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Master Thesis

Department of Industrial Management and Logistics

Forming an Inventory Control Policy in a Stochastic Environment

A Case Study at Sandvik Crushing and Screening

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Abstract

Title: Forming an Inventory Control Policy in a Stochastic Environment: A Case Study at Sandvik Crushing and Screening

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Background: For most companies that handle large material flows there are buffers between different stages in the supply chain, often referred to as inventory. The main reasons for having these inventories are to achieve economies of scale when handling material flows and to buffer against uncertainties when matching demand and supply. Hence, the main objective in inventory control is to decide when and how much to order and by doing so, balance conflicting goals. These goals could be to reduce operational costs and to reduce stock on hand while achieving a certain service level to the customers.

Purpose: Forming an inventory control policy for a new warehouse which is based on the demand from both the production of new crushers and from the aftermarket.

Research questions: (1) How to form an inventory control policy for a new warehouse? a) How to optimize the parameters in this policy to minimize the ordering costs and the inventory holding costs? (2) How does the lead time variability affect these costs?

Methodology: In this study, a framework presented by Yin (2009) and Hillier & Liebermann (2010) has been used to construct the research design. The initial step was to specify the problem at hand before the gathering of data was initiated which also included a literature study. Based on the gathered information, an initial analysis of the current system was performed before the mathematical model which represents the new inventory control policy was created. A statistical analysis of the lead times was conducted to provide input to the model. Finally, the constructed model was evaluated in a sensitivity analysis.

Conclusion: Based on the analysis of sales data, a compound Poisson process was chosen as an appropriate demand model. From the theoretical foundation and current practices at the case company, an (R, Q) policy with periodic review was chosen as the new inventory control policy. Since the case company currently experience variability in the lead times, this uncertainty was incorporated in the new policy. The study showed that in the future state, where the case company would operate with a shared warehouse with 95% fill rate and take stochastic lead times into consideration, the holding costs would increase while the ordering costs would be reduced. When analyzing the effect of lowering the lead time variability in the new policy, it was shown that the holding costs were reduced while the ordering costs increased. Finally, it was concluded that in the best-case scenario where lead times are assumed constant, the total costs in the future state would be reduced compared to the current system.

Keywords: Inventory Control, Stochastic Lead Time, Stochastic Demand, Input Analysis, Optimization

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Lund, June 2018
Anders Mattisson, David Alsmarker

Table of Abbreviations

BA - Business Area
BU - Business Unit
C&S - Crushing & Screening
CDF – Cumulative Distribution Function
CO - Customer Order
COV - Coefficient of Variation
ERP - Enterprise Resource Planning
IL - Inventory Level
IP - Inventory Position
KS - Kolmogorov - Smirnov
L - Lead Time
ML - Maximum Likelihood
MTO - Make-To-Order
MTS - Make-To-Stock
PA - Product Area
PDF -Probability Density Function
PO - Purchase Order
POS - Point-Of-Sales
R - Reorder Point
VBA - Visual Basic for Applications
T - Review Period
Q - Batch Quantity Size
SMRT - Sandvik Mining and Rock Technology
SMCL - Sandvik Mining and Construction Logistics
SRP - Sandvik Rock Processing

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1. Introduction

This chapter describes the background to this master thesis project, presents the case company and the problem formulation. It will also introduce the project purpose, focus areas and delimitations.

1.1 Background

In today's globalized world, companies are experiencing a continuously growing competition. Customers are requiring a high variety of, preferably customized, products to be delivered instantly with short notice. This development requires a logistics system that can deliver according to the customer's expectations while at the same time contribute to improve the company's financial performance (Chanukov, Becker & Windt, 2014). What makes the seemingly simple task to match demand and supply so difficult is the presence of uncertainty (Christopher, 2011). Variability always degrades the performance of an inventory system and will have to be buffered by some combination of inventory, capacity and time. (Hopp, Spearman, 2008). Today the total investment in inventories is enormous and the control of capital tied up in raw material, work-in-progress, and finished goods offer a substantial potential for improvement. In this context, supply chain management has become increasingly essential and the strategic importance of this area is today fully recognized by top management (Axsäter, 2006).

In order to meet the growing expectations from customers, an increased need of coordination and cooperation in the supply chain has emerged. Cooperation means that comparable activities are coordinated between different firms to achieve better results over time, which also includes cross-functional coordination. To achieve this, a system approach is needed where the total flow from the supplier to the final customer is synchronized which requires synchronization of both operational activities and capabilities within and between supply chain firms. Cooperation can also be an approach to accomplish reduction in supply chain inventories and reach other reductions in supply chain costs. For example, sharing of information regarding forecasts, inventory levels and marketing strategies can reduce uncertainty between the members of the supply chain (Mentzer, DeWitt, Keebler, Min, Nix, Smith & Zacharia, 2001).

Even though cooperation has the potential to reduce inventories in a supply chain, some inventory will be required. This is mainly due to two reasons: economies of scale and uncertainties. Economies of scale could be accomplished by creating batches through aggregating orders to accomplish increased efficiency. However, this process results in increased stock-on-hand. Additionally, supply and demand uncertainties in combination with the existence of lead times in ordering, production and transportation creates a requirement for safety stock. Even though several sources of uncertainty exist, it is still possible for most companies to accomplish reduction in their inventories without incurring additional costs by using advances in information technology and more efficient inventory tools (Axsäter, 2006).

The main objective in inventory control is to decide when and how much to order and by doing so, balance conflicting goals. Free tied-up capital for other purposes is one important goal with keeping low stock levels. However, different functions in the organizations might have different objectives. From the purchasing manager's perspective, ordering in large batches is preferable since it enables volume discounts. The production manager prefers using large batches in the production to reduce time-consuming setups.

From the production perspective, it is also desirable to have large buffers to avoid stops due to shortage of raw material. The marketing manager would like to have a high stock of finished goods to be able to provide customers a high service level. Finding the best balance between these goals is challenging but the purpose with inventory models is to accomplish this balance (Axsäter, 2006).

1.2 Company description

This thesis will be conducted at the Sandvik Group which is a global engineering company with around 43 000 employees worldwide. Sandvik relies heavily on their experience about industrial processes and expertise in material technology. In 2017 Sandvik had a revenue of 90.9 billion SEK with a profit margin of 14.6 billion SEK. The group is divided into three major business areas: Sandvik Machining Solutions, Sandvik Mining and Rock Technology and Sandvik Materials Technology. The group is specialized in the areas of tools and tooling systems for industrial metal cutting, equipment and tools, service and technical solutions for the mining and construction industries and advanced stainless steels and special alloys as well as products for heating products (Sandvik AB, 2018).

This thesis will focus on the Business Area (BA) called Sandvik Mining and Rock Technology which is a recent merger of Sandvik Mining and Sandvik Construction. Product areas (PA) are smaller units within the BA and this thesis will focus on PA Crushing & Screening, C&S. More specifically, the business unit (BU) called Stationary which focuses on stationary crushers and screeners will be the focal point of this thesis. The chosen BU mainly delivers crushers and screeners to the mining and construction industry (Sandvik AB, 2018).

1.3 Problem formulation

The case company currently has two legal entities that order case company specific components from the same suppliers. One of the legal entities supplies the aftermarket with components and the other entity produces and assembles new crushers. The ordered components are the same for both the legal entities but orders to the suppliers are today sent from two different ERP-systems and by different people with no coordination between the legal entities. During the recent year, when demand for these types of components has increased significantly, the variability in the number of purchase order (PO) lines and the weekly ordered quantity towards the suppliers has also increased. The case company is also experiencing a high variation in the replenishment lead times from the suppliers which is a concern since it affects the service level to the customers and the trust in the supply process.

Recently, the case company has gained control over the entire distribution network. Therefore, they want to investigate a future state, where the ordering of these components would be done to a shared central warehouse for both the legal entities. Since this state does not currently exists, the case company wants to investigate the holding costs and ordering costs for this centralized scenario. The stated purpose with this change would be to achieve economies of scale, improved service level and improved coordination of orders to the suppliers. Coordination is in this context defined as a change from independent ordering from the two legal entities to a coherent inventory control policy in a new warehouse, where demand of components from both the legal entities is taken into consideration. This thesis will therefore investigate how to construct an inventory control policy for these types of components and how the holding and ordering costs related to this policy are affected in this future scenario. As mentioned above, the case company expresses that the variability in the lead times is a concern. Therefore, lead times will not be assumed constant in the new inventory control policy and the holding and ordering costs related to the variability in lead times will be evaluated. In this evaluation, constant lead times will represent a best-case scenario.

1.4 Purpose of study and research questions

The purpose of this master thesis is to form an inventory control policy for a new warehouse which is based on the demand from both the production of new crushers and from the aftermarket.

The thesis will answer the following research questions:

1. How to form an inventory control policy for a new warehouse?
    a. How to optimize the parameters in this policy to minimize the ordering costs and the inventory holding costs?
2. How does the lead time variability affect these costs?

1.5 Project focus, delimitations and company directives

As described above, this thesis will focus on the new inventory control scenario described in Section 1.3. To consider a single echelon system, is the most significant company directive that has affected the direction of this project. The authors are aware that this study does not attempt to do a complete evaluation of this new scenario since that would have been a project larger than what is feasible in a master thesis project. However, this study will evaluate some aspects of this future scenario which will be one part of the case company's overall evaluation of this type of change. A full evaluation could also include the effect on transportation costs from the suppliers and the best geographical location of the warehouse.

The focus in this project will be to minimize the ordering costs and the holding costs given the case company's current choice of service level constraint, i.e. 95 percent of demand can be satisfied immediately from stock on hand. Since the case company has expressed that they experience variability in their lead times from the suppliers, this will be taken into consideration in the new inventory control policy. The effect of lead time variability on the holding and ordering costs will also be evaluated. Any other costs than above mentioned will not be considered. Since this project is limited in time, some external suppliers of high importance will be selected for further analysis. This selection will be based on the aggregated delivered value to both the aftermarket and the production of new crushers.

The project will be limited to customer critical components that are case company specific, so called key components. The characteristics of these components will be further described later in the report. The case company is currently working with other projects which will address the customer aspects in the defined scenario, hence the distribution to the customers from this shared warehouse has been excluded. The considered location of this new warehouse is not decided but it is assumed that the average length of the current lead times will not be significantly affected.

2. Methodology

This chapter describes and motivates the chosen research strategy and research execution used in this master thesis project. The aim is to help the reader to better understand how insights have been gained and how conclusions have been reached. It also explains how the gathering and analysis of data have been conducted in this project and how the authors have worked with research quality.

2.1 Research strategy

The choice of methodology in a research project depends on the project's objective, characteristics and purpose. There are mainly four different purposes of a research study: descriptive, exploratory, explanatory and problem solving. A descriptive study aims to map and describe how activities are working and how they are performed while an exploratory study generates a more in depth understanding of the activity and how it is executed. In the explanatory study, the researcher tries to find cause and effect relations and explanations to how a phenomenon or activities work or why they are performed in certain ways. Finally, the main purpose of a problem-solving study is to find a solution to an identified problem (Höst, Regnell & Runesson, 2006).

After having determined the purpose of the study, the researcher could use this choice in the evaluation of the appropriate research strategy. The research strategy is a method that follows a certain logic which aims at gathering and analyzing empirically found evidence (Yin, 2009). There are several different research strategies and four of these which, according to Höst et al (2006), are especially valuable in master thesis projects will be described briefly below.

2.1.1 Survey

This type of strategy is used to analyze broad problems and is a question-based investigation of sample type where the final objective is to describe or explain the current state of the studied problem or phenomenon. Key aspects that the researcher needs to consider when using this type of research strategy are which people to address and what type of questions that should be asked to these people. Survey is an appropriate method to use when the research project will describe a phenomenon (Höst et al, 2006).

2.1.2 Case study

The technical description of the case study could be divided into two parts (Yin, 2009). The first part states that the case study is an empirical investigation that analyses a phenomenon in the real setting where the boundaries between the phenomenon and the context itself are not always obvious. This means that the case study strategy would be used because the conditions, specific for the context, are of interest in the study because they are believed to be relevant for the studied phenomenon (Yin, 2009). Secondly, the case study handles situations where the variables of interest are more than the available data points. This means that existing theories need to be used to guide the collection and analysis of data. Additionally, the data which has been collected and analyzed needs to form a common base in a triangulation pattern (Yin, 2009). The case study strategy gives the researcher the possibility to keep the holistic characteristics of real-life events such as individual life cycles, small group behavior, organizational and managerial processes, neighborhood changes, school performance, international relations and the maturation of industries (Yin, 2009). A case study aims at describing a phenomenon or an activity in depth and could for example be used in an organization to understand the way of working. The studied object in the case study is often chosen of a special reason and the researcher does not aim for generalizable results. However, if several case studies are performed and some patterns are discovered, the case study strategy might also be useful in finding general patterns. Yet, since the cases have not been randomly selected (as is the case in the survey strategy), the results cannot be considered statistical proofs. On the other hand, the case study provides a deeper insight into the specific problem than the survey does. This research strategy is also more flexible than the survey because the collection of data and therefore the direction of the study can be changed as the project moves on. The case study method is an appropriate research strategy when the study will describe a phenomenon or an object in depth (Höst et al, 2006).

2.1.3 Experiment

When the researcher wants to explain causes to a phenomenon, a more structured research strategy is required, and the experimental design is then an option. For example, this strategy can be used to compare different technical solutions to each other but also to investigate the effect of different parameter values on the performance of a system or solution (Höst et al, 2006). This strategy deliberately differentiates the studied phenomenon from its context with the purpose to explore the isolated consequences of a change in one or a few specific parameters (Yin, 2009).

2.1.4 Action research

This type of research strategy is sometimes considered being a part of the case study strategy and aims at improving an activity or phenomenon while it is studied. Action research starts with the observation of a situation or phenomenon to identify the type of problem that needs to be solved. To perform this step, either the survey or the case study research strategy can be used. When having completed the observation stage, the researcher will try to find a solution to the identified problem. Research projects which use this strategy often aim at following the development during a period of time to accomplish the desired results, several cycles are often required (Höst et al, 2006).

2.2 The chosen research strategy

In this research project, the chosen research strategy is the case study strategy. The main reasons for this choice are:

1. This study is of a problem-solving type and will explore a future state where the case company operates with a new shared central warehouse. The thesis will also include an in-depth analysis of a suitable inventory control policy and investigate the circumstances in which the case company currently operates and how these circumstances affect the performance of the inventory control policy.
2. Since the problem at hand in the initial phase needs to be explored and more clearly defined, some flexibility in terms of performing the study is required. This is one of the main advantages of the case study approach.
3. Even though this study will be focused on a future state when developing the inventory control policy, the authors will keep a holistic approach and take into account current organizational structures, supply chain processes and product characteristics.

All of these factors are mentioned by Yin (2009) and Höst et al (2006) as favorable for choosing the case study approach as the appropriate research strategy.

2.3 Research design

As concluded above, this research project will follow the case study research strategy. Since the defined problem is complex and comprehensive, this master thesis will only consider the described case company. To accomplish and fulfill the research strategy, a research design is also required. This is a logical plan to take the research project from the start to the finish where the start is the initially posed questions and the finish is the conclusions or answers that the researcher wants to reach. The main purpose of the research design is to avoid the situation where the gathered empirical evidence does not provide the answer to the initially posed research questions (Yin, 2009). In this research project, a case study methodology presented by Yin (2009) together with a guide for operations research presented by Hillier & Liebermann (2010) will be used for conducting the study. Both these approaches will be described below and the way these approaches will be combined in this study will summarize this section.

2.3.1 A case study research approach

In this section the six-step approach to conduct a case study presented by Yin (2009) will be briefly described. This approach is described as a linear but iterative process (Yin, 2009).

2.3.1.1 Plan

In the planning phase the researcher should identify the research questions that will be used in the study. Furthermore, the investigator should compare and understand the differences of the case study research strategy to other methods. It is also in this phase where the researcher needs to get an understanding of the strengths and limitations of the case study strategy together with the different types of case studies that exist (Yin, 2009).

2.3.1.2 Design

Designing the study is a difficult part of doing the case study strategy since, unlike some other research methods, no account of methods exists where the researcher can choose the design that fits the best for the specific study. However, in this stage of the process the unit of analysis should be determined but also the probable case or cases that are to be studied need to be decided. Additionally, the relevant theory, propositions and the fundamental issues creating the need for the case study should be specified. This is also the stage in which the researcher needs to determine if the study should be a single, multiple, holistic or embedded case study. Finally, procedures to keep the case study quality should be established in this stage of the approach (Yin, 2009).

2.3.1.3 Prepare

After having determined that the case study research strategy is an appropriate choice for the specific study and after having designed the study itself, the researcher should prepare for conducting the project. This step includes acquiring the specific skills that are important for a case study researcher. Also, in order for a successful completion of the case study, the team needs to be synchronized in regard to the rationale behind the case study, what evidence is wanted, what variations that could occur and what would be potential supportive or opposing evidence for any given proposition (Yin, 2009).

2.3.1.4 Collect

In the data collection phase, all the conducted preparations and established procedures should be used and followed to ensure the quality of the conducted study. Several sources of evidence should be included to strengthen the quality of the final conclusions and a case study database which constitutes a formal assembly of evidence separated from the final case study report should be established. Finally, the researcher also needs to ensure that the chain of evidence is kept so the link between the asked questions, the collected data and the conclusions drawn are evident (Yin, 2009).

2.3.1.5 Analyze

When the case study evidence has been collected, the analysis phase will start. The analysis is preferably based on a general analytic strategy where four examples are: theoretical propositions, developing case descriptions, using both quantitative and qualitative data and examining rival explanations. These strategies will be the foundation for the five analytical techniques that could then be used to guide the analytical process in the case study. Pattern matching, explanation building, time-series analysis, logic models and cross-case synthesis are all possible approaches to use in the analysis phase. To accomplish a firm analysis, the researcher needs to include all available data that has been collected and present the evidence separate from any potential interpretations (Yin, 2009).

2.3.1.6 Share

The final part of the case study approach includes the sharing of the conclusions that have been reached. In this part of the approach, the investigator needs to identify the audience of the report from the case study, develop the report's compositional structure and provide the draft for review to others. Using both text and visual material in the composition of the case study and making sure to include sufficient evidence so that the reader can reach its own conclusions are aspects to consider when compiling the case study report. To accomplish a high-quality report, the content and design should be reviewed and rewritten until reaching a high quality (Yin, 2009).

2.3.2 An approach for operations research modeling

In this part, the approach for conducting operations research presented by Hillier & Lieberman (2010) will be briefly described. Operations research is a field of research focusing on problems that concern how to conduct and coordinate the operations (in other words, the activities) performed within an organization (Hillier & Lieberman, 2010). This thesis concerns inventory control which is a common field in operations research literature. The described approach will be used in this research project to adjust the case study approach presented by Yin (2009) to the field in which this study is performed.

2.3.2.1 Define the problem of interest and gather relevant data

The first step in conducting operations research is to define the problem at hand. In many cases, this problem is imprecisely defined which means that the investigator needs to start with analyzing the system that will be studied and try to determine a specific description of the problem which will be the starting point for the study. The problem definition phase also means that several aspects such as a relevant objective, potential constraints in terms of what can be done, affiliations between the studied field and other areas of the company, other possible directions of studies and potential time limits need to be decided. Here, deciding the appropriate objective is of highest importance to ensure that the involved stakeholders get the desired result of the study. The first phase of operations research often includes an extensive data gathering about the problem. The purpose is to create a thorough understanding of the studied problem but also to create a foundation for the mathematical model that will be formulated later in the study. In the data gathering process, additional people that originally were not involved in the study will need to be involved to acquire all the necessary information. With the increasing number and size of databases one of the major challenges is to identify the most valuable data out of all the available information (Hillier & Lieberman, 2010).

2.3.2.2 Formulate a mathematical model to represent the problem

After the problem is defined, it should be transformed into a form that enables an analysis of the problem. From an operations research perspective, this most often means to form a mathematical model of the problem. In general, models are an idealized representation of the reality which are used with the purpose to simplify the analysis and to show correlations. The mathematical model shows this idealization through mathematical expressions and symbols where the main parts are the objective function, the decision variables, the constraints and the parameters. The objective function represents the performance measures while the decision variables are the decisions that could be made to maximize the performance. In real-life settings there are most often limitations to these decisions which are represented by constraints in the mathematical model. Coefficients and constraints in the model are referred to as parameters and since these are approximated by the use of real data, a sensitivity analysis of the result is conducted to conclude how sensitive the results are to changes in the parameter values. The benefits of using a mathematical model is that it facilitates the determination of cause - and - effect relationships and enables consideration of all correlations at the same time. It is important that the model is correlated to the reality (Hillier & Lieberman, 2010)

2.3.2.2 Develop a computer-based procedure for deriving solutions to the problem

In the operations research field, the aim with the mathematical model is to enable a generation of solutions for the specified problem. The overall objective is to find the best or optimal solution to the problem through the use of certain algorithms. After the solution has been reached, a common step is to perform a what-if analysis to consider what would happen to the solution if some assumptions or parameters were changed. Also in this part a sensitivity analysis is necessary to determine the most critical parameters in the model (Hillier & Lieberman, 2010).

2.3.2.3 Test the model and refine it as needed

In the development process of a mathematical model, the accuracy of the model needs to be continuously evaluated. This includes taking care of potential bugs and errors in the model which will generate errors in the solution. The major errors need to be taken care of in the refining and validation process while some minor errors, that might never be detected, will always remain. However, the testing and validation process should ensure that the results generated by the model are sufficiently reliable to be used as conclusions from the operations research study. There are different methods to validate the model where testing of different parameter values and to use a retrospective test where historic data is used to reconstruct the past and see how well the model would have performed if used for this data (Hillier & Lieberman, 2010).

2.3.2.3 Prepare for the ongoing application of the model as prescribed by management

When an acceptable model has been reached and the aim is to use the model in a repetitive manner, the researcher needs to ensure that the future user of the model understands how it is designed and how it should be used. The system describing the application of the model will include a solution procedure (including post optimality analysis) and an operational procedure required for implementation. In many cases, this implementation guide is computerized and operationalized in a decision support system which will help managers to use the model in their decision making (Hillier & Lieberman, 2010).

2.3.2.3 Implement

The final step of the operations research process is the implementation of the results from the study. Implementation is conducted in several steps where the first step includes an explanation of the new system and how it is related to current operational practices. Secondly, the staff that will work with the new system is introduced to how it works. After concluding the implementation, it is important to gather feedback and to change the model when the underlying assumptions are changing. A documentation of the procedure used in the development process to enable replicability is also important in the concluding part of the study (Hillier & Lieberman, 2010).

2.3.3 The used research design in this project

This section will describe the research design which has been used in this project. The initial stage of the project was to choose the appropriate research strategy which is the major part of the planning step in the case study approach, according to Yin (2009). Continuing with the design process of the case study, both the above described approaches (the case study process and the operations research process) have been used. The definition of unit of analysis and detailed descriptions of the data gathering procedure (which are key steps in the design and prepare phases) will be further described in the next sections of the report. However, in Figure 1 the overall design of the study is presented where the links between the purpose of study, the research questions and the case study are presented.

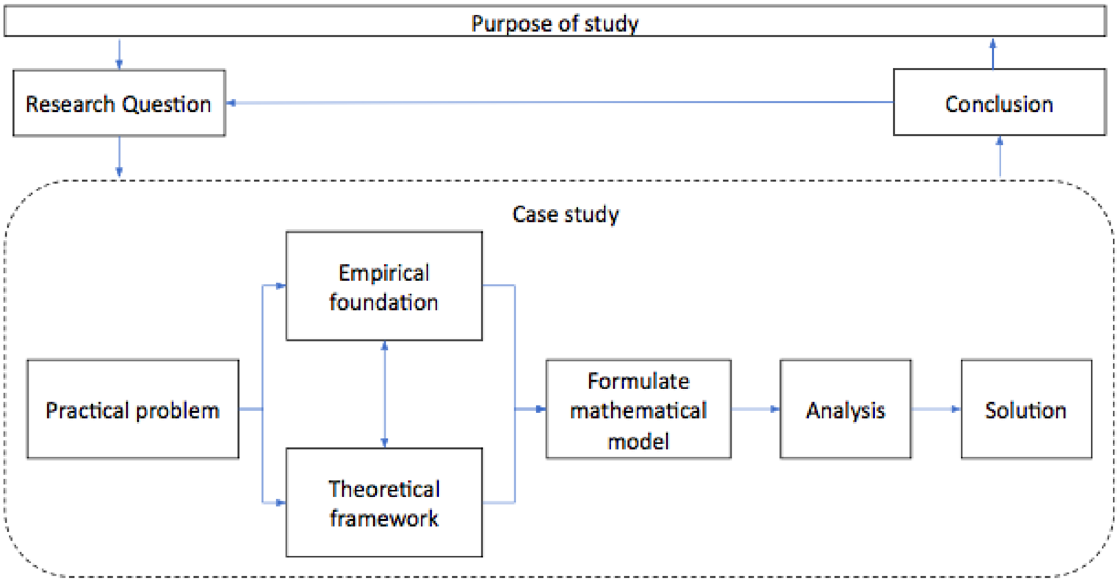

Figure 1. Overview of research strategy.

Figure 2 below describes the design of the case study in a more detailed manner. The first step of the study was to clarify and specify the problem definition by conducting interviews with some of the employees at the case company. Additionally, company directives and appropriate delimitations were taken into consideration to guide the direction of the study and the interpretation of the problem to ensure that the outcome of the study will solve the desired problem. The connection to the posed research questions was also evaluated and the alignment between the company problem description and the research questions was ensured. According to Figure 2 below, the second phase of the project was the data gathering step. At this stage, the major part of the data gathering was conducted but also a literature study was performed. Information gathered through the initial interviews with company employees together with relevant theory from the literature study, formed the basis for the system mapping. In addition to the qualitative data, also quantitative data from various systems used by the case company was collected. Data sources and strategies for data analysis which have been used will be further described in Section 2.5.4.

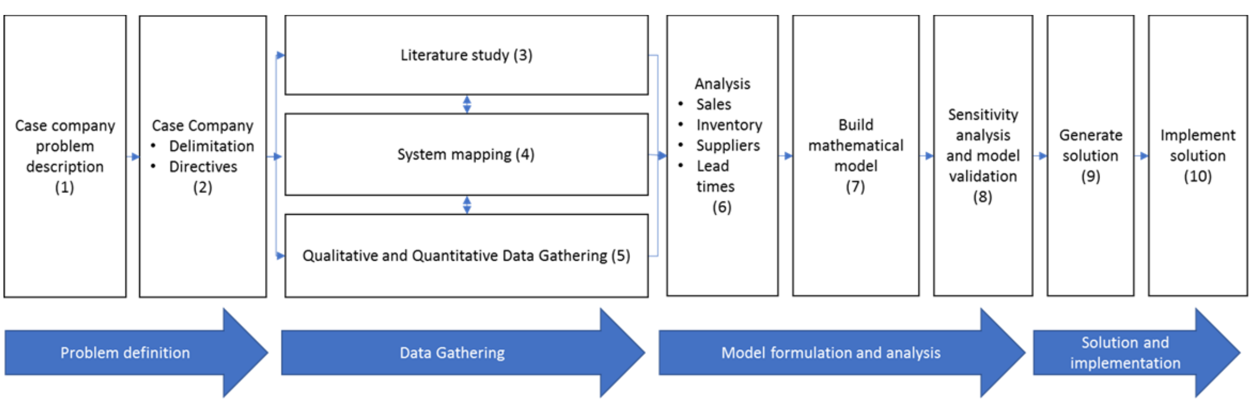

Figure 2. Summary of research design.

