Overstock of aftermarket parts in Africa at Sandvik Stationary Crushing and Screening

A case study of overstock root causes and construction of an OSMI framework

Master's Thesis
MIOM05 - Division of Production Management

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Abstract

Title: Overstock of aftermarket parts in Africa at Sandvik Stationary Crushing and Screening

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Background: An increase of customer expectations such as demand for more customizable options, shorter lead times and availability puts more and more pressure on a company's logistical processes. With fluctuating demand, inconsistent lead times and uncertainty around the world, variability is present and adds complexity to the logistical processes and needs to be handled appropriately to lower costs and match supply and demand.

Purpose: Find major root causes of the overstock situation in the region of Africa and suggest solutions to these identified causes. Furthermore, investigate the possibilities of redistribution and scrapping of current obsolete inventory.

Research questions:

1. What are the major root causes to the overstock situation in Africa?
2. How can these issues/root causes be mitigated and thereby reduce future overstock?
3. How can the current obsolete inventory be handled in terms of redistribution and scrapping?

Methodology: The methodology presented and used is based on Höst et. al. (2006) and the project procedure presented by Hillier & Liebermann (2010). The initial step was to define and investigate the severity of the overstock situation, to then analyze and find the root causes of this phenomenon, based on the literature study and input from company representatives. From these root causes, different solutions are presented to ideally avoid or mitigate the severity of these causes in the future. To reduce the current inventory obsolescence, a framework based on quantitative historic data is presented, which explores the possibilities of redistribution and scrapping.

Conclusion: Based on the analyzed data it was found that the two major root causes of overstock were the lag of the demand forecast for items that have lost demand and a manual forecast increase with no realized demand. It is concluded that there are operational possibilities of identifying potential loss of demand by studying the forecast accuracy on an item level, instead of on an aggregated level. Furthermore, it was found that there are possibilities of redistribution, mainly from Africa SA to SMCL to clear out obsolete and slow-moving inventory. Lastly, it was found that there is a significant non-zero probability of an item going from obsolete or slow-moving to moving again in the SMCL network, which dismisses the option of scrapping based on quantitative data and strengthens the argument of returning obsolete inventory from SA to SMCL.

Keywords: Inventory management, Overstock, Excessive inventory, Obsolete inventory, Redistribution

List of abbreviations

BA	Business Area
C&S	Crushing and Screening
COGS	Cost of goods sold
DC	Distribution center
KPI	Key performance indicator
OSMI	Obsolete and slow-moving inventory
PU	Production unit
RDC	Regional distribution center
SA	Sales Area
SKU	Stock keeping unit
SMCL	Sandvik Mining and Construction Logistics
SP	Spare part
SR	Stockroom
SRP	Sandvik Rock Processing Solutions
SS	Safety stock
WP	Wear part

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1 Introduction

The following section aims to briefly provide the reader with background information about the studied company. It will also present the problem formulation, delimitations and introduce the research questions.

1.1 Background

With today's global market, which is growing each year, an increase of customer expectations such as demand for more customizable options, shorter lead times and availability are increasing. This in turn puts more and more pressure on a company's logistical processes, to satisfy customers and not lose market shares to competitors. With fluctuating demand, inconsistent lead times and uncertainty around the world, variability is present and adds complexity to the logistical processes and needs to be handled appropriately to lower costs, as matching demand and supply gets increasingly more difficult with an increase in variability.

To cope with this variability, inventory is usually increased. However, keeping inventory with raw materials or finished goods is not free, such as inventory holding cost, and it is therefore of interest to keep the amount of inventory as low as possible without negatively affecting the business as a whole. Keeping too much inventory will lead to an increase of holding cost, while keeping too little will lead to lost sales or long customer waiting times, which will affect goodwill and thereby potentially reducing revenue.

1.2 Sandvik Group

This thesis will be done in cooperation with Sandvik AB. Sandvik is a Swedish-founded company, dating all the way back to 1862 in a town called Sandviken, located in the central part of Sweden. With approximately 40,000 employees worldwide and a revenue of 99 billion SEK during the year of 2021 and with a profit of approximately 14.5 billion SEK, it is recognized as one of the largest companies in Sweden. Sandvik is at its core a manufacturing and construction company within the mining and quarry industry. Apart from this, Sandvik also focuses on metalworking, additive manufacturing and material technology.

Sandvik is divided into three different BAs (business areas), namely Sandvik Mining and Rock Solutions (SMR), Sandvik Rock Processing Solutions

(SRP) and Sandvik Manufacturing and Machining Solutions (SMM). The focus in this thesis will lie entirely within Sandvik Rock Processing Solutions and their division called Stationary Crushing and Screening (C&S) that mainly delivers crushers and screeners of different types to the mining and construction industry.

1.3 Problem formulation

The mentioned division, C&S, is currently divided into several SAs (sales areas) around the world, where each SA has their own unique and non-unique problems. The SA in Africa currently suffers from an extensive amount of excessive inventory called overstock (see Chapter 4.5 and 5.4.1) for some of their products and is costing the company in inventory holding cost. Sandvik now firstly wants to know why this occurred in the first place and secondly how this can be avoided in the future. Therefore, identifying major root causes for their overstock situation is key to then be able to find potential solutions to these causes and construct a framework for dealing with the current obsolete inventory, considering redistribution and scrapping.

Ideally the solutions will prevent overstocking from happening in the future and not be a temporary quick fix that will resort back to the original situation in the near future.

1.4 Research questions

This thesis will seek to answer the following questions:

1. What are the major root causes to the overstock situation in Africa?
2. How can these root causes be mitigated and thereby reduce future overstock?
3. How can the current obsolete inventory be handled in terms of redistribution and scrapping?

1.5 Delimitation and project focus

As previously mentioned, this thesis will solely focus on the BA Sandvik SRP and the division stationary C&S. Furthermore, this thesis will focus on the aftermarket parts of this division, called wear parts and spare parts that will be further described later in this thesis. Initially the directives from the case company were to focus on only wear parts since, according to Sandvik, these were more subject to overstock. However, an analysis performed by the author will show that this is not the case and that spare parts are just as prone to overstock as wear parts, and will therefore also be included in this thesis.

SMCL (Sandvik Mining and Construction Logistics) is responsible for replenishments and redistributing the items across the globe for these aftermarket parts and therefore has SRs (stockrooms) all over the world. The focus will be entirely on SMCL's SR called C4 in Johannesburg and the SRs owned by the SA in different locations across Africa.

2 Methodology

The following section seeks to describe the used methodology for this master's thesis. The aim is to help the reader understand the reasoning behind this methodology and the chosen procedure.

2.1 Research strategy

Determining the research approach and the strategy is a vital part of the project and sets the standard and foundation for the entire thesis. Projects themselves can have different types of purposes, such as descriptive, explanatory or problem solving (Höst et.al. 2006). Therefore, this chapter seeks to briefly describe the different strategies and thereafter present the strategy that is chosen and considered most suitable for this specific thesis.

2.1.1 Survey

When the objective of the project is to describe or explain a current situation, problem or phenomenon, the survey method is appropriate. When conducting a survey, it is vital to understand and decide on who to ask and investigate. If the population is rather small, it is certainly possible to ask everyone. However, if the population is relatively large this might not be possible, and a sample of people need to be selected. Even if a sample is selected, the number of people that is included might still be hundreds of people, and an efficient way of gathering information from these can include a questionnaire of predetermined questions that is then further analyzed. (Höst et.al. 2006)

2.1.2 Case study

A project or a study that has its purpose to describe a phenomenon or situation in depth, in contrast to a shallower approach, such as a survey, should instead use the method case study. A case study describes a specific identified phenomenon and the conclusions from the project are generally limited to the specific case. However, if two cases are similar, arguments can be made that the conclusion might be applicable to the other cases, and by doing so, finding general patterns. The difference between survey and case study is the depth of the studies, where surveys are generally shallower, and a case study typically describes more in depth. A case study can and is typically used by a company or organization to understand the way of working. (Höst et.al. 2006)

During a case study the following methods are frequently used (Höst et.al. 2006):

- Interviews
- Observations
- Archival analysis

These data collection methods will be further described in Chapter 2.2.

2.1.3 Experiment

When the objective of a study is to find cause and effect to a specific phenomenon, the method experiment can be used. Experiment is a more structured approach compared to both surveys and case studies and can be used to compare different solutions to each other, for example, if solution A performs better than solution B in a specific aspect. It can also be used to analyze the impact of different parameters to a system. (Höst et.al. 2006)

2.1.4 Action research

Action research aims to improve something while it is being observed or studied. It starts off by observing the situation and to then pinpoint or clarify the actual problem that is then to be solved. In this step, a survey or a case study are useful techniques. When the problem has been identified, a solution is proposed, implemented and then evaluated. The process is iterative, meaning that after the evaluation, the problem is reassessed, and a new refined solution is proposed until the results are sufficient. (Höst et.al. 2006)

2.1.5 Chosen strategy

This project has a purpose of both explanatory and problem-solving, by explaining why there is overstock and solve for how this can be avoided in the future. Therefore, the strategy chosen for this project is case study, since the phenomenon should be investigated in depth and is tailored for the specific company. It could be argued that action research could be suitable for this type of project. However, due to the time restrictions and lack of implementation phase, and thereby also evaluation phase, it is dismissed. The company can, however, use the results from this project and conduct an action research on their own, with the described iterative process. Since it is not possible to isolate the impact that certain attributes have on the result, the method of experiment will not be used. Furthermore, the project needs a flexible approach, which based on the findings, can alter the path of the thesis. As stated by Höst et.al. (2006), the case study is a flexible method, and the questions or path of the project can be altered during the process, which further strengthens the choice of case study.

2.2 Data collection

2.2.1 Types of data

When collecting data, the type of data can be sorted into one of two categories - qualitative or quantitative. Quantitative data is usually numbers and statistics. Examples of quantitative data are length, amounts and frequency. To analyze this type of data, statistical analytical models are frequently used. Qualitative data however, is data that is information by words, meaning descriptive and usually detailed information. Analysis of qualitative data is based on sorting and categorization (Höst et.al. 2006). According to Höst et.al. (2006), both qualitative and quantitative data is preferred for complex problems.

2.2.2 Questionnaire

Gathering information and opinions from hundreds of people can be quite time consuming. An effective way of gathering large amounts of information and data from all these people is by using a questionnaire. A questionnaire is a list of predetermined questions that is sent to a selected group of people, called a sample. These questions are usually multiple-choice questions, which makes the analysis of the results simpler.

2.2.3 Interviews

Interviews can be divided into three different categories, namely structured, semi structured and open. A structured interview strictly follows a list of predetermined questions and can be compared to an oral questionnaire. Semi structured interviews also follow predetermined questions, however, these are mainly used as a guide for the interview and the course of the interview can change as it moves on. An open interview is when the interviewee more or less determines the path and content of the interview. (Höst et.al. 2006)

2.2.4 Observations

Observations can be described as documenting and understanding by listening or participating. The degree of visibility by the observed people or group can range from totally invisible, to the group being fully aware of the presence of an observer. The degree of participation can also vary, from none, to fully participating in the activity. Collecting data as an observer or participant can for example be done via a journal or different types of recordings, depending on the situation and the degree of visibility and participation. (Höst et.al. 2006)

2.2.5 Measurements

Measurements, as a type of data collection, refers to connecting a value to a certain attribute. For example, the length of a table, the height of a pole or the color of an apple. Measurements can, however, be divided into two separate types of measurements - direct and indirect. For example, direct measurements can, as previously mentioned, be the height of a pole, since this is done directly with a ruler or a measuring tape and the result can be directly seen on the ruler or tape. Indirect measurements are done by measuring other things, and then calculating the desired attribute. A great example is speed, where distance and time are typically measured and then the speed is calculated as the distance divided by the time. When measuring things there are bound to be errors, and these errors can, for instance, be classified as random, systematic or human errors. (Höst et.al. 2006)

What to measure is not always as straightforward as it seems. The length of a table is of course measured by the distance from one end to another, however, measuring attributes that concern people or organizations can be far more complex. Therefore, making sure that the correct or appropriate things are measured are vital. (Höst et.al. 2006)

2.2.6 Archival studies and analysis

During a time-limited project such as a thesis, it is not always possible to measure the data, and data that have been previously measured and documented by others is a necessity. Important to note is that this data has been collected for other purposes other than the current project and should therefore be validated before analyzing. (Höst et.al. 2006)

Data that have been collected by others can be categorized in the following way (Höst et.al. 2006):

- Processed material - data that has been collected and processed in, for example, academic journals and publications.
- Available statistics - data that has been collected and processed but conclusions from this have not been done.
- Registry data - data that has been collected for various purposes but has not been processed.
- Archive data - data or information that is not systemized as data.

2.2.7 Experimental design

When conducting experiments with several parameters and their impact on the output, the number of unique combinations quickly becomes rather large. For example, if an experiment with four different parameters, and two different settings for each parameter is used, the number of unique combinations becomes $2^4 = 16$ that should be investigated. However, there are techniques that can be used to reduce the number of experiments while still obtaining how the different parameters impact each other and the result. (Höst et.al. 2006)

2.2.8 Chosen data collection methods

For this project, the chosen method for data collection is mainly the use of archival studies and analysis. The main reason for the use of pre-existing data is due to the time restriction this thesis has, since the amount of data that would need to be measured, collected and summarized would be time consuming and leave no time for analysis of the data. However, using pre-existing data means that this data needs to be validated before analyzing to ensure that the data measures the correct attribute or phenomenon. Observations will in limited extent be used in the form of participations during meetings and will be used as a starting point and be complemented with additional data.

Lastly, interviews will be conducted with relevant employees or representatives at the organization to get an understanding of why some decisions are made and the logic behind them. For this type of interview, a semi-structured interview will be used, since a structured interview might miss important information that is not included in the question list. Experimental design will not be used since the project is not an experiment. Questionnaires will also not be used since there is no need to gather shallow information from a lot of different people, and instead in-depth data collection is desired.

In conclusion, both qualitative and quantitative data will be used in this project. The qualitative data will mainly be collected from interviews and observations while the quantitative data will be in the form of pre-existing data.

2.3 Project procedure

Since the project conducted could be considered rather large and comprehensive with the case company, it will follow an approach or procedure. This approach will take the thesis from start to finish and is based on the operations research modeling approach by Hillier & Lieberman (2010), but some modifications will be made to fit the case study in an appropriate way. The approach proposed by Hillier & Lieberman (2010), carries out the following steps:

1. Define the problem of interest and gather relevant data.
2. Formulate a mathematical model to represent the problem.
3. Develop a computer-based procedure for deriving solutions to the problem from the model.
4. Test the model and refine it as needed.
5. Prepare for the ongoing application of the model as prescribed by management.
6. Implement.

However, since this project will not implement the suggested solutions and framework, a modified approach is stated and described below.

1. Problem definition and data collection.
2. Data analysis and formulation of causes of overstock.
3. Deriving solution from the causes.
4. Investigate and construct a framework for obsolete inventory
5. Suggest solutions and framework to the company.
6. Refine solutions and framework.

2.3.1 Problem definition and data collection

The first step to the actual case project is to define the actual problem that needs to be addressed. The problem could at first be vague and lack a proper definition. This at first hand might seem like an easy task, but determining delimitations might not be as straightforward as one might think. When a project is performed at a company of this magnitude, including everything would be too great of a task and during this time period impossible to carry out. On the contrary, too narrow of a scope might lead to too much suboptimization and also running the risk of neglecting a holistic view of the actual problem.

In recent years, companies do not have the problem of having too little data, but rather having the luxury problem of having huge amounts of data and information (Geri and Geri, 2011). It is therefore important to be able to distinguish the data that is needed for the project compared to the data that is not. To know what data to look for, a literature study will be conducted, to investigate what others have found connected to overstock. Furthermore, discussions with a knowledgeable expert within the field of inventory will be consistently carried out to get an idea of what might be interesting and valuable to investigate. Representatives from the company will, with their insight and knowledge, also give their input of what can be further investigated. However, important to note is that all of these approaches should be used and combined to get different angles of the problem and avoid becoming biased.

2.3.2 Data analysis and formulation of causes of overstock

When the appropriate data has been collected, it is time to handle the data and find patterns within this data. Analyzing the data can be done in several ways, depending on the types of data that is found relevant for the project. Averages, deviations and boxplots are some tools that will be used to analyze the quantitative data. From the data analysis, conclusions will be made and different major root causes to the problem will be formulated. Important to note, as will be further discussed in Chapter 2.5, is that the formulated causes might not be the only reasons for the problem, but nonetheless approximately 80 % of the consequences can come from ~20 % of the possible causes, known as the Pareto-principle or the 80:20 rule (Alexandra-Maria Chaniotaki and Sharma, 2021).

2.3.3 Deriving solution from the identified causes

With the formulated causes, solutions will be generated. Worth noting is that a solution to these problems might generate improvement within the scope of the project, but the solutions can cause suboptimization and thereby worsen the situation for another part of the organization. This means that an optimal solution for the scope of the project might not be the optimal solution for the organization. With this in mind, it is not the goal to find the optimal solution, but rather to find a solution that improves the future state of the inventory.

2.3.4 Investigate and construct a framework for obsolete inventory

An investigation regarding redistributing and scrapping of obsolete inventory will be performed to determine if this is beneficial to the company. During this stage there will be the need for additional data collection.

2.3.5 Suggest solutions and framework to the company

While this project is conducted with frequent and consistent communication with the company, the solutions and framework are still in need of a formal presentation to the case company. These proposed solutions and framework will be presented to regional planners, supply chain specialists and different managers.

2.3.6 Refine solutions and framework

The solutions that are presented are in theory applicable and would improve the situation and reduce the amount of overstock in the future. However, theory and practice are two different things. Company representatives have more insight on what can and what cannot be done and implemented, and the solutions and the framework might need altering before they are suitable for company implementation.

