory control of these components, in order to guarantee the quality of the products. As expected, the percentage of components with a shelf life from the excess inventory is lower than from the total demand. Data about the exact shelf life is not available. If we, for example, assume that after one year the quality of these components already degrades, the €XX of inventory becomes write-off, since Company X expects to have no demand for it for at least one year ahead.

Table 3: Excess inventory with shelf life

Company X specific components

A part of the components are produced on Company X' specifications and are therefore not saleable. When these products are not usable for Company X anymore, they become waste. Figure 9 shows which part of the inventory that is needed for the already known future demand of Company X is Company X specific. The Company X specific components are also part of the cause of excess inventory at the EMS, since the MOQs are generally high when a manufacturer needs to fabricate for Company X only.

Figure 9: Part of spend that is Company X specific

Figure 9 shows that XX% of the total expected demand of Company X (approximately one year ahead) consists of components that are produced based on Company X specifications. In table 3 we calculated the same percentage for the current excess inventory (November 2018).

Table 4: Company X specific excess inventory

The proportion of Company X specific components compared to the total excess inventory is only XX%. A comparison between the excess inventory of components with a shelf life and Company X specific components shows that there is in total €XX overlap between these two characteristics of the excess inventory. This amount accounts for XX% of the total excess inventory and consists exclusively of PCBs.

2.2.4. Conclusion

The agreement of Company X with the EMSs to repurchase the excess inventory results in a current liability of €XX, which is expected to increase by €XX within the next quartile. We only take into account the excess inventory of EMS 3, EMS 2 and EMS 1, so the actual liability regarding the excess inventory at all EMSs will be even higher. A part of this inventory that is not covered by a certain demand and that has not been used the last twelve months, has no demand at all. The total value of the excess inventory with zero demand is for the three EMSs together €XX. The total excess inventory of these three EMSs together has a value of €XX. The part from this excess inventory that consists of Company X specific components is €XX. The part of the excess that has a certain shelf life is significantly smaller, namely €XX.

2.3. Classifying excess inventory based on cause

For determining what cause is worth investigating the most, an analysis is performed to classify the components which have an excess inventory. First we describe the data preparation we performed for this analysis in section 2.3.1. Subsequently, the rules of thumb we applied in order to classify the excess inventory have been elaborated in section 2.3.2. Finally, in section 2.3.3 the results of this analysis are presented.

2.3.1. Data preparation

To gain more insight in the size of the causes of excess inventory for the EMSs of Company X, their liability files are analysed. Each month, the EMSs send an overview with their inventory (on stock and on order) for Company X on component level. Company X has received these liability files from EMS 1 and EMS 3 for four months now (September to December). From EMS 2 only liability files from October until December are available. All the available files are included in this analysis, so also the variation of the inventory levels over time (the last months) are visible.

First some data preparation is required, since the liability files of EMS 3 contain duplicates. This implies that there are multiple rows for the same Company X item number, so for the same component. These duplicates cause that there is a difference in total excess value before and after consolidating. This is caused by the fact that a negative excess is not taken into account in the excess value. A negative excess inventory implies that there is more (expected) demand compared to the sum of the components that are on stock and on order. Table 2 shows an example of a component that causes a difference in excess inventory before and after consolidating.

Table 5: Effect of consolidating duplicate rows

The rows are merged using a Visual Basic Macros in Excel. The programming code for these macros is attached in appendix II. Only rows with a similar Company X item number and an equal price per unit are merged. Appendix II also gives an overview of the differences in total excess inventory before and after merging the rows.

2.3.2. Rules of thumb

The classes over which the excess inventory will be distributed is based on the causes of the excess inventory for Company X that were identified in section 1.4. In the following paragraphs we explain which causes are included in this analysis and what the rules of thumb for these causes are.

By the time Company X decided to outsource its production activities and thereby close its production facility, Company X built up an inventory buffer in order to guarantee delivery during the outsourcing process. A part of the current excess inventory might originate from this buffer. The cause 'Remainder inventory buffer from Production Facility X' is not influenceable anymore, since this was a one-time event from the past. However, this cause is included in the current selection of main causes, since Company X expects this cause to have a significant contribution to the current excess inventory levels and to obtain a more complete picture of the situation.

Section 2.1 describes that the cause 'lack of incentives to purchase efficiently' has been eliminated as possible core problem. This results in the following classes where we divide the excess inventory over:

- High MOQs
- Forecasting errors
- Lifecycle management
- Production Facility X: Remainder from outsourcing buffer

We assigned the excess inventory to one of these causes based on rules of thumb, which is explained in more detail below. When drafting these rules of thumb, we encountered that it is hard to establish a rule of thumb which determines what part of the excess inventory is caused by forecasting errors, since we cannot consider the excess inventory of each component individually. Therefore, we decided that remainder excess inventory, so the part that cannot be assigned to either the cause 'high MOQs' or 'Production Facility X', will end up in the class 'Forecasting/other'.

This class is further specified by excess inventory that is certainly caused by forecasting errors (referred to as 'forecast minimum') and excess inventory of products that have reached their end-of-life (further referred to as 'lifecycle management). The class 'lifecycle management' contains the excess inventory of components that have no future demand and no usage over the last year. The class 'forecast minimum' contains the excess inventory of components which have a certain amount on order, but which already had an excess without the ordered amount. Obviously, the forecasted demand has fluctuated, which has caused that there is inventory on order whilst there was already an excess. Furthermore, for the excess inventory assigned to 'high MOQs' a distinction is made between 'Company X specific' and 'generic' components.

A classification matrix is created to classify the excess inventory on component level to the three main causes. The level of excess inventory is determined by three factors, which are derived from the equation of excess inventory mentioned in section 2.2.1. The three factors are: the demand, the amount of components that are on stock and on the amount of components that are on order. Based on the levels of these three variables, the excess inventory of a certain component is assigned to one of the three main causes. For distribution of the excess inventory of the class 'Forecasting error / other' and 'High MOQs' over the sub classes, additional information is used. The formulas in appendix III shows how this is done.

All possible combinations of the three factors are elaborated in the classification matrix, see Table 6. As mentioned, this classification is based on rules of thumb, and therefore only gives an indication of the size of the causes. In the paragraphs below the table, the rules of thumb are explained.

Nr.	Factors				Causes		
	Demand	Stock	On order		MOQ	Buffer Prod. Facility X	Forecast / other
1	V	Stock >= Demand	V	→			
2	V	Stock < Demand	Excess < MOQ	→			
3	V	Stock < Demand	Excess >= MOQ	→			
4	V	Excess < MOQ	-	→			
5	V	Excess >= MOQ	-	→		*Takeover > stock* *Takeover > usage*	*Otherwise*
6	V	-	-	→	*No excess*		
7	-	V	V	→			
8	-	V	-	→		*Takeover > stock* *Takeover > usage*	*Otherwise*
9	-	-	V	→			
10	-	-	-	→	*No excess*		

Table 6: Classification matrix

If the component has demand (ordered or forecasted by Company X):

1. The stock level is already higher (or equal) than the demand, but there are also still components on order. This is caused by lowering the forecasted demand.
2. The stock level is not sufficient to cover all demand and there are some components on order. Also, the stock level plus the amount on order is bigger than the demand, so there is excess inventory, and the amount of excess inventory is lower than the Minimum Order Quantity. This implies that the excess inventory is caused by a too high Minimum Order Quantity.
3. The same conditions as rule two, but the excess inventory levels rise above the Minimum Order Quantities. This implies that there is too much on order due to lowering of the demand forecasted.
4. There are no components on order, because there is already more on stock than can be covered by the demand. This excess inventory is lower than the Minimum Order Quantity and therefore probably caused by a too high Minimum Order Quantity.
5. The same conditions as rule four, but now the excess inventory is higher than the MOQ. The excess inventory can be caused by either the takeover of inventory from Production Facility X or by forecasts/other. In case the amount of inventory of this component that the EMS took over from Production Facility X is higher than both the current stock level and the known past usage; the excess is probably caused by the takeover of this inventory buffer. If the current stock level or the past usage is more than the takeover from Production Facility X; additional components have been ordered in the meantime, so the excess inventory cannot be assigned to the outsourcing buffer and is therefore classified as 'forecast/other'.

6. When a component has a certain demand, but nothing on stock or on order; there is no excess inventory.

If the component has no demand at all:

7. If there is something on order; the excess must be caused by forecasting errors, regardless of whether there is something on stock or not (this applies to rule of thumb 7 and 9).
8. If there are some components on stock, but there is nothing on order; the classification of rule 5 applies.
9. If there is something on order; the excess must be caused by forecasting errors, regardless of whether there is something on stock or not (this applies to rule of thumb 7 and 9).
10. When a component has no demand and nothing on stock or on order; there is no excess inventory.

The translation of this classification to Excel formulas is shown in appendix III.

2.3.3. Results

The classification of excess inventory is made per EMS and per Business unit. See for the results of the excess inventory per EMS and per Business unit appendix IV and V respectively. Appendix VI provides an overview of the distribution of excess inventory per EMS over time. These graphs show that there are no major differences in excess inventory classification over the four months.

Figure 10 and Figure 11 provide an overview of the classification of the excess inventory for Company X in total. Figure 10 shows the proportion of the excess inventory value over the different causes. These values are calculated by first taking the average of the excess inventory per EMS per class over the different months and subsequently adding up these averages off all EMSs per class. What stands out in this chart, is that a big part of the excess inventory is assigned to the cause ‘forecast maximum’, which is the blue class in the chart. The class ‘forecast/other’, together with the classes ‘lifecycle management’ and ‘forecast minimum’ refer to the forecasting performance of Company X.

As the graphs in appendix IV show, there are certainly some differences per EMS in the distribution of excess inventory over the classes. The main differences are that for EMS 1 the MOQs and the takeover of inventory from Production Facility X are relatively major causes. EMS 3 has much more excess inventory compared to the other EMSs, but the distribution of excess inventory over the causes is in between the distribution of the other EMSs. EMS 2 has the lowest excess inventory levels, but what stands out is that relatively much excess inventory is assigned to the forecasting performance of Company X.

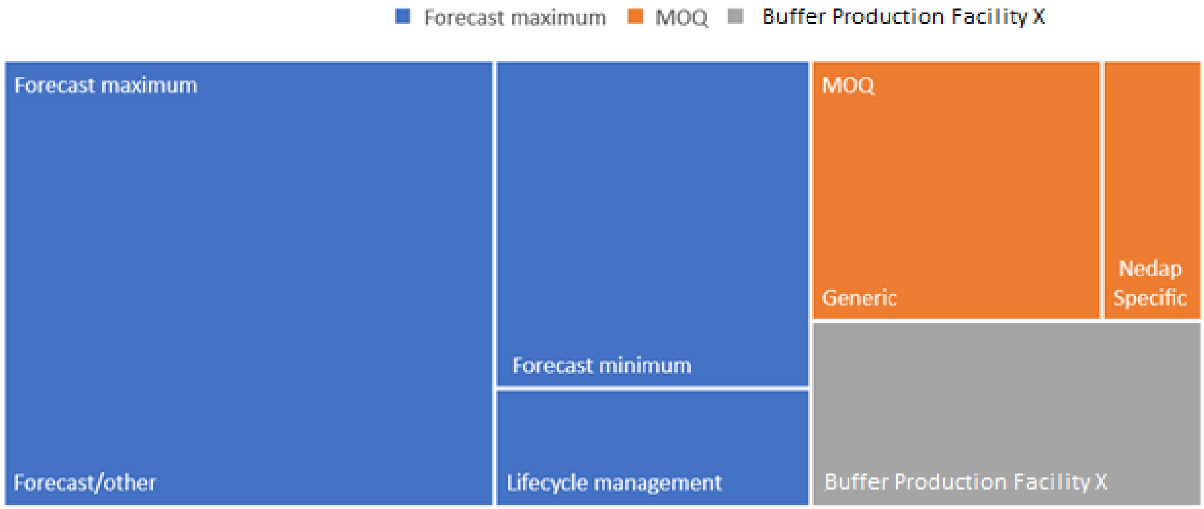


Figure 10: Chart excess inventory classification total

Figure 11 provides an overview of the classification of excess inventory over the four months. It shows that in broad terms the distribution of excess inventory over the causes is the same for each month. The value of the class 'Production Facility X' drops in November and rises in December, mainly caused by EMS 1 and EMS 2. This corresponds with the gradient of the total excess value of the EMS, as shown by the graph in Figure 12.

Figure 11: Graph excess inventory classification per month

However, if we zoom in on the distribution of the excess inventory per EMS per month, we see that it fluctuates. For EMS 1 and EMS 2 this fluctuation is better noticeable, since they have less excess inventory. A logical explanation for the fluctuation in the excess inventory distribution is that it is caused by the variability in demand forecasts. The demand forecasts together with the Company X orders determine what part of the inventory is considered as excess. Generally, a higher forecast implies lower excess inventory levels and the other way around.

Within this category, we make a distinction between excess inventory due to the phasing out of products/components (lifecycle management), excess inventory which is probably caused by forecasting errors (forecasting error / other) and excess inventory which is caused by forecasting errors with more certainty (forecasting errors minimum). Anyway, for almost each of the business units for all months the cause forecasting error is the biggest. The only exception on this statement is the month December for Business Unit A. The class 'Lifecycle management' dropped from November to December, caused by a certain rise in expected demand by €XX from November to December. Due to this, the excess inventory dropped, which results in the MOQs becoming the main cause of excess inventory for Business Unit A in December.

What we derive from the graphs in appendix V is that this variability is relatively large for the group 'Other', which includes the inventory of components on behalf of Production Facility X, multiple business units, other business units than the three in the scope of this research, or undefined business units.

Figure 12: Graphs total excess inventory per EMS and per business unit

Figure 12 shows that the excess inventory levels of Business Unit C are the most stable over the four months. September is left blank for Business Unit B, since there is no data of EMS 2 from September available and EMS 2 only produces for Business Unit B.

The demand consists for the main part of 'expected' demand, which causes the fluctuations in the excess inventory levels apparently. This indicates that the analysis is rather sensitive due to the dependence of the excess inventory level to the forecasts. To partly overcome this caveat, the analysis is performed for several months. Still for each month the conclusions that are directive for the further research are the same. Namely, identifying 'forecasting errors' as the main cause of the excess inventory.

Statistics

A statistical test is desirable to test whether there are significant differences over time in the distribution of the excess inventory over the causes per business unit per EMS. We have tried applying the statistical test using SPSS. However, after performing the test we can conclude that the results are not very valuable, since we have too few data points. Using the results for drawing conclusions about whether the differences are significant or not, would not be reliable. Due to the lack of available data, the analysis is too sensitive for outliers. Hence, we decided to exclude the results of the statistical test from this research.

2.4. Prioritization of causes

One way of determining what cause of excess inventory should be improved first, is just picking the cause with the greatest savings potential. However, there are more factors which affect the qualification of a certain cause for being the core problem. According to the definition of Heerkens and Van Winden (2012), the core problem must be influenceable, has no other causes and is the problem which has the greatest effect in case of multiple problems (Heerkens & Van Winden, 2012). From this definition, we derive three factors that affect the qualification for a cause to be the core problem. The absence of other significant causes to the core problem is a condition and not a criterion we can assess the causes on. Hence, two criteria for prioritization of the causes remain. These are: the influenceability (degree of influence) and the effectivity (degree of effect).

We use a decision matrix as method for this multi-criteria decision making problem. The weights of the criteria are regarded as equally important, because a less influenceable cause with great effect is considered as equally important as a more influenceable cause with less effect. Hence, we do not have to assign weights to these criteria.

The assessment matrix in Table 7 shows what a certain score on a certain criterion implies.

Score:	Influenceability	Effectivity
1	Company X can only slightly influence the cause	Addressing the cause slightly affects excess inventory at the EMS
2	Company X has influence on the cause, but is not the main influencer	Addressing the cause meanly affects excess inventory at the EMS
3	Company X is the main influencer of the cause	Addressing the cause mainly affects excess inventory at the EMS

Table 7: Assessment matrix

The main causes of excess inventory are:

- High MOQs
- Remainder from outsourcing buffer (Production Facility X)
- Product life-cycles (lifecycle management)
- Forecasting errors

The effect of the outsourcing buffer on the excess inventory levels nowadays is measured by quantifying the excess inventory that is a remainder from the outsourcing buffer at Production Facility X. Nevertheless, this cause is not influenceable anymore, so does not qualify for being the core problem of this research. In the decision matrix shown in Table 8, we assessed the three remaining causes on the two criteria. The scoring is performed by both the researcher and the company supervisor independently, which resulted in an equal scoring of all causes on both two criteria.

	Influenceability	Effectivity	Total
High MOQs	2	2	4
Lifecycle management	3	2	5
Forecasting errors	3	3	6

Table 8: Decision matrix

The scores on criterion 'Effectivity' have been determined based on the results presented in section 2.3.3. The scores for 'Influenceability' are subjectively determined by both the researcher and the company supervisor. High MOQs is a cause that belongs to the responsibility of the EMSs and is therefore less influenceable for Company X, meanwhile forecasting errors and lifecycle management are causes of Company X. Lifecycle management scores the same for effectivity as MOQs. According to the analysis of causes, lifecycle management is a smaller cause than MOQs but is more efficient to improve. MOQs will remain a cause of excess inventory while this is not the case for lifecycle management.

The sum of these two factors result in a total score per cause. The total scores only differ one point from eachother, which might indicate that the analysis is sensitive. Nonetheless, the difference in the scoring of the number one and number two cause originate from the criteria 'effectivity'. These scores are based on the analysis of section 2.3, which has shown notable differences between how much 'Lifecycle management' and 'Forecasting errors' contribute to the excess inventory. Moreover, multiplication of the scores would have led to the same ranking of the causes.

The cause which has the greatest score is "forecasting errors". Therefore, this cause has been identified as the core problem of this research.

2.5. Chapter conclusion

There are multiple factors contributing to the excess inventory posing a financial risk to Company X, which are described in section 1.4.1. The main factors are that the inventory becomes waste due to aging of the components and that the components fabricated on Company X' specifications cannot be sold. This in combination with the agreement between Company X and the EMSs to repurchase the inventory after it has not been moved within one year, results in the excess inventory posing a financial risk to Company X. In section 0 we quantified these factors, this gives an indication of the size of the problem for Company X.

The current inventory older than twelve months at only the three biggest EMSs is already worth XX% of Company X' operating profit. These three EMSs account together for €XX of excess inventory of components which have no demand at all. This inventory is classified as 'inactive' or 'obsolete' according to Figure 8. From the total excess inventory, only XX% consists of components with a shelf life. However, the part of excess inventory that consists of Company X specific components is significantly bigger, namely XX%. The quantification of the excess inventory and its characteristics indicate that the problem is definitely worth investigating for Company X.

In section 2.3 all the excess inventory has been classified to one of the main causes based on certain rules of thumb. This analysis showed us that for all four months and all three EMSs in scope, most excess inventory can be assigned to the cause 'forecasting errors'. The only exception on this statement is the month December for Business Unit A, when the excess inventory levels have dropped due to the sensitivity of the analysis for the forecasted demand.

Comparing the results over the business units shows us that for Business Unit A also the MOQs and the inventory buffer originating from Production Facility X seem to be a major cause. For Business Unit B relatively much excess inventory is assigned to forecasting errors and the distribution of the excess inventory over the causes is for Business Unit C in between the proportions of Business Unit B and Business Unit A. Anyway, for almost each of the business units for all months the cause Forecasting Errors is the biggest.

The classification of the excess inventory to the causes has served as input for prioritizing the causes. The prioritization of the causes is based on two criteria: influenceability and effectivity. Both the scoring by the researcher and Company X' Data Analyst resulted in same outcome: the forecasting errors should be identified as the core problem of the research. The cause Lifecycle Management is ranked at the second place and the cause High MOQs has given the lowest priority.

2.6. Research design (action problem)

The forecasting performance of Company X has been identified as the core problem of this research. Hence, the remaining part of this research will focus on improving the forecasting performance of Company X. In order to do so, we define the research design for solving this action problem in this section.

The description of the problem and the goal of this research according to the previous paragraph lead to the following main question:

RQ: How can Company X improve its liability by reducing (and avoiding further creation of) the excess inventory of materials and components at the EMSs?

To be able to answer this research question, the following sub questions will be answered by the approach mentioned per question.

SQ 1: What is the current situation of Company X regarding demand forecasting?

a) What are the current processes regarding demand forecasting at Company X?
b) What are possible methods for measuring the demand forecasting performance?
c) What is the current forecasting performance of Company X?
d) How can the effect of demand forecasting performance on excess inventory be determined?
e) What are the consequences of inaccurate forecasting for the inventory for Company X?

Sub question b and d are answered in chapter 3 by performing a literature review. Section 3.1 first provides some general information about demand forecasting. Section 3.2 gives answer to sub question b, by discussing several forecasting performance metrics. Hereby we make a distinction between metrics for measuring the accuracy and for measuring the bias. In section 3.3 sub question d is answered, by describing how the link between the demand forecasting performance and the inventory levels can be quantified.

