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Master Thesis

Improving the inventory management at a production facility

A research into the stockout of inventory at Voortman Parts Manufacturing 1 and solving it by improving the inventory control policies

Matthew Milner
June, 2022

UNIVERSITY
OF TWENTE.

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Preface

This report marks the endpoint of my research conducted at Voortman Steel Machinery and an important milestone in my education. Of which the last 3 years have been at the University of Twente. After completing my bachelors in Mechanical Engineering and Industrial Engineering & Management at Saxion, I continued with the pre-master and master of Industrial Engineering & Management, with a specialization in "Production & Logistics Management". I am glad to have made that choice to combine my interest in engineering and optimization of production environments.

I would like to thank Voortman Steel Machinery, especially the colleagues at Parts Manufacturing 1, for the opportunity to conduct this interesting research and for the kind and helpful contribution that they had in it. A special thanks to Mike Mansveld for supervising me during this project, providing constructive feedback and always being able to make time for interesting conversations. I would also like to thank Luc Stoverink for his help and for proofreading my thesis.

Furthermore, I want to thank my supervisors of the university, Matthieu van der Heijden and Engin Topan. Even though they were very busy teaching courses and supervising other students, they always found time to help me on short notice and give constructive feedback. I would also like to thank Matthieu for breaking the tunnel vision that I had at the start of the project, by suggesting to investigate the demand planning.

Lastly, I would like to thank my family, friends and girlfriend who supported me during this research. Dad, thanks for the discussions about the research and proofreading my thesis. I would also like to thank some fellow students, that by now I can definitely call my friends. Michiel, Ivo, Stan, Rob, Robin, Marije and Juliet, thanks for all the support during the pre-master and master. We worked on a lot of group projects together and always helped one another when needed. You guys made my time at the university fly by, despite having to work from home due to COVID-19.

I hope you enjoy reading this master thesis.

Matthew Milner
June, 2022

Management summary

This research proposes an inventory management tool which can help Voortman Parts Manufacturing 1 (VPM-1) reduce the unavailability of components (SKUs) directly consumed in production of the handling modules and help improve overall control of the inventory. The tool is designed to classify the inputted SKUs based on various characteristics and user input variables and determine appropriate inventory control policies and corresponding parameters to attain a target fill rate (the percentage of occasions stock can directly fulfil demand without backordering). VPM-1 is a department of Voortman Steel Machinery (VSM). The department manufactures roller conveyors (RC), cross transports (CT) and Cutting Tables. These modules are used for the handling of material past the advanced machining solutions that VSM develop. This research was initiated because VPM-1 have a gut feeling that the unavailability of stock is a significant and frequent disturbance to the flow of production orders. Moreover, the current way of ordering and managing inventory is insufficient to prevent this unavailability, which results in 'firefighting' for office and production staff and inflexibility of the production planning. The goal of this research is to gain knowledge in inventory management techniques and propose a solution which will reduce the backordering and stockout occasions of SKUs, such that the flow of production orders is not impeded. The main research question used to achieve this goal is:

"How can the inventory management of SKUs at VPM-1 be improved, to reduce the frequency of stockout occasions in production?"

The first phase of this research investigates the current situation regarding inventory management and the causes to the stockouts. VPM-1 use an Assemble-to-Order policy for their production-inventory model. The handling modules are produced according to a production order (PO) and, to reduce the total lead time the sub-weldments and sub-assemblies, also referred to as internally produced components, are produced to stock. This research focuses on the 601 SKUs that are directly consumed in the production processes of the handling modules. The average inventory investment for these SKUs is approximately €435.000, which is 70,6% of the total average inventory investment of VPM-1. The main replenishment strategy used is a demand strategy, also known as MRP-driven ordering: replenishments are based on known demand (reservations), reordering what is needed to fill POs, while taking into account any ordering requirements. Replenishment orders are placed based on the experience and intuition of the purchasing department. Demand for a PO is known at least 7 weeks before the loading date (shipping date), also known as the due date of a PO. Based on this lead time (LT) and the production stage in which the SKU is consumed, the due dates of the SKUs can be determined and therefore the available demand LT. During this investigation, a potential was found to improve the current demand LT considerably by taking demand information from the final sales layout into account. This would increase the demand LT by 4 weeks for RC and CT modules and 2 weeks for Cutting Table modules. Solely based on the confrontation between demand LTs and supply LTs, it was found that 57,5% of the SKUs can be procured on-order. And that the average inventory value of these SKUs (€261.000) can be significantly reduced. There is no historical data available on the fill rate of the SKUs in inventory. To get an indication of the fill rate, the ready rate (the percentage of occasions stock is strictly positive) is used. The average ready rate of the SKUs which cannot be procured on-order is 81,5%.

The designed solution is a tool that classifies the SKUs according to an adaptation of a stepwise approach found in literature in which the SKUs are classified based on their distribution by value, Net LT and their CV of demand during LT. If demand for a SKU is certain for the demand LT then the remaining period ($supply\ LT - demand\ LT = Net\ LT$) should be taken into account when determining inventory control policies. *Table 0.1* shows the classification of SKUs based on the current situation and available demand information. The four common policies found in literature can be categorised as continuous or periodic review policies with a fixed or variable lot sizes. Based on the literature, each class of the classification method is assigned a policy based on the characteristics of that class.

Table 0.1: The classification of the SKUs per class.

	Class 1	Class 2	Class 3	Class 4	Class 5
Classification type	C-item	A-item $Net\ LT \leq 0$ OR SKU required on-order	A-item $Net\ LT > 0$ $CV > 1$	A-item $Net\ LT > 0$ $0{,}5 \leq CV \leq 1$	A-item $Net\ LT > 0$ $0{,}5 < CV$
# SKUs	280	295	11	14	1

The subsequent phase investigates the performance of the inventory when applying the proposed inventory policies. The phase starts by calculating the policy parameters using demand data of 2017-2020 as a training set. Thereafter, a simulation study is carried out to analyse the performance using the demand data of 2021 and analysing how the proposed policies perform compared to the current situation. The results of the simulation show that the proposed policies achieve a significant improvement of the fill rate over the current situation. The average fill rate, of the SKUs that should not be procured on-order (class 1, 3, 4 & 5), improved from approximately 81,5% (the measured ready rate) to 98,2%. The average inventory value, however, does increase by approximately €46.000 (about 10,6%). The sensitivity analysis show that by: (1) removing a factor which overcompensated the continuous review policies, and (2) by changing the chosen policy of class 5 SKUs from a periodic review policy to a continuous review policy, the performance of the initial solution can be improved. The improved policies achieve the same fill rate against an average inventory value increase of approximately €20.000 over the current situation. There is however a potential for a further increase in performance if demand information from the final sales layout *is* included, increasing the demand LT of modules. Then the average inventory value of the solution is approximately €403.000, which is €32.000 (about 7,4%) less than the current situation, while maintaining the high overall fill rate. Besides the potential to significantly reduce the unavailability of SKUs by 16,7%, implementing the inventory management tool will: (1) increase purchasing control, (2) decrease the firefighting in the office and on the production floor, (3) create the possibility to increase the flexibility of the production planning and (4) provide VPM-1 the opportunity to understand the implications that longer supply LTs may have on the inventory.

The last phase of this research investigates an implementation plan for the proposed inventory management tool. A six-step plan is recommended. The first four steps are for a pilot. Testing the proposed policies on a small group of SKUs in practice and determining the efficacy in reducing the unavailability of SKUs. For this, the measurement of the fill rate in practice must be improved. If the pilot is deemed successful by the stakeholders the next step is to implement the policies for all the 601 SKUs. The last step is to research the remaining SKUs of VPM-1, which were excluded during this study, and the other manufacturing departments of VSM and investigate how the inventory management tool can be applied to improve their performance.

The main recommendations to VSM are: (1) to implement the inventory management tool and its ensuing inventory control policies, (2) to improve the overall demand planning by making the demand from the final sales layout available in SAP earlier and (3) implement ways to measure KPIs relevant to inventory management and to improve and invest in reliable data in SAP. Future research could extend the current research to the SKUs consumed in the internally produced components and investigate how forecasting can be applied to the inventory of VPM-1.

Table of Contents

List of Figures

List of tables

Glossary

ADI	Advance Demand Information
ATO	Assemble-to-order
CT	Cross Transport
(D)LT	(Demand) Lead Time
FAS	Final Assembly Schedule
FOQ	Fixed Order Quantity
IP	Inventory Position
ITR	Inventory Turnover Rate
MOQ	Minimum Order Quantity
MPSM	Management Problem Solving Method
OHI	On-Hand Inventory
PO	Production Order
RC	Roller Conveyor
SAP	Systems Applications and Products – The ERP-system which is used by VSG
SKU	Stock Keeping Unit – For this project SKUs are raw materials, supplier-bought components and internally produced components kept in the warehouse
SLT	Supply Lead Time
TBS	Time Between Stockout occasions
VMI	Vendor managed inventory
VPM	Voortman Parts Manufacturing
VSG	Voortman Steel Group
VSM	Voortman Steel Machinery

1 Introduction

In the context of completing my master's degree in Industrial Engineering and Management, I performed research at Voortman Steel Machinery for my master thesis. The goal of this research is to design a solution which improves the availability of components in the inventory of Voortman Parts Manufacturing 1 (VPM-1).

This chapter presents the introduction to the research starting with a company description followed by a problem description (*Section 1.2*). From that, the problem statement and research objective are defined (*Section 1.3*), including some likely causes and possible solution directions. Subsequently, in *Section 1.4* the research questions and accompanying methodology are introduced. The chapter concludes with the research scope (*Section 1.5*) and deliverables (*Section 1.6*).

1.1 Company description

Voortman Steel Machinery, together with Voortman Steel Construction, is a part of the Voortman Steel Group. Voortman was founded in 1968 by the Voortman brothers in Rijssen as a business for producing all kinds of machinery. The company was split into two separate entities in 1978, one for steel structures and the other for machinery. Since 1995 Voortman Steel Machinery (VSM) concentrates on developing and building CNC machines. The development and manufacturing of these machines is done at the headquarters in Rijssen.

Currently, VSM develop and manufacture advanced machinery solutions for steel beam and plate fabrication. The product range of the machinery can be divided into four categories:

- Beam processing;
- Flat and angle processing;
- Plate processing;
- Surface treatment.

VSM also offer their customers total processing solutions, called Multi System Integration. This makes it possible to fully automate the customers production process by connecting the various processing machines by cross transports, roller conveyors, product buffers and material sensors. To this end, the manual transportation of materials through the production process becomes obsolete due to one integrated production system. Progression of the process can be monitored in real-time, using Voortman's proprietary CNC control software, VACAM. *Figure 1.1* shows, one of VSM's profile processing machines, with an example of the handling systems (Voortman Steel Machinery, 2021).

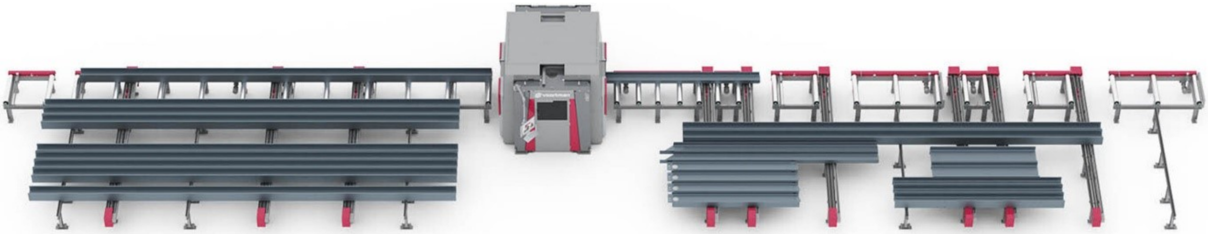

Figure 1.1: V807 robotic profile processor with handling system (Voortman Steel Machinery, 2021)

This project has been conducted at VPM-1, which is a department of VSM that, amongst other production processes, manufactures the roller conveyors (RC), cross transporters (CT) and Cutting Tables. The RCs and CTs are a part of the handling systems and are used for the transportation or buffing of the material. Although the handling systems are designed using standardized components, they have a high degree of configurability, depending on the number of machines being connected and the available space at the site of the customer. In general, the process of manufacturing the handling systems can be characterized as assemble-to-order (ATO).

Annually, Voortman sells roughly 5 km of RCs and 5 km of CTs. VPM-1 also produce the Cutting Tables which are used in the plate cutting and drilling machines of VSM. *Figure 1.2* shows an example of Cutting Table.

Figure 1.2: V310 plasma cutting and drilling machine, including the Cutting Tables (Voortman Steel Machinery, 2021).

1.2 Problem description

As mentioned, VPM-1 are responsible for manufacturing the handling systems which are used in conjunction with the plate and beam processing machines. The production of these handling systems is done on a ATO basis, once a production order (PO) has been filled in SAP (the ERP-system), by VSM. In that sense, VSM is VPM-1's customer. VPM-1 make use of an internal warehouse in which they store supplier-bought components and internally produced components (sub-assemblies and sub-weldments). The idea behind the use of a warehouse is to diverge from the old way of working, in which components are stocked to order for specific POs and are not allowed to be used for other POs. To a new way, in which they order to stock. The idea is that this makes production more flexible as the stock has been anonymised and may be consumed by any PO.

Components (from here on known as SKUs) are ordered from suppliers to stock once demand arises in SAP. Currently, this demand for SKUs is dependent on customer orders, known as projects. Once a project layout has been accepted by the customer, the handling modules in the project are converted into POs in SAP, which are then planned into production by the planner. SAP then generates a demand to purchase SKUs based on the BOM of the PO, the current inventory position of the stock, the expected lead time (LT) of the supplier and the due date of the PO. The senior operational buyer (from here known as buyer) purchases the SKUs from the supplier, in a certain quantity, based on intuition and experience. Only once a project is accepted by the customer and filled into SAP as POs can the buyer and planner have an insight into what exactly has to be produced. *Appendix A.1* shows the process of how demand for SKUs in inventory is generated.

VSM, and therefore VPM-1 are committed to improving their internal production processes. One of the situations VPM-1 would like to improve is to prevent or reduce the amount of 'firefighting' that is performed in the office and on the production floor, due to a large amount of backordered SKUs. Which in turn are a result of stockout occasions of the SKUs from inventory, which are required for the manufacturing of the POs. The frequency with which disruption due to unavailability of a SKU is experienced is estimated to be roughly one every three POs. It should be noted that while the occasional stockout situation has not yet resulted in missed shipping deadlines, it is regarded as an area to improve production (Mansveld, 2021).

The buyer and planner are constantly looking ahead in the timeline to purchase SKUs from suppliers and planning and starting up POs so that the supplier-bought and internally produced components are available on time for production. There are instances, e.g, in which POs are filled late by VSM into SAP or that sequences of POs in the timeline are changed, which with the planned inventory positions will lead to a stockout, and subsequently backorders, in the future. The firefighting in the office will then entail altering the planning or contacting (alternative) suppliers to try and bring orders for SKUs forward in time or placing rush-orders. Another consequence of the unavailability of stock, for the planner, is the inflexibility of the production planning. It becomes difficult for the planner to move POs forward in time if required to level the capacity of resources. On the other hand, the unavailability of SKUs during production has as a consequence that the operators need to stop production or deviate from the standard assembling procedure, if possible. For instance, when a certain sensor-cable is not in stock, the sensor should be installed, only it cannot be properly connected and tested. The stockout, therefore, entails that the missing SKU(s) are assembled onto the handling system at a later date in production or that more ad hoc solutions are required. The latter could be, to take the missing SKUs from finished end-products which have a late due date or, let a field engineer deliver and install the missing SKUs on-site during commissioning. All the mentioned consequences increase the overall cost.

The motivation for this research therefore is to *"research and design a solution to prevent or reduce the impact of stockout occasions of components on the production processes at VPM-1"*.

1.3 Problem statement and research objective

From the problem description the following problem statement has been defined:

"The current way of ordering and managing inventory is insufficient to prevent the unavailability of SKUs for POs due to stockout occasions. The unavailability results in 'firefighting' for the office and production staff and the inflexibility of the production planning. Which in-turn increases the overall cost of production."

At VPM-1 it is felt that backordering of SKUs due to stockouts can be mitigated by improving the inventory management. As poor inventory management may be the reason why SKUs are not ordered on time. Or that there is no anticipation for unforeseen events like: extensions on delivery lead time from suppliers or unplanned consumption of stock. These causes lead to unexpected stock usage, which lead to stockout of SKUs in inventory. By improving inventory management it is also possible to increase the flexibility of the production planning. By being able to deliver SKUs from inventory to production in a shorter time. Thus, also being able to decrease the overall manufacturing LT of the POs.

The research objective, which has been demarcated from the problem statement, the likely core problems and expected solution directions, is the following:

"Research and propose a solution to reduce the stockout occasions of SKUs, such that the flow of production orders is not impeded. This by gaining knowledge in inventory management techniques and researching if and how they can be used to improve the current inventory management of VPM-1."

The likely causes of the unavailability of SKUs have been accumulated in a problem cluster, see *Appendix A.2*, which was constructed by consulting the buyer and the planner of VPM-1. The causes are "likely", as the backorders due to stockout occasions have not been quantified, as of yet. Thus further investigation is required. The four likely causes are:

1. Short term, unplanned, consumption of stock
2. The inventory level is insufficient to cover demand due to suppliers.
3. The inventory level is insufficient to cover demand due to the lack of inventory control policies
4. The inventory level is insufficient to cover demand due to the required quantity of SKUs not being ordered on time.

The likely causes and possible solution directions are further elaborated in the following sub-sections and will be investigated in *Chapter 2.*

1.3.1 Likely causes to the stockout of SKU(s)

The first likely cause of a stockout is the *short term, unplanned, consumption of stock*. This refers to SKUs that are taken from stock to be used as spare parts in the field, and SKUs that are taken from stock due to an incorrect BOM of a current PO. VSM have a warehouse for stocking spare parts that are required frequently in the field, however, they cannot stock all SKUs. To avoid multiple stock locations for one SKU, the policy at VSM for spare parts is to stock and consume spare parts in and from the warehouse of the main consumer, i.e. VPM-1. A reservation for spare parts is often made in the form of safety stock.

The second cause is that the *inventory level is insufficient to cover demand due to suppliers* either delivering an insufficient quantity or delivering the SKUs late.

The third cause is that the *inventory level is insufficient to cover demand due to the lack of inventory control policies* to ensure that SKUs are ordered timely to cover the lead time of a replenishment, also known as supply lead time (SLT). No SKUs have a set reorder point and only a small percentage have a defined safety stock level. Moreover, the current way of ordering and purchasing SKUs is more demand-driven than inventory driven.

The fourth likely cause is that the *inventory level is insufficient to cover demand due to the required quantity of SKUs not being ordered on time*. The two main sub-causes for stockout due to this project planning issue are: (1) the POs are filled too late by project engineering, giving VPM-1 insufficient lead time to order and receive SKUs and produce the POs. And (2) the sequence in which POs are filled. The following situation is meant (see *Figure 1.3* for a conceptualization), in which order A is filled a week before a similar order B, however, order B has a due date one week earlier than order A. The buyer will order SKUs at suppliers with a delivery time and quantity that is in accordance with the production of order A. However, once order B is filled, the SKUs ordered for order A are now taken over by order B, which in the case the previous order date does not suffice this must be brought forward in time and possibly the quantity must be increased. This may result in a stockout of SKUs for either order.

