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The development of a decision tree used for inventory management of high-quality products in the OEM market in a long lead time environment

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Master Thesis

The development of a decision tree used for inventory management of high-quality products in the OEM market in a long lead time environment

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Abstract

Over the years, Company X has changed from being a distributor to an industrial service provider, making, among other things, high-quality mechanical engineering products in the original equipment manufacturers (OEM) market. This change has resulted in an assortment consisting of products with high-service level requirements, a high variety in demand patterns and long supplier lead times. The current inventory planning of the products for the five selected OEM customers within the business unit (BU) is regarded as sub-optimal. This research project aims to improve the design of the inventory management system for the more than 500 selected resulting in an increase control of stock levels and reducing working capital, stock outs and claims. A decision tree is developed for inventory management purposes which can determine a suitable inventory policy for a product based on a number of factors (e.g. demand characteristics, the availability of a customer forecast, lead time aspects, contractual agreements etc.). Next to the 2 currently applied inventory policies (reorder point policy and a forecast policy integrated in the ERP system), 2 more inventory policies are added to the inventory policies scope based on thorough analysis of the current situation. Besides, alternative strategies are considered, like holding no inventory or make an agreement with the customer. Using formulas and a tool in Excel, the decision tree is run through for all products in scope after which one of the possible inventory strategies is assigned to the product. Via an impact analysis the performance of the outcome is evaluated with the help of 2 Key Performance Indicators (KPIs), namely inventory costs and the service level. This analysis shows that the service levels increase on average for the products in scope, but that the inventory costs increase a bit as well. In the end, it is ensured that the improved design can be applied to more products in the company's assortment. The support tool for the decision tree is developed to ensure that the solution can be applied in practice. Besides, the 2 proposed new inventory policies can be implemented using the ERP system and the available inventory software package (i.e. Slim4) supplemented by the Excel tool.

Management summary

This report describes the processes and the outcomes of the master thesis project done at the one of the departments of a leading industrial service provider.

Problem statement
Company X serves customers in their original equipment manufacturing (OEM) or maintenance, repair and overhaul operations (MRO). Company X states that it is not always able to observe an upswing or downswing in demand and is therefore not able to recognize possible inventory issues on time. This can result in problems with meeting the predetermined delivery performance to their customers with possible claims as a result. On the other hand, Company X has to deal with excess inventory in situations in which too much products have been ordered. The current inventory planning of the products for the five selected OEM clients is regarded as sub-optimal. Company X states that they do not always have sufficient control over their supply chain operations. A number of reasons has been found resulting in this insufficient control.

1. There is no inventory planning and control policy that adequately deals with the complete supply chain and takes the various complex aspects into account.
2. Most of the inventory planning (e.g. making forecasts, setting inventory parameters) is done manually or managed by a software packages and is therefore prone to errors. It works out for products with predictable demand patterns, but that is only a part of the products.
3. A lot of products are delivered on a FCFS basis and there is no thorough check or judgment of customer orders most of the time.
4. A number of clients provide a forecast of their demand, but no fixed agreements are made about the format/structure of these forecasts and the accuracy of these forecasts are not checked extensively.
5. The high quality standards in combination with long lead times, give little room for adjustments and fixing quality issues.
6. Contractual agreements made for client specific SKUs can sometimes limit and impede the possibilities for inventory management.

Objective and research question
The goal of the research is to two-fold:

1. A detailed analysis of the focus products to get insights in the supply chain operations and inventory planning at Company X. With the help of this analysis, the inventory performance in the current situation is tested. Besides, the goal is to find a number of factors or elements which have a great impact on the possibilities for managing inventory at Company X.

2. A development of a classification system for the focus products for inventory management purposes. The products are classified based on a few criteria or characteristics which can influence the inventory strategy for a product. This classification system results in a number of 'trays' filled with products with the same inventory strategy for which the inventory parameters are calculated if necessary. Afterwards, performance of the developed system is tested with the help of two KPIs and possible adjustments can be made to the system based on these results.

Based on the problem statement and objectives, a central research question is formulated:
How can the inventory performance be improved for the products in scope with respect to costs and delivery performance, while maintaining the current service level with respect to lead time and other fixed agreements?

Analysis current situation

Several problematic factors/causes have been identified in the analysis of the current situation. The main conclusions are summarized below.

- All products in Company X assortment are generic and a first come first served (FCFS) strategy is applied for most products in case it is not a customer-specific product. The fact that most customer (sales) orders are not always judged extensively, makes things even worse.
- The process with respect to the customer forecasts is not well organized. First, there is no standard format or document for the forecasts communicated to the customers by which not all customer forecasts can be used for inventory management. Besides, the accuracy of the customer forecasts is not calculated and therefore not used in inventory management.
- The inventory software package (i.e. Slim4) Company X works with has its restrictions. First, it has a hard time making a demand forecast if there is not much historical demand information available (e.g. new products or slow-moving products) or if the demand pattern is very irregular. Next, the software assumes a normal distribution at all its calculations which is not 'valid' for much products in scope. At last, Slim4 doesn't take into account quantity discounts or structures at determining the replenishment quantities.
- The replenishment lead times are on average quite long and has a great impact on inventory management
- There is no strict policy concerning after how many months without sales the customer is contacted in case of a client specific product resulting in too much excess inventory
- The documentation for SKUs with contractual agreements (e.g. call-off contracts or safety stock agreements) is not well organized. Because of this, it is difficult to identify these SKUs and to take into account these agreements if necessary.
- Looking to the SKUs with dependent demand, it occurs that multiple article numbers are used for the same component which makes it hard to determine the total demand for these SKUs. Besides, the documentation for these SKUs is not well-organized.

Conceptual model

A classification system or decision tree is developed for inventory management purposes. In the first step, it is checked what the relevant factors (e.g. customer forecast, lead time and inventory parameter agreement) are in Company X supply operations which can affect the choice for a certain inventory policy. These relevant factors are analyzed in detail for each SKU and incorporated in the way of controlling inventory. Second, a demand analysis is performed on the basis of which SKUs are assigned to 1 of 5 the possible demand patterns (non-moving, smooth, intermittent, erratic or lumpy). At last, the SKU is assigned to one of the inventory strategies in scope for which afterwards the inventory parameters (e.g. reorder point, safety stock, order-up-to level) are calculated. The performance of the result of this analysis is tested with 2 KPIs namely inventory costs and the fill rate.

SKU classification and inventory control models

The following factors and criteria were included in the final decision tree:

- Customer forecast: The availability of a customer forecast is checked after which the forecast accuracy (i.e. MAPE) is determined in case a forecast is available. With the help of a set benchmark, it is determined if the customer forecast is accurate enough for using it in inventory management.
- Lead time: The length of the supplier lead time and customer lead time are compared.
- Service level agreement: It is checked if a service level agreement has been made between Company X and one of its customers about the SKU.
- Inventory parameter agreement: It is investigated if a contractual or verbal agreement has been made regarding the levels of the reorder point, base stock or safety stock.

- Supply contracts: A contractual agreement can be made between Company X and one of its customers or suppliers with respect to fixed replenishment/supply quantities, for example a call-off contract.
- Standard assortment SKU: This concerns basic industrial engineering components for which every customer expects Company X has this product on stock. This can be a reason to apply an alternative strategy not taking into account any factors or a certain cost considerations.
- Demand pattern: Different demand elements are analyzed, like the variability of the demand, the timing of the demand and the frequency of demand. The demand of the SKU can be classified into 5 possible categories which can impact the choice for an inventory strategy.

The outcome of the decision tree is presented in the following table.

Table 1: Outcome decision tree

Inventory strategy	**#SKUs**
MRP policy	59
No inventory	0
Follow contract	0
Set agreed parameters	?
(R, s, nQ) policy	122
Order-up-to policy	153
Cutoff transaction size policy	38
Make customer agreement	39
Contact customer or start depreciation	123
Total	534

Results

The performance of the different SKUs in scope is tested with the help of the inventory costs and the fill rate (i.e. service level) using efficient frontier graphs. An efficient frontier is the curve that results from graphing the trade-off between inventory cost and service level. On the other hand, the KPI results are calculated in a numerical way which makes it possible to say something about the overall results.

First of all, the inventory cost and service level (i.e. fill rate) are calculated for the new and old situation for the different SKUs. The outcome of these 2 measures are presented in a scatter plot and the efficient frontier curve is plotted in this figure. If one of the dots from the scatter plot is on this curve, it means it is not possible to achieve a better performance under the current conditions with the available inventory strategies. By comparing the 2 efficient frontier graphs with all the dots (which show the performance between inventory cost and service level for the SKUs), it can be checked if the performance is improved in the new situation. It is important to mention that KPIs are not calculated for which the inventory strategy is to contact the customer or to make a customer agreement. It is impossible to know how the strategy (and inventory parameters) for these SKUs will end up which makes it hard to draw any conclusions about the performance for these SKUs.

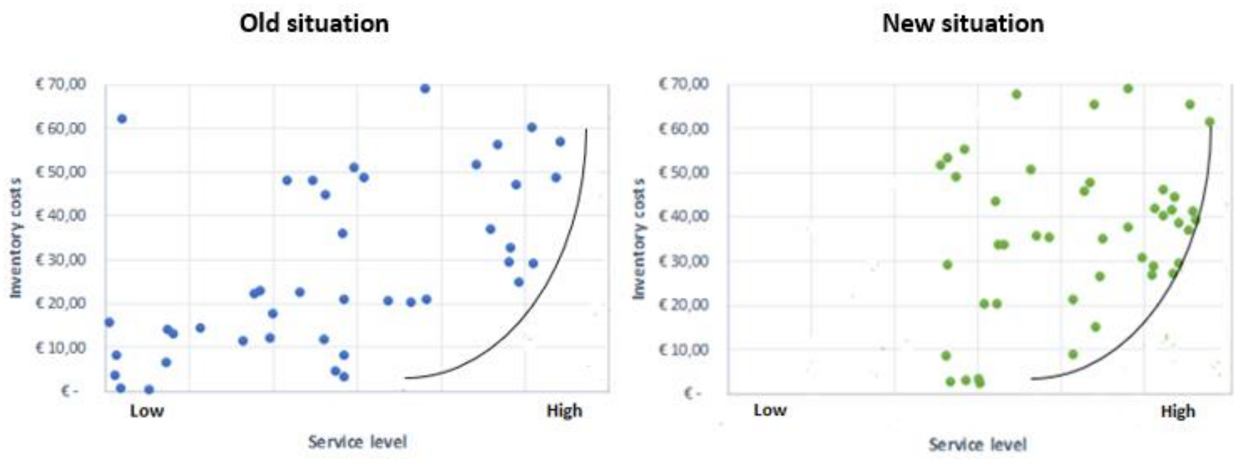

Figure 1: Efficient frontier graphs

As can be seen in the figure above, more dots move closer to the efficient frontier line which means that the performance for the SKU has been improved. A few dots are even on the line which indicates that the performance is optimal for these SKUs under the current conditions. The next table shows outcome for the KPI results for the different SKUs and indicates the difference between the new and old situation on average per SKU.

Table 2: Outcome KPIs

	#SKUs	ΔC/SKU	ΔP_2/SKU
KPIs calculated	372	€89	6,3%
KPIs not calculated	162	-	-

Concluding, the application of the decision tree (and the inventory strategy assigned to each SKU afterwards) results in an improvement of the service level (an average increase of 6,3% per SKU) against some extra costs.

Conclusion and recommendations

This thesis demonstrates that the decision tree can be used as a tool for inventory management classification. Using decision trees makes it possible to immediately create different 'trays' (categories) with SKUs and to make a distinction between SKUs easily. Besides, the application of it results to an improvement on the current situation.

Company X is advised to implement the following recommendations.

- Track the forecast accuracy (i.e. MSE and MAPE) for all SKUs with a customer forecast.
- Design an Excel file with a standard format where customers can fill in their forecasts and promote/offer this file to your customers.
- Create a general file for each business unit in which all the contractual or verbal agreements regarding inventory parameters or service levels are recorded.
- Start using one article number for all SKUs with dependent demand so that it is immediately known what the total demand for these SKUs is.
- Start working with a customer lead time for a part of the SKUs. If Company X start working with a fixed customer lead time for SKUs with a relatively small supplier lead time, Company X doesn't have to hold any inventory for these SKUs.
- Run through the decision tree for all SKUs and change the inventory strategy if necessary. Because Company X's product assortment is quite big, it might be an idea to not immediately perform this analysis for all SKUs, but to make a schedule per product group. When the decision tree is run through for all SKUs, it is important to do the analysis again every 6 months.

Preface

Before you lies the master thesis report I have written for the project I performed at Company X Alkmaar which is focused on the inventory management for products with high service level requirements in a long lead time environment. It has been written to fulfill the graduation requirements of the master degree program Operations Management & Logistics at Eindhoven University of Technology (TU/e). I was engaged in researching and writing this master thesis from July 2018 to March 2019. With the completion of this project I am looking back on not only an educational period working on the project, but also on my time as a student.

Without the help and support of some people, I would not have been able to reach this moment. Therefore, I want to take this opportunity to thank a few people.

First of all, I would like to thank my first university supervisor Rob Broekmeulen. You were always available and willing to answer my questions. Your advices helped me in understanding and solving the thesis' problem. Despite the fact that I struggled a lot with designing a suitable solution for the research problem, you kept believing I was able to complete the project. Additionally, I would like to thank my second university supervisor Alp Akçay.

Then, I would like to thank some people at Company X that guided me during this project. First, I would like to thank Johan Houtman and Job van de Sande for giving me the opportunity to do my master thesis project at Company X. They allowed me to conduct my research independently and supported me with their years of experience in the industry. Next, I want to give a special thanks to Johan Houtman. I enjoyed all our meetings where we spoke openly about many topics and you gave me really useful feedback on all of my ideas/findings. You helped me a lot in understanding, scoping and translating the business problem into a relevant project. At last, I want to thank all of my colleagues who helped me understand the processes of Company X, who helped me in my search for data and who made my time at Company X a very educational experience.

Finally, I want to express my gratitude to my parents, who have supported me my entire life in every endeavor I have undertaken. Then, I would like to thank all of my friends that made my time as a student legendary. The last 6,5 years were amazing and a period to which I owe a lot of beautiful memories.

I hope you enjoy reading this report!

Jakob Dirken, March 2019

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ADI	Average Demand Interval/Advance Demand Information
B2B	Business-to-Business
BOM	Bill Of Materials
BU	Business Unit
CSS	Central Sales Support
CV	Coefficient of Variation
EOQ	Economic Order Quantity
ERP	Enterprise Resource Planning
FCFS	First Come First Served
FD	Future Depreciation
IP	Inventory Position
IQR	Inter-Quartile Range
KPI(s)	Key Performance Indicator(s)
L	Lead time
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MCIC	Multi-Criteria Inventory Classification
MOQ	Minimum Order Quantity
MRO	Maintenance Repair Overhaul
MRP	Material Requirements Planning
MSE	Mean Squared Error
OEM	Original Equipment Manufacturer
OTIF	On Time In Full
OUL	Order Up to Level
PLT	Planned Lead Time
RFQ	Request For Quotation
SBA	Syntetos and Boylan Approximation
SCIC	Single-Criterion Inventory Classification
SES	Single Exponential Smoothing
SKUs	Stock Keeping Unit(s)
SLA	Service Level Agreement

1. Introduction

This research project was conducted at a leading international service provider, supplying its industrial customers with a broad range of mechanical engineering components. In addition, it provides related technical and logistical services. The offered products vary from generic mass products to high-quality and customized products. This research focusses on the inventory management of the products supplied to 5 clients in the OEM market. First of all, a classification system was developed for inventory management purposes which can determine a suitable inventory policy for a SKU based on a number of factors (e.g. demand characteristics, lead time aspects, contractual agreements). Then, the performance of the SKU classification system was tested with the help of 2 KPIs.

In this chapter, the context of the research is discussed. First, the thesis outline is described in section 1.1 after which background information on Company X is provided section 1.2. At last, the research topic and the motive for this research are discussed in section 1.3. The aim of the research is twofold: 1) to provide valuable insight for Company X and 2) to be scientifically relevant.

1.1 Thesis outline

Chapter 1 is the introduction to the thesis. The introduction includes a company profile of Company X and the motivation for the research. In Chapter 2, the research description is provided, including the problem statement and objective, the scope and assumptions, the research questions, and the research methodology. Chapter 3 is a summary of the literature study, which provides theoretical background of the research. Chapter 4 analyzes the current situation based on several facets, thereby validating the business problem. Based on the findings from Chapter 4, the conceptual design for the classification system is described in Chapter 5. Next, in Chapter 6, the classification system is modeled and the different classification steps is run through after which a certain inventory strategy is assigned to the SKUs in scope. Then, in Chapter 7, the inventory control policies in scope are explained in detail and the application is discussed. Chapter 8 elaborates on the results and discusses the performance of the designed system. Finally, Chapter 9 contains the conclusions of the research, including the recommendations to Company X, the limitations of the study, and the contributions to the academic literature plus suggestions for future research.

1.2 Company profile

The company in question is a leading supplier of mechanical engineering components and associated technical and logistical services. Over the years, Company X has developed into a leading-edge, innovative multi-product specialist and solutions provider to the industry. The goal of Company X is to deliver solutions to two industrial segments: Original Equipment Manufacturers (OEM) and Maintenance, Repair and Overhaul (MRO). In the OEM market, the focus lies on co-engineering and sharing know-how of products and applications with customers. In the MRO market, Company X's products, services and expertise are used directly for the maintenance of machinery and factories. Company X serves the chemical, energy, oil, gas, aviation, food, pharmaceutical, biotechnology, refining, and metal industries worldwide.

This research focusses on the products for five selected OEM customers from Company X and the scope of the products is within one of the company's divisions. The products within scope of this research are supplied to the OEM market. A big part of these products are tailor made and partly co-engineered with the client (i.e. the products are specifically designed to meet the requirements set by the clients). A complete supply chain is set up by Company X for these products in consultation with the OEM client. A long process takes place in which the products are developed, a suitable manufacturer has to be found and the products are tested multiple times. On the other hand, Company X supplies commodity products which are sold to multiple clients. These 'standard' products are offered by multiple companies active in the market Company X operates. These products are made of the common materials and have the usual sizes known to everyone in this industry.

1.3 Research topic and motivation

Company X sells commodity products and tailor-made (client specific) products to clients in the OEM market. These customers have extremely high requirements with respect to product quality and delivery performance. The client specific products are characterized by some critical factors. First of all, these products can have long lead times (up to 4 months) from Asia. Besides, OEM clients require a service level close to 100%. Next, these clients demand high quality products whereby most products need extra, elaborate quality checks when arriving at Company X's warehouse. There is always a risk that products are rejected at the check. Also, the demand for these products can be very unpredictable and varies a lot between products. Finally, a number of these clients provide a product forecast to Company X of which the accuracy differs a lot. These elements results in a complex forecasting and inventory management for these products which is difficult to manage. The situation in which no client is prioritised and unexpected internal orders can be placed makes everything even more complex.

Clients pay a lot of money to Company X and in exchange Company X has to supply high quality products and meet a strict delivery performance (service level). Not being able to meet the service level demand by the client can result in significant deterioration of the relationship with the client. Costly methods are sometimes used to meet this agreed service level, for example extra air freights. Because of these service level agreements, high safety stocks are set for a number of items just to be sure and this is costly as well. This sometimes results in additional depreciation cost for customer specific stock items that are no longer sold. Currently, Company X regards their inventory management for a part of its products within the focus product group as problematic. This mainly concerns the tailor-made (client specific) products. As an explanation Company X express that they have a hard time identifying what products deserve more attention (for example, because of contractual agreements) and for which products possible delivery problems can occur by a wrongly chosen inventory strategy. Therefore, Company X wants categorize its products in generic groups to get a better overview of the different stock items and to know which items have the same characteristics. Besides, Company X wants to know which factors in its business process and environment can impact the inventory strategy. Consequently, Company X has asked for an analysis of the products in scope resulting in a classification system for inventory management purposes. By means of these classification system, different products groups are created with a certain inventory control strategy for which the performance will be tested. The goal is to improve the service level for the products in scope and to save on inventory costs if possible.

2. Research description

In this chapter, first, the problem statement and the objective of the study are discussed in section 2.1. Second, in section 2.2, the scope of the research is defined. Then, in section 2.3, the research questions are discussed. Finally, the research methodology is explained in section 2.4.

2.1 Problem statement and objective

Company X serves customers in their original equipment manufacturing (OEM) or maintenance, repair and overhaul operations (MRO). Company X states that it is not always able to observe an upswing or downswing in demand and is therefore not able to recognize possible inventory issues on time. This can result in problems with meeting the predetermined delivery performance to their customers with possible claims as a result. On the other hand, Company X has to deal with excess inventory in situations in which too much products have been ordered. The current inventory planning of the products for the five selected OEM clients is regarded as sub-optimal.

Company X states that they do not always have sufficient control over their supply chain operations. A number of reasons has been found resulting in this insufficient control.

1. There is no inventory planning and control policy that adequately deals with the complete supply chain and takes the various complex aspects into account.
2. Most of the inventory planning (e.g. making forecasts, setting inventory parameters) is done manually or managed by a software packages and is therefore prone to errors. It works out for products with predictable demand patterns, but that is only valid for a part of the products.
3. A lot of products are delivered on a first come first served (FCFS) basis (which means that all the customer orders are fulfilled by the order of their arrival) and there is no thorough check or judgment of customer orders most of the time.
4. A number of clients provide a forecast of their demand, but no fixed agreements are made about the format/structure of these forecasts and the accuracy of these forecasts are not checked extensively.
5. The high quality standards in combination with long lead times, give little room for adjustments and fixing quality issues.
6. Contractual agreements made for client specific SKUs can sometimes limit and impede the possibilities for inventory management.

Purchasing products before demand is realized, results in risk (e.g. obsolete inventories). Decisions on quantities and timing of procurement orders and production orders effect the holding costs, supply risk and customer service. Because the production and supply lead time of the products are often longer than the required lead time of the customer, Company X is interested in how they can best manage their inventory such that they have more control and less costs while the service level is maintained. Besides, it is important to have more control over the supply chain and to be proactive towards suppliers and customers.

The goal of the research is to two-fold:

1. A detailed analysis of the focus products to get insights in the supply chain operations and inventory planning at Company X. With the help of this analysis, the inventory performance in the current situation is tested. Besides, the goal is to find a number of factors or elements which have a great impact on the possibilities for managing inventory at Company X (e.g. customer forecast, lead time aspects, contractual agreements).

2. A development of a classification system for the focus products for inventory management purposes. The products are classified based on a few criteria or characteristics which can influence the inventory strategy for a product. This classification system results in a number of 'trays' filled with products with the same inventory strategy for which the inventory parameters are calculated if necessary. Afterwards, performance of the developed system is tested with the help of two KPIs (service level and inventory costs) and possible adjustments can be made to the system based on these results.

The aim of the improved system/approach is increasing the control over the supply chain and to decrease the costs (inventory, transportation and claims) while maintaining/increasing the current service level. In addition, the new inventory system should be more based on data and rules and less on human interpretation, resulting in less error sensitive inventory management. Finally, it should be possible to apply the new approach to more OEM clients and products.

Based on the problem statement, the goals described before and the motivation of this project, the following main research objective is defined:
The analysis of the different SKUs for the 5 selected OEM clients and an improved design of the inventory management system for these items resulting in an increase control of stock levels and reducing working capital, stock outs and claims

2.2 Scope and assumptions

First, this project is limited to the product demand for 5 selected OEM clients from different sectors focused on products from one of the divisions. These products are from 3 different product groups. Therefore, other clients and divisions are beyond the scope. However, the goal is to deliver a solution that is easy applicable to a broader product range and to other business units as well.

Second, it should be strived for that it is possible to implement the (re)design in the current ERP system (i.e. SAP and Slim4). Though, other software (e.g. Excel) can be used when SAP or Slim4 is not able to handle the proposed solution and compromises would lead to a significant degradation of the proposed solution.

Next, the data in the ERP system and Excel files about for example, supplier lead times and cost prices, are assumed to be valid. A complete validation of the accuracy of this data will be too time consuming and therefore out of scope.

Finally, the research is focussed on the improvement of the supply chain operations of the specified products. In other words, in the design of the operations planning and control system the emphasis is on supply chain related aspects. Thus, quality management is not extensively studied and taken into account, but is dealt with by making reasonable assumption with respect to the yield of the various activities.

2.3 Research questions

Based on the problem statement and objectives, a central research question is formulated:

How can the inventory performance be improved for the products in scope with respect to costs and delivery performance, while maintaining the current service level with respect to lead time and other fixed agreements?

In support of this central research question, several other research (sub)questions are defined:

1) What are the characteristics of the context in which Company X works and how do these characteristics influence the supply chain operations and inventory planning?
2) What are the forecasting methods and inventory control systems that are currently used for the products in scope and what is the performance of these systems?
3) How can the inventory performance be improved for the products in scope?
   a) What technique or method should be applied for the classification process?
   b) Which factors, characteristics and data should be used to classify the products?
   c) What other inventory control models or inventory strategies can be possibly applied at Company X?
4) How does the new inventory system perform looking to two KPIs (inventory costs and fill rate) and how can these information be used to improve the solution/classification?
5) How can the improved model be implemented?