2.4 Reliability

Reliability refers to the reliability of the data collection and the analysis with regard to stochastic variations. In other words, how trustworthy the process and analysis are and if the procedure would be done by someone else, the results would be the same. The data in this project has been collected for other purposes than this project and can therefore be considered unbiased. Furthermore, the data available is often from longer periods of time, i.e., the data collection started several years ago, and thereby temporary fluctuations in demand do not impact the final results. To achieve even greater reliability, the data and analysis will be presented and discussed with company representatives to verify the quality and relevance of the data, the analysis and the conclusions. This is done through weekly instructions, guidance and supervision from the company.

2.5 Validity

Validity refers to the connection between what is intended to be measured and what is actually measured. Do we actually measure the correct things? It also refers to the assessment of the conclusions done in the project, if it proves what is supposed to be proven. It is therefore important and desirable to avoid making conclusions that X caused Y, when this might not be true and is caused by another phenomenon. According to Höst et.al, (2006), the validity can be improved by using triangulation, where the same phenomenon or objective is studied and analyzed by the use of different methods and techniques.

It is important to note that there might not only exist one reason for an excessive amount of stock, but there might be several root causes that add up, and in the end generate a larger problem. While the causes presented in this thesis are some major contributors to the problem, there are certainly other minor additional reasons behind the situation. These could for example be organizational misalignments and suboptimization within the company.

2.6 Replicability

Due to the nature of a case study, the results and conclusions might not be replicable in the future. Not necessarily because of the studied phenomenon, but due to variations externally and internally by the organization as time passes. Furthermore, if the same project and the same process would be conducted and followed by another organization, this might not be applicable due to the individuality of the company and the studied problem. This is previously mentioned in Chapter 2.1.2. If the case is somewhat similar, some results, assumptions or conclusions might be applicable, but this is not a guarantee and should be considered.

3 Literature study

As described in Chapter 2.3.1, both input from already conducted studies and input from the case company will be used. This chapter will further describe what others have found to be causes of excessive stock or overstock. Important to note is that these causes and conclusions might not be applicable to this case study, however it might give some ideas on what is worth investigating.

The uncertainty of demand means that under- and overstocking (this is described in Chapter 4.5) will always be present in the manufacturing business, especially when the products produced or provided by suppliers cannot be provided quickly in response to changing or realized demand (Song et al., 2021). This is also mentioned by Lee and Kesavan (2019), p. 203, that state that “excess inventory announcements may be an inevitable outcome of demand uncertainty”.

A study by Lee and Kesavan summarized that retail firms usually blame external factors, such as sluggish sales or obsolete and discontinued inventory as major drivers to excessive overstock, while not many firms consider internal efficiency and poor execution as a driver for overstock.

Other major root causes for overstock are summarized by Ahmed et al. (2020) and presented in Table 1 below.

Table 1, major causes of excess inventory (Ahmed et al., 2020)

	Major causes of excessive stock	Definition
1	Demand Variation/Change in Market Conditions	Effects of economic cycle/Change in customer demand
2	Supply Variations/Bulk Purchase	Suppliers push their distributors to purchase at discounted prices
3	Internal validation/Inadequate Planning & Execution Systems - Forecast Accuracy - Launches	Internal process in an organization, failure to use proper planning methods

4	Sales (Realistic) and Marketing (Dreamers)	Overly optimistic sales and marketing who push for forecast increase
5	Engineering/Changes in Design & Specifications	Improved product design
6	Production/Master Schedule Smoothing	Fluctuations in the production plan/Products may have a minimum order quantity (MOQ) requirement to manufacture
7	Accounting/Finance	When organizations use income to measure performance and not net flow; and excess inventory is not reflected in income statements
8	Forecasting Errors (Point 3)	Failure to anticipate decline in demand or sales over anticipation
9	Inventory Record Inaccuracies/Poor Stock Management	Errors in recording stock levels, locations, identification numbers
10	Long or Variable Lead Times	Long lead times encourage firms to increase safety stock
11	Obsolescence	Discontinued products with no more demand
12	Distribution Channel Adjustments/Item Relocation	Changes in stocking and shipping policies
13	Changes in Inventory Holding Costs	Increased inventory holding cost; thus, increased selling cost
14	Stock Cover	Change in stock cover policies

According to Matsebatlela and Mpofu (2015) the main contributor to overstock are the high demand uncertainties which in turn increase the amount of inventory to cope with the present uncertainty. Furthermore, they describe that when historical data is no longer applicable and not a good indication and prediction of future demand, an increase of inventory occurs, connecting to poor forecasting abilities.

The mismatch between actual demand and forecast seems to be a reoccurring problem in connection to excessive inventory, and the difficulties of predicting uncertain demand. Furthermore, in the summary conducted by Ahmed et al. (2020) it is also stated that internal factors and processes can contribute to excessive overstock, for example, bulk purchases/ordering and conflicting goals in terms of sales optimism by SA, which also according to Lee and Kesavan (2019) many firms do not consider when evaluating the reason behind overstock.

Long lead times and thereby the inability to quickly provide the products when demand changes may lead to an increase of safety stock and thereby increasing the amount of stock. However, it is stated by Song et al. (2021) and H. S. Lee and S. Kesavan (2019) that excessive inventory to some extent might be inevitable due to the presence of uncertainty.

4 Theoretical background

This chapter will provide the reader with relevant theory of inventory management to better understand the upcoming analyses.

4.1 Supply chain

A chain refers to pieces that are linked together, and a supply chain is a logistical system that transforms raw material to finished goods. A supply chain can be more or less complex depending on the number of involved parties, the type of goods and the geographical location. A simplified, generic serial supply chain is visualized in Figure 1 below.

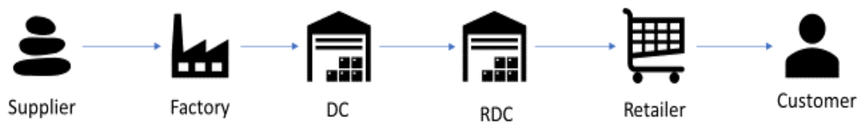

Figure 1, simplified visualization of a generic serial supply chain

4.2 Inventory management

Inventory management is a fundamental part of businesses that keep inventory, for example, manufacturing companies, since 25 to 50 % of a manufacturing firm's assets are connected to inventory goods (Biswas et al., 2017). Properly controlling the inventory can reduce the overall cost and thereby increase the company's profitability. In the upcoming chapters different methods, techniques and models will be briefly described that can be used to improve inventory management.

4.3 Demand behavior and patterns

Demand can have different behaviors or patterns and can according to Heinecke et al. (2011) be divided into separate categories based on two coefficients, namely the average interarrival time between demand and the variation of demanded quantities. The different demand categories are intermittent, lumpy, smooth and erratic. Intermittent demand shows a low variation in demanded or ordered quantity, but a high variation in interarrival times between demand. Lumpy demand is quite similar to intermittent demand, however, the variation in demanded quantity is greater than intermittent demand and is the most difficult out of the four demand categories to forecast. Erratic demand behavior has a low variation in interarrival time of demand, however, the variation of demanded quantity is high. The last demand pattern or category is smooth, which shows a low variation in both interarrival times and demand quantity. This is visualized in Figure 2, where CV^2 symbolizes the variation in demanded quantity and p is the average of the interval between two non-zero demand points. (Heinecke et al. 2011; Jusopov and Marofkhani, 2022)

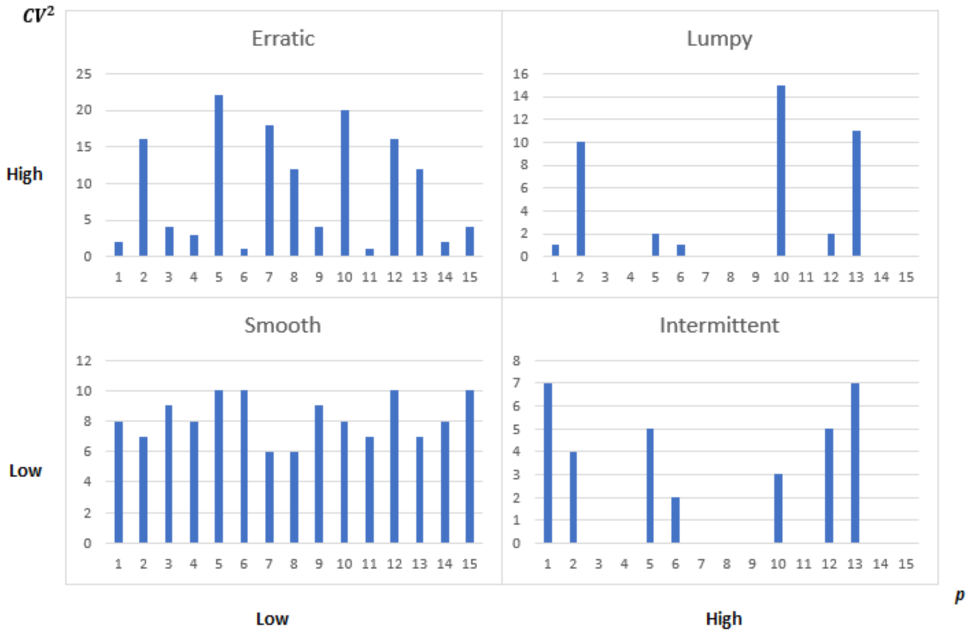

Figure 2, visualization of the four demand categories

4.4 Forecasting

A vital part of inventory management is to predict the future demand. Just as meteorologists try to predict the weather by weather forecasts, companies try to predict the demand via demand forecasts. There are different types of forecasting methods, both quantitative and qualitative, suiting different kinds of demands and with different complexity. The most common way of quantitative demand forecasting is extrapolating historical demand data, and by using the historical data try to predict the upcoming demand (Axsäter, 2015).

4.4.1 Simple moving average

One of the more common forecasting methods is the method moving average. The method is rather straightforward and simplistic in its calculations with only one parameter *N*. Moving average takes the demand during the last *N* periods and takes the average of this, and this average is the forecasted demand for the upcoming period. The expression for the demand forecast and the update procedure made at the end of period t for period τ is stated below, for all $\tau > t$, where x_k is the actual demand for each individual period k. (Axsäter, 2015)

$$\hat{x}_{t,\tau} = \hat{a}_t = \frac{x_t + x_{t-1} + x_{t-2} + \ldots + x_{t-N+1}}{N}$$

In Figures 3 and 4, the same demand is used to showcase the impact the parameter *N* has on the forecast. For Figure 3, *N=3* and for Figure 4, *N=6*. These figures clearly show the impact the parameter has when demand is rather random. When *N* takes a lower value, the forecast is more responsive to change, whilst when *N* is increased, the forecast is more even, and the "spikes" are evened out and the forecast can be considered smoother.

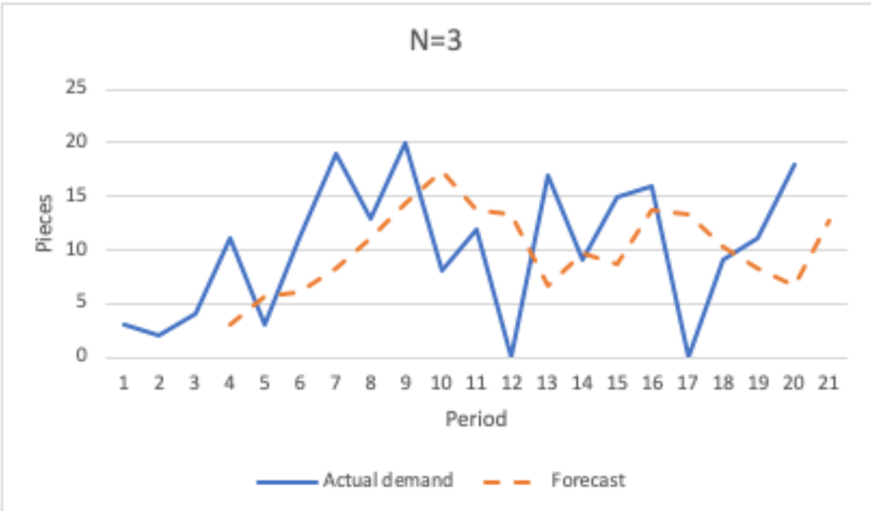

Figure 3, forecast performed with moving average, N=3

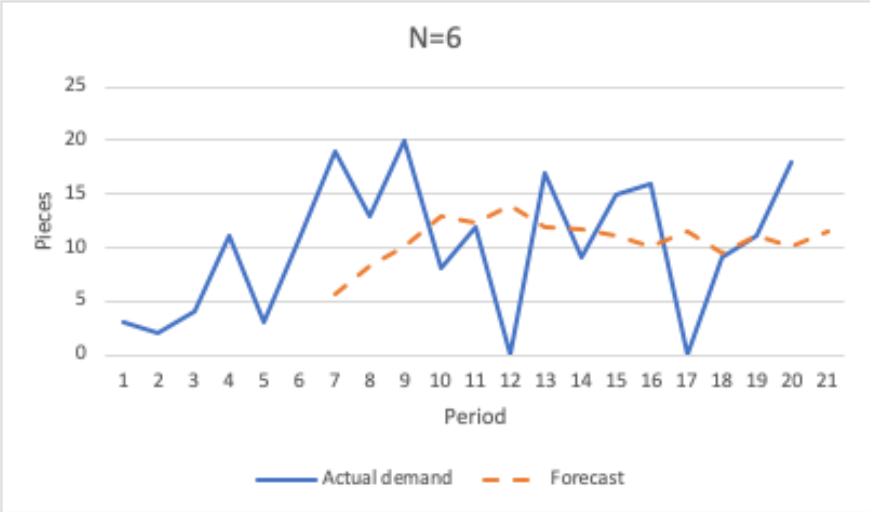

Figure 4, forecast performed with moving average, N=6

With moving average there is a delay in the forecast compared to the actual demand. The delay is rather difficult to see in Figure 3 and 4 and is more clearly shown in Figure 5 and 6. These figures clearly show the difference in delay when changing the parameter *N*.

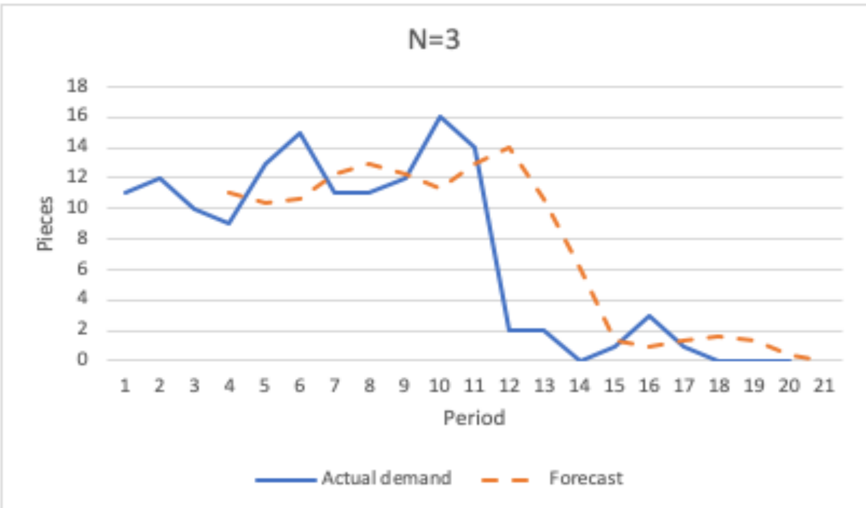

Figure 5, forecast lag with moving average, N=3

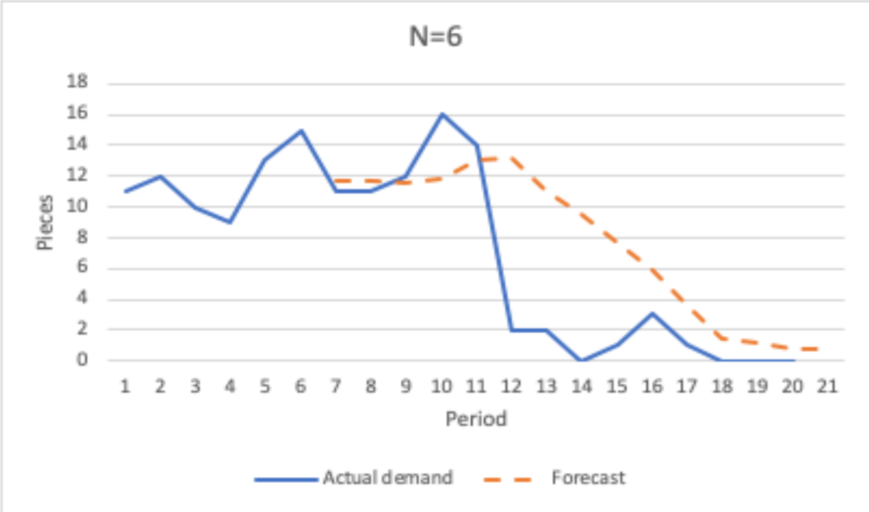

Figure 6, forecast lag with moving average, N=6

Taking these factors into consideration are important when setting the parameter *N* for the forecasting method moving average.

In conclusion, a lower *N* provides a more responsive forecast and is more influenced by high or low demand periods (demand spikes), while a higher value provides a smoother forecast that removes the demand spikes, but also has a longer delay.

4.4.2 Exponential smoothing

The forecasting method called exponential smoothing has a lot of similarities to the previous method, moving average. The main difference is the way the methods value new data versus old data. Moving average does not consider how new or old the data is, meaning that all data points contribute equally. This is not the case for exponential smoothing however. When using exponential smoothing, the contribution of new data compared to old data can be manipulated by modifying the constant $\alpha, 0 \leq \alpha \leq 1$. The larger the value of α, the more emphasis is put on the newest data and the opposite is true, i.e., lower value on α means more emphasis on the older data. The expression for the demand forecast and the update procedure made at the end of period t for period τ is stated below, for all $\tau > t$. (Axsäter, 2015)

$$\hat{x}_{t,\tau} = \hat{a}_t = \alpha x_t + (1 - \alpha) \cdot \hat{a}_{t-1}$$

Worth noting here is that exponential smoothing uses both the latest actual demand and the last forecast and that an initial value for a must be set

(Axsäter, 2015). In figure 7 and 8 the same data is used as previously with moving average, but now instead with exponential smoothing.