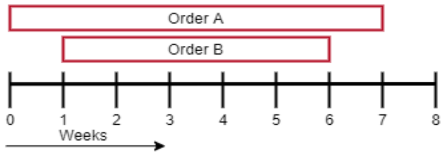

Figure 1.3: Conceptualisation of 'sequence of filling POs'

1.3.2 Solution directions

As mentioned, VPM-1 feels that backordering of SKUs due to stockouts can be mitigated by improving the inventory management. Within inventory management there are two solution directions which are thought to improve the current situation:

- Research and improve the *demand planning* of the SKUs
- Research and improve the *inventory control policies* of the SKUs

Figure 1.4 shows a conceptualisation of the demand planning, depicting what possible information is known about a SKU during a certain time horizon. Green shows the confirmed demand and red shows the stochastic demand, which could be based on information other than that of the filled POs. Before a PO is filled, an initial design is sent to a customer. This design already includes an indication of what handling systems are required. This information could be an input for the stochastic demand. Based on historic data one might be able to determine a bandwidth for certain components in which they are used.

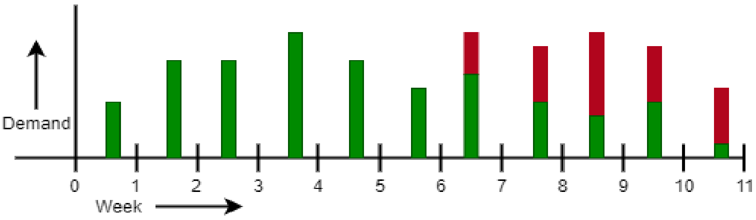

Figure 1.4: Conceptualisation of the demand planning for an SKU during a horizon of 11 weeks. In green the known demand and in red the stochastic (unknown) demand.

Another solution direction is to improve the current inventory control policies. To design a model which can determine a fitting policy for each SKU and find their safety stock levels and reorder points to obtain a certain fill rate while minimizing total inventory cost.

1.4 Research questions

Following from the research objective in the previous section, the following main research question is defined:

"How can the inventory management of SKUs at VPM-1 be improved, to reduce the frequency of stockout occasions in production?"

The research objective and main research question are an action problem. To streamline this research and solve the action problem the Managerial Problem-Solving Method (MPSM) is applied. The MPSM is a systematic approach to solve action problems (Heerkens & van Winden, 2016). MPSM consists of seven phases, of which the first phase, 'defining the problem', has been discussed in the previous two sections. The second phase is to formulate the approach to the problem, which will be dealt with in this section by structuring the sub-research questions according to the remaining six phases. First the research question for that phase is presented followed by the research design and sub-questions.

Phase 1: Current situation

Question 1 What is the current situation, regarding inventory management of the SKUs and what are the causes of the stockout of SKUs?

The goal of the first phase is to obtain a detailed insight into the current situation at VPM-1. As concluded from *Section 1.3* the main causes of the unavailability of SKUs require further investigation. For an insight into the current situation, the SKUs to base this research on need to be demarcated. This by, investigating the production-inventory model currently used by VPM-1 and extracting data from SAP relating to when certain SKUs are required in the production processes. Subsequently, the inventory should be characterised and the unavailability of SKUs investigated. Next, the current demand planning needs to be researched to determine at what point demand for the SKUs is known and find what the SLTs of the SKUs are. *Chapter 2* will provide the answer to Question 1 and the following sub-questions:

a. What is the current production-inventory model used by VPM-1?
b. What are the current inventory control policies that are in-place?
c. What is the current demand planning of the SKUs in inventory?
d. What are the supply lead times of the SKUs and are these accurate?
e. Which SKUs could be procured on-order?
f. What are the causes of the backordering and stockout occasions?

Phase 2: Literature research

Question 2 What inventory management methods are proposed in the literature, that suit the situation at VPM-1, with which the backordering of SKUs can be reduced?

In the second phase, literature research needs to be performed to find applicable theory which can be used to design and build a solution that reduces the backordering of the SKUs. The phase starts by finding inventory management theory that best suits the production system at VPM-1. Subsequently, classification methods should be researched that can be used to divide the large number of SKUs into groups, based on their characteristics, which can then be more easily controlled. Lastly, the available inventory control policies need to be researched in the literature and how the corresponding parameters should be determined. *Chapter 3* will provide the answer to Question 2 and the following sub-questions:

a. What inventory management theory found in literature can be applied to the production system of VPM-1?
b. What classification methods are available in the literature, to control the SKUs?
c. What inventory control policies are available in the literature and how should the parameters be determined?

Phase 3: Solution design

Question 3 What inventory management methods are most applicable for the SKUs and what should the design of the inventory management tool be?

In phase 3 an inventory management tool needs to be designed that, based on input variables, can determine for each SKU what inventory control policies are most suitable and can calculate the corresponding policy parameters. The phase starts by deciding on the classification method and classifying the large number of SKUs that were demarcated in *Chapter 2*. Thereafter, a decision needs to be made which control policies suit the classifications best. Lastly, an overview should be created that shows how the policy parameters are determined and with what data. *Chapter 4* will provide the answer to Question 3 and the following sub-questions:

a. How should the SKUs, identified in *Chapter 2*, be classified?
b. What inventory control policies are suitable for each classification?
c. How should the parameters of the chosen policies be determined?

Phase 4: Analysis of results

Question 4 What is the performance of the inventory when applying the proposed inventory management tool?

The proposed inventory management tool and the ensuing inventory control policies have to be tested to investigate what the performance of the inventory is compared to the current situation. To do this a simulation study will need to be performed. The phase should start by determining the inventory control policies using the proposed tool, inputting settings which compare to the current state. Thereafter, the simulation study needs to be checked if the results are reasonable. Lastly, a sensitivity analysis should be performed, in which the input settings are altered, to investigate how robust the solution of the proposed tool is. *Chapter 5* will provide the answer to Question 3 and the following sub-questions:

a. How can the performance of the proposed inventory management tool be best simulated?
b. Are the results from the simulation study valid and verifiable?
c. What is the performance of the inventory using the proposed inventory management tool in comparison with the current inventory performance?
d. How robust is the proposed tool to discrepancies in input settings and relaxations of constraints?

Phase 5: Implementation plan

Question 5 How can the proposed inventory management tool be implemented into practice?

In this phase, discussed in *Chapter 6*, an implementation plan needs to be created that describes how to implement the proposed inventory management tool into the current systems in use at VPM-1.

Phase 6: Conclusion and recommendations

In *Chapter 7* the last phase of this research is discussed. In this phase, the conclusion of the research is provided and recommendations are made for the improvement of processes and the current research. Moreover, suggestions are made for future research areas, to further improve the inventory management at VPM-1. The chapter is concluded with a discussion of the results.

1.5 Research scope

The research is limited to the logistical flow of the SKUs, used to produce the handling systems, that are entering and exiting the warehouse at VPM-1. To ensure that the research can be conducted within the limited time, the following additional boundaries are set:

- Only SKUs stored in the warehouse of VPM-1 are considered. There are larger inventories of SKUs at some suppliers but the assumption is made that they can always deliver from stock when an order is placed.
- The procurement procedure is not part of the research.
- The consumption of stock due to incomplete/incorrect BOMs are researched, however an improvement of the BOMs or the BOM generation procedure is not part of this research.

1.6 Deliverables

This project will research and develop a (prototype) inventory management tool following from the solution design, which can help reduce the stockout occasions and backordering of SKUs. Furthermore, it will deliver a proposal to implement the (prototype) inventory management tool into practise.

2 Current situation

This chapter describes all relevant information, to provide a clear insight into the current situation at VPM-1 and investigates the causes for the backordering of SKUs due to stockout occasions. This chapter will conclude by providing an answer to the first research question: *"What is the current situation, regarding inventory management of the SKUs and what are the causes of the stockout of SKUs?"*. The chapter starts by analysing the current production-inventory processes. Thereafter, in *Section 2.2* the inventory of SKUs is analysed and characterized. Subsequently, the demand and supply side are discussed. *Section 2.5* analyses the confrontation between the demand and supply side, to identify potential critical SKUs.

2.1 Current production-inventory processes

As mentioned in *Section 1.1,* VPM-1 produces three types of handling modules, namely: the Roller Conveyor (RC), the Cross Transport (CT) and the Cutting Table. The first two systems can be used in conjunction with one another to create an integrated production line that is capable of transporting the steel beams past multiple beam-processing machines. The Cutting Tables are used in the plate cutting and drilling machines that VSM manufactures. VSM uses standardised components to design and build their handling modules. Similar modules share roughly 90%-95% of their components. To create a tailor-made solution for their customers, using for instance Multi System Integration, VSM requires a high level of flexibility and configurability of the handling modules for the solution to fit into the customer's facility. To enable this, VSM has designed approximately 226 variations of the RC, 28 variations of the CT and 18 variations of the Cutting Tables. *Appendix A.3* provides more details pertaining to the configurability of the handling systems.

An overview of the production processes for the RCs and CTs can be found in *Figure 2.1*. The ATO-processes are shown in a bolder red than the production processes for the internally produced components. The ATO-flow is used to manufacture the modules and the other flow is used to produce the sub-weldments and sub-assemblies to stock, which are standardised and common in many modules.

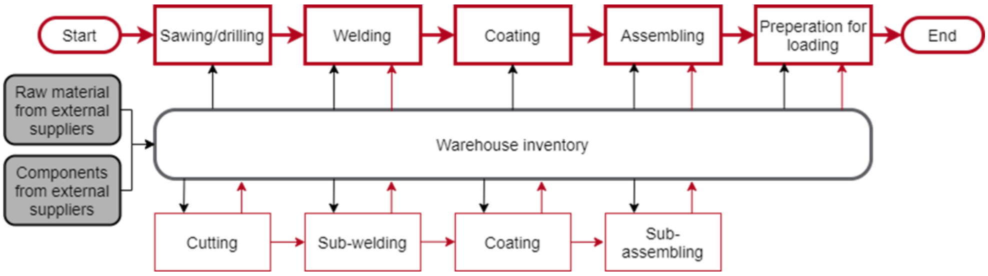

Figure 2.1: Flow diagram of production processes at VPM-1 for RC and CTs. ATO-flow is shown in bold compared to flow for internally produced components.

In the case of the Cutting Tables most of the SKUs are procured on-order from external suppliers, as they are voluminous. At VPM-1 they are then welded together, coated and assembled.

2.2 SKUs in inventory at VPM-1

In this section, the inventory is described. Starting with a general demarcation of which SKUs are in and out of scope. Subsequently, the remaining inventory is characterized and the current inventory control strategies are elaborated. The section finishes with some in-depth analyses of the inventory to indicate and describe the backordering and stockout.

2.2.1 General demarcation of SKUs in inventory

There are three types of inventory; (1) the raw materials, which are materials and components which are consumed in the production of the modules and in the production of the internally produced components. This type includes the supplier-bought materials and components and internally produced components which are later consumed in modules; (2) the semi-finished products, which are the work-in-progress (WIP). For instance, beams cut to length, waiting to be welded or welded frames waiting to be coated; (3) the end products, the finished modules. These are modules which have been completed and are ready to be shipped and delivered to the customer. Since the goal of this project is to reduce the unavailability of production stock, the research will solely focus on the first type of inventory.

The inventory that is focussed on during this project contains supplier-bought components and materials and internally produced components manufactured at VPM-1. In total there are 994 different SKUs which can be kept in stock and are required in the production of the RCs, CTs and Cutting Tables. This list of SKUs was accumulated by a detailed examination of all the module BOMs. The total value of the annual average stock for the past five years is illustrated in *Figure 2.2*. The values are determined by multiplying the cost price of the materials with the average inventory level of the SKUs.

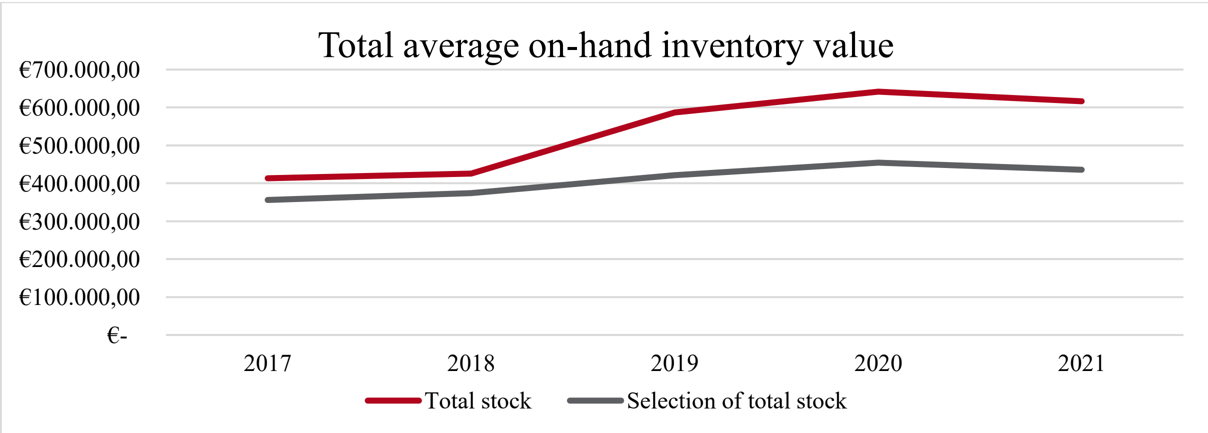

Figure 2.2: Total value of the annual average stock. In red the value of the 994 SKUs from the module BOMs and in grey the selection after the demarcation in Section 2.2.2.

Of the 994 SKUs, 162 are vendor managed inventory (VMI), where a certain supplier assumes responsibility for determining replenishment quantities for its customers (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017, p. 548). Due to this fact, these SKUs will be left out of scope for this project. The current replenishment strategy for these SKUs is two-bin. The components are mainly floor stock, e.g. nuts and bolts, and some more simple turning and milling components. Stockout of inventory is reviewed in a continuous improvement loop between VPM-1 and the supplier. The total average stock value, for 2021, for these SKUs, is €76.578, which is roughly 12,8 % of the total value for 2021.

The BOMs of the Cutting Table modules contain 27 sub-weldments and sub-assemblies, which in SAP are regarded as components which can be produced to stock. However, in practice, these SKUs, due to their volume, are always manufactured in accordance with a PO. Thus, in this research, these sub-weldments and sub-assemblies are seen as WIP, and cannot be stored in inventory. Their underlying components are now seen as SKUs which can be kept in inventory to fulfil POs for the modules, and are therefore in-scope.

To prevent overcomplication of the eventual solution design, due to a multi-level inventory problem, the following important assumption is made: *supplier-bought components which are consumed to produce internally produced components are left out of scope for this project. The assumption is that there is always sufficient stock to produce these components.* The idea of a multi-level inventory problem is that demand for the supplier-bought components which are consumed in the internally produced components stems from the demand for internally produced components in the production of the handling modules. In the instance where we ignore the stock required for the internally produced components, we have the situation in which internally produced components can be regarded, from the inventory point of view, as supplier-bought components, with VPM-1 as supplier. The time required for planning, purchasing and production of the internally produced components is compacted in the SLT. Moreover, the issue of stockout has more direct consequences for the production of modules, compared to the production of internally produced components.

Figure 2.3 shows a simple overview of the remaining inventory. Red shows the out-of-scope inventory and green shows the demarcated inventory, which supplies SKUs to the main production process. The green components will be further characterized in the following section.

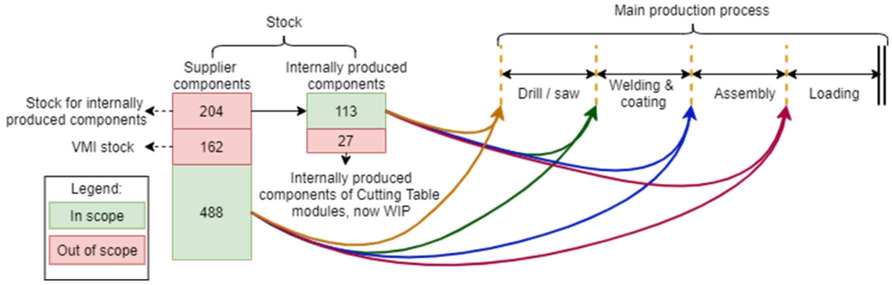

Figure 2.3: Overview of inventory at VPM-1 and the production process that the inventory supplies

2.2.2 General characterisation of SKUs in inventory

Following the demarcation, 601 SKUs remain. *Figure 2.2* illustrates, in grey, the total value of the annual average stock of the selection. The value of this selection in 2020 and 2021 is approximately 75% of that before the demarcation. A large contributing factor to this difference is the omission of the VMI.

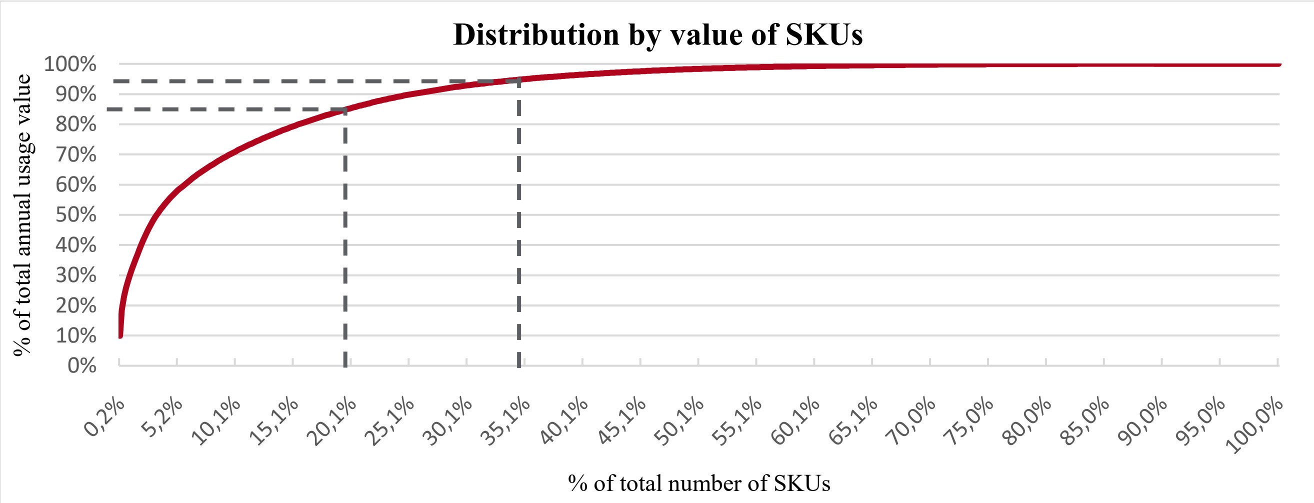

Figure 2.4: Distribution by value of SKUs for 2021

Distribution by value

Figure 2.4 shows the distribution by value (DBV) of the inventory, for 2021. According to Silver et al. (2017, p. 29), the DBV analysis is a useful tool to get an insight into the performance of the inventory and the most important SKUs. The total usage value of these SKUs, in 2021, was €5.815.000. Roughly 20% of the SKUs account for 85% of the total annual usage value in the inventory, these are the fast movers. Furthermore, 35% of the SKUs account for 95%. The remaining 65% are slow movers with more infrequent demand. The last 10,5% of SKUs have not had demand over the last year. Of these components, some have been moved to another warehouse, and are no longer stored at VPM-1. Others are possible customer-specific components which have not yet had any demand.

Inexpensive SKUs

In the selection, there are also roughly 25 comparatively inexpensive SKUs (<€2 per unit), with each an annual demand of over 500 units. The usage value of 2021 for these SKUs was €50.360, which is 0,9% of the total usage value. For these SKUs, a large amount of stock could easily be stored. To prevent backordering on such inexpensive SKUs it would therefore be beneficial to apply a simple solution in which larger quantities of these SKUs are ordered and stocked. As more advanced methods would likely not be more effective.