2.4 Research methodology

This research will look into the supply chain operations of several products especially focused on inventory management. To answer the research questions, qualitative and quantitative research has to be undertaken. The quantitative part will consist of a lot of data analysis. Data from both academic literature and the situation at Company X is needed. A literature review is performed for the former, and below enumeration is given that specifies the information regarding the latter:
- Replenishment policies
- Procurement data
- Inventory levels
- Sales data
- Forecast data
- Supplier and customer lead times
- Bill of materials
- Consumption data (historical data)
- Processes
- Costs and profit associated with every product

The information enumerated above can be found in SAP and in Excel files. However, help from Company X employees might be useful to be able to collect all this information.

The qualitative research is focussed on interviews and a literature study. Interviews can provide more in-depth knowledge about the current situation and the issues employees from different department at Company X experience. Internal documentation from Company X can supplement the interviews. Next, a literature study will be conducted to gather information about supply chain operations which will be used in the development of the solution and the deliverables to Company X.

Before the design phase can start, the problem provided by Company X needs to be validated and analysed. This will be done via interviews and data analysis. Interviews can help by discovering the current processes and systems in place (e.g. inventory policies, planning procedures). Furthermore, the data analysis can supplement and validate the interviews.

In the design phase of this project, the operations research model of Mitroff et al. (1974) proposed by Bertrand & Fransoo (2002) presented figure 6 is used. The model aims to solve the operations management problem in four phases. As indicated by the arrows, this is often not a clearly defined path that completely follows a direct route. Rework, feedback and validation are an important part of quantitative modelling. The framework helps to make sure all steps in proper research are completed.

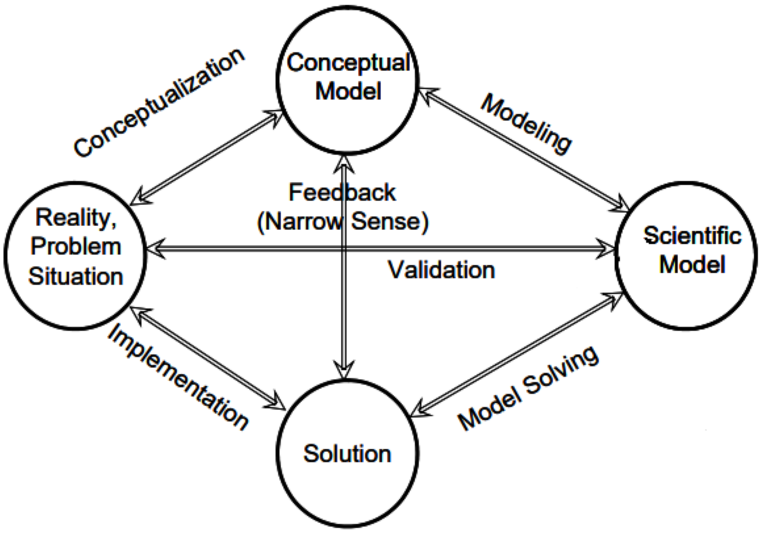

Figure 2: Operations research model (Mitroff et al., 1974)

The model ideally starts with a certain problem or question. This problem must first be scoped and stakeholders must be defined. Likewise, the goal and the relevance of the problem must be determined. After that, the first phase 'conceptualization' can be started. As can be seen in the figure, four phases are identified in the operations research model which will be briefly explained.

1. Conceptualization – In this phase a conceptual model of the problem is made. Decisions regarding the variables to include in the model, the model itself and the scope of the project will be made.
2. Modeling – By defining the causal relationships between variables the quantitative model is made in this phase.
3. Model solving – In this phase the quantitative model is solved for the situations and products described in the scope of the project after which the results can be analyzed.
4. Implementation – Finally the model that is built can be implemented. For this implementation recommendations towards Company X are made and an action plan is formulated.

The first part of the design phase is focused on the development of a classification system for the focus products. The second part is about the development of inventory control systems for the different classification groups. The proposed model can be developed and tested with several tools/software options in which the choice was made for Excel. The tests and evaluations are used to check whether the designed solution is feasible, robust and an improvement. It should be reliable considering the volatile forecasts of the client, the selected classification criteria and the possibilities with inventory control models.

Concluding, this master thesis will run through the steps from the operations research model proposed by Bertrand & Fransoo (2002), starting with the problem situation described in this chapter and the analysis of the current situation described in chapter 4. At that point, research questions 1 and 2 can be answered. Next, the conceptual model will be presented and developed in Chapter 5 after which research question 3 is answered. Model solving and implementation are done in chapter 6, 7, 8 and 9 where respectively the research questions 4 and 5 are answered. Moreover, the main research question will be reflected upon.

3. Academic context

An extensive literature study was conducted in preparation for this research project. This literature review looks into 2 different topics: 1) Classification methods for stock items 2) Inventory policies under advance demand information (e.g. a forecast provided). For more information, you are referred to the complete literature review.

Main findings from this literature study are discussed in this chapter and the insights are looked upon. In section 3.1, the main topic is classification methods for SKUs and in section 3.2, the focus is on inventory control system with special attention to inventory policies under advance demand information. Finally, in section 3.3, the main insights of the literature study are discussed and a research gap is identified.

3.1 SKU classification methods

In this section, important articles with respect to SKU classification are discussed and reviewed. First of all, the meaning of SKU classification and the goal of it will be described. Next, different methods to categorize SKUs will be discussed and a number classification techniques will be treated in more detail.

3.1.1 Classification aims and criteria

In production and operations management, firms often have to deal with many different products, or stock keeping units (SKUs). Here, SKU refers to an item that is unique because of some characteristic (such as brand, size, color, model) and must be stored and accounted for separate from other items. The production and inventory policies of these different SKUs are influenced by the characteristics of the product. Differences in annual sales volume, predictability of demand, product value, or storage requirements might result in different production and inventory policies (Van Kampen, Akkerman and Van Donk, 2012).

Inventory management is a very complex problem area and it is this complexity that has necessitated the development of intelligent systems to assist decision making. Different stocking items are associated with different underlying demand structures, which in turn require different methods for forecasting and stock control. Consequently, there is a need to categorize SKUs and apply the most appropriate methods in each category. Classification is the act or process of dividing things into groups according to their type (Cambridge dictionary). The way this task is performed has significant implications in terms of stock and customer satisfaction. Therefore, categorization rules constitute a vital element of intelligent inventory management systems (Boylan, Syntetos and Karakostas, 2008).

The most important reason for applying an inventory classification is that, in most practical cases, the number of different SKUs is too large to implement SKU-specific inventory control methods. Thousands of inventory items in companies even with moderate size increase the risk of losing sight of the most important items and spending unnecessary resources in controlling less important ones. Therefore, to efficiently and effectively manage such a large number of SKUs, a common practice is to group SKUs into a small number of classes and then set common target service levels, order/production quantities, reorder points, safety stock, etc. (inventory control parameters) for different SKU classes. This enables companies to more easily specify, monitor and control inventory performance for SKU classes, rather than for individual SKUs. (Yang, Li, Campbell and Sweeney, 2017). Concluding, the classification of SKUs can be used to facilitate decision-making for inventory policies and forecasting techniques.

Inventory classification has been intensively studied in the literature, within two broad categories: single-criterion inventory classification (SCIC) and multi-criteria inventory classification (MCIC). The ABC analysis, developed upon the Pareto principle, is one of the earliest and most widely used SCIC methods (Yang et al, 2017). The criterion often used is annual dollar usage or sales volume (dollar value per unit multiplied by annual usage rate). This method assumes that 20% of items are responsible for 80% of the annual dollar usage. Items are then categorized into class A, B, or C. Class A items are considered the most important, will typically contain items that account for 80% of the total annual dollar usage but only make up 20% of the total items. Class B items are considerably less important and typically contain 30% of the total items that are responsible for approximately 15% of the total annual dollar usage. The least important are class C items, which contribute the lowest total annual dollar usage but contain a large number of inventory items. They are responsible for approximately 5% of the annual dollar usage value and contain around 50% of the total number of items. Companies can afford to keep a higher stock of class B and C items than class A items, whereas class A items need to be monitored very closely (Iqbal, Malzahn and Whitman, 2017).

The traditional ABC method with 1 criterion is simple and easy to use. However, there are many other criteria (both quantitative and qualitative) that may significantly affect the classification such as: inventory holding unit cost, part criticality, demand pattern (seasonality), length and variability of replenishment lead time, life cycle phase, scarcity of raw materials (certainty of supply), order size requirement and stock-out unit penalty. Some of these may even weigh more heavily than dollar usage in the procurement planning and control of the item. Therefore, traditional classification methods cannot provide worthy results and including other criteria (especially those of qualitative ones) in the decision process is of particular interest (Torabi, Hatefi and Pay, 2012). Other examples of criteria that can be considered are substitutability, the rate of obsolescence (durability), repairability, stockability and commonality. Nonetheless, these criteria are often used in case of classification of spare parts only. The decision about how many criteria and which criteria to include is difficult and also dependent on which technique is used for the classification. Besides, this choice is also related to the goal of classification, like a minimum number of groups or cost minimization.

3.1.2 Classification techniques

The literature shows that many techniques have been used to classify inventory. As already mentioned before, the methods for SCIC are simple and everyone can understand it easily. The traditional ABC approach and the related fast, slow and non-moving (FSN) approach are examples that mostly sort products on a single characteristic. In the FSN technique, demand volume in a period is used to determine the product class. In the traditional ABC approach, the demand volume is generally multiplied by the unit price (dollar usage). After choosing for a certain measure, items will be categorized into 3 different classes (A, B or C) based on its portion in the total demand volume for example. Items with a high share in the total demand or classified as A and items with a low share in the total demand are classified as C. The calculations for SCIC techniques are really basic and the necessary data is easy to find. A drawback is that only 1 criterion is taken into account and other factors or combination of factors can make an item 'critical' as well.

A lot of techniques can be found in literature to classify SKUs. More complex techniques have been used to classify items applying MCIC and these methodologies can be categorized. A few examples of these methodologies are matrix-based methodology, cluster analysis, decision trees, analytic hierarchy process (AHP), genetic algorithm, neural networks, and optimization models (Iqbal et al, 2017). These techniques can be divided in 2 groups: judgmental and statistical. The main idea of the judgmental techniques is to capture the opinions of managers and to extract the sometimes tacit knowledge held by managers. Statistical techniques are based on data of a number of SKU characteristics. Within the statistical techniques there is a wide variety in the complexity of the technique and in the number of characteristics used. In the following table, a number of classification techniques are presented with a short explanation. For more information about this classification techniques, you are referred to the complete literature review and the articles referred to.

Table 3: Overview classification techniques

Classification technique	Explanation	More information
Analytical Hierarchy Process (AHP)	Different criteria are ranked using pair-wise comparisons.	Partovi and Burton (1993)
Cluster Analysis	Grouping objects of similar kind into respective categories based on characteristic features. It tries to identify structures within the data.	Ernst and Cohen (1990)
Decision Tree	The classification is performed in a stepwise fashion, one characteristic at a time	Eaves and Kingsman (2004)
Distance Modelling	Calculate a product's distance to a predefined reference point (such as the largest volume and the highest criticality factor) for all important characteristics, leading to a classification with A, B and C categories.	Chen, Li, Kilgour and Hipel (2008)
Genetic Algorithm	Generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover and selection. The algorithm is used to establish by learning the weights of the criteria and the AB and BC cut-off points from pre-classified items.	Guvenir and Erel (1998)
Neural Networks	Biologically inspired computer programs designed to simulate the way in which the human brain processes information. The outcome is an ABC like classification of inventory.	Partovi and Anandarajan (2002)
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	Determines the best alternative by calculating the distances from the positive and negative ideal solutions according to the evaluation scores of the experts. The ranking of the inventory items is performed based on the "relative closeness to ideal solution".	Bhattacharya, Sarkar and Mukherjee (2007)
Graphical Matrix	Consists of quadrants and the division of these quadrants is based on cut-off values for certain parameters. These cutoff values determine to which category a SKU is assigned	Syntetos, Boylan and Croston (2005)
Optimization Model	A weighted additive function was used to aggregate the performance of an inventory item in terms of different	Ramanathan (2006)

	criteria (e.g. annual demand volume, unit cost, product criticality and lead time) to a single score, called the optimal inventory score of an item. Based on the scores, items can be classified into classes A, B, or C.	

3.1.3 Classification and inventory performance

As already written before, the aim of SKU classification is to set generic forecasting and inventory control policies for items within the same group. The number of SKUs in an average company is too large to develop SKU specific control policies. Multicriteria inventory classification (MCIC) aims at creating classes of items to manage with a unique inventory control approach. Different cycle service levels (i.e., the probability of not incurring in a stock-out during a replenishment cycle) and type of inventory review (i.e., continuous or periodic with different review intervals) are then coupled with the generated classes in order to simplify the inventory management per class rather than per item. The relationship between the classification approach adopted and the inventory control applied to the generated classes is evident because the overall performance of the system depends on their coupling. Nevertheless, the MCIC mentioned before purely focus on the optimal classification of items and all these techniques are pure ranking methods. For the original problem we should not forget that the aim of the classification is not solely to classify items but to excel in the performance of inventory control policy. In the classification literature optimization models exist that concurrently classifies inventory items and selects appropriate policies for each product group with the objective of having an effective inventory performance i.e. the maximization of service levels and the minimization of inventory costs (Lolli, Ishizaka, Gamberini and Rimini, 2017).

An overview and description of different papers incorporating inventory performance in the classification process can be found in the complete literature of Jakob Dirken. The most recent paper is the one of Lolli et al. (2017) who have used an approach in which different classification techniques can be selected (e.g. ABC analysis, a matrix based methodology, AHP or NN). They proposed a framework for inventory classification and subsequently set an optimal inventory policy for each classification group. Afterwards, the inventory performance is tested by sensitivity analysis. The framework is applicable in case of intermittent demand as well. The framework consists of 5 steps represented in figure 7.

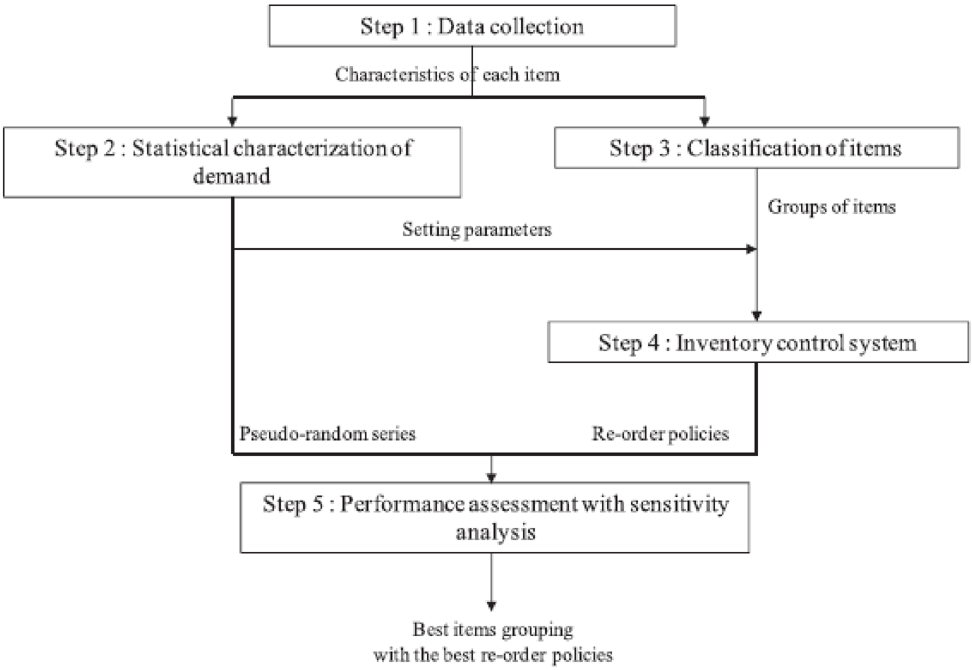

Figure 3: Framework (Lolli et al., 2017)

First of all, data needs to be collected for the items in the company's range to characterize all the items. These characteristics include the usage value (demand multiplied by the purchase cost), the replenishment lead time and the demand pattern. Second, demand is characterized by breaking it down into its constituent elements: the demand size and the time interval between successive nonnull demands (the inter demand interval). A probability density function (PDF) will be determined for both elements. Using these two PDFs, two pseudorandom series are generated and by combining them the compound pseudorandom time series are found. These pseudorandom series are necessary for simulative aims when the availability of observed data is not enough to make the results robust.

The goal of the third step is to classify the items into homogenous groups according to importance. The different MCIC techniques described before can be used to classify the different SKUs. Three classes are often generated, corresponding to A, very important items; B, important items; and C, least important items. A classification technique can be selected depending on the number of criteria and the availability of historical data. The next step is to develop reorder policies for each of the classification groups. A macro classification between inventory control systems considers the type of inventory review, that is, continuous and periodic, and the presence of uncertainty in the system, that is, deterministic and probabilistic models. In the continuous review, the stock level of all items is continuously monitored and a purchase order is placed when the stock level falls below a value called the reorder point s. In the periodic review, the stock level is monitored periodically every T review time period. The purchase order is placed for a quantity such that the stock level returns to the Order-Up-To Level S. Other reorder policies have been also developed for multistage assembly systems, capacity constraints, variable supply cost, uncertain demand, and lead time.

The last step is to do a performance assessment and a sensitivity analysis. In order to allocate the best reorder policy defined in Step 4 to the best classification scheme of items defined in Step 3, a complete simulation by means of the pseudorandom series defined in Step 2 is run. The performance of each simulation is evaluated on several KPIs, that is, criteria, which can be aggregated into a cost measure. Examples of KPIs include average holding value, average number of backorders and average number of emitted orders. The best couple policy classification has the lowest total cost. The framework proposed by Lolli et al. (2017) is quite complete and their approach can be applied to items with different demand patterns. Besides, one is not stuck to only a limited number of classification techniques and inventory approaches. At last, the effectiveness can be tested. A drawback is that the framework was only tested at a company operating in the field of electrical resistor manufacturing experiencing intermittent demand and therefore it is not sure if the approach also works well for companies in other sectors.

3.2 Inventory control systems

After or during the SKU classification process a certain inventory policy has to be determined for the different classification groups. Therefore, the remaining part of this literature study will be about inventory management and inventory policies.

3.2.1 General introduction inventory management

Inventory management refers to the process of ordering, storing and using a company's inventory: raw materials, components and finished products (Investopedia, 2018). The goal of inventory management is to have the right product, in the right place, at the right time. Inventory should be maintained in appropriate quantities in such a manner that the inventory cost is not very high and at the same time the losses due to shortage of inventory does not take place. Stocks (inventory) are created to carry out the normal activities of the company. Proper and timely determination of the optimal inventory control strategy allows freeing a significant amount of assets, frozen in the form of stocks, which ultimately increases the efficiency of resource use. Even though there are literally millions of different types of products manufactured nowadays, there are only two fundamental decisions that one has to make when controlling inventory (Zipkin, 2000):

1. How large should an inventory replenishment order be?
2. When should an inventory replenishment order be placed?

An inventory model attempts to represent an inventory problem to facilitate decision making. Typically, the inventory model enables us to rationally decide (1) how much to buy (2) and when to buy. In order to answer these questions, we need to develop inventory models which combines decision variables with situational parameters. The situational parameters are demand, lead time, unit purchase price and any uncertainties associated with demand and lead times.

Inventory models are often classified according to the nature of the system parameters (Votruba, 1988). When the value of the model parameters are well-defined and no random effects occur in the inventory process, the corresponding model is deterministic. If the parameters of the system are random values with a known probability and there is considerable uncertainty about future demands, distribution models are stochastic (probabilistic). If all of the model parameters do not change over time (time independent), it is called stationary. In case that they change over time (time dependent), the model is non-stationary. Static models are used when receiving a one-time decision about the inventory level for a certain period. On the other hand dynamic models are applied in the case of sequential decision-making about stock levels or to adjust earlier decisions, taking into account the changes taking place. Finally, the inventory level can be monitored at fixed moments over time (periodic) or can be monitored all the time (continuous).

Inventory policy is an operating framework or a standard operating procedure (SOP) in implementing an inventory model. Obviously, the inventory model will depend upon the choice of inventory policy adopted. These different policies can be classified in many ways. The following classification was introduced by Silver, Pyke and Peterson (1998):

- Continuous Review with fixed order quantity (s, nQ): Under this policy, the inventory status is continuously monitored. Whenever the inventory level reaches a predetermined level ‘s’ called the reorder level (ROL), a replenishment order of fixed quantity ‘Q’ (1 batch) or ‘n’ batches are placed.
- Periodic Review with fixed replenishment quantity (R, s, nQ): The inventory status is periodically reviewed under this policy after a fixed time interval ‘R’. When the review period is reached and the inventory level is below reorder level s, then n times Q units are ordered to bring the inventory level after ordering back to or above the reorder level s.
- Continuous Review with variable order quantity (s, S): The amount to order depends on the variable ‘S’ which is the order-up-to level or the maximum inventory level. As soon as the inventory position drops below the reorder level s, the amount of units is ordered which is needed to bring the inventory position after ordering back to the order-up-to level S.
- Periodic Review with variable replenishment quantity (R, s, S): When the review period is reached and the inventory level is below the reorder level s. The order size is determined by calculating the difference between the order-up-to level S and the stock on hand at the time of review.

This classification is based on 2 different factors: the method for reviewing the inventory level (periodic or continuous) and possible limitations in order quantities (fixed or variable). In practice in most situations a periodic review is applied, for example if delivery schedules are fixed (e.g., trucks visiting the warehouse only once every review period). Besides, fixed order quantities are used most of the time since suppliers or manufacturers set certain order requirements (only packages of 24 units or production in batches of 150 units).

The difficulties of inventory management has to do with uncertainties and the rapidly changing conditions these days. As a rule, there is no standard solution – the conditions at each company or firm are unique and include many different features and limitations. An occurring task of the mathematical models development and determining the optimal inventory control strategy is related with this problem. Features of inventory management models are that the resulting optimal solutions can be implemented in a fast changing situation where, for example, the conditions are changed daily. There is a need for new and effective methods for modelling systems associated with inventory management, in the face of uncertainty. Uncertainty exists regarding the control object, as the process of obtaining the necessary information about the object is not always possible (Ziukov, 2015). The solution of such complex tasks requires the use of systems analysis, development of a systematic approach to the problem of management in general. Inventory models are distinguished by the assumptions made about the key variables: demand, the cost structure, physical characteristics of the system. These assumptions may not suit to the real environment. There is a great deal of uncertainty and variability.

Nowadays, demand and lead times are not deterministic anymore, conditions are changing rapidly and high requirement are set to suppliers. In today’s ever changing markets, maintaining an efficient and flexible supply chain is critical for every enterprise, especially given the prevailing volatilities in the business environment with constantly shifting and increasing customer expectations. According to the paper of Gupta & Maranas (2003) various sources of uncertainty can be identified in these systems. Short-term uncertainties may include day-to-day processing variations, cancelled/rushed orders (supply disruptions), equipment failure, etc. Long-term uncertainty refers to raw material/final product unit price fluctuations, seasonal demand variations, changing demand patterns and production rate changes occurring over longer time frames. Building buffers (safety stocks) is a frequently used solution for most of the uncertainties. Since inventories are a big investment, choosing the right inventory model or policy is a key decision and optimizing the inventory parameters is crucial as well. Inventory control is especially difficult when demand is stochastic and nonstationary. If the probability distribution of a demand changes significantly from period to period, stationary inventory control policies (like (s, S), (r, Q) etc.) will lead to stockouts with unsatisfied demands or to larger inventories being carried than planned.

3.2.2 Inventory policies under advance demand information

In this section, particular approaches for managing inventories under demand and/or supply uncertainty are discussed. The focus will be on inventory policies with advance demand information (ADI). First, a short introduction will be given about ADI. Then specific inventory models incorporating ADI will be reviewed.

In most manufacturing and distribution environments, safety stocks constitute the principal approach in order to cope with the uncertainties in demand as well as in production, supply and transportation. An alternative way of protection against randomness would be to reduce demand uncertainty through increased information sharing between the partners of a supply chain. In practice, some information on future demands is usually available for each partner under varying forms ranging from forecasts to supply contracts. When used effectively, advance demand information serves to reduce the uncertainty in future demands thereby enabling better inventory and service performance (Karaesmen, Buzacott and Dallery, 2002). In particular, with information about future demand, a supplier may be able to reduce the need for inventory or excess capacity, which lowers the inventory holding cost. Customers may also benefit through improved service quality or lower costs.

ADI is a term that refers to information on future demand in general. Although ADI can take on different forms and may be enabled by a variety of technologies, it typically reduces to customers providing advance notice to their suppliers about the timing and size of future orders. This information can be perfect (exact information about future orders) or imperfect (estimates of timing or quantity of future orders). The information can also be explicit, with customers directly stating their intent about future orders, or implicit, with customers allowing suppliers to observe their internal operations and to determine estimates of future orders (Benjaafar, Cooper and Mardan, 2011).