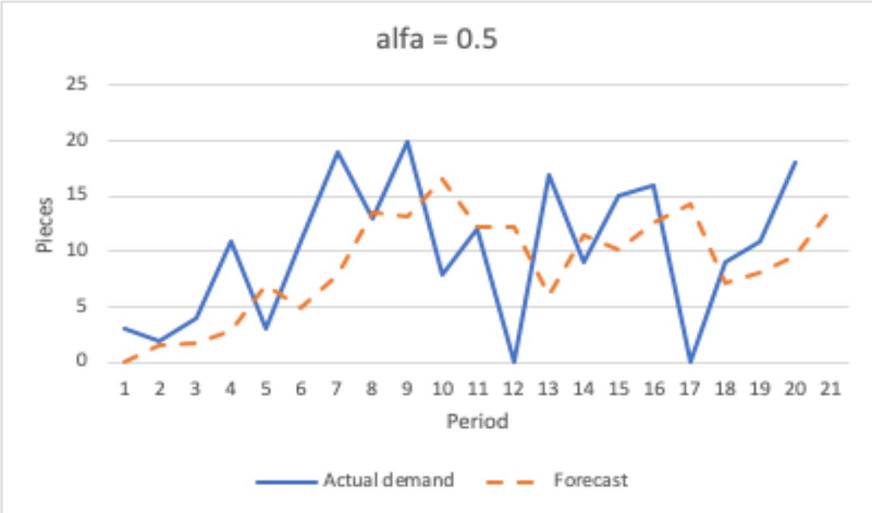

Figure 7, forecast performed with exponential smoothing, α *= 0.5*

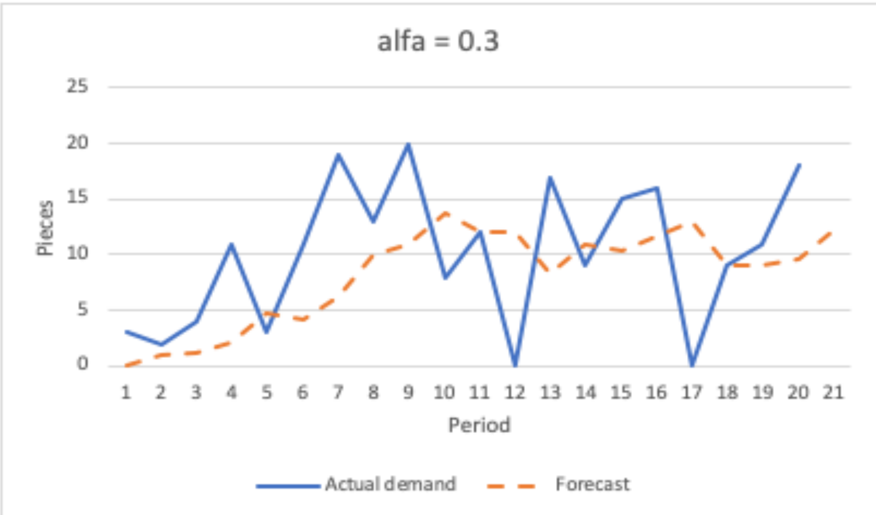

Figure 8, forecast performed with exponential smoothing, α *= 0.3*

As can be seen in Figure 7 and 8, the similarities with moving average are well pronounced, where a larger value for the constant α generates a more responsive forecast and a lower value for α generates a smoother forecast.

Since exponential smoothing is also based on historical data, there is bound to be lag. However, just as with moving average the lag differs when changing the parameter. This is visualized in Figure 9 and 10.

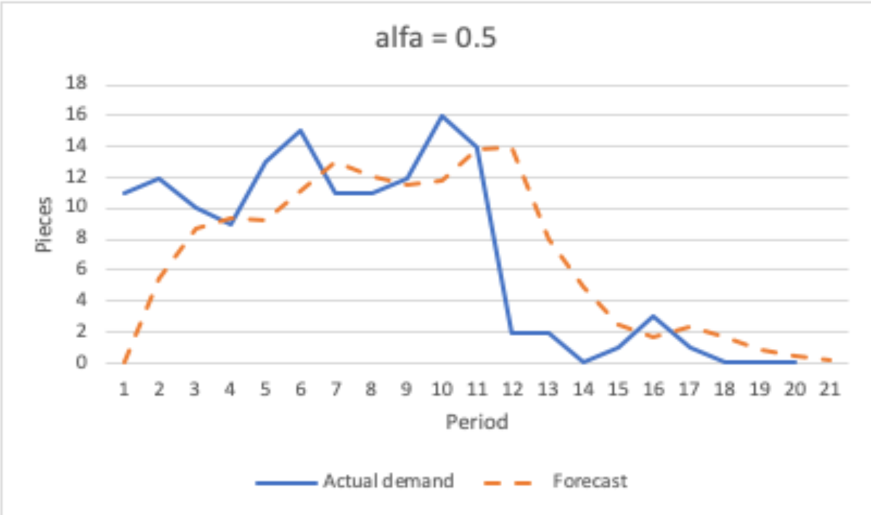

Figure 9, forecast lag with exponential smoothing, α = *0.5*

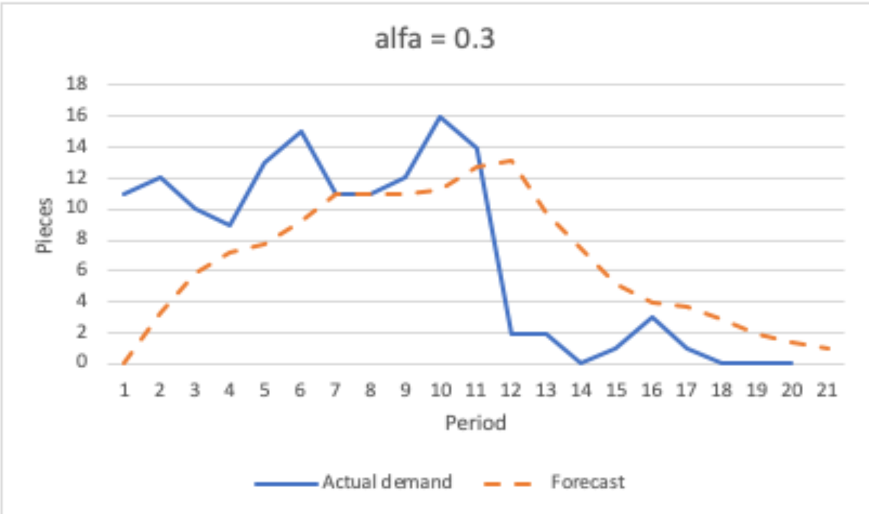

Figure 10, forecast lag with exponential smoothing, α = *0.3*

As expected, the more responsive value for α shows less lag compared to the smoother forecast with a lower value on α.

4.4.3 Trend and seasonality

Some demand might tend to show trends or some type of seasonality. During a product's early stages of its lifecycle, it is natural that demand has a positive trend to its demand, and the opposite when the product reaches the decline of its lifecycle. This leads to the need of a forecasting method that considers these trends. Fortunately, it is rather simple to extend the models to adjust for these trends. To adjust for seasonal demand or seasonal trends, a seasonal index can be added to the forecast. Christmas trees, Halloween costumes and ice cream are types of products that follow a seasonal demand. However, how the forecasting methods are adjusted to handle trends and seasonality will not be further described in this thesis due to the low percentage of items that showcase this kind of behavior. (Axsäter, 2015)

4.4.4 Croston's method

For intermittent demand patterns, moving average and exponential smoothing is not sufficient and another method should be used. For this type of demand Croston (1972) suggested a method where the forecast is only updated when there is demand, i.e., when demand is not zero. If demand is positive, two parameters are updated with exponential smoothing, the size of the demand and the time between two periods of positive demand. x_t still represents the demand in period *t*. However, new variables are introduced (Axsäter, 2015).

k_t = the stochastic number of periods since previous period with positive demand
$\widehat{k_t}$ = the estimated average of the number of periods between two periods with positive demands at the end of period *t*.
$\hat{d}_t$ = the estimated average of the total size of the positive demand at the end of period *t*
$\hat{a}_t$ = the estimated average demand per period at the end of period *t*

The updating procedure is done in the following manner:

If the demand in a period is equal to zero, i.e., $x_t = 0$:

$$\hat{k}_t = \hat{k}_{t-1}$$
$$\hat{d}_t = \hat{d}_{t-1}$$

If, however, the demand is positive, i.e., $x_t > 0$:

$$\hat{k}_t = \alpha k_t + (1 - \alpha) \cdot \hat{k}_{t-1}$$
$$\hat{d}_t = \beta x_t + (1 - \beta) \cdot \hat{d}_{t-1}$$

Where α and β are smoothing constants, $0 < \alpha, \beta < 1$.
These smoothing constants will affect how responsive or sensitive the forecast is to new data. This is previously discussed in exponential smoothing and the same logic applies here.

The forecast for the demand per period is calculated as:

$$\hat{a}_t = \hat{d}_t \,/\, \hat{k}_t$$

4.4.5 Manual forecast

All methods previously described use historical data to predict the future demand. However, in some cases information is known to affect future demand that has not affected historical demand, such as that a customer is lost to a competitor and thereby their demand vanishes, or that a customer changes to a product substitute and therefore switching the demand from one product to another. This information is not possible to model with the forecast methods previously described and is therefore in need of manual adjustments. Other factors that could lead to the need of manual adjustments are presented by Axsäter (2015):

- Price changes
- Sales campaigns
- Conflicts that affect demand
- New products without historical data
- New competitive products on the market
- New regulations

Axsäter further describes that it is never a good idea to manually input forecasts if it means just using historical data, and that a quantitative forecast method (as those previously described) should be used instead, to reduce the risk and the amount of occurring errors. Furthermore, a special problem with manual forecasting is the systematic errors of pessimistic or optimistic attitude when conducting the forecasts (Axsäter, 2015), running the risk of under- or overestimating the demand and thereby risking stockouts and overstock.

4.4.6 Forecast error and accuracy

A good forecast should be accurate, but nonetheless a forecast will never be perfect. How good a forecast is should be a vital KPI (key performance indicator) of a business, but there are several ways of measuring and calculating how accurate the forecast actually is. The accuracy of the forecast is usually based on the error of the forecast, meaning the difference between the forecasted demand and the actual demand. Some common methods are MSE (the mean squared error), MAPE (the mean absolute percentage error), MAD (mean absolute deviation) and MAE (mean absolute error) (Hyndman and Koehler, 2006). Each method has its strength and weakness when measuring the accuracy of the forecast and it is important to know how the accuracy is calculated and thereby also how it should be interpreted.

4.5 Stockout, overstock and dead stock

Inventory can be seen as an asset to a company that, for example, is classified as finished goods or work in process. Inventory management is a vital part of businesses that deal with physical products, as the main challenge is to keep just enough inventory to satisfy demand and avoid delays, whilst not keeping too much since this may become costly (Ulfig, 2012). Running out of stock while still having demand, also called stockout, is costly and unwanted due to the possibility of lost sales, loss of customer satisfaction (Biswas et al., 2017) and loss of trust from customers - all leading to potential loss in profitability. In some businesses where availability is an important aspect of supplier selection, stockout may be the reason for loss of market shares and customers. The opposite, where a company has an overflow or an excessive amount of inventory, is called overstock (Francia-Arias et al., 2020). Stock buildup and overstock occurs when the demand for a period is lower than forecasted and inventory therefore builds up and the inventory covers more demand than desired. This is be visualized in Figure 11.

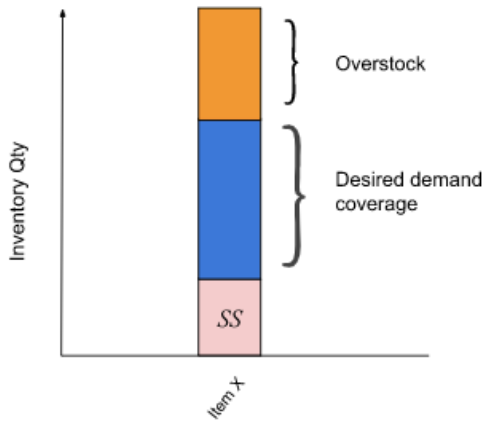

Figure 11, definition of overstock

Carrying too much inventory may appear to be costly in the aspect of tied up capital and inventory holding costs, such as warehouse fees, insurance and salaries (Ulfig, 2012) and might lead to a reduction in profitability. With poor inventory management and planning, the overstock situation might even go as far as the SR capacity being maximized and it is no longer possible to receive new goods before the old inventory has been cleared out. The nature and dynamics of sporadic, irregular and uncertain demand makes inventory management and forecasting difficult and is one of several possible reasons why overstock can occur.

Items that are currently in the inventory that are not being sold and do not have forecasted demand, are called dead stock. Dead stock might appear when an item has been phased out and is no longer in use or when a customer has switched to a product alternative. These items should be considered to be transferred to another SR or branch where there is projected demand and would generate sales. The items that are classified as dead stock are more or less just collecting dust and occupying unnecessary space at the warehouse. Action should be taken since this inventory does not add any benefit to the business.

Measuring overstock is usually done with demand forecasting to determine how many months of stock you have at your disposal. How many months worth of stock that is considered overstock is dependent on, for example, the type of product, industry and lead time demand. Which means that if the lead time is, for example, a few weeks, there is no need or benefit of carrying 12 months of stock.

4.6 Lead time

The lead time is defined as the time from order until arrival of goods at the SR or customer, i.e., fulfillment of the order. In today's business a lot of transactions of goods happen globally and lead times can be long, especially for large and heavy items. Just as demand can vary, the lead time can also be uncertain. The lead time includes, for example, transportation time, warehouse handling and eventual production time if the ordered item is not available in stock. If the item is available in stock the lead time becomes significantly shorter due to exclusion of production time or the exclusion of lead time from external suppliers.

4.7 (R, Q) order policy and fill rate

When dealing with ordering and replenishment there needs to be a defined policy. One of the most commonly used ordering-policies is the (*R, Q*) - policy, also known as reorder-point/order-quantity policy. The inventory position, $(= \text{stock on hand} + \text{on order} - \text{backorders})$ is continuously or periodically reviewed and when the inventory position reaches *R*, or below *R*, an order of quantity *Q* is placed (Axsäter, 2015). For continuous review and continuous demand, the inventory position will always be between *R* and R+*Q*. However, this is not always the case, for periodic review or when the triggering demand is greater than one unit it often occurs that the inventory position is below *R* and will therefore never reach *R*+*Q* when ordering (Axsäter, 2015). The process can be seen in Figure 12, where *L* is the lead time.

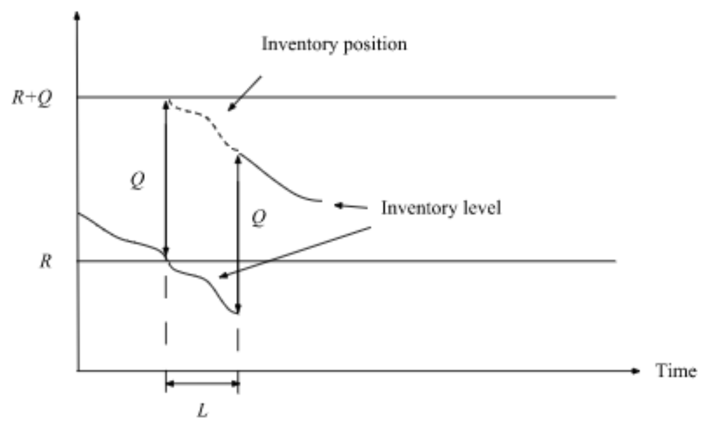

Figure 12, (R, Q) ordering policy for continuous demand with continuous review

The reorder point R is usually based on what service level that is desired. There are three commonly used service levels, denoted S_1, S_2 and S_3.

S_1 is the probability of no stockout during an order cycle. Consider a set of twelve order cycles. During these order cycles there was stockout during four of these twelve cycles, meaning that the service level is $S_1 = (12-4)/12 = 66.7\ \%$. The drawback of using this service level in practice is that it does not show how many sales are lost during the stockouts, if it was just one sale or one hundred sales.

S_2 that is also called *fill rate* measures the amount of demand that is satisfied directly from stock. Consider that the demand during a period is 54 pieces and 48 of these could be served directly from stock, this generates a fill rate of $S_2 = 48/54 = 88.9\ \%$.

The last type of service level, S_3, is called *ready rate* and is the percentage of time that the stock on hand is positive i.e., > 0.

According to Axsäter (2015), it is impractical to use individual service levels for each item, but also not suitable to have the same service level for all items. A solution is to group the items and determine a suitable service level for each item group. The fear of running out of stock and generating backorders or even lost sales might lead to a company setting the fill rate unreasonably high. This in turn might end in excess inventory and will thereby also be costly. The set service level should reflect the customer expectations and the cost of not having the item in stock when demand occurs, i.e., shortage cost.

The cost of a backorder, i.e., when an item is not in stock and the customer needs to wait for the item or more simply put; the cost of having a negative inventory level, may be difficult to determine and a company can therefore choose to work with service level constraints instead. However, there is a relation between the service level and the backorder cost, in which the backorder cost can be evaluated to see if the set service levels are reasonable or not. (Axsäter, 2015)

The following expression shows the relation between the service level and the backorder cost (Axsäter, 2015), assuming that the reorder point, R, is optimized for a given order quantity, Q.

$$S_2 = \frac{b_1}{h + b_1}$$

$S_2 = target\ fill\ rate$
$b_1 = backorder\ cost\ per\ unit\ and\ time$
$h = holding\ cost\ per\ unit\ and\ time$

The expression can then be solved for b_1 and gives the following expression:

$$b_1 = \frac{h \cdot S_2}{1 - S_2}$$

It is now possible to evaluate the backorder cost to see if the determined fill rate is reasonable or not.