SKUs purchased on-order
96 of the SKUs, used in the production of Cutting Tables, are voluminous. For this reason, these SKUs are purchased on-order from their suppliers. The total usage value in 2021 for these SKUs was €465.955, which is 8% of the total. 91 of these SKUs are procured from the same supplier. They deliver the cutting plates and folded plates, required in the welding stage, and the covers required in assembly. By purchasing these SKUs on-order, the minimum LT that VPM-1 can communicate with its customers is highly dependent on the SLT of the supplier.

Ordering requirements
In the selection of inventory there are SKUs which have one of three ordering requirements, as shown in *Table 2.1*; (1) a *Minimum Ordering Quantity* (MOQ), imposing that the amount of units ordered has to be at least a certain quantity (Park & Klabjan, 2014). (2) *a Fixed Order Quantity* (FOQ), imposing that the amount of units ordered is a fixed amount. This requirement is mainly placed on the internally produced components such as sub-weldments and sub-assemblies, for which the amount is often determined based on the experience and intuition of the production engineer and planner. Producing more than the FOQ may decrease the quality of the components. (3) placing a rounding value, also known as an *Incremental Order Quantity* (IOQ), on a SKU, imposing that the amount of units ordered is a multiple of that value. There are 22 SKUs in the selection which have both a MOQ and an IOQ in place. Based on this initial analysis there are a few recommendations made in *Appendix A.4* for the ordering requirements.

Table 2.1: # SKUs per ordering requirement

	#SKUs
Minimum Order Quantity (MOQ)	59
Fixed Order Quantity (FOQ)	42
Incremental Order Quantity (IOQ)	205

Current inventory control policies
The main replenishment strategy used is a demand strategy, also known as MRP-driven ordering: replenishments are based on known demand (reservations), reordering what is needed to fill POs, taking into account ordering requirements. Currently, there are lot-sizing procedures implemented in SAP to manage inventory, however, these have not been maintained and are therefore often ignored by the buyer. These policies were implemented years ago based on the experience and intuition of a tactical buyer and have never been updated or reviewed since. The two mainly implemented lot-sizing procedures are: (1) bi-weekly lot-sizing, compounding the known demand of two weeks and (2) lot-for-lot, ordering the net requirements pertaining to each period. Both lot-sizing procedures take into account the SLT. Based on these lot-sizing procedures SAP generates purchase order recommendations to the buyer as to when future replenishment orders need to be placed to cover demand, however, these do require extensive review by the buyer to ensure replenishment orders are placed on time. Moreover, to reduce the number of purchase orders the buyer will, based on his experience, compound some of the recommended purchase orders to one purchase order or increase the replenishment quantity if that generates a quantity discount.

Due to the method of working mentioned above, VPM-1 opted not to use reorder points for any of the SKUs. When the demand horizon is long enough, with 100% certainty that no changes in demand will occur, this would not be an issue. However, if unexpected changes in planning do occur, this could entail that the current on-hand inventory (OHI), and inventory on-order, are not sufficient to cover demand. For 90 SKUs (14,9%) in the selection, there are safety stocks in place, for which the level was determined based on the experience and intuition of the buyer and planner once a SKU stocked out frequently or when the SLTs from suppliers were uncertain. For 305 of the components (roughly 51%) there is a safety LT of one week in place. Thus, the delivery date for these SKUs is set to at least one week before they are required in production.

2.2.3 In-depth analyses of the inventory and stockout

In this sub-section, some in-depth analyses are performed which further characterise the inventory and give an indication as to the current state, regarding the backordering and stockout of SKUs. Stockout of SKUs is a phenomenon that is known to occur relatively frequently at VPM-1. It is however not possible to give a detailed analysis of the frequency of stockout occasions or the number of backordered SKUs over a longer period of time, as these occasions have not been monitored. On 11-10-2021 a tool was introduced at the warehouse, with which the employee notifies missing materials when picking SKUs from inventory for a PO. The results, thus far, are discussed in this sub-section. However, the monitoring will need to be performed over a longer period of time to give a more definitive conclusion.

Cost of backordering

In *Appendix A.5.1* the approximate labour cost of backordering a SKU has been analysed. Based on a practical example and input from stakeholders a formula for the labour costing was determined, see *eq. 1*. The formula is comprised of a fixed labour cost per stockout occasion and a variable labour cost per backordered SKU. X being the number of stockout occasions and Y the number of backordered SKUs. The costs are also dependent on two scenarios. *Appendix A.5.1* shows the breakdown of these costs. The first scenario applies if the SKUs arrive before the due date of the PO and the second scenario applies if the SKUs need to be delivered to the customer and installed by a field engineer. In the last instance, the cost of backordering the SKU should also include the transportation cost of the SKU to the customer. However, as VSM's customers are situated worldwide the transportation costs are heavily dependent on distance, SKU geometry and weight. For this reason, these costs have been omitted. The expectation is that scenario 1 occurs 75% of the time and scenario 2 occurs 25% of the time. The costs will likely differ when measured in reality, but an advantage is that it gives the manager an idea of which components have large potential backorder costs (due to frequent stockout occasions and/or many backordered units).

$$Labour\ cost\ due\ to\ backordering = €145 * X + €38{,}75 * Y \qquad 1$$

Monitoring of backorders

Table 2.2 shows the results of the backorder monitoring between 11-10-2021 and 06-04-2022. In the period, 57 out of 197 POs were missing SKUs when inventory was being picked for the production of the modules. Thus the occurrence of a PO missing materials was roughly once every three POs. The table also shows the total number of units required of the SKUs for that period. Using this, the individual fill rates can be determined. For 8 of the SKUs, the fill rate is below 90%. As the monitoring is performed over a small period, it is likely that for some SKUs there was only one stockout occasion where multiple POs have backordered. Moreover, the monitoring has been performed over a rather exceptional period, in which many POs were postponed, due to current world events, lengthening the time the suppliers have to deliver the SKUs. This does entail that the validity of the results compared to a more stable period could be put into question. As mentioned previously, it would be useful for VPM-1 to perform the monitoring over a longer period to get an insight into the frequency and impact of the backordering. Moreover, the data might show more patterns towards reoccurring backordering of certain SKUs, indicating the inventory control policies need improvement.

Table 2.2: Current results of monitoring backorders (11-10-2021 to 06-04-2022)

SKU	# POs	Total units back-ordered	Total units required	Fill rate
000-2960	1	5	321	98%
000-4720	10	18	70	74%
003-3917	3	9	17	47%
004-9811	1	1	3	67%
005-1909	12	62	100	38%
005-5921	14	67	414	84%
006-7818	6	36	468	92%
006-7821	1	1	25	96%
007-7952	1	14	250	94%
008-2763	2	2	56	96%
008-4040	6	12	414	97%
008-4812	4	6	50	88%
009-0606	3	6	17	65%
009-0974	3	5	13	62%
Total	**67**	**244**	**2218**	**89%**

Inventory turnover rate and inventory coverage

According to Silver, Pyke and Thomas (2017) useful analyses to review the inventory is the inventory turnover rate (ITR) and the inventory coverage. These analyses can be found in *Appendix A.5.2* and *Appendix A.5.3*. ITR is a primary aggregate performance indicator for inventory management measuring the average time between stock being bought and it being consumed. The higher the inventory turnover, the faster a company is replacing their stock and the less financial resources they have tied up in inventory. However, the flip side to this is when the turnover rate is too high, this can lead to stockouts and create massive and expensive expediting (Silver, Pyke, & Thomas, 2017, p. 10). *Table 2.3* shows the ITR for the last five years, for the SKUs in the selection. When comparing this to the manufacturing industry of commercial machinery, in the U.S., the turnover rate is high. The industry median is an ITR of 3,8 (ReadyRatios, 2021). This could be an indicator as to why stockouts occur at VPM-1. The 10% of SKUs with the highest turnover rates are internally produced components with a high annual usage and some supplier-bought components which are commonly used in POs, such as beams and geared motors. In the case where VPM-1 would consider an ITR > 10 to be too high, then 40,2% of SKUs would have a high likelihood of frequent stockouts. By increasing inventory levels for the SKUs the ITR would decrease, which by extension would decrease the frequency of stockout occasions.

Table 2.3: Inventory turnover rate, shown annually

Year	Inventory turnover rate	Inventory turnover (weeks)
2017	7,46	6,99
2018	14,06	3,71
2019	10,79	4,83
2020	11,74	4,44
2021	14,40	3,62

Inventory coverage analyses the expected time till the current stock level is depleted. This could be used as an indicator to find imbalances in stock, knowing which SKUs have a high OHI and a low usage, indicating excess or even dead stock (Silver, Pyke, & Thomas, 2017, p. 366). The analysis, however interesting, did not lead to any conclusive findings relating to the backordering or stockouts of SKUs. The analysis shows some imbalance in the coverage between SKUs. Roughly 15% of SKUs have a coverage of 1 year or more and an equal amount have a coverage of 3 weeks or less. Overall, the inventory seems to have a healthy coverage with the median being 5,2 weeks.

Ready Rate

The ready rate of a SKU is the fraction of time that OHI is strictly positive (Silver, Pyke, & Thomas, 2017, p. 249). Furthermore, the ready rate is equal to the fill rate in inventory systems with set reorder points and fixed optimal order quantities, where demand is normally distributed and backlogging is possible (Axsäter, 2006, p. 99). Although the assumption may not apply exactly to the current situation, it will give a good approximation of the current fill rate for the SKUs.

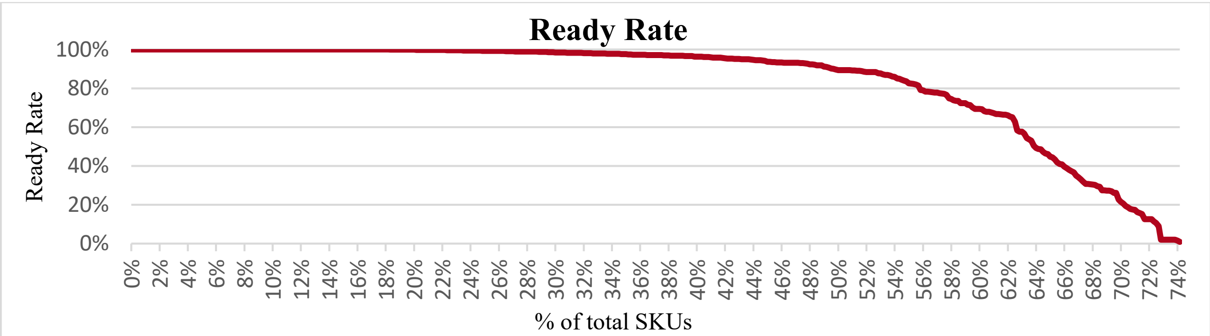

Figure 2.5: Ready rate of SKUs over the period 2020-2021.

Figure 2.5 shows the ready rate of the SKUs. The analysis uses inventory level data of 2020 and 2021. For the analysis, roughly 25% of SKUs have been removed as their data gave inaccurate ready rates. Details about the analysis and the exclusions that were made can be found in *Appendix A.5.4*.

18,3% of the SKUs have a 100% ready rate over their respective time periods. These SKUs have not stocked-out and can fill POs immediately from stock. However, 2,7% of these SKUs have not had any demand over the two years, indicating dead stock. Furthermore, the analysis shows that 43,3% of the SKUs have a ready rate larger than 95%. The graph displays a remarkable tail of SKUs with really low ready rates. Which can be an indication that SKUs backordering due to stock-out is a more frequent occurrence. Further analysis of these SKUs with a ready rate lower than 75%, shows that these are components with infrequent demand, for which it seems that demand is predicable for the buyer. As a pattern can be discerned where SKUs are only in stock for a limited amount of time before being consumed, thus bringing the stock-level back to zero. This is due to the available demand lead time. Compared to retail inventories, where demand is unknown until it has been consumed. In the case of VPM-1 demand for SKUs in inventory is dependent on module demand, which is known further in advance. In the following section this demand side is further analysed.

Conclusion of in-depth analysis

The results from the analyses do indicate the "gut feeling", that VPM-1 have about stockout and backordering of SKUs, to be correct. From the analyses, seeing that the inventory turnover rates are very high and the ready rate for more than roughly 57% of SKUs is lower than 95%, one could conclude that phenomenon of frequent backorders due to stockouts should be common and that the inventory being researched is in need of improvement. As this is true, there are some simple explanations as to why the values are so extreme. Due to long periods of available demand data (see *Section 2.3*) and the use MRP-driven ordering the buyer knows for many SKUs far enough ahead of time what the inventory level is supposed to be. Thus for these SKUs it would make sense that they could have an average inventory level near zero, the buyer can procure these components on-order. In *Section 2.5* the demand lead times and supply lead times are analysed to find the SKUs which should be procured on-order and which should be procured based on an inventory control policies. The expectation is that there are only a few SKUs which disrupts the production process due to backordering and by improving the inventory management based on the available demand data that backordering of these SKUs will be largely reduced.

2.3 Demand side

The section describes the demand side of the SKUs, which is derived from the demand for handling modules. When planning production and agreeing on LTs with suppliers and customers, VPM-1 prefer to work with *time buckets of a week*. This way slight changes in planning and delays, do not completely upset the production planning. Moreover, planning on a day to day level would require more planning capacity. The section starts by discussing the timeline of a customer project. Subsequently, the current demand planning is outlined, describing how and when demand is currently known. Furthermore, the unexpected and intermittent demand for the SKUs is analysed. And lastly, the demand in the preliminary stages is described.

2.3.1 Customer order lead time

Figure 2.6 shows a schematic overview in which the build-up of lead time for a customer order is outlined. VSM takes this into account when planning customer projects that include handling systems. As illustrated, projects that exclusively use Cutting Tables have a shorter LT, as the preliminary stage (marked in grey in *Figure 2.6)* is less complex. *Section 2.3.5* describes the preliminary stage in more detail. *Appendix A.1* gives a more detailed description of this demand process for the SKUs.

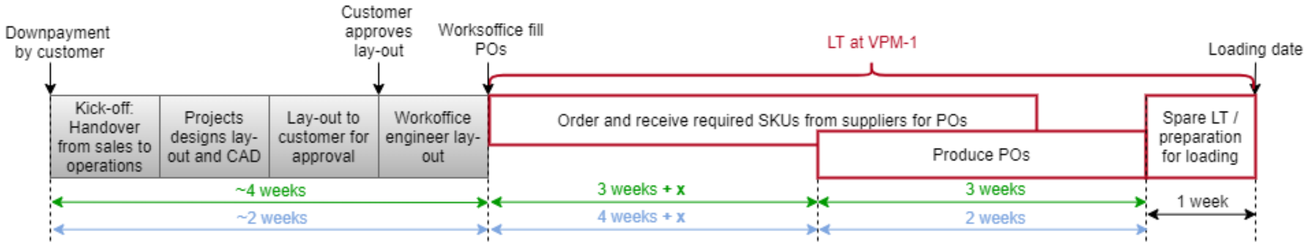

Figure 2.6: Schematic overview showing the build-up of the minimal LT VSM takes into account when planning customer projects with handling systems. In green the LT for projects including CT and RC modules and blue for projects exclusively using Cutting Tables.

The "loading date" is the (final) due date of a PO. It is the date on which the handling modules are loaded into the shipping containers. The minimal LT for a customer project with CTs and RCs is 11 weeks. However, often this is longer and can be between *11 to 20 weeks,* after downpayment. This is dependent on when the customer would like to receive their production line and what is possible in terms of resource availability. Thus, the total LT of customer projects can be highly variable. In *Figure 2.7* this lead time variability is illustrated.

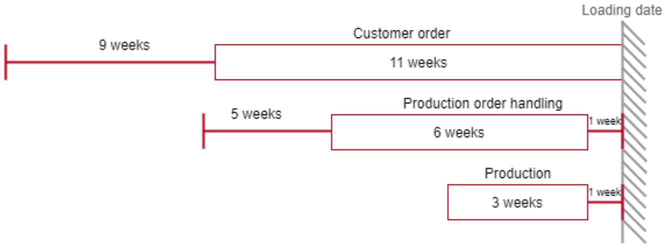

Figure 2.7: Schematic overview of the project LT variability used at VSM

The planner of VPM-1 plans production of the handling modules based on the loading date of the PO, due to this the *3 to 4 weeks* required for production, are at the end of the total LT. The minimal LT that VPM-1 requests from the central planner is *6 weeks*. However, the LT that VPM-1 is given can be highly variable, some POs are filled *8 to 10 weeks* before the loading date and some only *5 to 6 weeks*. When a PO is filled further in advance than the 7 weeks before loading, shown in *Figure 2.6*, this extra LT is "x", giving the buyer more time to order and receive SKUs. The weeks before and the moment of filling the POs will be further discussed in the following sections. The division of the LT at VPM-1, for the production of the handling modules, is given in *Section 2.3.4*.

2.3.2 Current demand planning

In the current situation, planned demand for the SKUs only arises once the POs for the modules are filled in SAP by Worksoffice, and the POs are planned into production by the planner of VPM-1. In the customer project timeline, this would be the fourth week, see *Figure 2.6*. At this point, planned demand *is 100% certain* and all the required SKUs are known. However, the final due date (loading date) *may not* be certain. There are occurrences where the customer's plant is not ready for installation of the production line on the agreed-upon date. Customers then ask for the loading date to be postponed. In this case, the planner has two options: (1) produce the handling for the system on the planned production dates and have the finished modules sit and take up space in the warehouse for the duration of the delay, or (2) move the production dates into the future, provided that production has not begun.

In the case of option 2, roughly 4 to 6 weeks before the loading date, the following situation occurs: at this point, the procurement of SKUs for that PO should have already been started or even completed. As the stock is anonymised the SKUs can be used by any PO. Moving the POs of the project into the future creates a gap in the production planning. To balance the resource utilization other POs are brought forward in time. The POs that are brought forward in time will consume the inventory that was originally intended for the POs that are moved into the future. However, if the POs that are moved forward in time have more demand for SKUs than the previous POs, then a stockout might occur for those POs. *Figure 2.8* visualises this situation. Order 2's loading date has been pushed back 2 weeks. This creates a gap in the production planning. To fill this, orders 3 and 4 are both moved up 1 week. Order 3 might now be consuming components which were initially procured for order 2. During the sensitivity analysis, the effect of this situation can be analysed by adding a one week safety lead time to the SKUs to prevent or reduce stocking out due to this situation. Moreover, by applying this one week safety lead time the flexibility of the planning will increase.

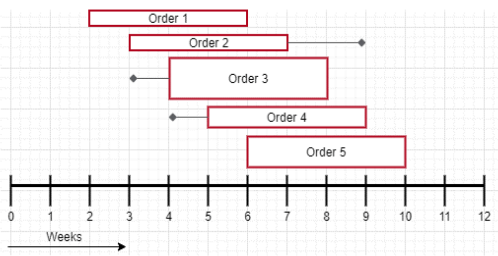

Figure 2.8: Conceptualisation of moving POs over the time horizon.

In addition to the slight uncertainty of the due date, the sequentiality of the POs being filled is not constant. When only taking the fill date of the POs as the only time demand for SKUs is known, it could be that demand "popsup" out of seemingly nowhere. However, the project has already been taken into account in the production planning, but demand for the SKUs only occurs when the project is filled into SAP. *Section 1.3.2* and *Figure 1.3* conceptualise this situation. The result is that stockout might occur if the SKUs procured for order A cannot cover order B. Or that after order B consumes SKUs, there is insufficient stock for order A.