The gathered information in the second phase of the project, formed the basis for the third part of the study, which is called *Model formulation and analysis* in Figure 2 above. Firstly, the collected data was used for an analysis of sales, inventory levels, suppliers and lead times. This was the part of the project where the selection of suppliers and items which have been included in the project was conducted. Also, a statistical analysis of lead times was performed which was a key step in answering the second research question regarding how the variability in lead times affect the constructed inventory control policy. Additionally, the mathematical model which formed the cornerstone in the new inventory control policy was formulated and constructed. The model was constructed based on the information gathered in the second phase of the project and was applied for the selected suppliers and items. By gathering data and building the mathematical model representing the new inventory control policy, the authors were able to answer the first research question regarding how to construct an inventory control policy for the new warehouse. In the last part of the model formulation and analysis part of the research design, a sensitivity analysis of the constructed model and the included parameters was conducted. An important part of the sensitivity analysis included an evaluation of the impact of the choice of batch quantities in the evaluated inventory control policy.

Finally, in the *Solution and implementation* phase according to Figure 2 above, a solution to the experienced problem described by the case company was generated. The mathematical model and the assumptions on which it was built constituted the foundation for answering the first research question. By combining the statistical analysis of lead times and the construction of the mathematical model, a basis for answering the second research question was formed. This project has not covered the whole implementation process, instead the authors have only been involved in the explanation of the results from the study and the constructed model to relevant stakeholders at the case company.

To conclude the research design section of this chapter, the interaction framework in Table 1 below shows how the used research design interacts with the proposed frameworks by Yin (2009) and Hillier & Lieberman (2010). The numbers in the framework shows the performed steps in the design of this case study and how they are connected to the described methods.

Table 1. Interaction between the research design and the above described frameworks.

Interaction framework	Case study methodology (Yin, 2009)					
Operations research (Hillier & Lieberman, 2010)	**Plan**	**Design**	**Prepare**	**Collect**	**Analyze**	**Share**
Define problem	1	1,2				
Gather relevant data			5	3,4,5		
Formulate a mathematical model to represent the problem					6,7	
Develop computer-based procedure to derive solutions from the model					7,9	
Test the model and refine it as needed					8	
Prepare for ongoing application of the model						9,10
Implement						10

2.3.4 Unit of analysis

One part of constructing the research design is to define the unit of analysis, i.e. the case that is to be studied (Yin, 2009). In this study, the unit of analysis is PA Crushing & Screening and more specifically, the inventory control in this Product Area. The analysis in this project has been focused on the inventory control in a new warehouse supplying both the aftermarket and the production of new crushers with customer critical components. This is a future state at the case company and how this state differs and is related to the current supply chain at Sandvik C&S will be further described in Chapter 4 and Chapter 5 of this report.

2.4 Research quality

In this part of the methodology chapter, four tests proposed by Yin (2009) to ensure research quality, the application of the tests and the proposed tactics to use these tests, will be presented. Thereafter, the considerations made, and the steps taken in this study to strengthen the research quality will be presented.

2.4.1 Construct validity

The first step in the quality testing procedure in a case study is to identify the correct operational measures for the concepts being studied (Yin, 2009). To accomplish this, three different tactics are proposed by Yin (2009). The first tactic is to use multiple sources of evidence for investigations in the same direction to achieve convergence in the line of questioning. Availability of several different sources is one of the strengths with the case study method and should therefore be used to make the conclusions from the case study more convincing and precise. This tactic is applicable in the data collection phase. Secondly, establishing a chain of evidence is also an appropriate tactic which should be applied in the data collection phase of the study. The idea is to enable the reader of the case study to follow the line of reasoning and the process from the research questions to the final conclusions. Finally, it is also suggested that the case study report is reviewed by sources that have provided information to the study (Yin, 2009).

2.4.2 Internal validity

For explanatory case studies where the researcher wants to find answers to why and how questions, this quality test is especially important to consider in the analysis phase. The researcher wants to avoid concluding that a phenomenon is caused by some factors while it is actually caused by some other circumstances. Additionally, exploring alternative conclusions and questioning the reliability in the reached conclusions is also related to the internal validity. This is especially important when certain conditions cannot be observed by the researcher (Yin, 2009). Some tactics that are mentioned to deal with the internal validity are to do pattern matching, do explanation building, address rival explanations and use logic models (Yin, 2009).

2.4.3 External validity

Making sure that the results from the conducted case study are transferable to other, similar cases has been a key challenge when conducting case studies. The issue is also to define the areas in which the results from the study are applicable. Through the replication of case studies where the outcome is expected to be similar, the strength of the results from the case studies can be improved and can then be said to support the suggested theory (Yin, 2009). Suggested actions to improve the external validity in single case studies is to use theory and in multiple - case studies, to use the replication logic (Yin, 2009).

2.4.4 Reliability

The final quality test aims at ensuring that if the case study was performed a second time by another researcher which would follow the same procedures, the outcome would be the same. Focusing on reliability means aiming for reducing bias and errors in the study. For the case study researcher, the reliability issue could be tackled through thorough documentation of procedures and results. In more detail, this means that appropriate tactics to ensure reliability is to use a case study protocol and develop a case study database in the data collection phase (Yin, 2009).

2.4.5 Research quality in this study

In this section, the actions taken to accomplish an increased research quality in this project will be described. To construct validity of the study, data has been gathered by using different methods and by using several different sources at the case company (sources of information will be described in Section 2.5.3). Furthermore, the gathered data has been reviewed and validated together with employees at the case company. In terms of internal validity, the results from the study have been compared with the information collected in the literature review in a pattern matching approach with the aim to understand whether the results are in line with the expected outcome of this type of study. To construct external validity of the conducted study, several different sources have been used when conducting the literature review. Also, the construction of the mathematical model and the statistical analysis of lead times has been based on well-known theory which makes the results from this study valuable for other companies which face the same challenges as the studied case company. Finally, to increase the reliability of the results of the study, notes and descriptions of used data sources and methods to reach the conclusions in the study have been collected and summarized. This will enable the case company to repeat the performed study if this would be of interest.

2.5 Data collection and data analysis

This section of the chapter will describe different available sources of data together with available methods to analyze the collected information. In the end of the section, a description of the data sources used in this study and the chosen analytical methods will be provided.

2.5.1 Types of data

The data that could be collected to a research study is either quantitative or qualitative. The quantitative data is information that can be counted or classified and includes characteristics such as color, weight, amount and shares. This type of data can be analyzed by the use of statistical analytical models. Qualitative data on the other hand, is information that mainly consists of words and descriptions with plenty of details and nuances. The qualitative data requires other types of analysis methods in terms of sorting and categorization. In order to analyze complex problems, it is preferred to use a combination of quantitative and qualitative data (Höst et al, 2006).

2.5.2 Sources of data

According to Yin (2009) there are mainly six sources of evidence that are usually used in a case study, these are documentation, archival records, interviews, direct observation, participant - observation and physical artifacts. Documentation is a source of evidence that is included in almost all case studies and is information that could come in many different forms such as agendas, minutes of meetings, formal studies or evaluations and personal documents (i.e. e-mail correspondence and notes (Yin, 2009). Another frequently used source of information is archival records, which could include service records, organizational records in terms of budget or personnel records together with maps and charts of a certain place (Yin, 2009, p.105). Furthermore, interviews are important sources of information for case studies. Even though the case study investigator needs to have a clear line of questioning, the interviews will probably be more conversational than would be the case when using the survey method (Yin, 2009). Since the case study aims at investigating current events, observations is a valid source of information for this research strategy. Observations could be used to experience the studied phenomena in the real-world context and could be done either through direct or through participant observations. The difference is that in a participant observation, the observer is taking some role in the situation or the studied phenomenon (Yin, 2009). Finally, physical artifacts in the form of technological devices, tools or instruments or work of art could be sources of evidence to a case study (Yin, 2009).

2.5.3 Analysis approaches

In the analysis part, the gathered data should be categorized, tabulated, tested or in other ways combined to be able to draw conclusions based on the empirical evidence (Yin, 2009). The analytical strategy can be divided into a quantitative and a qualitative approach where the choice depends on the characteristics of the gathered data (Höst et al, 2006). In the quantitative approach, statistical methods are frequently occurring. This approach can be used in two ways, to explore data with the purpose to gain a deeper understanding but also to show relationships and hypothesis that have been posed earlier. To explore data, using the mean or median together with statistical measurements of dispersion could be used. Other ways of exploring the data is through visualizing the data by using histograms or box-plots. Box-plots are also useful in the investigation of whether the data sets include misleading values which needs to be removed as early as possible in the analysis (Höst et al, 2006).

Law and Kelton (1997) present a complementary approach to conduct the qualitative analysis of a system which is shown in Figure 3 below:

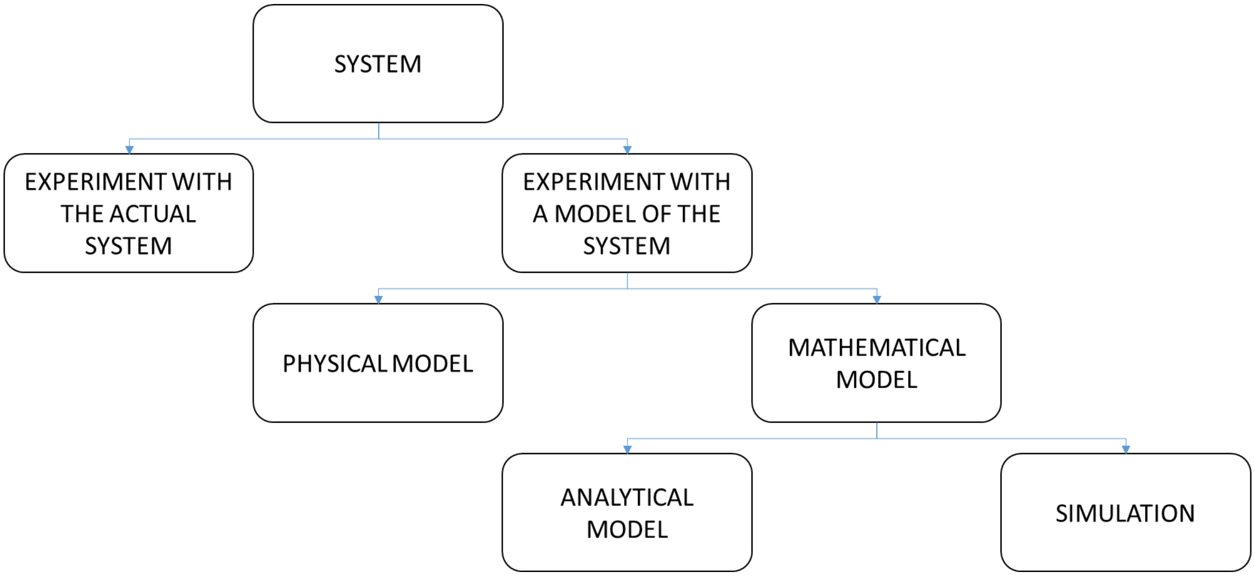

Figure 3. Framework to conduct a quantitative analysis adopted from Law and Kelton (1997).

According to this framework, there are mainly two approaches when conducting a quantitative analysis of a system. Either the experiment is done with the actual system or it is done through modelling the system. If the model is chosen, the analysis can be conducted by using either a physical or mathematical model. When using a mathematical model, this can be solved either by an analytical solution or by using simulation (Law and Kelton, 1997).

The character of the qualitative analysis is different than the quantitative approach, basically because the underlying data is different than the data set used in the quantitative approach. While the quantitative data is based on numbers, the qualitative data set consists of words and descriptions where the existence and in some cases the frequency of the existence of words are of interest. To conduct a qualitative analysis, four steps could be used: data gathering, coding, grouping and conclusions. The first step includes interviews, searches in archives and observations. In the second step, important quotes are connected to one or several keywords. This is followed by grouping where the coded parts of the texts are gathered where the purpose could be to study what different people have said about a certain keyword. Finally, conclusions are drawn based on the grouped data (Höst et al, 2006).

2.5.4 Data collection and data analysis in this study

This section describes the approach how data has been collected and analyzed in this study.

2.5.4.1 Chosen sources of information

In this project, several different sources of information have been used in the data gathering process. To answer the first research question regarding how to construct an inventory control policy for the shared warehouse, the following sources of information have been used: documentation, interviews and archival records. Documentation regarding current procedures and processes related to the current inventory control policies used by the case company has been studied. Additionally, informal interviews have been conducted with employees at the case company to form an understanding of the organization, processes and to get details regarding the future state which is considered in this project.

In terms of archival records, the main sources of information have been the ERP-systems and internal databases used by the case company. The information gathered from the internal databases and the ERP-systems include: sales numbers, purchase order data, historical fill rate levels and item master data. To perform the statistical analysis of lead times, internally used data including purchase orders during a period of four years, has been used. The statistical analysis has been used to answer the second research question regarding how the variability in lead times affect the performance of the inventory control policy. Data gathered through archival records are mostly of the quantitative character and has formed the basis for the mathematical model and the statistical analysis conducted in the project. A continuous dialogue with employees at the case company has been carried out to ensure that the chosen sources of data are reliable.

2.5.4.2 Chosen data analysis approach

Even though qualitative data has been gathered in this project, the main focus has been on analyzing and using quantitative data. Therefore, the quantitative data analysis approach has been the dominantly used in this study. Several of the statistical principles described by Höst et al (2006) have been used to analyze the gathered data. In the initial phase of the project, sales data, purchase order data and lead times have been characterized by their mean and the use of standard deviation to get an understanding of the collected information. An important step has also been to clean the collected data by examining extreme and unrealistic values. However, to answer the research questions the quantitative analysis has been carried out according to the model proposed by Law and Kelton (1997). Since it was not possible to try the solution using the real system, the analysis has been carried out by using a model of the studied system. In line with the operations research approach described in Section 2.3.2 a mathematical model has been constructed to analyze the inventory control policy in the new warehouse. This mathematical model has been solved using an analytical technique according to the inventory literature which will be described in detail in Chapter 3. The mathematical model has been programmed in Visual Basic for Applications (VBA) which is the programming language used in Microsoft Excel.

In the analysis of lead times a more rigorous statistical analysis has been carried out. The theoretical parts related to this analysis will be described in Section 3.3 and the main steps which have been conducted will be specified in Section 6.3.1. However, it can be concluded that two different software have been used to carry out the analysis. Firstly, Stat:fit which is a distribution fitting package that is connected to the simulation program ExtendSim was used (Laguna & Marklund, 2013). Secondly, the numerical computational program Matlab was used to verify and validate the results from Stat:fit.

3. Theoretical Background

The theoretical background which will be used in this thesis will be presented in this chapter. Main concepts and important terminology will be explained and connected to later stages in the report.

3.1 Supply chain management

This section describes different elements within the area of supply chain management related to this project.

3.1.1 Supply network

This section introduces the concept of supply chain. This concept is important to understand when describing the material flow and operations of the case company. Mentzer et al (2001) define a supply chain as: *"a set of three or more entities involved in the upstream and downstream flow of products, services, finances and/or information from a source to a customer."* This definition is visualized in Figure 4.

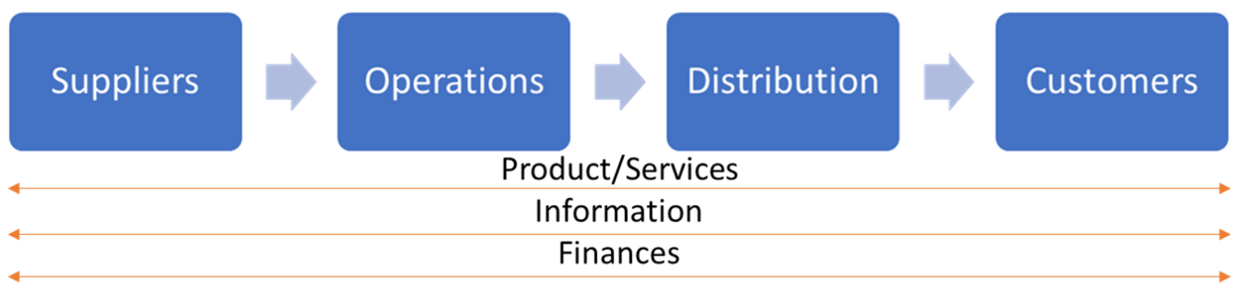

Figure 4. Supply chain adopted from Mentzer et al (2001).

In a supply chain, several independent organizations are involved in transforming raw materials to a finished product and deliver it to the end user in the supply chain, e.g. raw material and components producers, product assemblers, wholesalers, retail outlets and transportation companies are all members of a supply chain (Mentzer et al, 2001). The material that flows between these entities are raw materials, work-in-process, and finished products (Simchi-Levi, Kaminsky & Simchi-Levi, 2003). The flow of information are orders, forecasts, sharing of information such as inventory levels, sales promotion strategies and much more information that is necessary to perform activities and to make decisions (Mentzer et al, 2001). Finally, the cash flow in a supply chain are investments that enable operations and tied-up capital in inventories (Axsäter, 2006).

3.1.2 Distribution network

A distribution network can have many roles such as aggregate, distribute and add value. If a warehouse is placed closer to suppliers the function is more aggregating and on the opposite, distribution, occurs when a warehouse is placed closer to customer. There can also be value adding activities at a warehouse such as postponed assembly and relabeling which means that the warehouse may need to perform many roles at once. The number of echelons and the number of stock locations determine the degree of centralization in a distribution network. By reducing the number of echelons and stock locations, the degree of centralization increases (Johnsson & Mattsson, 2017). In this thesis, centralization mainly concerns reducing the number of stock locations.

The degree of centralization affects the potential to achieve closeness to customer and short delivery times at the trade-off for economic of scale, reduction in non-value adding activities, lower bullwhip effect, reduction in stock and reduced risk for obsoletion. With centralization, the service level from the warehouse will be maintained with less stock, but the time to reach the customer market will increase. (Johnsson & Mattsson, 2017). This theory will be used to evaluate the results from this study and to understand the trade-offs when using a single-echelon network.

3.1.3. The lead time gap

Reduced to its basic essence the goal of managing a supply chain is to match supply and demand. Therefore, most organizations face a fundamental problem: the logistic lead time it takes to procure, make and deliver the finished product to a customer is longer than the time the customer is prepared to wait for it. The challenge is to search for the means whereby the gap between the two times can be reduced if not closed (Christopher, 2011). The time difference between the logistic lead time and the time which the customer is prepared to wait can be described as (3.1). The gap can also be described as the time logistic lead time starts and when the customer order (CO) is registered. This is also called the decoupling point, since the supply chain transits from forecasts to actual customer orders. (Lumsden, 2006).

$$Lead\ time\ gap = Logistic\ lead\ time - Order\ fullfillment \quad (3.1)$$

Reducing the gap can be achieved by shortening the logistics lead time whilst simultaneously trying to move the customers' order cycle upstream in the supply chain by gaining earlier warning of requirements through improved visibility of demand. (Christopher, 2011). What makes this seemingly simple task to match supply and demand so difficult in reality is the presence of uncertainty (Christopher, 2011). According to Hopp & Spearman (2008) variability always degrades the performance of a system and variability will be buffered by some combination of inventory, capacity and/or time. An integral part of this project is to match demand and supply and hence buffer with the right amount of inventory. This project will also investigate the potential cost savings in stock due to reduction in lead time variability.

3.1.4 The Bullwhip effect

Lee, Padmanabhan & Whang (1997) define the bullwhip effect as a phenomenon where orders to the suppliers tend to have larger variance than sales to the buyer (i.e. demand distortion) and the distortion amplifies upstream in the value chain.

Lee et al (1997) continue to describe that the distortion of demand information implies that the manufacturer who only observes its immediate order data will be misled by the amplified demand patterns which will have serious cost implications. For instance, the manufacturer incurs excess raw material cost due to unplanned purchases of supplies, additional manufacturing expenses created by excess capacity, inefficient utilization and overtime. Moreover, the manufacturer incurs excess warehousing expenses and additional transport costs due to inefficient scheduling and premium shipping rates. Simchi-Levi et al (2003) describes that building excess inventory to hedge against the uncertainty will further increase the inventory holding costs.

According to Simchi-Levi et al (2003) there are five main factors which contributes to an increased variability in the supply chain: demand forecasting updating, lead times, batch ordering, price fluctuations and inflated orders. Demand forecasting updates by each individual actor in the supply chain, especially if these are done independently of each other, will increase the uncertainty and thereby also the safety stocks in the upstream supply chain. Also the existence of lead times is a cause of magnified variability since even small demand changes will incur significant changes in inventory control parameters if the lead times are long. For example, reorder points will be changed which will also increase the order quantities. The third mentioned factor causing increased variability is the use of batch quantities in the ordering process. Batching creates large order quantities which are followed by periods with no demand, increasing variability for the upstream supply chain actor. The next contributing factor is price fluctuations. Promotions and discounts will lead to an increased bullwhip effect since retailers will attempt to stock up when prices are lower. Finally, in some shortage situations customers will find out that they may not receive the requested quantity and will then inflate orders to make up for the anticipated shortfalls. This is also a common reason to the bullwhip effect which will increase variability in the supply chain.

Since variability is known to increase costs and reduce customer service, the methods to cope with the bullwhip effect is an extensively researched area. Simchi-Levi et al (2003), Lee et al (1997) and Nahmias (2013) suggest the following methods to decrease the bullwhip effect: reduce uncertainty, reduce variability, break batch quantities, reduce lead times and enter strategic partnerships. Reduced uncertainty could be accomplished by using centralized demand information, i.e. by providing each stage of the supply chain with complete information on actual customer demand, so called point of sales data. However, this can only reduce the bullwhip effect and not eliminate it since different forecast methods and buying practices may exist. Another action that will reduce the bullwhip effect is to reduce the variability originating from the customer demand process. This could be accomplished by using an everyday low pricing strategy. Furthermore, breaking batch quantities into smaller quantities or by receiving more frequent replenishments will also reduce the bullwhip effect. Another action with the same purpose is to reduce the lead times which for example could be accomplished by implementation of electronic data interchange. Finally, by engaging in a number of strategic partnerships, the bullwhip effect can be eliminated. The strategic partnership could include a coordinated inventory planning, transportation and ownership upstream and downstream in the supply chain.

3.2 Inventory control

This section describes the integral parts to create a new inventory policy. Axsäter (2006) explains that the purpose of an inventory control system is to determine when and how much to order and should be based on the expected demand, the stock situation and different cost factors. These areas will be described in this section of the theory chapter and will be used throughout the project. Firstly, the reader will be introduced to the concept of inventory. In this section, concepts from probability theory and statistics will be used. Therefore, a brief overview of relevant statistical topics is given in Section 3.3.1.

3.2.1 Inventory

The purpose of inventory is to cover demand over time, since the time it takes to procure, make and deliver a finished product is often longer than the time the customer is prepared to wait for it (Christopher, 2011). The other main reason is economic of scale and uncertainty in demand and lead time (Axsäter, 2006). When a customer demands items, the stock decreases until it is sufficiently low to order a new batch of items. The stock that is left when a new batch arrive is the so-called safety stock. The purpose of safety stock is to guard against variation in demand and lead time. Hence, stock that are not safety stock are often referred to as operational stock (Lumsden, 2006). A conceptual picture of an inventory is shown in Figure 5.

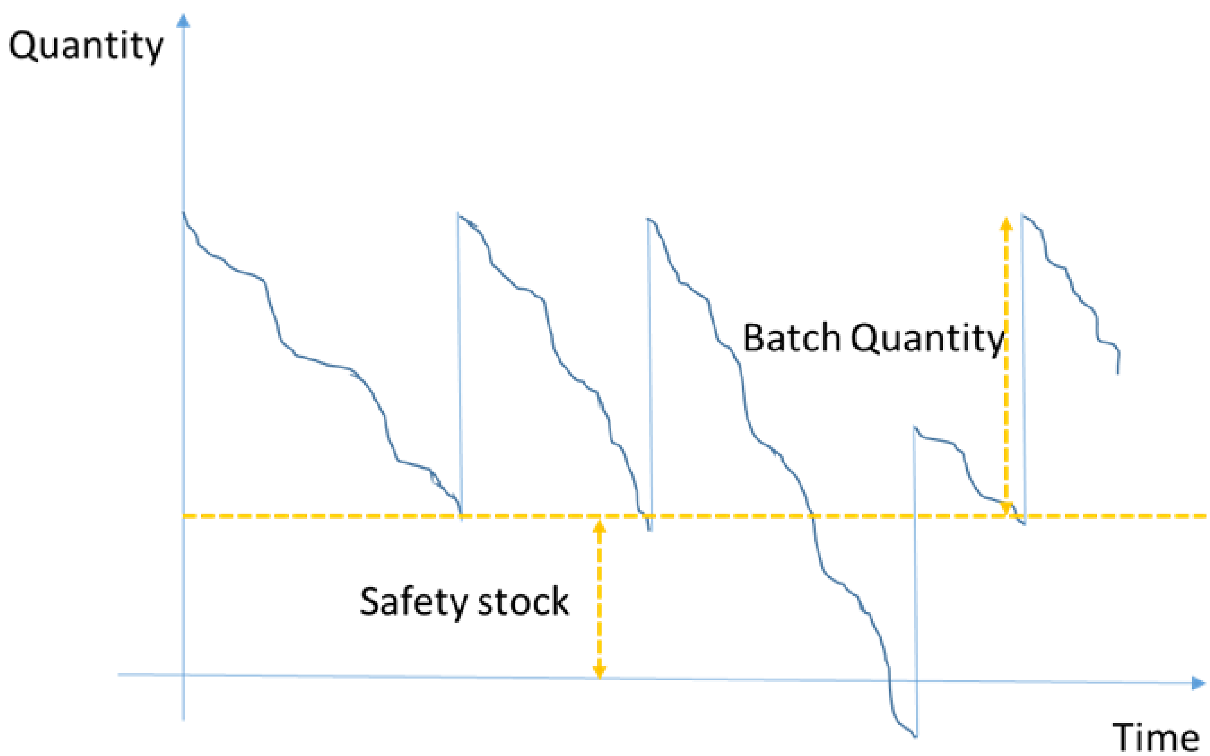

Figure 5. Inventory level as function of time in a conceptual inventory adopted from Lumsden (2006).