In chapter 4 the information acquired by the literature review is applied to Company X. This chapter starts with a description of the forecasting processes of the different business units in section 4.1. Hereby sub question a is answered. The processes are schematically represented using flowcharts. The different processes are compared and their main differences and similarities are discussed. The information for describing the forecasting processes is acquired by performing interviews with the employees of the different business units that are responsible for the forecasting task. These interviewees know the most about how the processes actually take place, because they are most closely involved. Three Company X business units are included in the scope of this research, so three interviews have been performed. For both the business unit Business Unit B and Business Unit A, two employees were interviewed to obtain a complete and reliable view of the process. For the business unit Business Unit C, only one employee has been interviewed, since their forecasting task is performed by only this employee.

In section 4.3 the forecasting performance of Company X is assessed by measuring both the accuracy and bias, whereby sub question c is answered. Prior to this, we perform an analysis after the demand patterns of the Company X products in order to judge how hard it is to forecast these products. This analysis and its results are presented in section 4.2. Section 4.3 contains a description of the forecasting performance analysis. The data used for this analysis are the actual and forecasted demand for the year 2018, derived from Company X' ERP-system. Earlier data about the forecasted demand is not available and at the time this analysis was performed, information about the actual demand in 2019 was not known yet. We measured the current forecasting performance by using the most appropriate metrics found in literature.

In section 4.4 we attempted to describe the link between the forecasting performance and the excess inventory levels by applying the information found in literature. However, it turned out that due to the lack of available data, this analysis would not provide valuable outcomes, so is excluded from the research. Due to this, we have no clear answer to sub question e. This has no major consequences for the further research, since the results would not constitute an important input for the further course of the research. The added value of the analysis would be helping with creating awareness within the organization and different business units around the importance of accurate forecasts.

SQ 2: Which possible improvements regarding reducing (and avoiding further creation of) excess inventory exist for Company X?

a) What are possible methods for increasing the demand forecasting performance?
b) What can Company X do to improve their demand forecasting performance?
c) What are other possible improvements for Company X to reduce and avoid further creation of the excess inventory at the EMSs?

Sub question a is answered by performing a literature review, which is elaborated in section 3.4. Sub question b and c are answered in chapter 5. We answer sub question b in section 5.1, by providing a road map to an improved forecasting performance. This roadmap is based in the information found in literature and the analyses performed after the demand patterns, the current forecasting processes and the current forecasting performance of Company X.

Sub question c is answered in section 5.2. This is divided in two parts: reactive and proactive improvements. The reactive improvements contain possibilities for reduction of the current excess inventory and by the proactive improvements Company X can avoid further creation of excess inventory. Sources of these suggested improvements are the methods found in literature and conversations with employees of Company X.

3. Literature review

With this chapter, phase 4 (solution generation) of the MPSM has been elaborated. First some general information about forecasting and its terminology is explained in section 3.1. Section 3.2 contains a description of forecasting performance measurements, whereby sub question 1.b is answered. Thereafter, in section 3.3, the effect of forecasting errors on the inventory levels are described. This section gives the answer to sub question 1.d. In section 3.4, we discuss different forecasting models, which provides the answer to sub question 2.a. Finally, in the section 3.5, the conclusions are drawn.

3.1. Forecasting in general

Forecasting is required in many different situations. These forecasting situations vary widely in their time horizons, types of data patterns, and many other aspects (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). For example, a distinction can be made between short-term, medium-term and long-term forecasts. The decision-making about future resource requirements, which is for example the purchase of raw materials and components, belongs to the medium-term forecasts (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). In section 3.1.1 other characteristics of forecasts are described. Subsequently, in section 3.1.2. the characteristics of demand that affect the demand forecasting method are discussed. In section 3.1.3 we describe what is stated in literature about the forecasting process.

3.1.1. Forecast characteristics

Forecasting is the process of making predictions for the future using past and present data. In an organizational context, there are many things that can be subjected to forecasting, like required maintenance, revenue growth, sales and demand. In literature, no distinction is made between sales and demand forecasting. Mentzer and Moon (2005) state that although they speak of 'sales forecasting', they are actually trying to forecast the demand, since what they want to know is what their customers demand so they can plan their sales on that. They define the sales forecast as the projection into the future of expected demand (Mentzer & Moon, 2005).

Apart from what is forecasted, there are also different kinds of forecasts. A distinction in kinds of forecasts can be made based on several factors, for example on the data available. If there is no (relevant) data available, qualitative forecasting methods must be used. When there is numerical information about the past available and it is reasonable to assume that past patterns will continue into the future, quantitative forecasting should be applied (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). Quantitative forecasting can in turn be divided based on data characteristics. Most quantitative forecasting problems use either cross-sectional data or time-series data. Cross-sectional data is collected at a single point in time and are mostly used for econometric forecasting, in which relations between variables are predicted (Brooks, 2008). In time series forecasting, the data is collected at regular intervals over time and used to predict the future values for this series. (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). Company X observes the demand in weekly time intervals, so the forecasting problem of Company X concerns time series data.

In time series analysis, a distinction between univariate and multivariate time series data can be made. Multivariate times series analysis is used for modelling the dependency between two or more time series variables (Singh, 2018). In univariate time series models, the data consists of a single time-dependent variable (Singh, 2018). Here, single observations are recorded sequentially over equal time increments, which is the case for the forecasting data of Company X.

Some other distinctions in forecasting are between (Brooks, 2008):

- point forecasts (predicts a single value) and interval forecasts (predicts a range of values with a certain level of confidence),
- one-step-ahead forecasts (predicts next observation only) and multi-step-ahead forecasts (predicts multiple steps ahead),
- in-sample forecasts (are generated for the training set, which is the same set of data that was used for estimating the forecasting model's parameters) and out-sample forecasts (which are generated for the test set) and
- rolling time windows (in which the length of the in-sample period is fixed, so every time a new observation is added, the oldest data point is dropped) and recursive time windows (in which, on the other hand, the start date of the in-sample period is fixed, so the length of the in-sample period increases by adding an observation) (Brooks, 2008).

3.1.2. Demand characteristics

There are several characteristics of demand which affect the choice of a forecasting technique. These characteristics with their demand pattern classification are explained in the next paragraphs under 'Demand patterns'. The demand characteristics which determine whether a data transformation methods should be applied in advance of generating forecasts based on this data, are described under 'stationarity'.

Demand patterns

Syntetos (2001) distinguishes four non-normal demand patterns, which are: slow moving demand, intermittent demand, irregular/erratic demand, lumpy demand. Demand is considered as slow moving in case of when demand occurs, it is only for a single unit or very few units. Silver et al (1998) define intermittent demand (also referred to as 'sporadic' demand) as "infrequent in the sense that the average time between consecutive transactions is considerably larger than the unit time period, the latter being the interval of forecast updating (p. 127)". We can therefore conclude that intermittence refers to the frequency in which demand occurs and not to the size of this demand. On the other side, regular/erratic demand does refer to the size of the demand when demand occurs. According to Silver et al (1998) demand can be considered as erratic if the variability is large relative to the mean. According to these definitions, erratic demand can also be intermittent. When this combination occurs, it is called 'lumpy' demand. Lumpy demand implies great differences in demand size and lots of periods with no demand (Munaron, 2017).

Syntetos, Boylan, and Croston (2005) operationalized the classification of demand patterns by the two parameters ADI and CV^2, which measures the regularity of demand in time and the variation in demand quantities, subsequently:

- Average inter-Demand Interval (ADI): the average interval between two consecutive demands, where N_{p_i} represents the number of periods with non-zero demand (Costantino, 2017).

$$ADI_i = \frac{\sum_{n=1}^{N_{p_i}} t_i^n}{N_{p_i}} = mean(t_i^n)$$

- Squared Coefficient of Variation (CV²): the standard deviation of the demand of item i, divided by the average demand d_i, where $d_i = \frac{\sum_{n=1}^{N_{p_i}} d_i^n}{N_{p_i}}$ (Costantino, 2017).

$$CV_i{}^2 = \left(\frac{\sqrt{\frac{\sum_{n=1}^{N_{p_i}} \left(d_i^n - d_i\right)^2}{N_{p_i}}}}{d_i} \right)^2 = \left(\frac{stdev\ (d_i^n)}{mean\ (d_i^n)} \right)^2$$

These two parameters classify the demand patterns as follows (Syntetos, Boylan, & Croston, 2005):

- Smooth demand (regular demand over time, with limited variation in quantity):
  - ADI < 1.32, CV² < 0.49;
- Erratic demand (regular demand over time, but large variation in quantity):
  - ADI < 1.32, CV² > 0.49;
- Intermittent demand (sporadic demand with limited variation in quantity):
  - ADI > 1.32, CV² < 0.49;
- Lumpy demand (sporadic demand with large variation in quantity):
  - ADI > 1.32, CV² > 0.49.

In Figure 13 the differences in demand patterns are schematically represented by graphs.

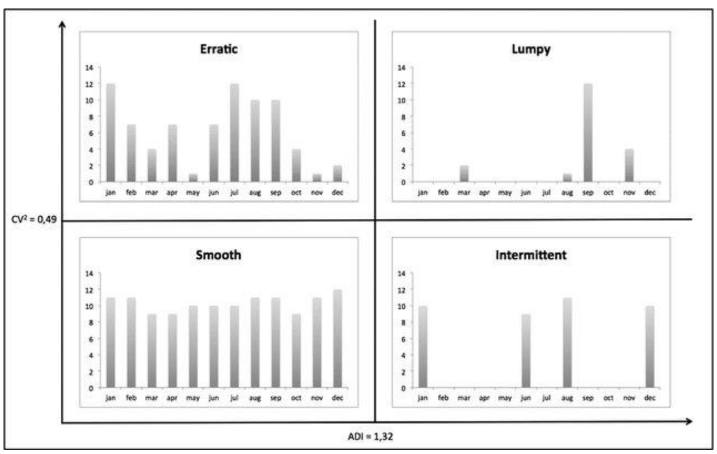


Figure 13: Demand patterns. Note: Reprinted from Spare parts management for irregular demand items, by Costantino et al. (2017), retrieved from https://www.researchgate.net/deref/https%3A%2F%2Fdoi.org%2F10.1016%2Fj.omega.2017.09.009 Copyright 2017 by Elsevier Ltd.

The classification of demand patterns as described above is based on the variability in the demand size and the variability in the length of the inter-demand intervals. This classification can be linked to the forecastability of the products, which is the ability to statistically forecast the product. The more the product moves to the upper right corner of Figure 14, the harder it is to forecast its demand pattern. We can therefore conclude that forecasting 'smooth' demand is the easiest, followed by 'erratic' and 'intermittent' demand. Obviously, generating accurate forecasts is the most difficult for 'lumpy' demand, since forecasting these items implies dealing with the issues of both high variability in size and in inter-demand intervals (Costantino, 2017).

Stationarity

Another characteristic for describing demand is the stationarity. Forecasts are based on extracted information which is continued into the future. Depending on the forecasting method, the extracted data needs to hold several assumptions about statistical characteristics. A common assumption is the stationarity of the demand data. This assumption implies that the data has stable statistical characteristics over time (e.g. mean, variance, etc.), so the statistical properties may not be dependent on the moment of observation. After all, "if we wish to make predictions, then clearly we must assume that something does not vary with time" (Brockwell & Davis, 2016). Data is for example non-stationary when an upward trend causes an increasing mean over time or when seasonality causes a varying variance over time. Seasonality should not be confused with cyclic behaviour, which implies the data is stationary (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). Cycles in time series data are fluctuations that have no fixed frequency, while in case of seasonality the fluctuations have an unchanging frequency which is associated with some aspect of the calendar (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018).

Data can be made (approximately) stationary by applying data transformation methods. Some common methods are discussed in section 3.4.2. Also, several methods for gaining insight in the time series components as trend and seasonality are described in section 3.4.1.

3.1.3. The forecasting process

Several researchers have described a framework for demand forecasting. Hyndman and Athanasopoulos (2018) distinguished the following basic steps of the forecasting task:

- <u>Step 1: Problem definition</u>. This includes understanding of how the forecasts will be used, who has an interest in the forecasts, and how the forecasting function fits within the organization.
- <u>Step 2: Gathering information</u>. Forecasting requires at least two kinds of information; statistical data and expertise of the people involved in the forecasting process.
- <u>Step 3: Preliminary (exploratory) analysis</u>. Exploratory analysis of the data starts with graphing it. Hereby, outliers and patterns as trends and seasonality can be recognized easily.
- <u>Step 4: Choosing and fitting models</u>. Multiple factors, like the availability of historical data and its characteristics, affect how well a model fits the data. It is common to compare two or three potential forecasting models. Fitting of these models implies the estimation of their parameters.
- <u>Step 5: Using and evaluating a forecasting model</u>. The accuracy of the forecasts produced by the model can only be properly assessed after the data for the forecast period have become available.

For most of the forecasting process descriptions the first step is the problem definition. This includes setting the goals and scope (determination of what has to be forecasted and for what horizon) of the forecasting. Hereafter, the analytical phase starts by gathering and exploratory analysing the data. Silver, Pike and Thomas (2017) described a more general framework from the analytical phase onwards, as shown in Figure 14. This process description emphasizes the cyclical nature of the forecasting process. Herewith, it focuses more on the using and evaluation of the model instead of the selection and building of a model.

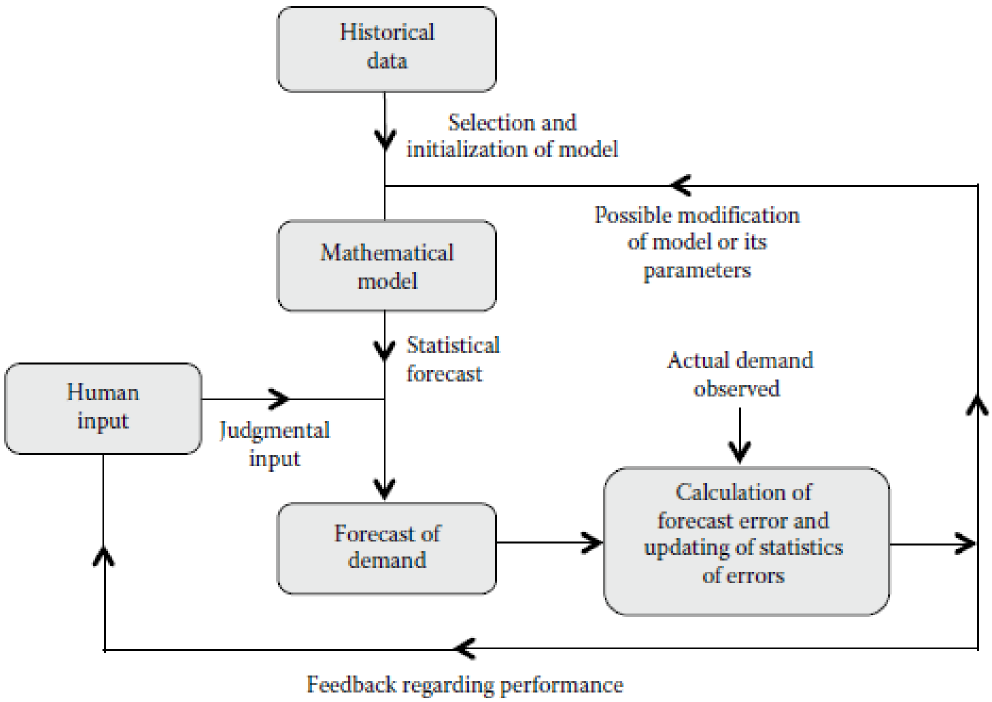


Figure 14: Framework for forecasting (Silver, Pyke, & Thomas, 2017, p. 74)

Duffuaa and Raouf (2015) schematically represented the forecasting process in a flowchart, which is shown in Figure 15.

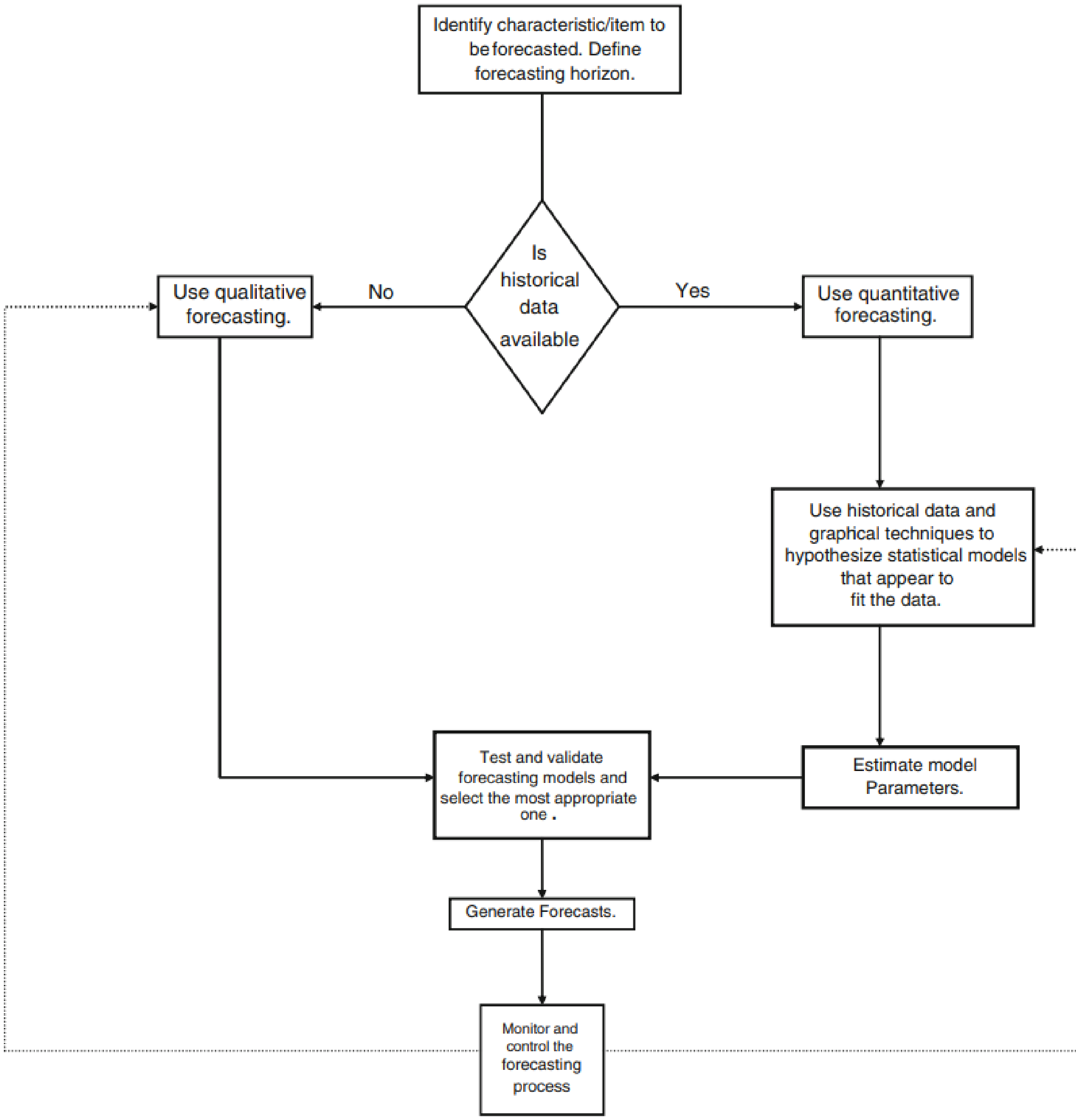


Figure 15: Forecasting process cycle (Duffuaa & Raouf, 2015, p. 21)

The main differences with the process described by Hyndman and Athanasopoulos (2018) are that Duffuaa and Raouf (2015) explicitly branch on the availability of historical data, which determines whether quantitative or qualitative methods are applicable, and that they have divided the activities differently over the steps. Moreover, the steps that have to be taken and their associated activities are pretty much equal.

3.2. Forecasting performance measures

Before evaluating whether a forecast is accurate, first a frame of reference is needed to determine when a forecast can be called accurate. Kolassa (2008) stated: “One cannot simply take industry-specific forecasting errors as benchmarks and targets”. The differences between companies and products are too large for useful comparison. Forecasting errors depend for example on the number of fast sellers, the presence of promotional activities or prices changes, data quality, etc. (Kolassa, 2008). Instead of external benchmarks, focus should be on internal forecast process improvement to guide in defining the forecasting accuracy. Hence, the forecasting accuracy can only be evaluated after the forecasting process has been adapted and another forecasting accuracy measurement has been performed, so a comparison of forecasting errors over time can be made.

When measuring the forecast accuracy, it is important to use data that were not used when fitting the model. It is therefore a common practice to separate the available data into two data sets; the training set and test set. The training data is used as input for the forecasting model and the test data is used for evaluating the forecasting accuracy (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). The size of the test set is typically 20% of the total sample and should be at least as large as the forecast horizon (Hyndman, Measuring forecast accuracy, 2014).