4.8 EOQ - economic order quantity

One of the most widely used methods to determine order quantity is by using the method called EOQ or economic order quantity. The EOQ-model is based on a few assumptions. Demand is assumed to be constant and continuous, order and holding cost is constant over time, the batch quantity does not need to be an integer, the whole batch is delivered at the same time and no shortages are allowed. The formula uses the following parameters with the corresponding notation:

h = holding cost per unit and time unit
A = order or setup cost
d = demand per time unit
Q = batch quantity (decision variable)
C = cost per time unit

Considering the parameters above, the objective is obviously to minimize the total cost C and to do this, modify the order quantity Q.
The cost C can be expressed as follows:

$$C = \frac{Q}{2}h + \frac{d}{Q}A$$

The first term represents the holding cost, where $Q/2$ is the average amount of stock during an order cycle, multiplied by the holding cost h. The second term represents how often an order needs to be placed during a time period according to the demand, multiplied by the order or setup cost A. This cost function is convex in Q, meaning it is possible to show that $C(Q)$ has a unique minimum and it is thereby possible to get the optimal order quantity, Q, that corresponds to the lowest cost. The optimal order quantity takes the following expression:

$$Q^* = \sqrt{\frac{2Ad}{h}}$$

This expression can then be inserted in the initial cost function to get the lowest cost with the given parameters. It can be shown that the method is insensitive to wrongly set cost parameters, meaning that underestimating the cost parameters A and h, which leads to a Q that deviates from the optimal Q^*, has very little impact on the increase of total cost. A 50 % increase of the order quantity ($Q/Q^* = 3/2$) will only increase the total cost by 8 % (Axsäter, 2015).

The method assumes that the order quantity can take any value, i.e., it does not need to be an integer. However, since the method is insensitive to changes it does not marginally affect the cost rounding to the nearest integer, if Q is relatively large. Furthermore, it can for some reason be advantageous to increase the order quantity significantly, to fill a pallet, a container or a box to be logistically beneficial but as it shows does not contribute to a remarkable cost increase.

4.9 Inventory turnover

The movement of stock in a SR or warehouse can be measured in the form of inventory turnover. Inventory turnover ratio shows how many times during a time period, usually during one calendar year, the inventory is sold and then replaced, i.e., how much time passes from the arrival of the item until it gets sold (Fernando, 2022; Ulfig, 2012).

The inventory turnover ratio is calculated by dividing the COGS (cost of goods sold) by the average amount of inventory in terms of value. A low inventory turnover ratio can be a sign of low sales or excessive amount of stock - also known as overstock, however, on the contrary a high inventory ratio can be a sign of strong sales but can also stipulate inadequate stocking leading to lost sales. (Fernando, 2022; Ulfig, 2012)

$$Inventory\ turnover\ ratio = \frac{COGS}{Average\ value\ of\ inventory}$$

For example, company X had sales, i.e. COGS, with a value of $100 million during the year of 2022, and by the end of the year it was reported that the inventory was valued to $22 million, compared to the end of 2021 where the inventory was valued to $17 million. The company's inventory turnover ratio can then be calculated as follows:

$$Inventory\ turnover\ ratio = \frac{100}{(22 + 17)/2} = 5.1$$

This ratio can then be translated into the number of days it takes on average to turn over the inventory, this is done by taking the 365 divided by the ratio, which in this case gives approximately 72 days.

According to Jenkins (2022), for most industries that do not deal with perishable items, a ratio between 5 and 10 is desired and considered good. However, this is industry specific, meaning that low volume-high margin industries tend to have a lower ratio compared to industries with high volume-low margin. Comparing the inventory turnover ratio against other companies within the same industry can give an idea on how well the company does, also known as benchmarking (Jenkins, 2022).

5 Introduction to Sandvik Group and Sandvik C&S

This section will describe the organization, the BAs, the products, their customers and market and their current inventory management and is based on public information, interviews and personal communication with company representatives.

5.1 Sandvik Group and the business areas

Sandvik AB is a Swedish company founded in 1862 in Sandviken, a town located in central Sweden, by Göran Fredrik Göransson. At the time the company was not called Sandvik AB, but was founded as Högbo Stål & Jernwerks AB. Just four years later, in 1866, the company went bankrupt but was reconstructed two years later under the name Sandvikens Jernverks AB. It was not until over a century later in 1972, that the company changed name to Sandvik AB. Sandvik AB has since then grown and adopted new BAs and is now one of the largest companies in Sweden in terms of revenue, and in 2021 the company had a total revenue of 99 billion SEK. Sandvik AB is at its core a manufacturing and construction company within the mining and quarry industry. Apart from this, Sandvik AB also focuses on metalworking, additive manufacturing and material technology. (Sandvik Group, n.d)

Sandvik AB is divided into different BAs. Previously there were four different BAs, but as of 2022 there are three remaining. The four different areas are listed below, and the current three BAs are visualized in Figure 13.

- SMR, Sandvik Mining and Rock Solutions
- SRP, Sandvik Rock Processing Solutions
- SMM, Sandvik Manufacturing and Machining Solutions
- SMT, Sandvik Materials Technology (as of 2022 this is listed as an independent company called Alleima and is no longer a part of Sandvik)

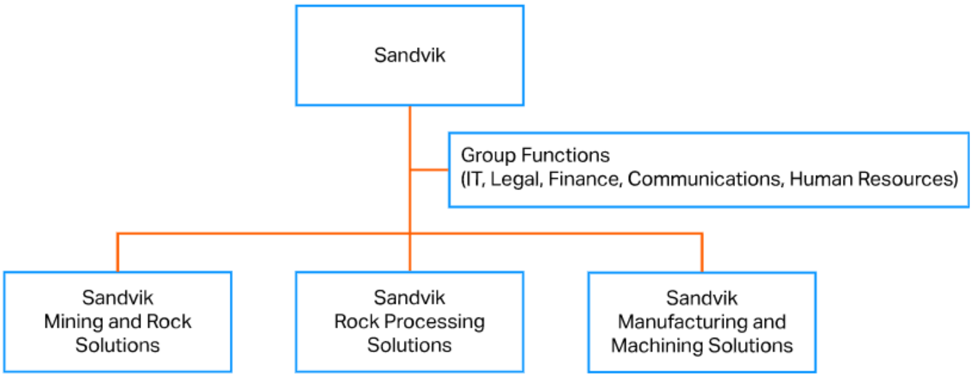

Figure 13, organization chart over the three current BAs. (Sandvik Group, n.d.)

The Sandvik Group's strategy is focused on a close collaboration with their customers and with the help of digitalization, RnD and innovation and sustainability, to help improve operations and achieve more with less. In 2018, the company was awarded as one of the most sustainable companies in the world by Corporate Knights. In 2016, a new strategy was implemented and focused on decentralization, where the three BAs of the Sandvik Group work in a decentralized manner. This means that each BA is responsible for their own performance and actions, independently of the others and in turn moves the decision-making closer to the customer and emphasizes the customer focus. (Sandvik Group, n.d.)

In this thesis the focus will entirely lie on the BA called Sandvik Rock Processing Solution. This BA is further divided into several divisions: Stationary Crushing and Screening, Mobile Crushing and Screening, Attachment Tools and Shanbao (Sandvik Group, n.d.), where the scope of the thesis is limited to the division of Stationary Crushing and Screening and their aftermarket. A further detailed organization chart and the focus is presented and highlighted in Figure 14.

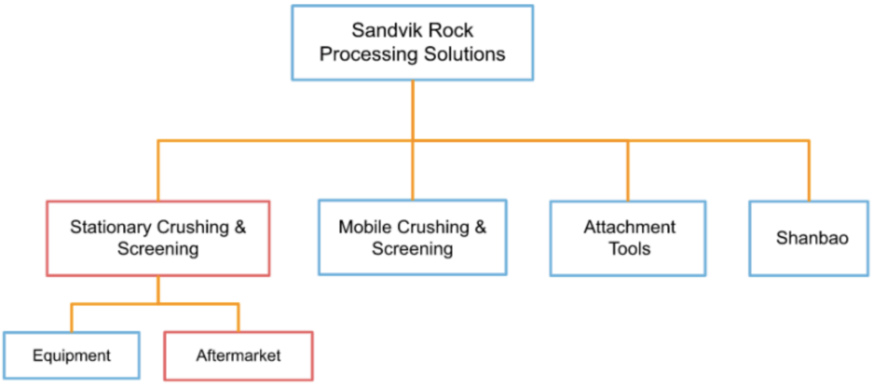

Figure 14, further detailed organization chart with highlighted focus

5.2 The products and components

5.2.1 The products

The products provided by Stationary C&S are divided into two main categories, crushers and screeners. The stationary crushers provided by C&S are further divided into different sorts of crushers, namely gyratory crushers, impact crushers, cone crushers and jaw crushers.

For larger rocks a jaw crusher might be suitable as a primary crusher to significantly reduce the size of the rocks to then be moved to secondary and tertiary crushers. The jaw crusher works in a way where two plates, called jaw-plates, crush the material between them. One of the jaw plates is fixed, while the other is moving with the help of an eccentric shaft and a flywheel, alternating the gap between them and thereby crushing the rocks between the plates. (Johansson, 2019)

The cone crusher ranges in different sizes but the crushing principle is the same for all cone crusher models. The material that is to be crushed is dropped into the feed opening. The mantle is a moving part that gyrates in an eccentric motion, the motion itself is non-centered which means that it slightly swings when in motion and thereby continuously alternating the gap between the mantle and the concave. The material gets crushed when the gap is at its smallest (the CSS) between the mantle and the concave and the crushed material then falls and exits through the bottom of the crusher. OSS is the largest distance between the mantle and the concave. (Sandvik Group, n.d.) The outside and inside of a cone crusher can be seen in Figure 15 and 16.

Figure 15, cone crusher of model CH420 (Sandvik Group, n.d.)

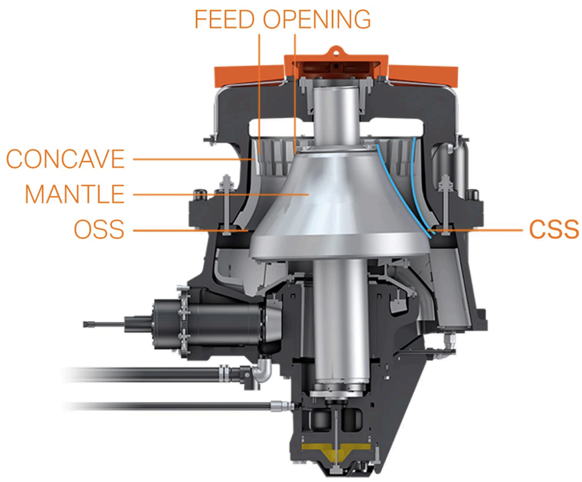

Figure 16, inside a cone crusher (Sandvik Group, n.d.)

5.2.2 Different type of components

The crushers carry different types of components and they are classified in different categories. These categories are *major components*, *key components*, *wear parts* and *spare parts*.

5.2.2.1 Major components

These components are the largest and most expensive components of the crushers. The major components are the main shaft, the bottom shell and the top shell. These are the base components for the crusher and the foundation for the entire product. The top shell is where material is dropped through and into the crusher to begin the crushing process. When the material has been dropped into the crusher, the crushing begins and the major component for the actual movement inside the crusher is the main shaft. As the name suggests, the bottom shell is placed at the bottom of the crusher and connects to the top shell to surround the whole crusher.

5.2.2.2 Key components

The key components are essential components of the machines and play an important role in the process. The key components are further divided into two categories, namely *service items* and *extended service items*, the difference being that extended service items have less than annual demand.

5.2.2.3 Wear parts

Wear parts are as the name suggests parts of the crushers that wear down and need replacing after a certain period of time. The wear parts include the mantle and the concave for the cone crusher (see Figure 16) and both the moving and the fixed jaw plates for the jaw crusher. The mantle is attached to the rotating major component - the main shaft and the concave is attached to the bottom shell. The mantle and concave come in different shapes, sizes and alloys (amount of carbon, manganese and chrome) to tailor the product to the desired customer need. Different types of rock require different types of wear parts to keep productivity and life span of the components at its maximum, meaning that the right component choice is essential. Sandvik has named the separate alloys and they differentiate in two different attributes: impact resistance and wear resistance. The different alloys and their attributes can be seen in Figure 17.

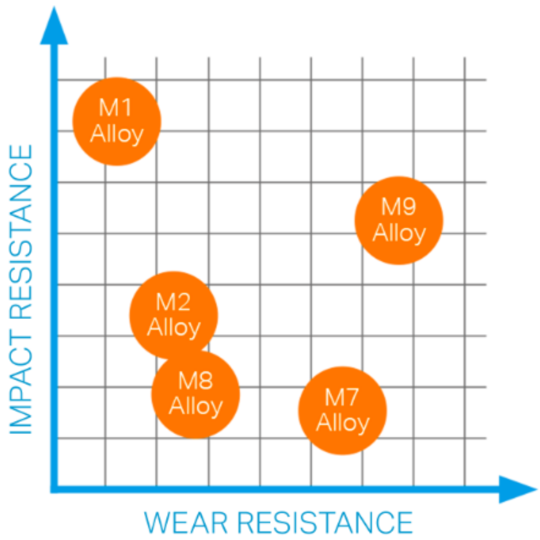

Figure 17, the different alloys and their attributes (Sandvik Group, n.d.)

Worth noting here is that the M2-alloy is currently being phased out and replaced by the new premium M9-alloy, which according to Sandvik offers up to 20 % longer life span compared to the standard alloys. The different alloys are not available for all different product models and will not be further discussed since this does not affect the project itself.

5.2.2.4 Spare parts

Spare parts are parts or components that need replacing when something in the machine breaks. Spare parts are further divided into three categories: *cheap spare parts, mid-range spare parts* and *expensive items.* Cheap spare parts are commercial items such as bolts, nuts etc. Mid-range spare parts are currently every other spare part, quote from Sandvik "everything else". The expensive items are parts that Sandvik does not stock and are sourced to order policy, and therefore has a category of its own. Cheap spare parts and mid-range spare parts contribute to 97 % of all SKUs (stock keeping units) from C&S aftermarket.

5.3 Current supply network and market

A simplified but yet explanatory visualization of the current supply network for C&S aftermarket can be seen in Figure 18.

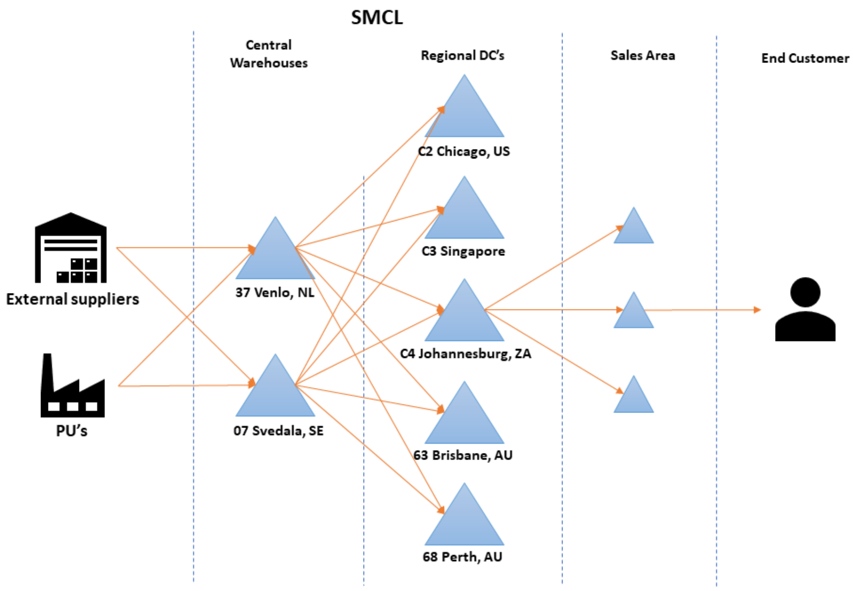

Figure 18, a simplified overview of the supply network

As of now, SMCL purchase their items from either the different PUs (production units) or from external suppliers. There are currently three different PUs. The first one is located in Svedala, Sweden, the second one in Pune, India and the third PU is located in Shanghai, China. However, the PU in Svedala is the only PU that is supplying SMCL with wear parts and spare parts, whereas the PUs in Pune and Shanghai are per the old Sandvik definition classified as "assembly centers" for the equipment. The PU in Svedala has its own foundry and other value adding activities such as material machining, painting, testing and assembly. However, they are limited on how much they can and are allowed to produce, which means that external suppliers are necessary to increase capacity and satisfy the demand. The PU in Svedala produces both types of aftermarket parts (wear parts and spare parts) that are usually make-to-stock, and equipment, which are new crushers. The crushers are make-to-order due to the low order volume.

Sandvik buys the items from external suppliers or via an internal transaction from the PU and the items are transferred to either SR07 or SR37 (see Figure 18). These parts are then further shipped and distributed to the regional warehouses where SMCL then sell internally to the SAs located in the different regions. It is then the SA that sells and provides the items to the end customer. Worth noting is that this visualization is simplified and that transactions can occur in between the different distribution centers (DCs) and also in between the SA's SRs which in turn adds further complexity to the supply network.

SMCL mainly have two different types of customers, these being mining and construction. Mining invests heavily on equipment and usually has a set of many crushers that are an essential part of their operations, meaning that downtime for these companies have a substantial negative impact on their business. Due to this, many of the mining customers have a small inventory at their own mining site in case of a breakdown or any other unpredictable event. Most of these customers have scheduled liner changes (mantle and concaves) and even take this opportunity to replace some spare parts that are worn down or more prone to failure. However, the customers in the construction industry do not work in the same manner. While in the mining industry the operations heavily revolve and rely on the crushers, this is not the same case for the customers in construction. Customers in this industry usually just have one or a few crushers and they usually do not carry any stock on their own. On top of this, these customers do not regularly have a scheduled liner change or change their spare parts as the mining customers do. They instead tend to push these parts to their limits and change them when they break or have worn down to its core. This in turn makes these customers demand short lead times and high availability of both wear and spare parts to reduce the down time of the crushers.