3.2.2 Stochastic demand distribution

In practice, demand is often considered random which in a certain period of time can be modelled as a nonnegative stochastic integer (Axsäter, 2006). For example, are components described in Section 4.2.2 demanded as integers. Therefore, it is necessary to find a suitable demand model before determining reorder points and safety stock that should buffer for randomness in demand and lead time.

Altay & Litteral (2013) describes that intermittent demand patterns are often characterized by variable demand sizes that occurs in irregular intervals. Hence, it is preferable to model demand from these two constituent elements: demand size and inter-demand interval. Therefore, the compound distributions (that explicitly consider the size-interval combination) are typically used in inventory control context. A categorization based on the size-interval combination is described in Table 2.

Table 2. Pattern categorization for random demand adopted from Altay & Literal (2011).

Pattern	**Description**
Smooth	Few periods of low or zero demand and low variability in the size of the demand
Erratic	Relatively few zero demand periods, but the demand size variability is high
Slow	Many zero demand periods and low demand size variability.
Lumpy	High demand size variability and a high level of intermittence.

In many practical cases, the demand during a certain period of time is most often a nonnegative integer. This means that it can be modelled as a discrete stochastic variable. However, demand can also be approximated as continuous when demand is fairly large. In the latter case it is common to use the normal distribution to decide the inventory control parameters (Axsäter, 2006). This is because of the central limit theorem which states that the sum of many independent stochastic variables will have a distribution that is approximately normally distributed, for more information see Blom, Enger, Englund, Grandell & Holst (2005). However, the drawback is that normal distribution has at least a small probability of taking negative values (Axsäter, 2006).

In many cases, it is instead deemed more appropriate to model the demand as a non-decreasing stochastic process where the increments are stationary and mutually independent. These types of processes can be represented by the limit of a sequence of compound Poisson processes (Axsäter, 2006). For that reason, it is reasonable to assume that the demand constitutes a compound Poisson process where customers arrive with a given intensity λ. However, in the compound Poisson process, the size of the customer demand is also a stochastic variable. In summary, this means that a compound Poisson process is characterized by the customer arrivals, which occur according to a Poisson process, and that the demanded number of items from each customer is also a stochastic variable. This stochastic variable is independent of the size of the demand from other customers and is also independent of the customer arrival intensity. Considering a short time interval Δt, the probability of having one customer arrival is $\lambda\Delta t$. The probability of having more than one customer arrival in this short time span can be disregarded. For a given time period t, the number of customers will then have a Poisson distribution where the probability for k customers, shown in (3.2) (Axsäter, 2006).

$$P(k) = \frac{(\lambda t)^k}{k!} e^{-\lambda t}, k = 0, 1, 2, \ldots \qquad (3.2)$$

Law & Kelton (1991) describe in this case, the average as well as the variance of number of customers is λt. However, in the more general compound Poisson distribution, Axsäter (2006) states that it is also necessary to determine the distribution of the demand size which is called the compounding distribution. If assuming that customers request an integral number of units then the compounding distribution is denoted f_j (for demand size j = 1, 2...). In the case that $f_1 = 1$ the demand is of pure Poisson character which means that the total demand is the same as the total number of customers. In the general case, the size of the demand is varying which requires the calculation of a distribution of the total demand size in a time interval t. Let f_j^k be the probability that k customers give the total demand j. In the calculations, $f_0^0 = 0$ and $f_j^1 =$

f_j. Given $f_j^1$the j-fold convolution of f_j, f_j^k can be obtained recursively as described by (Axsäter, 2006) and showed in (3.3).

$$f_j^k = \sum_{i=k-1}^{j-1} f_i^{k-1} f_{j-i}\,, \quad k = 2, 3, 4, \ldots \quad (3.3)$$

When the compounding distribution has been decided, the demand during a specified period of time, t, denoted $D(t)$, can be decided. Hence, the probability of demand j during a specific period of time t for k customer arriving at intensity λ in a compound Poisson process is described in (3.4) (Axsäter, 2006).

$$P(D(t) = j) = \sum_{k=0}^{\infty} \frac{(\lambda t)^k}{k!} e^{-\lambda t} f_j^k \qquad (3.4)$$

Now the average and the variance of demand during one unit of time can be determined as $\mu = \lambda \sum j f_j$ and $\sigma^2 = \lambda \sum j^2 f_j$, respectively. There λ is customer arrival intensity, j = demand size and f_j are the compounding distribution. Let μ' and $(\sigma')^2$ be the mean and variance of demand during the time t, then $\mu' = \mu t$ and $(\sigma')^2 = \sigma^2 t$. An interesting observation is that, variance over mean, ${\sigma^2}/{\mu} \geq 1$, which means that a compound Poisson model is best suited for demand with variance higher or equal to the mean (Axsäter, 2006).

In practice, it is convenient and computational effective to replace the general compound Poisson distribution by a Poisson distribution when $0.9 \leq {\sigma^2}/{\mu} \leq 1.1$ and a compound Poisson demand with a logarithmic compound distribution for ${\sigma^2}/{\mu} \geq 1.1$ (Axsäter, 2006). However, in this master thesis the demand of key components will be modelled as a general compound Poisson process for the purpose of accuracy but from an implementation perspective either approach is feasible. Further details on how the compound Poisson distribution will be used in the calculations will be provided later in this chapter.

3.2.3 Human judgement

Deciding an appropriate demand model is most often based on historical data. However, there are situations where human judgement is more suitable to use to estimate the future demand. For example, when there are known factors that will affect the future demand, but which have not affected the previous demand. Therefore, a forecasting system should be designed so that a manual forecast can replace automatic forecasts with ease. Examples when manual forecasts could be considered are price changes, sales promotions, conflicts that affect the demand, new products without historical data, new competitive products on the market and new regulations (Axsäter, 2006). In this project will some items that are newly introduced, outgoing and has certain customer specific requirement and which are therefore not suitable for statistical modeling, be handled manually.

3.2.4 Costs and service level

This section will describe holding costs, ordering costs, backorder costs and the related service level concepts which are used to optimize and evaluate when and how much to replenish.

Inventory holding costs are all costs that vary with the inventory level. The dominant part is often regarded as opportunity cost for capital tied up in inventory. Other parts can be material handling, storage, damage and obsolescence, insurance, and taxes. The holding cost per unit and time unit is often determined as a percentage of the unit value (Axsäter, 2006).

There are usually fixed costs associated with replenishments, independent of the batch size. When ordering from external suppliers, fixed costs could for example be order forms, authorization, receiving, inspection and handling and invoices from suppliers. In production, fixed costs are associated with setup and administrative ordering costs (Axsäter, 2006).

Shortage costs are various costs that can occur when an item is demanded and cannot be delivered due to a shortage. There are situations when a customer agrees to wait while the order is backlogged, but also situations when the customer switches to another supplier. If the sale is lost, the contribution of the sale is also lost. If the customer order is backlogged, there are often extra costs for administration, price discount for late deliveries, material handling and transportation. In any case, loss of goodwill due to shortage may affect sales in the long run. Because shortage costs are difficult to estimate, it is very common to replace them by a suitable service constraint (Axsäter, 2006). In this project, it will be assumed that all customer orders are backordered.

When determining a suitable reorder point we need to define the service level constraint (or shortage cost). Three well used service level definitions are (Axsäter, 2006):

1. Probability of no stock outs per order cycle.
2. “Fill rate” - fraction of demand that can be satisfied immediately from stock on hand.
3. “Ready rate” - fraction of time with positive stock on hand.

The first definition can be seen as the probability that an order arrives in time before the stock on hand is finished. This definition is very easy to use, but it does not take into consideration the batch size and is therefore not recommended for inventory control in practice. The fill rate and the ready rate make the determination a bit more complex but will give a much better picture of the customer service (Axsäter, 2006). In this project, the case company uses the “fill rate” definitions as their service level definition. The calculations when determining the new inventory control policy will therefore be based on this service level definition.

3.2.5 Ordering concepts

As mentioned earlier, the decision on when and how much to order should be based on the stock situation, the anticipated demand and different cost factors. When talking about the stock situation it is natural to think about stock on hand. However, an optimal ordering decision should also include outstanding orders that have not yet arrived and back orders that are units that have been demanded but not yet delivered (Axsäter, 2006). Let

$$Inventory\ position, IP\ =\ stock\ on\ hand\ +\ outstanding\ orders\ -\ backorders \quad (3.5)$$
$$Inventory\ level, IL\ =\ stock\ on\ hand\ -\ backorders \quad (3.6)$$

In this project, the inventory position will be used to decide appropriate reorder points and inventory level is used to calculate the expected stock on hand and in later steps, also the fill rate. Axsäter (2006) describes that an inventory control system can either be monitored continuously or be inspected in periodic intervals. When reviewing the inventory position at all time an order is triggered as soon as the inventory position is sufficiently low. The order will then be delivered after a certain lead time denoted, L. The lead time consists of transit time for suppliers and production time for internal orders. Additionally, the lead times also include time for preparation of order and for inspection at arrival of the order. An alternative to continuous review is to inspect the inventory position in constant intervals. The time interval between reviews is denoted T. This is called a periodic review inventory control system, since the inventory position is inspected at the beginning of each period and that all replenishment are triggered at these reviews.

Both alternatives have their advantages and disadvantages. Consider a review when no order is triggered, the next possibility to order is T time units later. Hence, the inventory position must guard against demand variations during L + T. On the other hand, with periodic review the possibility to coordinate orders between different items is better. Although modern information technology has reduced the costs for inspections will periodic review reduce the costs for the inventory control system. However, a periodic review with short review period (T) is of course very similar to continuously review (Axsäter, 2006).

In this project, different items can be controlled independently and in the future state, will be stocked at a single location. However, coordination of order can be obtained due to periodic review. According to Axsäter (2006) there are two main reason for coordinating the replenishment of a group of items. One reason is to achieve sufficiently smooth production load. It is when desirable to coordinate replenishment for different items so that they are evenly spread over time. The other reason is the complete opposite, trigger orders for a group of items at the same time. This can be advantageous in situation such as when get a discount if the total order from the same vendor is greater than a certain breakpoint or to reduce the transportation costs by filling a truckload (Axsäter, 2006).

3.2.6 An (R, Q) policy

When the inventory position declines to or below the reorder point (R), a batch quantity of size (Q) is ordered. If the inventory position is sufficiently low, it may be necessary to order more than one batch to get above R. In the case of periodic review, or if the triggering demand is more than one unit, it is possible that the inventory position is below R when ordering. For the purpose to give the reader better understanding of an (R, Q) policy with periodic review and continuous demand is shown in Figure 6 (Axsäter, 2006).

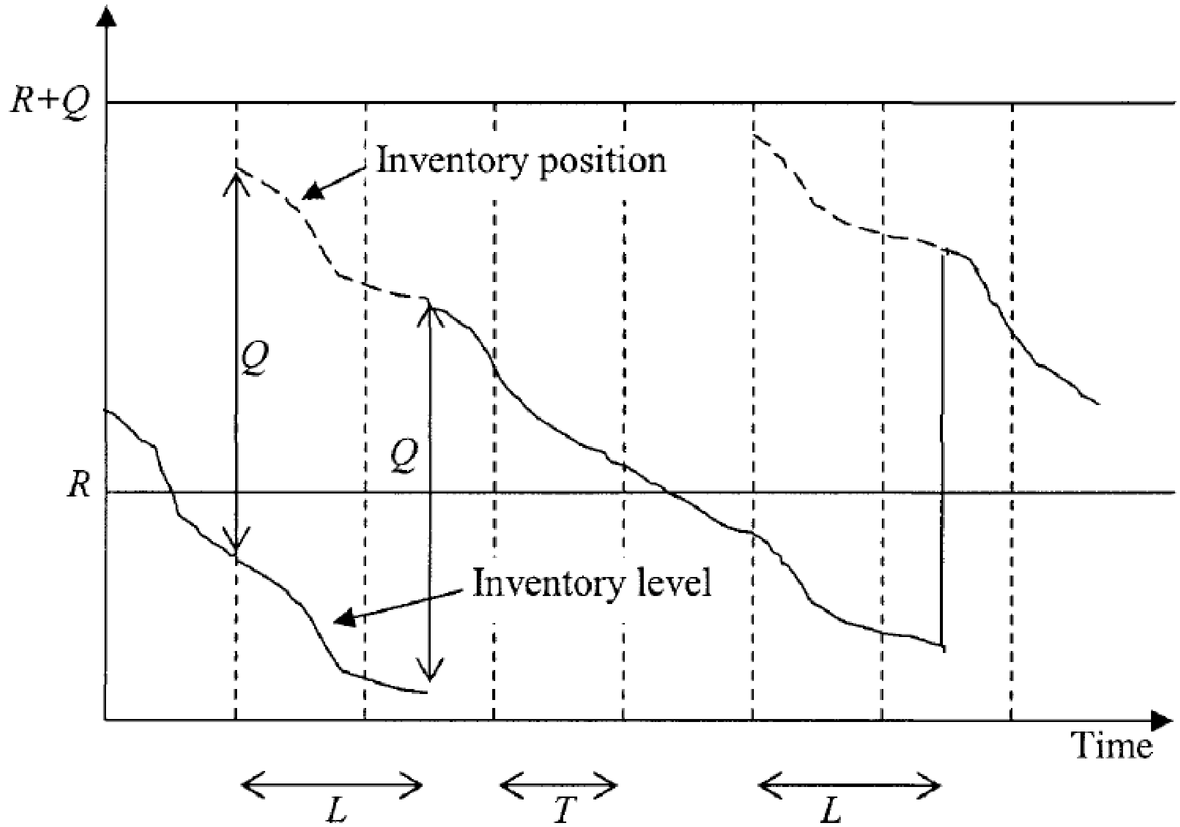

Figure 6. An (R, Q) policy with periodic review and continuous demand (Axsäter, 2006).

A natural question to ask is whether other better policies exists. Axsäter (2006) describes that in most situations an (R, Q) type is indeed optimal for a single-echelon inventory system with independent controlled items. It can be proved that a continuous review (R, Q) policy is optimal under the assumptions that there are no ordering costs but all orders must be multiples of a given batch quantity Q. This proof can then be generalized for other costs structures and to periodic review. Another situation that could be optimal for a single-echelon inventory system is allowing batch quantity to vary for the purpose of ordering up to a maximum allowed level. However, this policy is not necessarily optimal for problems dealing with service constraints (Axsäter, 2006). Further motivation for why an (R, Q) policy is deemed as an appropriate model in this case is described in Section 6.4.

3.2.6.1 Reorder point

As mentioned earlier in this chapter a compound Poisson process is a reasonable model for a non-decreasing process with stationary and mutually independent increments. Recall that the model is of interest when modeling relative low demand. This demand model combined with the service level definition fill rate will in this project be used to determine reorder points R in a periodic review (R, Q) policy. Recall that periodic review means that the inventory position is inspected at the beginning of each period and that all replenishments are triggered at these reviews. In the following sections, constant lead time will be considered. Then adjustments for stochastic lead times will be made.

An important assumption is when consumption takes place during a review period. It will be assumed that demand is spread out evenly since this is the most natural assumption in most applications. This assumption motivates why we need stock regardless of the length of lead time to buffer for the demand variation in between inspection intervals. (Axsäter, 2006). This assumption will later be used to calculate the expected stock on hand since the inventory level is unknown between the reviews. Hence will the expected inventory level be linearly interpolated between these reviews.

Now consider an arbitrary review time t. The order can be triggered at an inspection time t and be delivered after a lead time t + L. If no order is triggered at inspection, the next possibility to order is T time units ahead and next delivery will be possible at time t + T + L. Hence, the inventory position must guard against demand variations during L + T. Therefore, when determining the distribution of the inventory level it is necessary to consider these the two times L and L + T. As mentioned, L is of interest after a possible order is triggered and L + T is of interest if not an order is triggered at an inspection (Axsäter, 2006). The arbitrary review time t, lead time L and review period T is shown in Figure 7 for the purpose of clarifying their relationship to each other.

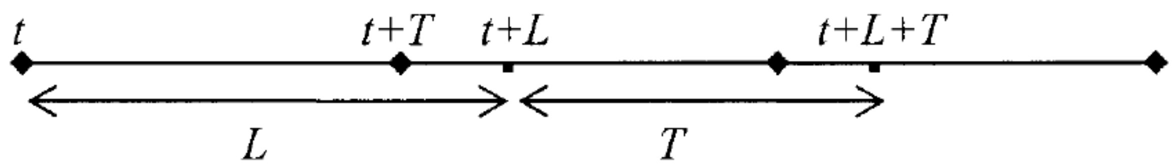

Figure 7. Considered time epochs (Axsäter, 2006).

Now the inventory position distribution and inventory level distribution will be determined, which will be used to calculate the fill rate and the corresponding reorder point, R, for compound Poisson demand. Axsäter (2006) proves that for compound Poisson demand, the inventory position in steady state is uniformly distributed on the integers $[R+1, R+Q]$. This is due to the fact that the inventory position, IP, triggers an order when at or below R units, i.e. $IP \geq R + 1$. When ordering one or more batches of size Q units IP will reach maximum, i.e. $R+Q$ or at least above $R+1$. i.e. $IP \leq R+Q$. Recall that we assume that no all demands are multiples of some integer larger than one. Therefore, it is evident that, in the long run, all inventory position is considered. Consequently, will IP steady-state distribution be uniformly distributed on $[R+1, R+Q]$, i.e. probability of IP, is $1/Q$. (Axsäter, 2006).

Let the inventory level, IL, be j and inventory level distribution be denoted as $P(IL = j)$ for $j \leq R+Q$. Let inventory position, IP, be $k = max\{R+1, j\}$ to $R+Q$, since inventory level can never exceed the inventory position during lead time. As described earlier, inventory level has a simple relationship with inventory position and since inventory position and demand during lead time, L, is independent we can condition on the inventory position. For more details please read Axsäter (2006). Then according to (3.7) below

$$P(IL = j) = \frac{1}{Q} \sum_{k=max\{R+1,j\}}^{R+Q} P(D(L) = k - j) \quad , j \leq R+Q \qquad (3.7)$$

Let IL’ and IL’’ be the inventory level at time t + L and t + L + T, respectively. For calculating distribution for IL’’ simple replace L with L + T in (3.7). (Axsäter, 2006) Finally we are now ready to define the fill rate for a compound Poisson distribution with periodic review.

Consider the interval between the two times t + L and t + L + T. Recall that the expected demand during one unit of time is μ and the expected demand in the considered interval of length T is μT. Then the part of the demand in the considered interval between t + L and t + L + T that cannot be met from stock on hand is backordered so it can be determined as $E[IL''^{-}] - E[IL'^{-}]$. Where $E[IL^{-}]$ is the expected number of backorders. Expected number of backorders are most easily obtained by taking the difference between expect stock on hand, $E[IL'^{+}] = \sum jP(IL' = j)$ or $E[IL''^{+}] = \sum jP(IL'' = j)$ for inventory level $j = 1, 2, \ldots, R + Q$ and expected inventory level, $E[IL] = R + (Q + 1)/2 - \mu L$ or $E[IL] = R + (Q + 1)/2 - \mu(L + T)$. Then the fill rate, i.e. the fraction of demand that can be satisfied immediately from stock on hand, for periodic review is defined in (3.8) (Axsäter, 2006).

$$Fill\, rate = 1 - \frac{E[IL''^{-}] - E[IL'^{-}]}{\mu T} \quad (3.8)$$

This is an iterative technique for determining the reorder point until given fill rate constraint is fulfilled. Next step will be to find optimal R and Q simultaneously that minimize costs for a given fill rate constraint.

3.2.6.2 Batch quantity

In practice, it is most common to determine the batch quantity from a deterministic model, as for example by using the well-known economic order quantity formula (Axsäter, 2006), (Johnsson & Mattson, 2017). However, it is also possible to optimize the batch quantity and the reorder point jointly in a stochastic model. Consider the inventory holding costs per item and time unit, h, ordering cost per order, A, cost per item K and expected demand per time unit. Then the average total costs per time unit can be determined as (3.9) (Axsäter, 2006):

$$C(R, Q) = A\frac{\mu}{Q} + hK\sum_{j=1}^{R+Q} jP(IL = j) \qquad (3.9)$$

Where μ/Q is the number of orders per time unit and expected stock on hand is $E[IL^{+}] = \sum jP(IL = j)$ (Axsäter, 2006). As mentioned earlier, the inventory level is not known in between reviews, hence the expected inventory level will be calculated as the average of the expected stock on hand at time L and time L+T, see Section 3.2.6.1. In this project a fill rate constraint makes finding optimum easier since an iterative technique is to optimize R given a fill rate for all relevant Q and choose the lowest expected total cost described above. In this project, it is relevant to not have a batch quantity larger than yearly demand.

3.2.6.3 Stochastic lead times

Finally, stochastic lead time will be considered. Axsäter (2006) describes how to handle sequential deliveries, that cannot cross in time, independent of the lead time demand. This is most common in practice. In this case a stochastic lead-time for a certain order may depend on the previous demand due to earlier order that have caused congestion in the supply system, but demand after the order will not affect the lead time. For discrete demand, such as compound Poisson demand, the distribution of the inventory level can be obtained by simply averaging over different lead times. Hence, probability of inventory level j can be described as in (3.10) and (3.11) below:

$$P(IL = j) = E_L\left\{\frac{1}{Q}\sum_{k=max\{R+1,j\}}^{R+Q} P(D(L) = k - j)\right\} =$$

$$\frac{1}{Q}\sum_{k=max\{R+1,j\}}^{R+Q} P(D = k - j) \ , j \leq R + Q \qquad (3.10)$$

Where

$$P(D = j) = E_L\{P(D(L) = j)\} \qquad (3.11)$$

In this master thesis, the impact of lead time variability will be analyzed. Gerchak & Parlar (1991) states that lead time variability is of interest since it affects the safety stock related costs. Song (1994) states that reducing lead times and their variability is an important focal point in process development. Song (1994) investigates the impact of lead time uncertainty on a base-stock policy and the related system performance. Lead times are considered being stochastic but exogenous and are not allowed to cross in time. The article concludes that an increased lead time variability increases the optimal base-stock level. Gerchak & Parlar (1991) states that lead times have often been considered being pre-determined in inventory literature but that the Just-in-Time philosophy has changed this view to considering the supply lead time being influencable, of course to an investment cost (Gerchak & Parlar, 1991).

When discussing and handling stochastic lead times, it is important to be aware of the definition of a lead time. According to Liao & Shyu (1991), the lead time (more formally denoted as the procurement lead time) is defined as the length of time between the point where the order is placed and when the ordered quantity could be used to satisfy customer demand. The authors state that the lead time consists of the following components: order preparation, order transit to the suppliers, supplier lead time, items transit time from suppliers and preparation time for availability. In this case the supplier lead time is defined as: the time between receival of the order by the supplier to the point in time where the goods are shipped from the supplier (Liao & Shyu, 1991). Some causes of variability in the supplier lead time phase will be described below.

Some more details and further causes to variable lead times will be provided here. Hopp & Spearman (2008) describes causes to variability in a manufacturing environment. Since the suppliers to the case company in this study, are manufacturers of components, the variability in lead times could be affected by these factors. The main mentioned causes are: “natural variability” (including minor process time fluctuations due to differences in operator is mentioned, machines and materials), preemptive outages, non-preemptive outages and rework. Natural variability is described as a cause which is often operator-related but also in automated processes, variability caused by composition of material exists. The second mentioned cause of variability is preemptive outages where an important factor to variability is breakdowns. This category includes events that are uncontrollable and is in most systems the most significant cause of variability. Except from breakdowns, also stops caused by power outages, operators being called away on emergencies and running out of supplies, are included in this category of causes to variability. Non-preemptive outages also cause downtime, but these types of events are, to some extent, possible to control. For example, process changeovers (setups) can be considered as non-preemptive outages when caused by changes in the production process which for example could happen in the case of preventive maintenance, breaks, operator meetings and shift changes. The idea is that this type of downtime can be controlled to occur between jobs and not during jobs. Finally, variability from rework is another key source of variability caused by quality problems. If a job at a workstation needs to be done twice because it was poorly executed the first time, this could be considered as outage of non-preemptive character. Rework could therefore be considered to cause the same effects as setups in terms that they take unnecessary capacity and creates variability in the process time. (Hopp & Spearman, 2008). A defective part in the supply chain can cause problem if it finds its way into the production process to cause scrap or rework problems. However, even if defective parts are screened out before they reach production, it can still cause negative effects. The reason is that they inflate the variability of delivery time. Scrap or rework problem at supplier plant can cause late delivery, or if some orders must be sent back because quality problems were detected upon receipt the delivery time will not be regular and predictable. (Hopp & Spearman, 2008)

3.2.6.4 Probability of ordering

This section describes how to calculate probability of ordering at an inspection in a periodic review control policy with a small modification of previous results from Axsäter (2006). During the same assumptions as mentioned earlier, the stationary distribution of inventory position will be uniform on the interval $[R + 1, R + Q]$. Hence, if an order is triggered at the inspection time t, the inventory position will be between $R + 1 \; to \; R + Q$ and if an order is not triggered the inventory position already is at least at $R + 1$. To trigger an order at the next inspection t + T, the demand during T needs to be large enough so that the inventory position declines to R or lower. This total demand size is given by the difference between the inventory position k and the reorder point R. Demand during the review period T is independent of the inventory position, hence condition on inventory position, $IP = k, \; k + 1, \dots, R + Q$ provides the following result (3.12):

$$F_X(k) = P(Order \; at \; reveiw \; T | \; R, Q) = \frac{1}{Q} \sum_{k=R+1}^{R+Q} P(D(T) \geq k - R) \qquad (3.12)$$

The formula above generates the probability of ordering one single item at the time of inspection. If dealing with several independent items, the likelihood of triggering an order for at least one of these items is given by the following results from statistics (3.13) (Blom et al, 2005):

$$F_Z(z) = 1 - [1 - F_{X1}(z)][1 - F_{X2}(z)] \dots [1 - F_{Xn}(z)] \qquad (3.13)$$

Where X_i is an independent stochastic variable i, such as demand for an item during review period T, $D(T)$. Z is minimum of n stochastic variables, such as several items with independent demand during review period T. These calculations will be used in section 6.4.2 and 6.6 thus sharing this information with supplier can create better condition for planning process and henceforth reduce lead time variation.

3.3 Distribution fitting and analysis of input data

In this master thesis, a statistical analysis of the lead times will be carried out. This is one step in answering the second research question regarding how the variability in the lead times affect the inventory holding and ordering costs. In Section 6.3.1, the methodology used when conducting this analysis has been described. In this section, the used theory behind this analysis will be further described.