According to the planner, a production planning with a time horizon of *7 weeks* can be assumed to be fixed. Past the 7 weeks, this is more prone to change due to the abovementioned situations (Schreurs, Personal communication - production planning horizon, 2021).

Lastly, demand for handling modules is, to a certain extent, known further in advance within VSM. As can be seen in *Figure 2.6*, there is a period between downpayment and the filling of POs for the handling modules, the "preliminary stage". For customer projects with RCs and CTs this stage is roughly four weeks. And two weeks for projects exclusively using Cutting Tables. In some instances, there are customer projects which contain uncommon and expensive modules with SKUs that have longer SLTs. In these instances, the project leader or central planner will signal VPM-1, after the kick-off, that these modules are coming and the SKUs should be ordered. Moreover, when customer projects are kicked-off the planner of VPM-1 will use the sales layout to estimate the required resource capacity and reserve this time in the production planning. *Section 2.3.4* investigates the extent to what is known about the handling modules in the preliminary stage..

2.3.3 Unexpected demand

Besides the *planned demand*, discussed in the previous sub-section, some of the SKUs do experience *unexpected demand*, which is taken out of stock on short notice. This demand has two causes, namely: (1) incomplete BOMs of the handling modules (mainly CTs) and (2) service and spare parts. Combining the fact that in the current situation most SKUs in the inventory are reserved for a certain PO, this could mean that unexpected consumption of the stock would result in future POs missing SKUs if no intervention occurs. For most of the SKUs in the selection no safety stocks have been determined to be able to handle this unexpected demand. And for the few SKUs which do have safety stocks, these may potentially be insufficient to cover the volume of unexpected demand. In *Appendix A.6.1* the detailed analysis can be found. In total 70 (11,6%) of the SKUs in the selection had unexpected demand, totalling 226 unexpected demand occurrences in 2021. 61,9% was due to incomplete BOMs and 38,1% due to service and spare parts. The usage value of 2021 for this demand was €42.709, which is 0,73% of the total usage value. Of the available data, only 36 SKUs had reoccurring unexpected demand. Thus, potential stockouts due to unexpected demand only apply to a small percentage of SKUs. For these SKUs, it would be beneficial to take the unexpected demand into account in the safety stock levels.

2.3.4 Intermittent demand

As mentioned in *Section 2.2.3*, it seems that there are several SKUs with intermittent demand. This could be a relevant characteristic when wanting to model inventory policies for these SKUs. In *Appendix A.6.2* the average time between demand occasions for the SKUs is analysed. 133 SKUs have rather intermittent demand. The demand is deemed intermittent if the average time between demand occasions is larger than 5 weeks. The data also shows that for most of these SKUs the demand sizes, when they occur, are non-unit sized.

2.3.5 Routing of SKUs in production

Figure 2.9 shows the current routing of SKUs in production. The figure shows the number of SKUs which are required at the various production stages in the production flow for the CT and RC and the Cutting Tables. The figure can be used to determine the demand lead time (DLT) of SKUs. The DLT is dependent on the due dates of the production stages, which in-turn are dependent on the loading date of a PO. The variability of the LT for VPM-1 is shown in the first part of the LT, with a time "x". If $x = 0$, then you have the minimum LT that VPM-1 requests from VSM. When taking the PO fill date as the only trigger for purchasing, as is currently done, it would mean for example that for components required for "Drill / Sawing" the order time is $3 + x$ and for "Final

Assembling CT & RC" the order time is $5 + x$. In *Section 2.4* the supply side is analysed, including the SLT of the SKUs. Using this information the SKUs can be categorised into groups which could be procured on-order and SKUs which are more critical and should be kept on stock.

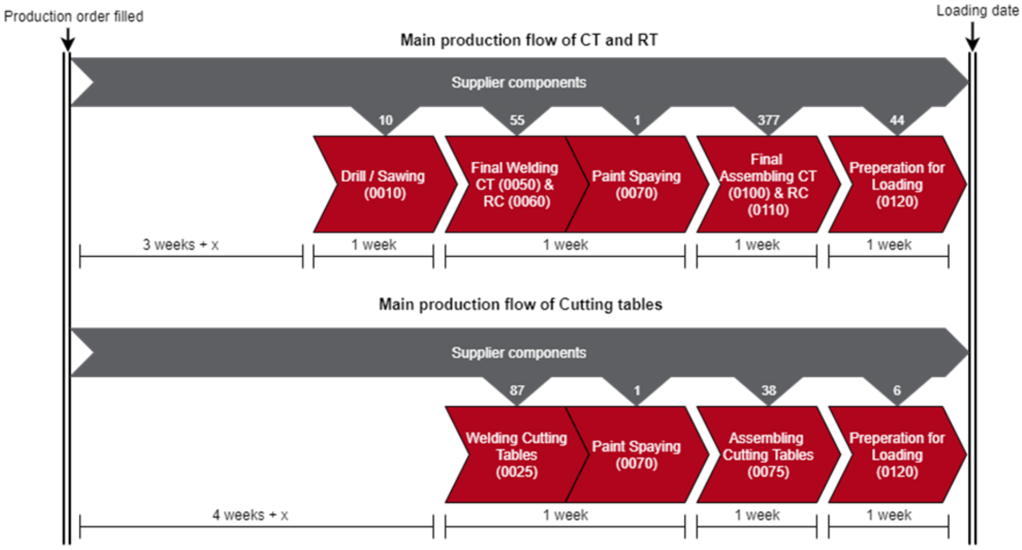

Figure 2.9:Routing of SKUs in production of CT&RC (top) and Cutting Tables (bottom)

2.3.6 Demand for handling modules in the preliminary stage

To gain insight into what is known about the demand for handling modules in the preliminary stage, mentioned in *Section 2.3.1*, interviews have been held with three key stakeholders involved in this process from sales to the final design of the project layout. A more detailed version of this sub-section can be found in *Appendix A.6.3*, in which the available information is further elaborated.

The preliminary stage starts after the downpayment, which occurs when the sales layout is finalized and approved by the customer. According to the team leader of sales support, *"before downpayment, there is no real certainty about the final design"* (Oude Avenhuis, 2021). The sales layout is designed using a configuration tool which uses standardised modules as building blocks, which include the processing machines and handling modules. Hence, after downpayment there is a design of the system available including required handling modules. However, this design does exclude certain customer-specific components which are later added by the projects department in the preliminary stage. Projects start by reviewing the system design as a whole, checking if all the modules are used correctly or if there are some which should be added or could be swapped out for other, better fitting modules. In the case of RCs, the latter does frequently occur. In most cases, the project engineer will try and adapt a design to reduce overall component usage, without compromising the system design. The project engineer could *not* give a clear estimation as to how much the deviation in SKU demand could be between the sales layout and the final design. This is heavily dependent on the SKU and its usage in a certain module. However, he indicated that for SKU consumption the sales layout is a good forecast of what eventually will be required for production. The sales layout could be seen as an upper bound of the size of SKU demand (ten Bolscher, 2021).

The stakeholders were asked to what degree (percentage) demand for the underlying SKUs (in the "standard BOM" modules), in the sales layout, concurs with that required in the finalized system design. Thus, to what extent can the sales layout be used as information on upcoming demand for SKUs. *Figure 2.10* shows a complete overview of when information on demand is known during the LT of a project and the "degree of certainty" (DoC) of this information. A distinction is made between various DoC, as they are different for RC, CT, Cutting Tables and customer specific components (CSC in Figure). Furthermore, it shows the number of SKUs for which that DoC applies are shown.

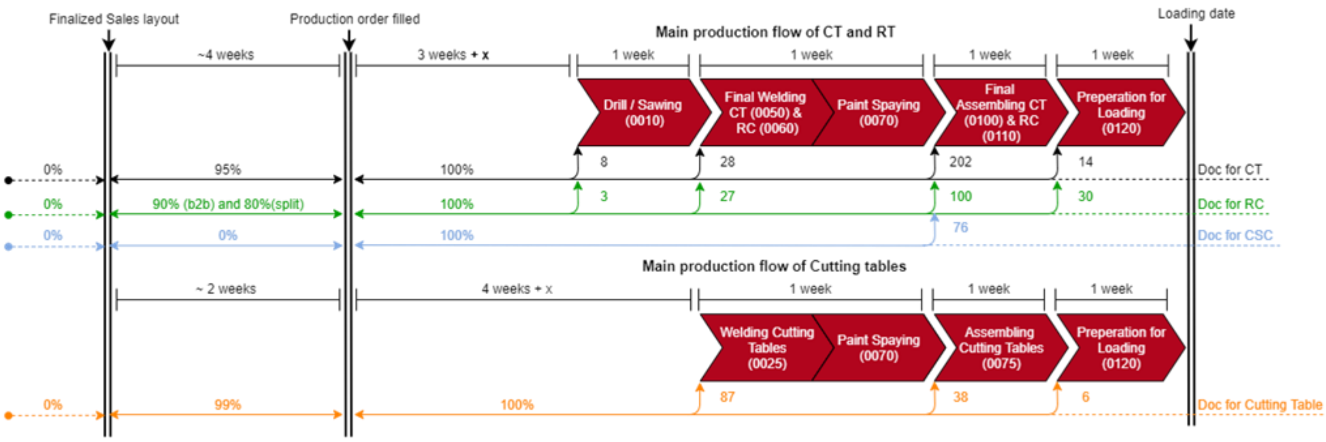

Figure 2.10:Overview of degree of certainty (DoC), during the LT of a customer project, per module type. The figure includes the number of SKUs which are required at a production stage per DoC.

The conclusion that is drawn is that there is a lot of improvement potential when it comes to demand planning for VPM-1. A lot of demand information of the modules is known, with some degree of certainty, before the orders are converted into POs and filled into SAP. Looking at *Figure 2.6* this could be an improvement of roughly four weeks for projects including RCs and CTs, and two weeks for projects with Cutting Tables.

2.4 Supply side

In this section, the SLTs and the accompanying variability are investigated and analysed. For the SLTs, interviews have been held with the buyer and the planner to find what these are for each SKU, as according to them the SLTs in SAP do not match with the LTs used in practice. The discrepancies between the lead times used by the buyer and planner and those in SAP are further elaborated in *Appendix A.3*. Moreover, using the available purchase order data to determine the realised LTs would result in inaccuracies. This is due to the current way of ordering. The SLT would be the delta between the date that the order is placed and the date the order is delivered. As, the buyer will, if demand is known far enough in advance, place an order with a delivery date based on when the SKU(s) are required in production. Not based upon the SLT. Which virtually increases the LT of that order from the supplier.

For the same reason, it is difficult to analyse the true variability of this LT. Yet, we can use the delivery date performance as a metric to analyse and give an indication of the LT variability, assuming the mean LT of the supplier is equal to the SLT, given by the buyer.

2.4.1 Supply lead times of the SKUs

Figure 2.11 shows the distribution of the SLT of the SKUs in inventory. What can be noticed is that most of the SKUs have a SLT of 4 weeks or less. However, 57 SKUs have an above average SLT of 5 weeks or more. Most of the components in these last buckets are required in the “assembly” and “preparation for loading” stages. Implying these SKUs have more LT before being required in production.

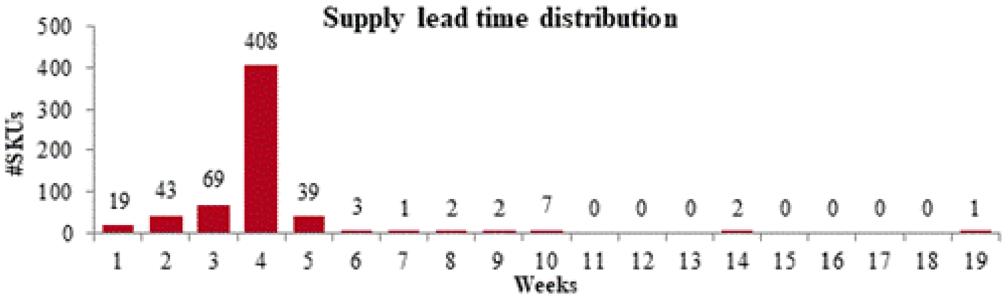

Figure 2.11: Supply lead time distribution of SKUs in inventory

2.4.2 Delivery date performance

For this analysis purchase order data from 2018 to 2021 is used. In the analysis the delta between the confirmed delivery date (the date that the supplier expects to deliver) and the actual delivery date (the date SKUs have been booked into inventory) in working days is determined. The analysis takes into account that processing received goods takes one day. In total there are 37 suppliers for the 488 SKUs in the selection that are purchased from external suppliers. The analysis does not take internally produced components into account, as there is no purchase order or equivalent data for these components available. The planner indicates that he plans the production of the internally produced components to be completed one week before consumption. The mean delta between confirmed and actual delivery dates for those SKUs is *0 days*, with a standard deviation of *5 days* (Schreurs, 2022).

Figure 2.12 shows the delivery date performance of the suppliers. The graph depicts for each supplier the mean and standard deviation in working days and the percentage of the total value of what the supplier delivered between 2018 and 2021. In the graph, the suppliers have been sorted in descending order by the number of deliveries each made in 2021. There are some suppliers with a negative mean delta, which indicates that on average they deliver earlier than expected. The suppliers that have delivered more than 50 times account for 88,1% of the total value. From the analysis one can also see that supplier 301766 has a large mean and standard deviation for their delivery date performance, however, the supplier has only delivered 5 times between 2018 and 2021, and delivered the SKUs in bulk.

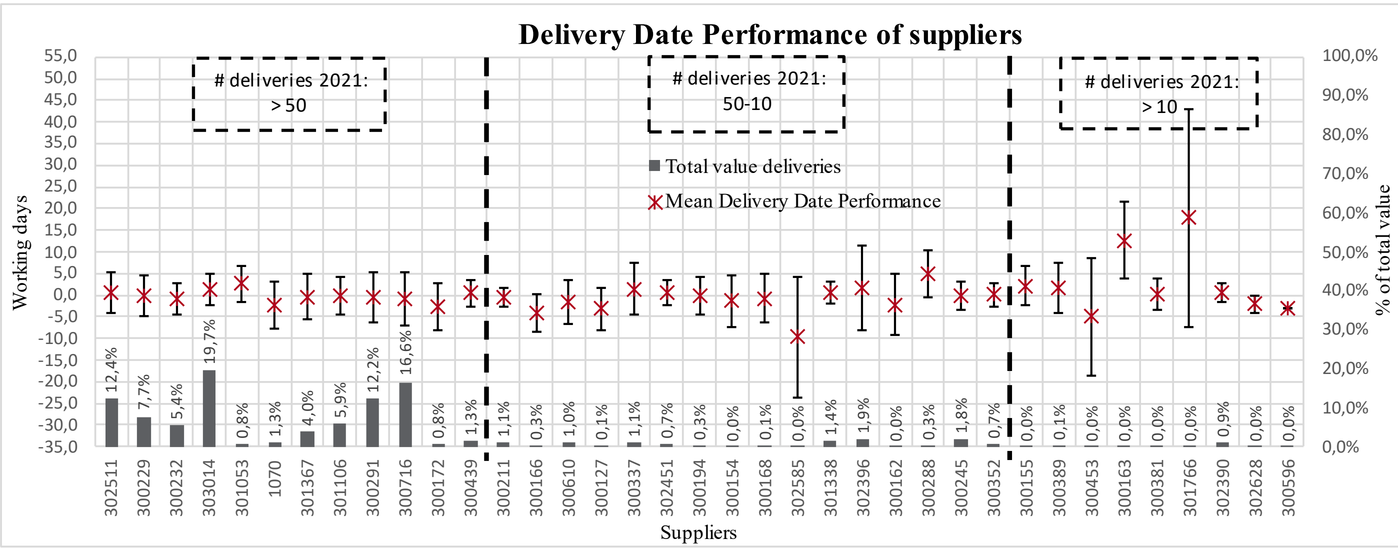

Figure 2.12:Delivery date performance of suppliers from period: 2018-2021

To conclude, most suppliers have a standard deviation of roughly 5 working days. When ordering SKUs from these suppliers it would be preferable to take this variability on the SLT into account in a safety LT. Moreover, the suppliers which deliver less frequently have the largest mean delivery performance and larger variation. For the SKUs that these suppliers deliver, the suggestion would be to apply a simple solution in which larger quantities are ordered less frequently, in the case they are relatively easy to stock. This will reduce the dependency on those suppliers.

2.5 Confrontation of demand & supply

In this section, the confrontation between the demand and the supply side is analysed. The analysis is performed using the routing information of the SKUs and the length of time that the demand for the PO is known before the loading date to determine the demand lead time (DLT) of the SKUs and compare it to the SLT of the SKUs. E.g. when the demand for a PO is known 7 weeks before the loading date, then the DLT for SKUs required at “Final Assembling” is 5 weeks. *Figure 2.13* shows the graphs for the CT & RC SKUs and *Figure 2.14* that of the Cutting

Tables. The separation is due to the difference in production stages. In the graphs, along the x-axis, the number of weeks that demand is known before the loading date is varied. In the analysis, the order requirements of the SKUs, i.e. MOQ, have been taken into account. SKUs are considered "on stock" when the SLT is longer than the DLT and when their order requirements are relatively high. The latter is considered high when the average number of weeks of coverage of the order requirement is larger than the DLT. SKUs which have a SLT equal to their DLT and a relatively low order requirement have been marked orange in the graphs, as these SKUs are at risk of stocking-out when purchased on order. SKUs are considered "on order" when they have a relatively low order requirement and their respective SLTs are smaller than their DLT. These are the %-SKUs which could be purchased on-order considering that demand is known x weeks before the loading date.

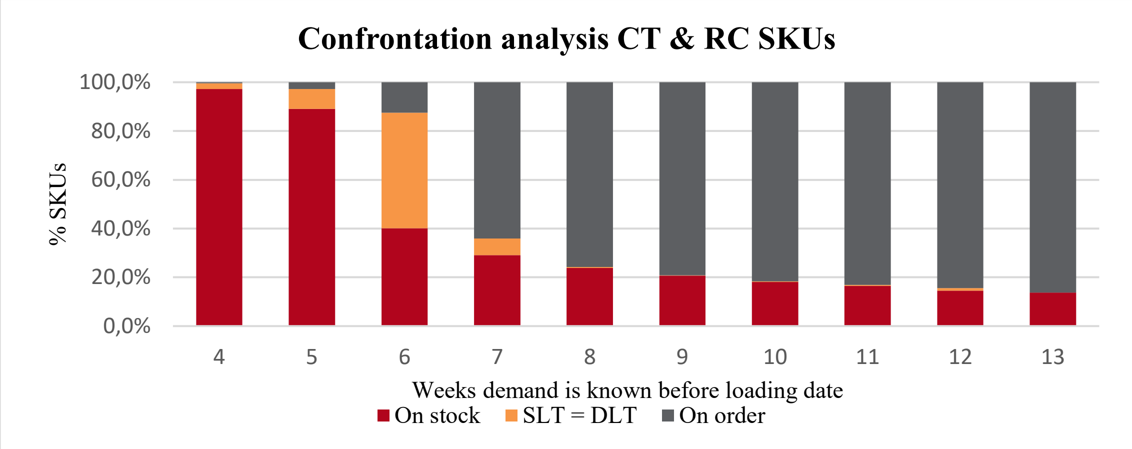

Figure 2.13: Confrontation analysis CT & RC SKUs.