The SAs, as previously mentioned, are the ones selling and providing the customers with the parts. There are currently nine different SAs located around the globe. These are Africa, CIS, China, India Pacific, Latin America, North America, North Europe, South Europe and Middle East and Oceania. However, due to Russia's invasion of Ukraine, there are no longer any sales in the region CIS. The scope of this project, as stated in Chapter 1.5*,* will solely focus on the SA and region of Africa. The SA is then further divided into different SA entities. The Africa SRs and their locations are visualized in Figure 19.

Figure 19, Africa SRs where SRC4 is marked with a green star

5.4 Current inventory management

5.4.1 SMCL's way of classifying and identifying overstock

As a global manufacturer and distributor Sandvik SRP and SMCL produce and carry a lot of different products, of various sizes, values and volumes. Together with uncertain demand, this causes difficulties in forecasting and therefore also in inventory management and balancing between stockouts and overstocking. In SMCL's, case this has led to an overstocking situation of certain products and is now costly for the company and impacts their profitability.

Firstly, it is essential to define how SMCL define and verify overstock at their SRs. Currently all inventory, excluding safety stock, that is not forecasted to be sold during the next 12 months is classified as overstock. This is visualized in Figure 20. The reason for why they are classifying overstock after 12 months is because it is after 12 months of no inventory movement that an item starts to classify as OSMI (obsolete and slow-moving inventory). OSMI-codes and their meaning will be further explained and discussed in the next chapter.

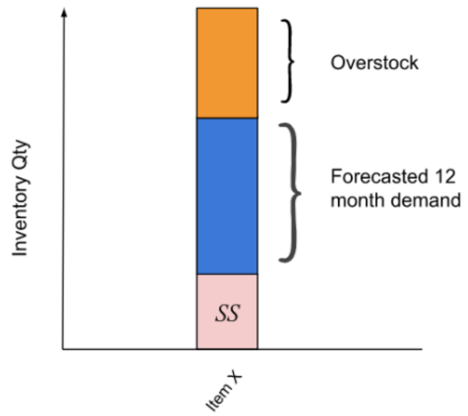

Figure 20, visual presentation of SMCL's definition of overstock

5.4.2 Fill rate, safety stock and reorder points

Historic fill rates are calculated as the fraction of demand that can be satisfied directly from stock, and this is not an exception for SMCL. However, how they determine the target fill rate is based on item cost and forecasted demand. They do not set individual fill rates for each item, instead they use a matrix and based on the unit cost and the number of forecasted order lines per year, group the items with similar characteristics and thereby get assigned a target fill rate.

5.4.3 Order quantity

As mentioned previously in Chapter 4.8, the EOQ technique or method is widely used by companies, and Sandvik, more precisely SMCL, is not an exception. EOQ is used by SMCL for items that have a relatively low value and sell in greater quantities. Meaning that when the reorder point is reached, the order quantity is equal to the EOQ. For items that are more expensive and/or have a lower forecasted demand, the order quantity is equal to the forecasted demand for the upcoming 14 days. Meaning that when the reorder point is reached, the amount that is ordered (order quantity) is equal to the forecasted demand during the next 14 days.

5.4.4 Forecasting methods and forecast accuracy

The main forecasting method that is being used is the simple moving average with $N=12$ months. Even though SMCL are using forecasting methods that handle seasonal demand behavior, the number of items that use this type of forecasting method are few and will therefore not be further discussed in this thesis.

The forecast accuracy method that SMCL uses for a certain item during a time period is calculated as follows, where FA is the forecast accuracy.

$$FA = 1 - \frac{|Order\ intake\ -\ Forecasted\ qty|}{Order\ intake}$$

However, since the volume for most items is relatively small and does not have smooth demand, a rolling three month forecast accuracy is used by the company instead and is calculated as follows, where $n = 3$.

$$FA = 1 - \frac{\sum_{i=1}^{n}|Order\ intake(i)\ -\ Forecasted\ qty(i)|}{\sum_{i=1}^{n} Order\ intake(i)}$$

5.4.5 OSMI-codes

OSMI describes the characteristics of an item, whether the item is new, moving, slow moving or obsolete.

SMCL currently use a coding system for each item in a specific SR and for a SA entity or SMCL, called an OSMI-code. The OSMI-code is specific for each SR but will also have a global OSMI-code, i.e., the item behavior to where the SR belongs, meaning the SA entity or SMCL. This is exemplified in Table 2.

The letter N is used for items that are new to that SR (N1) or an item that is re-introduced (N2). A moving item refers to an item that has been regularly demanded. These moving items are coded with M1. To describe obsolete inventory, the letter O is used along with a number from 1 to 5 to emphasize how many years the item has not been demanded from that specific SR, entity or in SMCL. To identify slow moving inventory, the letter S is used along with a number from 1 to 5, describing how many years of inventory that is currently stocked of that specific item, at a specific SR, entity or in SMCL, according to historical order intake. Note that an item can have different OSMI-codes, depending on which SR is referred to.

Table 2, exemplification of OSMI-codes

Item nr.	SR OSMI-code (SR)	Global OSMI-code (entity)
10-314-263-000	N1 (10)	O1 (Tanzania)
10-314-263-000	M1 (C4)	M1 (SMCL)

For this item, it is newly introduced in SR10 but is considered obsolete in Tanzania as an entity. The item is currently being regularly demanded from SRC4 and from SMCL.

6 Analysis

This section will investigate the presence of overstock in Africa and analyze the major root causes that have caused this issue. Furthermore, solutions to mitigate the found root causes will be presented.

6.1 Inventory turnover analysis

Since a good inventory turnover ratio depends on the industry, it is difficult to set a value that is universal and optimal for a company. It is, however, possible to benchmark the turnover ratio with other companies within similar industries to get an idea on how the company performs. In Table, 3 the inventory turnover in terms of days and per industry is summarized, which can then be translated to a ratio with the relation presented in Chapter 4.9.

Table 3, summary of median turnover days and ratio per industry for US listed companies (ReadyRatios, n.d.)

	Median turnover days (ratio) per year				
Industry [number of companies studied]	2020	2019	2018	2017	2016
Mining and Quarrying of Nonmetallic Minerals, Except Fuels [41]	71 (5.1)	49 (7.4)	60 (6.1)	59 (6.2)	62 (5.9)
Metal Mining [272]	113 (3.2)	71 (5.1)	79 (4.6)	65 (5.6)	109 (3.3)
Industrial and Commercial Machinery and Computer Equipment [299]	96 (3.8)	92 (4.0)	88 (4.1)	82 (4.5)	83 (4.4)
Miscellaneous Manufacturing Industries [70]	98 (3.7)	103 (3.5)	95 (3.8)	95 (3.8)	81 (4.5)

From the summarized table it can be concluded that the majority of the turnover ratios fall in the interval between 3.5 and 6 for industries that Sandvik SRP could possibly identify in.

The average number of days in inventory for Sandvik SRP as a whole, during the last 12 months, is 280 days, which translates to an inventory turnover ratio of 1.3. Comparing this ratio to the ratios presented in Table 3, it can be concluded that the ratio is significantly lower than the median of these industries, which could be a sign of overstock, according to Fernando (2022) and Ulfig (2012). Data earlier than this could not be provided by the company.

Furthermore, it would be interesting to look at the inventory turnover ratio for C&S aftermarket, and especially for the specific region of Africa - which is the scope of this project. However, this data is not available and therefore this analysis is not possible to perform.

The inventory turnover ratio does give an indication on how well the inventory moves or does not move on a financial and aggregated level. However, this KPI does not factor in individual items that are obsolete, meaning that a few SKUs might be overstocked or classified as dead stock while the rest of the inventory moves well and still gives a considerably good turnover ratio.

6.2 Analysis of the definition of overstock

In Chapter 5.4.1, it was described how SMCL currently define and verify their overstock. According to SMCL, there is no limited shelf life of their products and that this is not an issue when stocking the items. Therefore, the shelf life is not a limiting factor on how long the products can be stored before becoming obsolete. Currently SMCL use 12 months of forecasted demand for all items and for all SRs independently as their overstock limit. Using a higher limit, for example, using 12 instead of 6 months, might hide the fact that there is more overstock than initially anticipated. This can be visualized in Figure 21.

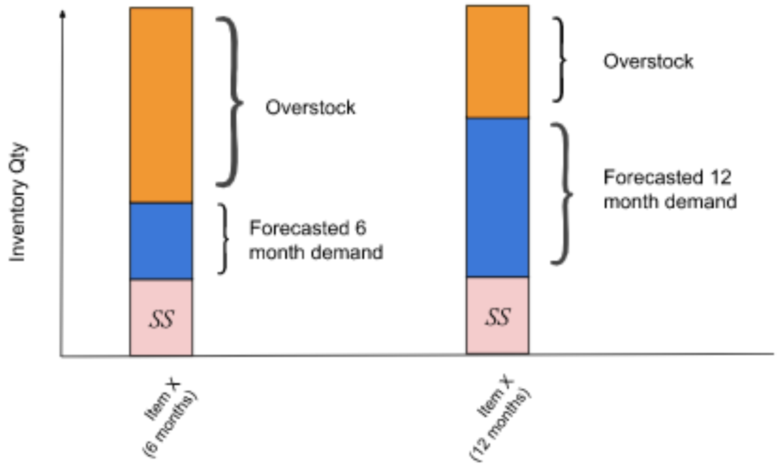

Figure 21, comparison of overstock when changing the limit

As shown in Figure 21, lowering the actual limit on where stock is classified as overstock might actually show that the company carries more excessive stock, and the situation being considerably worse than initially anticipated. This is under the assumption that the forecasted 12-month demand is greater than the forecasted 6-month demand. However, if the forecasted demand for 12 and 6 months are the same, it will result in that the amount of overstock will be equal. It could be argued that if these forecasts are both equal to zero that the overstock should instead be classified as dead stock and actions should be taken to remove them from the SR to eliminate the associated inventory holding cost and free up space for products that are forecasted to sell.

The explanation behind the overstock definition by the company is rather vague. This means that there is no other reason apart from after 12 months of no movement, it becomes OSMI. However, the lead time should be considered. Let us consider an item with a lead time of two weeks. There is no real benefit in keeping 12 months worth of stock for this item, since it can be rather responsive due to the short lead time. Compare this to an item with a lead time of 10 months, where it is now more necessary and justified to keep 12 months worth of stock. This would in turn create overstock limits specific for items and SRs based on the lead time.

6.3 Current overstock

The aftermarket products are divided into two different categories: wear parts and spare parts. Figure 22 to 25 shows the planned inventory per month, excluding safety stock on an aggregated SR level. Consider January 2023 in Figure 22. The planned inventory for this month is the stock on hand at the beginning of the month, plus the planned replenishments and minus the forecasted demand during this month.

6.3.1 Stockroom C4

The inventory value for wear parts in SRC4 is currently 53 %, and 47 % for spare parts of the total inventory value.

In Figure 22 and 23 it is visualized how much of the planned inventory will be and currently is classified per definition, as overstock. In these figures it is also possible to see how the overstock would increase if the limit would be set to 6 months rather than 12, as described in Chapter 6.2.

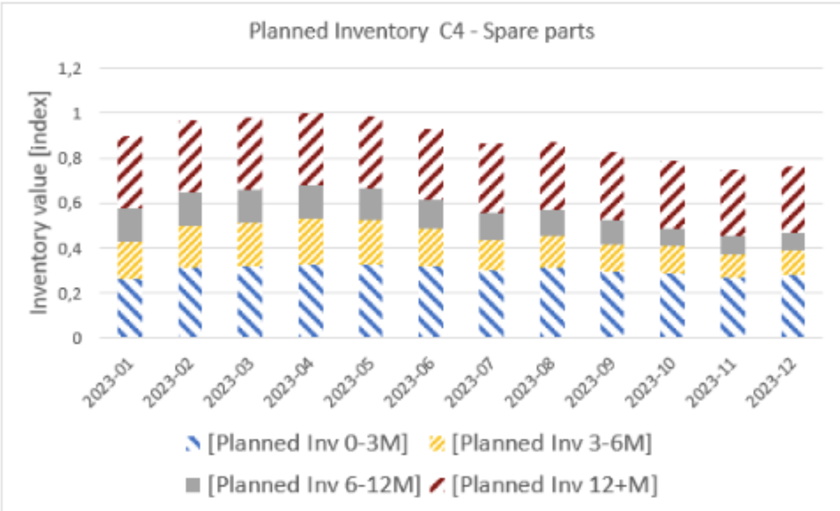

Figure 22, planned inventory consumption for spare parts in SRC4

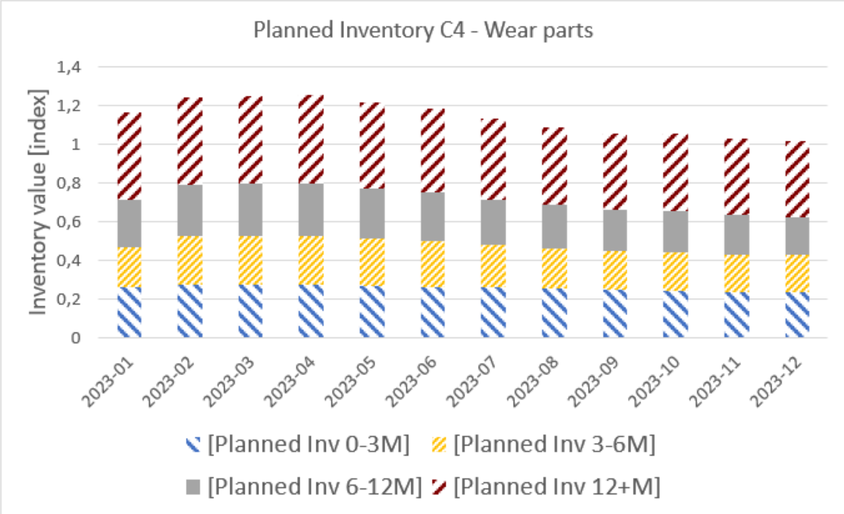

Figure 23, planned inventory consumption for wear parts in SRC4

As Figure 22 and 23 show, the total amount of inventory is set to reduce in the upcoming 12 months. However, this does not include the category "Planned Inv 12+M" that is of interest and is by definition classified as overstock. The planned inventory for 6 to 12 months seems to be reduced for both wear parts and spare parts for the rest of 2023, however, this is more noticeable for spare parts. The Planned Inv 12+M contribute to approximately, on average across the entire period, 35 % and 37 % of the total inventory value for spare parts and wear parts respectively. If all inventory from 6 months and later would be classified as overstock, the percentages would increase to 49 % and 58 % for spare parts and wear parts respectively. All percentages are summarized in Table 4. The percentage of inventory planned for consumption after 12 months compared to the rest of the inventory shows that there is improvement to be made and that there is a clear problem with overstock that currently does not seem to improve in the near future.

Table 4, inventory that is considered overstock in terms of percentage of the total inventory value in SRC4

	Percentage of inventory for 6+ months [%]	Percentage of inventory for 12+ months [%]
Spare parts	49	35
Wear parts	58	37

6.3.2 Sales area stockrooms

The same analysis is performed for the SA SRs that are scattered around Africa. The distribution for the inventory value between wear parts and spare parts is 59 % for wear parts and 41 % for spare parts. Note that all SA SRs in Africa are accumulated for this analysis to get an overview of the inventory and overstock at these SRs.

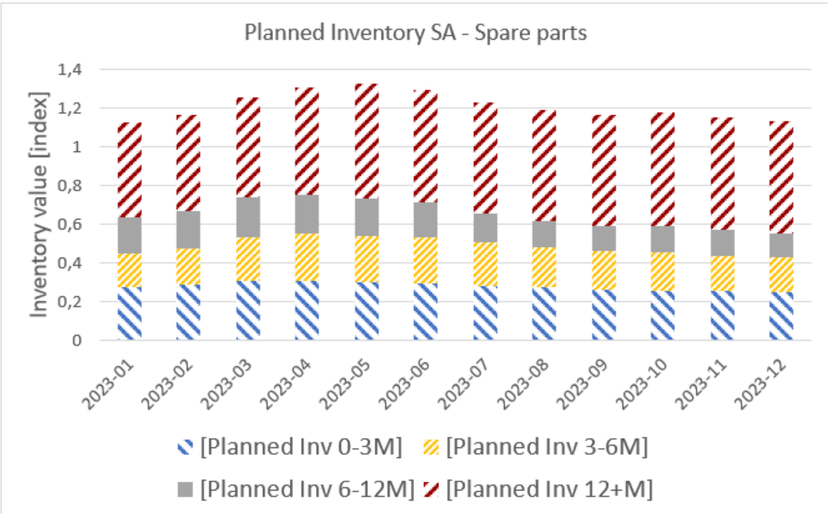

Figure 24, planned inventory consumption for spare parts in SA SRs

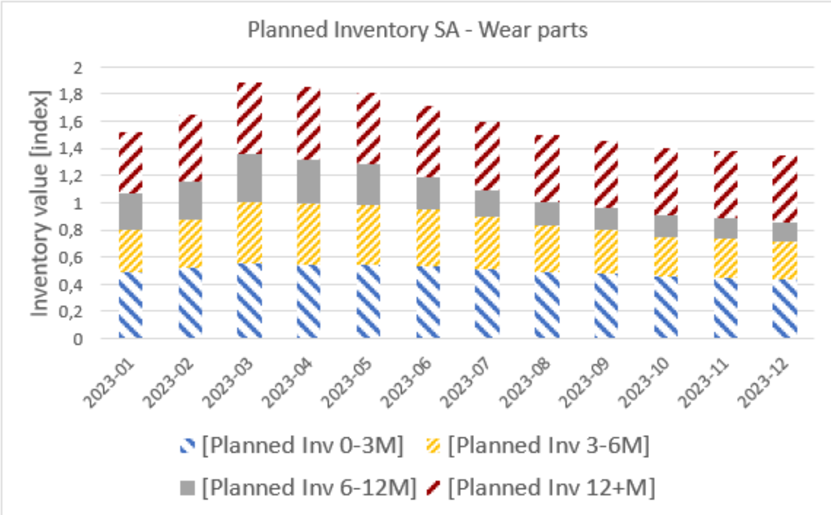

Figure 25, planned inventory consumption for wear parts in SA SRs

As can be seen in Figure 24 and 25, the overstock at the SA SRs are distinctive, just as for SRC4. The percentage of inventory that is not planned for consumption during the next 12 months in terms of value is approximately, on average for the entire period, 46 % for spare parts and 32 % for wear parts. However, if overstock is instead classified from 6 months and onward, the percentages increase to 60 % and 46 % for spare parts and wear parts respectively. These numbers are summarized in Table 5 below.