The next table gives an overview of different papers describing an inventory control policy under ADI. It gives an impression of what it is discussed in the different papers. For detailed information, you are referred to the papers itself

Table 4: Overview inventory policies under ADI

Paper	Policy	Variability Assumptions	Optimization	ADI	Solution technique	Review	Product	System
Hariharan and Zipkin (1995)	• Base stock • (s, S) policy	• Deterministic and stochastic lead times • Stochastic demand	Minimization of inventory costs	Perfect	Palm's Theorem	Continuous	Single	• Single echelon • Serial
Gallego and Özer (2001)	• State dependent (s, S) policy • State dependent base stock	• Deterministic lead times • Stochastic demand	Optimal base stock levels	Perfect	Dynamic programming	Periodic	Single	Single echelon
Tan, Güllü and Erkip (2007)	State dependent base stock	• Deterministic lead times • Stochastic demand	• Order-up-to points • Inventory cost	Imperfect	Algorithm	Periodic	Single	Single echelon
DeCroix and Mookerjee (1997)	Base stock	• Deterministic lead times • Stochastic demand	Minimize the costs of buying information	Perfect and imperfect	Algorithm	Periodic	Single	Single echelon
Van Donselaar, Kopczak and Wouters (2001)	Base stock	• Stochastic demand	Optimization of the order-up-to levels	Imperfect	Algorithm	Periodic	Multi	Single echelon
Karaesmen, Buzacott and Dallery (2002)	(S, L) policy	• Stochastic demand	Optimal release lead times and base stock levels	Perfect	Heuristic	Continuous	Single	Single echelon

Karaesmen, Liberopoulos and Dallery (2004)	Base stock	• Stochastic demand • Early fulfillment is possible	Optimization of inventory costs	Perfect	Graphical	Continuous	Single	Single echelon
Gayon et al. (2009)	Base stock	• Stochastic lead times • Stochastic demand	Minimize the expected discounted cost	Imperfect	Markov Analysis	Continuous	Single	Single echelon
Sarkar and Shewchuk (2016)	Base stock	• Stochastic demand • Early fulfillment is possible	Minimize the inventory cost	Perfect	Simulation-optimization procedure	Periodic and continuous	Single	Single echelon
Zhu and Thonemann (2004)	N.A.	• Stochastic demand	Minimize the sum of expected information, ordering, shortage penalty, and inventory holding costs	Imperfect	Dynamic programming	Periodic	Single	Single echelon
Toktay and Wein (2001)	Base stock	• Stochastic demand	Minimum total inventory holding and backorder cost	Imperfect	Heuristic	Continuous	Single	Single echelon
Gallego and Özer (2003)	Base stock	• Stochastic lead times • Stochastic demand	Inventory parameters that minimizes costs	N.A.	Dynamic programming	Periodic	Single	Multi echelon (series)

Tan (2008)	N.A.	• Stochastic demand	Improve forecast accuracy	Imperfect	Formula	N.A.	N.A.	Single echelon
Wang and Toktay (2008)	Base stock State dependent (s, S) policy	• Deterministic lead time • Stochastic demand • Flexible delivery	Inventory parameters that minimizes costs	Imperfect	Dynamic program Heuristic	Periodic	Single	Single Echelon
Chen, Yücel and Zhu (2017)	State dependent (L, U) policy	• Deterministic lead time • Stochastic demand	Minimize costs	N.A.	Dynamic programming	Periodic	Multi	Multi echelon

3.3 Conclusion and research gap

The aim of this literature study was twofold: providing an overview of the different techniques for classifying SKUs and subsequently analyzing inventory control systems that make use of advance demand information (e.g. a forecast provided by the client or order information). Besides, a general introduction has been given to the classification of stocking items and the fundamentals of inventory management. Based on the performed literature study, a research gap has been identified.

More and more customers set high requirements with respect to the service level a supplier must meet and the quality requirements that the products has to satisfy. On the other hand customers require suppliers to be more flexible with respect to changes in order sizes and the timing of deliveries. For example, a part supplier in the OEM market (e.g. Company X) has to meet a service level close to 100% in an environment with long lead times and changing demands. This fits in the overall trend of the 21st century where speed, time-to-market, rapidly changing markets and industry disruptions are becoming more important and common.

The first part of this literature study focused on the classification of SKUs. During the last 30 years a lot of research has been conducted to classification techniques for SKUs. First, most research was related to the ABC classification technique which is based on 1 criterion (dollar value). Afterwards, techniques were developed for MCIC and several criteria could be incorporated in the classification process. However, the aim of all this techniques is to purely rank the different stocking items (create multiple classification groups) and not to immediately include the effect on the inventory performance in the classification process. Only a few papers focus on that topic. Nonetheless, these papers haven't researched the situations with non-stationary (irregular) demand patterns, stochastic lead times and high service requirements (as described before). So, a first research gap has been identified here.

The second part of this literature study has looked into the fundamentals of inventory managements and the focus was on inventory control systems under advance demand information. Different situations/environments have been studied in which ADI is available, like deterministic vs stochastic demand, like deterministic vs stochastic lead times, perfect vs imperfect ADI, situations with different customer classes and situations with flexible delivery possibilities. However, the cases studied so far are all very specific and most researches took a few assumptions to make the situation less complex (for example possibility of backordering or zero lead times). The Company X case is quite complex with the highly variable demands, long volatile lead times and the high service level requirements. The ADI (forecast provided by the different OEM clients) is one of the few resources that can help to deal with this complex situation. A second research gap has been found in the use of ADI in environments with service levels, irregular demand patterns and long lead times.

Concluding, the situation in the 21st century asks for inventory control models that can deal with highly complex conditions. For the industry it would be more beneficial to have a model that can be used in a variety of cases in real-life situations. The research gaps identified has to do with the development of a SKU classification method including inventory performance in the analysis and the creation of inventory control model incorporating ADI. The developed models have to be applicable in complex environments as described before and everything has to manageable in real-life situations with stochastic demand and stochastic lead times.

4. Current situation and validation business problem

In the previous chapter, the academic literature was reviewed to provide a theoretical context to the business problem. In this chapter, the current situation regarding a number of business operations is discussed and the business problem is validated. First, in section 4.1, the different departments managing the supply chain operations are discussed and the total supply chain process is described in more detail. Second, in section 4.2 and 4.3, the current replenishment policies and forecasting methods are explained. Next, the SKU classification systems currently used at Company X are discussed in section 4.4 and then there is elaborated on the ERP system and inventory software in section 4.5. Furthermore, an introduction is given is to the SKUs in scope and the inventory performance is analyzed in section 4.6. A demand and forecast analysis is presented in section 4.7. Finally, in section 4.8, a data description is provided. In section 4.9, the main conclusions and findings from this chapter are summarized.

4.1 Supply chain planning and control

Company X has three main departments (the so-called 'triangle') which all have their own tasks and responsibilities towards the supply chain operations. First, the procurement department is responsible for everything related to purchasing products and dealing with suppliers. They place the replenishment orders to the suppliers and they have to ensure the orders arrive on time at the warehouse. Besides, the procurement department is responsible for selecting and setting up contracts with suitable suppliers which are able to produce/manufacture the products that meet the high-quality requirements of Company X and its customers. Second, the inventory management department is responsible for controlling the inventory levels for the stock items and setting up general inventory control policies. As an element of supply chain management, inventory management includes aspects such as controlling and overseeing ordering inventory, running the inventory analysis with the help of software tools and giving the triggers to the procurement department for placing an order to the supplier if necessary. Third, the sales department is the division of business that is responsible for selling products or services to customers. This department sets up the contracts with the customer and processes their sales orders. The sales team handles the different accounts, checks the sales orders and discusses possible issues with the client.

After this general introduction to the three departments, a description is provided to the internal processes at Company X. Besides, a visual representation is given in figure 8. The complete process within Company X is as follows. The process starts with a forecast from the client. In case no forecast is available, the analysis is done based on historical data with the help of an inventory software package (i.e. Slim4). Based on the customer forecast or the 'advice' (replenishment signal) of Slim4, the inventory management department sends purchase requests to the procurement department who in turn sends out purchase orders to the suppliers. All the purchase requests are checked by the procurement team. When the purchase order arrives at the warehouse, the quality department performs quality checks on a part of the received products. On the customer side or demand side of the business, the sales team processes the sales orders. If the client wants to order, they first ask for a request for quotation (RFQ) in case no fixed price agreement has been made yet. When the client agrees with the RFQ, they place an order which is processed by the order service team who processes it via the ERP system. The products with a fixed sales price or for which already a price agreement has been made are immediately processed into the ERP system. Next, the order is confirmed or rejected by the sales team. The assessment of these orders is not always done extensively for every sales order (no general sales order assessment policy exist) and a first come first served (FCFS) policy is applied for all products. This means that all incoming sales orders are fulfilled by the order of their arrival. If the order is accepted, the procurement team handles the overall fulfilment of the order. The final sales order (with a payment request) has to be accepted by the customer within 5 working days. Also, the replenishment orders to the suppliers needs to be confirmed by the supplier within 5 days. Besides, a certain service level is communicated to the supplier (in case of a contract) which has to be met. A service level for confirming orders and a service level concerning the on-time deliveries of orders.

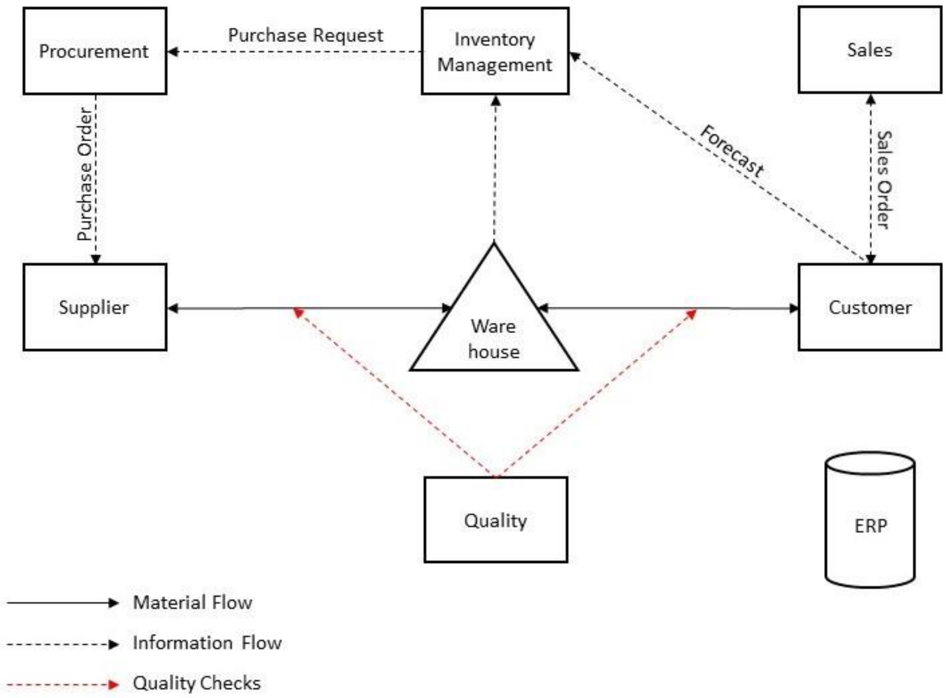

Figure 4: Company X operations planning and control system

When Company X receives a request from an customer to develop/supply a new product, this often takes a long time. First of all, the specifications need to be discussed with the client and drawings have to be made. Next, the complete sourcing process takes place in which a high-quality supplier has to be found and afterwards, the whole supply chain is set up. Then, test samples have to be produced which has to be approved by the client. Finally, the complete production can be started. This whole process with all the steps can take up to two years. Next, there is a general approach for selecting a suitable supplier. This starts with a RFQ from the sales department. Next, different supplier options are considered and a deliberation is made between quality, lead time and price.

Concluding, the approach regarding setting up the supply chain and managing the different processes is well organized. However, in practice, it frequently occurs that tasks overlap and then, it is not always clear which person is responsible. Besides, the FCFS principle applies to a lot of products which sometimes results in difficult situations. For example, an important and loyal customer can’t be served because of an earlier sales order placed by a new and small customer. Next, sales orders are not always judged extensively by the sales team. Because of this, an unexpected peak in consumption can occur which could have been prevented by signaling ‘unexpected’ orders from one-off customers. At last, quality issues and capacity problems at the supply side play a big role in the supply chain process.

4.2 Forecasting methods and inventory policies

In this subchapter more will be explained about the forecasting methods and inventory control policies at Company X. Starting with forecasting, Company X makes a forecast itself using exponential smoothing and Company X receives rolling forecasts from a number of big clients that are processed in the ERP system. These forecasts are used as an input for the 2 different inventory strategies applied at Company X which will be described in more detail.

As mentioned in section 4.1, the inventory department is responsible for determining the inventory policy for each SKU, setting the inventory parameters, analyzing historical sales data and making the planning of all the SKUs. In general, the planning covers a period of four months which is equal to the maximum lead time at Company X. The biggest part of the inventory is procured/produced by suppliers and the other part is produced/assembled by Company X itself. It is important to mention that all the inventory is not exclusive. This means that every customer is allowed to order products from the complete Company X's assortment even though some products (tailor-made) are produced for a specific client. In general, different planning profiles are used for making a distinction between the different SKUs. Planning profiles are used for setting inventory parameters for SKUs and as a recognition tool for the different products. A planning profile consists of a combination of letters and numbers (four characters as maximum). These characters indicate for example what kind of inventory it is (e.g. strategic or standard inventory), whether the SKU has a reorder point or not, if the SKU is manually controlled and whether the SKU has a customer forecast or not. In the end, a distinction can be made between products with a client forecast and products without a client forecast for which different policies are used. These inventory policies and the corresponding forecasting method will be discussed in the next paragraphs.

4.2.1 SKUs without a customer forecast

For SKUs without a customer forecast, the complete inventory analysis is done with the help of an inventory software package called Slim4. The approach used by Slim4 is called a reorder point policy or (R, s, nQ) policy. First of all, a forecast is made for these SKUs using exponential smoothing resulting in monthly forecasts which are proportionally divided over the weeks. These forecasts are based on historical sales data from the last 12 months. Sales from the last 3 months get a bigger weight factor in the forecast and the software tries to recognize a possible demand trend in the historical sales data (e.g. seasonality or an increasing/decreasing trend). The software package tries to select a suitable demand profile for the different SKUs based on the historical sales data and upon product hierarchies. These demand profiles show if it is normal SKU, seasonal SKU, slow-moving SKU or SKU with an irregular demand pattern. A tracking signal system is used to measure the accuracy of these forecasts. This system compares the forecasts with the actual demands (i.e. the forecast error) which are summed for each forecasted SKU and a signal/warning is given at a certain tolerance level (cumulative forecast error limit).

Based on these forecasts, a reorder point is determined and a certain safety stock is set based on a service level (resulting from the ABC classification), the length of the supplier lead time and the variation in the forecasted demand. Under this policy a replenishment order is placed if the inventory position is below the reorder point at the moment of reviewing by the software (once a day). The inventory position comprises items in stocks minus backorders plus incoming orders not yet received. The replenishment quantity is equal to the economic order quantity (EOQ) or the minimal order quantity (MOQ) at the supplier in case the MOQ is higher than the EOQ. The EOQ is the ideal order quantity a company should purchase for its inventory given the demand rate, ordering costs and inventory holding costs. When calculating the EOQ at Company X, the fact is taken into account that it is not desired that more than 40 weeks of demand is kept in inventory. Besides, purchasing rates and the discount structures at suppliers are not taken into account in this calculation. Once a month an analysis is conducted in Slim4 and new inventory parameters (safety stock and reorder point) can be set for some products depending on the outcome of this analysis. If a product has multiple customers and is frequently consumed, Slim4 determines basically everything. In case of low demand or seasonal influences, a more judgmental and manual approach is needed.

For the really slow-moving SKUs or SKUs with an irregular demand pattern, the inventory parameters are set manually by the inventory department instead of Slim4. These SKUs are assigned a special planning profile indicated by a ‘Y’. There is no fixed policy that determines when a product gets the planning profile ‘Y’. In most cases, the poor performance of Slim4 is one of the causes. The difference in approach comparing to the other SKUs is that the inventory management is done manually and there is frequent intervention (stricter control on the inventory levels). A higher safety stock level might be set or even a base stock policy can be applied. Under a base stock policy, the whole inventory planning and order behavior is focused on keeping the inventory level always above or equal to the base stock. This is a minimum level of inventory that always has to be available at the company. In most cases, this policy is applied on a request of the client, because the client demand a certain amount of SKUs that is in inventory all the time. This inventory level is then recorded in a contract. However, the documentation for SKUs with contractual agreements is not well organized.

4.2.2 SKUs with a customer forecast

In case of SKUs with a customer forecast, the inventory planning is a bit different. A number of customers provide a prognosis of their purchases to Company X that all differ in type, length and format. Most customers provide a prognosis with the weekly consumption for the first 3 months and then they give an indication for the monthly consumption for 3 to 9 more months. It is a rolling forecast for which an update is handed to Company X every week and this updated forecast is processed into the system once every 2 weeks. Like with the forecasts made using exponential smoothing, the customer forecasts are also analyzed with a tracking system. Every time a new forecast is provided by the different customers, this forecast is compared with the previous forecast and the percentual deviation is calculated. In case the percentual deviation between the two forecasts is bigger than 10%, the SKU in question is flagged. A customer with many flagged SKUs is contacted by the sales team.

The forecast provided by the client is processed into the ERP system (SAP) and then a forecast module integrated in SAP makes an inventory plan for these items. No reorder point is set for these items, only a certain safety stock is determined in consultation with the client most of the time (generally 6 weeks of sales). Based on the forecasts, safety stock and replenishment lead time, ‘tentative’ purchase orders are created in SAP. These purchase orders can still change based on the actual realized sales and updated forecasts provided by the customer every 2 weeks. Inventory management receives notifications when the ‘tentative’ purchase order has to be converted to a final purchase order. The planned order in SAP is then converted to a purchase request handled by the procurement department. Future purchase orders can also be adjusted and placed to an earlier point in time based on a customer forecast analyses (i.e. tracking system). If a critical moment is approaching (because of a big change in the forecast for example), a change can be made to the future planned purchase orders and an ‘emergency’ order can be placed. However, this is all done manually by the inventory department with a chance of error (no automatic check). Next, certain rules were determined by the inventory department for this inventory approach, called the forecast consumption rules. For example, a client can only consume a certain quantity more compared to the forecast provided by this client for a specific week or month (i.e. a transaction or order limit over a certain period). These rules are set to prevent the complete stock of a SKU can be emptied in one time.

The approach for the SKUs with a customer forecast is Material requirements planning (MRP) based policy. MRP is a planning and control system for inventory, production, and scheduling. The forecast module integrated in SAP schedules future purchase orders based on the customer forecasts and tries to ensure the needed SKUs are available on time. Of course, the sales orders which are already in the order book consume part of this forecast. Based on the forecast and the sales orders in the order book (plus safety stock), the forecast module or MRP system calculates exactly when replenishment orders need to be placed to be able to meet the customer demand.

It is important to mention that a number of customers provide a forecast to Company X, but that these forecasts are not processed into the ERP system. The central sales support (CSS) team is responsible for converting the forecasts in the right format/structure and to process the forecasts into SAP afterwards. However, CSS is only able to process the forecasts that are in a certain format and structure (Excel file, good overview of the week numbers and with Company X's article numbers). If the forecasts are offered in wrong format (PDF file) and the file is not well-ordered, the forecast is not used for inventory management. Because of this, the forecasts from 15-25 customers are not processed into the ERP system.

Concluding, forecasting based on a lot of historical sales data and forecasts provided by customers makes life easier for Company X. Besides, the tracking signal is a simple indicator that forecast bias is present in the forecast model selected by the software package. Next, it is a good initiative that the different customer forecasts are compared, but the forecast is not compared with the actual sales by which the accuracy of these forecasts is not known. Also, not using a standard format for customer forecasts results in an undesirable situation in which customer prognoses can't be processed into the system. On the other hand, there are some factors that can be improved regarding the inventory management. Generally, most analyses regarding demand and forecasts are done for a relatively short time period whereby the increasing/decreasing trend on long term basis is not recognized. For example, the new customer forecasts are only compared with the previous forecast making it difficult to recognize a trend in the data and only the big, abrupt changes are signaled. Next, the inventory software package (Slim4) has a hard time with slow-moving SKUs. There are only a few historical data points which makes it difficult to recognize a trend and to make an accurate forecast.

4.3 Current classification systems

Since the goal of this project is to develop a classification system for inventory management purposes and to create 'trays' for SKUs with the same characteristics, it is important to mention that there are already comparable systems at Company X. First of all, a system is set up to assign SKUs into different categories based on the type of inventory. Next, the well-known ABC systems is used to get insight in the importance of a SKU.

First of all, at the moment Company X uses an inventory classification system to get some insights and to possible clarify remarkable things in their inventory system. Products are classified into 7 different types. First of all, products can be classified as introduction or exit inventory. This is mainly done to warn people and to make people aware of this mutation. Second, items can be classified as generic if it is a standard item sold to different customers. On the other hand, a product can be categorized as slow-moving if the demand frequency is very low. Next, inventory can be classified as strategic if the stock is there on request of a business unit. Last, items can be classified as client specific or client related. Inventory is client specific if the items are developed and produced for 1 specific customer. Inventory is client related if the items are standard, but the product is ordered by 1 customer for more than 80% of this item's total demand. Concluding and for information, the client specific and the client related items will especially be of importance in this research.

On the other hand, there exists a so-called and well known ABC classification system at Company X. This system is based on the consumption value and inventory value for the different SKUs as already explained in Chapter 3. ABC analysis is an inventory categorization method which consists in dividing items into three categories (A, B, C): A being the most valuable items and C being the least valuable ones. Moreover, an extra dimension can be added to this ABC system. In this more elaborate system, a SKU can be classified as X, Y or Z. Next to the consumption value, there is also looked into the frequency of demand (the number of sales orders). This means that not only the total consumption is taken into account, but also the frequency of consumption. One of the applications of this ABC system at Company X is that there is a certain service level (and safety stock) attached to an A/X article. It is important to mention that this ABC system is not maintained very well in the last few years.

Concluding, two different classification systems are applied at Company X. First, dividing SKUs into 7 categories is a useful method to make a first distinction between SKUs and can be used as a recognition tool. However, it is only possible to do some simple analysis with this system. For example, showing how many SKUs are in each category (and what the corresponding inventory value is) and to indicate how many SKUs are introduction or exit inventory. Next, the ABC system gives insight in the importance/criticality of a particular item, but the system is not up-to-date. Besides, using 2 different ABC systems makes everything a bit confusing. For some of the articles the ABC system is applied and for another part the XYZ classification.

4.4 ERP system and inventory software

In this subchapter, an introduction is given to the Enterprise Resource Planning (ERP) system used at the company. The applications and functionality of the systems will be discussed. Besides, the software package used for inventory management is discussed and its functions are described.

First of all, SAP is Company X's ERP system and is used to manage almost all business operations and customer relations that have to do with ERP. The ERP package from SAP is designed to support and integrate almost every functional area of a business process such as procurement of goods and services, sale and distribution, finance, accountings, human resource, manufacturing, production planning, logistics & warehouse management. In short, SAP is used to handle replenishment orders, incoming purchase orders and to do the production/inventory planning. Besides, a lot of data regarding inventory/supply chain planning for all SKUs can be retrieved from SAP. To make this data more understandable, the software module Every Angle is used which is a tool that makes complex data from different tables from SAP understandable for business users. As mentioned before SAP is also used to process the customer forecasts for a number of SKUs and to do the inventory planning for these SKUs.

Besides SAP, Slim4, an inventory software system developed by Slimstock B.V., is used for the demand forecasting and inventory replenishment on product level for the products without customer forecasts. As written in section 4.2, Slim4 analyzes historical sales data, sets the inventory parameters (reorder point, safety stock) and determines the replenishment quantities (MOQ or EOQ). Slim4 is a dynamical system since all its parameters are calculated again at the start of each month. The system gives an order advice to the inventory planner to fulfill the demand. The replenishment advice takes into account a specified MOQ and an EOQ calculated with Camp's formula. In many cases, suppliers require orders consisting of at least a certain amount of case packs. So, in practice the EQQ is almost equal to the MOQ. All in all, Slim4 has been designed as an inventory replenishment system that is similar to an (R,s,S) system, but due to many restrictions of suppliers regarding batch ordering, it is used as an inventory replenishment system that is similar to an (R,s,nQ) system.

One of the drawbacks of Slim4 is that this system assumes there is a promotion too often in case of a peak demand. If the sales during a month are 2 or 3 times higher than the other months, Slim4 assumes this month includes a promotion and therefore excludes this month from the forecast. The software takes peaks in consumption out of the trend which is not always desirable. Besides, it doesn't account for quantity structures or quantity discounts when calculating the order quantity. Because of this, too many small orders are placed in some cases. Slim4 is designed to keep the inventory on hand as low as possible by only ordering sufficient goods to cover the review and lead time period taking into account the desired service level. It would be better to place a few larger replenishment orders, whereby Company X can take advantage of the quantity discounts or other quantity agreements with the supplier. Next, the possibilities with the application of demand distributions are quite limited with Slim4. Slim4 assumes that most SKUs have a normally distributed demand distribution which is not always the case in practice.

4.5 Data description

Since this research consists of a data analysis and calculations are done with the help of data, it is important to describe the data that is available and the possibilities/limitations of the available data.

Describing and documenting data is essential in ensuring that everyone who may need to use the data, can make sense of the data and understand the processes that have been followed in the collection, processing, and analysis of the data. Besides, carefully describing and documenting the content of the research data is essential to ensure the usability of data. Without this descriptive information, research data are simply a meaningless collection of files, values and characters. An extensive description also facilitates data discovery.

As this project is focused on classifying stock items into groups with a respective inventory control model, the collected data is almost all related to inventory. The dataset used in this study contains information from 534 SKUs of Company X. Most data is retrieved from the monthly inventory overviews made by the inventory management department for each BU. These data is supplemented with additional input retrieved from the ERP system. A distinction can be made between basic (raw) data and KPI data. For the KPI data a calculation is made and makes it already possible to say something about the characteristics of the SKU. The following table shows the available raw data with some explanation.