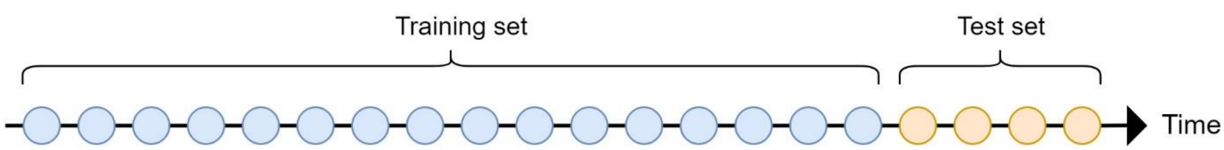


Figure 16: Dividing time series in data sets

Whether one forecasts future demand, production, maintenance, etc., a model’s forecasts are almost never 100% accurate. There exist numerous metrics for evaluating the forecast accuracy in literature. Each one of them has their own shortcomings, which generally resulted in next variants of the metric. Most forecasting performance metrics are based on forecasting errors. The definition of forecasting error is the difference between an observed value from the test data and its individual forecast produced using only data in the test. Unlike the term ‘error’ does appear, this difference is “not a mistake [but] the unpredictable part of an observation” (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). The equation of the forecasting error is given below. The training data is given by $\{y_1, \dots, y_T\}$ and the test data by $\{y_{T+1}, y_{T+2}, \dots\}$. The variable t defines the index of a period in the time series. The variable y_t represents the actual value at period t and $\bar{y}_t$ is the fitted or forecasted value at period t.

$$e_{T+h} = y_{T+h} - \bar{y}_{T+h}$$

Residuals are the differences between the observed value and its fitted value. The fitted value is defined as the forecast of y_t based on observations $y_1, \dots, Y_t$. The equation for residuals is as follows:

$$e_t = y_t - \bar{y}_t$$

The forecasting error differs from residuals in two ways. Residuals are determined on the training set and forecasting errors on the test set. Residuals can therefore be considered as an estimator of the forecasting error. The second difference is that residuals are based on one-step-ahead forecasts while forecast errors can also contain multi-step-ahead forecasts (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018).

The terms 'forecast fit' and 'forecast error' are often used interchangeably, but this is not correct (Mandal, 2007). The forecast fit refers to how successfully the forecasting method 'fits' the actuals (Vanguard Software Corporation, 2019). It describes the relative difference between actual historical data and hypothetical forecast data, which was generated by the forecasting model that is trained with the same historical data (Mandal, 2007). Hence, by analysing the residuals one can determine the forecast fit. Unlike the forecasting error, which describes the difference between the demand that was forecasted and the actual demand that occurred subsequently. The following sections describe some forecasting measures for accuracy and for bias. These measures can be applied on both the forecasting error and residuals. Since this information about forecasting measures will be used for measuring the current forecasting performance of Company X, we will use the term 'forecasting error' in the next paragraphs.

3.2.1. Accuracy

The forecast accuracy is the degree of closeness of the forecasted demand to the actual demand. There are several metrics for judging the forecast accuracy, which are categorized into four types by Hyndman (2006) based on the way of measuring and averaging the error. In the next paragraphs, these four categories with their most common metrics are discussed.

Scale-dependent errors

The forecast error is always on the same scale as the data. Hence, all accuracy metrics based on the forecast error (e_t) are scale-dependent. The most common scale-dependent errors are enumerated below (Hyndman, Another Look at Forecast Accuracy Metrics for Intermittent Demand, 2006). The values of the forecasting errors are in all three metrics either squared or made absolute, so negative and positive errors cannot offset each other (Hyndman, Another Look at Forecast Accuracy Metrics for Intermittent Demand, 2006). Herewith, the forecasting error is originally The added benefit of the last metric mentioned, the RMSE, is that it returns the measure to the original scale of the data by taking the square root of the MSE. The variable n represents the length of the time series.

- Mean Absolute Error or Mean Absolute Deviation (MAE or MAD) = $\frac{\sum_{t=1}^{n}|y_t-\bar{y}_t|}{n} = mean(|e_t|)$
- Mean Squared Error (MSE) = $\frac{\sum_{t=1}^{n}(y_t-\bar{y}_t)^2}{n} = mean(e_t^2)$
- Root Mean Squared Error (RMSE) $= \sqrt{\frac{\sum_{t=1}^{n}(y_t-\bar{y}_t)^2}{n}} = \sqrt{mean(e_t^2)}$
- Geometric Mean Absolute Error (GMAE) = $(\prod_{t=1}^{n}|y_t - \bar{y}_t|\,)^{\frac{1}{n}} = gmean(|e_t|)$

The scale-dependency of these metrics causes straight away their main shortcoming. These metrics are not meaningful for assessing a forecasting method's accuracy across multiple series, if the data is not on the same scale. The MAE is the easiest to understand and compute and is therefore the preferred metric of Hyndman (2006) for single series.

Percentage errors

The formula for the percentage error is: $p_t = 100e_t/y_t$. These errors are less scale dependent, which make them better suitable for comparing different data series. The most commonly used measure is the MAPE.

- Mean Absolute Percentage Error (MAPE) = $\frac{\sum_{t=1}^{n}|(y_t-\bar{y}_t)/y_t|}{n} * 100 = mean(|p_t|)$

Percentage error metrics have also some disadvantages. Zero values in the data causes that the measurement using percentage errors becomes infinite or undefined. Also when the values are close to zero the MAPE is unusable, because in that case extreme values cause that the distribution of percentage errors becomes very skewed. Intermittent data frequently contains zero values because of the occurrences of periods of zero demand, which makes using the MAPE meaningless.

Another disadvantage of the MAPE is that positive errors are heavier weighted compared to negative errors. For this reason, the accuracy metric used in the latest two M-competitions is the symmetric MAPE (sMAPE), which was proposed by Armstrong (1978, p. 348). The M-competitions are a series of competitions organized under direction of researcher Makridakis and with the goal to evaluate and compare the accuracy of forecasting methods (M-competitions, sd). However, no special attention has been paid to forecasting intermittent or lumpy demand in these competitions. Due to the presence of many zero-values in this data, the performance of the different forecasting methods can be different from the performance measured in the M4-competitions. For that reason, this research ignores the results of the M4-competettions for describing appropriate forecasting models for Company X in section 3.5.

Also the sMAPE has some disadvantages. The denominator can still be close to zero causing that the measurement becomes undefined and the sMAPE can have a negative value, which makes it harder to interpret.

- Symmetric Mean Absolute Percentage Error (sMAPE)

$$= \frac{2 * \sum_{t=1}^{n} \left(\frac{|y_t - \bar{y}_t|}{y_t + \bar{y}_t} \right)}{n} * 100 \; = mean(200\, |y_t - \bar{y}_t| \,/\, (y_t + \bar{y}_t))$$

Relative errors

Relative errors are an alternative to percentage errors for assessing forecast accuracy across multiple series, since they are also less scale dependent. These errors are made relative by dividing it by errors of a benchmark method. The relative error is given by: $r_t = e_t \,/\, e_t^*$. The naïve method is usually used as benchmark method. In the naïve method the most recent observation is used as a forecast (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). Two relative errors are:

- Median Relative Absolute Error (MdRAE) $= median\left(\left|\frac{y_t - \bar{y}_t}{\bar{y}_{t-1}}\right|\right) = median(|r_t|)$
- Geometric Mean Relative Absolute Error (GMRAE) $= \left(\prod_{t=1}^{n} \left|\frac{y_t - \bar{y}_t}{\bar{y}_{t-1}}\right|\right)^{\frac{1}{n}} = gmean(|r_t|)$

However, relative errors have the same disadvantage as percentage errors, since it would still involve division by zero when errors are small using the naïve method as the benchmark method.

Scaled errors

Hyndman and Koehler (2006) proposed an error which is independent of the scale of the data. This scaled error compares the error of the current forecast with the in-sample MAE from the naïve method. The naïve method uses the actual demand from the past period as a forecast for the next period, so it generates one-period-ahead forecasts. The formula for the scaled error is:

$$q_t = \frac{y_t - \bar{y}_t}{\frac{1}{n-1} \sum_{i=2}^{n} |y_i - y_{i-1}|}$$

Which brings us to the following formula of the MASE:

- Mean Absolute Scaled Error (MASE) $= \frac{\sum_{t=1}^{n} \frac{|y_t - \bar{y}_t|}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}}{n} = mean(|q_t|)$

In their research, Hyndman and Koehler (2006) compared the MASE with some commonly used forecast accuracy metrics on intermittent demand data. Their results proved that the MASE gives sensible results for different forecasting methods, where the other accuracy metrics (GMAE, MAPE, sMAPE, MdRAE and GMRAE) gave infinite, undefined or zero values for some forecasting methods.

Syntetos and Boylan (2005) suggested using the GMAE for intermittent demand data, because it would only involve division by zero when an inappropriate forecasting method is used. Nevertheless, this statement is refuted by both Hyndman (2006), by stating that “it is not clear that the naïve method is always inappropriate”, and Hoover, who indicated that division-by-zero are expected occurrences for repair parts with intermittent data series (Hyndman, Another Look at Forecast Accuracy Metrics for Intermittent Demand, 2006).

3.2.2. Bias

When measuring the forecasting performance, it is not only interesting to know the accuracy (the size of the error), but also its bias. A forecast bias occurs when it has a general tendency to either over or under predict. Herewith, the forecasting error can be a result of bias. Over-forecasting is the occurrence that the forecasted demand is generally more than the actual demand while under-forecasting is the other way around. Below two measures for bias are discussed.

- Mean Error (ME) $= \frac{\sum_{t=1}^{n}(y_t - \bar{y}_t)}{n} = mean(e_t)$

By calculating the Mean Error, the forecasting error is not made absolute. Due to this, the ME measures the bias instead of the accuracy. If the forecasts are consistently lower than the actual values, the ME will be positive. Consistently lower forecasting values than actual values, results in a positive ME metric and the other way around. Another measure for bias is the Mean Percentage Error (MPE), which is the MAPE but without making the percentage error absolute. According to DeLurgio (1998), the MPE is a relative measure of forecast bias that facilitates forecast model comparison (van Sommeren, 2011).

- Mean Percentage Error (MPE) $= \frac{\sum_{t=1}^{n}((y_t - \bar{y}_t)/y_t)}{n} * 100 = mean(p_t)$

In the MPE, the bias is related to the actual demand value, which makes it easier to interpret the size of the bias compared to using the ME. However, for intermittent demand series, the division by zero problem still exists using the MPE.

3.3. Effect of forecasting on inventory

Demand forecasting is one of the most critical issues of inventory management (Kocer, 2013). There is plenty of information about both forecasting and inventory control in literature. Nevertheless, there are only a few contributions that describe the bridge between these two (Teunter, Syntetos, & Babai, 2011). Uncertainty and a highly volatile variation in demand makes the inventory control problem complicated (Kocer, 2013). For intermittent demand, this complexity is even higher, since the sequence of zero values in the demand data is the most important factor for volatility of demand (Kocer, 2013).

One possible way of describing the link between demand forecasting and the inventory levels in the supply chain is by using the bullwhip effect. As already defined in section 1.3.3, the bullwhip effect is the phenomenon of increasing demand variability as one moves op in the supply chain. One of the main causes of the bullwhip effect is demand forecasting and an often mentioned consequence of this phenomenon is excessive inventories.

Several researchers investigated the effect of demand forecasting on the bullwhip effect. Chen et al. (2000) demonstrated that the "the smoother the demand forecasts, the lower the bullwhip effect" (Chen, Ryan, & Simchi-Levi, The Impact of Exponential Smoothing Forecasts on the Bullwhip Effect, 2000). Another insight demonstrated by their research is that longer lead times lead to a greater increase in variability. Xiaolong Zhang (2004) also performed research after the impact of the demand forecasting technique on the bullwhip effect. He investigated three different forecasting techniques for a simple inventory system with an first-order autoregressive demand process. His conclusion was that forecasting methods play an important role in the size of the impact of lead time and demand autocorrelation (when demand is influenced by the historic demand of the same time series) on the bullwhip effect (Zhang, 2004). Baganha and Cohen (1995) investigated a more complex model with an autoregressive demand process and a multi-echelon distribution system. Herewith they showed that the demand variability can be decreased by a centralized distribution system and the stabilizing effect of inventories (Baganha & Cohen, 1995).

The bullwhip effect can be quantified by dividing the variability of the order quantity placed to the manufacturer (q_t) by the variability in customer demand (D_t). This results in the following formula:

$$Bullwhip\ effect = \frac{Var\ (q_t)}{Var\ (D_t)}$$

However, even though demand forecasting is one of the biggest factors that affect the bullwhip effect, it is not the only factor contributing to the bullwhip effect. Moreover, there are also multiple factors that affect the occurrence of excessive inventory levels. Calculation of the bullwhip effect does not provide an exact quantification of the causal relationship between demand forecasting and inventory levels and can therefore not be considered as an exact quantification of the effect of forecasting on inventory.

3.4. Forecasting models

There are many different forecasting models discussed in literature with each their own advantages and shortcomings. We expect the gross of Company X' products to be classified as having 'intermittent' or 'lumpy' demand. Therefore, we pay most attention to describing forecasting methods that are suitable for this kind of demand patterns.

Qualitative forecasting is also referred to as 'judgmental forecasts'. Hyndman and Athanasopoulos (2018) state that when data are available, applying quantitative methods is preferable. Company X has historical demand data, so they use this information for their forecasts and hereby apply quantitative forecasting methods. Sometimes applying judgmental adjustments to the quantitative forecasts results in more accurate forecasts (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). A study by Syntetos, Nikolopoulos, Boylan, Fildes and Goodwin (2005) proved that this applies for products with intermittent demand. These adjustments are only effective when there is important additional information at hand which is not incorporated in the quantitative forecasting model yet. The benefits from applying judgmental adjustments only come to fruition when the undermentioned principles are taken into account (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018):

- Clearly **setting of the forecasting task** creates awareness of its importance and avoids distraction of the forecaster to irrelevant information.
- It is essential to use a **systematic approach**. For example, a checklist can be useful for identifying what information is important and relevant.
- **Formal documentation** contributes to consistency and accountability of the forecaster, which can lead to a reduced bias.
- By **systematically monitoring** the forecasting process, the forecaster can learn and improve the forecast accuracy from feedback and evaluation.
- **Segregation of the forecasters and users** is important because of their possibly differencing interests. Also, when for example after a cost-benefit analysis turns out that holding excess stock costs less than lost sales, management may decide to adjust the forecast upwards. These adjustments are no part of the forecasting process, but belong to setting goals or planning supply.

In the following sections we describe different quantitative methods according to literature. This starts with a description of time series decomposition and data transformation methods in section 3.4.1 and 3.4.2 respectively. These methods are not explicitly forecasting methods, but methods for preparation of the data which serves as input for the forecasting models. From section 3.4.3 on, the quantitative forecasting methods are described.

3.4.1. Time series decomposition

To better understand the time series, it is helpful to decompose the data in several components, which each their own data pattern category. This time series decomposition is often considered as an useful step in data exploration. In section 3.1.2, we already discussed the time series patterns: trend, seasonality and cycles. Usually trend and cycle are combined into one category; the trend-cycle component (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). Hyndman and Athanasopoulos (2018) distinguish two other categories: the seasonal component and a remainder component. The remainder component represent the unexplained variation of the time series data.

Originating from the 1920s, the classical time series decomposition method forms the basis of many present decomposition methods (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). The first step of this classical method for time series decomposition is estimating the trend-cycle by using the moving average smoothing method. Herewith the value of the trend-cycle at time t is estimated by averaging the time series values within k periods of t, according to the undermentioned formula, where $m = 2k$ represents the length of the seasonal period.

$$\widehat{T_t} = \frac{1}{m+1}\sum_{j=-k}^{k} y_{t+j}$$

By adding weights to the averages, the weighted moving averages smoothing method yield an even smoother estimate of the trend-cycle (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018).

The subsequent steps of the classical method after calculating the smoothed moving average $\widehat{T_t}$ are:

- Calculating the detrended series by: $y_t - \widehat{T_t}$.
- Calculation of the seasonal component $\widehat{S_t}$. The seasonal component for each t can be estimated by averaging the detrended values for that season.
- Calculation of the remainder component by: $\widehat{R_t} = y_t - \widehat{T_t} - \widehat{S_t}$

There are two ways of classical decomposition: additive decomposition and multiplicative decomposition. The multiplicative decomposition differs from the additive decomposition by replacement of the subtractions from y_t by divisions (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018).

As far as we know, there is no literature about application of time series decomposition methods to intermittent time series data. Logically, we think that if the components have a multiplicative relationship, the zero values would be problematic for decomposition. Additive decomposition would not pose a problem to intermittent data because of the absence of multiplication and division.

There are several other time series decomposition methods which are based on the classical method. X11 is such a method. It includes many extra steps and features in order to overcome the drawbacks of classical decomposition. Seasonal Extraction in ARIMA Time Series (SEATS) is another example of an alternative method, but its procedure works only with quarterly or monthly data. Seasonal and Trend decomposition using Loess (STL) is another alternative method, which is more versatile and robust. It is developed by Cleveland, Cleveland, McRae, & Terpenning (1990) and decomposes the data by estimating nonlinear relationships. Figure 17 by Brownlee (2017) shows an example of decomposed times series data.

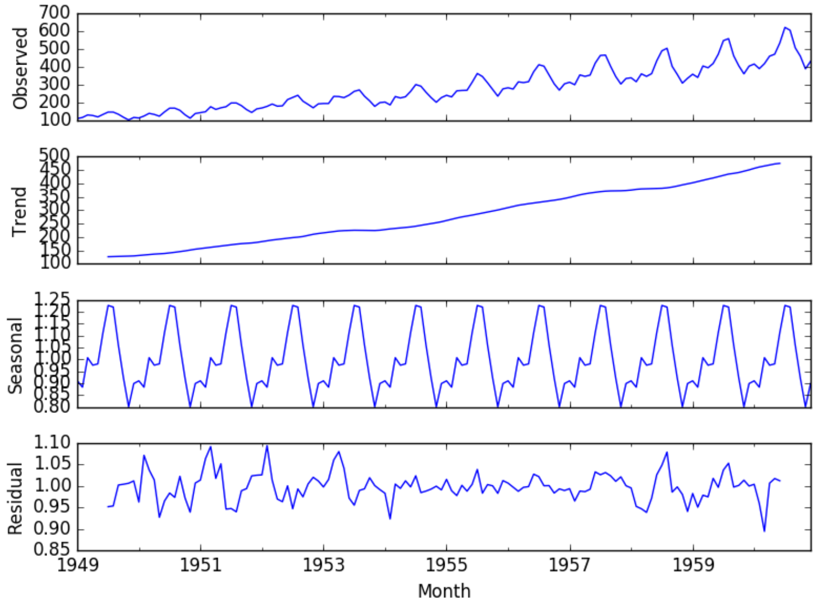


Figure 17: Multiplicative Decomposition of Airline Passenger Dataset. Note: Reprinted from How to Decompose Time Series Data into Trend and Seasonality, by Brownlee (2017), retrieved from https://machinelearningmastery.com/decompose-time-series-data-trend-seasonality/

3.4.2. Data transformation methods

As described in section 3.1.2, non-stationary data requires application of a data transformation method. Data transformation methods remove or reduce the sources of variation, leading to simpler patterns in the data which usually results in better forecasts (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018).

De-trending and de-seasonalizing

Data containing trends or seasonality have non stable statistical properties over time. By removing the trend, the data will stabilize along a horizontal line. What remains are the seasonal component and the remaining component. By de-seasonalizing, also the periodic fluctuations are removed. In section 3.4.1 we described methods for subtracting the different components from the time series data.

Data aggregation

Data aggregating implies combining data of different levels or groups to an overview on a higher level. These levels or groups can refer to any kind of hierarchy in time series data, for example time or product groups. By temporal aggregation of the time series demand data, the demand patters can be smoothed. Due to this, at a higher aggregation level low frequency components as trend/cycle will dominate, while at a lower aggregation level seasonality becomes clearer (Athanasopoulos, Kourentzes, Hyndman, & Petropoulos, 2017). Temporal aggregation can therefore be considered as a tool to better understand and model the data.

The aggregation level of the data also affects the forecasting performance (Zotteri, Kalchschmidt, & Caniato, 2005). So data aggregation can be applied for exploring the components of the times series data, as well as it can be used as a tool to improve the forecasting performance. Zotteri et al. (2005) showed an example of a forecasting technique that performed better on a higher aggregation level. However, they also mentioned that this conclusion is drawn for a specific set of data and cannot simply be generalized. It should therefore be investigated further for other specific situations.

3.4.3. Simple methods

The most familiar methods for forecasting intermittent demand are moving average, exponential smoothing, trend adjusted exponential smoothing and linear regression (Mishra, Yuan, Huang, & Ton Hien Duc, Intermittent Demand Forecast: Robustness Assessment for Group Method of Data Handling, 2014), which are explained in the paragraphs below. These methods have their own limitations. Therefore, the methods discussed in section 3.4.4 and 3.4.5 have been developed.