Table 5, inventory that is considered overstock in terms of percentage of the total inventory value in SA SRs

	Percentage of inventory for 6+ months [%]	Percentage of inventory for 12+ months [%]
Spare parts	60	46
Wear parts	46	32

6.3.3 Overstock quantity - spare parts compared to wear parts

Even though there is a distinct overstock in terms of value, it is interesting to analyze the amount of overstock in terms of quantity or pieces for each product type. In the previous chapters, it has been concluded that both spare parts and wear parts contribute to overstock, in both SRC4 and in the SA SRs.

Table 6, comparison between SRC4 and SA SRs for wear parts and spare parts in terms of value and quantity

SR	Components	Percentage of total overstock value [%]	Percentage of total overstock qty [%]	Percentage of total overstock value per piece [%]
C4	Wear parts	57	10	0.13
	Spare parts	43	90	0.011
SA	Wear parts	47	38	0.1
	Spare parts	53	62	0.07

As can be seen in Table 6 above, it starts to differ between SRC4 and the SA SRs in terms of quantity and value contribution. For SRC4, it can be concluded that they carry, in terms of overstocked quantity, mostly spare parts, while the majority of the overstock value is from wear parts. Since wear parts tend to be more expensive than the spare parts. In SA SRs, however, it is not that extreme. Even though the wear parts are more expensive and contribute more to the total overstock value, per piece, it seems to be more balanced than in SRC4.

In summary, the quantity of spare parts that are overstocked are greater than the quantity of wear parts. However, the wear parts carry more value per piece, meaning that decreasing the number of overstocked wear parts will yield more benefit in terms of inventory value, compared to decreasing the number of overstocked spare parts.

6.4 Lead time analysis

6.4.1 Comparison between air freight and sea freight lead times

For SMCL and for the SRs in Africa, lead times can become rather long due to long transportation times. To reduce the cost in terms of transportation costs and thereby increase profitability, SMCL tend to use sea freight as their main form of freight method when shipping from SR37 to SRC4 and some of the SA SRs (mainly located in west Africa). This is due to the nature of the shipped items, since these have a habit of being heavy and relatively large. For reference, some items can weigh up to several metric tonnes and air freight will therefore be costly and thereby not as profitable if the freight cost is paid by SMCL and not the customer. However, smaller items, for example, bolts and screws supplied from SR37 are sometimes air freighted to reduce lead time and reduce the risk of losing these small items in the large shipping containers, while not increasing transportation cost significantly. Even though the small items are sometimes shipped by air, the standard mode in the system is to ship by sea, meaning that there needs to be a manual adjustment to change to air freight. Since there are a lot of orders released by SMCL outbound every day, some with automatic release and some by manual release, it is time consuming to check every order whether or not air freight should be applied to each specific order or order line. This should ideally be automatically suggested by the system to the outbound planner to change the freight method to air instead of sea. According to the regional planning and logistics manager, it is considered beneficial to air freight items that have a weight of 50 kilograms or less. During the period May 2021 to February 2023, 2,257 order lines were dispatched from SR37 to Africa, where 1,230 had a weight lower than 50 kilograms. Out of these 1,230 order lines, 281 or approximately 23 % were shipped by air freight instead of sea freight. The average lead time when shipped by air is approximately a third of the lead time compared to sea freight. The lead times for the two transportation methods are visualized in Figure 26.

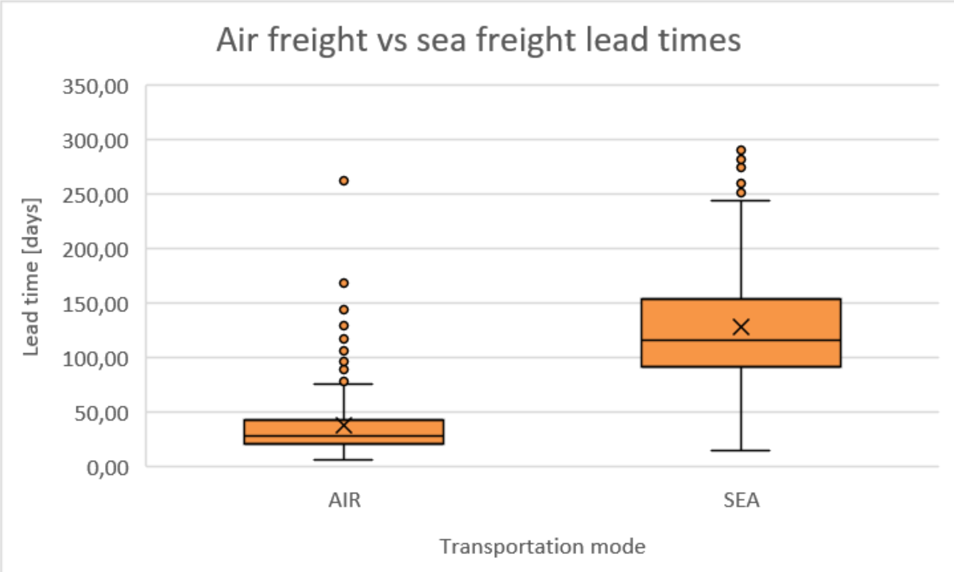

Figure 26, boxplot for air freight vs sea freight lead time

Shorter lead times increase responsiveness and will decrease the amount of safety stock needed for these items, since the safety stock is dependent on the lead time demand. This will, however, not reduce the overstock per definition, and will initially increase the inventory classified as overstock since the safety stock level will decrease. Consider Figure 20 in Chapter 5.4.1, if the amount of inventory is kept constant, i.e., the height of the staple, and the forecasted demand is the same, the amount the safety stock level decreases with will consequently be added to the overstock. However, decreasing the safety stock level will ideally in the long run decrease the total amount of inventory.

6.4.2 Lead times for sales area stockrooms

To get a more detailed insight of the lead time, it is beneficial to analyze the lead times for each studied SR independently, since these might vary due to, for example, different geographical locations. A separation between wear parts and spare parts lead times is made to see if there is any difference between the two item types. An overview of the studied SRs' lead times is displayed as boxplots in Figure 27. Note that the lead times for wear parts and spare parts for the same SR are placed next to each other to simplify the comparison.

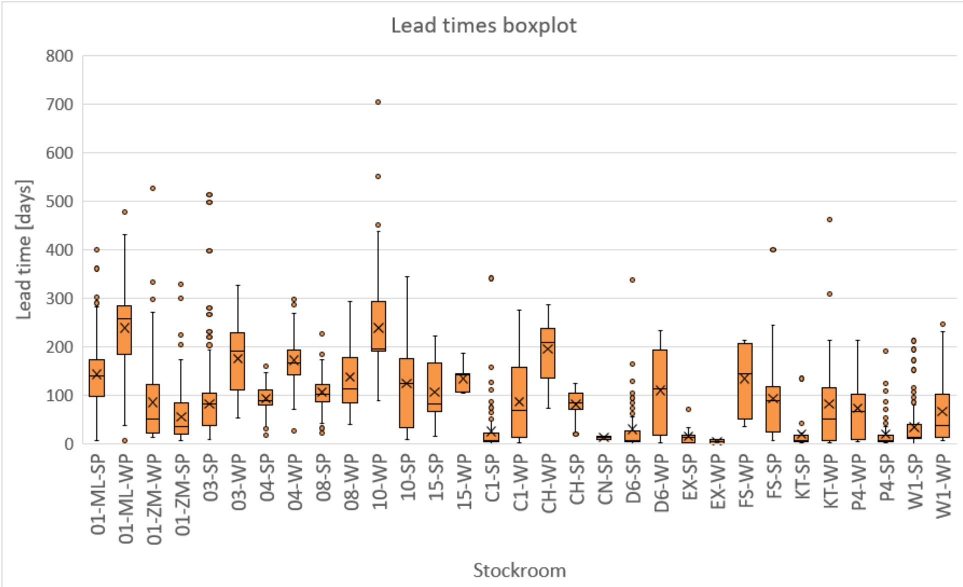

Figure 27, summary of lead times for SA SRs in Africa, separated between wear parts and spare parts

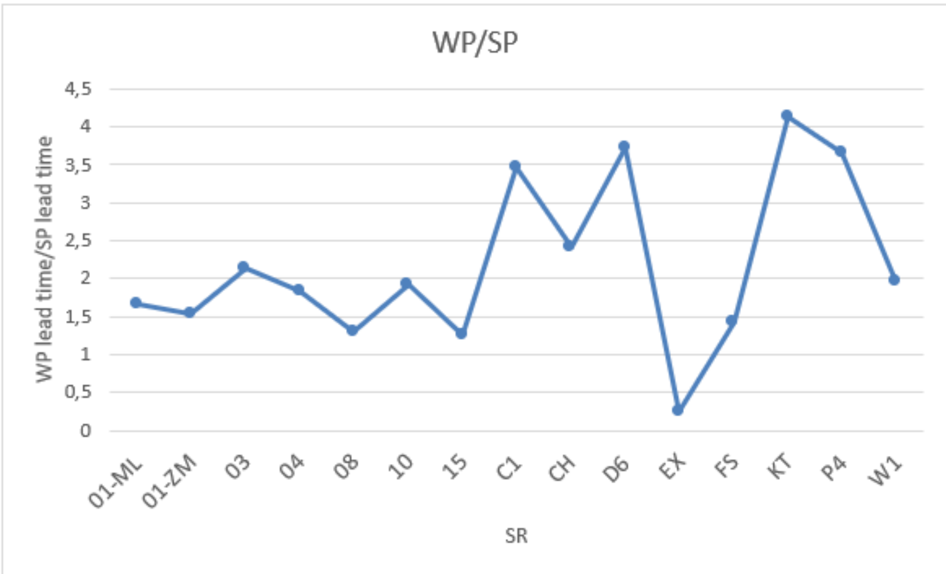

Figure 28, the ratio between the average lead time for wear parts and spare parts

As Figure 28 shows, the average lead time for wear parts is longer for the majority of the SRs compared to the average lead time for spare parts.

In SMCL's system, a lead time for each item and for each individual SR is given. However, these lead times assume that the item in question is currently in stock in the supplying SR (mainly SR37 and SRC4), i.e., unconstrained capacity. This becomes problematic when the item is not available and must be shipped from another SR, produced at the PU or ordered from an external supplier. The lead time might be displayed as 14 days, while in reality the lead time is much longer due to no availability and false promises regarding lead time to customers can occur - potentially leading to loss of goodwill. Unfortunately, these lead times are not recorded, and it is therefore not possible to compare these to the actual lead times and thereby analyze the accuracy.

Lead times to the SRs in Africa can be, as can be seen in Figure 27, rather long and somewhat inconsistent. This in turn means that the inventory needs to compensate for this inconsistency and insecurity and increase the safety stock to reach the target fill rate set by the company. While an increase in safety stock level does not impact the overstock per definition, it increases the total amount of inventory that is being kept. Variability in lead times could be because of transportation issues or delays, custom or inspection delays or stockouts from suppliers or supplying SRs. However, the underlying issue for lead time variability needs to be further investigated by the company to potentially improve the lead time consistency. Furthermore, the company should investigate why the lead time for wear parts tend to be longer than the lead time for spare parts.

6.5 Forecast and demand analysis

As previously mentioned in Chapter 2.7, one common contributor to overstock is over predicting demand, which is usually done by different forecasting methods. This is also something that Sandvik states, that there are additional unpredictable changes in demand on top of the stochastic demand that occurs. As this analysis will show, the sudden drop of demand, for example, loss of customers, is one major issue that causes overstock, since the forecast has a delay and does not recognize the sudden drop of demand as previously described in Chapter 4.4.1, and will thereby continue building stock if no actions are taken. Each month the rolling 12-month forecast is automatically updated, meaning how many pieces of each item are forecasted to sell during the upcoming 12 months. This forecast however is possible to manually change, but this is for better and for worse, as will be shown.

Table 7, example of rolling 12-month forecast for three typical behaviors

Month:	Jan	Feb	Mar	Apr	Maj	Jun	Jul	Aug	Sep	Okt	Nov	Dec	Graph
Item X	12	12	12	12	1	1	1	1	1	1	1	0	
Item Y	20	20	19	19	11	14	10	9	6	3	3	0	
Item Z	0	0	0	0	0	0	0	0	0	60	60	0	

In Table 7 above, there are three items that have a distinct and clear pattern that explain the three different situations that typically occur for overstocked items in Africa. Item X had for the first four months of 2022 a forecast to sell 12 pieces during the upcoming 12 months, which is in line with the order intake from 2021 which was 11 pieces. However, then there is a sudden drop in the forecast. Recalling the description of moving average, this does not happen with a relatively large *N*, which SMCL use, which means that this forecast has been manually adjusted to compensate for the loss of demand to avoid building stock of this item. Item Y, however, has the same issue but is not manually adjusted, meaning that the order intake has been significantly reduced (18 pieces in 2021 to 3 pieces in 2022) but the forecast slowly trickles down to zero due to the behavior of moving average. Since there is a forecast but no demand, this will lead to build up of stock that will not sell and will consequently then be classified as overstock. If it can be concluded that the demand has disappeared completely and is not just a temporary dip in demand, this forecast should have ideally been zeroed as soon as this was identified. The last item, item Z, has a behavior that is rather interesting. During almost the whole year the 12-month rolling forecast is zero, and this is due to no order intake during the last 12 months. However, in September something happens; it goes from zero to 60 pieces and then drops back down to zero. This is clearly a manual input, where the SA thought they had acquired a new customer and a yearly demand of 60 pieces, realizing two months later that in reality they had not, and items are now in the pipeline on the way to the SR that will not be consumed and will thereby be classified as overstock.

150 different items that contribute to approximately 90 % of the overstock value in SA SRs were classified with the following classifications system:

- X: The forecast has been manually lowered or drastically decreased.
- Y: The forecast has systematically decreased, typical behavior for moving average with large *N*.

- Z: The forecast was drastically increased, then to be drastically decreased.
- W: The forecast has been zero for the last 12 months, i.e., there is no forecast.
- O: The forecast has been showing some other behavior.

With this classification, the 150 items and the corresponding overstock value is sorted, and the results are shown in Table 8.

Table 8, summary of the overstock by classification

Classification	Percentage of the analyzed overstock [%]
X	31
Y	37
Z	15
W	2
O	15
Sum	**100**

Even though the forecast has been manually lowered, it still accounts for approximately 31 % of the studied overstock value. However, if the forecasts would not have been manually adjusted, but instead systematically decreased, it would have resulted in an even greater amount of overstock.

The objective would be to identify and remove the forecast of items that lose demand to avoid an unnecessary amount of stock, as is done with item X but not item Y. Manual adjustments to the forecast for items that have lost demand will yield a decrease in future overstock. For items that have the pattern or behavior as item Z, it is a question of accountability and what the information the manual input is based on. As of now, manual input or changes of the forecast does not follow a typical procedure or process, meaning that it can be changed by anyone with access and with nothing more than a hunch. According to SMCL, the newly acquired customer agreed to this yearly consumption, but the long lead times were not presented to the customer, who, when they realized, backed out of the deal due to a gentlemen's agreement instead of written contracts. This enlightens a new area of improvement of contract management and the transparency and process when acquiring new customers that needs to be investigated further by the company.

It is further analyzed if the behaviors in Table 7 were unique for the overstocked items compared to items that are prone to stockouts. It is found that the items that are prone to stockouts did not show the behavior of classifications Y and Z, which further strengthens the arguments that these behaviors cause overstock.

According to the regional planner for Africa, clean ups or manual adjustments of forecasts are performed continuously based on input from SA. However, as there is still a relatively large amount of inventory value with items classified as Y, there is room for improvements to further improve the future state of this problem.

Since SMCL use moving average with $N = 12$, the forecast is bound to lag behind significantly compared to changes in demand, as is visualized in Figure 5 and 6 in Chapter 4.4.1. A solution to this would be to decrease the parameter N so that the forecast is more responsive to changes in demand and thereby lower the amount of stock build up. As an example, let us consider a random item, called item X, with historic demand presented in Table 9.

Table 9, demand for item X for the last 12 months

Month	Demand [pieces]
Mar	304
Apr	349
May	276
Jun	162
Jul	321
Aug	386
Sep	513
Oct	173
Nov	398
Dec	660
Jan	83
Feb	775

Consider that this item would lose demand completely from next month (March) and onward, i.e., demand equals zero for these months. The forecast for each month using the simple moving average, with different values for *N* is presented in Table 10 for the upcoming 13 months.

Table 10, the forecast performed during the upcoming 13 months with N =12, N=9 and N=6

	N=12	N=9	N=6
Month	Forecast [pieces]	Forecast [pieces]	Forecast [pieces]
Mar	367	389	434
Apr	341	368	348
May	312	332	319
Jun	289	289	253
Jul	276	232	143
Aug	249	213	129
Sep	217	169	0
Oct	174	95	0
Nov	160	86	0
Dec	127	0	0
Jan	72	0	0
Feb	65	0	0
Mar	0	0	0
Sum:	**2,647**	**2,170**	**1,626**

If no manual adjustments would be taken, this would lead to an overstock of 2,647 pieces of this item. By using a lower value on the parameter *N,* the amount of overstock can be reduced by 18 % with $N = 9$ and 39 % with $N = 6$. Worth noting is that this does not consider other aspects of the operation, such as production. Production wants a smooth and even production every month, which is the reason why SMCL use $N = 12$. However, it could be argued that it should be lowered to 9 months to be more responsive while not dramatically impacting the smoothness of the forecast, but decreasing the amount of overstock when demand disappears or decreases significantly, where manual adjustments are not performed.