Table 5: Available raw data

Type of data	Comment
Product group	Name for the group of related products
Article number	Used by Company X, consists of 8 digits
Article description	Characteristics (name, dimensions)
Inventory type	Intro, exit, generic, strategic, slow-moving, client specific, client related
Customer code (+name)	Used by Company X, consist of 7 digits
Call-off contract (+ end date)	Inventory as a result of a contract (yes/no)
Article with dependent demand	Is this article used as a component for one or multiple articles i.e. part of a bill of materials (BOM) (yes/no)? This means that multiple article numbers and clients are attached to this article
Current inventory level	The number of stock items in pieces i.e. inventory on-hand
GIP/STP	Progressive (moving) average purchase price
Ordering costs	The expenses incurred to create and process an order to a supplier (i.e. €7)
Holding costs	The total costs of carrying inventory (yearly costs = 34% of GIP/STP
Stock Value (3 months)	Stock value of available stock valued in GIP/STP (monthly basis)
Stock value previous year	Viewed only for the current month
Stock value difference	Current stock value – Stock value last month
Consignment stock customer	Inventory held at customer, owner is Company X (# articles)
Consignment stock supplier	Inventory held at Company X, owner is supplier
Depreciation	Article in depreciation? 1=25%, 2=50% etc. (determined at the end of last year 31-12)
Automatic ordering	Yes/no. Can be set for each article. In case of yes: if the inventory position falls below the reorder point, an purchase request is created which is automatically converted to a final order
Minimum order quantity (+ rounding value)	For example: order at least 500 pieces and then you can increase your order with steps of 100 pieces
Outstanding customer orders	Backorders (total of all outstanding consumptions e.g. sales, transport, reservations)
Outstanding replenishment orders	Order quantity still needs to be delivered i.e. quantity-on-order (normal orders and production orders)
Planned lead time	The time which elapses from the moment a replenishment order is created until the moment the replenishment order arrives in the stock point (stated in SAP in calendar days)
Number of replenishment orders	Total orders in last 3, 6 and 12 months

Total corrected consumption	The number of articles sold over the last 12 months
Consumption levels (last 3 years)	The number of sold items in each month
Customer orders (last 3 years)	The total number of sales orders in each month
Replenishment levels (last 3 years)	The total number of purchased items in each month
Customer forecast available	Yes or no
Customer forecast numbers (coming year)	Expected sales in the next 12 months (viewed per month)

As can be seen in the table, only monthly sales and inventory values are available for analysis. This makes it more complex to recognize patterns as for example seasonality (within a month) in the historical sales data. The variation in demand within a month is also harder to detect
Besides, comparing the sales levels with the inventory levels is less accurate than comparing the weekly levels.

The next table describes the available KPI data with some comments.

Table 6: Available KPI data

Type of data	**Comment**
ABC sign	Importance of article based on sales ratio
Service level	An agreement about what percentage of the products should be delivered on time
Planning profile	Shows the inventory policy (as explained in Ch 4.3)
Reorder point	Inventory level of an item which triggers the action for placement of a replenishment order
Safety stock	A certain amount of inventory that a company holds to mitigate the risk of running out of stock
Average stock value	Based on the last 3 months
Inventory turn	$\frac{Sales\ in\ the\ last\ 12\ months}{Average\ inventory\ level\ (last\ 3\ months)}$
Inventory Position	Inventory on-hand plus quantity-on-order minus backorders
Future depreciation (FD)	Simulated depreciation number. Expected depreciation quantity at the end of the year
FD value	Value based on the simulation run. The current stock value is multiplied by the depreciation %
Residual stock	Remaining stock value after subtracting the FD value
Consumption value	Total sales in last 12 months multiplied by GIP/STP
Months with consumption (#)	The number of months with sales in the last 12 months
EOQ value	Optimal reorder quantity calculated using Camp's formula. In formula: $EOQ = \sqrt{\frac{annual\ demand\ rate * ordering\ costs}{holding\ costs}}$

As already mentioned before, calculations or analysis have been done to get the KPI data and this data tells something about the performance of a SKU. First of all, the ABC classification is based on the sales ratio and gives information about the usage of a product. Second, the inventory turn measures the speed at which your stock is replenished over a given amount of time. A high inventory turnover generally means that goods are sold faster and a low turnover rate indicates weak sales and excess inventories which may be challenging for a business. Next, the values related to FD indicates something about the consumption rate of a product which is also the goal with the # that shows the number of months with sales. At last, the service level indicates the importance of a product and the EOQ value the optimal order quantity.

Concluding, both raw data and KPI data is available. For performing the analysis and developing the classification system, the consumption values, customer orders, forecast numbers, planned lead times, call-off contracts, article with dependent demand and cost factors will be the most important data. The availability of only month data makes it difficult to recognize patterns in some cases.

4.6 SKU introduction and inventory performance

In this section, an introduction is given to the SKUs in scope and a few performance measures concerning inventory management are discussed. A general introduction to the 534 SKUs in scope is given and the reasons for selecting are clarified after which a few inventory measures (e.g. the inventory value and service level) are discussed.

The focus of this project is on the SKUs from 5 OEM clients within one of the BUs. This BU or division develops, among other things, O-rings, several types of seals, moulded rubber parts and profiles, and vibration dampers. The reason for selecting these particular clients is that they are all from different segments or industries (e.g. automotive or food industry). This makes it is more likely that more varied SKUs are selected with different characteristics. Besides, it ensures that the conclusions of this research give a broad picture and that the proposed solution is not only applicable for SKUs within a certain segment. The following tables give a short overview of the SKUs in scope.

Table 7: SKU overview per customer

Client	# SKUs	Client forecast	Inventory Value (Oct 2018)	Client specific	Client related	Generic	Exit
1	97	68	€150.301	68	24	1	3
2	40	0	€69.750	33	7	0	0
3	172	89	€163.520	141	28	0	3
4	123	0	€259.481	102	16	2	3
5	102	0	€49.533	29	64	1	8
Total	534	157	€692.585	373	139	4	17

Table 8: SKU overview per product group

Product Group	# SKUs	Client forecast	Inventory value (Oct 2018)	Average supplier lead time	Minimum supplier lead time	Maximum supplier lead time
A	247	77	€127.082	50 days	4 days	126 days
B	214	51	€471.494	69 days	4 days	200 days
C	73	29	€94.009	83 days	4 days	112 days
Total or average	534	157	€692.585	67 days	4 days	200 days

As can be seen in the tables, 534 SKUs are researched from which about 30% have a forecast provided by the customer. It is important to mention that for 46 more SKUs a customer forecast is available, but these forecasts are not processed into the ERP system due to the reasons as described in section 4.2.2. The SKUs with a customer forecast are for the biggest part client specific which means that this product is especially designed and manufactured for this client. The biggest part (363) of the SKUs are client specific. Furthermore, it is important to mention that the average supplier lead time is quite long (67 days or 2.2 months) which has a big impact on the supply chain operations. SKUs from the product group C have the longest supplier lead time on average.

The fact that the supplier lead times are on average quite long, is a reason to take a closer look to the supplier lead times for the SKUs in scope. A planned replenishment lead time is put into the ERP system for all the different suppliers. These lead times are validated twice a year and corrected if necessary. In the next table, the supplier lead times are divided into different categories.

Table 9: Supplier lead times overview

Category	Median	0 – 14 days	15 – 30 days	31 – 60 days	61 – 90 days	> 90 days
# SKUs	63	130	67	55	54	228
Sum		130	197	252	306	534

As can be concluded, a big part of the SKUs have a supplier lead time longer than 90 days (3 months). In order to make up for this, Company X must carry a lot of safety stock which has a big impact on the working capital. Besides, the long lead times result in a big amount of on-transit inventory. In short, the long supplier lead times for many SKUs have a huge impact on the inventory management at Company X.

After this short introduction to the SKUs in scope, a few inventory measures and KPIs are discussed in the remaining part of this subchapter. Since one of the main objectives of this research is to improve the service level or delivery performance towards the customers, it is important to check what the current numbers are. The average service level (per month) for the 3 product groups are studied for the period January 2018 to September 2018. Unfortunately, the service levels are not available on product level. However, these average service levels should give a reasonable representation for the SKUs in scope in the current situation. In the end, it can be concluded that the service levels are below the desired level in a few months. A service level above 95% is seen as 'acceptable' at Company X. In case of client specific SKUs the 'desired' service level is even higher (close to 100%).

Next, the waste of working capital is discussed. The following table shows the number of SKUs without sales in the last 12 months and gives information about the inventory value.

Table 10: SKUs without sales in period Sept 2018 - Oct 2017

Product group	#SKUs	#SKUs with IP	Inventory value (Oct 2018)
A	45	24	€4.921
B	50	11	€12.379
C	28	5	€174
Total	123	40	€17.630

The table above shows that about 33% of the SKUs without sales in the last 12 months still have an inventory position (SKUs on stock). Most of these SKUs belong to the product groups A and B. The biggest volume (in €) is in the product group B, namely over €12.000.

Next, the replenishment quantities are analyzed. Since the first principle is to place an order equal to the EOQ if possible, it might be useful to investigate for how many SKUs in scope this actually happens. Minimum order quantities set by suppliers can ensure that it is not possible to order the EQQ. The EOQ values for each SKU are available in the monthly inventory overviews and calculated using Camp's formula as mentioned in section 4.4. It is important to mention that for SKUs with a customer forecast the EOQ is not calculated, because the reorder quantities are purely based on the customer forecasts. The next table shows the outcome of this analysis.

Table 11: Reorder quantities (Sept 2018 - Oct 2015)

Category	#SKUs	EOQ	MOQ
Customer forecast	157	0	157
Other	377	5	372
Total	534	5	529

As can be seen in the table, the replenishment orders are almost never equal to the EOQ, because of order restrictions. Looking to the last 3 years, the EOQ value was only ordered for 5 SKUs. Therefore, it makes often no sense to calculate the EOQ in the situation of Company X.

Concluding, the 534 SKUs in scope have on average a long replenishment lead time and for a part of the SKUs a rolling forecast is provided to Company X by the customer. Next, Company X has in same cases big challenges achieving the 'desired' service within the 3 product groups in scope. At last, the replenishment orders are almost never equal to the EOQ value.

4.7 Demand and forecast analysis

In this section, a demand and forecast analysis is performed for the SKUs in scope. These analysis consists of a general description of the demand pattern and the search for demand trends. This analysis should give more insights in the type of SKUs Company X has to deal with. Before performing the demand analysis, the historical sales data is studied for outliers and seasonality. Besides, a forecast analysis is performed for the SKUs with a customer forecast in which the forecast accuracy is determined. The analysis is eventually performed for 440 SKUs in total. 94 SKUs didn't have any sales in the last 24 months by which no sufficient data is available to perform a good demand analysis.

Looking to the sales patterns for the products Company X supplies, there are a few general components which are important for all products. Company X operates in a business segment in which seasonal influences and large one-off sales orders play a big role. Company X supplies industrial engineering components to customers who are busier in a certain period of the year (seasonality) or who occasionally carry out large projects (large one-off sales orders). These factors have a big impact on the demand patterns for the products Company X supplies and have to be taken into account by analyzing the demand.

Before starting with the demand analysis, an issue has to be discussed concerning the total demand for each SKU. Generally, a distinction can be made between SKUs with independent demand and SKUs with dependent demand. Independent demand is demand for an end (finished) product, while dependent demand is the demand for the components used in end products. These components are listed in a bill of materials (BOM). These SKUs are components used in one or multiple end products. It is crucial to have an overview of the complete demand for these components. However, it occurs that multiple article numbers are used for the same component which makes everything complicated. One of the causes could be that for each end product a different article number is used for the same component. The documentation for these components is not well-organized. It is often only mentioned in an article note that there is also another article number used for the SKU in question. It is not very clear which different article numbers are used for the same component making it complicated to determine the total demand for each component. In the end, it is decided to make an assumption for the SKUs with dependent demand. This implies that it is assumed that the demand based on the 534 article numbers from the scope of this project is considered as the total demand for all components. It is not well documented which article numbers are used for the same component and because of this, it is impossible to accurately determine a component's total demand. For information, there are 95 SKUs with dependent demand from the 534 SKUs in scope.

First of all, possible outliers are detected in the historical demand data. Outliers are peaks in the historical sales data that are not considered to be representative for the overall pattern of demand. Whereas some fluctuations like seasonality of demand can be tracked in patterns over time, outliers are less predictable and uncommon. Unusual demand can be caused by events of which you have knowledge of (e.g., sales promotions, large one-time orders, etc.) or can be caused by events of which you have no knowledge of (competitor promotions, customer going out of business etc.). Actual outliers are peaks in the historical sales data for which no explanation can be found. The challenge with outliers in demand is that if not addressed, it leads to biased inventory demand forecasting and incorrect results of the inventory control model. As already mentioned in Ch 4.2, Slim4 also analyzes historical sales data in order to detect possible outliers after which these data point are removed if necessary. However, this data is not stored which makes it impossible to determine the performance of this outlier detection system.

The Interquartile Range (IQR) method is used to detect outliers which is method applicable to all distribution functions. The IQR is a measure of variability, based on dividing a data set into quartiles as described in Barbato, Barini, Genta and Levi (2011). Quartiles divide a rank-ordered data set into four equal parts. The IQR is calculated as the difference between the 75^{th} (Q_3: third quartile) and the 25th percentiles of the data (Q_1: first quartile). The IQR tells how spread out the "middle" values are and it can also be used to tell when some of the other values are "too far" from the central value. These "too far away" points are possible outliers, because these values are outside the expected range. A lower bound is calculated by subtracting X times the IQR from Q_1. Next, an upper bound is set by adding X times the IQR to Q_3. If a data point is below the lower bound or above the upper bound, it is viewed as being too far from the central values to be reasonable and it can deemed an outlier needing to be reviewed. In the end, only extreme outliers were removed from the historical sales data, so a X-value of 4 was chosen. The following table shows the outcome of this analysis. An description of the outlier analysis incorporating different bounds (X-values) can be found in Appendix A.

Table 12: Outliers

Total number of SKUs	# SKUs with outlier	# Detected outliers
440	50	87

Next, the historical sales data is studied for a possible seasonal pattern. Seasonality is a characteristic of a time series in which the data experiences regular and predictable changes that recur every calendar year. It is important to detect seasonality in historical sales data to see for which SKUs seasonality has to be incorporated in forecasting and inventory management. Historical sales data from 2017 and 2016 is studied to check for seasonal patterns. The historical sales data for the SKUs in scope was simply plotted to be able to recognize a seasonal pattern. The next table shows for how many SKUs a seasonal pattern is detected and what the division is within the 3 product groups.

Table 13: Seasonal pattern

Product group	Seasonal pattern	No seasonal pattern	Total	Seasonal Pattern (%)
A	39	179	218	17,9%
B	31	140	171	18,1%
C	8	43	51	15,7%
Total	78	362	440	17,7%

Afterwards, seasonality is removed from the time series data by calculating the seasonal indices. A seasonal index indicates how a periodic amount (e.g. a month) compares to the average of all periods such as a year. Seasonal indices can be used to deseasonalize and, thereby, uncover trends (smooth) in sales data in absolute terms. That means seasonal fluctuations or patterns can be removed from the data, and forecasts can be made with regard to future data values.

After the outlier detection and seasonality analysis, the actual demand pattern is studied for the different SKUs. First of all, the mean and standard deviation are calculated for all the SKUs (measured over the period from October 2017 to September 2018) to determine the coefficients of variation (CV). The CV is a statistical measure of the dispersion of data points in a data series around the mean. It is a useful statistic for comparing the degree of variation from one data series to another (in other words: the CV is dimensionless) and to determine how volatile the historical sales data for the different SKUs is. The outcome of this analysis is represented in the following table. Different categories are set up. Low values (i.e. less than 0.25) are associated with stable customer demand and higher values (i.e. greater than 1.0) are associated with unstable customer demand.

Table 14: Variability of demand pattern

Category	Limit values	#SKUs
Low variability (stable customer demand)	0 - 0,25	237
Medium variability	0,25 – 0,75	110
Highly variable (unstable customer demand)	>0,75	64
Total		411

No CV is calculated for SKUs without sales in the respective period (440 – 411 = 29 SKUs) as can be seen in the table. The demand for 64 SKUs is very volatile.

Second, there is checked for a positive or negative trend in the sales data for the SKUs in question. It is a general upward or downward movement of demand over time. The average monthly demand is calculated for the last 3 years and it is checked if there is an upward or downward movement in the average demand over the 3 years. The SKUs are divided into 3 categories: a positive trend, negative trend and no trend (horizontal). The next tables show the outcome.

Table 15: Demand trends

Category	#SKUs
Positive trend	96
Negative trend	77
No trend	267

Table 16: Demand trends per product group

Product Group	Positive trend	Negative trend	No trend
A	39	42	137
B	46	32	93
C	11	3	37

After this demand analysis the SKUs with a customer forecast are analyzed and the forecast accuracy is determined.

Section 4.3 shows that no extensive analysis is done to the accuracy of the customer forecasts at the moment and that the most recent forecasts are only compared with the previous forecasts. Since the first principle of forecasting is that forecasts are (almost) always wrong, it is important to investigate the accuracy of the forecasts. The realized sales and the forecast will be compared on a monthly basis and the percentual deviation will be calculated. The average replenishment lead time is chosen as time interval for the calculations. Let's say the average replenishment lead time is 2 months and the forecast for the sales in March is compared with the actual sales in March. Then, the forecast for March provided in the beginning January is used for the calculations. The forecast accuracy is only calculated for a part of the SKUs for 2 customers since these forecasts are processed into the ERP system. The percentual errors are calculated and the outcome is represented in the following tables.

Table 17: MAPE

Customer	#SKUs	Average % error	Median
1	38	39,64%	28,05%
3	63	55,41%	40,95%
Total	101	49,5%	35,4%

Table 18: MAPE limit values

Category	#SKUs
<25%	25
<50%	77

As shown in the tables, the average percentage error is close to 50%. Besides, a big part of the SKUs has a forecast error lower than 25% which means a number of outliers increase the total average error. As can be seen in the table, the forecast accuracy is calculated for 101 SKUs while for 157 SKUs a customer forecast is available as mentioned in table 7. The reason for this is that the order of the SKUs in the forecast files differs most of the time. Because it is very time-consuming to search for each individual SKU all over again, it was decided to copy the forecasts for the SKUs that were in the same order to one main file. Afterwards, it was checked for how many SKUs in scope the forecasts were in this main file. In the end, it was possible to calculate the forecast accuracy for 101 SKUs.

In the end, a quite big number of outliers is detected in the historical sales data for the SKUs in scope which are removed subsequently. The demand analysis shows that a small part of the SKUs (about 18%) have a seasonal components in its demand pattern. Next, most SKUs don't have a trend in its demand pattern and for 64 SKUs (of the 411 SKUs) the demand is very volatile. On the other hand, the forecast analysis shows that the forecasts provided by the customer are not always that accurate.

4.8 Conclusion

Several problematic factors/causes have been identified in the analysis of the current situation. The main conclusions are summarized below.

- All products in Company X's assortment is available to all customers and a first come first served (FCFS) strategy is applied for most items if it is not a customer-specific item. This means the complete inventory for a certain product can be consumed by a 'less important' or subsidiary customer which can cause problems (e.g. an important OEM client can't be served anymore). The fact that most customer (sales) orders are not always judged extensively and there is no extra check for remarkable, makes things even worse.
- The process with respect to the customer forecasts is not well organized. First, already putting future or 'tentative' orders in SAP makes everything inconvenient. Next, there is no format or document for customer forecasts by which not all customer forecasts are processed into SAP. At last, the accuracy of the customer forecasts is not calculated by comparing the customer forecasts with the actual sales.
- Slim4 has its restrictions. First, it has a hard time making a demand forecast if there is not much historical demand information available (e.g. new products or slow-moving products) or if the demand pattern is very irregular. Next, the software assumes a normal distribution at all its calculations which is not 'valid' for much products in scope. At last, Slim4 doesn't take into account quantity discounts or structures at determining the replenishment quantities.
- The replenishment lead times are on average quite long and has a great impact on inventory management
- Company X has a hard time in meeting the desired service levels. Unfortunately, the service level are not available on product level so that it can be determined what the problematic products are.
- There is no strict policy concerning after how many months without sales the customer is contacted in case of a client specific product resulting in too much excess inventory
- The documentation for SKUs with contractual agreements (e.g. call-off contracts or safety stock agreements) is not well organized. Because of this, it is difficult to identify these SKUs and to take into account these agreements if necessary.
- Looking to the SKUs with dependent demand, it occurs that multiple article numbers are used for the same component which makes it hard to determine the total demand for these SKUs. Besides, the documentation for these SKUs is not well-organized.

5. Conceptual model

The goal of this project is to develop a classification system for inventory management purposes which can determine a suitable inventory policy for a SKU based on a few factors (e.g. demand characteristics, lead time aspects, contractual agreements etc.). The whole approach is based on the paper from Lolli et al. (2017) and consists of 5 steps. First of all, all the necessary data needs to be collected for the SKUs in scope which is already described in section 4.5. Second, the demand of the different SKUs is analyzed by breaking it down into its constituent elements (i.e. the demand size and the demand frequency) and eventually make a demand pattern classification. Then, the SKUs are assigned to different classification groups by analyzing factors which can impact the choice for an inventory control policy and play a big role in the working environment of Company X. The next step is to make a selection of inventory control policies which can be applied in the situation of Company X. The last step is to do a performance assessment using 2 KPIs and to perform a sensitivity analysis afterwards. In the end, it will turn out for which SKUs in scope the inventory policy has to be changed comparing to the current situation. An overview of the analysis is shown in the next figure.

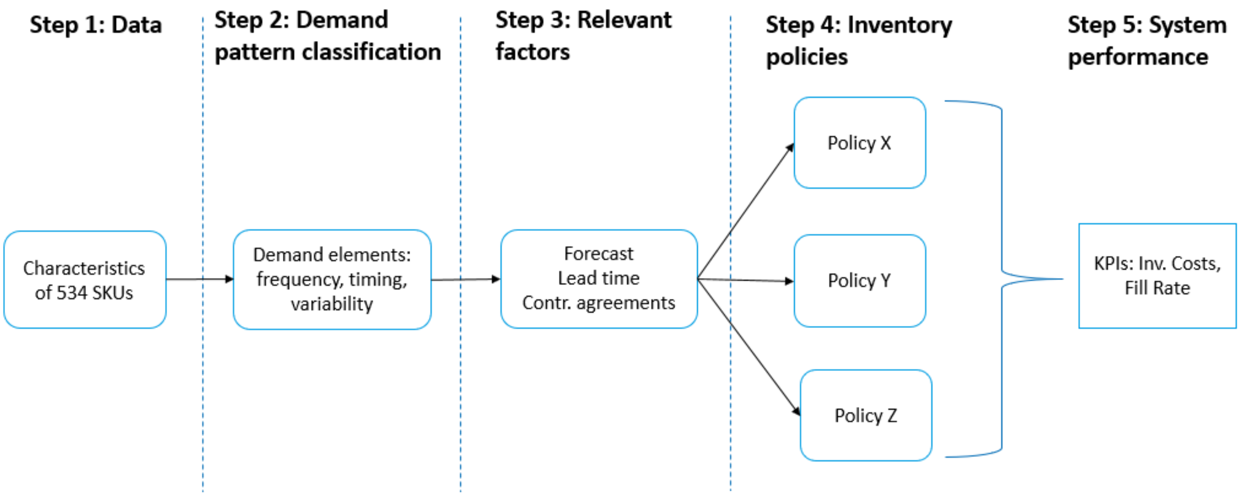

Figure 5: Model overview

As explained in Ch4, at the moment Company X does the inventory planning with the help of Slim4 and SAP. For SKUs without a customer forecast, the (R, s, nQ) policy integrated in Slim4 is applied for which the inventory parameters are set by Slim4 or manually. For SKUs with a customer forecast, the forecast module in SAP (MRP approach) is used which performs the whole inventory planning and sets a certain safety stock level. However, the performed analyses of the current situation shows that the desired service level is not met for a number of SKUs or only at too high costs. It can be the case that inventory parameters were not set correctly and that it is still possible to meet the desired service level applying Slim4 or SAP against acceptable costs. On the other hand, it is possible that the desired service level can't be met with the help of the current inventory policies and an alternative policy has to be selected.

An action plan or decision tree will be developed for inventory purposes in which the SKUs in scope will run through a few steps. First of all, the demand characteristics for the SKUs in scope are studied which will eventually result in a demand pattern classification. Since a SKU's demand behavior can affect the choice for an inventory strategy, it makes sense to perform an analysis of SKUs' historical demand data. In this step, different demand elements are analyzed, for example the variability of the demand and the timing of the demand. The outcome of this analysis will eventually result in a demand pattern classification.

Second, it is important to deepen into the factors which play a big role in the working environment of Company X. The analysis of the current situation indicates that replenishment lead times are on average quite long which has a big effect on Company X's operations. Next, a number of customers provide a forecast to Company X and these forecasts completely determine the inventory management for these SKUs. So, this is a factor to take into consideration and to analyze. Besides, the client specific SKUs and the possible contractual agreements attached to this (e.g. call-off contract with fixed replenishment quantities or strict service levels) have a big impact on the inventory planning. In short, the next step is to analyze these relevant factors and to determine its influence.