3.3.1 Basic concepts in statistics

When analyzing different business processes, it is important to realize that these are rarely completely deterministic. Instead they include some randomness which creates a need for statistical models to analyze the data generated from the process (Laguna & Marklund, 2013). When conducting random experiments, the numerical results are unknown beforehand. The result from these types of experiments could for example be the number of heads when throwing a coin. These types of variables, where the value is determined based on the outcome of random experiments, are called random variables which are often denoted X (Blom et al, 2005). A random variable could be either discrete or continuous, it is discrete when it only takes a finite number of values while it is continuous if the random variable can take any value in the range in which it is defined. (Blom et al, 2005).

The probability of having a specific outcome x of a stochastic variable is defined by the probability mass function (in the discrete case) which is often denoted $p_X(k)$ or by the probability density function (abbreviated PDF) which in the continuous case is denoted $f_X(x)$. These functions relate the outcomes of the random variable to their probability of occurrence (Blom et al, 2005). The probability of experiencing a certain outcome A from the random variable takes a value between 0 and 1 which is denoted as below:

$$0 \leq P(A) \leq 1 \qquad (3.14)$$

The probability of getting any of the defined outcomes of the random variable, for example getting either heads or tails in the coin experiment, is always equal to 1. It is often of interest to find the probability of getting a value less than a specific limit. This probability could be found by using the cumulative distribution function (CDF) which is denoted $F_X(x)$. For a discrete random variable, the CDF could be calculated by summarizing the probability mass function according:

$$F_X(x) = P(X \leq x) = \sum_{j \leq x} p_X(j) \qquad (3.15)$$

In the continuous case, the CDF is found by integrating the density function (where the lower limit depends on the range on which the random variable is defined):

$$F_X(x) = P(X \leq x) = \int_{-\infty}^{x} f_X(y)dy \qquad (3.16)$$

The cumulative distribution function takes values between 0 and 1. If x is chosen such that the area under the probability density function to the right of x is equal to a given number alpha (where $0 < \alpha < 1$) the result is the α-quantile which is often denoted x_α. (Blom et al, 2005).

A stochastic variable is completely defined by the probability mass function or the probability density function. However, in many cases it is sufficient to describe the characteristics in terms of the mean and the level of dispersion. The mean provides information regarding where the probability mass is located on average. To get a more specific description of the stochastic variable, a measurement of the dispersion of the probability mass is also needed. One of the most common measurements of dispersion is the variance and the standard deviation. The standard deviation is the square root of the variance. The relationship between the mean and the standard deviation can be described by the coefficient of variation (COV) which is calculated by dividing the standard deviation with the mean. (Blom et al, 2005).

If one wants to evaluate a posed hypothesis, using hypothesis testing is a well-known statistical method. Such a test is conducted by deciding a null hypothesis where the tests decides whether the hypothesis can be rejected or not. It is common to talk about the level of significance in connection with hypothesis testing which is often denoted with α, where α is:

$$\alpha = P(type - 1 - error) = P(reject\ H_0 | H_0\ is\ true) \qquad (3.17)$$

The highest allowed value of α is the chosen level of significance. This means that if $\alpha = 0.05$ the probability of type-1-error is allowed to be maximum 5 percent when rejecting a null hypothesis (Höst et al, 2006).

3.3.1 Distribution fitting and goodness-of-fit

When modelling a system, the historical data could be used in its current state but it is more common to try and match the historical data with a probability density function which is then used to create simulated data points which are used as input to the model. This way of handling the data is used because gathering data is expensive and historical data seldom include the extreme values which a probability density function generates. (Laguna & Marklund, 2013).

When modelling business processes, different times are often of most interest, as for example processing times and interarrival times. To model time (which is continuous), continuous probability density functions are most appropriate to use (Laguna & Marklund, 2013). Statistical analysis will in this master thesis be used to analyze supplier lead times and therefore probability density functions will be of most interest in this project. According to Laguna & Marklund (2013) empirical research have shown that a few probability density functions have proven especially useful in describing frequently observed random phenomena. They are therefore called theoretical or standardized distribution functions but even though they are named theoretical they are based on the observed patterns in real systems. Some of these distributions are the normal, beta, gamma and exponential distributions. (Laguna & Marklund, 2013). A distribution that will be especially related to this project is the lognormal distribution. This is a continuous probability distribution of a random variable which has a logarithm that is normally distributed. The probability density function has the following feature (Law & Kelton, 1991):

$$f_X(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{-(\ln(x)-\mu)^2}{2\sigma^2}} \qquad (3.18)$$

The mean and variance of the distribution are calculated as follows (Law & Kelton, 1991):

$$Mean = e^{(\mu+\frac{\sigma^2}{2})} \qquad (3.19)$$

$$Variance = \left(e^{\sigma^2} - 1\right)e^{\left(2\mu+\sigma^2\right)} \quad (3.20)$$

The parameters μ and σ are the location and scale parameters for the normally distributed logarithm $ln(X)$ (Law & Kelton, 1991).

To model business processes that includes randomness, it is important to identify a suitable and known probability density function that properly describes the studied process. In the initial stage of the analysis, several different PDFs should be considered and the most proper one to model the studied variable could be determined by using frequency charts or histograms. This is an appropriate method to identify potential candidate probability density functions. In the second step, the parameters of the candidate distribution should be calculated from the field data to be able to conduct statistical goodness-of-fit tests (Laguna & Marklund, 2013). To estimate the parameters of the distributions which possibly fit the lead time data gathered from the case company in this project, the maximum likelihood estimation will be used. Maximum likelihood estimation will be further described below. Anyhow, when using goodness-of-fit tests, it is important to be aware of that these tests cannot prove that the data follow the candidate distribution, but they can help to rule out some distributions which probably do not represent the data set (Laguna & Marklund, 2013). Two of the most common goodness-of-fit tests, the Chi-Square and KS-tests, which will be used in this master thesis will be described below. Laguna & Marklund (2013) states that there is no definite rule that defines which goodness-of-fit test that is best to use. However, it is stated that for large samples (defined as samples with more than 30 observations), the Chi-square test is more preferred than the KS-test. For smaller samples of data, the KS-test is preferred but this test has also been applied in a successful way for discrete probability distributions, so ruling out this test completely is not possible (Laguna & Marklund, 2013). Since the samples of data will be of varying size and since there is no definite rule to decide which goodness-of-fit test to use in certain situations, both these tests will be used in this master thesis.

3.3.2 Maximum-Likelihood Estimation

One method of estimating the parameters for the theoretical distribution which should be tested in the goodness-of-fit tests is to use the maximum likelihood (ML) estimation. The idea with this parameter estimation is to use the field data to find an estimation of the unknown parameter θ which maximizes the probability of getting this specific outcome of data points. (Blom et al, 2005). Most often it is assumed that the observed data $x_1, x_2, \ldots, x_n$ are outcomes of independent random variables having the same distribution, but the ML estimation works even though these assumptions are not fulfilled. If the random variable X is continuous, it has a probability density function $f(x;\, \theta)$ and if it is discrete, it has a probability mass function $p(x;\ \theta)$ where θ is an unknown parameter (Blom et al, 2005). Since time will be modelled in this thesis, the descriptions from now will be focused on continuous distributions. According to Blom et al (2005) the so-called likelihood-function (abbreviated as the L-function) can, if the random variables are independent, be described by the product of the individual probability density functions and then takes the form below:

$$L(\theta) = \mathrm{f}_{X_1, X_2, X_3, \ldots, X_n}(x_1, x_2, \ldots, x_n; \theta) \qquad (3.21)$$

The idea with using the maximum likelihood estimation is to find an estimate of θ such that the L-function is maximized. This means that the likelihood of getting the studied sample is as high as possible. The maximum likelihood estimator has several attractive properties. One of these are that it is consistent during general conditions. The estimator is not always unbiased but when the number of data points is large, it is approximately unbiased (Blom et al, 2005).

When trying to maximize $L(\theta)$, it is often appropriate to take the natural logarithm of the L-function, this function is often called the log-likelihood function. This is possible to do since the logarithmic function is monotonically increasing and therefore $ln(L(\theta))$ and $L(\theta)$ reaches the maximum in the same point. However, another advantage of taking the logarithm is that the products in the L-function turns into sums in the logarithmic function. This often makes it easier to find the maximum since it is easier to differentiate a sum than a product. By differentiating the log-likelihood function and setting the derivative to zero, it is possible to find the value of θ that maximize the log-likelihood function and then also the likelihood function. (Blom et al, 2005).

In this master thesis, the lognormal distribution will be of special relevance in the distribution fitting of lead times. Therefore, the ML estimations for the parameters in this distribution are provided below (Law & Kelton, 1991):

$$\mu = \frac{\sum_k \ln(x_k)}{n} \qquad (3.22)$$

$$\sigma^2 = \frac{\sum_k (\ln(x_k) - \mu)^2}{n} \qquad (3.23)$$

3.3.3 Chi-square test

After the parameters of one or several candidate probability density functions have been identified, the Chi-Square test could be used for further guidance in the process of determining whether these theoretical distributions are suitable to describe the sample data. The Chi-Square test is one of the most frequently used tests which compares the frequency distribution of the collected data with the theoretical distribution being tested. The difference is measured by a test statistic which follows the Chi-Square distribution. To use the test, the first step is to construct a histogram which provides the observed frequency of the data in different intervals (called bins). By using the upper and lower bound of each bin, the cumulative probability of the random variable taking values within this specific interval according to the tested theoretical distribution can be determined. In the test statistic, the difference between the observed frequency (according to the created histogram) and the expected frequency according to the tested theoretical distribution is calculated by using the formula shown below (Laguna & Marklund, 2013):

$$\chi^2 = \sum_{i=1}^{N} \frac{(O_i - np_i)^2}{np_i} \qquad (3.24)$$

Oi denotes the observed frequency, np_i denotes the expected frequency according to the evaluated theoretical distribution. It is a requirement that the expected frequency in each bin, i.e. np_i, is higher than five. If this is not the case, adjacent bins should be merged and N is the final number of bins after this consolidation. The difference between the frequencies is summed over all the evaluated intervals (the number of bins). Finally, the value of the test statistic is compared with the quantiles in the Chi-Square distribution, given a certain significance level and degrees of freedom. There are different ways of deciding the degrees of freedom, one alternative is to use the following formula: N-1-k where N is the number of bins and k is the number of estimated parameters in the evaluated theoretical distribution. A more conservative method is to use N-1, which is the way that will be used in this master thesis. If the test statistic is less than or equal to the quantile in the Chi-square distribution, the null hypothesis that the sample data comes from the tested theoretical distribution, cannot be rejected. However, this does not prove that the distribution is a good fit for the analyzed data, it just concludes that the difference between the empirical frequencies and the expected frequency according to the theoretical distribution is too small to reject the distribution as a potential fit (Laguna & Marklund, 2013).

3.3.4 Kolmogorov-Smirnov test

Another commonly used goodness-of-fit test is called the Kolmogorov-Smirnov test, from here on abbreviated KS-test, which compared to the Chi-Square test does not require a histogram of the field data. This is one of the main advantages of the KS-test compared to the Chi-Square tests combined with the fact that the KS-test gives reasonably trustworthy results even when the data set is limited in size. However, the two main disadvantages of this test compared to the Chi-Square test is that in the original description, all the parameters of the candidate distribution should be known and that the KS-test mainly applies for continuous distributions. The first disadvantage has been overcome through a modification of the test but it unfortunately only applies when fitting normal, exponential, or the Weibull distribution. However, in practical applications the KS-test is used for distribution fitting also for other distributions but in these cases the test tends to reject the hypothesized distribution more often than desired. This excludes some PDFs that potentially would have been a good fit to the field data (Laguna & Marklund, 2013).

The main difference between the two tests is that the Chi-Square measures the difference between the theoretical frequency distribution and the observed frequency in given intervals while the KS-test measures the absolute difference between the cumulative distribution function of the candidate distribution and the empirical cumulative distributions. This means that the first step in doing a KS-test is to create the empirical cumulative distribution function which is done by first sorting the field data from the smallest to the largest value. Assume that x_1, x_2,..,x_n is a sample of data ordered in the order above, then the empirical distribution function takes the following form:

$$F_n(x) \in \frac{Number\ of\ x_i \leq x}{n} \qquad (3.25)$$

This means that the function $F_n(x_i) = i/n\ for\ i = 1, \ldots, n$. After the data has been sorted from the smallest to the largest value, the largest absolute deviation between the two cumulative distribution functions F(x):

$$D^- = \max_{1 \leq i \leq n} \left[F(x_i) - \frac{i-1}{n} \right] \qquad (3.26)$$

$$D^+ = \max_{1 \leq i \leq n} \left[\frac{i}{n} - F(x_i) \right] \qquad (3.27)$$

The absolute deviation between the cumulative distribution function and the theoretical distribution is calculated by $D = max(D^-, D^+)$. When D has been determined, it is compared with the tabulated KS-value for the chosen level of significance and the sample size n. If the critical value of the KS statistic is greater than or equal to D, then the hypothesis that the field data come from the theoretical distribution cannot be rejected (Laguna & Marklund, 2013).

3.3.5 Inverse transformation method

One way of generating a one-dimensional distribution is to use the inverse method. This method can be used to generate almost any one-dimensional distribution if independent uniformly distributed random variables (in other words U(0,1)) are accessible. This can be done according to the following theorem presented by Blom et al (2005):

Theorem 8.1
Let F(x) be a cumulative distribution function with the inverse:

$$F^{\cdot 1}(y) = \min\{x: F(x) \geq y\}, 0 < y < 1 \qquad (3.28)$$

In other words $F^{-1}(y)$ is the smallest x-value for which $F(x)$ is greater than or equal to x. If U is $U(0,1)$ and we let $X = F^{-1}(U)$ then $P(X < x) = F(x)$ which in other words mean that X has F as cumulative distribution function.

In other words, this theorem means that by generating a random number, i.e. y, in the range between 0 and 1 (which represents a probability) and then take the inverse of the studied cumulative distribution function, it is possible to find the quantiles of the distribution, i.e. x, given a certain probability. In this thesis, lead times from the fitted distribution will be generated by using this theorem. However, random numbers from a U(0,1) will not be generated, instead the whole uniform range will be used to represent the distribution. For a picture of how this is done, see Section 6.3.3.

4. Background to Sandvik Group and Sandvik C&S

This chapter describes the organization, products, markets, customers and supply chain which are in focus of this study. The purpose with the chapter is to give the reader an understanding of the current situation at the case company and in which context this study is conducted.

4.1 Organization and business areas

As has been previously mentioned, the Sandvik Group is divided into three different business areas which can be seen in Figure 8 below. The business areas are divided into smaller units that are called Product Areas (PA). Under the new CEO Björn Rosengren, the Sandvik Group has adopted a new strategy which aims at further decentralizing the decisions in the organisation. This means that decisions have moved closer to the customer. During 2016 this new strategy meant that the responsibility of the profit and loss moved to the PAs which are now responsible for their own performance.

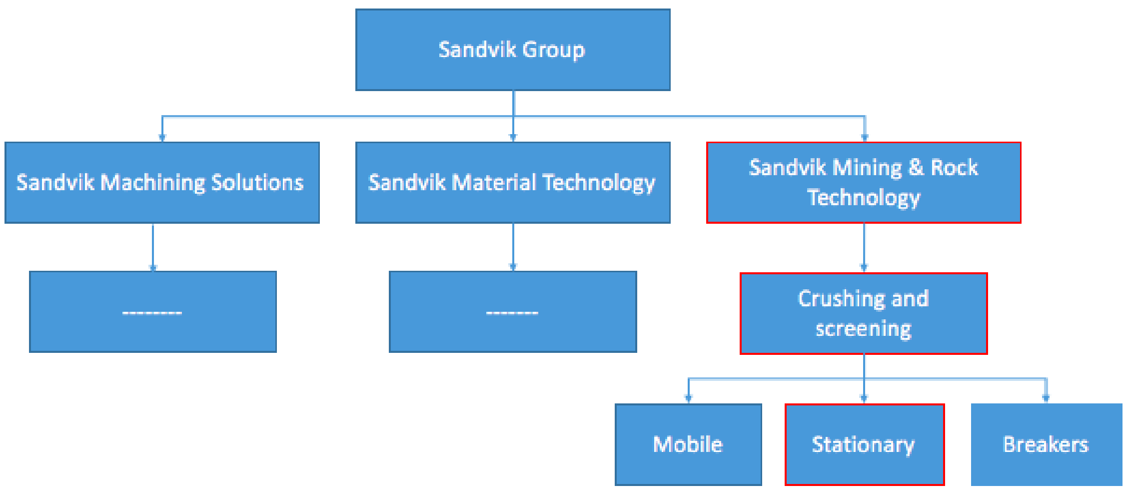

Figure 8. Organizational focus of this thesis.

The historic strategy of the Sandvik Group has been focused on high quality, a close collaboration with the customers, high focus on R&D and export. This strategy varies to some extent for the different business areas since they are currently performing differently and hence face challenges of varying kind in the future. Currently Sandvik Machining Solutions is the most profitable and is therefore classified as a business area in the growing phase. Sandvik Material Technologies is in the profitability focus phase while Sandvik Mining and Rock Technology is focused on stability. However, the objective of this business area is to move up through this ladder through the profitability and up to the growth phase. (Sandvik AB, 2018)

This study will be conducted in the business area called Sandvik Mining and Rock Technology (SMRT) which is the second largest in terms of revenue where revenues during 2017 reached 36.5 billion SEK and a profit margin of 15.7 percent. The business area delivers equipment and tools together with service and technical solutions to the two main customer segments; the mining industry and the rock excavation part of the construction industry. Mainly this includes equipment for drilling, cutting, breaking, crushing and loading provided by eight different PAs. For SMRT, the important priorities are to improve profitability which should be accomplished through growth in the aftermarket segment and through increased sales of parts and services on the installed base of equipment. The strategy also includes adding value by providing automated solutions with the aim to reduce volatility in earnings. Products are provided through 95 percent direct sales to mining customers while almost 50 percent of the sales is conducted through distributors for the construction segment. (Sandvik AB, 2018).

In Figure 8, a chart of the current structure of the organization at Sandvik Group is presented. As can be seen, the business areas are divided into different PAs which have their own individual strategies and are fully responsible for their own performance (Sandvik AB, 2018). The focal point for this thesis is the PA Crushing and Screening. This PA is then divided into three different business units (BU) where the BU called Stationary will be in focus in this thesis. In Figure 8 above, the organizational placement of this BU is shown.

4.2 Products and components

This section will describe the products which are produced by BU Stationary. Furthermore, the components which are included in these products will be presented. The type of components called key components will be in focus in this thesis.

4.2.1 Products

BU Stationary provides several different crushers for various types of applications. There are different crushers for various types of flows where the flow may be of different intensities and the processed material has different characteristics. For example, the case company provides crushers for both hard rock processing and processing of more easily crushed material such as soft rock and coal. The largest crusher is the gyratory crushers which is used for hard rock processing where the feed consists of large pieces of material. Another type of crusher is the impact crusher used in the aggregate, mining and quarrying sectors to produce sand and aggregates. The BU also delivers jaw and cone crushers where jaw crushers mainly are used to create smaller pieces of rock which could then be crushed into finer pieces using different types of cone crushers. Except from these different crushers, BU Stationary also provides screeners and feeders with the main application of sorting the material to be crushed and to feed the crushers with material. This master thesis will focus on components to cone crushers.

Cone crushers are most often used in the secondary and tertiary applications to crush hard rock and are suitable for use in both the quarrying and mining industries. In the quarrying sector, the main product from the cone crusher is aggregates for production of concrete, asphalt and railway ballast. The cone crushers are provided in several different sizes depending on the application, from the larger models CH895 to the smaller models CH/CS430. The largest cone crushers are only produced at the production site in Svedala while the smaller crushers are produced both at the site in Svedala and in China.

4.2.2 Product components

The crushers constructed by Sandvik consists of five categories of components. This categorization is fairly new within Sandvik and is dynamic in the sense that some components can change category depending on introduction of new crushers and changing customer demand. The different categories are: wear parts, major components, components, key components and commercial components. An introduction to the different categories will be provided below where key components will be described in more detail since this category is in focus in this thesis.

4.2.2.1 Wear parts

The moving parts in the crushers which are performing the crushing are called wear parts. These are made of a special metal called manganese and are therefore often called, just manganese. In the crusher, two wear parts are used to conduct the crushing, one is placed on the rotating mainshaft (which is a major component that will be further described below) and the other wear part is placed inside the bottom part of the crusher. When the mainshaft rotates, the manganese moves towards each other and thereby crush the rock. These components are continuously worn down when the crusher is used and the replenishments of these parts is therefore of more planned character than usual spare parts which are only replaced when they break (which happens more randomly). The wear parts are produced in the foundry in Svedala.

4.2.2.2 Major components

Major components are the three largest components in the crusher and constitutes the foundation for the crushers. The topshell is the major components in which the feeding of the crusher occurs. The rock that will be processed falls through the topshell into the crusher where it is crushed by the manganese attached on the rotating mainshaft. As a spare part, the mainshaft can be delivered with or without a mounted manganese. The final major component is the bottomshell which together with the topshell surrounds the mainshaft and the manganese. The bottom- and topshell together form the outer shell of the crusher and these two major components are bolted together. Connected to the bottomshell is also an engine which drives the crusher and creates the rotating movement of the mainshaft. The major components are the most expensive parts in the crusher and are included both in the construction of new crushers, but they are also sold as standalone spare parts.

4.2.2.3 Key components

Some of the components in the crushers are Sandvik specific, which means that there is a Sandvik drawing behind. Based on recommendations from the life cycle management team, some of the Sandvik specific components are classified as key components since they are especially valuable and important for the customers. They are therefore of special interest from an inventory control perspective. Key components are smaller than the major components and are of that reason also lighter. These are used both in new crushers and are also sold as spare parts to the aftermarket. Except from the size and weight, the key components are supplied differently than the major components. While major components are only produced by Sandvik SRP at the production facility in Svedala for both production of new crushers and for the aftermarket, the key components are supplied by both Sandvik SRP and by external suppliers. To clarify, some key components are produced by Sandvik SRP and in these cases, raw material is purchased from external suppliers which is then processed by Sandvik SRP to form finished parts. When finished, the parts are then sold as spare parts to the aftermarket and are also used in the production of new crushers. Other key components are not processed by Sandvik at all, instead they are purchased as finished parts straight from external suppliers.

4.2.2.4 Commercial and other components

The Sandvik specific components that are not classified as key components together with other components that are purchased from external suppliers belong to this last category (which by the case company is simply called spare parts). These are less critical components and are provided to customers from stock when needed. Commercial components could for example be different types of hoses together with nuts and bolts which are sold both as spare parts but are also used in the production of new crushers. These components are often small in terms of size and are of less value than both key and major components.

4.3 Markets and customers

The market for cone crushers and the components in these crushers can be divided into three categories: new crushers, reborn crushers and aftermarket. Buying new crushers is often a significant capital investment for many customers and therefore, the customer's buying pattern often follows their own business cycle. An order from a customer may vary from buying an individual crusher to a whole set of crushers, often referred to as a project order. A less capital-intensive solution is to rebuild a crusher system by exchanging a worn-out crusher by a new crusher and reusing auxiliaries and infrastructure, i.e. a reborn crusher. The geographical spread of the market for new and newborn crusher is shown in Figure 9.

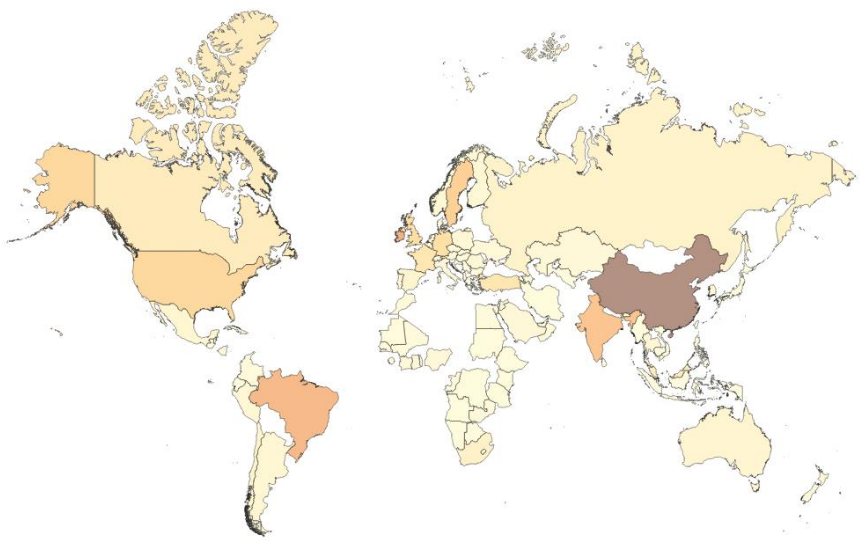

Figure 9. Sandvik C&S's markets for new and newborn crushers based on order intake 2007-2017.

The aftermarket consists of existing customers that are supplied with spare parts and wear parts when a component in a crusher is worn-out. Hence, demand for these components are generated when customers utilize the crusher, and therefore the aftermarket demand is less dependent on the business cycle. The target service level (defined as the fill rate) is now set to 95 percent, which this project will fulfill.

The case company customers can be grouped into two major segments: mining and construction. Mining customers are globally spread with large presence in countries where the mining industry is dominating. These customers typically buy large crushing systems with several interconnected crushers for the purpose of processing and crushing rocks and ores into smaller pieces. The time a mining customer is not operating is very costly, therefore they often keep stocks of spare parts on site in case of a breakdown. Therefore, mining customer are often proactive customers.

A typical construction customer is a road building contractor. They often do not own as many crushers as their mining counterpart. This segment is less proactive, and these customers typically do not hold any excess spare part inventory. Hence, construction customers seek fast delivery of spare parts when a breakdown occurs. There is a seasonal buying pattern among construction customer, however this is leveled out due to global t spread.

4.4 Supply network

The supply network of the studied business unit at the case company is presented in Figure 10 below. Starting upstream, the main manufacturing plant for cone crushers is in Svedala, Sandvik Rock Processing (SRP). This producing legal entity is replenished with raw material and components sourced from suppliers around the world. Finished components and other commercial items can also be sourced as spare parts directly to the central warehouses in Svedala, Sweden and to Venlo, Netherlands.

The Svedala site has a wide range of value adding activities such as foundry, machining, painting, assembly and testing. The site produces new crushers and many of the spare parts and wear parts for the aftermarket. New crushers are make-to-order (MTO) due to relative low sales volumes compared to the high capital investment. Meanwhile, components and raw material for the aftermarket and assembly are often make-to-stock (MTS) due to long replenishment lead times. The finished crushers are shipped directly to the customer and spare parts and wear parts are shipped to the aftermarket distribution network.