6.5.1 Identifying disappeared or decreased demand

To identify when demand for an item disappears might sound like an easy task, but it is not as simple in practice. Since a lot of items follow an intermittent, lumpy or erratic demand, it is near impossible to conclude if demand has disappeared or decreased or if it is just a period of low or zero demand by looking at the order intake. Input from the SA, that has direct contact with the customers, is a must to finally conclude if demand has really changed or not. However, qualitative input for thousands of items is not feasible and quantitative data to analyze is a must to reduce the number of items that need qualitative input. For the following two forecast accuracy analyses, the following will be considered: the forecast accuracy (FA) presented in Chapter 5.4.4 can reach zero in two different ways.

$$FA = 1 - \frac{|Order\ intake\ -\ Forecasted\ qty|}{Order\ intake} = 0$$

$$\Rightarrow \frac{|Order\ intake\ -\ Forecasted\ qty|}{Order\ intake} = 1$$

$$\Rightarrow |Order\ intake\ -\ Forecasted\ qty|\ = Order\ intake,$$
$$Order\ intake \neq 0$$

$$if\ Forecasted\ qty > Order\ intake$$
$$\Rightarrow Forecasted\ qty - Order\ intake = Order\ intake$$
$$\Rightarrow Forecasted\ qty = 2 \cdot Order\ intake$$

$$if\ Forecasted\ qty < Order\ intake$$
$$\Rightarrow Order\ intake - Forecasted\ qty = Order\ intake$$
$$\Rightarrow Forecasted\ qty = 0$$

The forecast accuracy becomes zero if the forecast is equal to two times the order intake. If the forecast is greater than two times the order intake, i.e., $Forecasted\ qty\ > 2 \cdot Order\ intake$, the forecast accuracy becomes negative, which will be interpreted as the forecast accuracy equals to zero. The forecast accuracy can also equal to zero if the order intake is greater than zero and the forecast is equal to zero, however, this scenario will not be further analyzed, since this causes a decrease in stock rather than stock build up. Furthermore, the definition does not consider when the order intake equals zero, since this is not defined. However, if the order intake and the forecasted quantity are both equal to zero, the forecast accuracy will be defined as 100 %. If, however, the order intake equals to zero, and the forecasted quantity is not equal to zero, the forecast accuracy will be defined as 0 %.

6.5.1.1 Analyzing the rolling three month forecast accuracy

Recall from Chapter 5.4.4, the forecast accuracy per month is calculated as follows:

$$FA = 1 - \frac{|Order\ intake\ -\ Forecasted\ qty|}{Order\ intake}$$

However, to better deal with demand that follows irregular demand, a rolling three month forecast accuracy is performed by the company, giving the following expression, where $n = 3$, which is set by the company:

$$FA = 1 - \frac{\sum_{i=1}^{n}|Order\ intake(i)\ -\ Forecasted\ qty(i)|}{\sum_{i=1}^{n} Order\ intake(i)}$$

This expression, where $n = 3,$ will be used for the analysis for the remainder of this chapter.

The forecast accuracies will acknowledge if an item is classified in the following criticality levels or not:

- Crit 1: The forecast accuracy has been zero for the last four months
- Crit 2: The forecast accuracy has been zero for the last three months
- Crit 3: The forecast accuracy has been zero for the last two months
- Crit 4: The forecast accuracy has been zero for the last month

Furthermore, analyzing the trend is helpful to understand whether the forecast accuracy is going down or not. Therefore, declining criticalities are introduced as follows, where $F = Forecasted\ qty$ and $OI = Order\ intake$:

- Declining crit 1: The forecast accuracy has been continuously decreasing for three months back, $F > OI$
- Declining crit 2: The forecast accuracy has been continuously decreasing for two months back, $F > OI$
- Declining crit 3: The forecast accuracy has decreased since the last month, $F > OI$

An example of an item classified as *crit 1* can be seen in Table 11.

Table 11, example of crit 1

Period	1 [%]	2 [%]	3 [%]	4 [%]	5 [%]
Forecast acc.	20	0	0	0	0

In Table 12 below is an item that is classified as *crit 2*:

Table 12, example of crit 2

Period	1 [%]	2 [%]	3 [%]	4 [%]	5 [%]
Forecast acc.	30	30	0	0	0

To showcase declining criticalities, namely declining *crit 1*, the following example in Table 13 can be used:

Table 13, example of declining crit 1

Period	1 [%]	2 [%]	3 [%]	4 [%]	5 [%]
Forecast acc.	75	80	65	50	30

This data and quantitative input can then be used to narrow down the number of items that need qualitative input from the SA. The lower the crit number, the more urgent the item needs qualitative input, to establish if loss or a decrease of demand has occurred.

As previously mentioned, the condition that the forecast is greater than the order intake for each period is required for each criticality to identify when demand is decreasing. However, it might be of interest to the company to also study when the order intake is greater than the forecast, to identify possible risks of stockouts. This, however, is outside of the scope of this thesis and will not be further discussed and analyzed. When analyzing all items with a recorded forecast accuracy in Africa, the following is concluded, summarized in Table 14.

Table 14, summary of forecast accuracy criticalities

Definition	Number of SKUs
Crit 1: Last 4 months with FA=0 and $F>OI$	2
Crit 2: Last 3 months with FA=0 and $F>OI$	5
Crit 3: Last 2 months with FA=0 and $F>OI$	9
Crit 4: Last month with FA=0 and $F>OI$	27
Decline crit 1: Continuous decline from Nov to Feb and $F>OI$	0
Decline crit 2: Continuous decline from Dec to Feb and $F>OI$	2
Decline crit 3: Decline from Jan to Feb and $F>OI$	26

As shown in Table 14 above, there are not a lot of items that showcase behaviors that classify them as critical, and it should therefore be possible to advise the SA of the demand state of these items and potentially make the necessary adjustments to the corresponding forecast.

6.5.1.2 Analyzing the monthly forecast

The downside of using a rolling three-month forecast accuracy is the delay that occurs. If demand would be considered smooth, it would be beneficial to instead use a monthly forecast accuracy to mitigate this delay and respond in better time. It can, however, still be used with other types of demand pattern, but the occurrence of a zero forecast accuracy would be more frequent. Let us consider the same items as before, but instead of a rolling three month forecast accuracy we look at the monthly accuracy. The number of items during February 2022 that had a monthly forecast accuracy of zero was 72 items, which is significantly greater compared to when using the three-month method, which had 27 unique items. It can be argued that getting qualitative input for all of these items is not feasible and would be too time consuming and a waste of resources. It is therefore of interest to also consider the value of the absolute forecasting error, i.e., multiplying the absolute forecasting error with the cost of the item, giving the following expression:

$$(*)\ C = |Order\ intake\ -\ Forecasted\ qty| \cdot Item\ cost$$

This is summarized in Table 15.

Table 15, the number of SKUs in each cost category, using the expression (∗) for C

Lower limit of *C* [EUR]	Upper limit of *C* [EUR]	Number of SKUs
0	100	26
100	500	15
500	5,000	18
5,000	No upper limit	13

With the cost *C,* it is easier to prioritize or filter out those items that are worth further investigating and it also enables quicker reactions compared to the three-month method.

It can be concluded that most of the items with forecast error equal to zero have a low forecasting error cost. However, some items have a marginally higher cost and are of interest and worth investigating further to potentially avoid stock buildup in terms of inventory value.

6.5.2 Forecasting methods

The demand of many products follows some kind of intermittent, lumpy or erratic demand pattern and different forecasting methods should be of interest to the company. A more detailed description and analysis of Sandvik SRP's demand patterns and characteristics and appropriate forecasting methods are described and suggested by Jusopov and Marofkhani (2022). They categorize the items based on value and demand variation in an ABC/XYZ matrix. They conclude that both Croston's method presented and described in Chapter 4.4.4, and the use of simple exponential smoothing presented and described in Chapter 4.4.2, are appropriate forecasting methods for the case company along with SBA (Syntetos-Boylan Approximation Method). Methods that handle intermittent demand better than simple moving average, such as Croston's method, should be considered to improve the forecasting ability of items that show this type of behavior. Considering the use of exponential smoothing instead of simple moving average can be shown to be beneficial where it gives the opportunity to put more emphasis on new and current data.

However, this will not be further investigated, and the company should refer to Jusopov and Marofkhani (2022).

6.5.3 Mapping large customers and their consumption

As mentioned in Chapter 5.3, there are mainly two types of customers with different demand behaviors, namely mining and construction. In Africa, the majority of customers fall under the category of mining customers and tend to have a steady consumption of wear parts and to an extent also spare parts. By mapping and documenting which crushers each customer uses and which liners (concaves and mantles) they use, together with the typical consumption rate, it is easier to know which items should be stocked and which should not.

6.6 Order quantity analysis

As stated by Ahmed et al. (2020), supply variations or bulk purchasing can be contributors to excessive stock. Lee and Kesavan (2019) also mention that internal factors are not often considered when analyzing causes of overstock. It is therefore of interest to investigate the order quantity methods used by the company.

The order quantity method used for each item group is determined by the matrix in Figure 29. The EOQ-formula presented in Chapter 4.8 is used for cheap items that have an annual higher volume. For items that are more expensive and/or have a lower forecasted demand, the order quantity is equal to the forecasted demand for the upcoming 14 days, which is presented in Chapter 5.4.3.

Order quantity						
		Cost class (lower limit)				
		0	>0	10	100	1000
Forecast order lines	>=52	N/A	EOQ	14D	14D	14D
	24-51	N/A	EOQ	14D	14D	14D
	12-23	N/A	EOQ	14D	14D	14D
	6-11	N/A	14D	14D	14D	14D
	4-5	N/A	14D	14D	14D	14D
	1-3	N/A	N/A	N/A	N/A	N/A
	0	N/A	N/A	N/A	N/A	N/A

Figure 29, order quantity matrix used by SMCL

According to Tsan-Ming Choi (2014), the EOQ model is applicable for items with low deviation in demand, without majorly compromising the results. However, if the demand shows larger deviations, other methods should be used. (Tsan-Ming Choi, 2014)

If there is a negative correlation between the annual forecasted order lines and the deviation of demand between periods, meaning that if the items that have high annual forecasted order lines also have low deviation in demand, the application of the EOQ model by SMCL is sufficient (Tsan-Ming Choi, 2014). Since the EOQ-model is rather robust in terms of estimation of parameters, such as the holding cost h and the set-up cost A, it is relatively forgiving if the company has troubles accurately determining these parameters.

Tsan-Ming Choi (2014) further describes that all items are not equally important to a company's overall performance. The example used is where an item costs \$1.5 and sells for \$3.0, and a customer buys 50 pieces annually. If this item would not be available in stock, the company loses out on only \$75 of gross profit per year. Which means that managing the inventory perfectly for this item would generate minimal benefit.

More complex and sophisticated methods should be applied for the more important items where the benefit is greater and the use of EOQ is suitable for the rest of the items, which for many firms represents the majority of items (Tsan-Ming Choi, 2014). This is in line with how SMCL use the model, i.e., for the cheaper items.

6.7 Fill rate analysis

How the target fill rate is set directly correlates with the level of safety stock needed to fulfill this target. An increase in target fill rate will consequently increase the safety stock level and thereby increase the total inventory being stocked. This will, however, not impact the overstock per definition but will nonetheless increase the total amount of inventory.

SMCL use, as mentioned in Chapter 5.4.2, a fill rate matrix based on an item's annual forecasted order lines and item cost, which then is the basis for the reorder point and the safety stock level. The target fill rate matrix used by the company is shown in Figure 30.

Target fill rates						
		Cost class (lower limit)				
		0	>0	10	100	1000
Forecast order lines	>=52	N/A	99%	99%	97%	97%
	24-51	N/A	99%	97%	97%	95%
	12-23	N/A	97%	97%	95%	95%
	6-11	N/A	95%	95%	90%	80%
	4-5	N/A	70%	70%	70%	70%
	1-3	N/A	N/A	N/A	N/A	N/A
	0	N/A	N/A	N/A	N/A	N/A

Figure 30, target fill rate matrix

The fill rate in Figure 30 can, with the help of the relation presented in Chapter 4.7, be translated into a backorder cost. To solve for the backorder cost, the inventory holding cost provided by the company is used. This holding cost is based on the annual forecasted order lines which are shown in Figure 31 and are presented as a percentage of the item cost. For items with forecasted order lines less or equal to two are not intended to be stocked and does therefore not have a predetermined carry rate.

Holding cost		
		Carry rate
Forecast order lines	>=52	30%
	24-51	
	12-23	50%
	6-11	
	3-6	80%
	1-2	N/A
	0	

Figure 31, the annual carry rate

With the inventory holding cost, it is possible to solve for the backorder cost. The relation presented in Chapter 4.7 grants the resulting backorder costs for each target fill rate group and are shown in Figure 32 as a percentage of the item cost.

Shortage cost						
		Cost class (lower limit)				
Forecast order lines		0	>0	10	100	1000
	>=52	N/A	2970%	2970%	970%	970%
	24-51	N/A	2970%	970%	970%	570%
	12-23	N/A	1617%	1617%	950%	950%
	6-11	N/A	950%	950%	450%	200%
	4-5	N/A	187%	187%	187%	187%
	1-3	N/A	N/A	N/A	N/A	N/A
	0	N/A	N/A	N/A	N/A	N/A

Figure 32, the resulting annual backorder cost

How different service levels translate to backorder costs are visualized in Figure 33 and it is clear that the backorder cost increases with an increase of service level for all carry rates (30 %, 50 % and 80 %) and should be considered when determining the target fill rates.

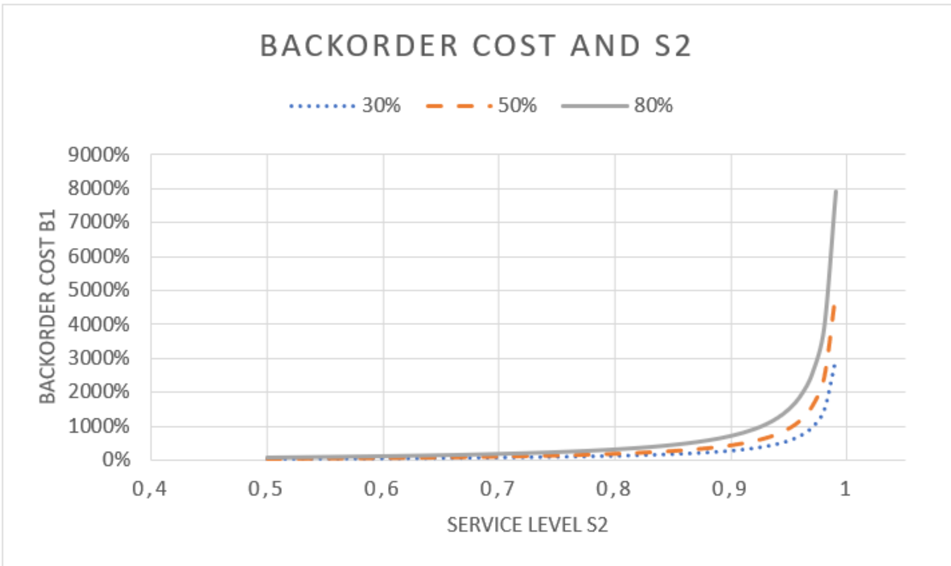

Figure 33, backorder cost vs fill rate

What is a tolerable backorder cost is case specific, meaning it is up to each individual company to decide how well this backorder cost reflects the potential loss of goodwill with customers. In an industry or market where availability is an important means of competition, a higher service level is justified, since failing to provide availability might not only generate loss of goodwill but might lead to a loss of customers and thereby a greater negative impact on the business.

If the target fill rate would be decreased for an item, as previously stated, the safety stock level would consequently also be reduced. This will initially increase the amount of overstock but the amount of total inventory at the time will remain constant. This is exemplified in Figure 34.

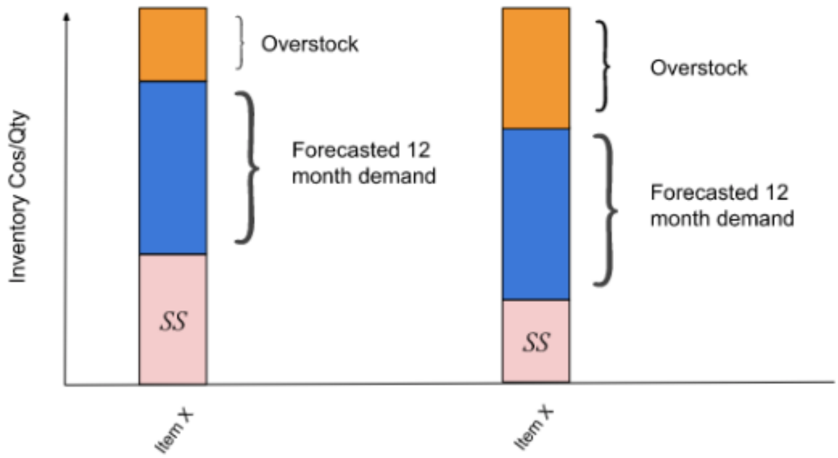

Figure 34, the initial impact of a decrease in safety stock

7 OSMI framework

According to Song et al. (2021) and Lee and Kesavan (2019) in Chapter 2.7, there will in most cases be some kind of overstock situation in a stochastic inventory environment. Even if the company takes preventive measures to mitigate overstock, the occurrence of overstock will still be present to some extent. Therefore, it is of interest for the company not only to implement solutions to the identified problems, but also implement a process on how to deal with excessive stock when it inevitably occurs. This framework will present different approaches and ideas to consider when implementing such a process.

7.1 OSMI analysis

To clarify the possibilities of redistribution and scrapping, it is of interest to analyze the OSMI, since this inventory is obsolete or is slow moving. As mentioned in the description of OSMI in Chapter 5.4.5, an item will have two OSMI-codes; one for the SR it is currently stocked in and one global code for the entity. It is possible that an item that is OSMI in SMCL is not OSMI in a SA entity, but according to representatives from Sandvik, the chances of this are low. Which means, that if an item is OSMI in SMCL, it is most probably classified as OSMI everywhere and this will be assumed for the upcoming analyses. The definition of each OSMI-code is explained in Chapter 5.4.5.