The last step is to assign one of the selected inventory policies to the SKU. A certain scope is set by which policies have to comply based on the working environment of Company X, the relevant factors and the SKU characteristics. In the end, the performance of the described model is tested with the help of two KPIs which are discussed in 5.1.2. The purpose of the analysis is improving the service level towards the customer by assigning a different control policy to a number of SKUs if necessary or changing the value of the inventory parameters for a part of the SKUs. It is a trade-off between working capital and service level (inventory efficient frontier). One has to make a choice between spending more money (and meeting the desired service level) or sticking to a certain ('acceptable') service level (and saving money). The next figure shows an example of an efficient frontier graph. In this example, it is looked into the service level and supply chain costs.

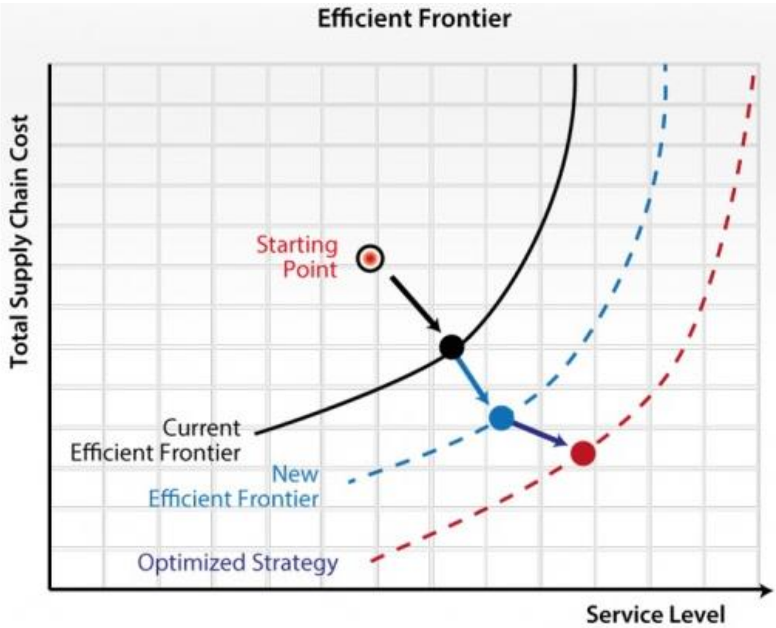

Figure 6: Example efficient frontier

The curve that results from graphing the trade-off between inventory cost and service level is called an "efficiency frontier". As service level requirements increase, the cost of inventory travels up along this curve. Inventory optimization can move an organization to an entirely new trade-off curve; a better efficiency frontier that produces higher service levels at lower inventory cost than was possible before. Using these curves, it can be checked if it is possible to meet the desired service levels with the current inventory policies for each SKU. In case it is not possible to reach this desired service level for a certain SKU, one has to change to one of the other inventory policies in scope.

5.1.2 System performance

As can be seen in the model overview, the performance of the new system will be measured by 2 different KPIs. The goal of this project to improve the service level for a number of SKUs and to reduce the waste of working capital (cost savings) for a number of SKUs if possible. Therefore, the inventory costs and the fill rate will be selected as KPIs. In the end, this will be a trade-off between inventory costs and fill rate (service level) as just discussed.

1. Inventory costs

Generally, the inventory costs consist of 3 components: ordering costs, holding costs and stock out costs. In this project, it is decided to only focus on the inventory holding costs, because the ordering costs are always the same caused by all the MOQs. A complicated factor is that the historical inventory on hand levels are not stored in a good way for all SKUs which makes it impossible to make a comparison between the old and new situation regarding average inventory levels. However, it is possible to compare the safety stock levels for the different SKUs in the new and old situation. The safety stock often has a big impact on the inventory value and inventory costs. On the one side, SKUs with too large safety stock levels are addressed and can possibly decreased. On the other hand, the safety stock levels for SKUs with problems in meeting the service level will be increased.

2. Fill rate

The fill rate is the long-term fraction of demand delivered immediately from stock, i.e. the inventory on hand. Since the supplier lead time is on average quite long at Company X, it is important to be able to supply from stock on hand and have sufficient inventory available all the time. It has a significant impact on your relationship with your customers. It affects whether they trust you and whether they choose to order from you over your competitors, because you are able to deliver immediately from stock.

5.2 Demand pattern analysis

As can be read in the model introduction, the demand characteristics for the SKUs in scope are analyzed and eventually the SKUs are assigned into different demand pattern categories. A demand pattern shows the variation in sales over the years and can give an indication for the future sales. Most of the time a repeatable cycle or other repetitions can be found in historical sales data. Categorizing SKUs into different type of demand patterns makes it easier to choose an inventory policy for your SKUs. Besides, it is impossible to select an inventory control policy without knowing what kind of demand you are encountering.

The different type of demand patterns can be categorized in many ways. A distinction can be made between fast-moving and slow-moving items. Fast moving items are items that are sold on a frequent basis (high demand frequency) and for which the average order quantity is not that small. Slow moving items are products with a low consumption rate and for which the number of customer orders is low during a year. On the other hand, a division can also be made between items with smooth demand patterns and items with irregular/fluctuating demand patterns. Smooth demand patterns show sales very regular in time and in quantity. The variability in demand is very low during the year and the time interval between customer orders is very constant. In contrary, irregular demand patterns show a great variation on a seasonal, monthly or weekly basis. The customer order differ in quantity a lot and the time between orders is not consistent.

The different SKUs in scope will be classified into a number of demand pattern groups by studying two demand elements or characteristics. First of all, the demand frequency is studied which is equal to the number of sales orders for a particular SKU in a given time period. Besides, the demand variability is analyzed which shows the variation in demand quantities.

The first part of the demand pattern analysis is focused on non-moving SKUs. The analysis of the current situation (Ch 4) shows that a big part of the SKUs in scope didn't have any product demand in the last 12, 24 or even 36 months. These so-called non-moving inventory has a big impact on a company's working capital and it is important to identify the SKUs belonging to this category. To identify the non-moving SKUs, one demand characteristic is studied namely the demand frequency. Historical sales data is studied and the demand frequency is determined by calculating average number of sales orders during a year. In the end, SKUs of which the number of sales in the last 12 months is equal to 0, are classified as non-moving.

In the remaining part of the demand pattern analysis, two demand characteristics are studied for the SKUs in scope, namely the frequency of demand and the demand variability. After this step, it is known what the demand pattern of these SKUs look like and SKUs are assigned into four possible demand categories. The whole process is based on the demand classification scheme of Syntetos, Boylan & Croston (2005).

This scheme categorizes demand patterns by determining the characteristics of a demand history with two coefficients:

- The first coefficient is the **Average Demand Interval** (ADI), it measures the regularity of a demand in time by computing the average interval between two demands. It gives an indication of the frequency of customer orders and the rate of consumption.
- The second coefficient is the **Square of the Coefficient of Variation** (CV^2), it measures the variation in the demand quantities. This measure is used to analyze the difference of spread in the sales data relative to the mean value.

The outcome of the calculation for both coefficients determines the type of demand pattern for each SKU. Based on these 2 dimensions and certain limit values, the literature classifies the demand profiles into 4 different categories:

- **Smooth demand** ($ADI < 1.32$ and $CV^2 < 0.49$): The demand is very regular in time and in quantity
- **Intermittent demand** ($ADI \geq 1.32$ and $CV^2 < 0.49$): The demand history shows quite constant levels of consumption but it occurs at infrequent, irregular and often unpredictable intervals.
- **Erratic demand** ($ADI < 1.32$ and $CV^2 \geq 0.49$): The demand has regular occurrences in time with high quantity variations.
- **Lumpy demand** ($ADI \geq 1.32$ and $CV^2 \geq 0.49$): The demand is characterized by a large variation in the quantity of demand and in the interval between two demands.

The next figure gives a graphical representation of the 4 different demand categories.

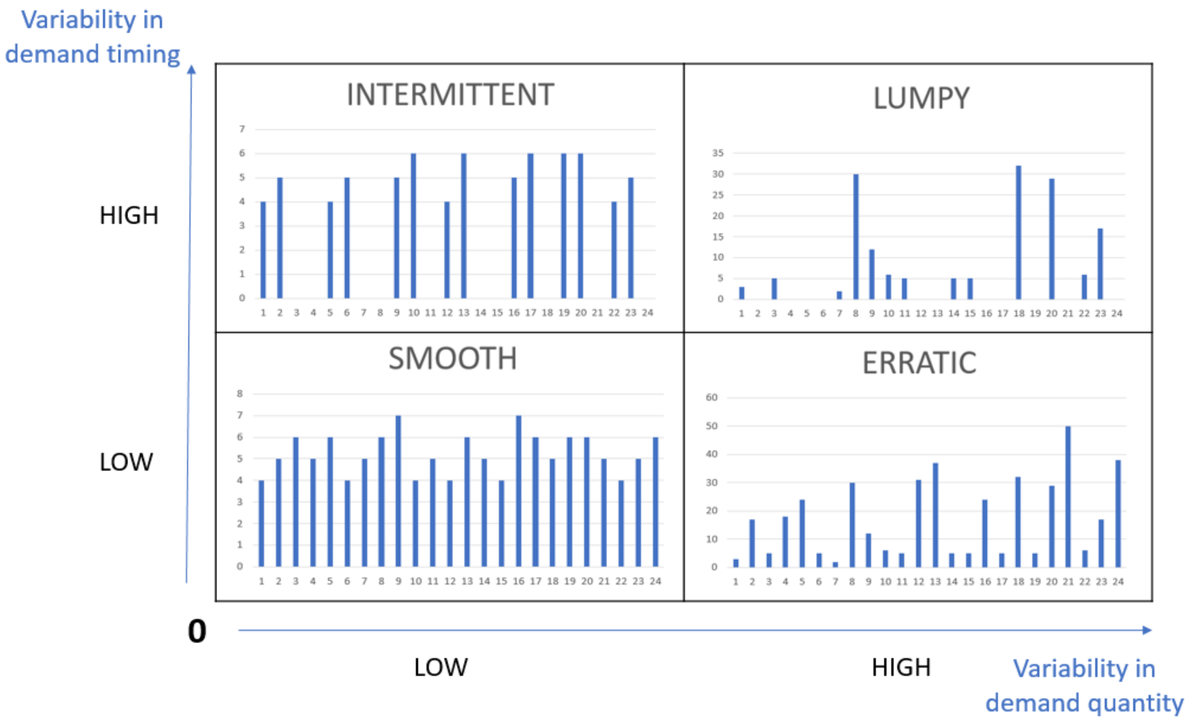

Figure 7: Demand categories (Croston, Boylan & Syntetos, 2005)

Concluding, the SKUs can be classified into 5 demand pattern categories. First, SKUs without sales in the last 12 months are classified as singular. Next, SKUs with a somewhat higher demand frequency can be classified as smooth, intermittent, erratic or lumpy. A graphical representation of the 5 demand patterns is presented below.

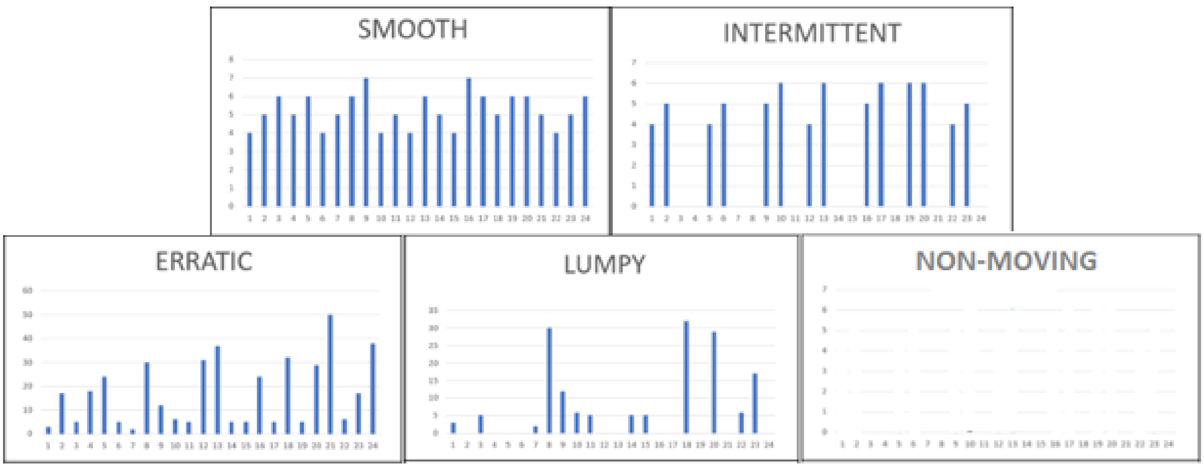

Figure 8: 5 possible demand patterns

In the end, the SKU is assigned to one of the 5 possible demand patterns. However, the demand behavior of each SKU is not always constant over time and changes are possible. For example, there can no sales for 3 months for a SKU with a smooth demand pattern at some point. Such a change or shift in the demand trend has to be recognized, so that actions can be taken on time (changing the inventory strategy and/or inventory parameters can be adjusted). Since one of the goals of this project is to reduce the waste of working capital, it is important that the decision tree is run through for all SKUs every 3 months. This ensures that all information is updated so that changes in demand are recognized and inventory strategies can be adjusted.

Besides, it has to be investigated if the cutoff values (for the ADI and CV^2) set by Syntetos, Boylan & Croston (2005) and the threshold value for the demand frequency are indeed well chosen for Company X's situation. It can be the case that the cutoff values result in a moderate performance of the classification tree and that other values possibly results in a better performance. Every situation is different the cutoff values determined by Syntetos, Boylan & Croston (2005) don't have to work well in every circumstances.

5.3 Relevant characteristics/factors

Before making a choice for an inventory policy, it is important to verify a few factors that can affect the choice for controlling the inventory. The type of product managed and factors around/within the business environment have an impact on the possibilities for controlling inventory. Inventory control policies should be prioritized around the nature of the inventory moving through the supply chain and should be matched to the type of SKUs in the assortment. In the next paragraphs, a number of factors affecting the way inventory is controlled, are described in detail.

5.3.1 Service level agreement

First, a strict service level agreement (SLA) can be made between Company X and one of its customers. Companies often have service level commitments with its customers on product availability, product quality and on-time deliveries. Under-performance against a SLA can result in penalties that are factored into the determination of contract price. Performance during a period is compared against a contracted service level and outcomes exceeding some allowed deviation are penalized. Since a lot of SKUs in scope are customized and specially designed for a customer, a contract has been signed which can include an agreed service level which has to be met by Company X. This agreed service level is fixed and Company X has to do as much as possible to achieve this service level. The customer keeps in track a so-called OTIF (On Time In Full) score which measures how often the customer gets the products they want at the time they want it (usually expressed as a percentage). An example of an OTIF score matrix is shown in the figure below. It is important to mention that it is not always clear to what extent these agreements have to be fulfilled by Company X and how exactly these service levels are described in the contract. Concluding, in case a SLA is made for a SKU, this can influence the inventory strategy. If the desired (and agreed) service level is not met with Slim4, this is a reason to change the strategy.

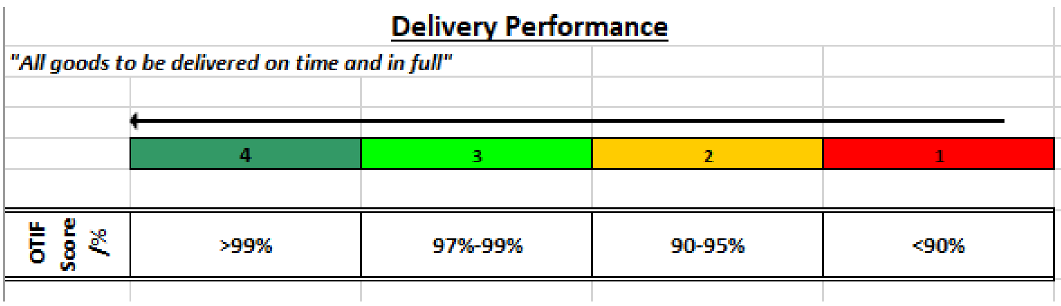

Figure 9: OTIF score matrix used by one of Company X's customers

5.3.2 Customer forecast

Second, the availability of a customer forecast affects the way inventory is controlled. As mentioned in Ch 4.2, a number of customers provide a prognosis of their purchases to Company X that all differ in type, length and format. Most customers provide a rolling forecast of their expected purchases in the coming 12 months indicated per month. Accurate forecasts can be valuable in inventory planning and affect the choice for controlling the inventory. As described in the literature study in Ch. 3.2.2, ADI in the form of a customer forecast is really beneficial for the inventory management of companies and especially to Company X with its long supplier lead times. In such an environment, it is crucial to collect as much ADI as possible.

It is important to determine the accuracy of these customer forecasts and to decide if it is useful using the customer forecast for the SKU in question. In Ch 4.7, the realized sales and the forecast were compared on a monthly basis and the percentual deviation was calculated in case a customer forecast was available. After all the calculations are performed, a certain benchmark has to be set to determine if the forecast is accurate enough which can be done by comparing the level of forecast accuracy for the different SKUs with each other. With the help of these outcomes, this benchmark can be set looking to different measures (e.g. the median and average) and in consultation with Company X. In case the forecast is considered as accurate, this changes the way the inventory is controlled. The whole inventory planning can be based on these forecast and no inventory model has to be selected. A certain safety stock is set and the forecast module from SAP can do the inventory planning for these SKUs.

Concluding, a limit value is set for the level of accuracy of the customer forecasts. If the level of accuracy is below this value, the customer forecast is used for inventory management. If not, the customer forecast is not used and an own demand forecast is made for the SKU.

5.3.3 Lead time

Lead times are one of the most important foundational components of inventory planning. Since Company X has a lot of SKUs in its assortment with a relative long replenishment lead times, it is important factor to take into account. More inventory is required if the replenishment lead time is longer. At Company X a planned lead time is set in the ERP system (SAP) for most SKUs which is updated twice a year. The planned lead time (PLT) refers to the budgeted time between the moment a replenishment order is placed until the moment the product arrives at the warehouse.

On the other hand, there is lead time to the customer. The costumer lead time is equal to the period starting from the time when a customer orders some products from the assortment to the time when the products are delivered to the customer. In case the customer lead time is longer than the supplier lead time for a SKU, Company X as a wholesaler can manage this SKU by holding no inventory. If a customer order is placed, Company X places a replenishment order at its supplier and can immediately deliver the ordered products to its customer to fulfil the order.

The replenishment lead time is a key component of inventory control policies since it directly influences the safety stock level and reorder point level. It is important to mention that the calculated inventory parameters (safety stock and reorder point) has to be corrected with a certain factor depending on the way the demand is forecasted as described in the paper of Prak, Teunter and Syntetos (2017). These correction is larger at a longer replenishment lead time. Concluding, lead time plays a crucial role in inventory control.

5.3.4 Supply contract

Supply contracts can also affect the method for managing inventory. It occurs that Company X and one of its customers made agreements about fixed replenishment quantities which have to be purchased over the year. In this situation, a contract is set up in which it has been agreed that Company X keeps a certain amount of SKUs on stock and that the customers purchases these SKUs within a certain time period. This restricts the choice for an inventory control policy. These so-called call-off contract is a purchase order which enables bulk orders over a period of time (for example a year), usually negotiated or predetermined pricing. It allows the supply of materials to be secured over multiple delivery dates and it is normally used when there is a recurring need for a particular product from the customer. Concluding, when Company X has a call-off contract with one of its customers, this determines the complete inventory strategy most of the time and no inventory control model has to be applied.

5.3.5 Inventory parameter agreement

A contractual agreement can be made with a customer regarding base stock levels or other inventory parameters (reorder point and safety stock level). One of the requirements of a customer can be that always a certain amount of SKUs (a base stock level) is available at Company X all the time. A base stock level is a minimum level of inventory that always has to be available at the company in order to fulfill customer orders with a delay no greater than expected by customers. The whole inventory planning and order behavior is focused on keeping the inventory level always above the base stock. In short, the base stock level agreed in the contract determines the way the inventory is controlled.

On the other hand, it happens that customers demand that Company X works with a certain safety stock level. As explained in Ch 4.2, SKUs with a customer forecast get a certain safety stock level which is often determined in consultation with the customer. In some cases, a strict agreement is made with the customer and the level of the safety stock is recorded in a contract. Because of this, no changes can be made to the inventory parameters. Concluding, a contractual agreement can ensure that the inventory parameters (i.e. base stock level or safety stock) are fixed and predetermined.

A big disadvantage in Company X's situation is that there is no clear overview of these agreements about inventory parameters. There doesn't exist a file in which is described for which SKUs such agreements have been made and what this agreement entails.

5.3.6 Standard assortment SKU

It can be the case that Company X wants to have a certain fixed inventory level for a SKU. These so-called standard assortment SKUs are basic industrial engineering components for which every customer expects Company X has this product on stock. This concerns for example standard sizes O-rings or certain type of seals which you can buy at every technical wholesaler. Not having these SKUs on stock may result that a customer decides to switch to one of Company X's competitors. Not taking into account any factors or a certain cost considerations, a base stock level is determined for these standard assortment SKUs, for example one or two times the MOQ. It is a somewhat more 'subjective' factor. Besides, it is for an outsider impossible to determine what a standard assortment SKU is. An assumption or agreement with Company X has to be made how to deal with these SKUs.

5.4 Inventory policies in scope

Next, an inventory control policy is assigned to each SKU. Because the goal of this project is to improve the service levels for the SKUs in scope, the focus is on service oriented inventory control models. Besides, a choice is made for periodic review models in an environment in which backordering is allowed. In the end, the reorder point policy integrated in Slim4 is selected as main model on the basis of which all the possible policies are derived. In case it is not possible to achieve the desired service level applying the main model, a few other policies are considered. In the remainder of this subchapter, the different policies are discussed.

5.4.1 (R, s, nQ) policy

First of all, a standard reorder point policy or a so-called (R, s, nQ) policy is a possible strategy that can be applied in the situation of Company X. It is the policy that is integrated in Slim4 and by which the inventory planning for most SKUs is currently performed. As already explained, a replenishment order is placed if the inventory position drops below the predefined reorder point at the moment of reviewing. This reorder point consists of two components: a certain inventory level to cover the demand during the lead time and a certain safety stock level. This reorder point is determined on the basis of the forecasts made using exponential smoothing. The reorder quantity is equal to the EOQ. If the MOQ at the supplier is bigger than the EOQ, the reorder quantity is equal to the MOQ which will probably the case for most SKUs. As studied in Ch4.6, the reorder quantity is almost never equal to the EOQ for most SKUs in scope. A graphical presentation of this strategy is shown in the following figure.

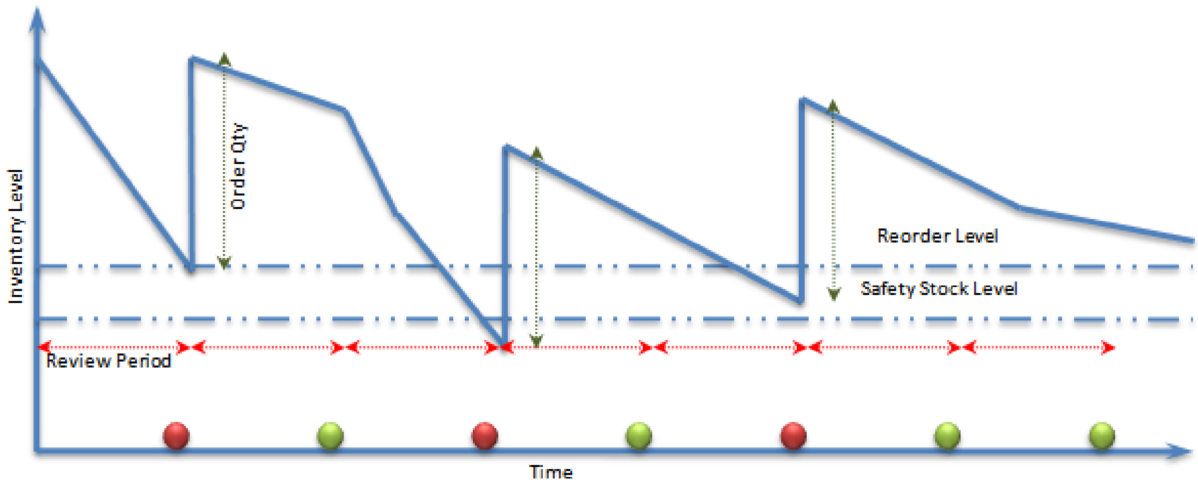

Figure 10: (R, s, nQ) policy

A detailed description of the (R, s, nQ) policy is provided in de Kok (2012).

In practice, this policy performs well for SKUs with a constant demand stream with a small variability in order quantities (i.e. smooth demand pattern), because of the Normal distribution assumption made by Slim4 as mentioned in Chapter 4. This also results in some limitations. In case of a slow-moving SKU or a SKU with an irregular demand pattern, Slim4 has a hard time making an accurate forecast and consequently, set the correct inventory parameters (safety stock and reorder point).

5.4.2 MRP inventory control

Second, the SKUs can be managed with a MRP approach using the forecast module integrated in SAP. This is the approach that is currently used for SKUs with a customer forecast as described in Ch 4.2. The forecasts are processed into SAP and then the forecast module makes an inventory planning for the specific SKU. A certain safety stock level is set and the forecast module in SAP determines when a replenishment order has to be placed based on the customer forecasts, the outstanding sales orders and the safety stock level. The complete inventory planning depends completely on the requirements entered in the forecast module, which take into account safety stock, minimum order quantities, forecasted demand and actual demand. The main objective is to plan the future replenishment orders based on requirements and to order the required quantities on time for fulfilling customer demand.