At the Svedala site there is an internal transition of ownership to Sandvik Mining and Construction Logistics (SMCL) as aftermarket items are moved to the finished goods inventory, Svedala 07. Simultaneously there is a transition of enterprise resource planning (ERP) system from M3 that covers the site operations in Svedala to System 21 that covers the global aftermarket. There is almost no integration between the systems and therefore SMCL has low visibility into M3. SMCL is responsible for the distribution network for the aftermarket which ranges from the central warehouses in Svedala 07 and Venlo 37 to regional distribution centers at several strategic locations worldwide. Further downstream, once more aftermarket items transfer internal ownership to Sandvik C&S's sales areas before reaching the end consumer.

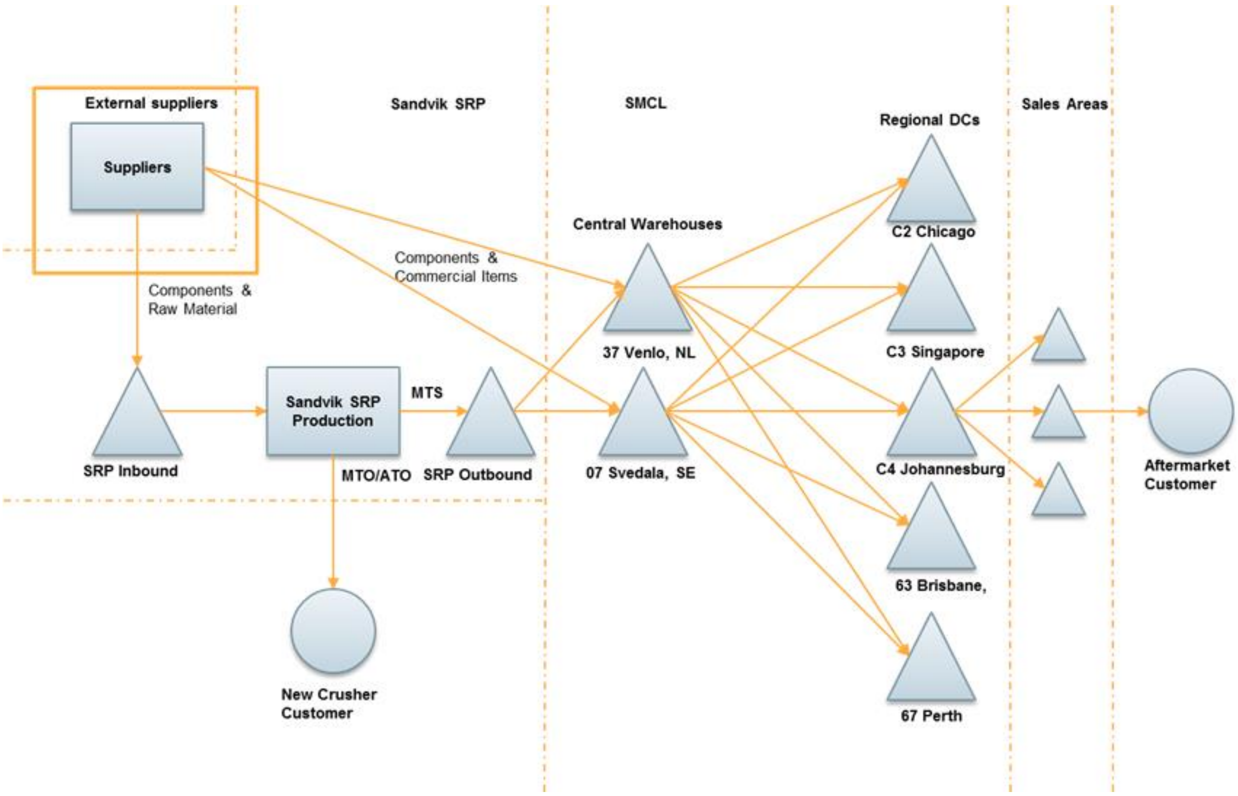

Figure 10. The current supply network at Sandvik Crushing and Screening.

The focus in this master thesis will be on the aftermarket network (SMCL) and the producing legal entity (SRP) and the suppliers which provide these two legal entities with key components. These suppliers are marked with a square in Figure 10 above. Purchase orders from the two entities are today placed independently of each other from the two different ERP-systems. However, in a future state (which will be described more thoroughly in Section 6.1) the case company will operate with a new shared warehouse for both the legal entities. This means that the requirements of key components from both the legal entities will be taken into consideration when constructing the new inventory control policy for the warehouse in this future state. In the next chapter, an analysis of the current system is conducted to form a basis and understanding that will later be used when constructing the new inventory control policy in the future state.

5. Analysis of Current System

In this section, the current system in terms of sales, inventory and purchasing will be described. The idea with this chapter is to provide the reader with an understanding of the current operations and structures at the case company and to enable a comparison with the new inventory control policy that will be described in Chapter 6. This part of the report is related to the first step of the Model formulation and analysis phase described in the research design chapter in Section 2.3.2.

5.1. Supplier base and supplier selection

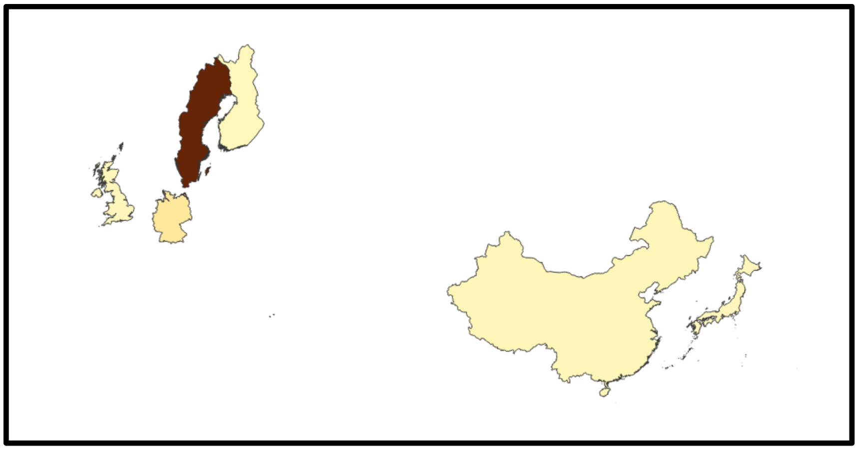

Figure 11. Supplier location for sourcing of key components.

Since the focus of this report is to create a new inventory control policy for key components supplied by external suppliers to a new shared warehouse, the first step in the analysis was to get an understanding of how the two studied legal entities (the producing entity in Svedala (SRP) and the aftermarket entity (SMCL)) are currently supplied. Firstly, the geographical location of the suppliers was analyzed where the results could be seen in Figure 11. Secondly, it was also concluded that approximately 50 000 purchase order lines were issued from these two entities during 2017.

Since key components are in focus in this project, the suppliers who provide these components have been analyzed further. Based on the initial analysis of the purchase order data, it could be concluded that 20 suppliers provide the two entities with key components. Figure 12 shows the total purchased cost volume of key components divided on the different suppliers. As can be seen, almost 70 percent of the cost volume is purchased from supplier A, B and C and more than 80 percent of the cost volume is directed to the five largest suppliers.

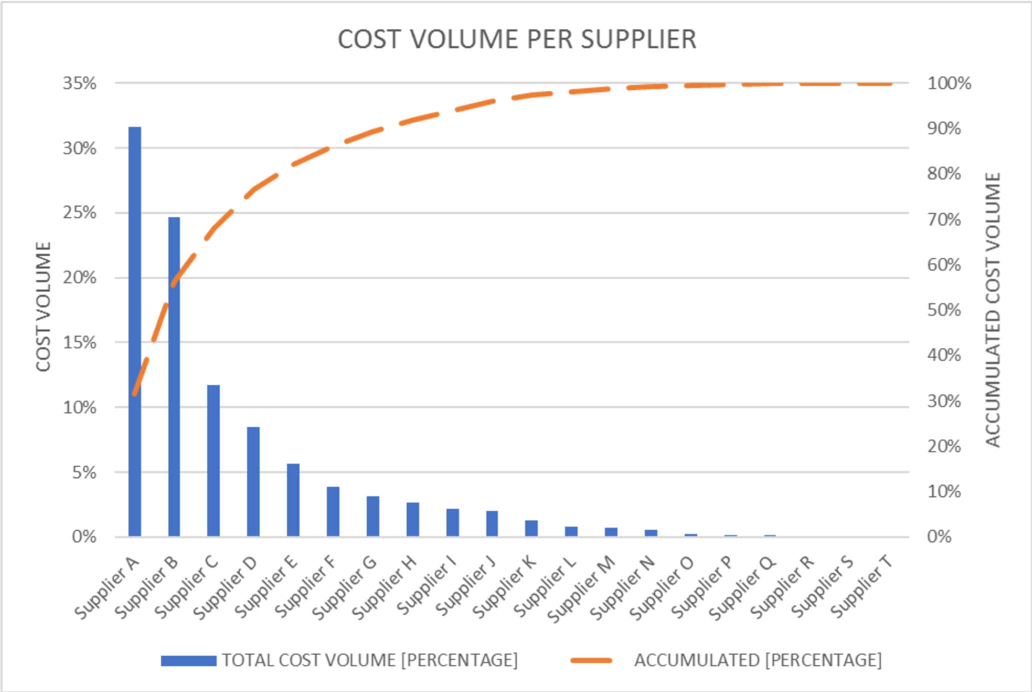

Figure 12. Overview of purchased cost volume during 2017 divided per supplier.

Since this project is limited in time, these three suppliers have been chosen for further analyses. So the new inventory control policy which will be constructed to answer the first research question will be focused on the items supplied by these three suppliers.

5.2 The three largest suppliers

Even though, the suppliers have been selected based on the purchased cost volume of key components it is also important to get an understanding of the total deliveries to the case company by these suppliers. The analysis conducted in this section is based on purchase order data from 2017. Table 3 shows the split of purchased value both between the two legal entities and between key components and other materials bought from the three selected suppliers.

Table 3. Overview of ordering during 2017 to the selected suppliers.

	Supplier A			Supplier B			Supplier C		
	SRP	**SMCL**	**TOTAL**	**SRP**	**SMCL**	**TOTAL**	**SRP**	**SMCL**	**TOTAL**
PO Lines	43%	57%	697	38%	62%	260	47%	53%	249
Key components	26%	90%	434	69%	74%	187	42%	87%	164
Other	74%	10%	263	31%	26%	73	58%	13%	85
Purchased quantity	43%	57%	5917	24%	76%	4121	38%	62%	806
Key components	15%	84%	3230	56%	85%	3220	64%	96%	674
Other	85%	16%	2687	44%	15%	902	36%	4%	132

Table 3 above shows the split of purchased quantity and the number of PO lines between the two legal entities but also between key components and other materials bought from these three suppliers. The figures shown in Table 3 will be discussed in the descriptions of the selected suppliers in Section 5.2.1, 5.2.2 and 5.2.3.

As has been described by Axsäter (2006) in Section 3.2.4, there is often a certain cost related to placing a replenishment order and the factors which affect this cost are also described. In the calculations to answer the posed research questions in this project, this cost has been provided by the case company and is currently 75 EURO per purchase order line. This number will be used to calculate the total cost of ordering the key components from these three suppliers. Using this cost per order line, it can be concluded that the cost during 2017 of ordering key components from Supplier A has been 32 550 EURO, from Supplier B it has been 14 025 EURO and from Supplier C the ordering cost has been 12 300 EURO. In the next sections, the three chosen suppliers will be further described.

5.2.1 Supplier A

Supplier A is a Swedish manufacturer of metal details made of aluminum and bronze. The supplier has manufacturing sites in both Sweden and Finland where the details are casted and machined in the same production facility. From this supplier, the case company is buying both key components but also other types of items. As can be seen in Table 3, Supplier A is an important provider of other materials than key components to the producing legal entity which are then machined and used in the production of new crushers. However, for the aftermarket, Table 3 shows that the majority of both the PO lines and the purchased quantity to Supplier A are finished key components which are then sold as spare parts. In terms of both number of PO lines and in purchased quantity, the split between the two legal entities is fairly equal. From the gathered data it could also be concluded that the total number of POs for key components from the two legal entities to Supplier A, was 202 during 2017.

5.2.2 Supplier B

This supplier is located in Germany and produces advanced engineering plastics for several different industrial sectors, such as the oil and gas, food, transport and chemical industry. The supplier has two main manufacturing sites, one located in Germany while the other is located in the Czech Republic. According to Table 3, the majority of both the PO lines and the purchased quantity to supplier B originates from the aftermarket network and it could also be noted that the key components, both in terms of number of PO lines and quantity, is greater for the aftermarket than for production of new crushers for this supplier. The total number of POs to Supplier B from both the two legal entities was 103 during 2017.

5.2.3 Supplier C

The third selected supplier is a Swedish supplier of details and parts in metall. Table 3 shows that from SRP, this supplier receives approximately the same number of PO lines for key components as for other types of components and materials. However, in terms of quantity the key components are a majority of the total number bought from Supplier C by SRP. As can be seen in Table 3, from the aftermarket network perspective, Supplier C is mainly a supplier of key components which can be noted both in terms of number of PO lines but also in regard to the purchased quantity. Supplier C is in terms of quantity a much smaller supplier on an aggregated level than Supplier A and Supplier B. Finally, the gathered data shows that Supplier C received 98 POs from both the legal entities during 2017.

5.3 Current inventory and fill rate situation

To enable a comparison with the new inventory control model, some data regarding the current stock situation for the three suppliers has been compiled in Table 4 below. The data in Table 4 shows stock data for the two central warehouses in the aftermarket network and for the producing legal entity. The studied business unit at the case company uses 10 percent of the item cost as the holding cost which is based on several factors described in Section 3.2.4. Using this percentage, the average holding cost for the items related to the three selected suppliers is approximately 228 102 EURO on a yearly basis. For Supplier A, the cost is 99 766 EURO, for Supplier B the holding cost is 61 870 EURO and for Supplier C the holding cost is 66 466 EURO. The item costs used in the calculations are standard costs for the studied items to eliminate the impact of price fluctuations. These costs will also be used in the new inventory control policy to calculate the total costs in the future scenario.

Table 4. Overview stock data in current system during 2017.

	Total number of items	**Average total stock [quantity]**	**Stock value [EURO]**
Supplier A	65	628	997 657
Supplier B	10	416	618 696
Supplier C	32	198	664 663

As has been previously mentioned, the service level measure used by the case company is the fill rate definition which is described by Axsäter (2006) in Section 3.2.4. During 2017 the fill rate has been 78 percent for items supplied by Supplier A, 71 percent for items supplied by Supplier B and 67 percent for items supplied by Supplier C. As can be noted, the fill rate does not reach the desired level of 95 percent.

Some reasons to the low fill rates, are uncertainty in the supply process and a significantly increased demand for key components during 2017.

5.4 Ordering

This section will describe the current sales of key components and the purchase order pattern to the three selected suppliers. The aim with this section is to analyze the gathered data which will be the foundation for the model construction but also to analyze the current lead time variability which the case company is experiencing. In this section, the aggregated requirements for key components from both the aftermarket and production of new crushers will be discussed. When aggregation is mentioned in this section, it means that either the sales from the two legal entities or the purchase orders from the two legal entities have been aggregated in the way that can be seen in Figure 13 below.

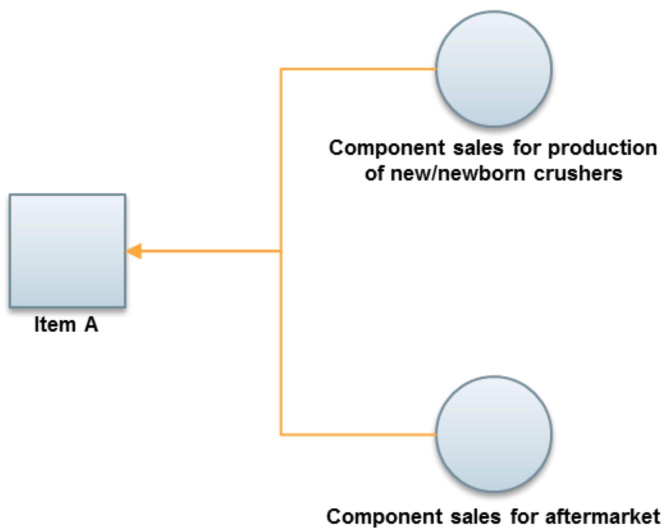

Figure 13. The aggregated requirements for a key component from both the aftermarket and the production of new crushers.

5.4.1 Sales order pattern

In this section, sales for key component from the selected suppliers will be analyzed. The purpose is to find the real point-of-sales (POS) to decide an appropriate demand model for the inventory control policy that will be constructed to answer the first research question. The data will also be used to analyze the bullwhip effect in the current supply chain network. POS data is the sales from the case company to the actual customers (i.e. not sales between legal entities within the case company). By using the POS in all the steps in the supply chain, it is possible to reduce the bullwhip effect according to Section 3.1.4. For the case company, this would be possible since they control the whole distribution network.

This section also describes the sales of key components related to new/newborn crushers and to the aftermarket. In this project both markets are analyzed and aggregated to create a complete picture of key components sales characteristics. The data from the aftermarket and the sales of new/newborn crushers are collected from sales reports. The data was cleaned from errors due to entry mistakes in the computer-generated report. To analyze the requirements of key components generated by sales of new/newborn crushers, a bill-of-material provided by a case company employee (currently working with bill-of-materials) was used. The combined sales from each market is compiled in Table 5 below.

Table 5. Overview for number of customer order (CO) lines and sales quantity for key components in 2017.

	Supplier A			**Supplier B**			**Supplier C**		
	Newborn/ New	After-market	Total	Newborn/ New	After-market	Total	Newborn/ New	After-market	Total
Number of CO lines	28%	72%	3474	19%	81%	1830	51%	49%	799
Sales quantity	24%	76%	3957	15%	85%	2354	44%	56%	921

Customer order pattern for 2017 is characterized as a time series by weekly number of order lines and weekly sales quantity in terms of mean, standard deviation and coefficient of variation for key components related to each supplier (see Section 3.3.1 for descriptions of various statistical concepts). This characterize the volatility on the different markets and the benefit in terms of less variability when aggregating the sales from both markets, see Table 6.

Table 6. Overview of weekly number of order lines and sales quantities.

		Supplier A			**Supplier B**			**Supplier C**		
		New/ Newborn	**After-market**	**Total**	**New/ Newborn**	**After-market**	**Total**	**New/ Newborn**	**After-market**	**Total**
Weekly number of CO lines	Mean	18.6	48.2	66.8	6.7	28.5	35.2	7.9	7.5	15.4
	Std. Dev	11.8	12.1	16.2	3.0	6.6	7.4	5.1	2.5	5.6
	COV	0.63	0.25	0.24	0.45	0.23	0.21	0.65	0.33	0.37
Weekly sales quantity	Mean	18.6	57.5	76.1	6.7	38.6	45.3	7.9	9.8	17.7
	Std. Dev	11.8	16.6	19.5	3.0	10.2	10.8	5.1	3.8	6.1
	COV	0.63	0.29	0.26	0.45	0.26	0.24	0.65	0.38	0.35

5.4.2 Purchase order pattern

Section 5.2 provides an overview of the total ordering from the two studied legal entities at the case company and a short description of the three selected suppliers. In this section, the weekly ordering pattern towards these suppliers will be analyzed to provide insights for the construction of the new inventory control policy which will be described in Chapter 6. As can be seen in Table 7 below, the general pattern is that the weekly number of order lines from the aftermarket network (i.e. SMCL) for key components is higher than which is the case for the producing entity (i.e. SRP). Also, the purchased quantity is higher for the aftermarket network than for the producing entity for all the three suppliers.

Table 7. Weekly ordering data during 2017, key components only.

		Supplier A			Supplier B			Supplier C		
		SMCL	**SRP**	**Total**	**SMCL**	**SRP**	**Total**	**SMCL**	**SRP**	**Total**
Weekly number of PO lines	Mean	6.85	1.50	8.35	2.31	1.33	3.63	2.21	0.94	3.15
	Std. Dev.	7.34	1.98	7.81	2.45	2.14	3.33	2.72	1.07	3.34
	COV	1.07	1.32	0.94	1.06	1.61	0.91	1.23	1.14	1.06
Weekly purchase quantity	Mean	54.79	7.33	62.12	51.46	10.46	61.92	9.19	3.77	12.96
	Std. Dev.	67.10	9.69	68.31	79.51	20.31	81.82	12.45	4.68	15.35
	COV	1.22	1.32	1.10	1.55	1.94	1.32	1.35	1.24	1.18

What should also be noted is the coefficient of variation for both the weekly number of order lines and the weekly ordered quantity. This is higher when looking at each individual legal entity than when considering the aggregated purchase order data from both the entities. In the cases of these three suppliers, this means that aggregating the purchase orders from both the legal entities seems to reduce the variability in the ordering process.

When studying the purchase order data, it was also found that the purchase orders were placed several times a week to the same supplier. According to discussions with employees at the case company, there is no coordination in the producing legal entity between how purchase orders are placed and the production planning. The production is conducted on a weekly basis but purchase orders are placed when needed, regardless of the day in the week. Also, several purchase orders are placed from both the producing legal entity and the aftermarket network to the same supplier in the same week. This finding was confirmed through discussions with the case company. However, in terms of deliveries from the suppliers, this is mostly done once a week.

In the analysis of the current system, an initial analysis of the lead times has also been conducted. This analysis was based on data provided by the case company of delivered purchase orders during a four year period. For each item supplied by the three selected suppliers, an analysis of the current variability in the lead times was analyzed. This was an analysis carried out to confirm the statements by the case company that they are experiencing variability in the lead times. Figure 14 below shows the coefficient of variation (please see description of this term in Section 3.3.1) for the investigated items, supplied by the three selected suppliers. As can be seen, the coefficient of variation is especially high for Supplier B and for some items supplied by Supplier A. The coefficient of variation varies between 0.05 and 0.6 for the investigated items which initially might not seem that problematic, but it should be remembered that the lead time from these suppliers varies between and 8 and 17 weeks. This means that even small changes in the lead time causes significant additional waiting time for the case company. According to interviews with employees at the case company, no follow-up of the causes to the lead time variability is currently conducted. This means that no cause-and-effect relationship between different factors such as the planning process at the case company, transportation, quality issues at the supplier and the lead time variability exists today.

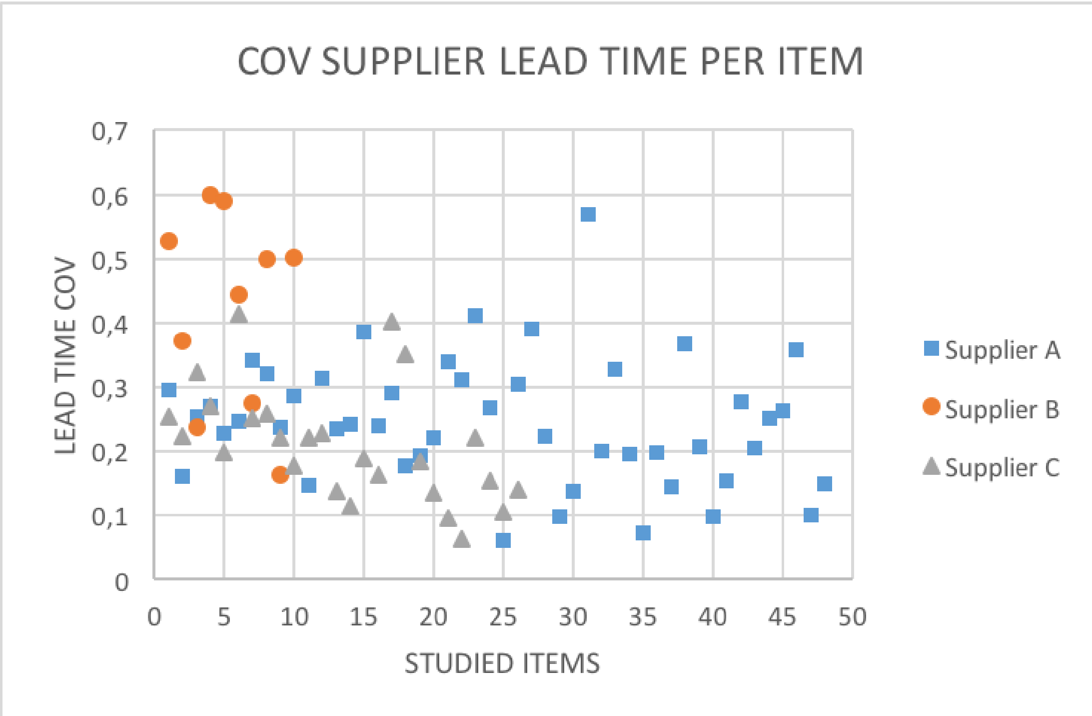

Figure 14. Lead time variability for the investigated items.

5.4.3 Comparison

To conclude the analysis of the ordering patterns in the customer orders and purchase orders respectively, both Table 6 and Table 7 shows that the variation in both the number of orders and the ordered quantity (both in the purchasing and sales process) is reduced when data from several entities are aggregated together. In terms of the number of purchase order lines and the purchased quantity, the coefficient of variation was reduced when the requirements from the producing legal entity and the aftermarket network were aggregated together. This trend was especially significant when analyzing the data for Supplier B which during 2017 experienced a high variability, especially in the weekly ordered quantity, from both the legal entities and where the aggregated quantities were less variable.

The same pattern can be seen in the sales data. Table 6 shows that for Supplier A the coefficient of variation in the component requirements from the production of new crushers is much higher than the aggregated variation in component demand when both the market segments are added together. This pattern is similar for the items which belong to Supplier C, where the component demand for production of new crushers is more variable than the aftermarket sales.

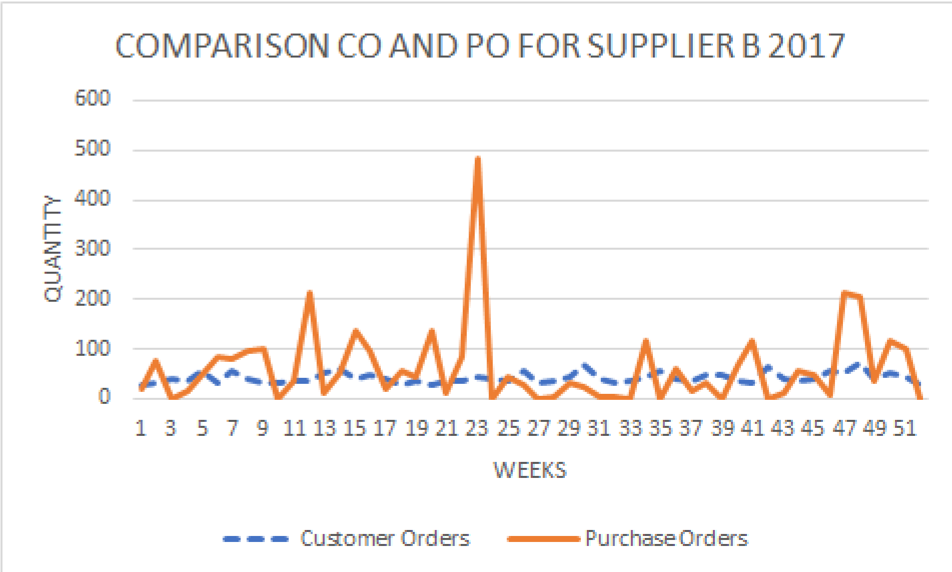

Figure 15. Graphical comparison of customer and purchase order patterns.