7.1.1 OSMI in SMCL

Let us consider all items that were available in stock in all SMCL SRs during January 2022 and the items' corresponding global OSMI-code. The data is summarized in Table 16.

Table 16, summary of OSMI-codes for all SKUs available in SMCL's SRs in January 2022

OSMI-code	Number of SKUs	Percentage of all SKUs [%]
N1	395	7
N2	166	3
M1	2,877	54
O1	416	8
O2	276	5
O3	150	3
O4	85	2
O5	91	2
S1	436	8
S2	148	3
S3	56	1
S4	42	1
S5	204	4
SUM	**5,342**	**100**

The largest share of items has the code M1, which means that the item was being demanded by SA from SMCL at the time. However, the items that are to further investigate in this chapter is the OSMI, meaning items with the code O1 to O5 and S1 to S5. During the year of 2022 some of the items with these OSMI-codes changed and became M1 again, which means that just because an item becomes obsolete or slow moving does not mean that the item is forever in this state. Table 17 shows the percentages of items that were classified as OSMI in January 2022 but were classified as M1 or not available in December 2022.

Table 17, change of OSMI-code during 2022 for SMCL global. NA = Not available

OSMI-code Jan. 22	OSMI-code Dec. 22	Percentage of total share for corresponding OSMI-code [%]
O1	M1	15
O2	M1	10
O3	M1	7
O4	M1	4
O5	M1	2
O1	NA	19
O2	NA	53
O3	NA	73
O4	NA	75
O5	NA	46
S1	M1	47
S2	M1	32
S3	M1	29
S4	M1	29
S5	M1	8

Some of the items were in stock in the month of January, but for some reason were not available in stock in December, i.e., “NA”. There are two possibilities of this occurring in SMCL; either the item was sold or the item was scrapped. According to a company representative, scrapping is not frequently performed, meaning that items that are no longer available in stock (classified as NA) have most probably been sold.

7.1.2 OSMI in SA entities

The same OSMI-analysis is performed for two of the largest SA entities, namely Mali and Tanzania. The distribution between the different OSMI-codes for the two entities are presented in Table 18 below.

Table 18, distribution of the inventory in terms of OSMI-code in Mali and Tanzania

	Mali		Tanzania	
OSMI-code	Number of SKUs	Percentage of all SKUs [%]	Number of SKUs	Percentage of all SKUs [%]
N1	5	3	15	8
N2	2	1	18	10
M1	76	43	42	23
O1	44	25	40	22
O2	17	10	17	9
O3	0	0	15	8
O4	2	1	1	1
O5	2	1	2	1
S1	22	13	16	9
S2	4	2	8	4
S3	1	1	5	3
S4	0	0	3	2
S5	0	0	1	1
SUM	**175**	**100**	**183**	**100**

The change of OSMI-code for the different entities is also studied, in the same manner as for SMCL performed in Chapter 7.1.1. This analysis is presented in Table 19.

Table 19, change of OSMI-code during 2022 for the entities Mali and Tanzania. NA = Not available

		Mali	Tanzania
OSMI-code Jan. 2022	OSMI-code Dec. 2022	Percentage of total share for corresponding OSMI-code [%]	Percentage of total share for corresponding OSMI-code [%]
O1	M1	27	3
O2	M1	6	12
O3	M1	-	0
O4	M1	0	0
O5	M1	0	0
O1	NA	25	5
O2	NA	35	47
O3	NA	-	73
O4	NA	0	0
O5	NA	0	50
S1	M1	36	50
S2	M1	50	50
S3	M1	0	40
S4	M1	-	33
S5	M1	-	0

Interestingly, the two different entities, Mali and Tanzania, show different behaviors in terms of change in OSMI-codes. For example, only 3 % of items classified as O1 in January in Tanzania were classified as M1 in December, compared to 27 % of the O1 items in Mali. Since there is such a clear distinction between the two entities, a general conclusion cannot be made for how items behave and move between OSMI-codes in the SA entities. An analysis should therefore be performed for all different entities to understand how the movement of OSMI-codes occurs in each individual entity. However, the entities carry fewer SKUs compared to the entirety of SMCL and it can be argued that there are not enough data points in the entities to make a well-founded quantitative conclusion. Also, worth noting is that "NA" for this analysis could mean that the item has been sold, scrapped or returned to SMCL, meaning that it is not possible to make the same assumption as was done for the SMCL analysis and requires further investigation if this information is of interest to the company.

7.2 Redistribution of OSMI

Uncertain demand often results in inventory imbalances and can be balanced by shipments between stocking locations in the same echelon, also known as lateral transshipments (Feng et al., 2023). The company could, by proactively identifying excess inventory, reduce inventory obsolescence by reallocating them to other lateral SRs or even upstream SRs (Mo et al., 2021). This strategy can in turn reduce the cost if performed correctly (Mo et al., 2021; Nakandala, Lau and Shum, 2017) and reduce the mismatch between supply and demand (Feng et al., 2023).

The research regarding redeployment of excessive service parts, i.e., spare parts, is by some considered insufficient and result reports of the applications of this in practice are missing (Mo et al., 2021; Nakandala, Lau and Shum 2017). Furthermore Mo et al. (2021) mention that there is a lack of solutions to apply for excessive inventory due to the high decision complexity and Paterson et al. (2011) state that it is not fully understood when redistribution should take place when ordinary ordering decisions are considered simultaneously. Paterson et al. (2011) further describe that optimal solutions for lateral transshipments can generally only be found for systems with a few stocking locations and that current research could be developed further for multi-location problems to improve the transshipment policies. Since Sandvik have a greater number of stocking locations, it is therefore not of interest to implement or suggest such a policy to the company, but rather highlight possibilities and ideas to consider.

For redistribution there are mainly two possibilities, namely proactive redistribution and reactive redistribution (Mo et al., 2021; Paterson et al., 2011).

7.2.1 Proactive redistribution

Proactive redistribution could be described as moving the stock for a specific item from one SR that does not have forecasted demand of this item and transferring it to a SR that does have forecasted demand for this item. However, there might be some constraints in terms of redistributing, such as the ability or capacity in the workforce to perform this redistribution from the SRs in Africa. Some SRs might have better capacity to perform this type of task than others and should be considered when making this type of implementation, since the SR is now doing a return which not only implies practical work, but also administrational effort.

Inventory that is classified as OSMI in the different entities in Africa contributes to approximately 35 % of the inventory value in the SA SRs. Out of the OSMI, in terms of value in these SRs, 85 % is classified as M1 in SMCL, which shows that there is a lot of potential to redistribute this inventory back to SMCL. When the inventory is in SMCL, the items can be distributed to the correct RDC (regional distribution center) or SA that have demand for the specific item. However, to avoid unnecessary transportation costs and to potentially reduce the redistribution lead time, the item can be directly distributed to the correct RDC or SA from Africa, bypassing the item first being transported to the closest SMCL SR. The possibilities of transportation routes should be further investigated by the company, since there might be limitations in export/import regulations and transportation modes.

7.2.2 Reactive redistribution

For the company in its current state, it might be challenging to perform proactive redistribution, since the majority of the SRs within the company are already at full capacity. Transferring a greater batch from one SR to another might not be possible and reactive redistribution is therefore more suitable. Paterson et al. (2011) claim that reactive distribution is more suitable for items that have a relatively low transportation cost and a high holding cost that fails to meet demand immediately. Reactive redistribution for SMCL would mean that when a sales order is received from the SA, the item is re-sourced to a SR with overstock of this particular item or where the item is classified as OSMI, instead of sourcing from SR37 or from external suppliers. The lead time from Africa to Europe can become relatively long due to long transportation times, which is important to bear in mind when re-sourcing an order to be supplied from a SR in Africa rather than from SR37. For this reason, it is more suitable to re-source a future order, meaning an order that has a required delivery date in several weeks or months, compared to an order that is required earlier.

Apart from considering the lead times, one aspect that should also be considered is the transportation cost in comparison to the holding cost and the purchase price. This is visualized in Figure 35.

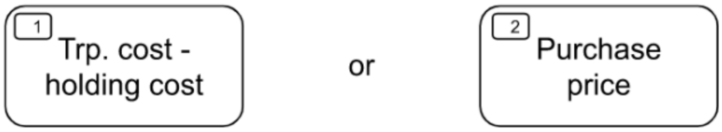

Figure 35, cost decision

For these decisions new variables are introduced:
$TC = transporation\ cost$
$h = holding\ cost$
$A = purchase\ price$

If the transportation cost minus the holding cost is less than the purchase price, i.e., $TC - h < A$, the item should be redistributed. However, if $TC - h > A$ the item should instead be purchased.

Let us consider item X that has a purchasing cost of €100, has a lead time from external suppliers or internal PU of 30 days and has an annual carry rate of 30 %. This item is available in an African SR and is classified as overstock. To redistribute or ship this item from a SR in Africa to SR37 takes 90 days and costs €50. If the required delivery date is less than 90 days, it would be necessary to purchase this item from an external supplier or to supply it from the internal PU to satisfy customer requirement. However, if the required delivery date is >90 days, it is in terms of lead time possible to re-source this order to be supplied through the African SR. Since the item is classified as overstock, it is not forecasted to sell during the upcoming 12 months and based on the forecast makes the holding cost for this item at least $0.30 \cdot 100 =$ €30. The different decisions then give us the following costs:

Decision 1 (re-distribute): $50 - 30 =$ €20
Decision 2 (purchase new item): €100

For this particular item, redistributing is more cost efficient for the company and should be the way to proceed for this particular order. However, for items that are heavy and have a higher transportation cost, this might not be the case and should be evaluated in the same way. Also, worth noting is if the holding cost would increase, meaning it would be 50 % or 80 %, it would further strengthen the decision to redistribute rather than purchase new goods. This example considers a lead time of 90 days, however, as discussed in Chapter 6.4 lead times can be significantly reduced for items below 50 kilograms, due to the possibility of air freight. This will reduce the lead time significantly and expand the opportunity of reactive redistribution.

Since the lead time for reactive redistribution from Africa is typically longer than the lead time from external suppliers or from the main DC in Venlo, it will not reduce the potential backorder cost at the receiving SR. However, if the lead time would be shorter for redistribution compared to purchase of new goods, the reduction of potential backorder cost at the receiving SR would further strengthen the decision of redistribution (decision 1). Let us consider an item that is out of stock in a hypothetical SR. While there is a stockout, demand occurs for this item, generating a backorder and consequently a backorder cost. Since the backorder cost is defined per unit and time, the longer the backorder exists, the higher the cost. If the redistribution lead time would be shorter than the lead time for purchase of new goods, this would result in the backorder existing for a shorter period of time and thereby reducing the resulting backorder cost.

Redistribution will not only be cost beneficial for the individual order but will in the long run clear out excessive inventory and free up space for inventory that is more beneficial to keep in stock and avoid potential future scrapping.

7.3 Scrapping

Items that are classified as overstock or OSMI and do not have any demand from any SR, meaning redistribution is not an option, could be considered being scrapped to avoid unnecessary holding costs. Scrapping tends to be performed locally at the SR, but for some smaller SRs that do not have this capability, the items are transported to the nearest SMCL SR to be scrapped. However, this transportation cost will be neglected for this analysis.

7.3.1 Scrapping in SMCL

In December 2022, 5 % of the inventory kept in SMCL's SRs in terms of value was classified as obsolete (O1 to O5), 16 % as slow moving (S1 to S5) and 79 % as moving (M1), new (N1), or re-introduced (N2). This would mean that if all inventory classified as obsolete would be scrapped, it would decrease the inventory value by 5 % in SMCL SRs. How the 5 % are divided between O1 through O5 are presented in Table 20.

Table 20, percentage of inventory value in SMCL SRs for O1 to O5 in December 2022

OSMI-code	Percentage of total inventory value [%]
O1	2.5
O2	1.5
O3	0.23
O4	0.22
O5	0.52

Based on the information in Table 17, it is difficult to argue that OSMI should be scrapped, since a portion of items that are classified as OSMI are a year later classified as moving. Together with the low benefit of scrapping, it should be generally avoided if no other qualitative input is available. Under the assumption that "NA" implies that the item has been sold and would thereby be classified as M1 if it was available in stock, further argues against scrapping of OSMI in SMCL.

7.3.2 Scrapping in Africa SA

It was stated in Chapter 7.2, that 85 % of the OSMI in Africa SA SRs is classified as M1 in SMCL. Let us now instead consider items that are classified as OSMI in Africa SA entities and also classified as obsolete (O1 to O5) in SMCL. This is summarized in Table 21.

Table 21, proportion of OSMI value in Africa SA that is classified as obsolete in SMCL

SMCL OSMI-code	Percentage of Africa SA inventory value [%]
O1	0.27
O2	0.36
O3	0.12
O4	0.06
O5	0.03

Considering this, it yields a low benefit of scrapping inventory in Africa SA, since the decrease of actual inventory value is relatively low. Furthermore, considering the probability of OSMI becoming non-OSMI could result in unnecessary scrapping. Therefore, scrapping in Africa SA should be avoided if no additional qualitative input is available and should instead be returned to SMCL to increase the possibility of OSMI becoming moving, since the probability of this happening is arguably greater than in the entities.

8 Conclusions

This chapter consists of conclusions and discussions for each research question presented in Chapter 1.4.

8.1 Research question 1

What are the major root causes to the overstock situation in Africa?

Throughout the analysis in Chapter 6, different aspects and factors have been investigated and considered. It was found that the two major causes of overstock were connected to the demand forecast, namely classification Y and Z, presented in Chapter 6.5. Classification Y, i.e., the systematic decrease of the demand forecast when demand has disappeared completely and there occurs a stock build-up due to the lag of the forecast. Classification Z, i.e., when an item demand forecast ramp-up resulted in no demand, and instead lead to stock build-up due to no realized demand.

It was found that the order quantity system that the company uses is not a major root cause for the overstock. Furthermore, based on the target fill rates set by the company, the corresponding backorder cost becomes rather high. However, as stated in Chapter 6.7, this is case specific, meaning that there is no universal rule of thumb to follow, and it is up to company management to decide what is a suitable fill rate. A higher fill rate will nonetheless increase the total inventory level.

8.2 Research question 2

How can these root causes be mitigated and thereby reduce future overstock?

By analyzing and studying the forecast accuracy on item level instead on an aggregated level, it is possible to identify items that have potentially lost demand and manually adjust these forecasts to avoid the forecast lag and thereby also avoid unnecessary stock build-up, i.e., classification Y. However, this approach relies on frequent communication and complementary qualitative input from the SA, since it is by only performing quantitative analyses not possible to safely determine if demand has disappeared or if it is just a period of low or zero demand for intermittent, erratic or lumpy demand patterns.

To avoid the behavior of classification Z from occurring, it is in the company's interest to improve the process and accountability of manual ramp-ups of the demand forecast. As of now, manual input or changes of the forecast does not follow a typical procedure or process, meaning that it can be changed by anyone with access and with nothing more than a hunch. According to the company, newly acquired customers might agree to a yearly consumption, who, for different reasons backed out of the deal, due to gentlemen's agreement, instead of written contracts. This enlightens a new area of improvement of contract management and the transparency and process when acquiring new customers.

Apart from the direct major root causes described above, there are other implementations the company can perform to reduce inventory, such as automatically suggesting air freight for order lines below a specific weight. This would lead to improved lead times and thereby also reduce the safety stock level needed for these items.

8.3 Research question 3

How can the current obsolete inventory be handled in terms of redistribution and scrapping?

During the second phase of the analysis, namely the OSMI framework, it was found that 85 % of the OSMI, in terms of value, in Africa SA is being demanded somewhere in the SMCL network. This shows that the possibility for redistribution of OSMI is well pronounced. Furthermore, the probability of OSMI becoming demanded again is significant within SMCL, which means that even if the item is considered OSMI in both the African entity and SMCL, it should be returned to SMCL to improve the chances of selling this item.

On the contrary, scrapping should generally be avoided if no other qualitative input is available, since scrapping yields relatively low benefit in terms of inventory value and SR capacity. Additionally, the probability, seen in Table 17, of an item being demanded again is rather significant, which further strengthens the argument to avoid scrapping based on quantitative data.

8.4 Future work

Since this thesis did not include the implementation of the solutions and the framework, the next step for the company is to implement this way of working, to improve the future state of their inventory. However, there are other aspect and issues that were found during this thesis that were not further investigated, due to the scope of the thesis and the restriction of time.

Firstly, the company should further investigate how to handle the process of manual forecast ramp-ups and the accountability of manually adjusting forecast, as described in Chapter 6.5, to avoid the situation where there is no realized demand to an increased forecast. Secondly, to avoid customers backing out of deals, due to the non-binding nature of gentlemen's agreement, the possibility of written contracts should be considered and investigated to avoid customers backing out of agreed upon terms. In the lead time analysis, it was found that the average lead time for wear parts was longer than the average lead time for spare parts. This was not further investigated due to time restrictions and should be of interest for the company to investigate further. Furthermore, the expected lead times presented in the system are not recorded, meaning that it is not possible to evaluate the accuracy of the expected lead times in comparison to the actual lead time. This could be valuable to the company, since accurately predicting the lead times will improve performance of their inventory management and their confidence of lead time promises to their customers.

8.5 Contribution

This thesis has not only analyzed root causes for the overstock in Africa and a framework regarding redistribution of obsolete inventory, but has also provided guidelines for other BAs within Sandvik and Sandvik SRP to apply when analyzing why overstock has occurred for their products and their possibilities of implementing redistribution. As stated in Chapter 2.1.2, the results and conclusions from the project are generally limited to the specific case. However, if two cases are similar, arguments can be made that the conclusion might be applicable to the other cases, and by doing so, finding general patterns. Which means that other BAs within Sandvik or other external companies might find the same results and come to the same conclusion. Nonetheless, the general process and way of working could be applicable for other case studies with similar presumptions, even if the results and conclusions differ.

What could be specific for this case study, that could potentially differ from other cases, are the long lead times, the low volume of demand and the frequent occurrence of intermittent, erratic and lumpy demand.

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