At the moment, one of the biggest restrictions of this approach is that the safety stock level is set randomly and is not based on the forecast error. The accuracy of the customer forecasts is not calculated by which it is not known how reliable they are.

5.4.3 Order-up-to policy

Because Slim4 has a hard time managing SKUs with not that many historical data points (slow-moving SKUs), an alternative policy has to be proposed for these SKUs with an intermittent demand pattern. A policy that might be suitable for SKUs with intermittent demand is the order-up-to level policy described in Teunter and Sani (2009). They produced a paper to calculate order-up-to levels for SKUs with intermittent demand. In this paper, Croston's forecasting method is used to determine future demand. What differs from the Exponential Smoothing method (integrated in Slim4) is that Croston only updates the forecasts if a positive demand occurs. Not taking the zero demand periods into account should be better while forecasting intermittent demand and should result in a better performance.

As just mentioned, a demand forecast is made using Croston's method which is related to exponential smoothing. These Croston forecasts need to be transformed into an expected total lead time demand which can be used to calculate the order-up-to levels. Besides this, an estimate for the forecast error is needed. This expected value and the forecast error are used to determine the inventory control parameters. The strategy is based on the fact that only action is taken in each period with a positive demand. In case there is period with positive demand, the following steps are followed:

- The demand occurs,
- Stock on hand, stock on order and backorder levels are updated,
- The order-up-to level is updated which is equal to the demand during lead time plus safety stock
- If the inventory position (on hand – backorders + on order) is less than the order-up-to level then the difference is ordered,
- An order arrives if one has been placed L period ago.

5.4.4 Cutoff transaction size policy

Another alternative control policy is selected for SKUs with a great variability in demand sizes (erratic demand). As mentioned before, the (R, s, nQ) policy integrated in Slim4 is not able to manage SKUs with an irregular demand pattern. Most of the time, a number of extremely large sales orders result in a disruption of the inventory system. In order to avoid disrupting the inventory system, a cutoff transaction size of X units can be specified such that customer demands with sizes exceeding X units will be filtered out of the inventory system and treated as special orders. These special orders are partially fulfilled and the remaining part of the sales order is fulfilled at a later point in time (or just rejected). This is most likely advantageous for the normal-sized customer orders following after an extremely-sized customer order as the stock is not depleted completely. Likewise, due to the reduced variability, the inventory level can be reduced.

It is proposed to manage these SKUs with the cutoff transaction size policy described in Mak & Lai (1995). They have analyzed an order-up-to level inventory system with a cutoff transaction size X. The system routinely satisfies customer orders with a size smaller than or equal to X. For customer orders with transaction sizes larger than X units, the system would only supply the cutoff amount (X units). The excess units would be refused and delivered at a later point in time (backordering). The demand distribution was approximated by a stuttering Poisson distribution (i.e., a compound Poisson distribution where the order sizes have a geometric distribution) and they presented an algorithm to determine the optimal order-up-to level for a given cutoff transaction size X. This cutoff size ensures that extremely large orders are removed. These large orders normally complicate and blur the forecasting.

5.4.5 Remaining strategies

A few more inventory strategies can be applied in the situation of Company X of which an enumeration is given below. These remaining strategies are less elaborate, have a more heuristic and are not described in scientific papers as the 6 policies explained before.

1. No inventory: Holding no inventory is an option for SKUs for which the customer lead time is longer than the supplier lead time. If a sales order is placed for this SKU and this sales order is bigger than the inventory position, a replenishment order is placed equal to the MOQ at the supplier.
2. Follow contract: In case of a call-off contract, it is possible that only the conditions/agreements from the contract are followed. At the beginning of the contract, 1 large purchase order is placed for a customer and then the sales orders of this customer are fulfilled. In the end, only the agreements from this contract has to purely met.
3. Set inventory parameters: A certain fixed safety stock level, reorder point and/or base stock level has to be set in case of a contractual agreement. Based on this, the inventory for these SKUs is managed. Besides, a base stock level (equal to the MOQ) has to be set for the SKUs classified as standard assortment SKUs on which the complete strategy is based.
4. Make customer agreement: It is possible that an agreement with the customer is made for a certain SKU, because of the irregular/unpredictable demand pattern for this SKU. This means that the customer is requested to provide a forecast to Company X or that agreements are made about a specific base stock level.

5.5 Conclusion

The figure on the next page shows the final decision tree or classification system. The white rectangles represent the different components affecting the choice for an inventory policy which have to be analyzed for each SKU. On the other hand, the yellow rectangles are the inventory strategies in scope that can be assigned to the SKUs for which afterwards the inventory parameters (e.g. reorder point, safety stock, order-up-to level) are calculated. The performance of the result of this analysis is tested with 2 KPIs namely inventory costs and the fill rate. In the end, a trade-off has to be made between the desired fill rate and the costs that have to be made for this purpose, using the efficient frontier graph.

First of all, it is checked if there is a service level agreement (SLA) made for the SKU, if there is a customer forecast available and what the length of the supplier and customer lead time is. It is not important to know what the demand pattern of the SKU looks like for these 3 factors. A SLA only determines the desired service level for the SKU and in case of a customer forecast, the SKU can be controlled by following the forecast. If the customer lead time is bigger than the supplier lead time, the SKU in question can be controlled by holding no inventory, so it is not important how the demand pattern looks like.

After running through these 3 factors, a demand analysis is performed on the basis of which SKUs are assigned to 1 of 5 the possible demand patterns (smooth, intermittent, erratic, lumpy or non-moving). Then, 3 more components are investigated: the possibility of a supply contract, a possible inventory parameter agreement and whether it is a standard assortment SKU or not. For these 3 factors, it is crucial to know what the demand pattern is for the SKU. In case of a supply contract, there is often more demand to the SKU (from other customers) than is defined in the supply contract. If there is an inventory parameter agreement for a SKU, it happens a lot that only an agreement is made about the safety stock and that the reorder point or order-up-to level still needs to be defined based on the demand pattern. At last, it is only important to know if a SKU is considered as a standard assortment SKU in case of a slow-moving SKU which is only possible with an intermittent or lumpy demand pattern.

Concluding, the proposed decision tree can be used to assign an inventory policy to the SKUs in scope. Using efficient frontier graphs, the difference between the new and old situation with the help of 2 KPIs. In the end, a balance has to be found between inventory costs and fill rate.

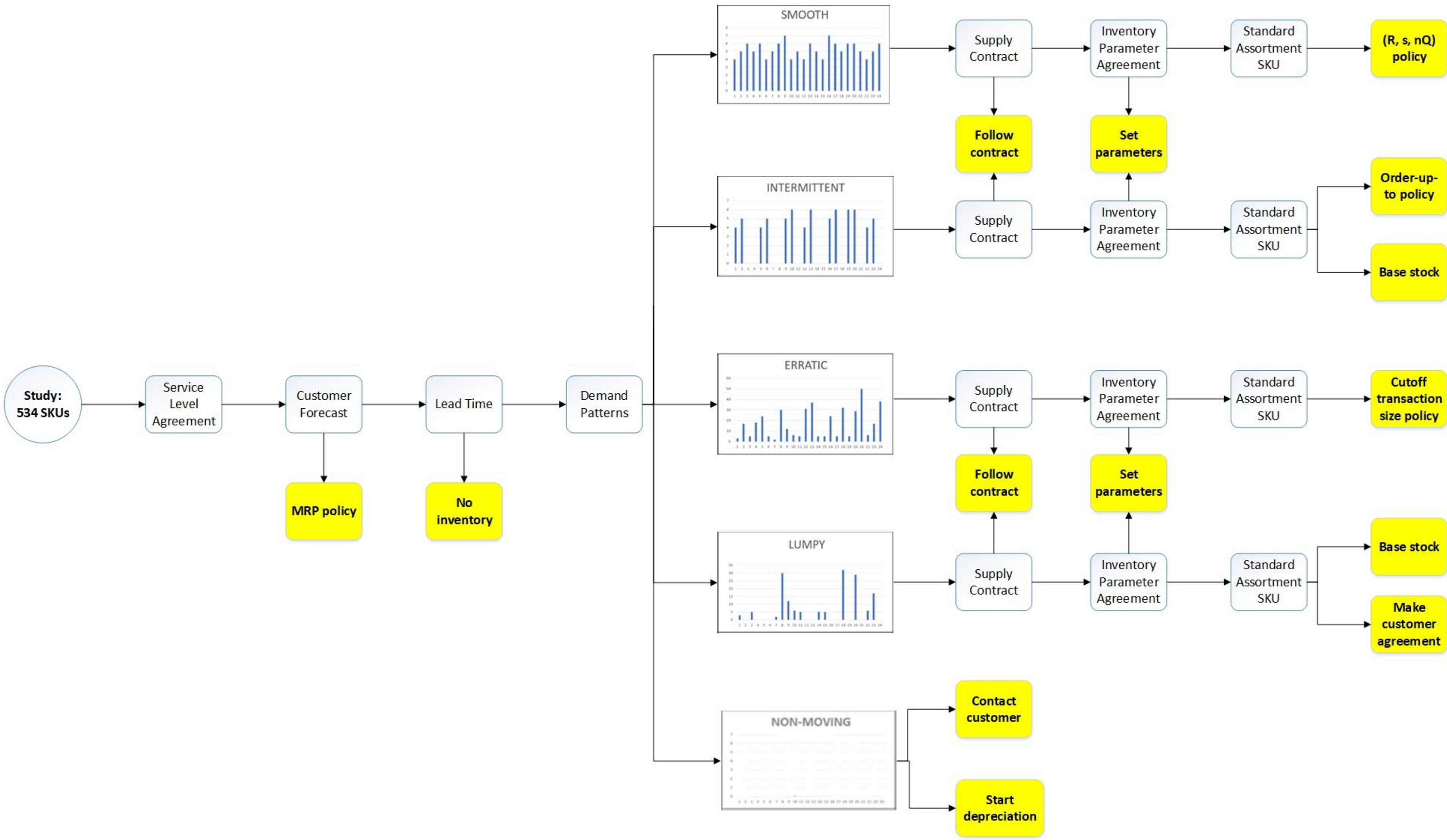

Figure 11: Decision tree

6. SKU classification

The previous chapter investigated the conceptual design for the inventory classification system. In this chapter, the different steps from the developed classification system is run through for the SKUs in scope. It is focused on the relevant factors/characteristics which can influence the choice for an inventory strategy. The outcome and considerations at each step are discussed. Afterwards, it is known what inventory strategy is assigned to each SKU.

6.1 Service level agreement

The first step in the system is to check if there is a SLA with the customer concerning the delivery performance (on-time deliveries) of the product. Under-performance against a SLA can result in penalties and possible claims that has to be paid by Company X. However, it is important to mention that is not always clear how 'strict' the service level agreements stated in these contracts are. A lot of customers don't even communicate a certain service level to Company X. Most costumers only want that there is a constant demand stream and that the number of delays (and backorders) is limited. If that is the case, the customer won't complain when the service level is not exactly met.

In the end, it is decided in consultation with Company X to make a distinction between customer specific and not customer specific products. The desired service level for customer specific (tailor-made) products is 99% and the desired service level for the other products is 95%. The outcome with the number of products is shown in the table below.

Table 19: Outcome service levels

Category	Service level	#SKUs
Customer specific	99%	407
Other	95%	127
Total		534

6.2 Customer forecast

Second, it is checked if there is a customer forecast available for the SKU in question and how accurate this forecast is. The realized sales and the forecast are compared on a monthly basis and the percentual deviation (i.e. MAPE) is calculated. In case the customer forecast for a SKU is considered as accurate enough, this SKU can be controlled the help of the SAP forecast module. The forecast analysis shows that the average MAPE is quite high (49,5%) for the 101 SKUs studied and that this percentual error is below 25% for only 25 SKUs. Looking to the median (35,4%) and in concertation with Company X, it is decided to set the limit value at 40% which means that SKUs with a MAPE higher than 40% are not considered as accurate enough. The outcome with the number of SKUs are presented below.

Table 20: Customer forecast limit values

Category	#SKUs
<40%	59
>40%	42
Not calculated	56
Total	157

6.3 Lead time

It is investigated what the length of the customer and supplier lead time for each SKU is. Company X as a wholesaler can manage a SKU without holding any inventory in case the customer lead time is longer than the supplier lead time. If a customer order is placed, Company X places a replenishment order at its supplier and can immediately deliver the ordered products to its customer to fulfil the order. However, Company X has to deal with relatively long supplier lead times (the median is about 2 months). Besides, Company X does not work with fixed (planned) delivery times towards the customers for each SKU. In most cases, a delivery date is agreed with the customer which is often 2 or 3 days after the sales order is placed. Because of this, the 'no inventory' option is not possible for the SKUs in scope. However, it may apply to SKUs in Company X assortment that are not in the scope of this project.

After these 3 steps, a first distinction can be made between the SKUs in scope and a number of 'trays' are created to which a certain inventory is attached. The next table gives an overview of the results so far.

Table 21: Provisional outcome decision tree

Tray	#SKUs	Inventory strategy
Customer forecast	59 98	MRP policy ?
Lead time	0	No inventory
Remaining SKUs	475	

As can be seen in the table, 59 SKUs have already been assigned an inventory strategy. It is not necessary to run through the demand pattern step for these SKUs. For the remaining 475 SKUs, the demand pattern is analyzed and classified into 5 possible categories, after which the 3 remaining steps are run through.

6.4 Demand pattern

The next step in the classification system is to analyze demand characteristics and to classify the demand into 5 possible categories. As can be read in the previous chapter, 3 demand characteristics are calculated to classify the demand pattern, namely demand frequency, the timing of demand and the variation in demand quantity. The 5 demand pattern categories are illustrated below.

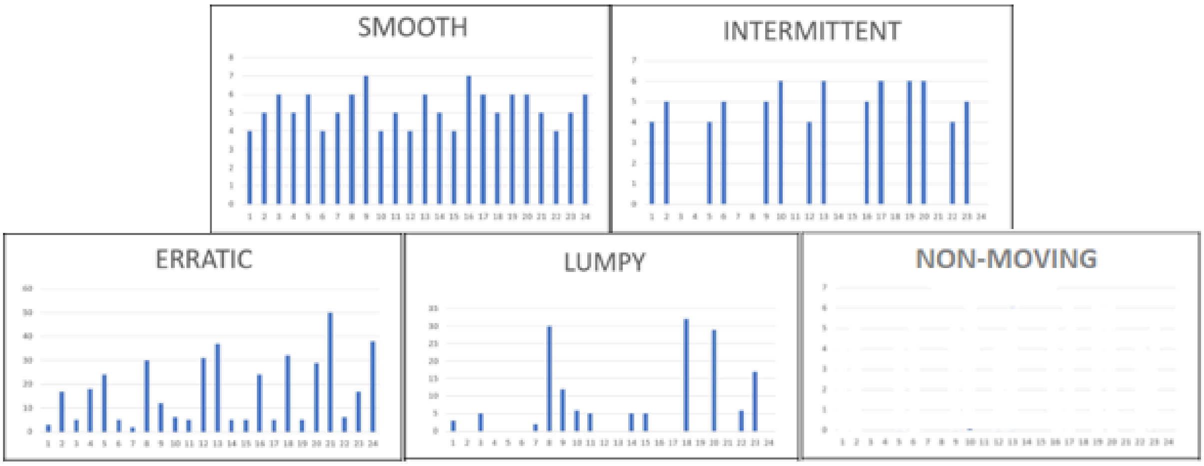

Figure 12: Overview demand patterns

To calculate the 3 demand characteristics, the following formulas are used.

1. Demand frequency: This is simply summing the number of sales orders for a particular SKU over the last 12 months. In formula: $F = \sum_{t=1}^{t=12} O_t$, in which O_t is the number of sales orders during a certain month.
2. The timing of demand: The average interval between two demands is computed. It is calculated by the following formula: $ADI = \frac{\sum Intervals\ between\ non\ 0\ demand\ periods}{\sum Periods\ with\ demand}$. A period will be equal to one month the calculation will be performed based on customer orders from the last year.
3. Demand variability: The coefficient of variation is calculated for each SKU which is a measure of relative variability in the sales data. In formula: $CV^2 = (\frac{\sigma_D}{\mu_D})^2$ (σ_D is the standard deviation of the demand and μ_D is the average demand). The calculation is done with the help of monthly sales levels from the last year.

As already written in Chapter 5, the cutoff values for the 3 demand characteristics are based on the paper from Syntetos, Boylan and Croston (2005). Using these cutoff values, the SKUs in scope are assigned to 1 of the 5 possible demand patterns. The performance of these cutoff values has to be questioned and the values have to be evaluated (and adjusted if necessary). In the end, it is decided stick to the proposed cutoff values and not to perform an analysis for other values. The biggest reason for this is a lack of time. Besides, all the papers from Syntetos, Boylan and Croston are cited a lot and because of this, it is plausible that the information from their research results in an acceptable performance.

Calculating the 3 demand characteristics and performing the analysis leads to the following outcome of the demand pattern classification as presented in the table.

Table 22: Demand pattern classification

Category	#SKUs
Smooth	122
Intermittent	153
Erratic	38
Lumpy	39
Non-moving	123
Total	475

Besides, a graphical representation is made in which the outcome of the demand pattern analysis is presented. The figure shows what the exact division is looking to the inventory types used at Company X as explained in Chapter 4.

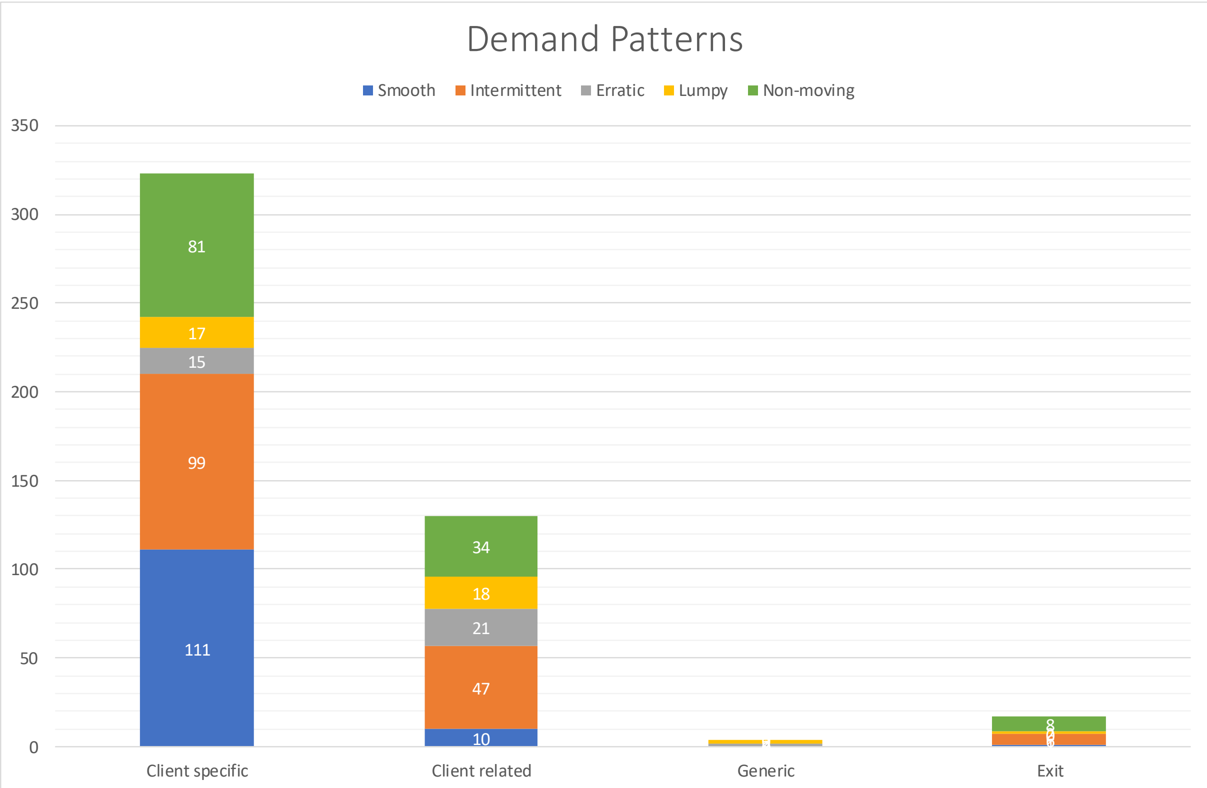

Figure 13: Demand pattern classification

6.5 Supply contract

It is checked if there is a call-off contract has been set up for one of the SKUs in scope, what the due date of this contract is and what this contract entails. Company X may have put a certain amount of SKUs on stock for a specific customer which have to be bought by the customer before a certain date. The contract can determine the complete inventory strategy for the SKU in case the total demand for the SKU in question consist of the amount defined in the contract. It means that Company X only has to place one big purchase order for this SKU once and purely has to fulfill the customer orders for this SKU. It seems that such an agreement is made for 1 SKU in scope. However, it appears that this SKU has a defined reorder point and safety stock. The call-off contract was set up to put additional SKUs on stock for 1 customer which means that this call-off contract doesn’t influence the inventory strategy. Concluding, none of the SKUs in scope belong to this category. However, it regularly happens that Company X produces 1 batch of tailor-made SKUs for a specific customer that needs to be purchased within an agreed time period by this customer. So, this option may apply to SKUs in Company X assortment in which one big replenishment order is placed and no specific inventory policy has to be applied.

6.6 Inventory parameter agreement

It is possible that a contractual or verbal agreement is made with a customer regarding a certain base stock level or safety stock. As a result of such agreements, the inventory parameters are predetermined. This results in a situation in which the inventory strategy is already completely determined (base stock) or the choice for a strategy is limited (safety stock). As discussed in the previous chapter, there is no clear overview of SKUs for which inventory parameter agreements have been made with the customer. Because the inventory parameter agreements are not properly recorded and it is for an outsider impossible to determine which SKUs belong to this category, it is decided to assign none of SKUs to this category. However, these agreements influence the inventory strategy and it is important to make a separate category for these SKUs.

6.7 Standard assortment SKU

At request of Company X, a separate category is made for basic mechanical engineering SKUs for which a fixed inventory level or base stock level is set not taking account any factors (e.g. supplier lead time or service level) or cost aspects. A base stock level is set equal to the minimum order quantity at the supplier and it is not needed to make a demand forecast for these SKUs. Company X classifies this SKU as a standard assortment SKU of which always a certain number of SKUs have to be on stock. As already mentioned in the previous chapter, it is impossible to determine for an outsider what these standard assortment SKUs are. Therefore, it is decided to assign none of SKUs in scope to this category. However, it is a factor that determines the complete inventory strategy for a SKU if you know what these standard assortment SKUs are.

Since all the steps of the classification system have been run through, it is possible to give an overview of the different classification 'trays'.

Table 23: Final outcome decision tree

Inventory strategy	**#SKUs**
MRP policy	59
No inventory	0
Follow contract	0
Set agreed parameters	?
(R, s, nQ) policy	122
Order-up-to policy	153
Cutoff transaction size policy	38
Make customer agreement	39
Contact customer or start depreciation	123
Total	534

7. Inventory modeling

The previous chapter discussed the different steps from the proposed classification system and applied the system to the SKUs in scope. As the inventory strategy is known for the SKUs in scope, this chapter explains the different strategies in scope. The expressions used to generate and solve the different inventory strategies are disclosed and the application of the inventory strategy is discussed. For a part of the SKUs in scope, the inventory parameters will be the same as in the current situation since contractual agreements have been made or an accurate customer forecast is available for example. For the other part, the inventory parameters are different since a new strategy is applied to the SKU. In section 7.1, an introduction is given to inventory policies in general and the notation is introduced. Afterwards, in section 7.2 and 7.3, the forecasting methods are discussed and the different inventory policies are explained in detail.

7.1 Introduction

Based on chapter 6, it can be concluded that a number of factors play an important role when applying a certain inventory strategy and that these factors affect the choice for an inventory policy. First of all, the availability of a customer forecast plays a role. In case such a forecast is available, this can be used as input for the inventory policy. If not, a demand forecast has to be made for the SKU. Next, the choice for a desired service level is important and is used as input for the control policy. Furthermore, the length of the supplier lead time is a crucial factor and used to calculate the inventory parameters. At last, the (forecasted) demand and the standard deviation of it are crucial parameters for applying an inventory policy as can be concluded based on the demand pattern analysis.

Before proceeding, the following notation is introduced which is used throughout this chapter. It is important to mention that all variables/parameters are on a single product level. The used time unit is months.