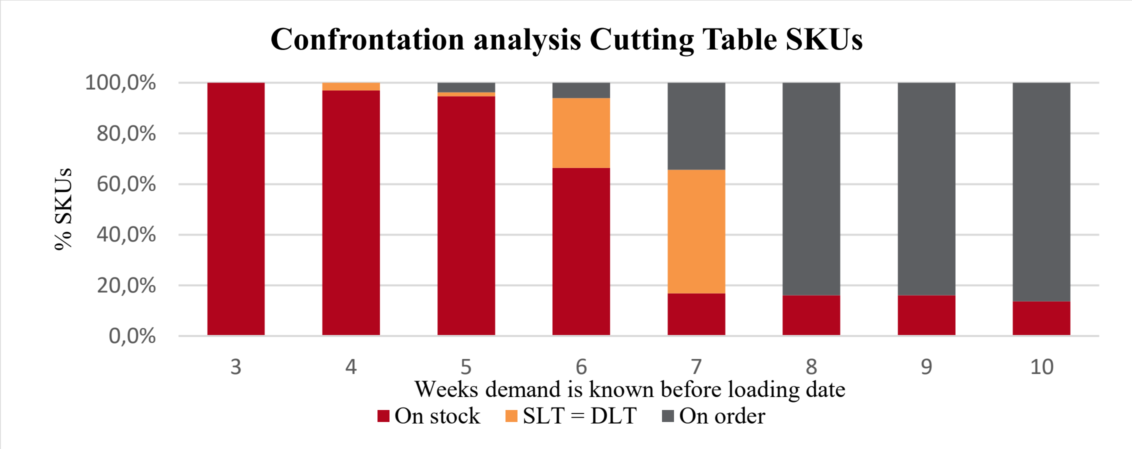

Figure 2.14: Confrontation analysis Cutting Table SKUs

In the current situation, the minimal number of periods that demand for a PO is known before the loading date is *7 weeks*. For the CT & RC SKUs this could mean that 64,1% could be purchased on-order and arrive at least a week earlier than required in production. Another 6,8% could be purchased on-order, however, it would arrive in the same week as it is required in production, thus making them more critical. For this group it would be advisable to class these as "on stock"-SKUs, to reduce the chance of stockout. For the Cutting Tables 34,4% could be purchased on-order and arrive at least a week earlier than required and 48,9% would arrive in the same week as it is required. One can see from the graphs that when the demand is known further in advance, i.e. by improving the demand planning, that more SKUs could be purchased on-order. If there is a desire from management to decrease this minimal project LT, then more SKUs will need to be procured "on inventory". From the analysis one can also find for which SKUs inventory policies will need to be researched.

2.6 Conclusions

This chapter investigated the current situation at VPM-1, regarding inventory management of the SKUs and the possible causes of the unavailability of SKUs for POs, to provide an answer to the first research question: *"What is the current situation, regarding inventory management of the SKUs and what are the causes of the stockout of SKUs?"*. In this section, the research question is answered by answering the corresponding sub-questions.

What is the current production-inventory model used by VPM-1?

VPM-1 use an ATO policy. The handling modules are produced in accordance with a production order. To reduce total lead time, VPM-1 produce the sub-weldments and sub-assemblies, that are consumed in the main production process, to stock. The focus of this research is the inventory for the handling modules, as stockout for these SKUs has a larger impact. Thus, the components consumed in the production of the sub-weldments and sub-assemblies are left out of scope, and the assumption is made that there is always sufficient stock to produce these components.

What are the current inventory control policies that are in-place?

The main replenishment strategy used is a demand strategy, also known as MRP-driven ordering. Customer project POs which are filled into SAP and planned into production, trigger the procurement of SKUs when the inventory position of those SKUs is or will be below zero. Once triggered the buyer will purchase the SKUs based on experience, future reservations and any order requirements the SKUs may have. Currently, there are lot-sizing procedures implemented in SAP to manage inventory, however, these have not been maintained and are therefore often ignored by the buyer. At VPM-1 there are few other inventory control policies in place, e.g. reorder points or order-up-to-levels. Only 14,9% of the SKUs in the selection have safety stocks in place, for which the level was based on the experience and intuition of the buyer and planner. And 51% of the SKUs have a safety LT in place of one week. Besides these, there are no other inventory control policies in place.

What is the current demand planning of the SKUs in inventory?

Currently, demand for POs is known at least 7 weeks before the loading date. The DLT of a SKU can then be determined based on when these are required in production. For instance, SKUs required in the "Drill / sawing"-stage are required in week 3 + x, where x is the extra DLT that demand is known past the 7 weeks.

The demand planning, however, may be improved considerably by taking into account the information which is known from the sales layout. By taking the demand information for SKUs as an upper bound will improve the demand planning by 4 weeks in the case of projects that include CT & RC modules, and 2 weeks for projects with Cutting Tables.

What are the supply lead times of the SKUs and are these accurate?

Approximately 90% of the SKUs have a SLT smaller than 5 weeks. With roughly 68% having a SLT of 4 weeks. Most suppliers have a standard deviation of roughly 5 working days on their delivery date performance. When ordering SKUs from these suppliers this variability on the SLT should be taken into account in a safety LT.

Which SKUs could be procured on-order?

From the confrontation analysis between the demand and supply side, performed in *Section 2.5,* the conclusion can be drawn that in the current situation with a demand planning of at least 7 weeks 57,7% of the SKUs could be procured on-order. This is without taking into account possible safety lead times and without the improvements to demand planning. In theory, this will mean that the average inventory investment of this 57,7% of SKUs (€261.482) can be reduced. As these components do not need to stay in inventory for long periods of time. For the remaining SKUs inventory control policies should be investigated to be able to attain a certain fill rate target.

What are the causes of the backordering and stockout occasions?

The analyses in *Section 2.2* confirm that roughly one in three POs have missing SKUs. The high degree of backorders could be reflected in the overall high inventory turnover rate and the lower ready rates of some SKUs. From the analyses, the expectation is drawn that the disruption in the production process due to backordering is likely caused by a small group of SKUs. Which in-turn could be caused by the current way of ordering and the lack of inventory control policies for these SKUs. Other causes that were found to induce the stockout occasions are:

- The current demand planning. The movement of POs over the time horizon and the sequentiality of the POs.
- The unexpected demand due to incorrect BOMs and consumption of service and spare parts.
- The delivery performance of the suppliers.

To conclude, there are three options which could reduce the backordering and stockout occasions: (1) improve the demand planning by using the SKU demand from the sales layout as an upper bound or (2) investigate and implement inventory control policies or (3) a combination of both options 1 and 2. The expectation is that by improving the inventory management based on the available demand data that backordering of these SKUs will be largely reduced.

The next chapters will research possible models which can vary the inventory policies of the SKUs based on their current demand planning, that of the new demand planning and that on various DLTs of POs. Hereby being able to determine which SKUs should be kept in-inventory and which should be procured on-order.

3 Literature study

In this chapter, the literature research is performed to find applicable theory which can be used to design and build a solution that reduces the backordering of SKUs. This chapter is concluded by providing an answer to the second research question: "*What inventory management methods are proposed in the literature, that suit the situation at VPM-1, with which the backordering of SKUs can be reduced?*". The chapter starts by researching literature that can best describe the production system found at VPM-1. Subsequently, in *Section 3.2*, classification methods for the SKUs are researched. Lastly, in *Section 3.3*, suitable inventory control policies which can be applied to the production system of VPM-1 are researched and the equations are given.

3.1 Connecting current situation with inventory management theory

At VPM-1, handling modules are manufactured that serve as an infeed, outfeed or buffer between the various processing machines that VSM sells to her customers. The handling modules are produced to order, meaning that there is a certain "frozen period" in which demand for a module is known and certain. Silver et al. (2017) refer to this as the "grace period". The traditional scope of inventory management is strictly focused on commodities inventory, as in a retail store. Most models reflect this view by treating demand as purely exogenous, unanticipated events (Hariharan & Zipkin, 1995). Demand for an item is only known and certain when it has occurred. To improve the certainty and to know what items to keep in stock, and in what quantity, commodity inventories employ (aggregate) forecasting. Hariharan & Zipkin (1995) extend some of the basic inventory models to allow for advance ordering, in other words taking into account the "frozen" period in which demand is known and certain. They call the time from a customer's order until the due date the *demand lead time* (DLT). The actual demand, thus only occurs on the due date. Hariharan & Zipkin (1995) find an intuitive and appealing conclusion: "*Demand lead times are, in a precise sense, the opposite of supply lead times*." That is, the effect of a demand lead time on overall system performance is precisely the same as a corresponding reduction in the supply lead time". This adds to the point that was made in *Section 2.5,* by improving the demand planning, by incorporating information from the sales layout, will decrease the period in which demand for a SKU is unknown, thus decreasing the required physical (safety) inventory to satisfy the uncertainty.

Rostami-Tabar & Sahin (2015), Tan et al. (2007), Gallego & Özer (2001) and Lu et al. (2003) continue with the concept set by Hariharan & Zipkin (1995) by creating inventory models which incorporate advance demand information (ADI) to investigate the effect they have on various productions systems. Rostami-Tabar & Sahin (2015) make use of "perfect" ADI, with which they insinuate that the information known during the ADI period is known and certain. Tan et al. (2007) study the effect and the incorporation of "imperfect" ADI, in which a certain probability p a portion of the prospective demand materializes in the current period and becomes actual demand and a portion will appear in the system with a probability r in one or more periods or will leave the system. Gallego & Özer (2001) research optimal inventory control policies under ADI and find that state-dependent (s, S) and base-stock policies are optimal for stochastic inventory systems. The three previous studies all research single product production systems, Lu et al. (2003) however, study a multi-item Assemble-to-Order system with ADI. In which multiple end products are assembled, each using multiple components in varying quantities. The system described and studied by Lu et al. (2003) does not completely describe the production process of VPM-1 that is served by the inventory which is being studied in this research. The production system at VPM-1 is a multi-item, ATO-system, with multiple production stages which manufactures multiple end products. The items are consumed in different stages of production and thus have different DLTs to one another.

Hautaniemi & Pirttilä (1999) describe a useful concept, a Fixed Assembly Schedule (FAS) which, reminiscent of the DLT by Hariharan & Zipkin (1995), is the fixed time when an item is consumed in production. Thus this is the specific DLT of a SKU. An example: if the DLT of a PO is 7 weeks and a SKU is consumed in the assembly stage, using *Figure 2.6*, one can see that the FAS is 5 weeks.

3.2 SKU-classification

As inventories often consist of hundreds or even thousands of SKUs it is preferable to use classification methodologies to determine the appropriate control policies for each SKUs, instead of simulating and testing to find the optimal policy for each SKU individually. This also helps to distinguish the crucial SKUs which require the most managerial attention. Added benefits of classifying SKUs are: to determine possible forecasting methodologies, to determine what inventory model to use for the demand (continuous/discrete) and based on these classifications determine what target service levels to set.

The most widely used method to classify items into different categories is by performing an ABC-analysis (Cakir & Canbolat, 2008). A popular criterion to use is to classify the items, using the Pareto principle, based on their annual usage value (Flores & Whybark, 1987). The classification, however, is often done by taking only one criterion into account. A method which takes multiple criteria into account is the Analytic Hierarchy Process (AHP) (Cakir & Canbolat, 2008). The general idea is to derive a single scalar measure of importance by subjectively rating the criteria and/or the inventory items. The subjectivity involved in the analysis is also the single most important issue (Ramanathan, 2006). Ramanathan (2006) proposes a weighted linear optimization methodology for classifying inventory items using multiple criteria. Besides annual usage value, an important criterion to classify inventory items is based on their demand uncertainty, using an XYZ-analysis (Dhoka & Choudary, 2013). Lastly, Hautaniemi & Pirttilä (1999), present a simple structured classification methodology in which the inventory items are classified in a stepwise manner.

As the expectation is that the ABC and XYZ-analyses and the stepwise classification approach are the most applicable methods in the case of VPM-1, these are further detailed in *Sections 3.2.1 - 3.2.4*.

3.2.1 ABC-analysis

The ABC-analysis is one of the most widely used ways to classify the SKUs in different groups to determine the amount of control effort each SKU requires. The ABC-analysis could be based, as the DBV-analysis in *Section 2.2.2*, on the annual usage value of the SKU (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017). The analysis is easy to use and intuitive for inventory managers. The class A SKUs are the “critical few”, relatively few components which account for a relatively large amount of annual usage value. The class C SKUs are the opposite, they are the “trivial many”, a relatively large number of SKUs which account for a relatively small portion of the annual usage value. The class B SKUs are the SKUs which fall between these two categories.

Class A SKUs should receive the most personalized attention from management. These SKUs need to be controlled tightly and monitored closely. Often the 80/20 pareto-rule is used for the class A, roughly 20% of the SKUs which account for 80% of the total usage value.

Class B SKUs account for the second highest usage value, roughly 15%. Approximately 30% of SKUs fall within this category. The inventory management for these SKUs can be mostly controlled by computed-based systems.

Class C SKUs account for the lowest total usage value, roughly 5%. Often this class contains the largest percentage of SKUs, approximately 50%. For these SKUs the decision system should be kept as simple as possible. Typically, for these low-value SKUs, a relatively large number of units are kept on hand to minimize the inconvenience caused by stockouts of these insignificant SKUs (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017).

3.2.2 XYZ-analysis

Besides the ABC-analysis which classifies SKUs based on their monetary value, a classification can be done based on the demand uncertainty of the SKUs, the XYZ-classification (Dhoka & Choudary, 2013). The demand uncertainty is determined using the coefficient of variation (CV), see *eq. 2*. σ is the standard deviation of demand and $\bar{X}$ is the demand average. The period over which the demand data are aggregated should be chosen wisely, common periods are daily, weekly or monthly. In the case of VPM-1 weekly would be appropriate.

$$CV = \frac{\sigma}{\bar{X}} \qquad 2$$

The SKUs are ranked and classified according to their CV. SKUs with CV < 0,5 are classified as X-items. As the SKUs have more predictable demand patterns. SKUs with a CV > 1 are classified as Z-items. As there is a strong fluctuation in the demand patterns for these SKUs. The SKUs with a CV between 0,5 and 1 are Y-items as they have medium demand uncertainty.

3.2.3 ABC-XYZ analysis

The ABC and XYZ classification methods can also be combined. In that case both the annual usage value and the demand uncertainty are taken into account. The ABC-XYZ analysis has 9 classes, shown in *Table 3.1*. The classification method can be used to determine the service level targets for each class and determine for each class what inventory policies could be most effective to attain the service level targets.

Table 3.1: Classification classes of the ABC-XYZ analysis.

	X	Y	Z
A	AX	AY	AZ
B	BX	BY	BZ
C	CX	CY	CZ

3.2.4 Stepwise procedure to classify SKUs

Hautaniemi & Pirttilä (1999) present a simple, but systematic and practical procedure to classify SKUs into five groups. The research is based on a case-company with an Assemble-to-Order (ATO) production environment and the main approach and procedure seem applicable to VPM-1's production environment. Hautaniemi & Pirttilä (1999) argue that generally there are three main criteria to keep classification simple and easy to understand: (1) value of usage, (2) supply lead time compared to the final assembly schedule (FAS, comparable to demand lead time of a SKU) and (3) demand distribution patterns.

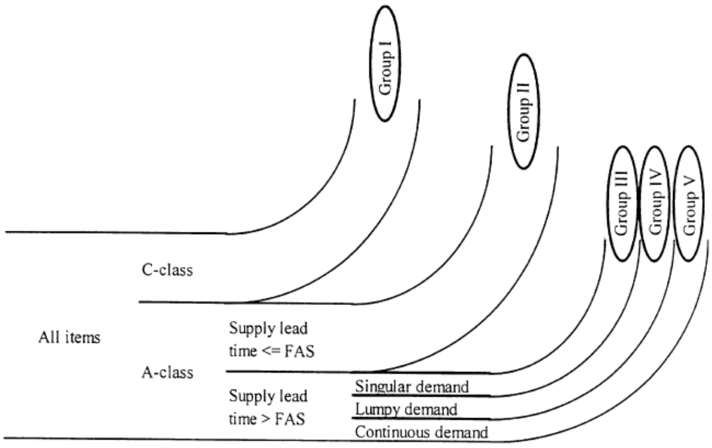

Figure 3.1: SKU classification process (Hautaniemi & Pirttilä, 1999)

In *Figure 3.1* the systematic approach is illustrated. The three abovementioned criteria are used sequentially to separate the SKUs into the different classes. The first step of the classification is an ABC-analysis, of which the authors found that only the A- and C- classes suffice. The procedure separates SKUs with a low value of usage (C-items). In the second step the SKUs are separate whose SLT is shorter than FAS, for these SKUs the inventory management of the SKU is based on firm customer orders. In the third step the SKUs are grouped based on their demand patterns. Singular demand implies that the SKU has demand now and then, usually one unit per order. Demand is often modelled as Poisson distribution. Lumpy demand implies demand for these SKUs also occurs now and then, however, the quantities demanded are variable. They have not defined a known distribution for which the demand can be modelled. The last group of SKUs have continuous demand, according to Hautaniemi & Pirttilä (1999) this demand can be derived from the sales forecast of end-products.

Just as the ABC-XYZ analysis each group can be used to determine the service level target and the inventory control policy which should be applied for that group.

The stepwise approach as proposed by Hautaniemi & Pirttilä (1999) seems very applicable for the production system at VPM-1. This could possibly be improved by combining the knowledge from the Dhoka & Choudary (2013) on demand uncertainty. Added benefit of applying this methodology compared to the ABC-XYZ-analysis is a reduction of categories in which the SKUs can be classified.

3.3 Inventory control policies

According to Winston and Goldberg (2004) inventory control models answer two questions: (1) when should an order be placed? And (2) how large should each order be? The answers should be based on the inventory position (IP), the (forecasted) demand and various cost factors, for instance holding and shortage costs. The decisions made by an inventory control policy should be based on the IP instead of the inventory level. The inventory level is only the physical on-hand stock. And the IP includes outstanding purchase orders and backorders, see *eq. 3*.

$$Inventory\ position = Inventory\ level + outstanding\ orders - backorders \qquad 3$$

Table 3.2 shows the four most common inventory policies. The policies are categorized in continuous or periodic review and fixed or variable lot size. With a continuous review policy the inventory is continuously monitored. When the IP drops below a reorder point (s), an order is placed. On the contrary, with a periodic review policy the inventory is only monitored at certain points in time. The duration of time between the reviews of the state of the inventory is called the review period (R). An order is either placed at the start of every review period or at the start of the review period if the IP has dropped below the reorder point (Silver, Pyke, & Thomas, 2017). An advantage that periodic review has over continuous review is the possibility for multi-item coordination, the replenishments of the SKUs can be coordinated. For instance if the SKUs are purchased from the same supplier. The replenishments of SKUs for a certain supplier could be reviewed on the same day. With continuous review this is harder to do, as an order for a SKU is placed directly when the IP drops below the reorder point (Silver, Pyke, & Thomas, 2017). An advantage that continuous review has is that less safety stock is required compared to periodic review. In the case of continuous review the safety stock only needs to cover the variability of lead time demand. Whereas, with the periodic review the safety stock needs to cover the variability over the lead time demand plus the review period (Axsäter, 2006).

Table 3.2: Inventory control policies (van der Heijden, 2021-d)

	Continuous review	Periodic review
Fixed lot size	(s, Q) or (s, nQ)	(R, s, Q) or (R, s, nQ)
Variable lot size	(s, S)	(R, S) or (R, s, S)

With a fixed lot size the order quantity is always the same, or a multiplicative of the order quantity. This value is often based on the Economic Order Quantity and ordering requirements of a SKU. With a variable lot size the quantity purchased from the supplier is variable, with the goal to attain a certain IP, the order-up-to level (S).