Linear Regression

The idea behind a simple linear regression model is that there is a linear relationship between the forecasted demand y_t and one predictor variable x. The coefficient β_0 is the intercept and β_1 represents the slope of the line. The random error ε_t represents the deviation of the data points from the straight line. This results in the following equation (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018):

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$$

(Weighted) Moving Average

We already described the moving average smoothing method as a method for time series decomposition in section 3.4.1. This method is also used for demand forecasting and can be combined with assigning weights to the data points. In that case, the observations closer to the time period being forecasted are weighted more heavily. The formula for the forecasted demand according to the weighted moving average method (WMA) is:

$$\hat{y}_t = \frac{1}{n} \sum_{j=t-n}^{t-1} w_j y_j$$

Exponential Smoothing

Demand forecasts produced by the exponential smoothing method (ES) are weighted averages over past observations, with exponentially decreasing weights the older the observations get (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). The formula below represents the calculation of the forecasted demand according to the simple exponentially smoothing method (SES). This method is applicable for data without any clear trend or seasonality (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018).

$$\hat{y}_t = \alpha * y_{t-1} + (1 - \alpha) * \hat{y}_{t-1}$$

The ability of simple exponential smoothing to forecast demand patterns which often have zero values has been questioned and was the reason Croston proposed a new method in 1971 (Segerstedt & Levén, 2019).

3.4.4. Croston's method

Most forecasting methods for intermittent demand are based on Croston's ideas (Croston, 1972). In turn, Croston's method (CM) is based on exponential smoothing and appeared to be superior to this classic method (Willemain, Smart, Shockor, & DeSautels, 1994). The basic idea of Croston's method is that the forecasting of intermittent demand is divided into two parts; one for the size of the demand (Z_j) and one for the intermittent demand interval (P_j) (Segerstedt & Levén, 2019). The calculation of the forecasts according to Croston's method is explained in the following paragraphs.

Y_t represents the demand during time period t and X_t is the binary variable indicating whether demand occurs at time t. Furthermore, j_t is the number of periods with non-zero demand during time interval [0, t], so its equation is: $j_t = \sum_{i=1}^{t} X_i$. Moreover, Y_j^* is the size of the jth non-zero demand and Q_j the interarrival time between Y_{j-1}^* and Y_j^*. The following equations represent the forecast for the $(j+1)$th demand size and inter-demand interval respectively.

$$Z_j = (1-\alpha)Z_{j-1} + \alpha Y_j^*$$

$$P_j = (1-\alpha)P_{j-1} + \alpha Q_j$$

Alpha (α) represents the smoothing parameter and can take a value between 0 and 1. The h-step ahead forecast is determined by calculating the mean demand rate ($\hat{Y}_{n+h}$). In this formula, ℓ is the last period of demand, so $\ell = j_n$.

$$\hat{Y}_{n+h} = \frac{Z_\ell}{P_\ell}$$

3.4.5. Modifications to Croston's method

Notwithstanding, also limitations of Croston's methods have been highlighted. As a result of this, several researchers proposed different modifications of Croston's method. Syntetos and Boylan (2001) stated that Croston's separate estimates of the demand size and the inter-demand interval are correct, but cause a bias if they are combined as a ratio. They suggested a new estimator of the average demand to overcome this shortcoming (Syntetos, Boylan, & Croston, 2005):

$$\hat{x}_t = \left(1 - \frac{\alpha}{2}\right)\frac{\hat{z}_t}{\hat{p}_t}$$

This adjustment to Croston's method is known as the Syntetos-Boylan Approximation (SBA). Syntetos, Boylan and Croston (2005) developed a categorization of demand patterns based on the variables ADI and CV^2, determining the most appropriate forecasting method. See Figure 18 for this classification matrix. Teunter and Sani (2009) supported that this method outperforms Croston's method when most periods have zero demand.

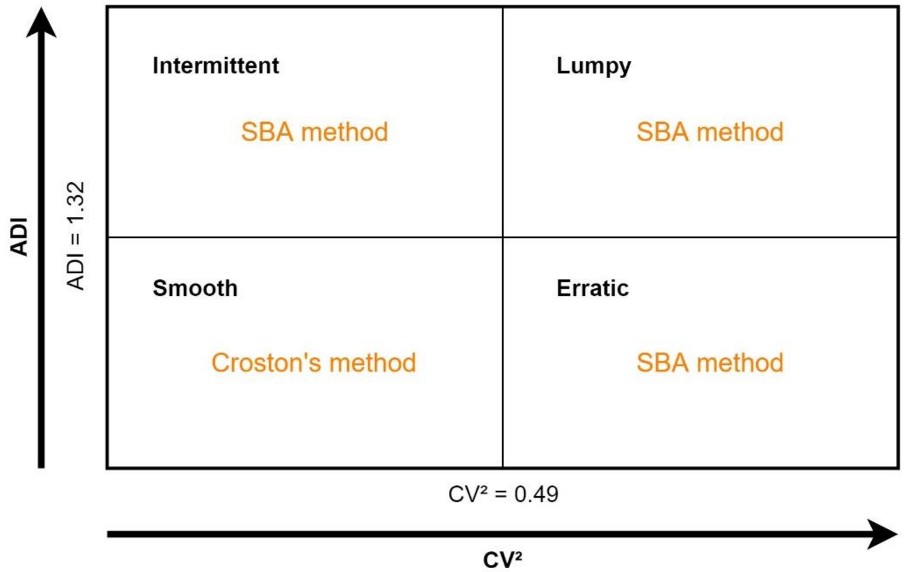


Figure 18: SBC classification matrix (Syntetos et al., 2005)

Levén and Segerstedt (2004) proposed a modification of Croston's method based on the idea that the time between demand and demand size is not independent. This modification turned out to get poor results, since it is more biased than Croston's method, especially for highly intermittent series (Kourentzes N. , 2013). This resulted in the suggestion of Wallström and Segerstedt (2010) to replace "backward coverage" by "forward coverage". Segerstedt (2019) concluded that both the method of Levén and Segerstedt (2004) and the method of Wallström and Segerstedt (2010) overestimates demand too much.

A limitation of Croston's method is that it does not update the forecast after periods of zero demand. After all, a long period without demand occurrences should be an incentive to reduce the forecasted demand. Teunter, Syntetos and Babai (2011) suggested a combination of updates every time period, for estimating the probability that demand occurs and if so, what the demand size would be. They adjusted Croston's method by proposing multiplication of the estimate of the demand size by the probability to have a non-zero demand, instead of dividing the demand size by the estimate of the inter-demand interval. This adjustment resulted in the TSB method, which is useful in cases where inventory obsolescence should be linked to forecasting (Petropoulos, Kourentzes, & Nikolopoulos, Another look at estimators for intermittent demand, 2016).

Multiple researchers compared forecasting methods for intermittent demand. The most recent study, by Segerstedt and Levén (2019), has proved that in general Croston's method is still superior over the methods that made adjustments to this method. These adjusted Croston methods often solve a limitation of Croston's method, but get a new limitation in return. For instance, the TSB method showed a tendency to underestimate demand (Segerstedt & Levén, 2019) and if we do not have periods with zero demand, the SBA method is biased by the factor $\left(1-\frac{\alpha}{2}\right)$ (Doszyn, 2018). However, in more specific situations, the adjusted Croston methods might result in a better forecasting performance.

The last modification to Croston's method we want to discuss is the Modified SBA method (Babai, Dallery, Boubaker, & Kalai, 2019). This method is kind of a combination of the adjustments the SBA method and the TSB method made to Croston's method. The SBA method removes the bias from Croston's method by multiplying the estimated demand with a certain factor. The TSB method tackles the issue of Croston's (and the SBA method) that it does not adjust the forecast downwards in case of periods with zero demand. This issue is overcome by updating the demand probability instead of the demand interval, and doing so in every period. The researchers that proposed the 'Modified SBA method' describe it as follows: "In periods with positive demand the new method updates the demand sizes, the demand intervals, and the estimator, similar to SBA, but in any time period if the actual demand interval becomes higher than the most recent estimated demand interval (which is likely to happen when the risk of obsolescence increases), the update becomes in every period similar to the probability of occurrence in TSB" (Babai, Dallery, Boubaker, & Kalai, 2019).

3.4.6. Model fitting

After a certain forecasting model is chosen, it needs to be fitted to the data set. The 'model fitting' implies picking the right mathematical representation for the data. The training set is used for model fitting and the fit can be evaluated using the test set. In the following sections, we discuss some methods and metrics that are suitable for evaluating the model fit.

Cross Validation

When there is not much data available, it might be undesirable to split it into a training and test set. Moreover, in case of short time series, the forecast accuracy measures applied on the test may provide unreliable information. Time-series cross validation is an approach to deal with this problem (Hyndman, Measuring forecast accuracy, 2014). The process of this approach is repeatedly fitting a forecasting model on a training set and testing it on a test set. In every repeated measure, the training set is increased by one period and the test set is reduced by one period. This process is schematically represented in Figure 19 , where the blue part represents the training set and the orange part the test set. On each test set the forecast accuracy measures are calculated and in the end these results are averaged.

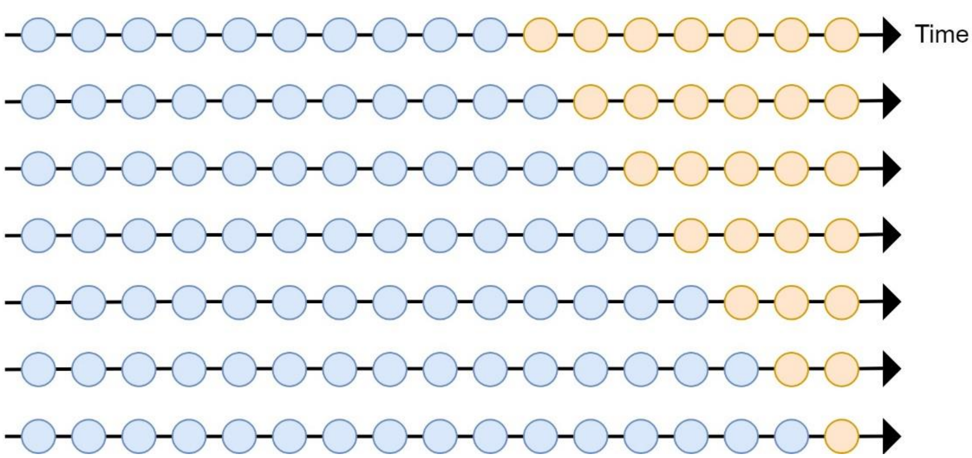


Figure 19: Cross validation

The main disadvantage of this approach is the computation it incurs, since the repeated measures need to be performed for all combinations of models and time series. An alternative is Akaike's Information Criterion, which is an approximation and easier to calculate.

Akaike's Information Criterion

The information criterion proposed by Hirotugu Akaike (1973) is a criterion for selecting the model by estimating the relative quality among other models, given a set of data. Akaike's Information Criterion (AIC) measures the model quality by estimating the information lost after fitting to the data. Hence, the lower the AIC, the better, since more information is captured in the model then. It measures the goodness-of-fit (how well a model fits the data set) and penalizes it for the number of estimated parameters, to prevent overfitting. This is because an increasing number of parameters in the model almost always goes along with an increased goodness-of-fit. The AIC can therefore be considered as a trade-off between goodness-of-fit and complexity of the model. Overfitting is the condition of the model in which it relies too much on training data and therewith fails to fit additional data or make reliable predictions. The formula for AIC is given below, where k represents the number of estimated parameters and L the maximum likelihood.

$$AIC = 2k - 2 * \ln(L)$$

A limitation of AIC is that can only be used for a relative test and is therefore not suitable for testing a model in an absolute sense (Moffatt, 2019). Konishi and Kitagawa (2008) have shown that in a general setting, that the AIC is asymptotically equivalent to cross validation. This makes AIC a suitable measure for relative model quality, with a smaller computation time than the time needed for CV.

Bayesian Information Criterion (BIC)

A variation on the AIC is the Bayesian Information Criterion (BIC), also known as the Schwarz Bayesian Criterion (SBC). Proposed by Gideon E. Schwarz (1978), the BIC is formally defined as:

$$BIC = \ln(n)\, k - 2 * \ln(L)$$

In a practical sense, their only difference is the size of the penalty, since the BIC penalizes model complexity more heavily (Wang & Liu, 2006).

Computational Complexity

A different kind of measure for evaluating a forecasting model is the computational complexity (CC). This metric does not measure the model fit, but “the time needed to train a given model and use it for extrapolation” (Makridakis, Spiliotis, & Assimakopoulos, Statistical and Machine Learning forecasting methods: Concerns and ways forward, 2018). The formula of the CC is defined as the mean computational time of the model to forecast a time series, over the corresponding computational time using the naïve method. Measuring the CC is only relevant when evaluating the more complex forecasting methods.

3.5. Chapter conclusion

Numerous of forecasting performance metrics exist in literature. These metrics can be divided in performance measures for the forecasting accuracy or for the bias. The forecasting accuracy tells something about the size of the forecasting error and a bias occurs when the forecasts have a general tendency to either over or under predict. In the measures for bias, the forecasting error (difference in actual and forecasted demand) is not made absolute.

In turn, the measures of forecasting accuracy can be categorized into four types based on the way of measuring and averaging the forecasting error (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). These four categories are: scale-dependent errors, percentage errors, relative errors, and scaled errors. Most of the metrics are not appropriate for data that contains many zero values, since the results become undefined or infinite then.

We propose to use the Mean Absolute Scaled Error (MASE) for measuring the forecasting accuracy in chapter 4. Division by zero does not pose a problem for this metric and it is also scale independent, so we can calculate one value per business unit and do not have to consider every product individually. In addition to the accuracy measure MASE, the Mean Error (ME) is calculated for measuring the bias.

Bridging the link between the forecasting accuracy and the (excess) inventory levels, can be done by measuring the bullwhip effect. The bullwhip effect is the phenomenon that the demand variability increases as one moves up in the supply chain. One of the main causes of the bullwhip effect is forecasting errors and a consequence is excess inventories. Quantification of the bullwhip effect can therefore indicate the effect of the forecasting performance on the excess inventory.

Forecasting performance is also dependent of the forecastability of the demand pattern. Demand patterns can be classified based on two demand characteristics: Average inter-Demand Interval (ADI) and Squared Coefficient of Variation (CV^2). The combination between these two variables result in a classification of four demand patterns: Lumpy, Intermittent, Erratic and Smooth demand. Smooth demand is the easiest to forecast, followed by erratic and intermittent demand, and lumpy demand is the hardest to forecast. The differences in these demand patterns cause that the most appropriate forecasting methods might also differ per class. The analysis in section 4.2 will show that most of Company X' products have an intermittent demand pattern.

For intermittent demand, Croston's method is the most frequently used method (Doszyn, 2018). The basic idea of Croston's method is to divide the forecasted demand into two parts, which are both calculated using exponential smoothing; one for the size of the demand and one for the intermittent demand interval. The TSB method (Teunter, Syntetos, & Babai, 2011) and the SBA method (Syntetos, Boylan, & Croston, 2005) are modifications to Croston's method. The SBA method removes the bias from Croston's method by multiplying the estimated demand with a certain factor. The TSB method tackles the issue of Croston's method (and the SBA method) that it does not adjust the forecast downwards in case of periods with zero demand. A combination of these two adjustments to Croston's method resulted in the Modified SBA Method, which has proven its performance in many cases dealing with obsolescence (Babai, Dallery, Boubaker, & Kalai, 2019).

4. Current forecasting method and performance

The EMSs of Company X have stated that the forecasts of Company X are not accurate. In the previous part of this report, an indication is given of the part of the excess inventory that is surely caused by forecast inaccuracies. This analysis has also shown that the category forecast/other is rather big. This implies that a big part of the excess inventory cannot be assigned to forecast inaccuracies with certainty, but might also be caused by inaccurate forecasts. Further investigation of the forecasting performance of Company X is therefore valuable.

In section 4.1 the current forecasting processes of the different Company X business units are described and compared. In section 4.2 the analysis of the demand patterns of the Company X products are discussed. Section 4.3 contains a description of the current forecasting performance. In section 4.4 we link the forecasting performance to the excess inventory, followed by a chapter conclusion in section 4.5.

4.1. Process description

In this section we first provide some figures about the forecasting rows of Company X to the EMSs, followed by a description of the differences in the forecasting processes of the different business units. We refer to appendix VII for the flowcharts of the different forecasting processes.

The three Business Units of Company X which are included in the scope of this research have together 240 products to forecast. Table 9 shows the number of forecasting rows (products) that the Business Units forecast to the EMSs. Each product is only forecasted to one supplier, so the table does not contain duplicates. The forecasting horizon of every business unit is one year and even if they contractually agreed to send biweekly forecasts, most of the times the business units sent the forecasts every week, when they also place orders at the EMSs.

	EMS 3	EMS 1	EMS 2	Total
Business Unit A	5	48		**53**
Business Unit B	90	20	8	**118**
Business Unit C	46	23		**69**
Total	**141**	**91**	**8**	**240**

Table 9: Forecasting rows Company X

We performed interviews with the different business units to gain insight in the current processes of demand forecasting at Company X. Each business unit forecasts on their own manner. Appendix VII contains the flowcharts of the forecasting process per business unit. We compared the different forecasting processes, resulting in Table 10. This table provides an overview of the similarities and differences that are described in the next sections. The information in the table represents the general forecasting processes of the business units, so reality might sometimes be not as black-and-white as it is being presented in this table.

Element:	**Business Unit A**	**Business Unit B**	**Business Unit C**
Seasonality	✓	✓	✗
Customer forecasts	✗	✓	✓

Horizon of customer forecast	*n/a*	20 weeks	1 year
Purchase commitment customers	*n/a*	✗	✓
Sales input through CRM	✓	✓	✗
Automated upload CRM	✗	✗	*n/a*
B-products	✓	✓	✗
MTO/MTS	*MTS*	*MTO*	*MTO/MTS*
Manual adjustments	✓	✓	✓
Communication about product life-cycles	✓	✓	✓
People involved	*1*	*5*	*1*
Review forecast when PO placed	✓	✓	✓

Table 10: Comparison of forecasting process

Both Business Unit A and Business Unit B expect to have seasonality in their demand pattern. Business Unit C does not expect to have seasonality in their demand pattern, but does not exclude that the individual forecasts of the customers contain seasonality. The biggest customers of Business Unit B and Business Unit C send a monthly forecast of their expected demand. Only for the customers of Business Unit C these forecasts go along with a commitment to actually purchase (a part of) the forecasted demand. Herewith their customers are forced to aim for accurately forecast their demand, which is currently not the case for the customers of Business Unit B.

The Sales departments of Business Unit B and Business Unit A provide input to the demand forecast by filling in their expected demand in the CRM system. For both these business units, these forecasts are not automatically uploaded in the demand forecast in the ERP-system. For Business Unit B the export format from CRM is not applicable for uploading in the ERP-system and Business Unit A does not want an automated upload due to the subjectivity of the forecasted demand by Sales. For Business Unit C the Sales employees provide orally input for the demand forecast. None of the Sales departments of the different business units is assessed on the reliability of their input. We can conclude that currently the decentralized forecasting processes of the business units consist of many manual steps with judgmental input. This results in an inefficient and subjective forecasting process.

Both Business Unit A and Business Unit B have some B-products. These are products from which the forecasted demand can be derived from the forecast of another product (an A-product). Most of the products of Business Unit A are produced to stock, which implies that the forecaster monitors the stock levels and places a purchase order when necessary. Business Unit B only purchases based on customer orders and for Business Unit C this is a mix between purchasing to order and purchasing to stock. This means that both Business Unit A and Business Unit C also maintain an inventory of finished goods.

The last difference we address is the number of people involved in the forecasting process. For Business Unit A and Business Unit C the forecasts are generally produced by a single employee, while for Business Unit B multiple employees are involved. Dividing the responsibility of the forecasting task over multiple employees results in flexibility on one hand, but a generally greater bias and forecasting error on the other hand (Crane, 2009).

4.2. Demand pattern

Assessing the accuracy of the forecasts sent by Company X is related to how hard it is to forecast the demand of Company X' products. For determination of the extent to which the products of Company X are forecastable, an analysis of the demand pattern is required. By performing this analysis, the Company X products are classified according to the classification explained in section 3.1.2. Conform to this classification, the products are divided over four classes of demand patterns; intermittent, lumpy, erratic, and smooth demand. This classification is based on two parameters:

- CV^2. Variability can be measured by different metrics. To classify the products based on their demand pattern, the squared coefficient of variation needs to be calculated.
- ADI. For calculation of the Average inter-Demand Interval, first data about the inter-demand intervals is required. Dividing the total forecasting horizon by the number of demand occurrences, only provides an indication of the ADI, since the periods of zero demand before the first demand occurrence and the periods of zero demand after the last demand occurrence are taken into account. In case of many data, it does not whether you take these periods of zero demand into account or not because the differences are not significant. In the case of Company X, we do not have many data (only 2018), so we determined the exact ADIs by applying an VBA-code to the demand data. The code of this macro is attached in appendix IX.