Table 24: List of variables and parameters

Variable/Parameter	Definition
ρ_t	Critical inventory point
μ_t	Mean (forecasted) demand size
σ_t	Standard deviation of the (forecasted) demand size
R	Review period in months
L	Replenishment lead time in months
k	Service factor
Z	Desired service level
α	Smoothing factor for the level
γ	Smoothing factor for the trend
δ	Smoothing factor for the seasonal pattern
D_t	Actual demand period t
F_t	Demand forecast period t
l_t	Level estimate period t
b_t	Trend estimate period t
sn_t	Seasonal factor estimate period t
ε_t	Forecast error
σ_t^{ε}	Standard deviation forecast error
MAD_t	Mean absolute deviation

$\boldsymbol{P_t}$	Demand interval between demand in period t and previous period
$\boldsymbol{PF_t}$	Demand interval forecast
$\boldsymbol{Y_t}$	Croston's demand size forecast
$\boldsymbol{s_t}$	Reorder point
$\boldsymbol{SS_t}$	Safety stock
$\boldsymbol{S_t}$	Order-up-to level or base stock level
$\boldsymbol{X}$	Cutoff transaction size
$\boldsymbol{A}$	Exception threshold factor
$\boldsymbol{IP_t}$	Inventory position
$\boldsymbol{BO_t}$	Backorders

The inventory policies in scope of this project are all based on a reorder point policy (integrated in Slim4) with periodic review (i.e. (R, s, nQ) policy) and the possibility of backordering. A generic expression or formula exists on the basis of which the reorder point or critical inventory point can be calculated and from which all (R, s, nQ) policies are derived. This formula is as follows:

$$\rho_t = \sum_{i=t+1}^{t+L+R} F_i + k\sqrt{\sum_{i=t+1}^{t+L+R} \widehat{\sigma_i^2}} \qquad (1)$$

This formula consists of a dynamic forecast which changes over time. The length of the forecast that is incorporated is dependent on the replenishment lead time and the review period. Next, a service factor is included which is based on the desired service level. By taking the inverse of the standard normal cumulative distribution function at the desired service level, the service factor k can be determined. In formula:

$$k = \Phi^{-1}(Z) \qquad (2)$$

The higher the desired service level, the higher the service factor and the more safety stock needs to be held. At last, $\hat{\sigma}^2$ is the forecast variance calculated over a lead time plus review period.

The inventory control policies in scope and its application are discussed in the remaining part of this chapter. It is important to mention that all the formulas and expressions are derived from the generic formula discussed before. At each policy, parts from this generic formula are replaced so that the policy can be applied in practice.

7.2 Forecasting methods

Before moving on to the application of the inventory policies in scope, the forecasting methods are discussed. As mentioned before, a customer forecast is provided for a part of the SKUs in scope. A demand forecast has to be generated for the rest of the SKUs in scope. On the other hand, it is not always needed to make a demand forecast. Exponential smoothing (integrated in Slim4) and Croston method (as proposed in Ch5) will be discussed in detail. Besides, a short recap is provided to the customer forecasts.

7.2.1 Exponential smoothing

Exponential smoothing is the forecasting method that is integrated in Slim4. Different type of exponential smoothing methods exist of which single exponential smoothing (SES) is the most basic one. SES assumes that the data fluctuates around a reasonably stable mean (no trend or consistent pattern of growth). The following forecasting equation is used.

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

In case a linear trend and/or a seasonal factor is incorporated to the forecast, these components are added to the forecast equation. The extension for the trend is called Holt's method or double exponential smoothing. Two smoothing equations are needed: one for the level and one for the trend. In formula:

$$l_t = \alpha D_t + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{4}$$
$$b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1} \tag{5}$$
$$F_t = l_{t-1} + b_{t-1} \tag{6}$$

Triple exponential smoothing or the Holt-Winters method is the most extensive form of exponential smoothing. The Holt-Winters method comprises the forecast equation and three smoothing equations: one for the level, one for the trend and one for the seasonal component with corresponding smoothing parameters. In formula:

$$l_t = \alpha(D_t - sn_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{7}$$
$$b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1} \tag{8}$$
$$sn_t = \delta(D_t - l_t) + (1-\delta)sn_{t-m} \tag{9}$$
$$F_t = l_{t-1} + b_{t-1} + sn_{t-m} \tag{10}$$

Depending on the type of SKU one or more components can be added to the forecast. In case sufficient historical sales data is available, Slim4 should be able to recognize a trend and/or seasonal pattern and include it into the demand forecast. Slim4 selects a suitable exponential smoothing variant for the SKUs and tries to optimize the smoothing parameters.

7.2.2 Croston method

The second forecasting technique is the Croston method which relies on the interval between consecutive demands and the size of these demands. it was developed based upon the Simple Exponential Smoothing method. The Croston method consists of two steps. First, separate exponential smoothing estimates are made of the average size of a demand only incorporating the non-zero demand periods. Second, the average interval between demands is calculated.

However, Syntetos and Boylan (2005) proved that Croston method is biased and they showed evidence which suggests losses in forecast accuracy. Because of this, the Syntetos and Boylan Approximation (SBA) for Croston method is used to make the demand forecasts. SBA is to a large extent based on Croston's original method. In order to overcome Croston's bias, Syntetos & Boylan added a correction factor to the forecast equation. The SBA for Croston method can mathematically be described as follows:

$$Y_t = \alpha D_t + (1-\alpha)Y_{t-1} \; if \; D_t > 0 \tag{11}$$

$$PF_t = \alpha P_t + (1-\alpha)PF_{t-1} \; if \; D_t > 0 \tag{12}$$

Based on the Croston demand size forecast (Y_t) and the demand interval forecast (PF_t) the forecast of demand per period after period t is equal to:

$$F_t = \left(1 - \frac{\alpha}{2}\right)\frac{Y_t}{PF_t} \tag{13}$$

These demand forecasts are used to calculate the forecast error measured as the Mean Absolute Deviation (MAD).

$$MAD_t = \alpha|D_t - Y_t| + (1-\alpha)MAD_{t-1} \tag{14}$$

7.2.3 Customer forecasts

It is not necessary to make a demand forecast for all SKUs in scope as a number of customers provide forecasts to Company X. These are rolling forecasts which give a prognosis of their expected purchases in the coming 12 months. In Ch 4.7, the actual sales and the customer forecasts were compared on a monthly basis and the forecast error was calculated for a part of the SKUs. These forecast errors are used to determine the standard deviation of these forecast errors. In formula:

$$\sigma_t^{\varepsilon} = \sqrt{\frac{\sum|\varepsilon_t - \bar{\varepsilon_t}|}{n}} \tag{15}$$

As can be seen in Ch 6.2 and explained in Ch 4.7, the forecast error was not calculated for a part of the SKUs due to data issues. To be able to determine σ_t^{ε} also for these SKUs, an additional forecast is made using exponential smoothing. This additional forecast is compared with the actual sales and the forecast error is calculated using the following formula:

$$\varepsilon_t = |D_t - F_t| \tag{16}$$

Afterwards, it is possible to calculate σ_t^{ε} with the help of (14).

7.3 Inventory control policies

In Chapter 5, a number of inventory policies are proposed which can be applied in the situation of Company X. This section discusses the proposed policies in more detail and describes how to apply the policy in practice. First, it is discussed which of the two forecasting methods is used (if necessary) as described in the previous section. Then, the formulas used to apply the inventory strategy are disclosed and the application of it is discussed. The generic expression (formula 1) introduced in section 8.1 is used as starting point for each policy. The different SKU classification steps that have been run through for all the SKUs in scope in the previous chapter, has resulted in the following division for the inventory policies.

Table 25: Overview inventory control policies

Inventory control policy	#SKUs
(R, s, nQ) policy	122
MRP policy	59
Order-up-to policy	153
Cutoff transaction size policy	38
Total	372

As discussed in Chapter 5, the replenishment lead time plays an important in determining the inventory control policy and applying it in practice. It was also discussed that the safety stock level needs to be corrected with a certain factor depending on the length of the replenishment lead time as described in Prak, Teunter and Syntetos (2017). When demand is forecasted the safety stock has to be corrected with a certain percentage. This percentage is bigger as the lead time increases. The reason for this correction is that the forecast errors for different periods of the lead time are positively correlated. The next tables show the corrections for different lead time periods. In this case a lead time period is equal to 1 month. The first table shows the percentual increases in safety stock level if σ_t is used to calculate SS_t. The second table shows the outcome for the σ^{ε}_t approach.

Table 26: Safety stock correction approach 1 (Prak, Teunter & Syntetos, 2017)

Lead time periods	α=0.1	α=0.2	α=0.3
1	0%	0%	0%
2	2%	5%	7%
3	5%	10%	14%
4	7%	14%	20%
5	10%	18%	26%
6	12%	22%	32%

Table 27: Safety stock correction approach 2 (Prak, Teunter & Syntetos, 2017)

Lead time periods	α=0.1	α=0.2	α=0.3
1	3%	5%	8%
2	5%	11%	16%
3	8%	15%	24%
4	10%	20%	31%
5	12%	25%	37%
6	15%	29%	43%

7.3.1 (R, s, nQ) Policy

First of all, a demand forecast has to be using exponential smoothing integrated in Slim4. A possible positive/negative trend or a seasonal component is incorporated in these forecasts by analyzing historical sales data. The historical sales data are monthly consumption levels which means that every generated demand forecast is a monthly forecast. In short, formulas (3), (6) and (10) are used to make a demand forecast.

With the help of the generated demand forecasts, μ_t and σ_t are determined by which the reorder point can be calculated. First, the standard deviation of the demand forecasts generated by exponential smoothing is calculated which results in a certain σ_t. With the help of k, L, R and σ_t, the safety stock is determined which replaces the second part in (1). In formula:

$$SS_t = k\sqrt{L+R}\sigma_t \tag{17}$$

Then, μ_t is calculated by taking the average of the forecasted monthly demands. μ_t replaces the sum of the forecasts after which the reorder point is calculated with the next formula:

$$s_t = (L+R)\mu_t + SS_t \tag{18}$$

A detailed description of the (R, s, nQ) policy is provided in de Kok (2012).

A replenishment order equal to the EOQ or MOQ is placed if the inventory position drops below the reorder point s_t. The application of this policy should be possible with Slim4 as is currently done. The applied (R, s, nQ) policy is quite dynamic. The safety stock and reorder point are updated each month. A review period of 1 day is applied like in the current situation.

7.3.2 Order-up-to policy

Teunter & Sani (2009) produced a paper to calculate order-up-to levels for products with intermittent demand. First of all, a demand forecast is generated using SBA of Croston method often to SKUs with a historical demand pattern consisting of a lot of zero demand periods. A demand forecast per period is generated with formula (13) and the forecast error measured as the MAD is calculated with (14).

Afterwards, the variance of the forecast error for the lead time plus review period demand can be calculated which replaces $\hat{\sigma}^2$ in (1). In formula:

$$\sigma_{L+R}^{\varepsilon}{}^2 = \frac{2\beta^2}{2-\alpha} + (L+R)\left(Y_t^2 * \frac{1}{PF_t}\left(1-\frac{1}{PF_t}\right) + \frac{\beta^2}{PF_t} + \left(\frac{(2+\alpha)}{2-\alpha}\frac{(\beta)^2}{PF_t}\right)\right) + (L+R)^2 * \left(\frac{\alpha}{2-\alpha}\right) * \left(\frac{PF_t - 1}{PF_t^3} * \left(Y_t^2 + \frac{\alpha}{(2-\alpha)} * \beta^2\right) + \frac{\beta^2}{PF_t}\right) \tag{19}$$

β can be can be calculated with the following expression.

$$\beta = 1.25MAD_t\sqrt{1-\frac{\alpha}{2}} \tag{20}$$

Next, an expression is also needs to created which can replace the sum of the forecasts over L+R in (1). μ_t is used for this and can be calculated as follows.

$$\mu_t = Y_t + (L+R) * F_t \tag{21}$$

Afterwards, an order-up-to level (critical inventory point) is calculated using the following expression.

$$S_t = \mu_t + k\sigma_{L+R}^{\varepsilon} \tag{22}$$

Formulas are created in Excel to calculate the inventory parameters for the SKUs managed by this control policy. It is possible to set an order-up-to or base stock level with the help of Slim4. The review period is equal to 1 week.

7.3.3 MRP policy

The forecast module integrated in SAP has a MRP like approach and is able to do the inventory planning for SKUs with a customer forecast by analyzing a lot of data. The module collects and analyzes data like forecasts, actual demand, supplier lead time, minimum order quantities and the inventory position. A certain safety stock is set to deal with uncertainties in supply and unexpected fluctuations in demand. This policy is different than the other inventory policies in scope, because only the safety stock part from (1) is used. The next formula is provided to calculate the safety stock level for these SKUs.

$$SS_t = k\sqrt{L}\sigma_t^{\varepsilon} \tag{23}$$

Service factor k and the standard deviation of the forecast error σ_t^{ε} are used to determine the safety stock level. The policy is applied with the help of the in SAP integrated forecast module. The safety stock level has to be updated every month. The forecast module schedules the future replenishment orders and determines how much to order.

7.3.4 Cutoff transaction size policy

An inventory control policy with a cutoff transaction size is applied to SKUs with an erratic demand pattern characterized by irregular, large peaks in order sizes which blur the forecasting and inventory system. A demand forecast is made using exponential smoothing which is integrated in Slim4. Slim4 applies forecast equations (3), (6) and (10) to generate demand forecasts for the SKUs in questions. With the help of these demand forecasts, an order-up-to level is set and a certain cutoff transaction size is determined.

In consultation with Company X, a heuristic approach is set up for applying this cutoff transaction size policy in practice. The cutoff transaction size is determined by defining a so-called exceptional threshold factor A. The value of A is typically somewhere between two and five, and is subjectively determined based on the number and quantity of the peak demands, without considering the cost for alternatively delivering the large orders. With the help of the generated demand forecasts, μ_t and σ_t are determined after which the cutoff transaction size can be calculated.
In formula:

$$X = \mu_t + A\sigma_t \tag{23}$$

Sales order sizes equal or below X are delivered immediately from stock. If the sales order size is above X, an amount equal to X is delivered and the remaining quantity is backordered. The level of X for each SKU is communicated to the customers so that they know what the new approach is. Besides, the demand lead time for the backorders has to be indicated. As the cutoff transaction size is known, the order-up-to level can be determined. The order-up-to level S is calculated with the next formula:

$$S_t = (L + R + 1)\mu_t + k\sqrt{L + R}\sigma_t \tag{24}$$

Formulas in Excel are used to calculate the cutoff transaction size and the order-up-to level. In the end, it is possible to apply this policy with Slim4 by which an order-up-to level can be set. An additional rule has to be integrated in Slim4 for the cutoff transaction size.

8. Impact analysis

In this chapter, the impact of the proposed classification system with the corresponding inventory strategies is analyzed by calculating 2 KPIs. First, in sections 8.1 and 8.2, the methods for calculating the inventory costs and fill rate are discussed for the SKUs in scope. Next, in section 8.3, the system performance is evaluated using efficient frontier graphs in which a trade-off is made between costs and service. The impact analysis is only performed for the SKUs who got assigned the(R, s, nQ) policy, MRP policy, order-up-to policy and cutoff transaction size policy. The advice for the rest of the SKUs is to contact the customer or to make a customer agreement. It is impossible to know how the strategy (and inventory parameters) for these SKUs will end up which makes it hard to draw any conclusions about the performance for these SKUs.

Before proceeding, the list with variables and parameters need to be extended a bit.

Table 28: Extension list of variables and parameters

Variable/Parameter	Definition
$\boldsymbol{P_2}$	Fill rate/Service level
$\boldsymbol{I_t^{OH}}$	Inventory on hand
$\boldsymbol{h}$	Inventory holding costs in € per unit of inventory on hand
$\boldsymbol{C}$	Total inventory holding costs in €

8.1 Inventory costs

Generally, the inventory costs includes the holding costs, ordering costs and backordering costs. As just discussed, it is hard to determine the total inventory costs for each SKU in real-life situations. Therefore, the inventory cost calculations are focused on the inventory on hand levels (I_t^{OH}). The inventory on hand and the corresponding holding costs are used to calculate the total inventory holding costs for each SKU. By determining the average inventory on hand over a certain time period, a good indication can be given of the average inventory holding costs. Besides, a safety stock comparison is done for a part of the SKUs in which the safety stock levels in the new and old situation are compared by expressing them in the holding costs. The safety stock is usually a big part of the inventory on hand and is therefore a good measure/indicator for the inventory costs.

First of all, the DoBr tool developed by Van Donselaar and Broekmeulen (2014) can be used to evaluate the performance of the (R, s, nQ) policy. By filling in the reorder point, lead time, review period, μ, σ, the case pack size and MOQ, the expected inventory on hand at the begin of the lead time period can be calculated as well as the expected inventory on hand at the end of the lead time plus review period. With the help of these numbers, an average inventory on hand level can be determined. By multiplying these average inventory on hand levels with the holding costs, the inventory costs can be calculated for each SKU. In formula:

$$C = h\left(\frac{E\left[I_{t+L}^{OH}\right] + E\left[I_{t+L+R}^{OH}\right]}{R}\right) \tag{25}$$

Next, the SKUs controlled with the MRP approach (forecast module SAP), order-up-to policy and cutoff transaction size policy are evaluated based on the safety stock level. As discussed in Chapter 7, the safety stock level is currently chosen in a subjective way and is often equal to 6 weeks of sales. In the new situation, the safety stock level is determined based on the standard deviation. In the end, the safety stock levels are multiplied by the SKU holding costs to calculate the costs for holding an amount equal to the safety stock level by which it is possible to make a cost comparison. In formula:

$$C = h \times SS_t \tag{26}$$

8.2 Fill rate

The fill rate is chosen as the service measure for the performance of the developed classification system. As mentioned in Chapter 5, the focus of the project is to improve the service level (i.e. fill rate) and the corresponding costs to achieve a desired service level are considered as less important. The goal is to achieve a service level of at least 95% for all SKUs.

With the help of the DoBr tool by Van Donselaar and Broekmeulen (2014), it is possible to determine the fill rate for the SKUs in scope. The following formula is used to calculate this P_2-rate.

$$P_2 = 1 - \frac{E[BO_{t+R+L}] - E[BO_{t+R}]}{E[D_{t+R}]} \tag{27}$$

As already mentioned before, the DoBr tool can be used to determine what s_t is needed for the SKUs managed by the (R, s, nQ) policy to achieve a certain fill rate. It is checked what fill rate is achieved with the current s_t and what the additional holding costs are for achieving the target fill rate for each SKU.

A service level comparison based on the safety stock level is performed for the SKUs managed with the MRP policy, order-up-to policy and cutoff transaction size policy. As explained in Chapter 7 and can be seen in formula 1&2, a desired service level is used to calculate the safety stock level for each SKU. It is checked what the average desired service level was applied for safety stock levels in the old situation. Afterwards, it is checked what extra costs are needed to achieve the desired service level which is calculated using (28). The following formulas are used to calculate the applied service levels (Z-values) for the old safety stock:

$$k = \frac{SS_t}{\sqrt{L + R}\sigma_t^{\varepsilon}} \tag{28}$$

$$Service\ level\ (Z) = \Phi(\mathrm{k}) \tag{29}$$

8.3 Results

In this section the outcome of the KPIs is discussed for the different SKUs. The expectation is that the performance is improved for most SKUs. Two different efficient frontier graphs are presented which show the difference in the possible performance between the new and old situation. As explained in Chapter 5, an efficient frontier graph shows the trade-off between inventory costs and service level.

With the help of the formulas and tools described in the first part of this chapter, the inventory cost and service level (i.e. fill rate) are calculated for the new and old situation. The outcome of these 2 measures are presented in a scatter plot for all SKUs. Besides, the efficient graph is plotted in this figure which shows the possible trade-off between costs and service in case the inventory strategy is optimized. If one of the dots from the scatter plot is on this line, it means it is not possible to achieve a better performance with the current inventory strategy.

It is important to mention that it is decided to perform the graphical efficient frontier analysis for only a part of the SKUs in scope and to give an overview of the results for all the SKUs in the end. The reason for this is that the figure becomes very unclear and everything is not good visible if you plot all SKUs in one figure. The inventory costs vary a lot between the SKU in scope (from €1 to more than €10.000) which makes it complicated to make an accessible figure. In the end, 40 SKUs are selected which should give a good view and representation for the rest of the SKUs.

First of all, the outcome for the old situation is sketched. As can be seen in the graph, there is enough possibilities for improving the performance of the different SKUs. A lot of dots are relatively far from the efficient frontier line. In the current situation, too much SKUs are in the "low" service level area. The goal is to achieve the desired service levels using the decision tree and the proposed inventory strategies.

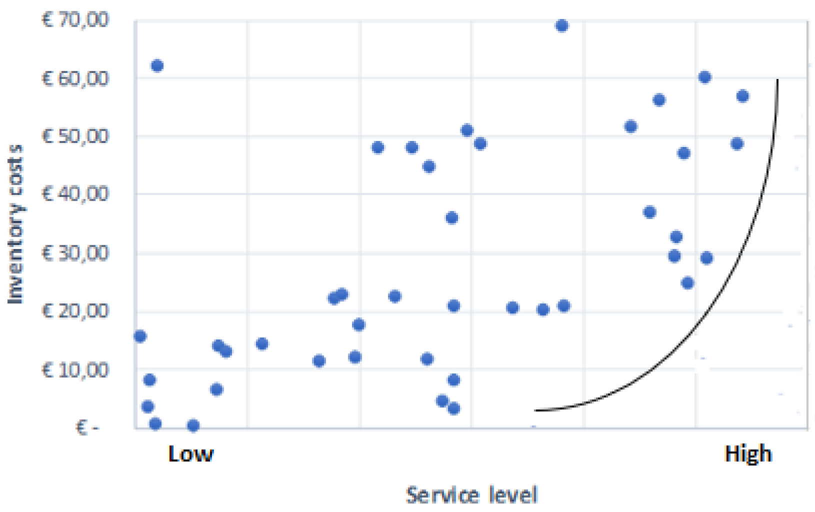

Figure 14: Efficient frontier old situation

Second, the performance in the new situation is shown in figure 19. The decision tree is run through for all SKUs in scope and possible changes are made to the inventory strategy or inventory parameter values (reorder point, order-up-to level etc.). As can be seen in the graph, more dots move closer to the efficient frontier line which means that the performance for the SKU has been improved. A few dots are even on the line which indicates that the performance is optimal for these SKUs under the current conditions.

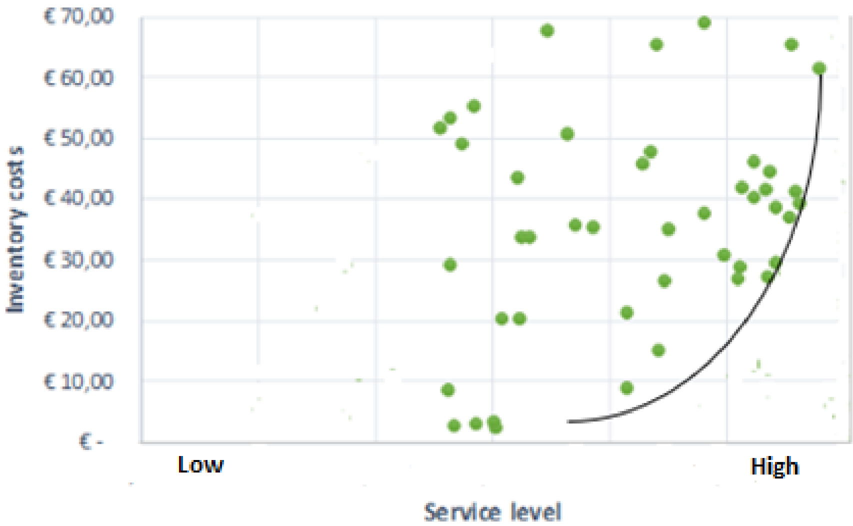

Figure 15: Efficient frontier new situation

In the end, an overview is given of the KPI results for the 372 SKUs which got assigned one of the 4 inventory control policies. The next table shows the difference in outcome for the inventory costs and service level between the new and old situation on average per SKU.

Table 29: KPI results

	#SKUs	ΔC/SKU	ΔP_2/SKU
KPIs calculated	372	€89	6,3%
KPIs not calculated	162	-	-

Concluding, the application of the decision tree (and the inventory strategy assigned to each SKU afterwards) results in an improvement of the service level (an average increase of 6,3% per SKU) against some extra costs. However, for a big part of the SKUs even a better performance is achieved while the inventory costs are almost the same or decreased. It can be concluded that the application of the decision tree and adding 2 more inventory policies results in a better inventory performance.

9. Conclusion and recommendations

In this final chapter, first, the conclusion of the research is discussed in section 9.1. Second, based on the research findings, recommendations to Company X are provided in section 9.2. Third, in section 9.3 the limitations of this master thesis project are described. Finally, in section 9.4 the contribution to the existing literature is discussed and a guideline for future research is provided.

9.1 Conclusion

In this section, the research questions from Chapter 2 are answered.

1) What are the characteristics of the context in which Company X works and how do these characteristics influence the supply chain operations and inventory planning?

The environment of the products is characterized by long supplier lead times and high-quality requirements which is typical for the OEM market. Most of the products in scope are client specific which means that these products are tailor made and partly co-engineered with the client. The customer specific products are distinguished by some critical factors. First of all, these products can have long lead times (up to 4 months) from Asia. Besides, most of these products require a service level close to 100%. Next, OEM clients demand high quality products whereby most products need extra, elaborate quality checks when arriving at Company X's warehouse. There is always a risk that products are rejected at the check. Finally, the demand for these products can be very unpredictable and a good forecast is not always provided by the client. These elements results in a complex supply chain operations and inventory planning for these products which is difficult to manage. The situation in which no client is prioritised and unexpected internal orders can be placed makes everything even more complex. Concluding, long supplier lead times, demanding customers and high-quality requirements have a big impact on the supply chain operations.

2) What are the forecasting methods and inventory control systems that are currently used for the products in scope and what is the performance of these systems?