However, the most significant reduction in variability can be noted in the comparison between the aggregated sales data and the purchase order data. For the three suppliers, the coefficient of variation in terms of weekly ordered quantity is 1.1, 1.32 and 1.18 for Supplier A, Supplier B and Supplier C when considering the purchase order data. The actual variation in the customer demand is lower and the coefficient of variation in the ordered quantity for the items from the three different suppliers are 0.26, 0.24 and 0.35 for Supplier A, Supplier B and Supplier C when considering both the aftermarket network and the producing legal entity aggregated. Figure 15 shows graphically the difference in the ordering pattern between customer orders and purchase orders.

This means that moving upstream in the supply chain, the variability in the weekly ordered quantity is increasing. This is a practical example of the bullwhip effect which was described in the theory chapter in Section 3.1.4. According to Lee et al (1997), the increased variability incurs increased costs for stakeholders when moving upstream in the supply chain, especially in the existence of long lead times, since the variability increases the reorder points and thereby the inventory levels. In Section 3.1.4 it was also described that one potential action for reducing the bullwhip effect is by reducing the uncertainty. This could be done, for example by providing each supply chain actor with actual customer demand. Since the current supply chain network at the case company includes several steps and the demand information from customers has not been communicated all the way upstream in the supply chain, this type of amplified variability occurs. This lack of information depends on several different factors, one being that the business unit at the studied case company quite recently gained control of the entire supply chain. However, this amplification of variability in the ordered quantity upstream in the supply chain, is also the reason to why the actual customer sales data will be used in the construction of the new inventory control policy and not the quantities in the historical purchase order data. This is a reasonable assumption and would be implementable since the case company currently has control of the entire distribution network.

6. Model Construction

This chapter describes the future state which will be the basis for constructing the new inventory control policy. Furthermore, the constructed mathematical model will be described and the results from this model will also be provided. The conducted lead time analysis and the effect of lead time variability in the new model will also be analyzed. This chapter describes the second and third step of the "Model construction and analysis" phase shown in the research design in Section 2.3.2.

6.1 The considered system

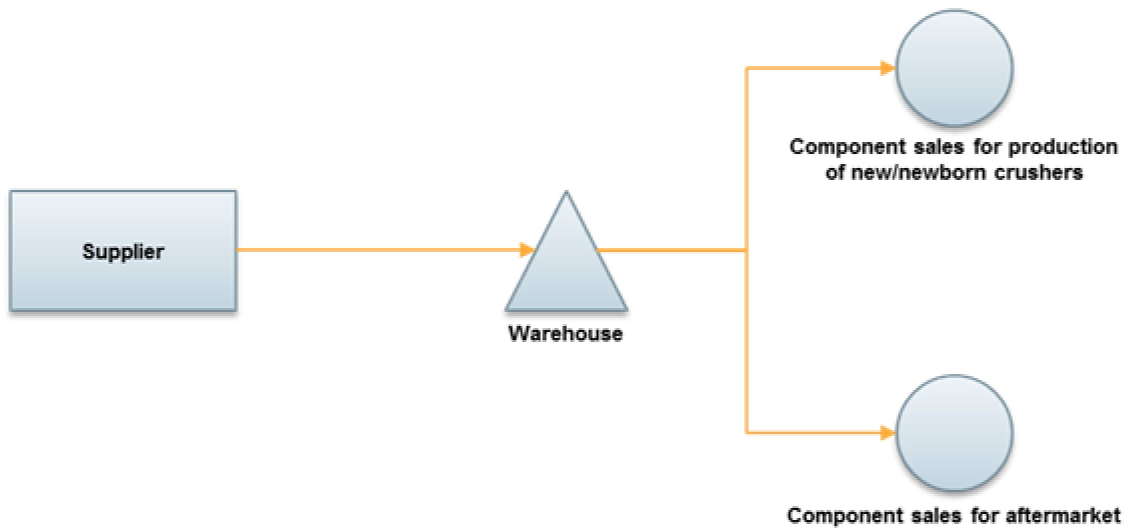

Figure 16. System model for the future scenario at Sandvik C&S.

The system that will be modeled when answering the two research questions posed in this master thesis project is described in Figure 16 above. In this model, the difference to the current supply chain structure which was showed in Section 4.4, is that the sales areas and the five regional warehouses have not been considered. However, the requirements of key components from both the producing legal entity and the aftermarket network will be taken into consideration when constructing the new inventory control policy for this scenario. Today the two legal entities are placing their orders to the suppliers independently of each other. In the future scenario presented above, the purchase orders to the suppliers will be generated from a new warehouse based on the sales from both the legal entities. As has been stated in the delimitations, to consider a new shared warehouse and to model the system as a single echelon system are company directives which form the direction of the solution approach.

In Section 3.1.2 Johnsson & Mattson (2017) states that the potential with an increased centralization is to accomplish increased economies of scale, reducing the bullwhip effect and reducing both stock and the risk for items becoming obsolete. It is also stated that by aggregating the inventory, it is possible to maintain the same service level with less stock. However, a higher degree of centralization increases the time to the customer market (Johnsson & Mattsson, 2017). Furthermore, as stated by Mentzer et al (2001) cooperation and coordination is another approach to accomplish reduction in supply chain inventories. These are the potential benefits the case company wants to be investigated and quantified and therefore, the first research question is related to how an inventory control policy that considers the requirements of key components from both the two legal entities, can be constructed in this scenario. However, as has been stated in the delimitations in the introduction chapter, the distribution of parts to the aftermarket customers from the new warehouse will not be considered in the model investigated in this thesis. Additionally, the project will not evaluate the best geographical location of the warehouse.

6.2 Demand model analysis

Recall from Section 3.2.2 that the compound Poisson distribution is of great interest when modeling relatively low demand with high variation, more precisely when the variance over mean for demand is equal to or greater than one. Historical sales data gathered from the case company which combines the sales of key components generated by demand from sales of new crushers but also sales to the aftermarket during 2017 shows that in most cases the compound Poisson distribution is indeed a good choice as demand model in this study, see Figure 17.

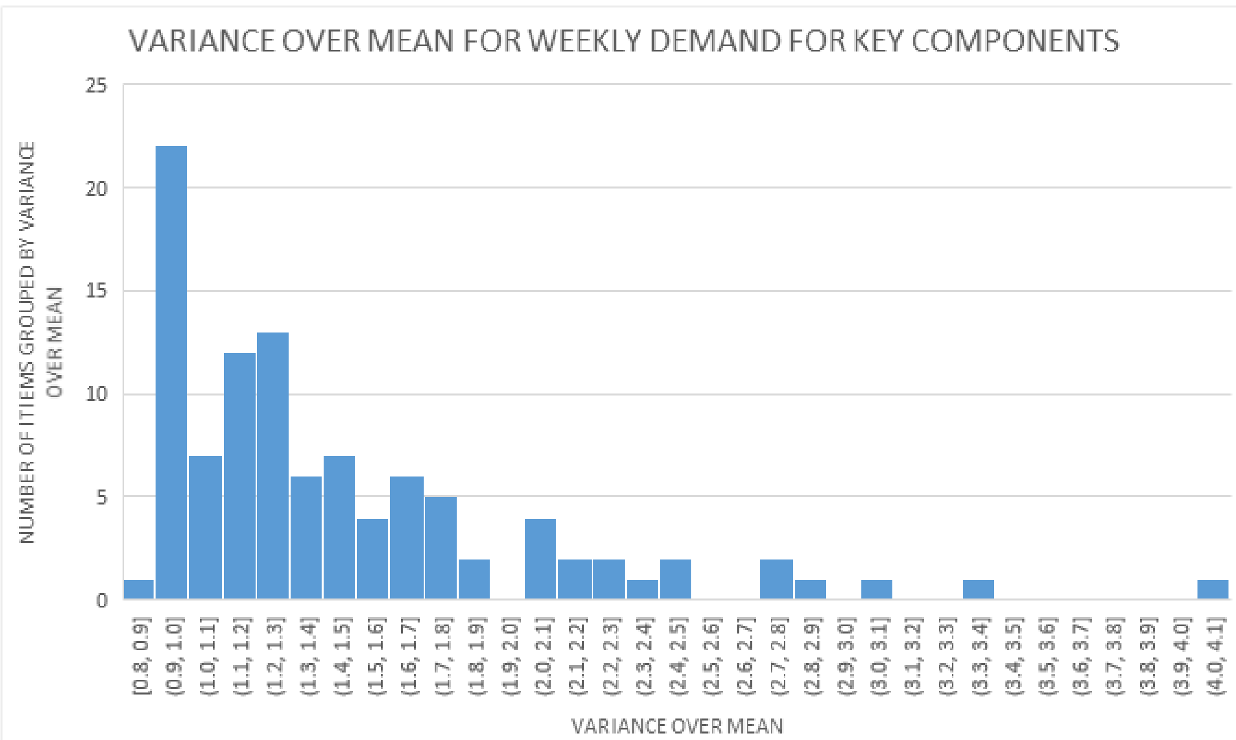

Figure 17. Variance over mean for weekly demand for key components.

Recall from Section 3.2.2 that a compound Poisson distribution consists of two independent distributions, one distribution for customer arrival intensity and one for how many items a customer request. Figure 18 below shows the arrival intensity per week for key components from supplier A, B and C. These arrival intensities will be used when constructing the new inventory control model.

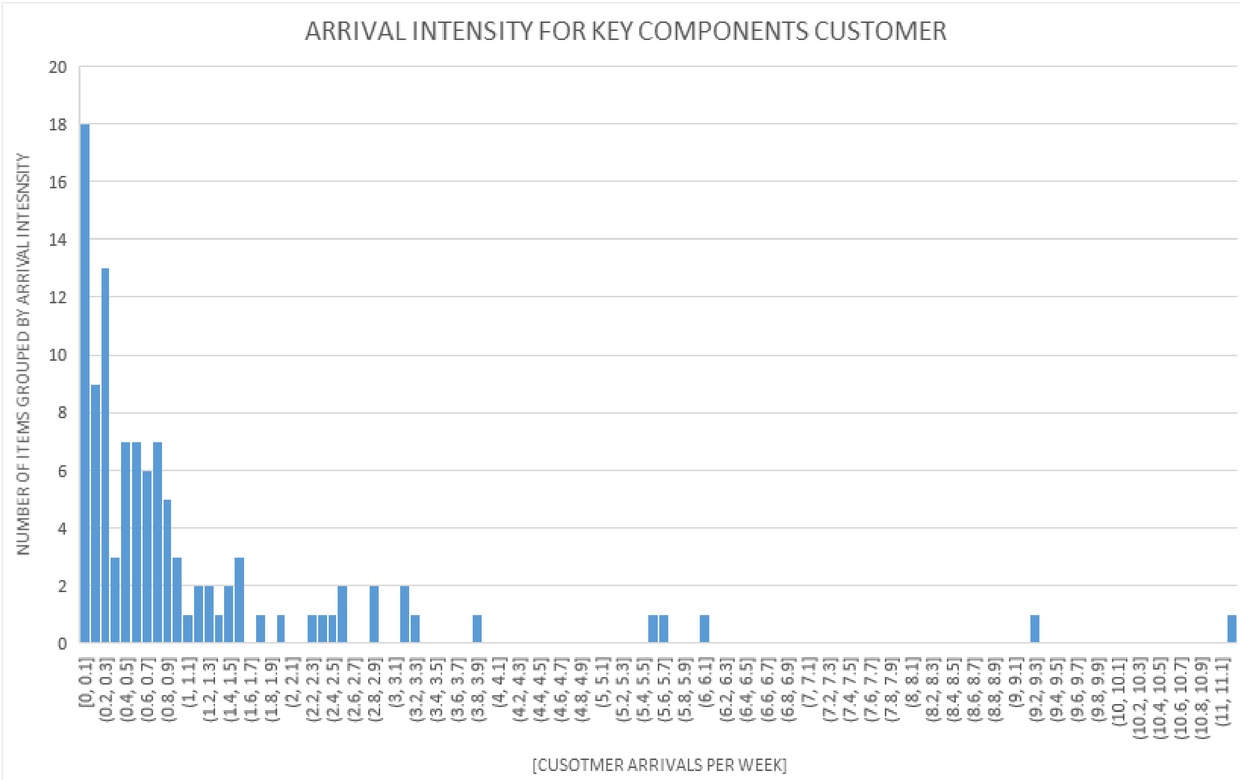

Figure 18. Arrival intensities for customer for key components

As can be seen in Figure 18, arrival for most items is below two customers per week, which could be considered fairly low for a global market. The compounding distribution is shown in Figure 19 by a Box-plot diagram for all considered items in this study. Note that the likelihood of one customer ordering one item, in other words f_1 in Figure 18, is on average very high (around 87 percent), which could also motivate using a pure Poisson distribution as demand model for some of the studied items. The compounding distribution will be limited to the demand size ten in this study, to save computational power. This assumption excludes 0.2 percent of the total requested quantity during 2017. However, it is easy to increase the length of the compounding distribution if deemed necessary.

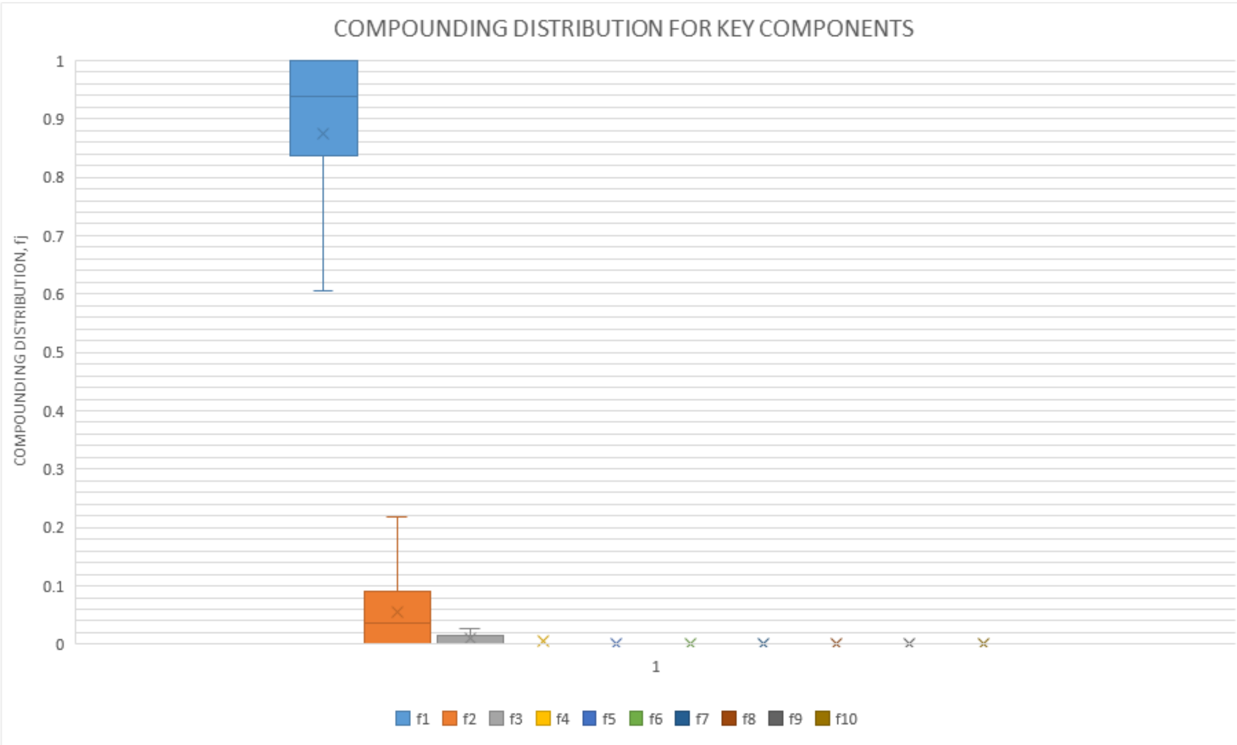

Figure 19. Compounding distributions for key components where the cross represents the mean and the lines represents different quantities for all f_i.

6.3 Lead time analysis

To be able to answer the second research question regarding how the lead time variability affects the performance of the constructed inventory control policy in the future scenario, a statistical analysis of the lead times has been carried out. The theoretical parts related to this analysis have been described in Section 3.3.

6.3.1 Input analysis of lead times

The main reason for conducting an input analysis of the lead times has been to fit a theoretical probability density functions to the lead time data. If a theoretical distribution can be fitted to the data, it is possible to change the shape parameter of this distribution to simulate a reduced variability in the lead times. The analysis of the lead times was performed in the following steps:

1. Items were classified according to their standard lead time
2. Data cleaning
3. Distribution fitting

These steps were performed for all the items from the three selected suppliers. Standard lead time is here defined as the agreed lead time between the case company and the suppliers. These are the lead times currently used in the case company’s inventory control policies.

In this chapter, the used procedure to conduct this analysis will be described in detail. The same procedure has been conducted for all three suppliers but in this section the analysis of Supplier B will be presented in more detail to provide an understanding of the procedure used in this project.

Firstly, the data which was the foundation for the analysis was a data set of historical lead times to the aftermarket network. This data set has been used in internal projects within the case company and has therefore been considered reliable. The data set included some purchase orders which, at the time of extraction, had not been delivered and these were therefore excluded from the analysis since the actual lead time of these orders could not be determined. The reason for doing the analysis only based on deliveries to the aftermarket was because this was the longest available data set and the difference in geographical distance between Sweden and the Netherlands (where the central warehouse for the aftermarket is located in the current supply chain setup) does not affect the lead times to a great extent. As has been stated in the delimitations in Section 1.5, it has been assumed that the average length of the lead times to the warehouse in the future state will not be changed.

As described above, the first step included a classification of the items based on their standard lead time. This classification was done because items with the same standard lead time should in the constructed inventory model, have the same characteristics in terms of mean and variability. Supplier B delivers ten key components to the business unit studied in this project and these items had three different standard lead times. In Table 8 below, the item categories and the number of data points (purchase order lines) after data cleaning for each category is summarized.

Table 8. Summary of categorization of Supplier B items

Category	Standard Lead Time [days]	Number of Items	Number of Data Points
1	42	7	184
2	56	2	60
3	28	1	11

Before the data was inserted in Stat:fit, it was cleaned from extreme values. These types of values included lead times equal to zero but also lead times that were longer than two standard deviations from the mean were reviewed in detail and in special cases removed. The data was then inserted into Stat:fit which fits the data to several different probability density functions. Figure 20 shows the received graphical results from Stat:fit.

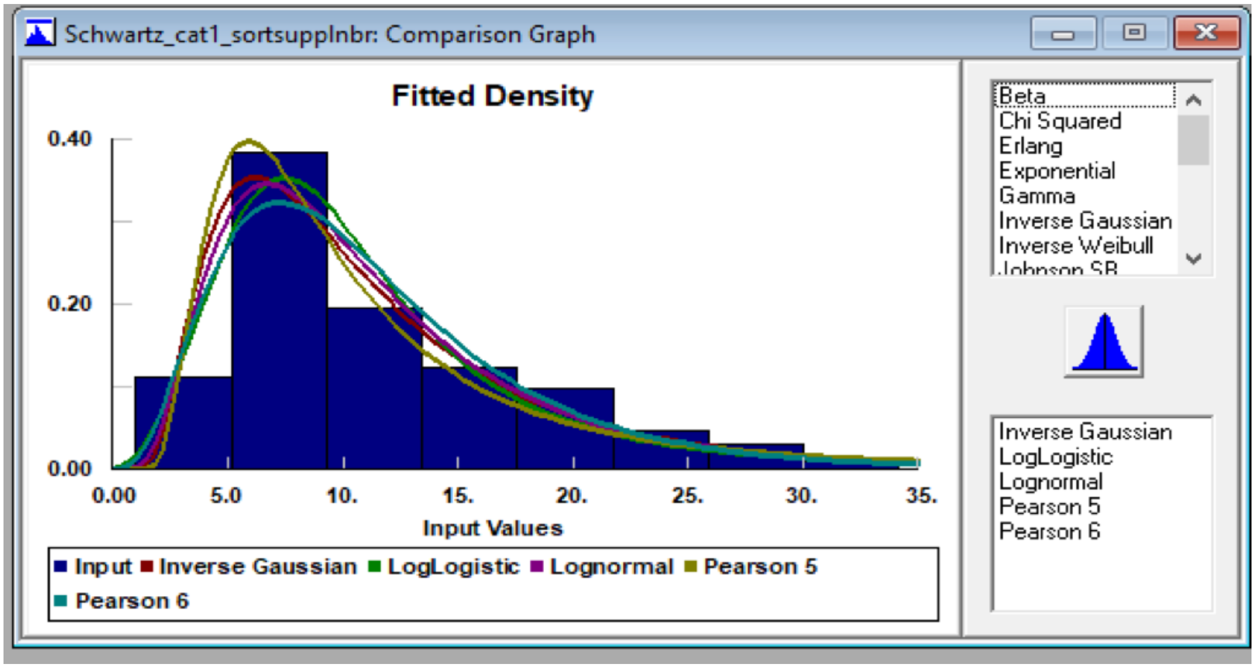

Figure 20. Graph of fitted distributions from Stat:fit.

From the program, a ranking of the most appropriate distributions were provided where the five highest ranked distributions were plotted in a diagram according to Figure 20 above. This process was conducted for each lead time category. Stat:fit also provides an overview of which distributions that cannot be rejected as potential fits to the data based on three different goodness-of-fit tests. Two of these tests, the Chi-Square test and the KS-test, have been used in this study to assess which potential distributions that fit the investigated data. The structure of these tests and their advantages and disadvantages have been described in Section 3.3 by Laguna & Marklund (2013) and by Law & Kelton (1991). Stat:fit also calculates the ML estimations of the parameters in the distribution, according to the procedure presented by Blom et al (2005) and Law & Kelton (1991) in Section 3.3.2. The suggested distributions from Stat:fit were then tested in Matlab using the same set of data and built-in functions for performing the Chi-Square and KS-test. Figure 21 below shows the plot of the lognormal distribution together with a histogram of the data from Category 1.

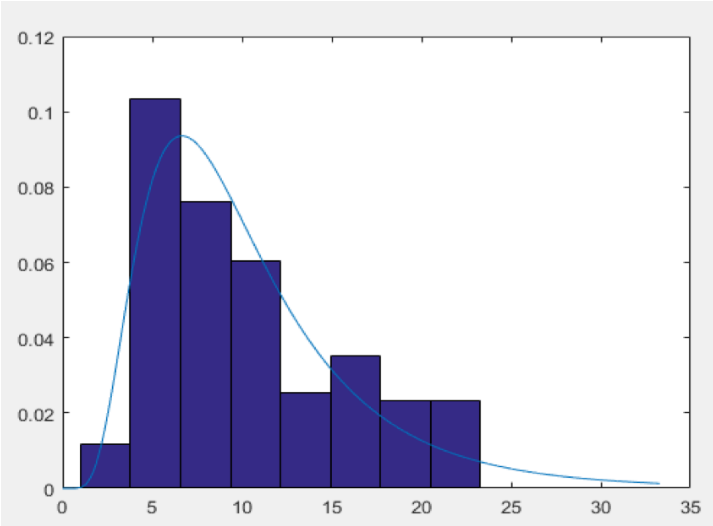

Figure 21. Histogram of Category 1 lead time data and the PDF of the associated lognormal distribution.

This was done to validate the results from Stat:fit and to ensure that the correct settings had been applied when performing the initial tests. The results from the distribution fitting for the three categories belonging to Supplier B can be seen in Table 9 below:

Table 9. Overview of results from distribution fitting for Supplier B.

	Top 5 distributions	**KS-test (alpha = 0.01)**	**Chi-square test (alpha = 0.01)**
Category 1	Inverse Gaussian	Not rejected	Not rejected
	Lognormal	Not rejected	Not rejected
	Pearson 6	Not rejected	Not rejected
	Pearson 5	Not rejected	Not rejected
	Log-logistic	Not rejected	Not rejected
Category 2	Inverse Gaussian	Not rejected	Not rejected
	Lognormal	Not rejected	Not rejected
	Pearson 6	Not rejected	Not rejected
	Pearson 5	Not rejected	Not rejected
	Log-logistic	Not rejected	Not rejected
Category 3	Inverse Gaussian	Not rejected	NA
	Lognormal	Not rejected	NA
	Pearson 6	Not rejected	NA
	Pearson 5	Not rejected	NA
	Log-logistic	Not rejected	NA

As has been described in Section 3.3 by Laguna & Marklund (2013), there is no general rule to decide which goodness-of-fit test that is most appropriate to use in all situations. This is why two tests have been used in this master thesis. It is also important to recall, that the goodness-of-fit tests do not prove that the data comes from a certain distribution, they just provide support in rejecting some distributions which with high probability does not describe the data properly. However, as can be seen in Table 9 above, the number of data points in Category 3 were too few to enable an evaluation by using the Chi-square test.

As can be seen in Table 8, there are several distributions that are not rejected for all the three categories of items. These are the inverse gaussian, Pearson 5, log-logistic and the lognormal distributions.

6.3.2 Results from the input analysis of lead times

The process which has been described above, has been conducted for all the three selected suppliers included in this study. In total, twelve different categories of items (based on the standard lead time) were investigated. The overall results from the distribution fitting for all categories is summarized in Table 10. This table shows the number of times the distributions were ranked among the top five distributions in Stat:fit when they were also not rejected by at least one of the used goodness-of-fit tests. From the table it can be concluded that the most frequently occurring distributions were the log-logistic distribution and the lognormal distribution. Table 10 also shows the number of times the distributions were not rejected by the used standard statistical tests respectively. The distributions are ranked according to the number of times the distributions were not rejected by the Chi-square test.

Table 10. The least rejected distributions from the distribution fitting for all categories of items.