The demand data we use for this analysis are the bookings of received goods at Company X, since there is no data available of the actual customer demand. The pattern and sizes of these posted receipts is almost equal to the actual customer demand. However, Company X sometimes places orders at the EMSs to have finished goods on stock for quick delivery to the customer. As a consequence of this, there also periods of less demand of Company X to the EMS. This might causes that the ADI and CV^2 are a little higher than they would have been by using actual customer demand data.

The graph in Figure 20 represents the distribution of the products over the variables ADI and CV^2, which determine the classification of the demand pattern of the product. The y-axis of the graph has a logarithmic scale in order to fit all products in the graph. Appendix X shows these graphs per business unit.

All individual products that are forecasted have an ADI of above 1.32, which implies that there is no product with a 'smooth' or 'erratic' demand pattern. The average ADI of all Company X products is approximately: 3,81 weeks. This is the weighted average, so the ADI per product is multiplied by the number of times this average ADI occurs (so the number of times demand has occurred for this product). The ADIs per business unit are as follows:

- Business Unit B: 4,48
- Business Unit C: 3,19
- Business Unit A: 4,08

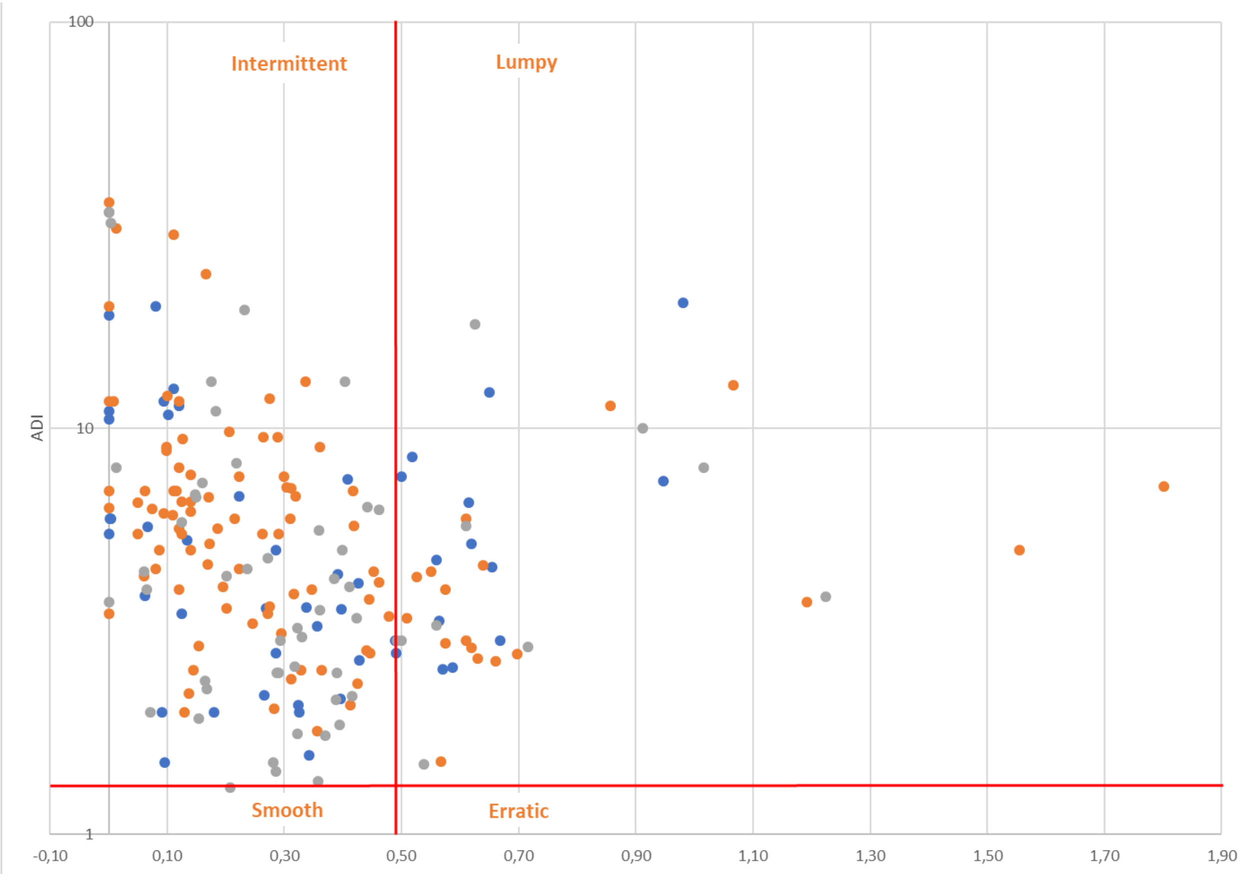


Figure 20: Classification of demand patterns

We can conclude that most products of Company X have an intermittent demand pattern and that the remaining Company X products have a lumpy demand pattern. A lumpy demand pattern is even harder to forecast, because of the higher variability in demand size.

Figure 21 shows the same graph as presented in Figure 20 but now the datapoints are sized after the value of the product, which is calculated by multiplying the purchase price of the product by its demand of 2018. This graph shows that there is no significant difference in the classification the products from the different business units of Company X. Therefore products of the different Company X business units can be regarded as being approximately equally hard to forecast. In appendix XI the bubblecharts per business unit are shown.

What stands out in the bubblechart of Figure 21 is putting the products in proportion after their value (calculated by multiplying the purchase price by the demand of 2018), shows that in general, the products with the highest value are closer to having a smooth demand pattern than the low value products. Since this implies that the ability of statistically forecasting these products is relatively high, improving the forecasting method using statistics is expected to be effective for reducing the liability.

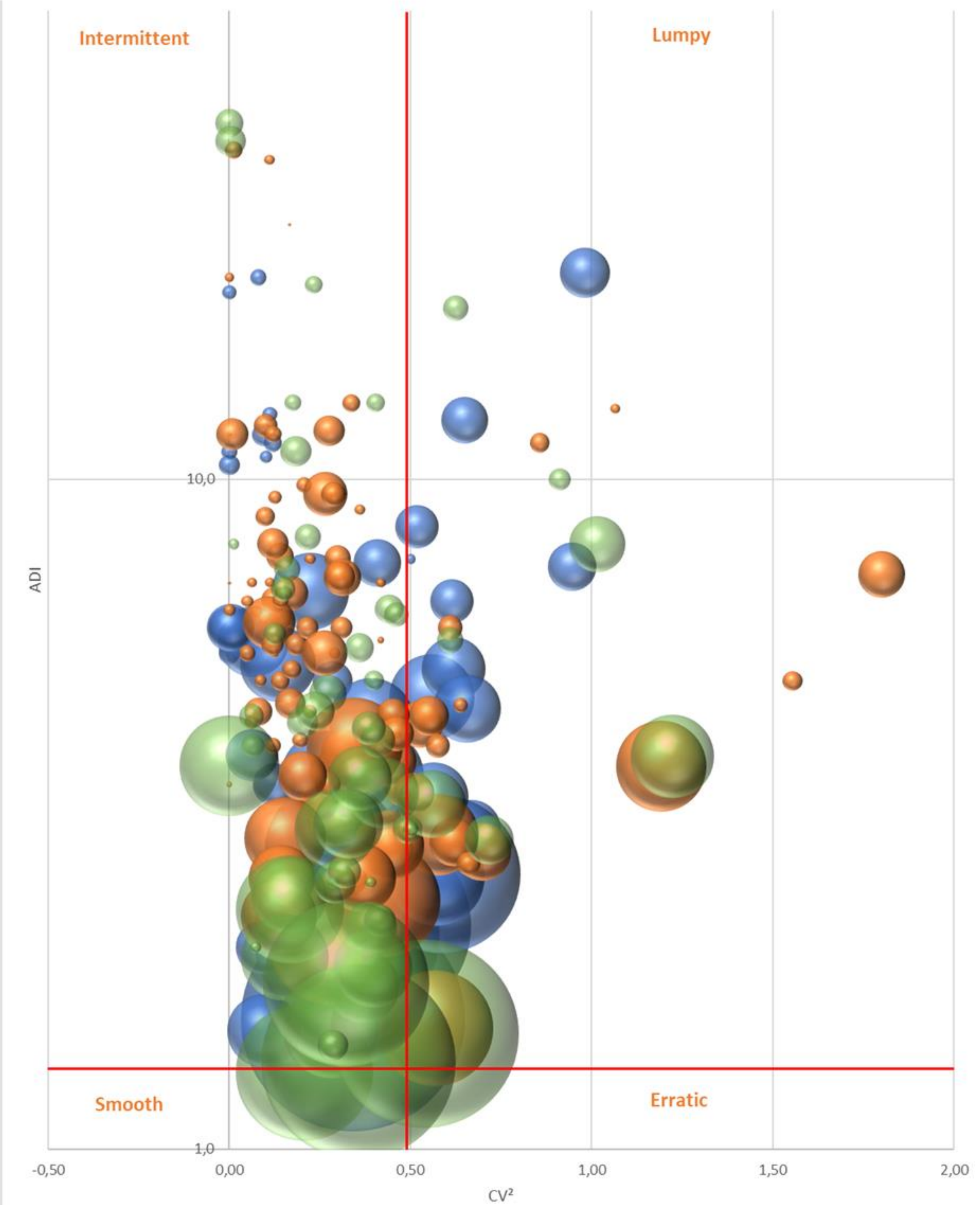


Figure 21: Demand patterns bubble chart

4.3. Forecasting performance

In the following sections the forecasting performance analysis is explained. Section 4.3.1 describes the method that is applied for this analysis. In section 4.3.2 and 4.3.3, the caveats and results are discussed respectively.

4.3.1. Method

Each Company X business unit forecasts on their own manner. Hence, this analysis is performed per business unit. The forecasted demand needs to be compared with the actual demand. The actual demand is the amount of goods received in a certain week. The forecasted and received goods are specified per week, but this is not the level of accuracy Company X wants to measure the forecasting performance on. Therefore, we performed the analysis with an accepted interval of four weeks.

The goal of this analysis is to compare the forecasting performance of the business units and to have a zero-measurement for determining whether a forecasting model improves the forecasting performance.

There is no need to divide the data into two sets, because the forecasts that will be evaluated are not made based on a model which has used certain training data. Hence, all available data can be used for evaluating the forecasting performance.

We do not asses the forecast accuracy over different forecasting horizons, because there is not much information available for forecasting accuracy of many periods ahead. Only the forecasts of 2018 are available and besides, we can only compare it with actual demand until now, so week 8 of 2019.

Metrics

We have to measure the forecast accuracy of multiple time series, since we measure the forecasting performance of multiple business units which all have multiple products. Hence, the scale-dependent measures are not suitable.

We use MASE, because this is the most appropriate metric for intermittent-demand data (Hyndman, Measuring forecast accuracy, 2014). This metric is also used in the M-competitions and has advantage over the more common MAPE that it is suitable for times series with zero values and that it weights the errors equally, MAPE weights positive and extreme errors more heavily. In addition to assessing the forecasting accuracy based on the MASE, we also measure the bias by calculating the ME (Mean Error).

There is no general scale of judgement for interpreting MASE. We only use it as a baseline measurement for determining the improvement of a new forecasting method. The lower the score of the MASE, the better, and a MASE of 1 implies that the current forecasting is as accurate as the forecast would be using the 'simple' naïve method.

The MASE is not an appropriate method for seasonal demand. Since Business Unit A and Business Unit B expect to have seasonality in their demand, the normal Naïve method is not suitable. Also, the shorter the forecast horizon becomes, the bigger the change is on solely zero values. Since Company X has a relatively large ADI (3,81), this would result in often division by zero. An alternative is using the seasonal naïve method, which uses past actual values of the same 'season' as forecasting values. Also this adjustment is not possible in the case of Company X, since we have too less data available, namely only one year. Therefore we determined to adjust the Naïve method. Per product, one naïve error calculated, which is the average over the total forecasting horizon. Hence, the naïve is not updated after the forecast horizon of the concerned forecasting row. It is important that when Company X calculates the forecasting accuracy after improving, it uses the same formula for the Naïve method. The formula of the adjusted MASE is:

- Adjusted Mean Absolute Scaled Error (aMASE) $= \frac{\sum_{t=1}^{n} \frac{|y_t - \bar{y}_t|}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}}{n}$

Data preparation

The forecasting horizon starts at week 13 of 2018, because the average lead time of the EMS to Company X is twelve weeks and the first forecast included in the analysis originates from week 1 of 2018. Hence, we assume the demand for twelve weeks ahead are already orders and are therefore excluded from the forecasting performance analysis. These values are removed by applying the VBA macro 'EmptyCellsOrderPeriod' from Appendix XII.

Most business units do not sent a new forecast every week. Company X has agreed with the EMSs that the latest forecast remains, until a new forecast is sent. For this reason, we copied each forecasting row if no new forecast has been sent the subsequent week. This is done by running the VBA macro 'InsertCopiedFcRows' from appendix XII.

4.3.2. Caveats

We noticed the following caveats for the analysis of the forecasting performance:

- There is no data available of the dates of orders placed of Company X at the EMSs. Therefore we compare the forecasted demand with the actual received goods. Herewith we assume 100% delivery performance of the EMSs. This assumption has been overcome partly by also performing the analysis by handling an accepted time interval of four weeks. As Figure 22 shows, the vast majority of the delivery performance falls within a time interval of four weeks. This implies that even if the orders are received two weeks early or two weeks late, the forecast is considered as correct.
- The naïve method assumes one-period ahead forecasts. Company X forecasts multiple periods ahead, which is generally harder to do. The only data input for the naïve forecast is the demand of the preceding period. So, in the situation where Company X forecasts multiple periods ahead, the naïve forecast is made based on data that could not have been known by the time the data was produced. With interpreting the aMASE, we have to take into account that the 'simple' naïve method is not a representative forecasting method for Company X.
- When there is an amount forecasted but there are very less received goods, this is penalized severely. This is because the aMASE divides the forecasting error by what the error would be in case of the naïve method and the naïve error is very small in case of very less received goods.
- On the other hand, when there is a certain amount forecasted but there are no received goods at all, the forecasting error is not taken into account since the naïve forecast error is zero and division by zero is not possible. This involves 256 forecasting rows from a total of 9994, which are excluded from the analysis.

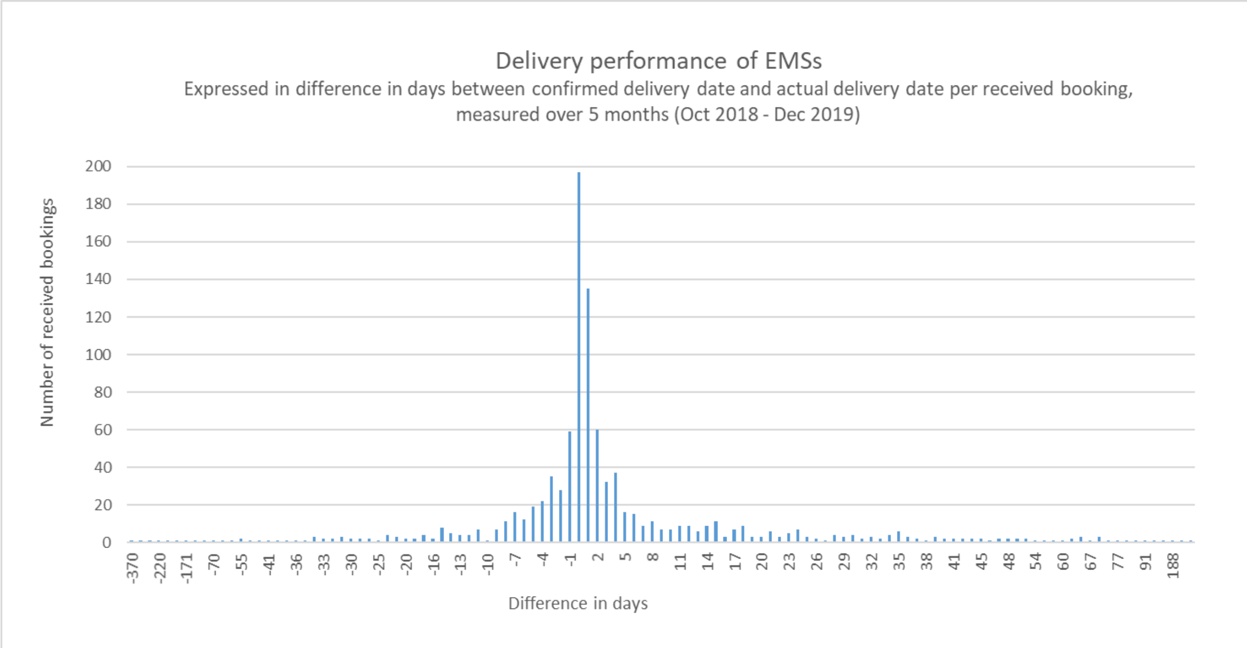


Figure 22: Delivery performance EMSs

4.3.3. Results

First we describe the results of calculating the aMASE per business unit. Subsequently, the results of calculating the Mean Error (bias) are discussed.

Accuracy

The values of the aMASE that resulted from the test are shown in Figure 23.

Figure 23: Scores aMASE zero-measurement

We performed some sensitivity analysis of the accepted forecast time interval on the aMASE. Company X forecasts 52 periods ahead, from which each period represents one week. The results of the columns with an accepted time interval of 'one week' imply that if for example a certain amount was forecasted for week i and received in week $i + 1$, this is considered as incorrectly forecasted. Using a four weeks interval, this forecast would be considered as correct.

We expected the forecasting accuracy to be higher when using the four weeks' time interval, because in that case the forecasts are assessed less strictly. However, the results show something different. This can be explained by the forecasting performance metric we used. The aMASE compares the forecasting errors with the expected forecasting errors using the naïve method. We also used a broader accepted time interval of four weeks for determining the forecasting errors according to the naïve method. Since the aMASE is a ratio, this causes that the values of the aMASE only become more extreme, but the ranking of the business units after their forecasting accuracy remains the same.

The values of the aMASE derived from figure 24 serve as a baseline measurement for the validation of the design after the forecasting method has been improved. For all business units, the value of the aMASE is higher than 1, which means that the forecasting errors are bigger than they would have been using the simple Naïve method. However, the Naïve method only forecasts one period ahead and is therefore not representative for the case of Company X, where forecasts are generated for multiple periods ahead. Nevertheless, the values of the aMASE still show us that there is certainly room for improvement of the demand forecasting accuracy.

Bias

The bias is calculated by first determining the total bias per forecast row, which is the total actual demand minus the total forecasted demand. A forecast row contains the forecast over the whole forecasting horizon of a certain product sent in a certain week. The forecast rows have different forecast horizons. Therefore we calculated the average bias per forecasted week for each forecast row. We do not analyse the bias of each product separately, so we want to be able to add up the bias of the different products. For this reason, the average bias per forecasting row is multiplied by the price of that product.

We want to see the course of the bias over the weeks that the forecasts are sent. Some forecasting weeks contain more forecast rows than others. Therefore we take the average of a certain forecasting week over the different rows. These values are on the y-axis of the graphs of Figure 24, Figure 25 and Figure 26. So, the values in the graphs below represent the average bias for one time period (week) including all products for which a forecast has been sent a certain forecasting week. These forecasting weeks are represented on the x-axis of the graphs.

Figure 24: Bias Business Unit B

Figure 25: Bias Business Unit C

Figure 26: Bias Business Unit A

The results correspond with the expectations of Company X' Data Analyst. Figure 24 shows us that Business Unit B has a positive bias over the whole year. A positive bias implies that the forecast was too low. From the forecasts sent by Business Unit B we derive that they forecast most demand in the near future. The phenomenon that most forecasted demand is in in the near future also applies to the other business units, but is the most extreme for Business Unit B. This is shown by the graphs in appendix VIII. The forecasts of the early weeks of 2018 contain forecasts for a year in advance, so multiple periods (weeks) ahead. The forecasts sent later in 2018 that are included in this analysis are only for the periods from which the actual demand is known. Hence, the forecasts sent later in 2018 are a few periods ahead and have therefore relatively less average bias for Business Unit B than the forecasts sent in early 2018.

For Business Unit C we can conclude that their bias varies over time and that they have some (mostly negative) outliers. This tells us that the proportion forecasted demand to actual demand is not stable. The negative outliers imply that there has been forecasted way too much, which results in excess inventories.

The graph of Business Unit A has an increasing trendline of the bias over the year 2018. It starts with a negative bias and has a positive bias later on. This implies that in the beginning of 2018 Business Unit A forecasted too much and later in the year they forecasted too low. This phenomenon can be explained by that they want to compensate the excess they forecasted at the beginning of the year, by forecasting too little towards the end of the year.