(s, Q)- or (s, nQ)-policy

A continuous review policy with fixed lot size. The height of the reorder point (s) is equal to the expected demand during lead time plus the safety stock. Every time the IP drops below s the fixed lot size fixed lot size (Q) in ordered. The (s, Q)-policy is often referred to as the two-bin policy (Silver, Pyke, & Thomas, 2017). The (s, nQ)-policy is similar to the (s, Q)-policy where there is a possibility to order a multiplicative n of Q.

(s, S)-policy

A continuous review policy with variable lot size. Analogous to the (s, Q)-policy an order is made when the IP drops below the reorder point. The lot size that is ordered is the difference between the reorder point s and the order-up-to level S. If all demand transactions are unit sized, then the (s, S)- and (s, Q)-policies are identical. Because the replenishment order will always be made when the IP is exactly s. Only if the transactions can be larger than unit size will the replenishment quantity of the (s, S)-policy become variable. The (s, S)-policy is frequently referred to as a min-max system as the IP, except for a possible momentary drop below the reorder point, is always between minimum level s and maximum level S (Silver, Pyke, & Thomas, 2017).

(R, s, Q)- or (R, s, nQ)-policy
A periodic review policy with fixed lot size. The IP is checked every R periods whether an order needs to be placed. If the IP during the review is equal to or lower than s an order is placed of size Q. In this instance it is also possible to purchase a multiple n of Q using the (R, s, nQ)-policy.

(R, S)- or (R, s, S)-policy
A periodic review policy with variable lot size. Also here the IP is checked every R periods. In the case of an (R, S)-policy every period an order is placed to raise the IP to the order-up-to-level S. The size of the order is $S - s$. With the (R, s, S)-policy an order is only placed if the IP is equal to or below the reorder point.

3.3.1 Policy selection

Currently there is no standard procedure to select an appropriate policy for each SKU. Silver, Pike & Thomas (2017) do defined a rule of thumb for class A and B SKUs, see *Table 3.3*. A SKUs are the most important SKUs in the inventory, that is why it would make sense to use more complex and more management intensive policies to ensure a higher target service level. B SKUs are not as important but still need to be monitored from time to time. For C SKUs Silver et al. (2017) recommend to use a more simple approach, being an (s, Q)- or (R, S)-policy with parameters that need little attention. These are however rules of thumb, a good approach would be to simulate the different policies and rank them according to their overall performance. According to Petrovic & Petrovic (2001) this is particularly a good method when customer demand is uncertain. Performance criteria could be (time based) fill rate and total relevant costs.

Table 3.3: Rules of thumb for selecting the form of the inventory policy (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017, p. 245)

	Continuous review	Periodic review
A items	(s, S)	(R, s, S)
B items	(s, Q)	(R, S)

3.3.2 Policy parameter determination

In this section the parameters pertaining to the policies mentioned in Section 3.2.1 are described and the formulas to determine the values of these parameters are defined.

(Fixed) order quantity (Q)
For fixed lot sizing the most commonly used formula in inventory management to determine the order quantity Q is the Economic Order Quantity (EOQ), see *eq. 4*. It is known as the formula of Camp. The formula is used to determine the optimal order quantity. A are the fixed ordering costs, v is the variable unit price and r is the carrying cost of a unit (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017).

$$Q^* = EOQ = \sqrt{\frac{2AD}{vr}} \qquad 4$$

The order quantity to use for a SKU is however also dependent on its ordering requirements. In the case of a minimum order quantity (MOQ), Q should be max $\{EOQ, MOQ\}$. In the case of a fixed order quantity (FOQ), Q should equal FOQ, regardless of the EOQ. And lastly in the case of incremental order quantity (IOQ), Q should be rounded up to a multiplicative n of the IOQ.

Review Period (R)

Sezen (2006) has studied the effect of the length of the review period R, they found that inventory performance is quite sensitive to the duration of the review period. They conclude that the appropriate length of the review period is largely dependent on the variability of the demand. The higher the demand variability, the shorter the review period should be. A relatively simple method for determining the review period is by using the cycle time of an SKU based on the determined EOQ divided by the annual demand, see *eq. 5* (Axsäter, 2006; Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017). Where fixed setup costs A should include the costs for reviewing the inventory and the resulting R should be restricted to reasonably small number of feasible discrete values.

$$R = T^* = \frac{Q^*}{D} = \sqrt{\frac{2A}{vrD}} \quad (5)$$

Eq. 5 determines a review period on an individual SKU level, however, it could be beneficial to coordinate the review period among multiple SKUs. This multi-item coordination could be done by grouping the SKUs by supplier, with a basic replenishment time interval T for the product family. Factors m_i are then chosen such that that SKU i is replenished every m_iT periods (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017). The (dis)advantages are given below:

+ Savings on purchasing costs: quantity discounts depending on total order size
+ Savings on transportation costs (e.g. creating a full truck load)
+ Savings on ordering costs: Setup is cheaper for items within the same product family. Moreover, this will reduce the cost of the purchasing employee).
+ Ease of scheduling: Managers think in terms of suppliers rather than SKUs
- More cycle stock: trade-off against reduced ordering/setup costs, discounts.
- More complexity, resulting in higher system control costs.
- Reduced flexibility / more variation in customer service from a single item perspective: As an order is not placed at a point in time that is most optimal for that single item.

Undershoot

The formulas to determine the reorder point s and order-up-to level S are based on the assumption that a replenishment order is placed exactly when the reorder point is hit. However, in reality this is rarely the case. Undershoot is the difference between the reorder point and the IP after a replenishment order has been placed. There are two main factors which cause the undershoot: (1) non-unit sized demand in the case of a continuous review period, illustrated in *Figure 3.2* (van der Heijden, 2021-c) and (2) the waiting time until the next review in the case of a periodic review period, illustrated in *Figure 3.3* (Silver, Naseraldin, & Bischak, 2009).

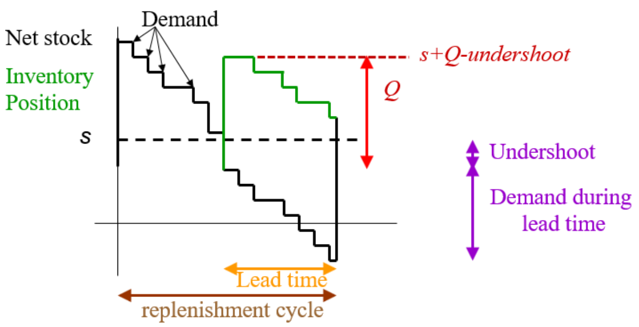

Figure 3.2: Undershoot due to demand size in a (s,Q)-policy (van der Heijden, 2021-c)

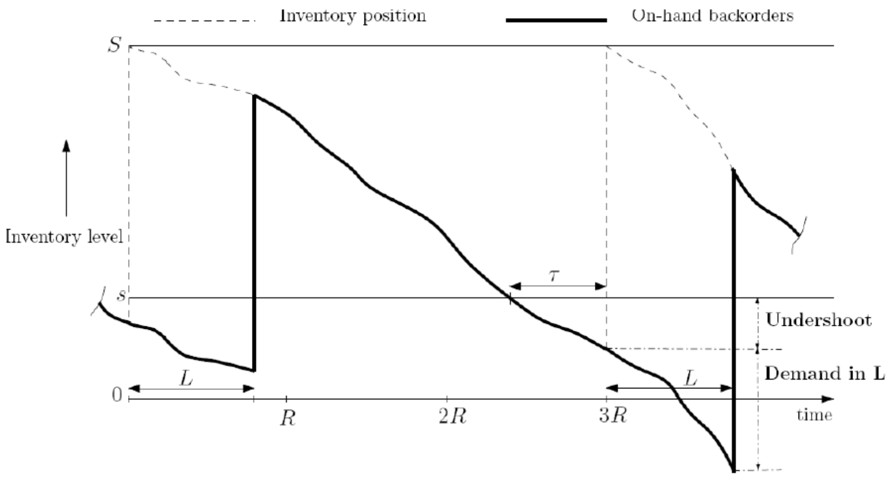

Figure 3.3: Undershoot due to periodic review (R,s,S)-system (Silver, Naseraldin, & Bischak, 2009)

Non-unit sized demand
Figure 3.2 shows the behaviour of a (s, Q)-policy where demand sizes can exceed a single unit. Just before the demand occurs the net-stock (OHI) is larger than the reorder point s, for example OHI is 42 units and s is 40. As the demand occurs, for example 5 units, the OHI drops below the reorder point. The undershoot in that case is 3 units.

The expectation and variance of the undershoot Z can calculated using *eq. 6* and *eq. 7* for the case of a continuous demand distribution, where Y is the demand size. *Eq. 8* and *eq. 9* can be used in the case the demand distribution is discrete (Silver, Pyke, & Thomas, 2017).

Continuous demand distribution:

$$E[Z] = \frac{E[Y^2]}{2E[Y]} \tag{6}$$

$$Var[Z] = \frac{E[Y^3]}{3E[Y]} - \frac{1}{4}\left(\frac{E[Y^2]}{E[Y]}\right)^2 \tag{7}$$

Discrete demand distribution:

$$E[Z] = \frac{E[Y^2]}{2E[Y]} - \frac{1}{2} \tag{8}$$

$$Var[Z] = \frac{E[Y^3]}{3E[Y]} - \frac{1}{4}\left(\frac{E[Y^2]}{E[Y]}\right)^2 - \frac{1}{12} \tag{9}$$

Waiting until next review
The undershoot problem is more serious when comparing it to the continuous review period as the inventory can only be replenished at certain moments in time. In *Figure 3.3* can be seen that only in between 2R and 3R does the OHI level drop below the reorder point. The next order will only be placed at 3R and will only come in L periods after that. As replenishment opportunities are only possible every R periods, the undershoot is based on demand during the review period D_R. The expected undershoot can be calculated using the same formula, however by D_R instead of Y, see *eq. 10*.

$$E[Z] \approx \frac{E[D_R^2]}{2E[D_R]} = \frac{\sigma_R^2 + \hat{x}_R^2}{2\hat{x}_R} \tag{10}$$

Reorder point (s)
The reorder point s is the point at which a replenishment order should be placed when the inventory position is equal to or below it. In the case of a continuous review the reorder point should cover the demand during the supply lead time (SLT) $(\hat{x}_L)$. For the periodic review case the reorder point should cover demand during SLT and review period $(\hat{x}_{R+L})$. The reorder point is equal to the expected demand during SLT + the safety stock. The

safety stock is the inventory kept to satisfy demand when there are component shortages, because the demand exceeds the amount expected for a given period. The safety stock is a safety factor k multiplied by the standard deviation of the demand during SLT (σ_L) (Silver, Pyke, & Thomas, 2017). The calculation for the reorder point for the continuous review and periodic review are given in *eq. 11* and *eq. 12* respectively. As mentioned previously undershoot could also be taken into account when determining the reorder point, in that case *eq. 13* and *eq. 14* apply for the continuous review and period review respectively (Silver, Pyke, & Thomas, 2017).

$$s = \hat{x}_L + k\sigma_L \quad (11)$$
$$s = \hat{x}_{R+L} + k\sigma_{R+L} \quad (12)$$
$$s = \hat{x}_L + E[Z] + k\sqrt{Var[x_L] + Var[Z]} \quad (13)$$
$$s = \hat{x}_{R+L} + E[Z] + k\sqrt{Var[x_{R+L}] + Var[Z]} \quad (14)$$

The safety factor k can be calculated via numerous service level KPIs. For a (time-based) fill-rate (P_2), see *eq. 15*. For this calculation the Normal loss function $G(z)$ is used to find the k. Silver et al. (2017) give an Excel formula for $G(z)$, see *eq. 16*, which can be used in combination with the goal seek function to find the optimal k.

$$G(k) = \frac{Q(1 - P_2)}{\sigma_L} \quad (15)$$

$$G_u(k) = NORMDIST(k, 0,1, FALSE) - k[1 - NORMDIST(k, 0,1, TRUE)] \quad (16)$$

For C-items, however, a simple approach is to base the safety factor on the Time Between Stockout occasions (TBS), using *eq. 17*. Silver et al. (2017) recommend to use a large TBS (e.g. 5-100 years), because (1) a single PO may consist of many C-items and (2) holding costs are low, thus high safety stocks are justified.

$$k = \Phi^{-1}\left(1 - \frac{Q}{D * TBS}\right) \quad (17)$$

For the (R, s, S) and (R, s, Q)-policies a more complicated formula is required to calculate the safety factor, see *eq. 18*. Here the function $J(z)$ is used for the standard Normal distribution. To find k the Excel formula in *eq. 19* can be used in combination with the goal seek function.

$$J(k) \approx \frac{2(1 - P_2)\hat{x}_R(S - s + E[Z])}{\sigma_{R+L}^2} \quad (18)$$

$$J_u(k) = (1 + k^2)[1 - NORMDIST(k, 0, 1, TRUE) - k * NORMDIST(k, 0, 1, FALSE)] \quad (19)$$

Order-up-to-level (S)

The order-up-to-level S is the maximum IP. If an inventory control policy is chosen that uses a reorder point, i.e. (s, S)- or (R, s, S)-policy, when the IP is equal to or below the reorder point a replenishment order is placed of size equal to the Q, if the demand is unit-sized, see *eq. 20* (Axsäter, 2006). In the case demand is not unit-sized undershoot should be taken into account, see *eq. 21* (van der Heijden, 2021-e). *Figure 3.4* shows the order size of a replenishment for an (s, S)-policy.

$$S = s + (S - s) = s + Q \quad (20)$$
$$S = s + (S - s) - E[Z] \quad (21)$$

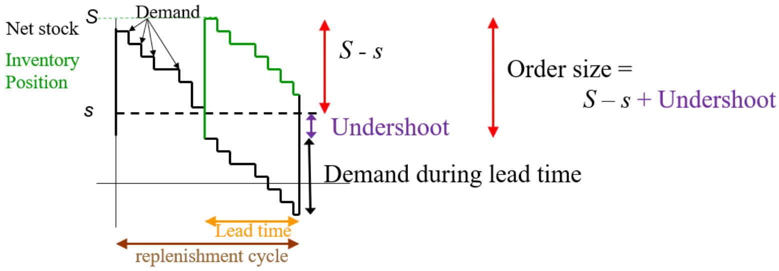

Figure 3.4: (s,S)-policy including undershoot (van der Heijden, 2021-e)

If an inventory control policy is chosen without a reorder point, i.e. (R, S)-policy, then the order-up-to-level should be sufficient to cover demand during the review period R plus demand during the SLT. The order-up-to-level S can be determined with *eq. 22*.

$$S = \hat{x}_{R+L} + k\sqrt{Var[x_{R+L}]} \tag{22}$$

3.4 Conclusion

In this chapter a literature study was performed to provide an answer to the second research question: *"What inventory management methods are proposed in the literature, that suit the situation at VPM-1, with which the backordering of SKUs can be reduced?"*. In this section the answer is given by answering corresponding the sub-questions.

What inventory management theory found in the literature can be applied to the production system of VPM-1?
The production system at VPM-1 can be described as a multi-item, multi-stage ATO-system with multiple end products. Demand for the end products, modules, is known and certain for a number of periods before the due date, also known as the "frozen period". This is important information to take into account to prevent unnecessary levels of stock are kept. As there are multiple production stages in which the SKUs are consumed, the DLT of an individual SKU is less than the frozen period. The DLT of an individual SKU is also known as the Fixed Assembly Schedule (FAS), which is dependent on the DLT of PO. As the demand information during the period FAS is known and certain it should be taken into account when determining the parameters of inventory control policies. The policies should only account for the unknown period of demand $SLT - FAS$. In literature, especially for manufacturing environments, inventory management research has been performed to see the effect of including advance demand information (ADI). ADI can be used to extend the frozen period of demand or to reduce the uncertainty over the unknown period. In the case of VPM-1, ADI can be used to research the use of final sales layout information.

What classification methods are available in the literature, to control the SKUs?
For SKU classification several articles were considered that classify items based on single and multiple criteria. However, a structured stepwise classification methodology presented by Hautaniemi & Pirttilä (1999) is found to be the most applicable when combined with the XYZ-analysis by Dhoka & Choudary (2013). The use of ADI, demand information that is available from the sales layout, also needs to be taken into account when classifying SKUs.

What inventory control policies are available in the literature and how should the parameters be determined?
For the inventory control policies four common inventory control policies were found. These can be distinguished into continuous or periodic review policies and replenishing with either fixed or variable lot sizes. The most suitable control policy is dependent on the SKU and the class in which it is categorized. The control policy parameters can be calculated using the formulas in *Section 3.3.2*.

4 Solution design

In this chapter the proposed inventory control policy parameter tool is described. The solution is currently built to work for the 601 SKUs which have been found in *Chapter 2* by exploding the BOMs of the RC, CT and Cutting Table modules. *Figure 4.1* shows the sequence of this chapter and the tool. This chapter starts by concisely describing the input data and variables used by the tool. *Section 4.2* describes the classification process of the SKUs into various classes. *Section 4.3* describes how the inventory policies are selected for each SKU based on their classification and ordering requirements. Subsequently, the policy parameters are determined in *Section 4.4* for each SKU, moreover, giving an overview of the applied formulas for each policy. Thereafter, in *Section 4.5* the constraints of the tool are given. Lastly, the chapter is concluded by providing an answer to the third research question: *"What inventory management methods are most applicable for the SKUs and what should the design of the inventory management tool be?"*.

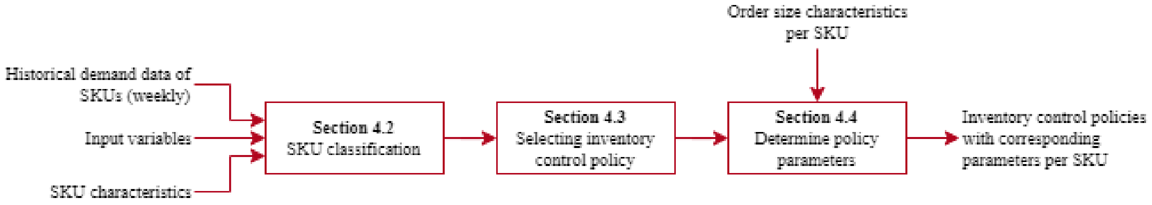

Figure 4.1: Flow diagram of the inventory control policy tool.

4.1 Input data

For the tool to be able to classify the SKU, select a fitting control policy and determine the accompanying policy parameters it requires certain input data of the SKUs, as shown in *Figure 4.1*. The input variables and historical demand data are discussed in *Sections 4.1.1* and *4.1.2* respectively. Besides these, the tool requires certain SKU characteristics to be inputted, an overview of these is shown in *Table 4.1*.

Table 4.1: SKU characteristics

SKU characteristics	Note
Material number	
Special procurement type	
Module type	*CT, RC or Cutting Table (or one with shortest DLT_{known})*
Unit price	
Ordering cost	*€28,85 based on 2021*
Holding cost rate	*% of unit price*
Routing step	*Production stage in which SKU is consumed*
Supply LT	*In weeks (integer value)*
Ordering requirements	*Fixed, Minimal and/or Incremental Order Quantity*

4.1.1 Input variables

The tool is built to determine the optimal control policies for the inputted SKUs based on four input variables which can be altered by the user. The first variable is the *minimal DLT of a PO*. This is the minimal time, in weeks, that demand for a PO is filled in SAP and is known before the due date (loading date), as mentioned in *Section 2.3.1,* this is the period after the preliminary stage. Using this value, and the known production routing of the SKU, the known DLT of a SKU can be determined. According to the literature found in *Section 3.1* this is the final assembling schedule (FAS) of a SKU, however for simplicity in this research it is referred to as DLT_{known} of a SKU.