Distribution	Chi-Square-test ($\alpha = 0.01$) [Number of times not rejected]	KS-test ($\alpha = 0.01$) [Number of times not rejected]	Stat:fit ranking [Number of times ranked among top 5 distributions]
Lognormal	4	7	7
Log-logistic	3	7	8
Pearson 5	3	6	6
Pearson 6	3	5	5
Inverse Gaussian	2	3	5

Based on the results from Table 10 above, all the lead times for the twelve investigated categories of items will be approximated with the lognormal distribution. The choice of the lognormal distribution is based on the fact that this distribution has been ranked top five in the ranking by Stat:fit in seven out of twelve evaluated categories and in all those cases it has been approved by the KS-test and by the Chi-Square test in the majority of the cases. However, as mentioned by Laguna & Marklund (2013) it should be remembered that in the original version of the KS-test, the parameters of the fitted distribution should be known beforehand. This is not the case in this study, but the test still provides an indication that the lognormal distribution could represent the gathered lead time data. This is also strengthened by the fact that in the majority of the cases where Stat:fit ranks the lognormal among the top five distributions, it is not rejected by the Chi-Square test which is a test that does not require the parameters to be known in advance. This result together with the fact that the employees at the case company mostly uses Microsoft Excel which has built-in functions for handling the lognormal distribution (which is not the case for the log-logistic distribution) were two major reasons to why the lognormal distribution was chosen instead of the log-logistic distribution. Another reason for using the lognormal distribution instead of the log-logistic distribution was that it is easier to estimate the parameters using the ML-estimation which makes it more useful from a practical point of view. Other factors that made the lognormal an appropriate distribution to use when modelling lead times is that this distribution cannot take negative values and it is simple since it only has two parameters. These factors were considered when choosing this distribution as an approximation.

When conducting the distribution fitting, it was concluded that for some investigated categories, there were no distribution that could be fitted to the data. In those cases, the data was approximated by using the lognormal distribution and the parameters to the distribution were estimated by the ML estimation as described by Law & Kelton (1991) in Section 3.3.2. The effect of this approximation on the results was a reduced level of expected stock on hand with a maximum of five percent when the lead times were estimated with the lognormal distribution compared with the results when using the empirical distribution. These calculations were performed on six different items in the categories where no distribution could be fitted to the data. Since the difference was not more severe, the lognormal has been considered being a reasonable good approximation also for these categories.

6.3.3 Generating lead times from the lognormal distribution

After choosing the lognormal distribution to represent the lead times in all the twelve categories of items, the two parameters of the lognormal distribution were gathered from Stat:fit and Matlab. These parameters were calculated by using the ML estimation described by Blom et al (2005) and Law & Kelton (1991) in Section 3.3.2. Once again, two software were used to validate the results.

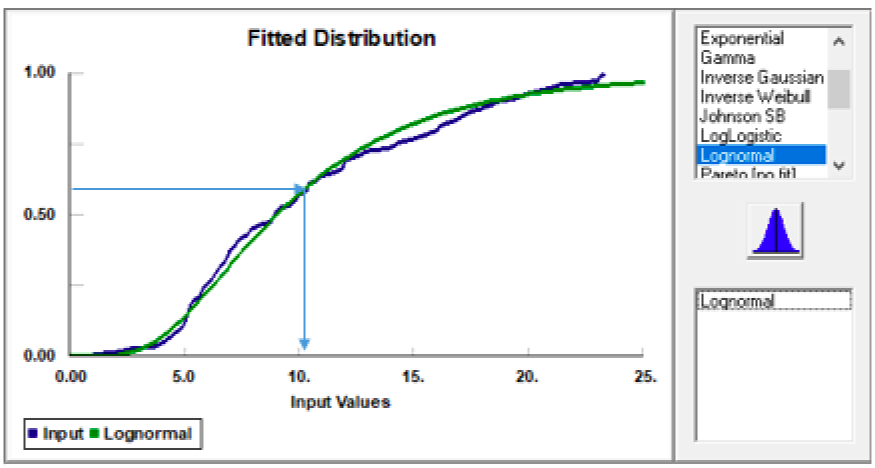

Figure 22. Empirical CDF compared to CDF of lognormal distribution for data in Category 1 for Supplier B.

From the CDF of the fitted lognormal distribution with parameters calculated based on the gathered data, lead times were generated by using a modified version of the inverse transformation method described by Blom et al (2005) in Section 3.3.5. The modification used in this project was that instead of generating $U(0,1)$ random variables, the whole range between 0 and 1 was represented in a vector of 100 values equally spread out in this interval. In this study, it was chosen to generate numbers in the whole interval between zero to one instead of relying on a random number generator. The reason for this was because it was desirable to get values from the whole distribution to get an unbiased representation of all the possible lead time outcomes in the underlying empirical data. The 100 values were used as probabilities in the inverse transformation method to generate quantiles (i.e. lead times) from the lognormal distribution. A graphical illustration of the procedure is shown in Figure 22 above. This was done by using the built-in Excel function called *LogNorm.Inv* and the estimated parameters for each of the categories. 100 lead time values were generated for each item in each category and these were then used in the mathematical model to calculate the demand during lead time, a process that will be more thoroughly described in Section 6.4.

6.3.4 Creating lead time scenarios

In the future scenario with a shared warehouse and a common inventory policy, the producing legal entity and the aftermarket network will not send purchase orders to the suppliers independently of each other as is the case today. A hypothesis at the case company is that this change will contribute to accomplishing more stable lead times. As described in Section 3.2.6, most inventory control models consider the replenishment lead time to be constant. This is also how the case company handles lead times today. However, since the case company has expressed that the variability in lead times is a concern, the lead times will be modelled with the lognormal distribution fitted to the data for each item category. Since the case company currently does not do any follow-up regarding the causes to the lead time variability, it cannot be concluded that the future scenario investigated in this thesis will lead to decreased lead time variability.

However, to evaluate the effect of the lead time variability, five different lead time variability scenarios have been created. Based on the fitted lognormal distribution for each item category, the standard deviation of this distribution has been reduced with 25 percent in each step. This was done by using Stat:fit where the mean of the distribution was held constant while only reducing the standard deviation. Stat:fit generated new parameters for the lognormal distribution for each of these scenarios. These new parameters were then used in the same way as described in Section 6.3.3 to generate lead times for the items in each category (according to their standard lead time) from the lognormal distribution for each evaluated scenario. By this procedure, it was possible to evaluate the effect on the holding and ordering cost for different scenarios of lead time variability ranging from the current experienced variability (as shown in the gathered empirical data) and the constant case which according to Axsäter (2006) is the most common way of handling lead times in inventory control models. The results from the lead time variability scenarios are discussed in Section 6.5.

6.4 A new inventory control policy

In the modelled system, as well as in the real system today, items are controlled independently of each other. Furthermore, it is assumed that demand not immediately satisfied from stock on hand, is backordered. As described in Section 6.1, a single location will be evaluated. Today Sandvik C&S already orders in batches, hence this will also be applied in the new model. With these settings, Axsäter (2006) as described in Section 3.2.6 states that an (R, Q) policy is the best choice. An (R, Q) policy is also a good choice when using service level constraints according to Section 3.2.6. Furthermore, having a fixed batch quantity is more predictable than having varying batch quantities. Today Sandvik C&S uses the service level definition fill rate and the appropriate mathematical definition, as described in Section 3.2.6.1, will therefore be used in the construction of the new inventory policy.

According to the demand analysis in Section 6.2, the customer arrival intensity is fairly low and the integral number of items requested per customer is often one or a few more. Additionally, the variance over mean is over 0.9 in almost all cases, see the sales analysis in Section 6.2. Hence a compound Poisson model is deemed to be a suitable choice according to theory Section 3.2.2.

One main goal of this project is to aggregate orders from both entities in a new shared warehouse. A periodic review will therefore be used in line with theory Section 3.2.5. Additionally, since global demand occurs at any time it is more convenient for purchasers to use a periodic review and the inspection cost will be lower according to theory Section 3.2.5. Today, the production planning at Sandvik SRP is made on a weekly basis and in most cases, the suppliers deliver goods to the case company once a week. Hence a weekly inspection period is chosen for the new model. However, the additional cost for safety stock will be further analyzed. According to the case company, the experienced variability in lead times is of concern. The analysis of historical lead times in Section 5.4.2 confirms that there is variability in the lead times from the three selected suppliers and of that reason this variability will not be disregarded in the new inventory control policy. The lead times will be modelled under the assumption that there are sequential deliveries. This means that orders do not cross in time, as described in theory Section 3.2.6.3.

When the optimal R and Q has been determined for all items, inspection periods can be chosen such that all items to a certain supplier are ordered once a week. Alternatively, orders of different items can be placed on different days during the week to smooth out the ordering towards the suppliers. Inspection of these different item categories can therefore occur on different days throughout the week. This is a benefit of using a periodic review as described in Section 3.2.5.

In summary, the system will be modelled as a single-echelon (R, Q) policy with periodic review that minimizes inventory holding costs and ordering costs under a given fill rate constraint. The model will be constructed in VBA.

6.4.1 Model formulation

This section describes the *Building mathematical model* step in the research design, described in Section 2.3.2. The algorithm shown in Figure 23 will generate an (R, Q) policy with periodic review that minimizes inventory holding costs and ordering costs given a fill rate constraint. In Appendix I, the VBA code that has been used to implement the new inventory control policy can be found.

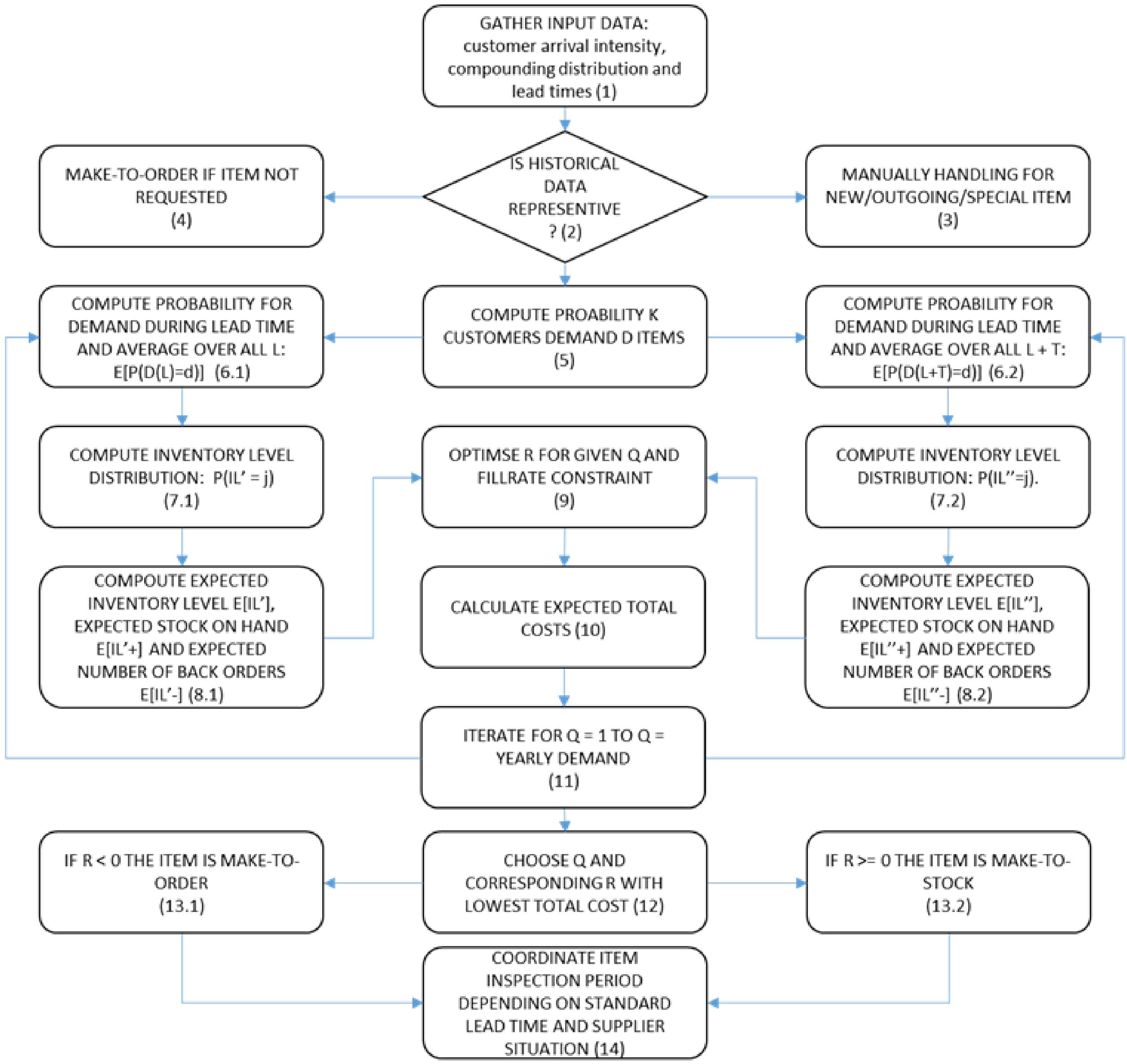

Figure 23. Flow chart over the new inventory policy.

The first step in the algorithm is to (1) gather and clean data of lead times, customer arrival intensities and the compounding distribution. The second step is to (2) value if the historical data is sufficient to be modelled as a compound Poisson distribution, as described in Section 3.2.2. Newly introduced and outgoing items together with items that have specific customer requirement should be handled manually (3), see Section 3.2.3. If an item is not included in the previous descriptions but (4) it has not been demanded in the time period covered by the gathered data set, the item will be classified as make-to-order (MTO). It is important that the length of the data set is sufficiently long. These steps are necessary to ensure that the demand model will be an appropriate choice. For items where a compound Poisson distribution is an appropriate choice as demand model, the next steps are (5-10) to determine a reorder point R that minimizes the ordering costs and holding costs given a fill rate constraint and the batch quantity Q. The formula to compute (5), the probability that k customers demand d items is found in Section 3.2.2. Calculate (6.1-6.2) the demand during lead time distribution (i.e. Compound Poisson distribution) as explained in Section 3.2.2.

Calculations for inventory level distribution and different inventory level performance indicators (7.1,7.2,8.1,8.2) are described in Section 3.2.6.1, likewise for (9) the fill rate calculation. The total costs which is determined by the expected inventory level and the expected number of order lines is calculated as described in Section 3.2.6.2. The next step (11) is to iterate (5-10) for a sufficiently large number of batch quantities and then choose the batch quantity that accomplishes the lowest cost. Since only the lowest reorder point that satisfy the fill rate constraint given Q is of interest, the number of combinations of R and Q is limited. Therefore, (12) the R given Q that yields the lowest total costs under the fill rate constraint is chosen as the optimal combination. If (13.1) R is negative the item will be considered as MTO otherwise make-to-stock (MTS). Finally, when both R and Q have been optimized for all items belonging to a certain supplier, the inspection can be (14) coordinated such that orders for items are triggered at the same time to minimize the number of purchase orders or to trigger volume discount. The items can also be ordered on separate days to spread out the quantity during the week. In this project a review period of one week has been chosen but other inspection periods can also be used.

6.4.2 Model results

By using the formulated model, the optimal R and Q for each item that achieve a 95 percent fill rate at the lowest total cost, have been determined. The results from the model in terms of holding costs, ordering costs, expected stock on hand and the expected number of order lines for each supplier are shown in Table 11 below.

Table 11. Results from the new system for one year.

SUPPLIERS	A	B	C
EXPECTED STOCK ON HAND [UNITS]	800	485	296
EXPECTED NUMBER OF ORDER LINES	252	56	119
AVERAGE FILL RATE	95.3 %	95.1 %	95.4%
HOLDING COSTS [EURO]	123 218	65 596	105 014
ORDERING COSTS [EURO]	18 913	4 212	8 955
TOTAL COST [EURO]	142 131	69 808	113 969

The model also yields the probability of triggering an order at inspection according to theory from Section 3.2.6.4., see Table 12 below. This is information that the case company can provide to the suppliers to create more predictability in the suppliers' production and purchase processes.

Table 12. Probability of triggering at least one order line at review if all items for a supplier are reviewed at the same time.

SUPPLIER	A	B	C
PROBABILITY TO TRIGGER AT LEAST ONE ORDER LINE AT REVIEW	99 %	68 %	91 %

6.4.3 Comparison to previous model

Table 13 below shows a summary of the results from the current system. In Table 14, the changes in costs when comparing the future scenario with the current system, are shown.

Table 13. Summary of results from the current system 2017.

SUPPLIER	A	B	C
AVERAGE STOCK ON HAND [UNITS]	628	416	198
NUMBER OF PO LINES	434	187	164
AVERAGE FILL RATE	78 %	71 %	67 %
HOLDING COSTS [EURO]	99 766	61 870	66 466
ORDERING COSTS [EURO]	32 550	14 025	12 300
TOTAL COST [EURO]	132 316	75 895	78 766

Table 14. Cost changes when comparing the new system with the current system

SUPPLIER	A	B	C
HOLDING COSTS	+ 24%	+ 6%	+58%
ORDERING COSTS	- 42%	- 70%	- 27%
TOTAL COST	+ 7%	- 8%	+ 45%

When comparing the results between the future scenario and the current system it can be concluded that the results vary between the different suppliers. The general trend is that the expected stock on hand in the future scenario will increase and therefore the holding cost will also increase for all the three suppliers. This is reasonable since the fill rate has been increased for all the items supplied by the chosen suppliers. Furthermore, an additional reason for the increased holding costs is that the stochastic lead times have been taken into consideration in the new model. The increase in holding cost for Supplier C will also be the largest since this supplier had the lowest fill rate in the current system. This supplier also has several very expensive items which have significantly higher expected stock on hand in the new model since they have high variability in the lead times. Additionally, Supplier C is a supplier where the same components are also produced by SRP, which means that raw-material and work in process have not been included in the finished goods inventory from the current system. This also leads to a higher difference in the comparison between the two systems. However, in the new scenario the ordering costs have been reduced for all three suppliers and the reason for this is because the number of order lines to the suppliers will be reduced since they are coordinated from one warehouse instead of being placed independently from the two legal entities which is the case today.

6.5 Effect of lead time variability

Since the case company has expressed that the variability in the lead times which they are experiencing is a concern, the new inventory control model has taken this variability into consideration. This has also enabled an evaluation of how the variability affects the holding costs and ordering costs in the new inventory control policy. As described in Section 6.3.4, the case company hopes that an aggregated ordering from a new shared warehouse in the defined future state, will contribute to stabilizing the lead times. Hence, the effect on the inventory holding costs and the ordering costs for different reductions in the variability has been estimated in five different scenarios, according to the description in Section 6.3.4.

Since the holding costs depend on the expected stock on hand, the effect of a reduced lead time variability on this parameter will be discussed here. The result from the different scenarios can be seen in Figure 24 below. As has been discussed in the previous section, the expected stock on hand will increase for all the selected suppliers in the new scenario where stochastic lead times are taken into consideration. However, when reducing the lead time variability this will have implications for the expected stock on hand for all the three suppliers since the lead time variability creates increased variability in the lead time demand, as described by Song (1994). As explained in Section 3.2.6, Axsäter (2006) states that the variability in demand during lead time increases the need of inventory to cover the uncertainty. Simchi-Levi et al (2003) also states that when the lead times are long (which they are for replenishments from the selected suppliers) small changes in the lead time demand will lead to high impact on the reorder points. Hence, when the uncertainty is reduced the reorder points will decrease which will also mean that the expected stock on hand will be reduced. This can be seen in Figure 24 below.

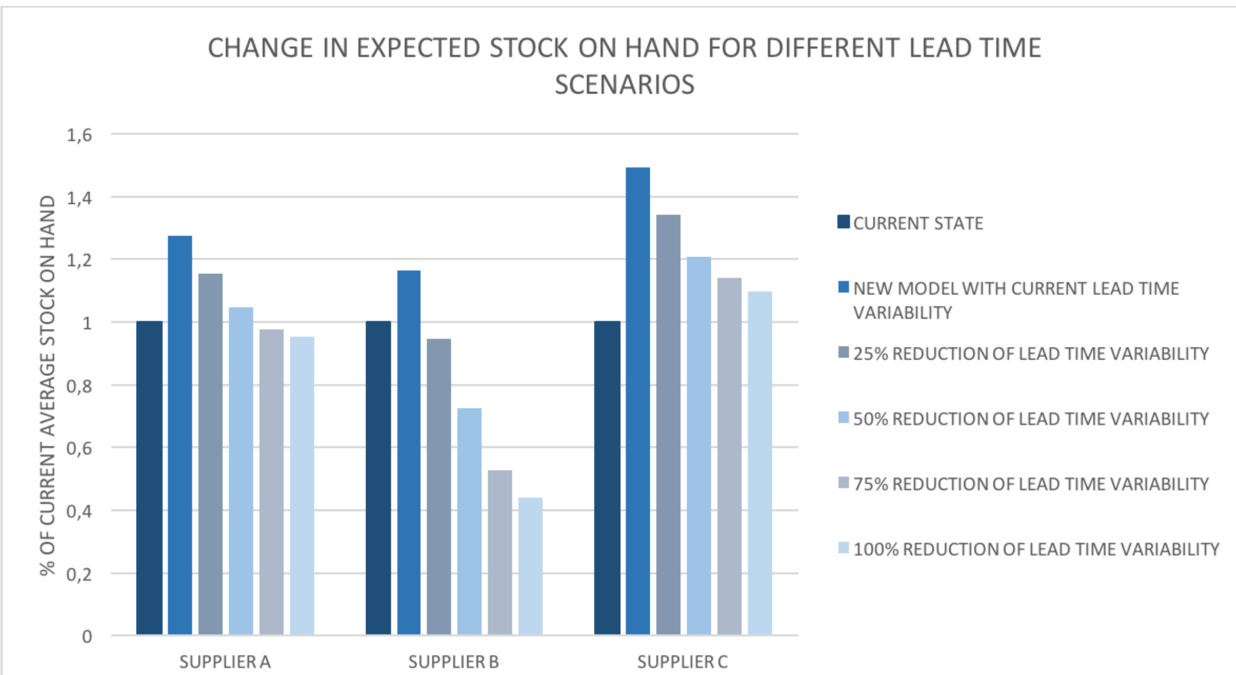

Figure 24. Expected stock on hand reduction for different degree of lead time variation.

The highest impact of the lead time variability can be seen for Supplier B. As shown in Section 5.4.2, this was the supplier with the highest variability in the studied lead times. The expected stock on hand for Supplier A will be reduced the least, one reason for this being that the lead time variability was the least compared to the two other suppliers. According to Hopp & Spearman (2008) variability will need to be buffered in some combination of time, inventory or capacity and in this analysis it has been shown that the case company needs to buffer for the lead time variability with inventory. In the scenario where the variability has been reduced to zero (i.e. the lead times are assumed constant) the total reduction in expected stock on hand (for all the three suppliers) compared to the current system is 244 units which is a 20 percent reduction. This would mean a 10 percent reduction in inventory holding costs and an improved fill rate to 95 percent.

To determine how the ordering cost is affected by reducing the lead time variability, the expected number of order lines for different levels of variability has been analyzed. As can be seen in Figure 25 below, the number of order lines will increase when the lead time variability is reduced. This also means that the ordering costs will increase since it is proportional to the expected number of order lines. However, between the different steps of reduction of the variability, the number of order lines might also decrease. These jumps in the curve can be explained by the optimization algorithm which is used to calculate R and Q in the new inventory policy. When minimizing the total cost by changing R and Q simultaneously, different combinations of these two parameters may accomplish the optimal cost value. This means that the total cost curve is not convex and therefore a higher Q is sometimes optimal to fulfill the service level constraint and still minimize the costs. As described by Axsäter (2006), the expected number of orders per time unit is calculated as the average demand per time unit divided by Q. Therefore, the expected number of order lines will depend on the choice of optimal Q in the used optimization algorithm and if Q is larger in a certain scenario, the expected number of order lines might decrease, even though the lead time variability also decreases. However, the general trend is that reduced lead time variability, increases the expected number of order lines for all three suppliers but this trend includes some deviations between the different lead time scenarios. In the best-case scenario where the lead time variability is reduced to zero, the expected number of order lines will be 499 to all the suppliers which is a reduction with 36 percent compared to the current situation.

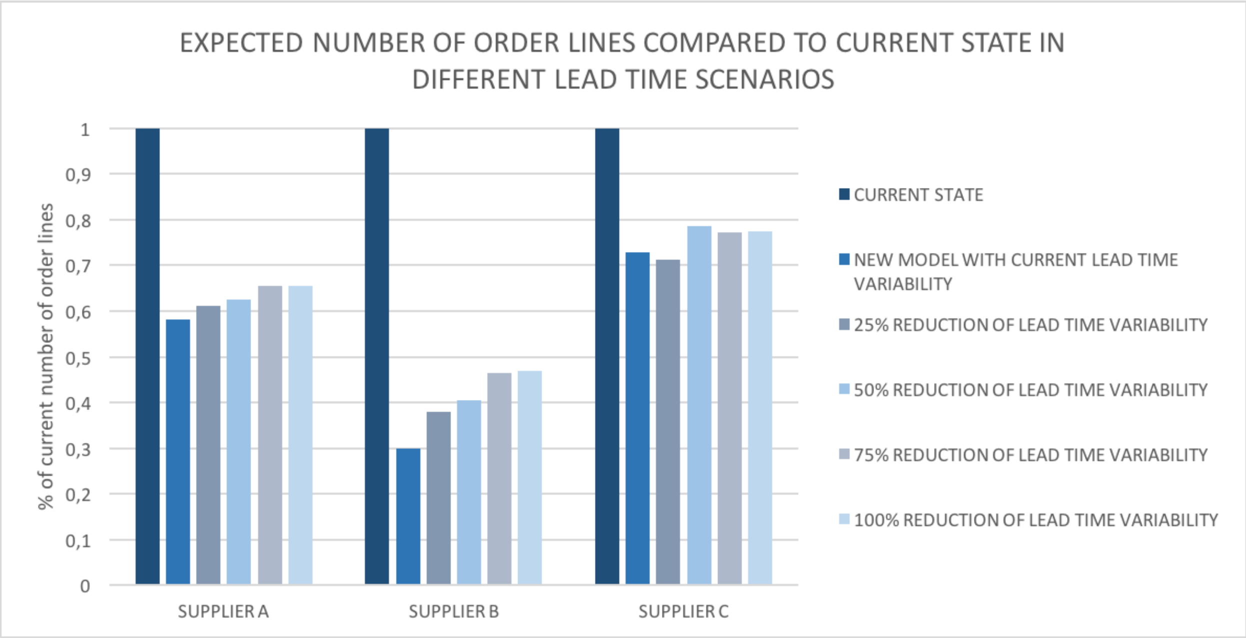

Figure 25. Expected number of order lines for different lead time scenarios.

Finally, the related costs of the lead time variability will be presented. The same scenarios as has been analyzed before, have been considered here. As seen in Figure 26, the potential reduction of costs related to reducing the lead time variability differs between the three suppliers. As described earlier in this section, the main contribution of the cost reduction by reducing the lead time variability comes from the reduction in the expected stock on hand and thereby the reduced holding cost. Since the number of order lines increases when the lead time variability is reduced, the ordering costs will increase. What can be seen in Figure 26 is that for both Supplier A and Supplier B the total costs in the scenario where the lead time variability has been assumed to be zero (i.e. the lead times are constant) will be lower than in the current system. This is supported by Johnsson & Mattson (2017) who states that an increased centralization (i.e. where the number of stock locations is reduced) will reduce the required stock on hand while maintaining the customer service level. For Supplier C, the costs will be 15 percent higher in the future state even though the lead times are assumed to be constant. This is because the increase in required stock on hand to reach a 95 percent service level is not compensated by the reduction of stock on hand which could be accomplished by the centralization. However, in the best-case scenario where lead times in the future state are assumed to be constant, the total costs for all the three suppliers could be reduced with 14 percent compared to the current state.