4.4. Bullwhip effect

As described in section 3.3, the bullwhip effect is the phenomenon that the demand variability increases as one moves up in the supply chain. One of the main causes of the bullwhip effect is demand forecasting errors and an often mentioned consequence of this phenomenon is excessive inventories. In this section, we want to quantify the effect of the forecasting performance on the excess inventory by analysing the bullwhip effect. Since inaccurate demand forecasting is not the only factor contributing to the bullwhip effect, this analysis only provides an indication of the causal relationship between demand forecasting and inventory and cannot be considered as an exact quantification of the effect of forecasting on inventory.

The bullwhip effect can be quantified by dividing the variability of the order quantity placed to the manufacturer (q_t) by the variability in customer demand (D_t). Hence, for this analysis we need data of the order Company X places at the EMSs and about the orders Company X' customers places at Company X.

There is currently no data available of the orders Company X places at the EMSs. An alternative for this is the data of the forecasts sent by Company X to the EMSs. Since the EMS purchases based on Company X forecasts, the forecasts can be considered as the Company X orders. Also, data about the orders placed by Company X' customers is not available. As an alternative we can use the data of the received goods (posted receipts) at Company X. The delivery performance of the EMSs is not 100% (see Figure 22), but this does not pose a problem for this analysis, since we only consider the *size* of demand and not *when* it occurs. Therefore, if the amounts of the received goods correspond with the amount of the customer orders, this data is representative.

Since we only have data of 2018, all forecasting rows have different horizons. This implies that if we calculate the bullwhip effect per forecasting row, these rations are based on a different number of values. To overcome this problem, we only take into account the first forecast of each product, so the forecast with the longest horizon. For most products this is the forecast sent in the first week of 2018.

Our data contains many zeros, since we are dealing with intermittent demand data. We can either include or exclude the zeros from the data. Excluding the zeros implies that we only take into account the size of the demand when demand occurs. This provides a distorted picture of the actual variability. Besides, this would result in even less data. Therefore, we determined to include the zeros in the demand data.

When calculating the bullwhip effect ratio, we found that the analysis is too sensitive for outliers, because our data contains many zeros. For example, a product for which in whole 2018 for only one week an amount of 400 is forecasted and which had only one time a posted receipt of 130, results in a bullwhip effect ratio of more than 11. Also, from a part of the forecasting rows either the forecasted demand or posted receipts entirely consists of zeros. Herewith the variability also becomes zero, resulting in an either zero or impossible bullwhip effect ratio.

Because of the caveats mentioned in the paragraphs above, we concluded that the analysis of the bullwhip effect would not result in reliable outcomes. Therefore, we decided to exclude this analysis from the research. The added value of this analysis would be to gain more insight in the variability of the demand from Company X to the EMSs. Not only the accuracy of the forecasts affect the excess inventories, but also the extent to which these forecasts fluctuate. The results of this analysis would provide extra evidence to why stable forecasts are important to reduce excess inventories. This would help with creating awareness within the organization and different business units around the importance of accurate forecasts and the added value of the proposed improvements.

4.5. Chapter conclusion

Each Company X business unit generates demand forecasts on their own manner. In this paragraph we summarize the main differences and similarities between these processes, which are discussed in section 4.1. From the three business units only Business Unit A does not receive demand forecasts of customers. For Business Unit B the biggest customer forecasts 20 weeks ahead and the second biggest customer one year ahead. The forecasting horizon of the customers of Business Unit C is one year ahead and go along with a certain purchase obligation, which is not the case for Business Unit B. Furthermore, the forecasting processes of Business Unit A and Business Unit B are generally the same, except for the number of employees involved in the process and whether they purchase based on sales orders or finished good stock levels. The demand forecasts of Business Unit B are generated involving multiple employees, while for Business Unit A and Business Unit C this is generally performed by a single employee. What stands out in all the forecasting process is that they consist of many manual steps with judgmental input. This is not only inefficient, but also increases the subjectivity in the forecasting process, which generally leads to more variability in the forecasted demand.

The analysis after the demand pattern classification showed that there are no major differences between the business units. Most products are classified as having an intermittent demand pattern and the remaining products have a lumpy demand pattern, which is even harder to forecast. Putting these products in proportion after their value (calculated by multiplying the purchase price by the demand of 2018), shows that in general, the products with the highest value are closer to having a smooth demand pattern than the low value products. Since this implies that the ability of statistically forecasting these products is relatively high, improving the forecasting method using statistics is expected to be effective for reducing the liability.

The baseline measurement for the forecasting performance is most valuable after the forecasting method has been improved and a second forecasting performance measurement has been performed. However, there are several conclusions we can already draw from the baseline measurement. For all business units, the value of the aMASE is higher than 1, implying that generating forecasts using the simple Naïve method would result in smaller forecasting errors compared to the current forecasting method. An important caveat we want to address with this statement, is that the Naïve method is not totally representative for the case of Company X, where forecasts are generated for multiple periods ahead. However, the values of the aMASE still show us that there is certainly room for improvement of the demand forecasting accuracy.

The course of the bias of the different business units over the year 2018 is totally different. For Business Unit B the bias was positive over the whole year, but showed a negative slope. This indicates that Business Unit B forecasts too low, which can be explained by the fact that Business Unit B forecasts most demand in the near future, resulting in the forecast running empty towards the end of the forecasting horizon. The bias of the forecasts of Business Unit A show a positive slope, crossing the x-axis in the middle of the year. This is the result of too high forecasts at the beginning of the year, which are compensated by lower forecasts towards the end of the year. The slope of the bias of Business Unit C is in between the graphs of Business Unit B and Business Unit A and is slightly negative with a negative slope. It shows some outliers, which indicates that the proportion forecasted demand to the actual demand is not stable.

5. Improvements

In this chapter the answer to sub question 5 is described. In the section 5.1 we discuss how Company X could improve their forecasting performance. With this section, phase 5 (solution choice) of the MPSM has been executed. Section 5.1 also contains a stepwise description of how phase 6 (solution implementation) and phase 7 (solution evaluation) of the MPSM should be carried out. In section 5.2 additional possible improvements for excess inventory reduction are described.

The improved forecasting method is described as a roadmap. The main reason is that the Sourcing department is overarching the business units. Since the forecasting task of Company X is decentralized over the business units, the improvements should be implemented separately. Therefore, a roadmap which can be followed for each business unit is valuable. Another practical reason is that the demand data of only the last year is currently available. To obtain also older data, the IT department of Company X needs to make adjustments to the ERP-system, which requires some more time due to the current transition to a newer version of the ERP-system.

5.1. Improved forecasting

What we derived from the forecasting performance analysis is that the forecasts of Company X are neither stable nor accurate. By analysing the forecasting processes of the three business units we concluded that several steps in the forecasting process are based on subjectivity resulting in manual adjustments in the forecasts. Company X has many different products, in combination with the manual steps this makes the forecasting process inefficient.

There is quantitative data available of the historic demand. According to Hyndman and Athanasopoulos (2018), one should always use quantitative forecasting methods when this is possible. We expect that using a statistical method for forecasting would result in more stable and accurate forecasts and more efficient forecasting processes. In the following sections, we describe the roadmap to an improved forecasting performance using statistical methods for Company X. Statistical forecasting methods imply using statistics based on historical data to predict the future.

The roadmap we describe is based on the forecasting processes and statistical methods explained in the literature review. The description of the process towards statistical forecasting in literature are very general. Therefore, we will split up some of the steps and elaborate them extensively, resulting in a more detailed roadmap to an improved forecasting method for Company X. Following the steps of the roadmap will result in a new forecasting method, which combines statistical forecasting with manual adjustments based on Sales input and customer forecasts.

In the next paragraphs we describe the roadmap by following its steps. The roadmap itself is presented subsequently. The demand forecasting task of Company X is a decentralized process over the business units. Therefore, the roadmap should be followed for each business unit individually. A member of the Sourcing team can participate in the project teams to be the link between the different business units. We would recommend starting implementation of the improved forecasting method with the business unit Business Unit B. They already initiated improvements to their forecasting task and also have the greatest desire to improve their forecasting accuracy by applying statistical methods. Furthermore, their forecasting process is currently very inefficient due to many manual steps, which makes improving their forecasting task even more effective. Each year, the forecasting model should be re-established by the employee(s) who is responsible for the forecasting task, by executing step 5 and 6 for each product again.

Step 1

The first step is the initiation of the project. A project group should be formed, that consists of at least three members: one employee of the Sourcing team, the employee of the business unit who actually executes the forecasting task and another employee of the business unit who is involved in the forecasting process, like from Sales. This project team remains the whole project. In the kick-off meeting the goals should be set and a planning should be made. First the broader goals, like where forecasts will actually be used for, should be set, before deciding about for example the actual desired forecasting accuracy level. Once the goals are set, the project team can establish the range of products that will be included. Gathering the time series data requires help of the IT department, since the data of multiple years ago is not available yet and adjustments have to be made to the ERP-system in order to gather this data.

Company X has to decide whether they want to procure special software for forecasting or whether their current software is sufficient. This depends on, among other things, the budget that is available for improving the forecasting performance and the desired level of forecasting professionalization. The decision about the forecasting tool overarches all forecasting business units and should therefore also involve all business units.

Statistical forecasting is possible in for example Microsoft Excel. However, there are some drawbacks of using Excel. The forecasting tool has to be built from scratch, which will take more time and effort until it will reach the level of development of existing forecasting software. Also, if Company X wants to create (and remain) uniformity in the forecasting processes of the business units, special forecasting software might help. Whenever Company X has decided to procure a forecasting tool, the supplier of this tool will also participate in the project group. Another option is to develop a forecasting application in the ERP system. In order to investigate the feasibility of this option, the IT department of Company X should be involved in the project.

Step 2

Step two of the roadmap comprises assigning the most appropriate forecasting method to the products. From the range of products that should be forecasted, statistical forecasting is not always possible or the most appropriate method. Therefore, the products are divided in several categories. Two variables determine how the product should be forecasted: its lifecycle phase and the (expected) demand occurrence. For new products (phasing-in) we make another distinction based on whether the products are totally new or whether they have an comparable demand pattern to an existing product, so we can use the demand rate of that matching product, which is for example the case if a new product replaces another.

The distinguished forecasting methods are:

- Statistical forecasting (for phasing-out products with a regular demand occurrence the Sales input is also important).
- Purchase to order (long lead times). This implies that these products will not be forecasted and have therefore long lead times. These products are ordered after Company X has received a customer order.
- Judgmental forecasting (totally based on Sales input). These are the product which have no demand data available (yet), but should be forecasted since long lead times are not accepted.

Generating forecasts for these products is subjective, so in terms of sensitivity it is wise to consult multiple sources.

Summarized, the decision tree in appendix XIII says that products with an (expected) regular demand pattern should be forecasted statistically and products with an (expected) incidental demand pattern should not be forecasted. Additionally, products that are phasing-in and have an expected regular demand pattern should be forecasted statistically if comparable data is available. Otherwise, the forecasts should be generated judgmentally.

Literature does not provide an operationalization of when a certain demand pattern can be forecasted statistically and when this is not recommended. Therefore, whether a product has an incidental or regular demand pattern should be determined judgmentally.

Step 3

Step three to six will be executed for each product individually. The range of products to forecast statistically have been determined in step 2. If the product range of the zero-measurement differs from the new selected product range, these products should be excluded from the zero measurement as well. Removing outliers is a rather subjective step in the data exploration phase. Deciding whether an outlier should be removed from the dataset should be based on whether the outlier is really incidental and should be excluded for generating future predictions.

There is no clear answer to the question how many datapoints are sufficient for time series forecasting (Hyndman & Kostenko, Minimum sample size requirements for seasonal forecasting models, 2007). Due to this, it is also not clear when exactly time series decomposition should be applied and when this is not required. Typically, the split between the training and test set is 80-20. We recommend to test the forecasting model for at least one year of data, considering the possible seasonal effects and the dataset of the zero measurement, which also contained one year. This implies that the total dataset should contain at least five years of data. When this is not possible for Company X, cross validation is an alternative. The process of this approach is repeatedly fitting a forecasting model on a training set and testing it on a test set. In every repeated measure, the training set is increased by one period and the test set is reduced by one period. On each test set the forecast accuracy measures are calculated and in the end these results are averaged. In practice this means that step 5 and 6 of the roadmap are executed iteratively.

Croston's method assumes stationarity. Because of this, from products whereof Company X expects to have seasonality in the demand pattern, additive time series decomposition should be applied. In contrast to multiplicative decomposition, additive decomposition would not pose a problem to intermittent data because of the absence of multiplication and division. The steps of time series decomposition are described in section 3.4.1 and an example has been elaborated in appendix XIII. The result of the time series decomposition are several components of the demand data. Only the remainder component of the times series data is included in the new dataset, which is used for statistical forecasting. In case when no clear trend is visible, the trend cycle component can be added up to the remainder component, and thereby also be included in the new dataset. If a certain trend is visible, this should be forecasted separately and then be combined with the forecast of the remainder.

In case a trend has been noticed in the time series data, Holts linear trend method should be applied (Hyndman & Athanasopoulos, Forecasting: Principles and Practice, 2018). This is nothing more than applying exponential smoothing to the time series data of the trend and adding this up to the forecast. The equation for the forecast consists of the forecast of the remainder component (ℓ_t) and the trend component (b_t). The equations for the forecasted demand ($D'_{t+h|t}$) and the trend component are as follows:

$$D'_{t+h|t} = \ell_t + h * b_t$$

$$b_t = \beta^* * (\ell_t - \ell_{t-1}) + (1 - \beta^*) * b_{t-1}$$

The optimal value of smoothing parameter (β^*) should be determined as described in the step model fitting.

Step 4

As mentioned in the previous step, also step 4 should be executed for each product individually. Nevertheless, we have analysed the demand patterns of the Company X products, and concluded that the differences in demand patters do not affect the choice for the best suitable statistical forecasting method.

We propose to apply the Modified SBA method, which is a combination of two adjustments to Croston's method. Alternatives that are closely related to the Modified SBA method are; Croston's method, the TSB method or the SBA method. Nevertheless, we expect the Modified SBA method to show the best results for the demand data of Company X. The motivation for this method is explained in the roadmap.

The framework of reference only consists of the zero measurement currently. We propose to also select a simple statistical forecasting model to extent the framework of reference. Comparing the results of the Modified SBA method with both the zero measurement and the forecasting performance of a simple statistical methods provides insight in the results of applying statistical forecasting as the differences in forecasting performance of different statistical models as well. The simple statistical model we propose for benchmarking is the Moving Average method. This method can be implemented easily, because it does not require setting of parameters, whereby the model fitting step can be skipped.

Step 5

As already described in step 3, cross validation should be applied in case of an insufficient dataset. It incurs a long computational time, so should be avoided when it is not really necessary. Iteratively setting the smoothing parameters, calculating the forecasted demand an determining the values of the performance metrics can be automated using a VBA macros in Excel. Whether this is desirable depends on the size of the product range that will be forecasted statistically. For Business Unit C it might be workable to perform these steps manually, while for Business Unit B and Business Unit A a simulation is desirable.

Step 6

In the previous step the optimal parameter settings of the selected models are determined. Using these settings, we now generate forecasts for the time interval of the test set. To have another frame of reference besides the zero measurement, it is advisable to also generate forecasts using a simple statistical method like the moving average method. This method does not require parameter settings, only a warm up period to , which should be equal to the warm up period used for the Modified SBA method.

If the test set covers for example one year of data, we can first generate forecasts for one year ahead and then decrease this forecasting horizon with one period each time, moving this data point form the forecasting period to the available data. For each generated forecast, the aMASE and bias should be calculated. Each forecasting period is weighted equally when determining an overall aMASE. Therefore, the aMASE of a certain forecasting row, should be weighted after the number of periods that are forecasted in that row. The longer the forecasting horizon, the more periods are forecasted, the heavier the aMASE is weighted.

The bias is analysed by plotting its course over the year. Each week of the year has one value for the bias of the forecasts sent in that week. The forecasting horizon of the forecasts sent that week is similar for all products, so the ME does not have to be weighted after the number of periods in the forecasting horizon. To be able to sum the bias of different products, we multiplied the ME with the purchase price per product. Now all ME of a certain forecasting week can be added up. The model with the lowest aMASE and a ME close to zero, is the best.

The computational time is not necessary to compute, since the statistical models do not entail that many calculation steps. Taking into account the computational time of the methods would become valuable in case of comparing more complex models, like neural networks.

In case of disappointing results, alternative statistical models can be tried, depending on the nature of the forecasting error. For example, if the results show a positive bias, the forecasted demand is too low. In that case, it might be worth investigating whether the TSB method performs better. The TSB method disregards the adjustment of the SBA method to remove the bias from Croston's method. Hence, the factor $\left(1-\frac{\beta}{2}\right)$ should be removed from the demand size estimator. This adjustment to the statistical model goes along with executing step 5 and 6 of the roadmap again.

Step 7

Last but not least, the forecasting task should be designed. The responsibilities concerning generating forecasts, but also maintaining the forecasting model, must be assigned. Maintaining the forecasting model implies updating the dataset, controlling its performance by monitoring the forecasting errors and reviewing the statistical model. Review of the statistical model should be performed each year for each product, in order to re-establish the optimal values of the smoothing parameters. In case of non-stationary demand data, also the seasonal component and trend component should be updated by applying time series decomposition and model fitting, subsequently.

Care should be taken with making manual adjustments to the statistically forecasted demand. Negative adjustments are generally more effective than positive adjustments (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). A principle that should be taken into account for considering manual adjustments is that collaboration is important. Sales, Operations, and if possible the customers as well, should be involved in the establishment of the forecasted demand, in order to reduce the subjectivity.

Furthermore, Company X should consider to link a certain purchase obligation to the forecasts sent by the customer. Herewith Company X can oblige its customers to purchase a part of their forecasted demand, which encourages them to forecast accurately.

ROADMAP TO AN IMPROVED FORECASTING PERFORMANCE

STEP 1

Project initiation: define people, goals, tools and scope

1. Create a project group.
2. Define the goals and tools.
3. Determine the level of fulfilment of the products to forecast: finished or semi-finished. Resulting in a range of products to forecast.
4. Gather the time series data of the demand of these products.

STEP 2

Product segmentation: select the best forecast approach

Statistical forecasting might not be the most appropriate approach for all products. Therefore we classify the products based on several variables to a certain product segment.

1. Classify the products based on three variables:
   - Whether demand occurs regularly or incidentally (projects).
   - Lifecycle phase of the product: Old products (decreasing demand), New products (increasing demand) or Normal products.
   - And in case of a new product with an expected regular demand pattern: whether this product replaces another product or is totally new.
2. The product segmentation results in the most suitable forecasting method per product. Select the range of products which should be forecasted statistically.
3. Determine the following parameters per product:
   - Forecast horizon: the length of time that is forecasted should be at least as long as the longest component lead time (including manufacturing time), but not longer than neccessary, since forecasting further in the future is less accurate.
   - Time intervals: the 'buckets' of time in which demand is forecasted. Currently this is weekly, but a higher aggregation level results generally in a higher accuracy. So if monthy time intervals are sufficient, this is preferred.

Refers to Appendix XIII for a vizualization of the decision tree

STEP 3

Data exploration: analyze and preprocess the data

1. Select the parameters for assessing the forecasting performance. We propose using the aMASE for the accuracy and the ME for the bias, see section 4.3.1 for the motivation.

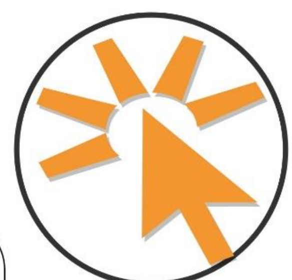
$$\text{Mean Error (ME)} = \frac{\sum_{t=1}^{n}(y_t - \bar{y}_t)}{n}$$

$$\text{Adjusted Mean Absolute Scaled Error (aMASE)} = \frac{\sum_{t=1}^{n} \frac{|y_t - \bar{y}_t|}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}}{n}$$

Refers to appendix XIII for a detailed description of time series decomposition

2. Perform the zero-measurement. This implies assessing the current forecasting performance on the selected parameters. This analysis is already performed in this research, see section 4.3.
3. Data preparation:
   - Like the old saying: Garbage in, garbage out. Therefore, clean the data by removing outliers (the datapoints that should not be taken into account for forecasting).
   - Divide the data in a training and test set (typically 80-20 split) and determine whether there is sufficient data or cross validation should be applied. Products with a rather high ADI and a monthly time interval, have relatively less data points, so cross validation is recommended.
4. Use (additive) time series decomposition to determine whether the demand data is stationary.
5. Apply data transformation methods in case of non-stationary data. When time series decomposition has been applied, this step is already performed. If a certain linear trend in the time series data has been noticed, Holts linear trend method should be applied.