The second variable is the DLT_{extra}, the number of weeks of demand information that is known further in advance than currently used. In this instance taking into the demand information which is known from the final sales layout. In *Section 3.1*, this demand information this was introduced as Advance Demand Information (ADI). As mentioned in *Section 2.3.5*, the demand information from the final sales layout could increase the DLT by four weeks for CT and RC modules and two weeks for Cutting Table modules.

The third variable is the *Safety LT*, in weeks. This variable can be used to fictively increase the supply lead time (SLT), which in-turn increases the Net LT. The Net LT can be calculated using *eq. 23* and is the LT with which the policy parameters are determined. As compared to more classical inventory environments where no information about demand is known before it arrives, in production environments, and in the case of VPM-1, demand is known and fixed for a certain period, $DLT = DLT_{known} + DLT_{extra}$, also known as the grace period. This demand can be reserved. The inventory rules, like the reorder point must then be determined to cover the remaining LT.

$$Net\ LT = (SLT + Safety\ LT) - DLT = (SLT + Safety\ LT) - (DLT_{known} + DLT_{extra}) \quad 23$$

In the tool the assumption is made that the SLTs are deterministic and the deliveries of the replenishment orders are always in full. However, by using safety LT, the actual stochasticity of the SLT could be taken into account and the effects of late deliveries reduced.

The fourth (set of) variable(s) that can be altered by the user are the *Target Fill Rates* of the classes 3 till 5 (these are introduced *Section 4.2*). Or in case of C-items (class 1) the *Time Between Stockout* occasions (TBS), in years. Changing the target fill rate will impact the Expected Shortage Per Replenishment Cycle (ESPRC)–calculations, which in-turn impact the safety factor with which the level of safety stock is determined per SKU. Changing the TBS of a SKU will directly impact the safety factor.

4.1.2 Historical demand data

An important input for the tool is sufficient historical demand data of the individual SKUs. The available data set is subsequently divided into a training set and a testing set. The training set (2017-2020) is used to ascertain the input parameters for the policy selection and to determine the parameters of the chosen policies. The demand data of 2021 is used as a testing set in *Chapter 5* to find the performance of inventory control policies.

To obtain a sufficient set of demand data, the goods issued data of the SKUs from inventory is taken over this period from SAP. This data is independent of the demand data of the parent modules. This data contains the planned demand for POs and the unexpected demand due to service and spare parts and incomplete BOMs of CT modules. However, it does occur that for some SKUs the historical demand data are lacking. This may be due to the SKU being new or replacing another SKU in an assembly. This demand has been extended by looking at the demand data of the parent modules and translating this demand using BOM information and the known production routing of that component. As it is dependent on the routing of the SKU when it is consumed from stock.

In all other cases, where it is not possible to obtain sufficient data for a SKU through the use of the previous two steps, the available data are replicated over the missing periods using a form of bootstrapping. The available data are taken as an empirical distribution and for each period, before the first known data point, a random demand is taken from the distribution to be the demand of that period.

4.2 SKU classification methodology

Figure 4.2 shows the schematic overview of the SKU classification method used for the tool.

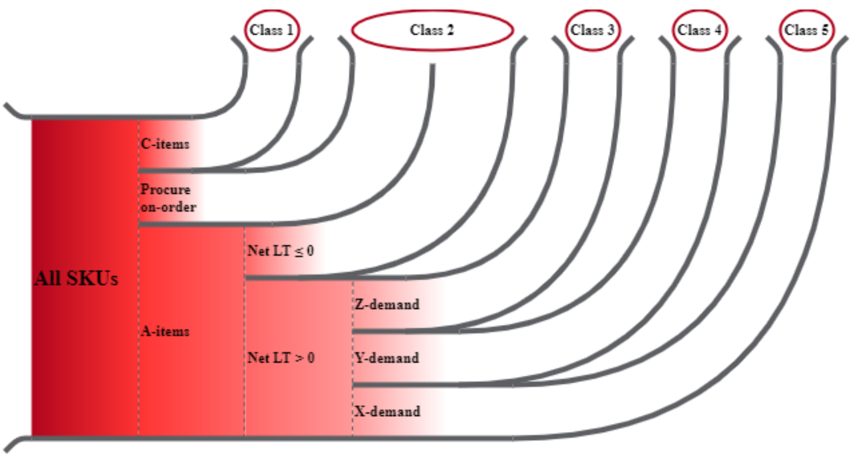

Figure 4.2: SKU classification method, adapted from (Hautaniemi & Pirttilä, 1999).

The SKU classification process described by Hautaniemi & Pirttilä (1999), see *Section 3.2.5*, has been slightly adapted in three key areas to suit the needs for this research. (1) Before performing the AC-analysis the SKUs which need to be procured on-order are filtered out. These are SKUs that due to their volume cannot be stocked and SKUs that do not have any demand in 2021. As the 601 SKUs used in this research have been found by exploding the BOMs of all the modules, it does occur that some SKUs no longer have any demand as they might have only be used in specific modules which are rarely sold, or they have been replaced by another SKU. (2) classifying the A-items based on their Net LT, see *eq. 23*, compared to Hautaniemi & Pirttilä (1999) who only check if SLT ≤ FAS. (3) further classifying the SKUs with a Net LT larger than 0 using the XYZ-analysis into class 3, 4 and 5.

By classifying the SKUs in the various classes a distinction in the use of policies and target fill rates per class can be made. *Table 4.2* shows the number of SKUs in each class, when taking the current minimal DLT for a PO of 7 weeks, no DLT_{extra} and one week of safety LT into account.

Table 4.2: Number of SKUs per class, taking current DLT and safety LT into account

Class 1	Class 2	Class 3	Class 4	Class 5
280	295	11	14	1

4.2.1 AC-analysis

The first stage in the SKU classification is the AC-analysis. This analysis is used over the ABC-analysis, based on the results found by Hautaniemi & Pirttilä (1999), stating that the two categories would be sufficient. Moreover, using the extra category would only increase the number of classes. The AC-analysis, like the DBV-analysis in *Section 2.2.2*, uses the annual usage value of the SKUs. The annual usage value is the result of the annual demand multiplied by the unit price. To ensure that some of the historical demand data are taken into account the annual demand data of 2021 is exponentially smoothed with that of previous years, using *eq. 24* and a larger smoothing factor of $\alpha = 0{,}7$. *Figure 4.3* shows the Pareto curve of the AC-analysis.

$$\hat{x}_t = \alpha * x_t + (1 - \alpha) * \hat{x}_{t-1} \quad (24)$$

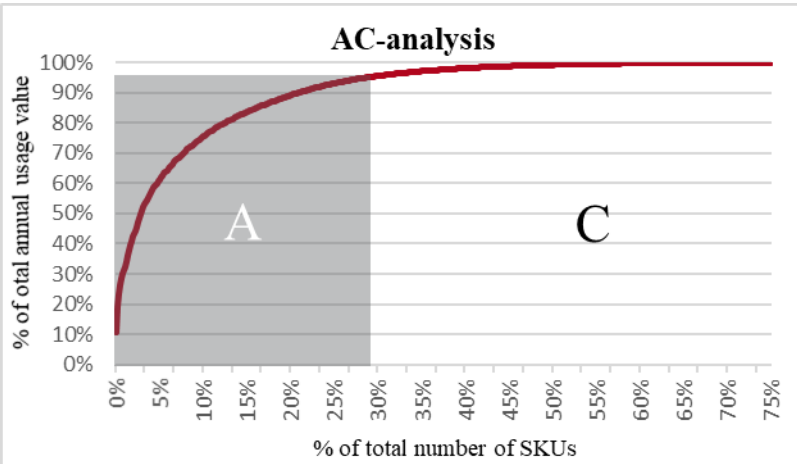

Figure 4.3: Pareto curve of AC-analysis

Roughly 28,5% of the SKUs are classified as A-items which account for 95% of the total annual usage value. A further 46,6% of the SKUs are classified as C-items and account for the last 5%. The remaining 25% of the SKUs have not been taken into account as they either had no demand in 2021 or should only be procured on-order.

4.2.2 XYZ-analysis

For the XYZ-analysis the SKUs, in this case A-items, are categorized by their CV (*eq. 2*) of demand during their replenishment lead time, in this case Net LT. For this the average and standard deviation of the demand over this period is required. For the average demand per period simple exponential smoothing is applied, using *eq. 24*, to ensure that the latest demand data are taken more into account compared to the older data. α is optimised per SKU to minimize the MSE over the period 2017-2020 (van der Heijden, 2021-a). The standard deviation is taken over all the periods. SKUs with a CV of 0,5 and lower are classed as X-items. X-items have relatively constant and predictable demand. SKUs with a CV between 0,5 and 1 are classed as Y-items, these have medium demand irregularity. SKUs with a CV larger than 1 are classed as Z-items as these have very irregular demand, which is difficult to predict.

4.3 Selecting an inventory control policy

Table 4.3 shows an overview of the policies chosen to be applied on the various SKU classes.

Table 4.3: Control policy options per class

Class 1	Class 2	Class 3	Class 4	Class 5
$(\boldsymbol{s}, \boldsymbol{Q})$	MRP	(s, S) & (s, nQ)	(s, S) & (s, nQ)	(R, s, S) & (R, s, nQ)

Class 1 contains the C-items, the less important SKUs, for which the demand and price per unit is relatively low. To avoid investing a lot of time in the monitoring of this stock a simple (s, Q)-policy, using TBS, is chosen as it is good enough to control these type of SKUs (Silver, Pyke, & Thomas, 2017). Another possibility for C-items, according to Silver et al. (2017), is to apply an (R, S)-policy with a long review period. The latter is not initially chosen, but will be tested in *Chapter 5*.

Class 2 contains SKUs that are either: required to be procured on-order; have no demand in 2021 or; have a sufficient LT to be procured on-order. For these SKUs the policy choice is to have these driven by MRP-data, to reduce OHI.

For class 3 and 4 either an (s, S) or (s, nQ)-policy is applied to the SKU, dependent on the ordering requirements of that SKU. Due to the higher demand variability of the Y and Z-items a continuous review policy seems appropriate, also taking in to account the recommendations given by Silver et al. (2017) in *Table 3.3*. In the case that a SKU has a FOQ or IOQ then the (s, nQ)-policy should be applied, as the replenishment order size is fixed or should be a multiple of an IOQ. In the other cases the (s, S)-policy is applied, taking into account that the replenishment order size is at least as large as the MOQ, if applicable.

For class 5 either an (R, s, S) or (R, s, nQ)-policy can be applied, also dependent on the ordering requirements of that SKU. Due to the lower demand variability compared to the Y and Z-items, the X-items are easier to predict and a static inventory control policy is appropriate for these SKUs (Silver, Pyke, & Thomas, 2017).

4.4 Determining the Policy Parameters

In *Table 4.4* an overview is given of the formulas used to determine the parameters of the policies which have been chosen in the previous Section. In
Table 4.5 the formulas used to determine the safety factor k are given. The safety factor is determined by calculating the $ESPRC_{target}$, and using the goal function in Excel and the approximation formulas for $G_u(k)$ and $J_u(k)$ (*eq. 16* and *eq. 19* respectively) find the value k that makes $ESPRC$ equal to $ESPRC_{target}$. By using these equations the assumption is made that demand of SKUs is always Normally distributed. In *Section 4.5* this assumption is discussed in more detail. Another important aspect of the model is that if k, determined with the goal function is negative, it should be set to 0 as this would otherwise lead to negative safety stocks and possibly negative reorder points, which are not desirable in this case. An effect this change will have is that the policy will likely achieve a fill rate which is a lot higher than the target. In *Section 5.2.4* the model is validated and this effect, by only allowing nonnegative safety stocks, is discussed.

For the (s, Q)-policy for C-items *eq. 17* is used to calculate the safety factor, where a large TBS is applied to ensure that the chance of a stockout occasion is small. Silver et al. (2017) recommend a TBS of 5 to 100 years.

Table 4.4: Overview of formulas used to determine control policy parameters

Policy	Safety Stock	Reorder point	Order-up-to-level
(s, Q) *C-item*	$SS = k\sigma_L$	$s = \hat{x}_L + SS$	N/A
(R, S)	$SS = k\sigma_{R+L}$	N/A	$S = \hat{x}_{R+L} + SS$
(s, nQ) *A-item*	$SS = k * \sqrt{(\sigma_L)^2 + Var[Z]}$	$s = \hat{x}_L + E[Z] + SS$	N/A
(s, S)	$SS = k * \sqrt{(\sigma_L)^2 + Var[Z]}$	$s = \hat{x}_L + E[Z] + SS$	$S = s + Q - E[Z]$
(R, s, S)	$SS = k * \sqrt{(\sigma_{R+L})^2 + Var[Z]}$	$s = \hat{x}_{R+L} + E[Z] + SS$	$S = s + Q - E[Z]$
(R, s, nQ)	$SS = k * \sqrt{(\sigma_{R+L})^2 + Var[Z]}$	$s = \hat{x}_{R+L} + E[Z] + SS$	N/A

Table 4.5: Overview of formulas used to calculate $ESPRC_{target}$ and ESPRC per policy

Policy	$ESPRC_{target}$	$ESPRC$
(R, S)	$(1 - P_2)\hat{x}_L$	$\sigma_{R+L}G(k) - \sigma_L G\left(k\frac{\sigma_{R+L}}{\sigma_L} + \frac{\hat{x}_R}{\sigma_L}\right)$
(s, nQ) *A-item*	$(1 - P_2)Q$	$\sqrt{(\sigma_L)^2 + Var[Z]} * G(k)$
(s, S)	$(1 - P_2)Q$	$\sqrt{(\sigma_L)^2 + Var[Z]} * G(k)$
(R, s, S)	$(1 - P_2) * (Q + E[Z])$	$\frac{\sigma_{R+L}^2 * J(k)}{2\hat{x}_R}$
(R, s, nQ)	$(1 - P_2) * (Q + E[Z])$	$\frac{\sigma_{R+L}^2 * J(k)}{2\hat{x}_R}$

The order quantity Q is calculated using the EOQ-formula (*eq. 4*). The value Q is rounded up to the nearest integer. In case the SKU has ordering requirements these are also taken into account. Order quantities of SKUs with a MOQ are rounded up to be at least MOQ. Order quantities of SKUs with an IOQ are rounded up or down to the nearest multiple of IOQ. Order quantities of SKUs with a FOQ are set to FOQ.

The review period of an SKU is determined using *eq. 5* with a maximum of 12 weeks for C-items and a maximum of 4 weeks for A-items (Ros, 2022).

For C-items the period over which demand during LT is determined is equal to the $SLT + safety\ LT$, which is used in the calculations of the parameters. For A-items this period is equal to the Net LT. So in the case of C-items they are not controlled by known demand during a fixed period $(DLT_{known} + DLT_{extra})$. The main decision for this is to propose a simple policy for the C-items.

For the inventory policies of the A-items (class 2 -5) undershoot is taken into account when determining the policy parameters. For the continuous review policies, the average and standard deviation of the order sizes over the data from 2017–2020 are determined. The expected undershoot and the variance of the undershoot are calculated using *eq. 6*, *eq. 7* and *eq. 10*. Where the assumption is made that the order sizes are normally distributed.

4.5 Constraints of tool

In this section a brief discussion is held regarding the constraints of the tool designed in this chapter. Starting with the first drawback being the distinction made between X, Y and Z-items based on the CV of their weekly demand. In its current state, the tool does not vary the demand distributions for the various SKUs based on the CV values, for all SKUs the demand is assumed to be Normally distributed. Demand distributions have not been fitted using hypothesis testing as it would be very time intensive for all 601 SKUs in Excel, with varying lengths of demand data. However, Silver et al. (2017) recommend a rule of thumb: use a Normal distribution if the demand during LT is larger than 10 and the CV of that demand is smaller or equal to 0,5. If demand during LT is smaller than 10 units a (compound) Poisson distribution is recommended. If demand during LT is larger than

10 units and the CV of demand during LT is larger than 0,5 Silver et al. (2017) recommend to use a Gamma distribution, to prevent possible underestimation of the safety stock required. For the undershoot the distributions of the order sizes of SKUs have also been assumed to be Normally distributed. The resulting policy parameters are already a huge improvement over the current situation, in which no proper policy parameters are in place.

Table 4.6: Division of SKUs across demand distributions

Demand distribution	#SKUs
(Compound) Poisson	181
Gamma	84
Normal	41

Looking at the classification made in *Table 4.2* there are 306 SKUs which are controlled using inventory policies (class 1, 3, 4 & 5). *Table 4.6* shows the division of the SKUs when evaluating which demand distributions should be used for these SKUs, according to the rule of thumb mentioned above. In general most of the policy parameters of the SKUs, modelled with a Normally distributed demand, are (slightly) over estimated, when analysing the simulation results in *Chapter 5*, using the settings of the current situation in which the *minimal DLT of PO* is 7 weeks and the safety LT is 1 week. This where underestimation was expected. This is most likely due to the small Net LT with which the policy parameters are determined, sometimes only 1 week. For the SKUs with an underestimation and lower fill rates there are some practical adjustments which could be made to improve the performance, these are further elaborated in *Chapter 5*.

When the user would like to include the demand information known from the sales layout, the assumption is that this DLT_{extra} is perfect. In other words, the demand information is 100% accurate. The tool does not take into account the "Degree of Certainty" (DoC) as mentioned in *Section 2.3.5*. This was decided to the reduce complexity, due to time restrictions. The result is that replenishment orders might be slightly overestimated. As according to Ten Bolscher (2021) the size of SKU demand from the sales layout could be seen as an upper bound of the actual size of SKU demand. Thus the effect of this assumption to backordering of SKUs should limited.

The SLTs are assumed to be deterministic and the deliveries of the replenishment orders are assumed to always be in full. In reality, as seen in *Section 2.4.2,* this does not completely reflect reality in which there is a certain stochasticity to the delivery accuracy of the suppliers. Moreover, it does occur that suppliers deliver the purchase order in parts, possibly due to their own supply shortages. However, by using some safety LT, the stochasticity of the SLT might be taken into account and the effects of late deliveries reduced.

As the tool currently only determines inventory control policies based on historical demand data of the individual SKUs an assumption is made that the SKUs have independent demand to one another. However, in reality this is not the case. Often SKUs interact in pairs as they might appear in BOMs in equal amounts. This assumption might have more of an impact if forecasting of SKU demand is incorporated that updates the expected demand during a period and therefore the demand during LT. However if the tool is say run once a month with fresh data, removing the older data would also result in updates to the policy parameters. The expectation is that the demand at VPM-1 is that seasonal factors are negligible. Therefore, only trend, level and random fluctuations remain. If the tool is run with a frequency of one month the trends should be taken into account. However, a certain lag will always occur as parameters are only updated after demand has occurred.

4.6 Conclusion

In this chapter the inventory control policy tool is designed to determine a fitting inventory control policy and corresponding parameters for each SKU. To provide an answer to the third research question, the corresponding sub-questions are answered in this section.

How should the SKUs, identified in Chapter 2, be classified?
The SKUs are classified using an adapted stepwise classification method of Hautaniemi & Pirttilä (1999). The first step is an AC-analysis, dividing the total group of SKUs based on their annual usage value. Next, the A-items are divided based on their Net LT. The Net LT of a SKU is dependent on the (1) minimal DLT of a PO and

the production stage in which the SKU is consumed, (2) extra DLT due to the use of demand information from the final sales layout, (3) the SLT of the SKU and (4) the safety LT. Subsequently, the A-items with a $Net\ LT > 0$ are divided based on their CV. *Table 4.7* shows the number of SKUs per class, taking into account the current minimal DLT for a PO of 7 weeks and a 1 week safety LT.