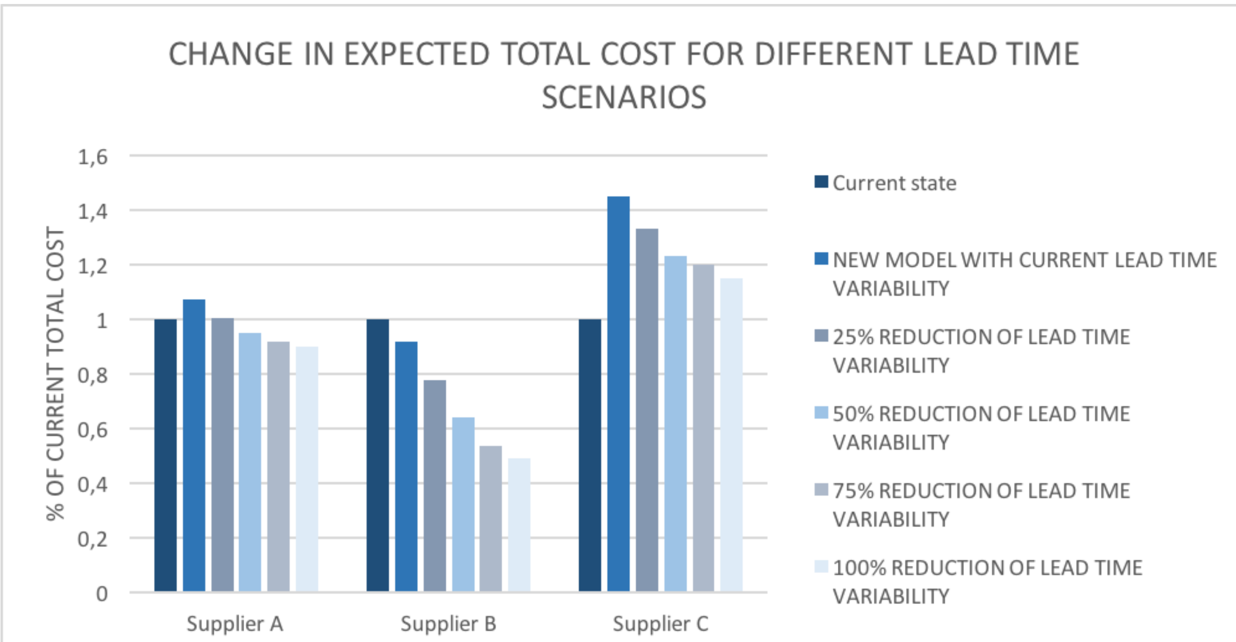

Figure 26. Change in expected total cost for different lead time scenarios.

6.6 Sensitivity analysis

This chapter describes the robustness for several factors in the model, exemplified by one representative item. These factors are included in the sensitivity analysis because they are most uncertain and not given by the case company. Conducting the sensitivity analysis is part of the suggested actions in the operations research framework presented in Section 2.3.2.2 and is also the final part of the Model formulation and analysis phase of the research design described in Section 2.3.2. Firstly, the impact on the solution depending on the choice of review period will be evaluated, see Figure 27.

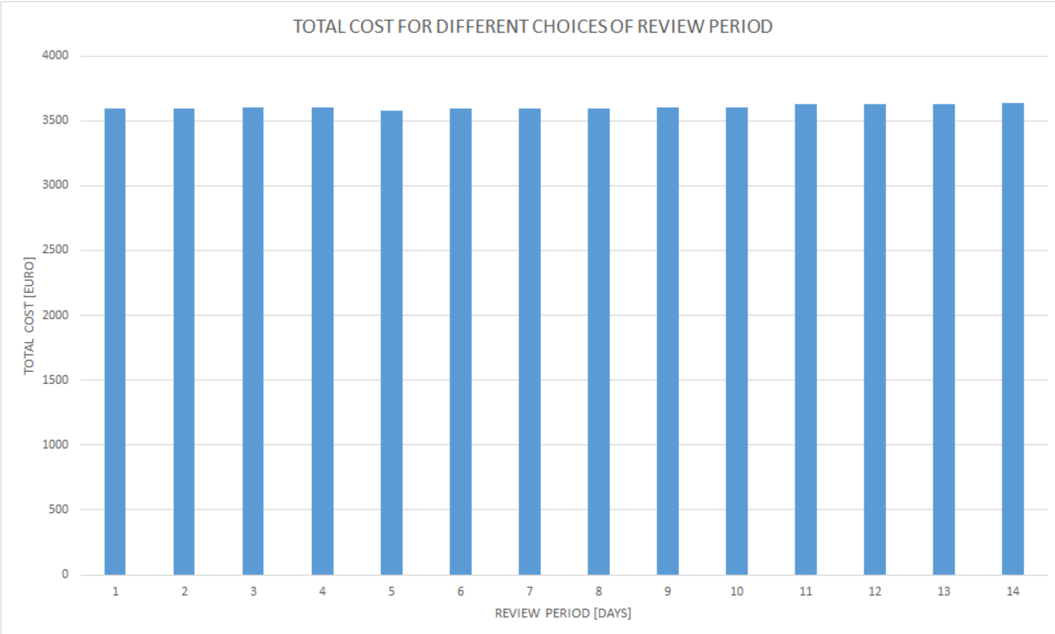

Figure 27. The bar chart shows the effect of different choices of review period on total cost.

By analyzing the effect on the total cost for different choices of review periods, it can be concluded that the model is robust to the choice of review period. At least when comparing a seven day (i.e. one week which has been chosen in this project) with one day review period. The uneven pattern in the total cost curve in Figure 27 above, occurs because the service level might sometimes be slightly over 95 percent due to the fact that R and Q are integers and after a change, a less costly combinations become feasible. The small impact on the total cost for different choices of review periods, depend on the long lead times for replenishments of items from the selected suppliers. Hence, a change in review period with a couple of days will not create large differences in the total cost. In the next paragraph, the effect on the total cost of changing the batch quantity and the likelihood of ordering at inspection will be evaluated, see Figure 28.

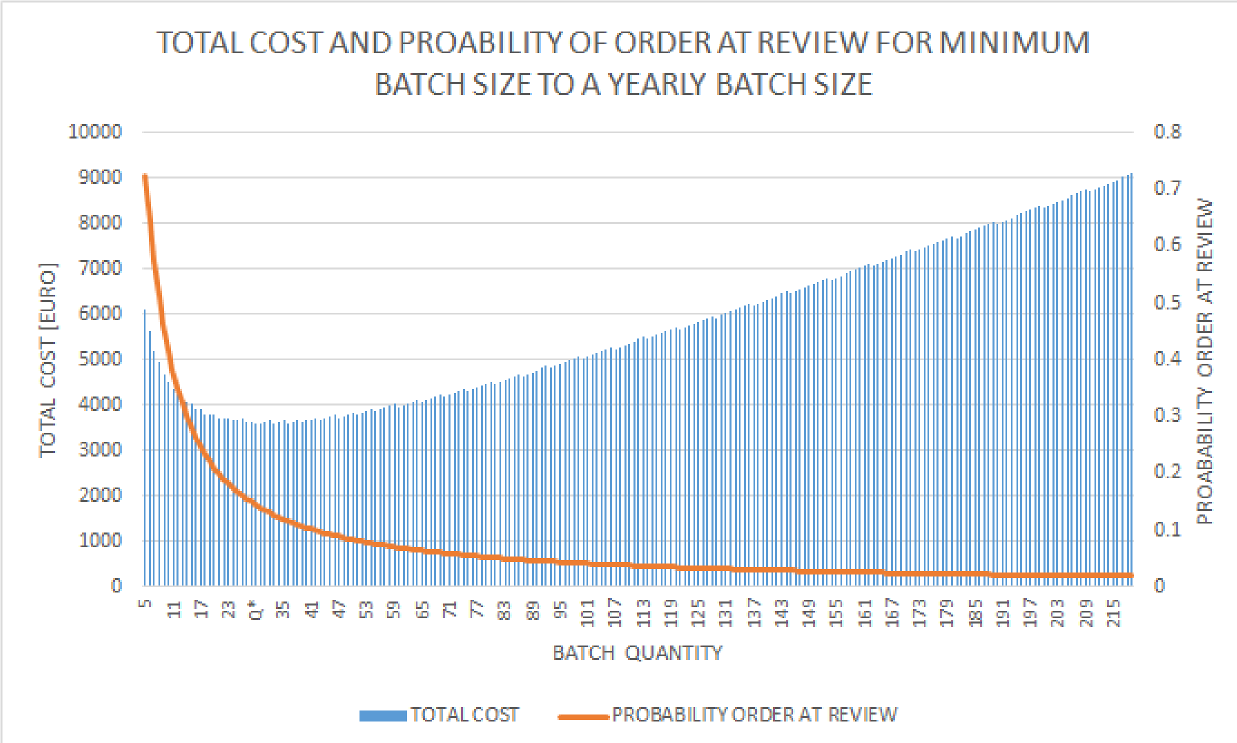

Figure 28. Probability of order increase than batch quantity decreases in size while cost is increasing.

The total cost is calculated for different batch sizes, from a batch size equal to the average weekly demand to a batch size equal to the yearly demand. What can be seen in the graph is that the total cost curve is not convex. Instead the curve has small jumps which is caused by the fact that R and Q are integers and since the fill rate may be slightly over 95 percent, changing Q and R might make an earlier infeasible solution become available. Since the curve is not strictly convex, it is necessary to analyze a large number of batch sizes to find the minimum. However, as seen in the curve it is not necessary to consider an infinite amount of batch sizes to find minimum, especially since the case company do not want to order a year of demand at once. It can also be concluded that when the batch size decreases, the probability of ordering at a weekly inspection increase.

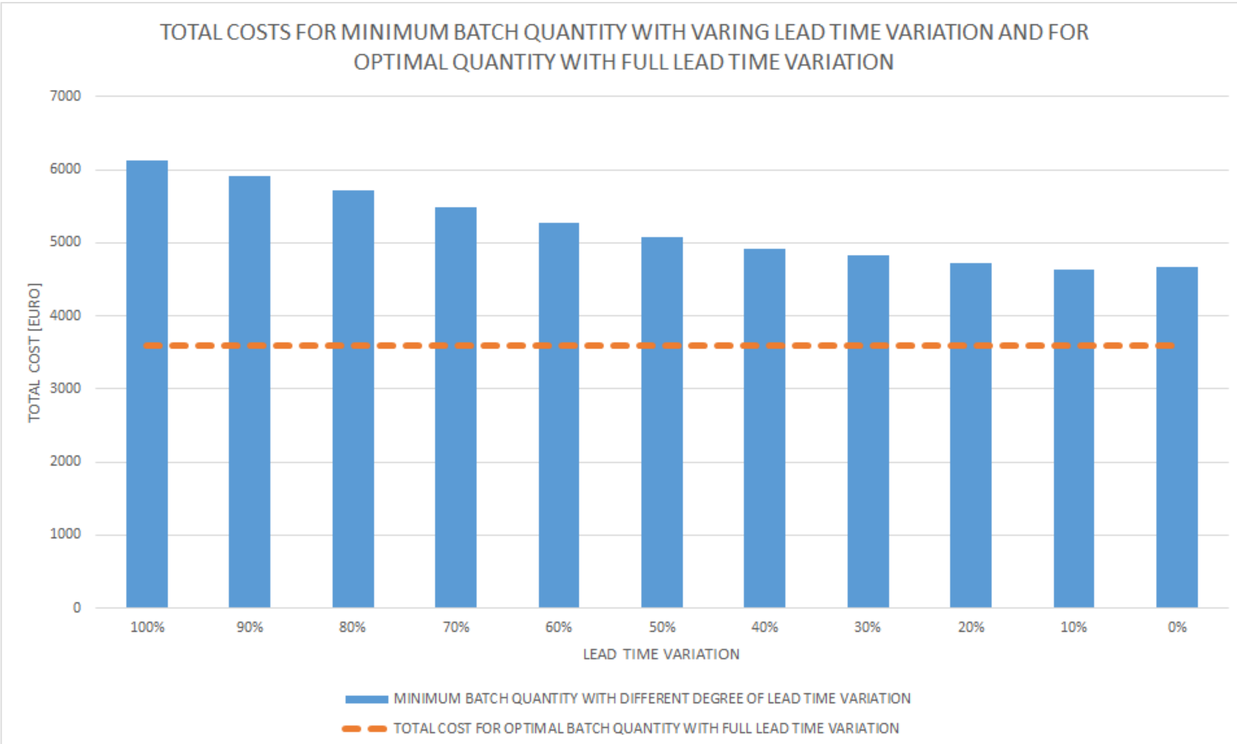

Figure 29. If assuming weekly batch sizes and maximum lead time reduction no break-even is reached.

According to Lee (1997), breaking batch sizes might reduce the bullwhip effect and combined with the previously analysis which shows that the probability of ordering at inspection increases when reducing the batch size, a smaller batch size will create better predictability for suppliers. However, not choosing the optimal batch quantity will come at an additional cost. On the other hand, if the benefit of reducing the lead time variability is greater than the cost for reducing batch size, it could be an interesting way to reduce the variability in lead times. Observations from Figure 29 show that it will not pay-off, but for around 6 percent of the considered items a potential break-even can be reached (at around 30 to 50 percent reduction of lead time variability). These are the items with the highest lead time variability and as seen in Section 6.5, the cost savings are the largest in the range between 25 to 50 percent reduction in lead time variability. However, the benefit that be accomplished by reducing the batch quantity is very uncertain since Sandvik C&S do not follow up on root causes to the lead time variability and therefore there might be other issues than the choice of batch quantity that affect the lead time variability, as described in Section 3.2.6.3.

7. Conclusion

This chapter consists of answering the research questions and a concluding discussion.

7.1 RQ 1: How to construct an inventory control policy for a new warehouse?

The first research question which this project has aimed at answering was how to construct an inventory control policy for the new shared warehouse in the future state. Through this project it has been concluded that this new inventory control policy could be constructed through gathering data from both the legal entities which require key components. The second step includes identifying the demand model which describes the combined demand of key components from both the aftermarket network and for the entity which produces new crushers. In this study, it has been concluded that the demand for the studied components is low but has a high variability. For this type of demand, a compound Poisson distribution has been shown to be a suitable model. Based on the case company settings and the delimitations in this study, theory suggests that the (R, Q)-policy is a suitable choice and this policy has been optimized to satisfy the desired fill rate which the case company has defined as the target fill rate for these types of components. Furthermore, the two parameters in the (R, Q) policy have been optimized to minimize the inventory holding and ordering costs under the given fill rate constraint. This has been done by an algorithm where, for a range of Q values, the corresponding reorder points R that satisfy the fill rate constraint have been calculated. Then, the combination of Q and R that yields the lowest total cost for each item has been chosen. As has been shown in the analysis chapter, the total cost of holding inventory and ordering will increase in the future state where the fill rate is 95 percent and the stochastic lead times are taken into consideration, compared to the current system.

By considering the current procedures and practices at the case company in terms of deliveries from the chosen suppliers and the production planning, it was concluded that a periodic review inventory model was appropriate. This will enable a coordination of orders to the suppliers on a weekly basis and will reduce the need for frequent inspections which are currently used by the case company. The periodic review solution also provides flexibility. If the ambition is to spread out the ordering over the week to the same supplier, this could be accomplished by ordering different items with the same standard lead times on separate days throughout the week. This would enable deliveries from the supplier of all these items at once, since they are supposed to have the same standard lead time. However, the periodic review also enables the case company to only send one order for all items that are supplied from the same supplier on a weekly basis. This would reduce the number of POs to the suppliers to a minimum of around 52 per year.

In the sensitivity analysis of the constructed model, it has been shown that the cost is not sensitive to the choice of review period. One contributing factor to this is that the considered lead times are long and choosing between a daily inspection and a weekly inspection when the lead times are between 8-17 weeks, does not have a large impact on the studied costs. Furthermore, the conducted sensitivity analysis showed that a reduction of batch quantities to increase the probability of ordering weekly, could not be compensated financially by reducing the lead time variability to zero. This was investigated because studied theory suggests that more frequent replenishments, reduces the variability in the ordering process.

7.2 RQ 2: How does the lead time variability affect the total cost?

The second research question concerned how the variability in the lead times which the case company currently experiences, affect the total costs (i.e. the holding costs and the ordering costs) related to the new inventory control policy. In this study, the lead time data gathered from the case company was fitted to theoretical probability density functions. It was found that the lognormal probability density function in many of the tested item categories could be used as an approximation to represent the empirical lead times.

In the new inventory control model, it was evaluated how the lead time variability affected both the inventory holding costs and the ordering costs. Firstly, it was found that the largest impact on the expected total cost could be seen for Supplier B where the lead time variability had been most severe during the studied time period. In most inventory models, the lead times are considered to be constant and in several scenarios where the variability was reduced in steps, the effect on the total costs were evaluated before finally reaching the level where the lead times were considered constant. What could be seen in these scenarios was that the expected stock on hand decreased when the lead time variability was reduced. However, the expected number of orders increased with a reduced lead time variability meaning that the ordering costs increased in these scenarios. Yet, it could be concluded that there is a potential for the case company to consider finding the root causes to the lead time variability because if they are considered in an inventory control model, they incur additional costs. If they are assumed to be constant while they are actually varying, this could instead lead to underestimation of the required reorder points to cover the lead time demand for these customer critical items.

To summarize, the total costs compared to the current system will increase in the future state where the fill rate is 95 percent and the stochastic lead times are taken into consideration system. However, by reducing the lead time variability the costs can be reduced in the future scenario. If the lead times in this scenario are also assumed constant, the case company can reduce the total costs for the items supplied by two of three investigated suppliers. For the third supplier, the costs will increase compared to the current system if the fill rate is raised to 95 percent from the current level of 67 percent, even if the case company operates with a shared warehouse and assumes the lead times are constant. Anyhow, the total costs for all the suppliers could in the future scenario and assuming a best-case scenario (where the lead times are assumed constant) be reduced with approximately 14 percent compared to the current system while at the same time accomplishing a 95 percent fill rate.

7.3 Future research and implementation

This project has evaluated the consequences for the inventory holding costs and ordering costs in a future scenario where orders to the suppliers of key components are sent from a new shared warehouse. This is a future scenario defined by the case company and this study has provided insights regarding how an inventory control policy for such a warehouse could be designed and how the current variability in the lead times experienced by the case company affects the inventory holding and ordering costs. However, to actually implement this solution there is some future work that needs to be done by the case company.

First of all, it is necessary to investigate an ERP-system that can handle the demand for both the legal entities which enables this type of aggregation and centralized scenario. Also, it is necessary to investigate how the inbound transportation of the key components should be handled and coordinated. It is also of interest for the case company to investigate how this new inventory control model will affect the transportation costs, which have been excluded from this study. Furthermore, the geographical location of the warehouse should be investigated.

In this study, a distribution fitting has been conducted to evaluate the effects of the lead time variability. If the case company would like to use the lead time data as an input in the inventory control system without conducting a distribution fitting, this would be enabled by using the empirical distribution of the lead time data. However, starting to follow up the root causes for the lead time variability could be a first step in trying to accomplish more stable lead times from the suppliers.

This project has contributed to the current inventory literature as an empirical case in the field of inventory control of spare parts. The study has also shown the impact of the lead time variability in an (R, Q) inventory control policy. In this study a certain type of components have been analyzed, but the process and results are also applicable for other items than which have been studied in this project. A potential extension of the study could be to conduct more case studies at other companies and in other industries to further generalize the results. The developed model is built on well-known theory within inventory control and statistical distribution fitting and even though the conclusions from this thesis are based on the current circumstances at the studied case company, the solution and thereby the conclusions are applicable for other companies facing the same issues as the studied case company.

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Appendix A. VBA code

'Below you find an example of a subroutine in VBA for computing the probability that k customers order j units (denoted fjk in Axsäter (2006)).

'When calling the subroutine you need to specify:
'i_max = the largest number of units a single customer can order (the maximum demand size).
'k_max = the maximum number of customer arrivals that can occur with reasonable probability during the considered lead-time
'd_max = the largest number of units that k_max customers can demand.
'pdf_compounding_dist = the probability density function for the demand size of a single customer, i.e., a vector indexed (0 to i_max) where the index corresponds to the quantity demanded and the value associated with that index is the probability for a single customer to demand this amount.
'f_j_k_vector = two dimensional vector (j,k) indicating the probability that k customers demand j units. It is these probabilities that the subroutine computes. Note j=0 to d_max and k=0 to k_max.

```
Sub Dist_f_j_k(k_max, i_max, d_max, pdf_compounding_dist, f_j_k_vector)

Dim i, d, k As Long 'k = customer, d = demand, i = number of units
Dim temp1, temp2, f_j_k, sum_prob, sum_i As Double

ReDim f_j_k_vector(d_max, k_max)
 'Note: d denotes the total amount of demanded units which in
 'Axsäter (2006) is referred to as j

For d = 0 To i_max
  If d = 0 Then
    f_j_k_vector(d, 0) = 1
    f_j_k_vector(d, 1) = 0
  ElseIf d >= 1 Then
    f_j_k_vector(d, 1) = pdf_compounding_dist(d)
    f_j_k_vector(d, 0) = 0
  End If
Next

For d = 1 To d_max
  For k = 1 To WorksheetFunction.Min(d, k_max)
    sum_i = 0
    For i = (k - 1) To (d - 1)
      sum_i = sum_i + f_j_k_vector(i, k - 1) * f_j_k_vector(d - i, 1)
    Next
    f_j_k_vector(d, k) = sum_i
  Next
```

```
Next

End Sub

'Below you find an example of a subroutine in VBA for computing the probability of stochastic demand j
in the time interval t (denoted P(D(t) = j) in Axsäter (2006)). In this subroutine in VBA stochastic lead
times is regarded.

'When calling the subroutine you need to specify:
'k_max   = the maximum number of customer arrivals that can occur with reasonable probability during
the considered lead-time
'd_max   = the largest number of units that k_max customers can demand.
'L_vector = one-dimensional vector indicating all lead time outcomes.
'P_DL = one-dimensional vector indicating the probability of stochastic demand d in an interval t.

Sub calc_P_DL(k_max, d_max, L_vector, f_j_k_vector, P_DL)
' Computes P(D(L)=d)

Dim k, d, i As Long 'k = customer, d = demand, i = index
Dim sum_k As Double
ReDim temp(d_max, UBound(L_vector)) As Double 'matrix for lead time demand for different L
ReDim P_DL(d_max) As Double
         'Note d denotes the total amount of demanded units which in Axsäter (2006) is referred to as j

For i = 0 To UBound(L_vector)
   For d = 0 To d_max
   sum_k = 0
      For k = 0 To k_max
         sum_k = sum_k + WorksheetFunction.Poisson(k, lambda * L_vector(i), False) * f_j_k_vector(d,k)
      Next
      temp(d, i) = sum_k
   Next
Next

For d = 0 To d_max
   For i = 0 To UBound(L_vector)
      P_DL(d) = P_DL(d) + temp(d, i) / (UBound(L_vector) + 1)
   Next
Next

End Sub

'Below you find an example of a subroutine in VBA for computing the probability of inventory level j
(denoted P(IL = j) in Axsäter (2006)).
```

```
'When calling the subroutine you need to specify:
'R = reorder point
'Q = batch quantity
'P_DL = one-dimensional vector indicating the probability of stochastic demand d in an interval t.
'P_IL = one-dimensional vector indicating the probability of inventory level j

Sub calc_P_IL(R, Q, P_DL, P_IL)
'Computes P(IL = j)

Dim j, k, i As Long 'j = inventory level, k = inventory position, i = index
Dim sum_k As Double
ReDim P_IL(R + Q) As Double

For j = 0 To R + Q
   sum_k = 0
   i = WorksheetFunction.Max(R + 1, j)
   For k = i To R + Q
         sum_k = sum_k + P_DL(k - j)
   Next
P_IL(j) = (1 / Q) * sum_k
Next

End Sub

'Below you find an example of a subroutine in VBA for computing fill rate as Axsäter (2006).

'When calling the subroutine you need to specify:
'R_opt = reorder point (that eventually is going to be optimised for an certain fill rate)
'Q = batch quantity
'L = average of all lead time outcomes
'T = review period
'CPD_m = mean of the compounding Poisson distribution
'P_DL = one-dimensional vector indicating the probability of stochastic demand d in an interval L.
'P_DLT = one-dimensional vector indicating the probability of stochastic demand d in an interval L+T.
'P_IL = one-dimensional vector indicating the probability of inventory level j
'fill_rate = fill rate outcome returned from the subroutine
'E_IL = expected inventory level (at time interval L)
'E_IL_positive = expected stock on-hand (at time interval L)
'E_IL_negative = expected number of backorders (at time interval L)
'E_ILT = expected inventory level (at time interval L + T)
'E_IL_positive_T = expected stock on-hand (at time interval L + T)
'E_IL_negative_T = expected number of backorders (at time interval L + T)
```

```
Sub Fillrate_calculation(R_opt, Q, L, T, CPD_m, P_DL, P_DLT, fill_rate, E_IL, E_IL_positive,
E_IL_negative, E_IL_T, E_IL_positive_T, E_IL_negative_T)

Dim P_IL() As Double 'P(IL=j)

Call calc_P_IL(R_opt, Q, P_DL, P_IL)

E_IL_positive = calc_E_IL_positive(P_IL)
E_IL = calc_E_IL(R_opt, Q, L, CPD_m)
E_IL_negative = calc_E_IL_negative(E_IL_positive, E_IL)


Dim P_ILT() As Double 'P(IL=j) for L + T

Call calc_P_IL(R_opt, Q, P_DLT, P_ILT)

E_IL_positive_T = calc_E_IL_positive(P_ILT)
E_IL_T = calc_E_IL(R_opt, Q, L + T, CPD_m)
E_IL_negative_T = calc_E_IL_negative(E_IL_positive_T, E_IL_T)

fill_rate = 1 - ((E_IL_negative_T - E_IL_negative) / (CPD_m * T))

End Sub

'Below you find an example of a function in VBA for computing probability of ordering at inspection.

'When calling the function you need to specify:
‘R = reorder point
‘Q = batch quantity
‘P_D = one-dimensional vector indicating the probability of stochastic demand d in an inspection interval
T.

Function calc_P_order(R, Q, P_D)
'Calculate probability of ordering at inspection

Dim k, j As Long j = demand, k = inventory position
Dim temp As Double

temp = 0
For k = R + 1 To R + Q
    For j = k To UBound(P_D)
        temp = temp + P_D(j - R)
    Next
Next
```

```
calc_P_order = temp / Q

End Function
```