STEP 4



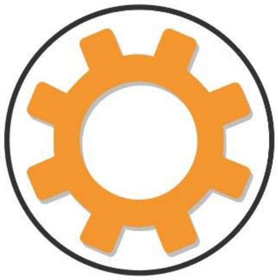
Model selection: choose the statistical model(s)

1. Select one or multiple statistical forecasting models which are suitable for intermittent time series data.
   We propose to select the Modified SBA method (Babai et al., 2019).

   Motivation for 'Modified SBA method':
   According to the SBC-classification (Syntetos et al., 2005), the SBA method outperforms Croston's method for intermittent, lumpy and erratic demand. This is not the case for smooth demand, but none of Company X' products appears to have a smooth demand pattern, see section 4.2. The TSB method is specifically useful for situations in which inventory obsolescence is linked to forecasting (Teunter, Syntetos, & Babai, 2011). This appears to apply to the situation of Company X, since a part of their excess inventory can be assigned to the cause 'Lifecycle management', see section 2.3. The Modified SBA method combines the adjustment of the SBA method to Croston's method in order to reduce the bias, with the idea of the TSB method to update the forecast also after periods of zero demand in order to deal with inventory obsolescence. For this reason, the Modified SBA method is the most appropriate method for Company X.

2. Select a simple model for benchmark. Applying the simple Naïve method is already part of calculating the aMASE, but this method is not representative for multi-period ahead forecasts. We propose to select the moving average method, because linear regression requires a predictor variable and exponential smoothing is already applied in Croston's method and its adjustments.

STEP 5



Model fitting: estimate model parameters using the training set

1. Use cross validation when there is not enough data available.
2. Set the initial values of the variables Z_{t-1} and T_{t-1}, by calculating them over the warm-up period (k-1 periods).
3. Iteratively set the parameters of the selected models and calculate the aMASE and ME over the training set.
   The parameters for the Modified SBA method are:
   - Alpha, typically between 0.1 and 0.3. This is the smoothing parameter for the demand size.
   - Beta, also typically between 0.1 and 0.3. This is the smoothing parameter for the demand occurence.
4. Select the values for the parameters which result in the lowest aMASE and ME close to zero.

Refers to appendix XIII for a detailed description of model fitting

STEP 6

Model testing: calculate aMASE using test set and compare

1. Generate forecasts for the test set using each selected model: the Modified SBA method and the Moving Average method are proposed.

   Moving average: $D'_t = \frac{\sum_{j=t+1-n}^{t} Z_j}{n}$

2. Calculate the aMASE and ME per model.
3. In case of multiple complex models also take into account the computational time (expected to be unnecessary for the Modified SBA method) and compare the forecasting performance (aMASE and ME) of the different models.
4. Compare the best model from the previous step with the zero measurement and determine whether the differences are significant. Decide based on this whether the improved model should be adopted. In case of disappointing results, another statisital method can be considered.

STEP 7

Process design: organize the forecasting task

1. Design the forecasting task with its corresponding roles and responsibilities.
2. Define the forecasting frequency, so how often the forecast is updated and reviewed.
3. The statistical forecasts should be compared with the input of Sales and (if applicable) the customer forecasts. Determine the bandwith of the differences to be considered for manual adjustments. It is also advisable to link a certain purchase obligation to the forecasts by the customers, because this encourages them to forecast accurately.
4. Pay special attention to defining the steps of monitoring and controlling of the forecasting performance. The model fitting step should be performed yearly, to re-estabilish the optimal values of the smoothing parameters and (if applicable) redetermine the seasonal and trend component.
5. Also, the process for the products that have to be forecasted judgmentally should be designed, in the sense of who is responsible and who provides input.
6. Finally, use and evaluate the forecasting model.

5.2. Additional improvements

Besides improving the forecasting performance, there are also other possibilities for excess inventory reduction. There are three modes by which inventory reduction can be accomplished (Tersine & Toelle, 1984):

1. Increasing the outflow (demand) of items
2. Limiting the inflow (supply) of items
3. Reducing the excess inventory levels

Mode 1 and 3 imply reactive approaches to excess inventory. These options are discussed under 'reactive'. We do not only want to reduce excess inventory, but also avoid creation of it. Mode 2 comprises the proactive approaches for reducing excess inventory. Improving the forecast accuracy is one of these approaches. Alternatives are discussed under 'proactive'.

5.2.1. Reactive

The longer the excess inventory is retained, the more money it costs. Most components depreciate over time, and in many cases quite quickly. Therefore, ignoring is arguably the worst way of dealing with excess inventory (Tashjian, 2016). Inventory that will no longer be used should be disposed as early as possible. We distinguish two different approaches for reactively reducing excess inventory: disposal and lateral transshipments.

Disposal

The excess inventory of components which do not have any expected demand anymore, can be reduced by either selling or scrapping. Obviously, selling is preferred over scrapping, because this might generate revenues instead of costs. Nevertheless, this is no option for Company X specific components.

In some cases, the costs of keeping the inventory may outweigh the actual value of the inventory (Nnamdi, 2018). Several studies have been performed after determining the optimal disposal quantities, mostly by applying dynamic programming (Tersine & Toelle, 1984). In the case of Company X, the EMSs foot the bill of the warehousing costs of their inventory. Therefore, determining optimal disposal quantities is not relevant for Company X. However, inventory of components which have no demand at all and Company X expects that this remains, should either be sold or scrapped as early as possible. Selling the components to material brokers generally yields a small fraction of the value of the components, typically only 3 to 5 percent of the initial purchase price (Tashjian, 2016). If it is possible to return the inventory to the supplier, this option should be considered . The most easy way of trying to get rid of the excess inventory is to return it to the supplier.

Another option for disposal of inventory is breaking down the materials and finding a market for them at the highest possible price. There exist several partners for this 'structured disposal' of electronics components. These organizations actively market the components across multiple channels simultaneously, to a broad audience of users. Generally, the return on the excess inventory is higher, but it requires more patience.

Lateral Transshipments

Company X has multiple components which are used in different products. Therefore, the EMSs of Company X do have some components inventory in common of these so called 'shared components'. An excess at one EMS could possibly be taken over by another EMS. Lateral transshipments are inventory movements between locations of the same echelon (Paterson, Kiesmuller, Teunter, & Glazebrook, 2009). We performed a simple analysis to indicate the possible savings of applying lateral transshipments.

The analysis is performed based on the spend file of November 2018 and includes the EMSs: EMS 2, EMS 1, EMS 3 and EMS 4. EMS 4 does not belong in the scope of this research, but is included in this analysis to provide a more complete picture of the situation. Per components all known demand (so orders and forecast) is subtracted from the inventory. This results in a positive or negative inventory level. The individual excess inventory of a certain component at an EMS is multiplied by the lowest price of the different purchase prices the different EMSs pay for the same component. When we compensate the inventories of equal components at different EMSs and multiply them by the lowest purchase price, the total excess inventory becomes €XX lower. This implies that the excess inventory can be reduced with €XX using lateral transshipments between the inventories of these four EMSs. Herewith we do not take into account the transportation costs, so this amount does not cover the exact savings potential.

5.2.2. Proactive

Besides improving the forecasting accuracy, there are some other possibilities for Company X to avoid further creation of excess inventory. In the following paragraphs we discuss risk pooling, lifecycle management and some other improvements subsequently.

Risk pooling

As already mentioned under 'Lateral Transshipments', the EMSs do have some inventory of components in common, since Company X has multiple components which are used in different products. Yet, there is no collaboration between the EMSs. The lack of collaboration for inventory management of these components is inefficient, and can therefore be considered as waste. This waste comes in two types: the excess inventory at two locations (EMSs) and the purchase price of the components.

Figure 27 shows the proportion of so-called 'shared components' to components which are used by only one EMSs. The ratio is calculated based on the spend of the EMSs for the Company X demand that is known (orders and forecasts for approximately one year in advance). The shared components can be used by two or more EMSs. Also EMS 4 is included in this analysis, since their data is was also available and it gives a more representative view for Company X.

Figure 27: Part of spend that is used by multiple EMSs

The first inefficiency implies that different EMSs keep the same components in stock. A high Minimum Order Quantity would therefore result in excess inventory at both the EMSs, although this perhaps would be no problem in case of cooperation. The effect of MOQs on the excess inventory levels can therefore be reduced by risk pooling. Risk pooling is a way to reduce the bullwhip effect and with this also the excess inventory at the EMSs. It causes a reduction of the total variability of demand by consolidation of individual variabilities of demand (Oeser, 2015). The demand can be aggregated across for example locations or products. In the case of Company X, risk pooling over locations would imply that the EMSs have to collaborate for Company X or Company X needs to facilitate this by insourcing the inventory management. Risk pooling is a strategic decision. Company X should first determine whether they want this level of involvement in purchasing components and materials, since they outsourced their production activities to be able to focus on their core business, which is product development. Hereafter, it is might worth investigating what the options and corresponding yield and costs of implementing risk pooling are. Risk pooling becomes even more interesting in case of dual source procurement. If Company X outsources the production of certain products to multiple EMSs, both these EMSs needs to keep inventory of the components for these products. Also a higher Coefficient of Variation in the demand patterns of the products result in a greater benefit from risk pooling. The Coefficient of Variation of the products of Company X are rather high, which is shown in the bubble chart of section 4.2.

The second inefficiency we address regarding the 'shared components' is the differences in purchase prices of the different EMSs. An example of a component that is used by multiple EMSs is the 'XX'. EMS 3 purchases it for €XX per unit while EMS 1 purchases it for €XX per unit from another distributor, but both originating from the same manufacturer. A simple analysis on the expected demand (orders and forecasts) for approximately one year in advance showed us that Company X can already reduce their expenses with €XX by only purchasing the 'shared components' for the lowest purchase price per component known. Therefore, we would recommend Company X to negotiate with the manufacturers about the purchase prices of some specific components.

Lifecycle management

In section 5.1 we recommended Company X to use the Modified SBA method for statistical forecasting. One of the advantages of this method is that it adjusts the forecasted demand downwards after periods of zero demand. However, when a product reaches its end-of-life, this is not enough to avoid creation of excess inventory. The phase-out of a product should therefore be communicated proactively in a timely manner. Although the forecasters of the different business units indicated that they communicate proactively about the phasing out of products, still some excess inventory is assigned to the cause Lifecycle Management. Hence, we recommend Company X to proactively address the excess inventory by monitoring the (decreasing) demand patterns. Special attention should be paid to excess inventory of component that are perishable.

Components which have inventory but no demand at all, directly pose a financial risk for Company X, since they become Company X' liability within one year. Company X takes note of these inventories by the liability files that are sent by the EMSs. It might be valuable to develop a tool (for example a VBA macro) which assigns the excess inventory of components (based on forecasted demand, stock level, value, shelf life, last usage dates, etc.) to a certain risk level. This classification determines where the focus should be and which excess inventories require a certain decision or action. This automated prioritization of excess inventory contributes to efficiently processing the liability files.

Other improvements

While executing the different analysis, we encountered that there are multiple inventory record inaccuracies. Not all data fields of all products are filled correctly for all products. For example, different unit measures (liters, kilograms, etc.) are used for a certain component. Also the purchase price of the components should always be filled. All deviating and empty fields should be selected and revised by the EMSs. This also applies to the agreements about MOQs and allowed inventory levels of components and materials. Quantification of these agreements results in a tighter control of Company X' liability regarding the inventory of the EMSs.

Another possibility for proactively preventing accumulation of excess inventory is by encouraging Product Development to use less Company X specific components and more components that are already used in other Company X products. By using less unique items, the effect of the MOQs on the inventory levels can be reduced.

5.3. Chapter conclusion

Reducing the current excess inventory levels requires a reactive approach. Inventory of components whereof Company X expects to have demand in the (near) future can be retained. The other excess inventory should be either disposed (sold or scrapped) or transferred to an EMSs who can use the inventory. The excess inventory can already be reduced by more than €XX, by applying these so-called lateral transshipments between the four biggest EMSs of Company X.

At least as important as reducing the current excess inventory levels is avoiding further creation of excess inventory in the future. This requires a proactive approach. The main recommendation of this research is applying the Modified SBA method as a statistical forecasting method for Company X. The advantages of this method are that it can deal with intermittent demand and takes into account inventory obsolescence. The roadmap of section 5.1 describes the steps to be taken to implement statistical forecasting for the different business units.

Other proactive approaches to preventing the build-up of excess inventory in the future are: risk pooling, proper lifecycle management and adjusting Company X' Product Development policy. Risk pooling implies the aggregation of demand across the EMSs, so the total variability of demand of the individual EMSs can be reduced. The EMSs have to collaborate and Company X needs to facilitate in this process, therefore this is a strategic decision about the level of involvement of Company X to the inventory management of the EMSs.

Communication about the phasing out with the EMSs is important, since it would result in the build-up of excess inventory otherwise. The recommended Modified SBA method deals with inventory obsolescence by adjusting the forecasted demand downwards after periods of zero demand. Notwithstanding, when a product reaches its end-of-life, this is not enough to avoid creation of excess inventory. The phasing out of a product should therefore be communicated proactively in a timely manner, so no unnecessary inventory is purchased and the remaining inventory can be finished.

Another possibility for proactively preventing accumulation of excess inventory is by encouraging Product Development to use less Company X specific components and more components that are already used in other Company X products. By using less unique items, the effect of the MOQs on the inventory levels can be reduced.

6. Conclusion and Recommendations

This chapter includes the conclusions and recommendations of this research. The sub questions are already answered by the different chapter conclusions. In this chapter, we answer the main question of this research:

How can Company X improve its liability by reducing (and avoiding further creation of) the excess inventory of materials and components at the EMSs?

The core problem of this research that has been identified is the forecasting performance of Company X. Since the EMSs purchase based on the forecasts sent by the Company X Business Units, these forecasts have a major impact on the inventory levels.

Generating demand forecasts is a decentralized process over the business units, and currently consists of many manual steps with judgmental input. This results in an inefficient and subjective forecasting process. The forecasting task and its output are dependent of the person who executes it. In terms of flexibility and consistency, this is not desirable.

An analysis after assessment of the forecasting performance of Company X showed us that the forecasts sent are neither accurate nor stable. For all business units, the value of the aMASE is higher than 1, implying that generating forecasts using the simple Naïve method would result in a smaller forecasting error compared to the current forecasting method. An important caveat we want to address with this statement, is that the Naïve method is not totally representative for the case of Company X, where forecasts are generated for multiple periods ahead. However, the values of the aMASE still show us that there is certainly room for improvement of the demand forecasting accuracy.

The trendline of the forecasting bias over the year 2018 of the different business units all showed a different slope. For Business Unit B the bias was positive over the whole year, but showed a negative slope. This indicates that Business Unit B forecasts too low, which can be explained by the fact that Business Unit B forecasts most demand in the near future, resulting in the forecast running empty towards the end of the forecasting horizon. The bias of the forecasts of Business Unit A show a positive slope, crossing the x-axis in the middle of the year. This is the result of too high forecasts at the beginning of the year, which are compensated by lower forecasts towards the end of the year. The slope of the bias of Business Unit C is in between the graphs of Business Unit B and Business Unit A and is slightly negative with a negative slope. It shows some (mostly negative) outliers, which indicates that the proportion forecasted demand to the actual demand is not stable. The negative outliers imply that there has been forecasted way too much, which results in excess inventories.

Classification of the demand patterns of the Company X products showed that most of Company X' products have an intermittent demand pattern and the remaining part has a lumpy demand pattern. Putting these products in proportion after their value (calculated by multiplying the purchase price by the demand of 2018), shows that in general, the products with the highest value are closer to having a smooth demand pattern than the low value products. Since this implies that the ability of statistically forecasting these products is relatively high, improving the forecasting method using statistics is expected to be effective.

We recommend Company X to apply statistical forecasting, in order to create less variability in the forecasted demand, to have a more efficient forecasting process and to have an increased forecasting accuracy by reducing the subjectivity in the forecasting process. For intermittent demand, Croston's method is the most frequently used method (Doszyn, 2018), since it can deal with the zero values in the data. The basic idea of Croston's method is to divide the forecasted demand into two parts, which are both calculated using exponential smoothing; one for the size of the demand and one for the intermittent demand interval. The TSB method (Teunter, Syntetos, & Babai, 2011) and the SBA method (Syntetos, Boylan, & Croston, 2005) are modifications to Croston's method. The SBA method removes the bias from Croston's method by multiplying the estimated demand with a certain factor. This adjustment has proven its performance for data that contains many zero values, which is the case for Company X. The TSB method tackles the issue of Croston's method (and the SBA method) that it does not adjust the forecast downwards in case of periods with zero demand. This adjustment is especially valuable in cases where inventory obsolescence is linked to forecasting, which is the case for electronic components.

The Modified SBA method combines the adjustment of the SBA method to Croston's method in order to reduce the bias, with the idea of the TSB method to update the forecast also after periods of zero demand in order to deal with inventory obsolescence. For this reason, the Modified SBA method is the most appropriate forecasting method for Company X. According to the Modified SBA method, the expected demand is calculated using the formulas below.

Modified SBA method (Babai, Dallery, Boubaker, & Kalai, 2019):

$$D'_t = \left(1 - \frac{\beta}{2}\right) * \frac{Z'_t}{T'_t}$$

where

$$If\ D_t > 0\ then \begin{cases} Z'_t = Z'_{t-1} + \alpha * (Z_t - Z'_{t-1}) \\ T'_t = T'_{t-1} + \beta * (T_t - T'_{t-1}) \end{cases}$$

$$If\ D_t = 0\ then \begin{cases} Z'_t = Z'_{t-1} \\ T'_t = \begin{cases} T'_{t-1} + \beta * (T_t - T'_{t-1}) & if\ T_t > T'_{t-1} \\ T'_{t-1} & if\ T_t \leq T'_{t-1} \end{cases} \end{cases}$$

D_t : Demand for an item at time t

D'_t : Estimate of mean demand per period made at time t for period $t+1$

Z_t : Actual demand size at time t

Z'_t : Estimate of the demand size at time t

T_t : Actual demand interval at time t

T'_t : Estimate of the demand interval at time t

α, β: Smoothing parameters $(0 \leq \alpha \leq 1, 0 \leq \beta \leq 1)$

The forecasting processes of the different business units are decentralized. Therefore we provide a roadmap to an improved forecasting process. This roadmap should be followed for each business unit separately. We recommend Company X to start with implementing statistical forecasting for the business unit Business Unit B. They are currently reorganizing their demand forecasting task and have the greatest desire to apply statistical forecasting. Moreover, the graphs in appendix V show that improving Business Unit B's demand forecasting accuracy is expected to be effective for reducing their excess inventory. Summarized, the steps of the roadmap are:

- **Step 1**. <u>Project initiation</u>: define people, goals, tools and scope.
- **Step 2**. <u>Product segmentation</u>: select which products should be forecasted statistically, which ones judgmentally and which ones should not be forecasted, based on their expected demand pattern.
- **Step 3**. <u>Data exploration</u>: analyze and preprocess the data. Perform a baseline measurement using the forecasting performance metrics aMASE for accuracy and ME for bias (has already been done in this research). Perform time series decomposition on the demand data if there is a chance that it contains seasonality or a trend. An example of time series decomposition has been elaborated in

appendix XIII. Split the time series data in a training set for model fitting and a test set for model testing (80-20 ratio).

- Step 4. Model selection: choose the statistical model(s). As explained above, we propose to apply the modified SBA method. We recommend to also select a simple statistical forecasting method like the moving average method, in order to extent the framework of reference. Comparing the results of the Modified SBA method with both the zero measurement and the forecasting performance of a simple statistical method, provides insight in the results of applying statistical forecasting and the differences in forecasting performance of different statistical models.
- Step 5. Model fitting: estimate the model parameters. The modified SBA method contains smoothing parameters (α and β), which require setting of their optimal values. This implies iteratively setting different values of these parameters and calculating the performance metrics over the training set. The combination of values which results in the lowest aMASE and ME close to zero is labeled as optimal. An example of model fitting has been elaborated in appendix XIII.
- Step 6. Model testing: calculate the aMASE (and ME) over the test set and compare. Generate forecasts for the test set using each selected model (Modified SBA method and Moving average method). Calculate the aMASE and ME for these forecasts and compare these scores with the scores from the baseline measurement.
- Step 7. Process design: organize the forecasting task. The responsibilities concerning generating forecasts, but also maintaining the forecasting model, must be assigned. Maintaining the forecasting model implies updating the dataset, controlling its performance by monitoring the forecasting errors and reviewing the statistical model. Review of the statistical model should be performed each year for each product, in order to re-establish the optimal values of the smoothing parameters. In case of non-stationary demand data, also the seasonal component and trend component should be updated by applying time series decomposition and model fitting, subsequently.

Besides improving the forecasting performance, there are also other possibilities for reducing the excess inventory levels. These can be divided in reactive and proactive approaches. The core problem regarding the liability of Company X due to excess inventories at the EMSs is (partly) a result of inaccurate forecasts by Company X. Other causes are the MOQs of the components and communication about the lifecycles of the products. Excess inventory due to the phasing-out of products should be communicated proactively in a timely manner. The recommended Modified SBA method deals with inventory obsolescence by adjusting the forecasted demand downwards after periods of zero demand. Notwithstanding, when a product reaches its end-of-life, this is not enough to avoid creation of excess inventory.