Two inventory control systems are used at Company X at which a distinction is made between SKUs with/without a customer forecast. First, the SKUs without a customer forecast are managed with an inventory software package called Slim4. The (R, s, nQ) policy is integrated in Slim4 and a demand forecast is made using exponential smoothing. Second, the SKUs with a customer forecast are managed with the help of the forecast module from SAP which is a MRP based approach. The forecast provided by the customer is processed into SAP and then SAP makes an inventory plan for these SKUs. A certain safety stock level is set and the forecast module determines when the replenishment orders are placed based on the forecasts, safety stock, MOQ and replenishment lead time.

Overall, Company X is performing reasonably well in terms of the realized service levels for the 3 product groups in scope of this project. However, it is important to mention that the performance was far below the desired level in a number of months. Besides, on average the service levels are a little bit below the level Company X considers as 'acceptable'. The enumeration below provides an overview of the current state of the inventory control systems. These points are the result of the analysis of the current situation (Chapter 4) and indicate the areas for improvement.

- All products in Company X assortment is available to all customers and a first come first served (FCFS) strategy is applied for most items in case it is not a customer-specific item. This means the complete inventory for a certain product can be consumed by a 'less important' customer which can cause problems (e.g. an important OEM client can't be served anymore). The fact that most customer (sales) orders are not always judged extensively and there is no extra check for remarkable, makes things even worse.

- The process with respect to the customer forecasts is not well organized. First, already putting future or 'tentative' orders in SAP makes everything inconvenient. Next, there is no format or document for customer forecasts by which not all customer forecasts are processed into SAP. At last, the accuracy of the customer forecasts is not calculated by comparing the customer forecasts with the actual sales.
- Slim4 has its restrictions. First, it has a hard time making a demand forecast if there is not much historical demand information available (e.g. new products or slow-moving products) or if the demand pattern is very irregular. Next, the software assumes a normal distribution at all its calculations which is not 'valid' for much products in scope. At last, Slim4 doesn't take into account quantity discounts or structures at determining the replenishment quantities.
- The replenishment lead times are on average quite long and has a great impact on inventory management
- Company X has a hard time in meeting the desired service levels. Unfortunately, the service level are not available on product level so that it can be determined what the problematic products are.
- There is no strict policy concerning after how many months without sales the customer is contacted in case of a client specific product resulting in too much excess inventory
- The documentation for SKUs with contractual agreements (e.g. call-off contracts or safety stock agreements) is not well organized. Because of this, it is difficult to identify these SKUs and to take into account these agreements if necessary.
- Looking to the SKUs with dependent demand, it occurs that multiple article numbers are used for the same component which makes it hard to determine the total demand for these SKUs. Besides, the documentation for these SKUs is not well-organized.

3) How can the inventory performance be improved for the products in scope?

a) What technique or method should be applied for the classification process?

A decision tree is used as method for the classification process. A number of steps is run through which are all focused on inventory management related factors. These relevant factors or characteristics are analyzed and impact the choice for an inventory control policy. Examples of relevant factors are demand characteristics, lead time aspects or contractual agreements. After running through these steps, it is possible to determine a suitable inventory strategy for all SKUs in scope.

The main reason to select a decision as classification method is its simplicity. The graphical representation makes it easy to interpret and explain to executives. Besides, the fact it handles one criteria at a time makes it very structured. Next, decision trees are suitable for handling both categorical and quantitative factors. At last, using decision trees makes it possible to immediately create different 'trays' (categories) with SKUs and to make a distinction between SKUs easily.

b) Which factors, characteristics and data should be used to classify the products?

An action plan or decision tree will be developed to determine for which SKUs the inventory control policy has to be changed in order to meet the desired service level. First of all, it is important which factors play a big role in the working environment of Company X. Second, the demand patterns for the SKUs in scope are studied which will eventually result in a demand pattern classification. The following list gives an overview of the different steps and factors that are used in the classification process for each SKU. A short explanation of the factors is provided as well.

- Customer forecast: The availability of a customer forecast is checked after which the forecast accuracy (i.e. MAPE) is determined in case a forecast is available. With the help of a set benchmark, it is determined if the customer forecast is accurate enough for using it in inventory management.
- Lead time: The length of the supplier lead time and customer lead time are compared.
- Service level agreement: It is checked if a service level agreement has been made between Company X and one of its customers about the SKU.
- Inventory parameter agreement: It is investigated if a contractual or verbal agreement has been made regarding the levels of the reorder point, base stock or safety stock.
- Supply contracts: A contractual agreement can be made between Company X and one of its customers or suppliers with respect to fixed replenishment/supply quantities, for example a call-off contract.
- Standard assortment SKU: This concerns basic industrial engineering components for which every customer expects Company X has this product on stock. This can be a reason to apply an alternative strategy not taking into account any factors or a certain cost considerations.
- Demand pattern: Different demand elements are analyzed, like the variability of the demand, the timing of the demand and the frequency of demand. The demand of the SKU can be classified into 5 possible categories which can impact the choice for an inventory strategy.

These factors are used to classify the products in scope and to assign a suitable inventory strategy to each product.

c) What other inventory control models or inventory strategies can be possibly applied at Company X?

Next to the (R, s, nQ) policy (integrated in Slim4) and the forecast module from SAP, 2 other inventory control models can be applied at Company X which will be shortly explained.

First, the order-up-to policy described in Teunter and Sani (2009) can be applied at Company X. Teunter & Sani (2009) produced a paper to calculate order-up-to levels for products with intermittent demand. In this paper, Croston's forecasting method is used to determine future demand. What differs from the Exponential Smoothing method (integrated in Slim4) is that Croston only updates the forecasts if a positive demand occurs. Not taking the zero demand periods into account should be better while forecasting intermittent demand. These Croston forecasts need to be transformed into an expected total lead time demand which can be used to calculate the order-up-to levels. Besides this, an estimate for the forecast error is needed. This expected value and the forecast error are used to determine the inventory control parameters.

Next, the cutoff transaction size policy proposed in Mak & Lai (1995) is applicable in the situation of Company X. They have analyzed an order-up-to level inventory system with a cutoff transaction size X. The system routinely satisfies customer orders with a size smaller than or equal to X. For customer orders with transaction sizes larger than X units, the system would only supply the cutoff amount (X units). The excess units would be refused and delivered at a later point in time (backordering). The demand distribution was approximated by a stuttering Poisson distribution (i.e., a compound Poisson distribution where the order sizes have a geometric distribution) and they presented an algorithm to determine the optimal order-up-to level for a given cutoff transaction size X. This cutoff size ensures that extremely large orders are removed. These large orders normally complicate and blur the forecasting.

At last, a number of more heuristic inventory strategies can be applied at Company X. First of all, it is possible to simply holding no inventory in case the customer lead time is bigger than the supplier lead time. Second, a possibility is to make an agreement with the customer about a certain base stock level. Besides, Company X has a lot of SKUs with contractual agreements (e.g. call-off contract or inventory parameter agreement). For these SKUs, the inventory is managed based on the conditions from these contracts.

4) How does the new inventory system perform looking to two KPIs (inventory costs and fill rate) and how can these information be used to improve the solution/classification?

The performance of the different SKUs in scope is tested with the help of the inventory costs and the fill rate (i.e. service level) using efficient frontier graphs. An efficient frontier is the curve that results from graphing the trade-off between inventory cost and service level. On the other hand, the KPI results are calculated in a numerical way which makes it possible to say something about the overall results.

First of all, the inventory cost and service level (i.e. fill rate) are calculated for the new and old situation for the different SKUs. The outcome of these 2 measures are presented in a scatter plot and the efficient frontier curve is plotted in this figure. If one of the dots from the scatter plot is on this curve, it means it is not possible to achieve a better performance under the current conditions with the available inventory strategies. By comparing the 2 efficient frontier graphs with all the dots (which show the performance between inventory cost and service level for the SKUs), it can be checked if the performance is improved in the new situation.

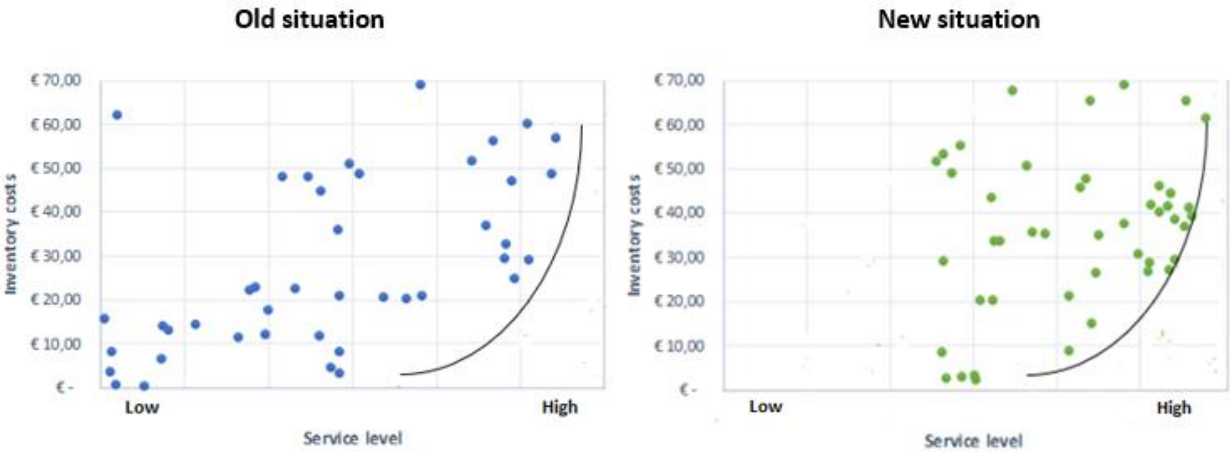

Figure 16: Efficient frontier graphs

As can be seen in the figure above, more dots move closer to the efficient frontier line which means that the performance for the SKU has been improved. A few dots are even on the line which indicates that the performance is optimal for these SKUs under the current conditions. In the end, an overview is given of the KPI results for the 372 SKUs which got assigned one of the 4 inventory control policies. The next table shows the difference in outcome for the inventory costs and service level between the new and old situation on average per SKU.

Table 30: KPI results

	#SKUs	ΔC/SKU	ΔP_2/SKU
KPIs calculated	372	€89	6,3%
KPIs not calculated	162	-	-

Concluding, the application of the decision tree (and the inventory strategy assigned to each SKU afterwards) results in an improvement of the service level (an average increase of 6,3% per SKU) against some extra costs.

5) How can the improved model be implemented?

The improved model consists of two parts: the decision tree and the proposed inventory control policies (2 new policies are introduced). First of all, it is explained how the decision tree can be implemented after which it is discussed how the new introduced inventory policies can be applied at Company X.

First, the decision tree can be implemented using an Excel file. The monthly inventory overviews (which are available for all Company X' employees) are supplemented with additional data to be able to run through all the steps of the decision tree. Besides, formulas are created to determine the demand pattern for each SKU and to calculate the forecast accuracy (i.e. MAPE). However, to fully implement the decision tree more data needs to be stored, especially with respect to inventory parameter agreements or service level agreements.

Second, the inventory policies can also be implemented with the help of Excel for the most part. Formulas are created in Excel to calculate the inventory parameters (reorder point and safety stock for the SKUs managed by forecast based policy. Because the (R, s, nQ) policy is integrated in Slim4, the resulting parameters can simply be entered into Slim4 to apply the policy. Next, formulas are created in Excel as well to calculate the order-up-to level for the SKUs for which an order-up-to policy is applied. It is possible to set an order-up-to level with the help of Slim4. At last, formulas in Excel are used to calculate the cutoff transaction size and the order-up-to level for the SKUs managed by the cutoff transaction size policy. In the end, it is possible to apply this policy with Slim4 by which an order-up-to level can be set. An additional rule has to be integrated in Slim4 for the cutoff transaction size.

9.2 Recommendations

In this section, the recommendations to Company X are discussed. The enumeration below gives an overview of the different recommendations that Company X is advised to implement.

- Track the forecast accuracy (i.e. MSE and MAPE) for all SKUs with a customer forecast. Currently, the forecast accuracy is not calculated by which this factor can't be included in the calculation of the safety stock level. Besides, it is important to contact a customer if the forecast accuracy is very low and to make agreements about this.
- Design an Excel file with a standard format where customers can fill in their forecasts and promote/offer this file to your customers. Currently, the forecasts of approximately 20 customers is not used, because the forecasts can't be processed into SAP. By offering a standard format, this problem is easily solved.
- Create a general file for each business unit in which all the contractual or verbal agreements regarding inventory parameters or service levels are recorded. On this way, these agreements are clear for everyone and is it known for everyone what the due date of these agreements are.
- Start using one article number for all SKUs with dependent demand so that it is immediately known what the total demand for these SKUs is. Currently, different article numbers are used for the same component through which the total demand for each component is difficult to figure out.

- Start working with a customer lead time for a part of the SKUs. Currently, Company X doesn't work with a fixed lead time towards the customer for each SKU and often a certain delivery date is agreed with the customer. If Company X start working with a fixed customer lead time for SKUs with a relatively small supplier lead time, Company X doesn't have to hold any inventory for these SKUs.
- Run through the decision tree for all SKUs and change the inventory strategy if necessary. Because Company X's product assortment is quite big, it might be an idea to not immediately perform this analysis for all SKUs, but to make a schedule per product group. When the decision tree is run through for all SKUs, it is important to do the analysis again every 6 months.

9.3 Limitations

In this section, the limitations of the research are discussed.

- The forecast accuracy was not calculated for all SKUs with a customer forecast whereby an assumption has been made for a part of the SKUs. Besides, the forecast accuracy was only calculated for 1 time interval (2 months) and no calculations were performed for other intervals. Next, a limit value of the forecast accuracy was set which determines if the customer forecast is used for inventory control, but it was not checked if other values result in a better performance.
- The total demand for SKUs with dependent demand was not double checked and an assumption was made for these SKUs. Therefore, it is possible that the decision tree has to run through again for a part of these SKUs.
- When determining the inventory costs, only the holding costs are included. The ordering costs and stock-out (backordering) costs were not taken into account.
- The performance of the decision tree was only tested for one fixed value for the 3 cutoff values in the demand pattern step (i.e. ADI, CV^2 and demand frequency). It was not investigated if a better performance can be achieved by selecting other cutoff values.

9.4 Scientific contribution and future research

Finally, the contributions of this research to the literature and suggestions for future research are discussed.

The contributions to the existing literature are as follows:

1. The development of an inventory classification system for inventory management purposes which immediately calculates the inventory performance in an environment with non-stationary (irregular) demand patterns, stochastic lead times and high service requirements.
2. Adding to the existing literature through a case study on inventory classification systems and examining the performance.

Suggestions for future research:

1. The development of an inventory classification system whereby the proposed inventory control policies are tailor-made and especially developed for the business environment where the company is part of.
2. The development of an inventory classification system which is applicable and takes into account multi-echelon inventory management.

References

Ahn, H. S., & Kaminsky, P. (2005). Production and distribution policy in a two-stage stochastic push-pull supply chain. *IIE Transactions*, *37*(7), 609-621.

Babai, Z., & Dallery, Y. (2006). An analysis of forecast based reorder point policies: The benefit of using forecasts. *IFAC Proceedings Volumes, 12(2)*, 1564-1569.

Barbato, G., Barini, E. M., Genta, G., & Levi, R. (2011). Features and performance of some outlier detection methods. *Journal of Applied Statistics*, *38*(10), 2133-2149.

Benjaafar, S., Cooper, W. L., & Mardan, S. (2011). Production-inventory systems with imperfect advance demand information and updating. *Naval Research Logistics (NRL)*, *58*(2), 88-106.

Will M. Bertrand, J., & Fransoo, J. C. (2002). Operations management research methodologies using quantitative modeling. *International Journal of Operations & Production Management*, *22*(2), 241-264.

Bhattacharya, A., Sarkar, B., & Mukherjee, S. K. (2007). Distance-based consensus method for ABC analysis. *International Journal of Production Research*, *45*(15), 3405-3420.

Boylan, J. E., Syntetos, A. A., & Karakostas, G. C. (2008). Classification for forecasting and stock control: a case study. *Journal of the operational research society*, *59*(4), 473-481.

Cao, M., & Zhang, Q. (2011). Supply chain collaboration: Impact on collaborative advantage and firm performance. *Journal of operations management*, *29*(3), 163-180.

Chakravarty, A. K. (1981). Multi-item inventory aggregation into groups. *Journal of the Operational Research Society*, *32*(1), 19-26.

Chakravarty, A. K., Orlin, J. B., & Rothblum, U. G. (1982). A partitioning problem with additive objective with an application to optimal inventory groupings for joint replenishment. *Operations Research*, *30*(5), 1018-1022.

Chen, Y., Li, K. W., Kilgour, D. M., & Hipel, K. W. (2008). A case-based distance model for multiple criteria ABC analysis. *Computers & Operations Research*, *35*(3), 776-796.

Chen, L., Yücel, Ş., & Zhu, K. (2017). Inventory management in a closed-loop supply chain with advance demand information. *Operations Research Letters*, *45*(2), 175-180.

Clark, A.J., & Scarf, H. (1960). Optimal policies for a multi-echelon inventory problem. *Management Science*, *6*, 475-490.

DeCroix, G. A., & Mookerjee, V. S. (1997). Purchasing demand information in a stochastic-demand inventory system. *European Journal of Operational Research*, *102*(1), 36-57.

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

Ernst, R., & Cohen, M. A. (1990). Operations related groups (ORGs): a clustering procedure for production/inventory systems. *Journal of Operations Management*, *9*(4), 574-598.

Gallego, G., & Özer, Ö. (2001). Integrating replenishment decisions with advance demand information. *Management science*, *47*(10), 1344-1360.

Gallego, G., & Özer, Ö. (2003). Optimal replenishment policies for multi-echelon inventory problems under advance demand information. *Manufacturing & Service Operations Management*, *5*(2), 157-175.

Gayon, J. P., Benjaafar, S., & De Véricourt, F. (2009). Using imperfect advance demand information in production-inventory systems with multiple customer classes. *Manufacturing & Service Operations Management*, *11*(1), 128-143.

Gupta, A., & Maranas, C. D. (2003). Managing demand uncertainty in supply chain planning. *Computers & chemical engineering*, *27*(8-9), 1219-1227.

Guvenir, H. A., & Erel, E. (1998). Multicriteria inventory classification using a genetic algorithm. *European journal of operational research*, *105*(1), 29-37.

Hariharan, R., & Zipkin, P. (1995). Customer-order information, leadtimes, and inventories. *Management Science*, *41*(10), 1599-1607.

Holweg, M., Disney, S., Holmström, J., & Småros, J. (2005). Supply chain collaboration: Making sense of the strategy continuum. *European management journal*, *23*(2), 170-181.

Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making* (pp. 58-191). Springer, Berlin, Heidelberg.

Iqbal, Q., Malzahn, D., & Whitman, L. (2017). Statistical analysis of multi-criteria inventory classification models in the presence of forecast upsides. *Production & Manufacturing Research*, *5*(1), 15-39.

Iravani, S. M., Liu, T., Luangkesorn, K. L., & Simchi-Levi, D. (2007). A produce-to-stock system with advance demand information and secondary customers. *Naval Research Logistics (NRL)*, *54*(3), 331-345.

Jain, C. L. (2007). Benchmarking forecasting models. *The Journal of Business Forecasting*, *26*(4), 15.

Karaesmen, F., Buzacott, J. A., & Dallery, Y. (2002). Integrating advance order information in make-to-stock production systems. *IIE transactions*, *34*(8), 649-662.

Karaesmen, F., Liberopoulos, G., & Dallery, Y. (2004). The value of advance demand information in production/inventory systems. *Annals of Operations Research*, *126*(1-4), 135-157.

Kok, A.G. de, (2012). *Analysis of stock control models for one location with one product*, Lecture notes for the course Introduction Inventory Control, Eindhoven University of Technology.

Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management science*, *43*(4), 546-558.

Lolli, F., Ishizaka, A., Gamberini, R., & Rimini, B. (2017). A multicriteria framework for inventory classification and control with application to intermittent demand. *Journal of Multi-Criteria Decision Analysis*, *24*(5-6), 275-285.

Mak, K. L., & Lai, K. K. (1995). Optimal (s, S) policy for an inventory system when the demand can be partially satisfied. *International Journal of Systems Science*, *26*(2), 213-231.

Mitroff, I. I., Betz, F., Pondy, L. R., & Sagasti, F. (1974). On managing science in the systems age: two schemas for the study of science as a whole systems phenomenon. *Interfaces*, *4*(3), 46-58.

Nag, B., Han, C., & Yao, D. Q. (2014). Mapping supply chain strategy: an industry analysis. *Journal of Manufacturing Technology Management*, *25*(3), 351-370.

Olhager, J. (2003). Strategic positioning of the order penetration point. *International journal of production economics*, *85*(3), 319-329.

Olhager, J. (2010). The role of the customer order decoupling point in production and supply chain management. *Computers in Industry*, *61*(9), 863-868.

Partovi, F. Y., & Anandarajan, M. (2002). Classifying inventory using an artificial neural network approach. *Computers & Industrial Engineering*, *41*(4), 389-404.

Partovi, F. Y., & Burton, J. (1993). Using the analytic hierarchy process for ABC analysis. *International Journal of Operations & Production Management*, *13*(9), 29-44.

Prak, D., Teunter, R., & Syntetos, A. (2017). On the calculation of safety stocks when demand is forecasted. *European Journal of Operational Research*, *256*(2), 454-461.

Ramanathan, R. (2006). ABC inventory classification with multiple-criteria using weighted linear optimization. *Computers & Operations Research*, *33*(3), 695-700.

Saaty, T. L. (1990). How to make a decision: the analytic hierarchy process. *European journal of operational research*, *48*(1), 9-26.

Sarkar, S., & Shewchuk, J. P. (2016). Advance demand information and early fulfilment in inventory management with two demand classes. *International Journal of Logistics Systems and Management*, *25*(2), 175-198.

Silver, E. A., Pyke, D. F., & Peterson, R. (1998). *Inventory management and production planning and scheduling* (Vol. 3, p. 30). New York: Wiley.

Stadtler, H. (2015). Supply chain management: An overview. In *Supply chain management and advanced planning* (pp. 3-28). Springer, Berlin, Heidelberg.

Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society*, *56*(5), 495-503.

Tan, T. (2008). Using imperfect advance demand information in forecasting. *IMA Journal of Management Mathematics*, *19*(2), 163-173.

Tan, T., Güllü, R., & Erkip, N. (2007). Modelling imperfect advance demand information and analysis of optimal inventory policies. *European Journal of Operational Research*, *177*(2), 897-923.

Teunter, R. H., Babai, M. Z., & Syntetos, A. A. (2010). ABC classification: service levels and inventory costs. *Production and Operations Management*, *19*(3), 343-352.

Teunter, R., & Sani, B. (2009). Calculating order-up-to levels for products with intermittent demand. *International Journal of Production Economics*, *118*(1), 82-86.

Thomas, J. J., & Wallis, K. F. (1971). Seasonal variation in regression analysis. *Journal of the Royal Statistical Society. Series A (General)*, 57-72.

Toktay, L. B., & Wein, L. M. (2001). Analysis of a forecasting-production-inventory system with stationary demand. *Management Science*, *47*(9), 1268-1281.

Torabi, S. A., Hatefi, S. M., & Pay, B. S. (2012). ABC inventory classification in the presence of both quantitative and qualitative criteria. *Computers & Industrial Engineering*, *63*(2), 530-537.

Van Donselaar, K., & Broekmeulen, R. (2014). *Stochastic inventory models for a single item at a single location.* [Beta working paper 447].

Van Donselaar, K., Kopczak, L. R., & Wouters, M. (2001). The use of advance demand information in a project-based supply chain. *European Journal of Operational Research*, *130*(3), 519-538.

Van Kampen, T. J., Akkerman, R., & Pieter van Donk, D. (2012). SKU classification: a literature review and conceptual framework. *International Journal of Operations & Production Management*, *32*(7), 850-876.

Votruba, L. (1988). 7 Inventory Models. *Developments in Water Science*, *32*, 278-301.

Wang, T., & Toktay, B. L. (2008). Inventory management with advance demand information and flexible delivery. *Management Science*, *54*(4), 716-732.

Yang, L., Li, H., Campbell, J. F., & Sweeney, D. C. (2017). Integrated multi-period dynamic inventory classification and control. *International Journal of Production Economics*, *189*, 86-96.

Zhou, H., & Benton Jr, W. C. (2007). Supply chain practice and information sharing. *Journal of Operations management*, *25*(6), 1348-1365.

Zhu, K., & Thonemann, U. W. (2004). Modeling the benefits of sharing future demand information. *Operations Research*, *52*(1), 136-147.

Zipkin, P. H. (2000). *Foundations of inventory management*. Boston: McGraw-Hill.

Ziukov, S. (2015). A literature review on models of inventory management under uncertainty. *Verslo Sistemos ir Ekonomika*, *5*(1).

Appendix A: Outlier analysis

Table 31: IQR method with X=1,5

Total number of SKUs	# SKUs with outlier	# Detected outliers
534	176	405

Table 32: IQR method with X=2

Total number of SKUs	# SKUs with outlier	# Detected outliers
534	124	258

Table 33: IQR method with X=2,5

Total number of SKUs	# SKUs with outlier	# Detected outliers
534	100	191

Table 34: IQR method with X=3

Total number of SKUs	# SKUs with outlier	# Detected outliers
534	74	135

Table 35: IQR method with X=3,5

Total number of SKUs	# SKUs with outlier	# Detected outliers
534	59	108