An approach for reducing the impact of the MOQs on the excess inventory is applying risk pooling, which means in practical terms aggregation of the inventory on a certain location. This is worth investigating for Company X, since XX% of Company X' demand consists of 'shared components'. Risk pooling does not belong to the 'quick-wins', since it is rather complex to implement. Hence, we propose risk pooling as a suggestion for further research. This improvement becomes even more interesting in case of dual source procurement, when the same product can be supplied by two EMSs. The different scenarios for risk pooling with their extent to which Company X is involved in the purchasing process and their corresponding costs, benefits and drawbacks should be investigated and compared. Performing this research requires a corporation with the suppliers, so this is a prerequisite for this research.

Furthermore, Company X should encourage its Product Development to use even more 'shared components', especially for products which production is accommodated at the same EMSs. The benefits of more shared components are both the purchase price and the relatively lower MOQs. Additionally, the risk that inventory becomes obsolete decreases when its demand is divided over multiple products.

Reducing the current excess inventory levels requires a reactive approach. Inventory of components whereof Company X expects to have demand in the (near) future can be retained. The other excess inventory should be either disposed (sold or scrapped) or transferred to an EMSs that can use this inventory. The excess inventory can already be reduced by more than €XX, by applying these so-called lateral transshipments between the four biggest EMSs of Company X.

7. Limitations

In this chapter we discuss the limitations of the research, starting with the scope. This research solely included the inventory of materials and components at the EMSs. The EMSs produce only to Company X orders, but not all Company X business units purchase to customer order. Generalized, the business unit Business Unit A purchases to stock and the business unit Business Unit C purchases partly to stock. This implies that besides the inventory of components and materials, they also have a certain amount of finished goods on stock. A reduced inventory of materials and components at the EMSs means therefore not necessarily that the liability is reduced, since these components and materials can be included in the inventory of finished goods. The liability of the inventory of finished goods is even higher compared to the inventory of materials and components, since more value is added to this inventory. To provide a complete picture of the inventory management situation at Company X, research after the inventory of finished goods is recommended.

Another point of discussion is the assumptions made for the different analyses. The analysis of the classification of the excess inventory to causes has been very directive for this research. This analysis is based on self-constructed rules of thumb which are applied on data provided by the EMSs. Also, the excess inventory of a certain component is in total assigned to a certain cause. Division of excess inventory over multiple causes per component is not possible according to the particular rules of thumb. Because of these limitations of the analysis, we are aware the analysis only provides an indication of in which proportions the causes contribute to the excess inventory. The results should therefore not be used for decisions requiring exact amounts of the excess inventory causes, but solely providing an indication. Determination of exact values requires an one by one analysis of the excess inventory on component level, which will ask a lot of effort.

The amount of excess inventory depends on the demand of Company X for one year in advance. The biggest part of this demand originates from forecasts and not from orders, so is expected demand. Fluctuation in the forecasts sent results therefore also in fluctuation in the excess inventory levels, which in turn results in fluctuation in the classification of the excess inventory to the causes. To (partly) overcome this problem, we took into account all available data of the EMSs about the excess inventory. Four months (September to December, 2018) were included, so we could see the course of the distribution of the excess inventory over the causes. This showed us that the analysis certainly has some sensitivity, but still for each month the conclusions that are drawn from the results would be the same. Namely, identifying ‘forecasting errors’ as the cause with the greatest effect.

With classifying the inventory over the tree causes mentioned, we assume that the excess inventory is not caused by incorrect inventory management of the EMSs. Company X performs audits at the EMSs, but this does not provide a hundred percent guarantee that they execute their inventory management correctly all the time. Nevertheless, the outcomes of these audits caused that Company X has enough confidence in the correctness of the inventory management of the EMSs.

Besides the stationarity as described in section 3.1.2, another assumption of Croston’s method which is worth noticing is the independence of both the demand sizes and demand intervals, and the independence of these variables mutually (Altay & Litteral, 2011). For some of Company X products, the demand of a period might be dependent of the demand on its previous period. However, a stable forecast requires a more holistic view to the distribution of demand over the whole horizon. Forasmuch the excess inventory, it is not desirable to increase the forecast for the next period if there was a disappointing demand the latest period. So even if the demand size and interval might not be totally independent, they should be considered as independent in order have a stable forecast. In case of products with an incidental demand, so which demand pattern is largely dependent on some major projects, this independence assumption might pose a problem. Notwithstanding, these products will not be forecasted statistically according to the product segmentation step in the roadmap. Instead, these products will be forecasted judgmentally, so the independence assumption is not applicable. If Company X expects that the demand of different products is mutually dependent because they are almost equally, they can aggregate the demand of these products in order to make the independence assumption valid for the product group.

The final point of discussion we address is that the recommended 'Modified SBA Method' is recently proposed and has therefore not been assessed extensively yet. However, it is based on some other methods, which already have proven their performance. Moreover, the model has to be tested anyway, so in that case the only risk that comes along with applying such a fairly new method is the time and effort lost after this method appears to perform insufficiently.

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Appendix I: Agreements Company X - EMS

Not available online

Appendix II: Consolidation of rows VBA

Not available online

Appendix III: Excel formulas

Not available online

Appendix IV: Results per EMS

Not available online

Appendix V: Results per business unit

Not available online

Appendix VI: Results per EMS per month

Not available online

Appendix VII: Flowcharts forecasting processes business units

Not available online

Appendix VIII: Forecast and finished product inventory

Not available online

Appendix IX: Demand time intervals VBA

```
Sub DemandInterval()

Dim i, j As Integer
Dim DemandA, DemandB As Integer
Dim Count, DemandInterval, IntervalNr As Integer

'Do for all rows (products that are forecasted)
For i = 3 To 233
    IntervalNr = 70
    'Loop through all weeks (week 1 of 2018 until week 8 of 2019)
    For j = 6 To 65
        'Determine first week that has demand and assign weeknumber to variable DemandA
        Do While Cells(i, j).Value < 1
            j = j + 1
        Loop
        DemandA = Cells(2, j).Value

        'Determine second week that has demand and assign weeknumber to variable DemandB
        Count = j + 1
        Do While Count < 67 And Cells(i, Count).Value < 1
            Count = Count + 1
        Loop

        'Write length of time interval between subsequent demand to cell in the end of the row
        If Count < 66 Then
            DemandB = Cells(2, Count).Value
            DemandInterval = DemandB - DemandA
            Cells(i, IntervalNr).Value = DemandInterval
            IntervalNr = IntervalNr + 1
        End If

    Next j
Next i

End Sub
```

Appendix X: Demand classification graphs

Not available online

Appendix XI: Demand pattern bubble chart per Business Unit

Not available online

Appendix XII: Data preparation VBA

```
Sub InsertCopiedFcRows()

Dim i As Integer
Dim LastRow As Integer
Dim NumPastWeeks As Integer
Dim x As Integer

'Remove filters
ActiveWorkbook.ActiveSheet.AutoFilter.Sort.SortFields.Clear

'Sort rows on ItemNo and FcYearWeek by sorting HelperColumn (ascending)
ActiveWorkbook.ActiveSheet.AutoFilter.Sort.SortFields.Add _
    Key:=Range("G1:G7079"), SortOn:=xlSortOnValues, Order:=xlAscending, _
    DataOption:=xlSortNormal
With ActiveWorkbook.ActiveSheet.AutoFilter.Sort
    .Header = xlYes
    .MatchCase = False
    .Orientation = xlTopToBottom
    .SortMethod = xlPinYin
    .Apply
End With

'Define LastRow as the row number of last row that contains a value and initialize rownumber variable i
LastRow = Cells(1, 2).End(xlDown).Row
i = 2

'Loop through all rows
Do While i <= LastRow

    'If the forecasting week of selected row is before the last forecasting week of 2018 and _
    either the subsequent forecasting week is not equal to the forecasting week + 1 _
    or the item number of the subsequent forecasting row is not equal to the selected row
    If Cells(i, 2) < 201851 And _
    (Cells(i + 1, 2) <> Cells(i, 2) + 1 Or _
     Cells(i + 1, 6) <> Cells(i, 6)) Then

        'Copy and insert the row
        ActiveSheet.Cells(i, 1).EntireRow.Select
        Selection.Copy
        Selection.Insert Shift:=xlDown

        'Clear forecasts of past weeks
        NumPastWeeks = Cells(i + 1, 2).Value - 201800
        For x = 1 To NumPastWeeks
            Cells(i + 1, x + 7).ClearContents
        Next x

        'Adjust the YearWeek to the subsequent week
        ActiveSheet.Cells(i + 1, 2).Value = Cells(i, 2).Value + 1

        'Mark inserted row
        ActiveSheet.Cells(i + 1, 1).Select
        Selection.ClearContents
        With Selection.Interior
            .Pattern = xlSolid
            .PatternThemeColor = xlThemeColorAccent2
            .ThemeColor = xlThemeColorAccent2
            .TintAndShade = -0.249977111117893
            .PatternTintAndShade = 0.599993896298105
        End With
    End If

    'Redefine last row and jump to next row by increasing rownumber i by one.
    LastRow = Cells(1, 2).End(xlDown).Row
    i = i + 1

Loop

End Sub
```

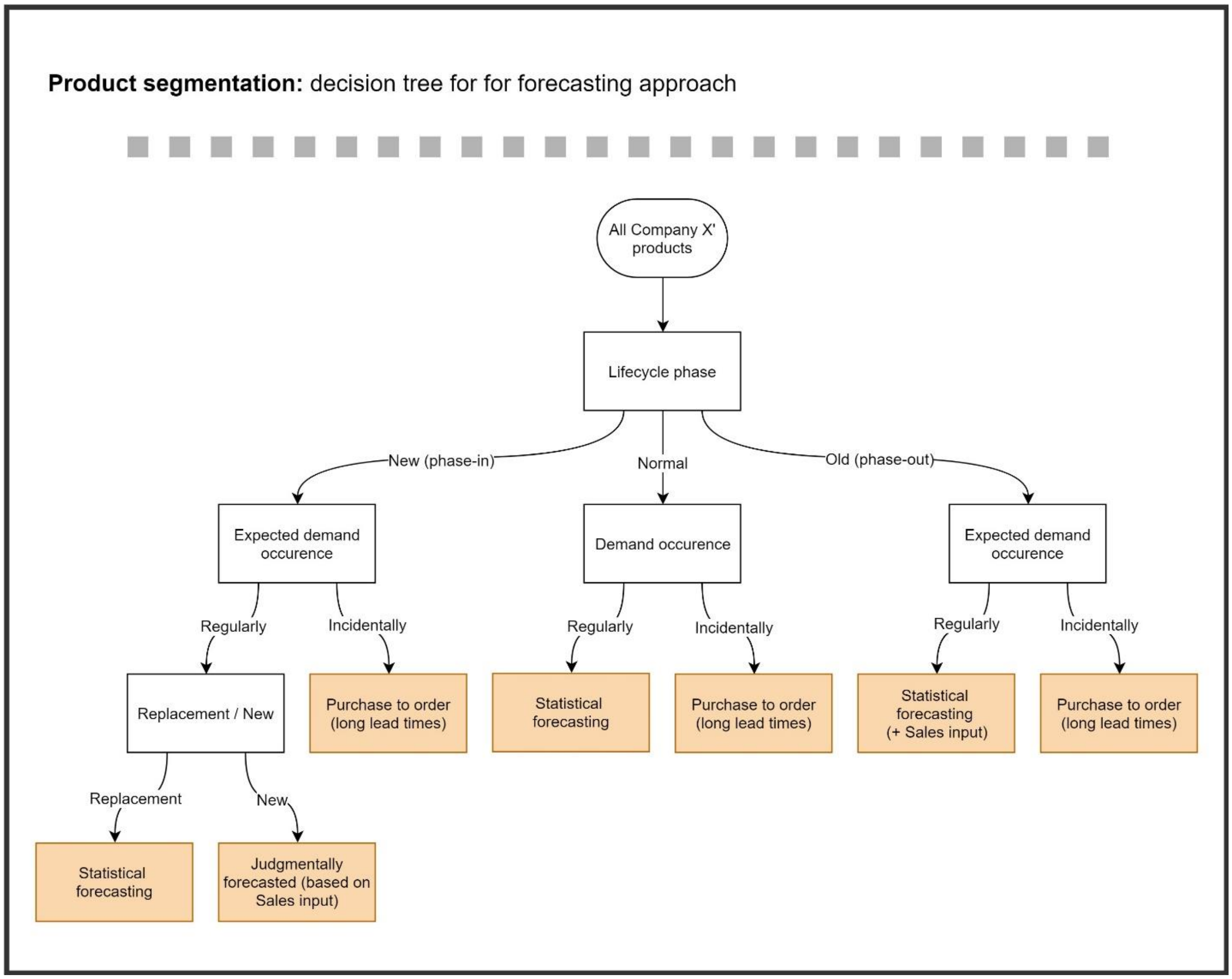
```
Sub EmptyCellsOrderPeriod()

Dim i As Long
Dim j As Integer
Dim Yearweek As Long

'Loop through all rows
For i = 2 To 9995
    'Assign value of column Yearweek to variable
    Yearweek = Cells(i, 2).Value
    'Loop through columns forecasting horizon
    For j = 8 To 44
        'Go to next row if the forecasting week is before 201813, because order period is already empty
        If Yearweek < Cells(1, 8) Then
            Exit For
        End If
        'Delete forecast for the time period of 12 weeks ahead from forecasting week on
        If Cells(1, j).Value = Yearweek Then
            Range(Cells(i, j), Cells(i, j + 11)).ClearContents
            Exit For
        End If
    Next j
Next i


End Sub
```

Appendix XIII: Attachments to roadmap



Model fitting:

Modified SBA method (Babai, Dallery, Boubaker, & Kalai, 2019):

$$D'_t = \left(1 - \frac{\beta}{2}\right) * \frac{Z'_t}{T'_t}$$

where

$$If\ D_t > 0\ then \begin{cases} Z'_t = Z'_{t-1} + \alpha * (Z_t - Z'_{t-1}) \\ T'_t = T'_{t-1} + \beta * (T_t - T'_{t-1}) \end{cases}$$

$$If\ D_t = 0\ then \begin{cases} Z'_t = Z'_{t-1} \\ T'_t = \begin{cases} T'_{t-1} + \beta * (T_t - T'_{t-1}) & if\ T_t > T'_{t-1} \\ T'_{t-1} & if\ T_t \leq T'_{t-1} \end{cases} \end{cases}$$

D_t : Demand for an item at time t

D'_t : Estimate of mean demand per period made at time t for period $t+1$

Z_t : Actual demand size at time t

Z'_t : Estimate of the demand size at time t

T_t : Actual demand interval at time t

T'_t : Estimate of the demand interval at time t

α, β: Smoothing parameters ($0 \leq \alpha \leq 1, 0 \leq \beta \leq 1$)

1. The exponential smoothing technique requires a warm-up period, since the first k-1 values of the dataset are used for computing the initial values of Zt and Tt for the kth data point. Set the initial values of the variables Z't and T't to realistic values. The foremost data point can be used as initial value, but requires a long warm-up period and thereby more data.
2. Choose initial values of the smoothing parameters Alpha (for demand size) and Beta (for demand occurence). According to literature (Segerstedt, 2019), the expected optimal values of both smoothing parameters are within the following interval [0.1 ; 0.3]. A higher smoothing constant implies a less smoothened forecast, since the latest data point is weighted heavier.
3. Calculate all Z't, T't and D't with corresponding error subsequently. Calculate per set of smoothing parameters the MASE and ME:

- Mean Absolute Scaled Error (MASE) $= \dfrac{\sum_{t=1}^{n} \dfrac{|Z_t - D'_{t-1}|}{\frac{1}{n-1}\sum_{i=2}^{n}|Z_i - Z_{i-1}|}}{n}$
- Mean Error (ME) $= \dfrac{\sum_{t=1}^{n}(Z_t - D'_{t-1})}{n}$

4. Iteratively set the smoothing parameters and calculate the MASE and ME (bias) over the training set.
5. Select the values for the parameters which result in the lowest MASE and which has a ME (bias) close to zero.

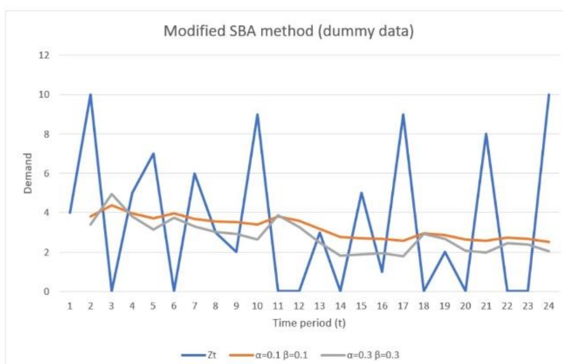
Example with dummy data

3.

Month (t)	*Zt*	*Z't*	*T't*	*D't-1*	*Error*
1	4	4,00	1,00		
2	10	4,60	1,00	3,80	
3	0	4,60	1,10	4,37	
4	5	4,64	1,19	3,97	
5	7	4,88	1,17	3,70	
6	0	4,88	1,25	3,96	-4,0
7	6	4,99	1,33	3,69	2,3
8	3	4,79	1,30	3,57	-0,6
9	2	4,51	1,27	3,51	-1,5
10	9	4,96	1,24	3,38	5,6
11	0	4,96	1,32	3,80	-3,8
12	0	4,96	1,48	3,58	-3,6
13	3	4,76	1,64	3,17	-0,2
14	0	4,76	1,67	2,77	-2,8
15	5	4,79	1,70	2,71	2,3
16	1	4,41	1,63	2,67	-1,7
17	9	4,87	1,57	2,56	6,4
18	0	4,87	1,61	2,94	-2,9
19	2	4,58	1,65	2,87	-0,9
20	0	4,58	1,69	2,63	-2,6
21	8	4,92	1,72	2,58	5,4
22	0	4,92	1,75	2,72	-2,7
23	0	4,92	1,87	2,68	-2,7
24	10	5,43	1,98	2,50	7,5
ME					...
MASE					...

4.

	FC Trial 1	*FC Trial 2*	*FC Trial 3*	*FC Trial 4*	*FC Trial 5*	*FC Trial ..*
α	*0.1*	*0.1*	*0.2*	*0.2*	*TBD*	*TBD*
β	*0.1*	*0.2*	*0.1*	*0.2*	*TBD*	*TBD*
ME	...	...	...	...	...	...
MASE	...	...	...	...	...	...



Time series decomposition:

1. (*Optional*) Aggregate the weekly data into monthly data in case the time buckes have been set to months.
2. Compute the trend-cycle component using the formula for the moving average smoothing method from section 3.5.1. In case of monthy data with a yearly seasonal effect, which is expected to be the case for Business Unit A and Business Unit B, m = 12. The estimate of the trend-cycle is unavailable for the first few and last few observations (Hyndman & Athanasopoulos, 2018). For m = 12 this implies that the first 6 and last 6 observations have no trend-cycle estimate. Therefore, multiple (at least three) years of demand data needs to be available, so a pattern becomes visible. More years of data would result in a more reliable calculation of the time series components.
3. Compute the detrended series by substracting the trend-cycle component from the times series data.
4. Compute the seasonal component by averaging the detrended time series per period t. For monthly data with a yearly seasonal effect the seasonal components consists of 12 values. Adjust the 12 values of the seasonal component so they add up to zero.
5. The remainder component is calculated by substracting the trend cycle component and the seasonal component from the time series data.

Example with dummy data

1.

Week	1	2	3	4	5	6	7	8
Demand	6	0	10	4	7	0	6	3

Month (t)	1	2
Yt	20	16

2.

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
Yt	20	16	1	3	9	1	28	14	23	17	29	23	24	10	7	3	5	6	9	26	14	14	28	23	6	10	0	4	6	1	0	17	26	15	25	17
Tt							15	15	16	16	15	15	15	15	15	14	15	15	13	13	12	11	12	11	11	11	11	12	12	12						

3.

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
Yt-Tt							13	-1	7	1	14	8	9	-5	-8	-11	-10	-9	-4	13	2	3	16	12	-5	-1	-11	-8	-6	-11						

4.

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12	Total	Average
St	2,0	-3,3	-9,8	-9,5	-8,3	-9,7	4,1	6,1	4,5	1,8	15,3	10,0	3,3	0,27

Month (t)	1	2	3	4	5	6	7	8	9	10	11	12	Total
St	1,7	-3,5	-10,0	-9,7	-8,6	-9,9	3,8	5,8	4,2	1,5	15,0	9,8	0,0

5.

Month (t)	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6
Rt	8,8	-7,0	3,1	-1,0	-0,8	-1,4	7,1	-1,5	2,0	-1,6	-1,6	1,2	-8,3	7,6	-2,6	1,5	1,4	1,9	-6,5	2,1	-1,4	2,2	2,2	-0,6