Table 4.7: Number of SKUs per class, taking current DLT and safety LT into account

Class 1	Class 2	Class 3	Class 4	Class 5
C-item	A-item $Net\ LT \leq 0$ OR SKU required on-order	A-item $Net\ LT > 0$ $CV > 1$	A-item $Net\ LT > 0$ $0{,}5 \leq CV \leq 1$	A-item $Net\ LT > 0$ $0{,}5 < CV$
280	295	11	14	1

What inventory control policies are suitable for each classification?
Table 4.8 shows the chosen control policy options per class. For class 3, 4 and 5 it is dependent on the ordering requirements of the SKUs which policy is chosen. If there are no ordering requirements then a control policy featuring an order-up-to-level is chosen, else a control policy with a fixed replenishment quantity.

Table 4.8: Control policy options per class

Class 1	Class 2	Class 3	Class 4	Class 5
(s, Q)	MRP	(s, S) & (s, nQ)	(s, S) & (s, nQ)	(R, s, S) & (R, s, nQ)

How should the parameters of the chosen policies be determined?
An overview of the required calculations are given in Table 4.4 and
Table 4.5. For the calculations the expected demand during LT and the standard deviation of this LT are used. These values are based on historical demand data of 2017-2020.

5 Analysis of results

In this chapter the proposed inventory management tool and the ensuing inventory control policies are tested using a simulation model and the results are analysed. This chapter provides the answer to the following research question "*What is the performance of the inventory when applying the proposed inventory management tool?*". The chapter starts by determining the inventory control policies and the accompanying parameters using the tool designed in *Chapter 4*, inputting the settings which are comparable to the current system. In *Section 5.2* the simulation model is presented, verified and validated. Thereafter, in *Section 5.3*, the results of the simulation are given and discussed. Lastly, in *Section 5.4,* a sensitivity analysis is performed in which various input settings and constraints are altered to investigate how robust the solution of the proposed tool is.

5.1 Determining control parameters

To determine the control parameters for each SKU, the formulas and knowledge from *Section 4.4* is used. *Table 5.1* shows the input variables used. In the current situation the minimal DLT of a PO (time between filling the PO in SAP and the loading date of PO) is also 7 weeks. Moreover, currently no demand information from the final sales layout is used, therefore, DLT_{extra} is equal to 0. The safety LT is set to 1 week as this is how the planner currently plans POs. The decision is made to take a TBS of 5 years for C-items as this should ensure that a large quantity of SKUs are kept on stock to prevent stockout occasions. For the target fill rates of the A-items the decision is made to vary these between 95% - 99% based on the demand uncertainty of these classes. In *Section 5.4* a sensitivity analysis is performed in which amongst other things these variables are changed to analyse the effect these have on the results.

Table 5.1: Input variables for determining control parameters

Input Variable	Value
Carrying cost	*22%*
Minimal DLT of a PO	*7 weeks*
DLT_{extra}	*0 weeks*
Safety LT	*1 week*
TBS	*5 years*
Target Fill Rate Class 3	*95%*
Target Fill Rate Class 4	*97,5%*
Target Fill Rate Class 5	*99%*

5.2 Simulation model

To test and find the performance of these new control policies a simulation model was created using Excel VBA. The simulation model has been built to simulate the control policies over the complete year of 2021 and compare the performance to that of the current inventory. To ensure that the system is in more of a steady state when measuring the performance over 2021, a warm-up period of one year (2020) is used. By doing this, the results are not negatively influenced by the excessive backordering that occur due to initialisation problems.

By applying historical demand data the simulation model is stochastic. Moreover, it is discreet, in each period of one week a decision is made on the size of the replenishment order. A period of one week is chosen as this is the time bucket that VPM-1 prefers to work with when planning production and to discuss LTs with suppliers. The model thus assumes that all the demand for SKUs of POs in a given week is consumed at the start of the week. This however, means that the model does not completely reflect reality. As a production stage might take a week, some POs may start on other days during the week, thus not strictly consuming SKUs at the start of the week. Additionally, in reality the buyer can also order SKUs each day. Implying that if on, for instance, a Wednesday the reorder point of a particular SKU, with an (s, Q)-policy, has been passed, the buyer can place an order Q at the end of that day. One other implication of one week periods, is that when a SKU has a FOQ, it does not work correctly. An example of this can be found in *Appendix A.8*. A FOQ means that a replenishment order, if required, may only be of size FOQ. In the case that the average demand per period is larger than FOQ, the SKU would always backorder. In reality however, it is an ordering requirement when ordering on a daily basis. It is for instance possible to place an order on Monday and Wednesday if required. Thus in the simulation SKUs with an FOQ are treated equally to SKUs with an IOQ, if required, a multiplicative of FOQ is ordered to increase the IP above the reorder point.

The decision made each period is dependent on the control parameters of the policies, the IP and the demand known during the DLT. The latter two make up the "Economic" inventory position, see *eq. 25*. The IP is dependent on the stock in the pipeline, the amount of SKUs backordered and the ending OHI, a.k.a. net stock (see *eq. 26*), of that period.

$$Economic\ IP = IP - (demand\ during\ DLT_{known} + demand\ during\ DLT_{extra}) \tag{25}$$

$$\begin{aligned} Net\ stock = max\{0, (starting\ OHI + received\ replenishment\ order - realised\ demand \\ - demand\ backordered\ in\ previous\ period)\} \end{aligned} \tag{26}$$

In the simulation model the lot sizing procedures, as currently implemented in SAP, have been modelled for the SKUs controlled by MRP (Class 2).

The VBA code used for the replenishment order decisions can be found in *Appendix A.7*. In the following sub-sections the input and output data are shortly described, an example of the simulation for one SKU is shown and lastly the verification and validation for the simulation model is given.

5.2.1 Input data

To perform the simulation, input data are required. Starting with the data required for determining the control policies, as mentioned in *Section 4.1*. These are the SKU characteristics, the input variables by the user and the historical demand data. Demand data from 2017-2020 is used as a training set to determine the control parameters and demand data of 2021 is used as the testing set for the simulation. The data is aggregated using time buckets of a week. Lastly, to obtain a realistic simulation the actual inventory levels for the start of the warm-up period are used.

5.2.2 Output data

To determine the performance of the control policies two important KPIs are measured per SKU, the realised fill rate and the average OHI. The realised fill rate is the summation of demand directly fulfilled from stock divided by the total realised demand. The average OHI is the summation of the ending OHI of each period divided by 52 weeks. To determine the aggregate performance of the inventory the realised fill rate of each SKU is averaged. Moreover, the average OHI of each SKU is multiplied by the unit price and summed to determine the total average OHI value of the inventory. These KPIs can be compared to the current situation. Anther KPI being measured is the expected cost due to backordering, using *eq. 1*. The latter is to give management an indication of the cost of backordering. Other outputs from the simulation are:

- When to place a replenishment order and the size of the order
- Number of orders placed
- Number of weeks with a stockout

5.2.3 Visualisation

In this sub-section an example of the simulation for SKU 235 is given. *Figure 5.2* shows the first 15 periods of the simulation and *Figure 5.3* shows a graphical visualisation of this simulation. The control policy parameters are based on the input data in *Table 5.1*. Detailed SKU information can be found in *Figure 5.1*. The Net LT, with which the parameters have been determined is equal to *2 weeks*. The reorder point (s) for SKU 235 is *29 units*. The SLT is *6 weeks* and the lot size (Q) is equal to *40 units*. In the second period a replenishment order is placed as the Economic IP (18 units) is lower than s. An order Q is placed to attain an Economic IP higher than s. The order of 40 units is delivered at the start of period 8. The received replenishment order of 40 units in period 4 is due to an order which was placed in the warm-up period. *Figure 5.1* also shows the realized fill rate, which for SKU 235 is 100%, meaning no SKUs have stocked out in 2021. However, in period 14 this was pretty close to occurring as the ending OHI in that period was 1 unit.

SKU Info	
SKU ID	235
SKU Class	4
SKU Policy	(s,Q)
Supply LT (weeks)	6
DLT_known (weeks)	5
DLT_extra (weeks)	0
Initial pipeline stock	40
Initial on-hand inventory	45
Initial demand backordered	0
Review period (weeks)	2
Target fill rate	97,5%
Realized fill rate	100,0%
Average on-hand inventory	36,019
Lotsize	40
Safety Stock	10
Reorder point	29
Order-up-to-level	0
Total demand	618
Nr. of orders placed	15

Figure 5.1: Simulation information of SKU 235

Weeknumber	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Beginning on-hand inventory	45	45	37	25	55	46	31	18	34	21	42	27	57	41	1
Received replenishment order	0	0	0	40	0	0	0	40	0	40	0	40	0	0	40
Realized demand	**0**	**8**	**12**	**10**	**9**	**15**	**13**	**24**	**13**	**19**	**15**	**10**	**16**	**40**	**0**
Demand fullfilled from stock	0	8	12	10	9	15	13	24	13	19	15	10	16	40	0
Demand backordered	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ending on-hand inventory	45	37	25	55	46	31	18	34	21	42	27	57	41	1	41
Total pipeline	40	40	80	40	80	80	120	80	80	80	80	80	80	80	80
Inventory position	85	77	105	95	126	111	138	114	101	122	107	137	121	81	121
Demand during DLT_known	54	59	71	74	84	84	81	73	100	81	78	75	85	77	86
Demand during DLT_extra	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Economic inventory position	31	18	34	21	42	27	57	41	1	41	29	62	36	4	35
Replenishment order	0	40	0	40	0	40	0	0	40	0	40	0	0	40	0

Figure 5.2: First 15 periods of the simulation of SKU 235

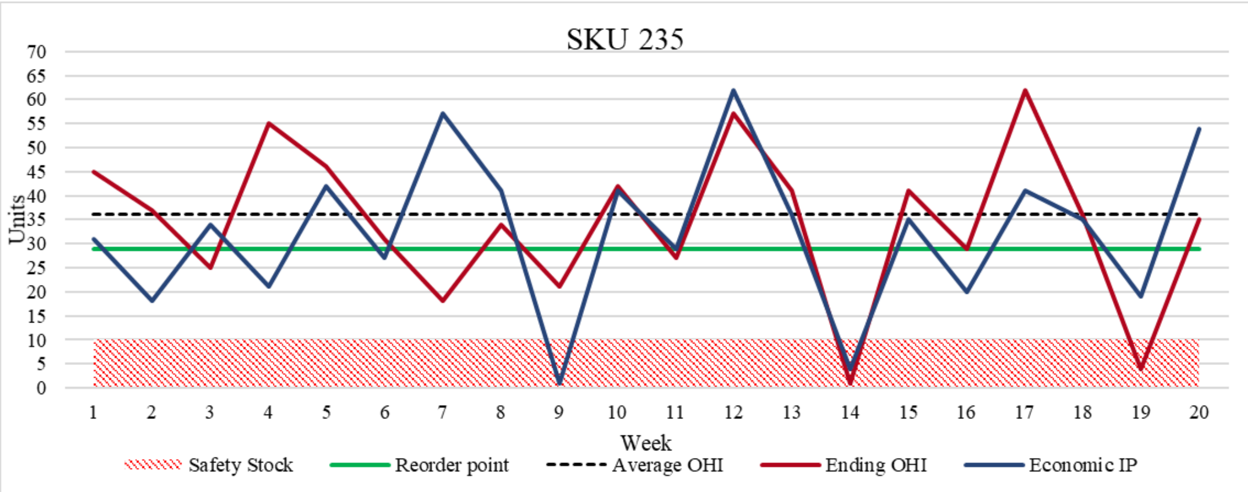

Figure 5.3: Graphical visualisation of the simulation in Figure 5.2 of SKU 235.

5.2.4 Verification & validation

Verification is concerned with determining whether the simulation model is correctly implemented when comparing it to the conceptual model. Validation is the process of determining if the model is an accurate representation of the system, *"for the particular objective of the study"* (Law, 2014).

Verification

To verify the simulation model, the model should be thoroughly checked if it meets all the requirements. According to Law (2014) one of the most powerful techniques that can be used to verify a discrete-event simulation is to perform a “trace”. Which is to examine the state of the simulated system after each event and check if it works as intended compared to hand calculations. This was performed for multiple SKUs for each control policy to check if the simulation would place a replenishment order, for the correct amount in the right period. This included, checking if the model takes into account the ordering requirements set on the SKUs. In the case of an FOQ, checking if it works similar to an IOQ, as mentioned in *Section 5.2*. The simulation was run under a variety of settings of the input parameters, to verify and see if the output parameters were reasonable. A part of the simulation of SKU 235 can be found in *Section 5.2.3*, where these graphs are used for the hand calculations. Moreover, the SKUs were also tested using a periodic review policy, verifying that an order is only placed on the review opportunities.

Validation

To validate the simulation model the most definitive test is to establish that its output data closely resemble the output data that would be expected from the actual system (Law, 2014). The best way to do this is to input the current control policies and accompanying parameters and run the simulation. Unfortunately, as mentioned in *Section 2.2.*2, currently there are no defined inventory control policies in place to manage the SKUs. Which makes comparing the model to reality impossible. The ordering is mainly MRP-driven, where the buyer reviews the future demand of confirmed POs and orders a sufficient amount to cover those orders. The current way of ordering is heavily dependent on the knowledge and experience of the buyer. Thus, even if all SKUs were modelled using MRP as their control policy, the data would not resemble the actual performance of the system. To still be able to validate the simulation model however, separate aspects of the model are validated using stakeholders as an alternative, reviewing if the simulation results are reasonable. If the simulation results are consistent with a perceived system behaviour then the model is said to have *face validity* (Law, 2014). The stakeholders are the group leader and planner of VPM-1.

The first aspect that is validated is the *use of a nonnegative safety factor* k. As mentioned in *Section 4.4* the choice was made to only allow the model to apply a nonnegative k, because otherwise this would lead to negative safety stocks and possibly negative reorder points. The effect is that the resulting policies achieve a fill rate which is higher than their target. To validate that the model determining the policy parameters and the simulation model do not contain bugs, the policy parameters have been run allowing a negative k, varying the target fill rate. *Table 5.2* shows the results of the simulation of the 168 A-items. The results show that due to the nonnegativity constraint the policies cannot realise their target fill rate and remain larger than 90%. However, when this constraint is relaxed the SKUs obtain similar results to the target fill rate, showing that there are no bugs in the model or simulation model.

Table 5.2: Target and realised fill rate of 168 A-items, allowing negative safety factors vs. not allowing them. Min. DLT of PO =4, Safety LT=0 and without undershoot for continuous review policies

Negative safety factor?	#k's set to 0	Target fill rate	Realised fill rate
Not allowed	49	95%	94,5%
Not allowed	131	85%	91,3%
Not allowed	154	75%	90,5%
Not allowed	160	65%	90,3%
Allowed	-	95%	94,2%
Allowed	-	85%	86,3%
Allowed	-	75%	75,4%
Allowed	-	65%	65,7%

The second aspect that is validated is the *use of available demand information*. The model takes into account the available demand information of a SKU, based on the production routing of a SKU, knowing in what stage it is consumed. This information, together with the minimal DLT of a PO, determines the DLT_{known} of a SKU. Moreover, in the model it is possible to take into account a safety LT and DLT_{extra} from the sales layout. The stakeholders confirm that the amount of weeks used is actually available and consistent with the production stages.

The third aspect that is validated is the *use of a warm-up period*. This was done by comparing the results of the simulation with and without a warm-up period, see *Appendix A.9*. Without the warm-up period many SKUs in inventory which had demand in the first few weeks, within the SLT, would have lower fill rates. Because the SKUs would backorder as the OHI on 1-1-2021 would not be sufficient to cover demand during the SLT. With the warm-up period, the simulation is not affected by this initial negative performance and is in a steady state.

The fourth aspect which was validated is the *use of historical demand data*. Using the demand data of 2017-2020 as a training set to determine control policy parameters and using 2021 as the testing set, resulting in outputs of the model that can be compared to how the actual system performed. In addition, using 2020 as the warm-up period ensures that the simulation is in a steady state in 2021.

The fifth aspect which was reviewed with the stakeholders is *the size of the time buckets*. The idea behind the time buckets of one week is that it would resemble more generally the planning buckets which the planner uses to plan production. However, as production stages of a PO might take a week to complete, POs may start production on varying days of the week, dependent of course on the size of the POs. Thus stock might not be consumed at the start of the week. In reality if the economic IP would pass the reorder point on any day during the week, the buyer could place an order with the supplier. Yet, due to the use of weekly periods the assumption has been made that the buyer only has one opportunity in a week to place an order. Because of this reasoning the simulation results are reasonable on a more macro scale, but likely overestimate the real system in case of continuous review policies.

The last aspect which is validated are *the output KPIs*. The output KPIs are similar to those that management uses. The results of the simulation under various input parameters were reviewed and deemed to be reasonable, the resulting average inventory values were in an expected range, when comparing it to the current average inventory value. The results of the simulation model are given and discussed in *Section 5.3*.

5.3 Simulation model results

In this section the results from the simulation model are discussed when applying the control policies which were determined using the input settings shown in *Table 5.1*. Firstly, some general results and remarks are provided and are followed by some patterns found when analysing the badly performing SKUs and possible ways to prevent or reduce these.

Table 5.3 shows the results of the simulation per class. The first row of *Table 5.3* shows the division of the SKUs over the classes when applying the input variables in *Table 5.1,* to determine the control policy parameters. The average fill rate over all SKUs is 99,1%. The average fill rate of A-items is 99,8%.

Table 5.3: Results of the simulation per class, taking $min.DLT\ of\ PO = 7\ weeks,\ safety\ LT\ = 1\ week\ and\ without\ DLT_{extra}$ *into account.*

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	280	295	11	14	1	601
Avg. fill rate	98,2%	100,0%	97,9%	99,3%	100,0%	99,1%
Total backordering cost	€ 110.927	€ -	€ 1.928	€ 34.245	€ -	€ 147.099
Total avg. OHI value	€ 111.138	€ 220.792	€ 49.298	€ 96.983	€ 3.366	€ 481.578
Current avg. OHI value	€ 42.620	€ 338.908	€ 22.777	€ 30.266	€ 815	€ 435.386
Difference in OHI value	€ 68.518	€ -118.116	€ 26.522	€ 66.717	€ 2.551	€ 46.192

As mentioned in *Section 2.2.3* in the current situation fill rate over the whole of 2021 was not measured, thus a comparison between the current state and the future state using the simulation results is difficult. A tool was introduced at the warehouse during this research, to start measuring the fill rate of the inventory. However, this was only performed over a small period of 2021 and the tool has been filled rather inconsistently since introduction. Moreover, a large portion of the SKUs which have been marked as backordered in the tool, are MRP-driven in the simulation. As this is similar as to how these SKUs are controlled in reality this means the simulation results are most likely better (fill rate is 100%) due to unforeseen events in reality, i.e. shortages at suppliers due to worldwide parts supply issues; the buyer not receiving a notification to procure the correct amount on time; the buyer procuring SKUs too far ahead of time, resulting in demand "popping-up" out of nowhere, as described in *Section 2.3.2*. The other option is to compare the results to the ready rate of the SKUs over the same period an assuming this is a good indication of the fill rate over this period. The ready rate over that period is on average 81,5% for classes 1, 3, 4, 5 SKUs. Meaning the use of the proposed inventory control policies can attain an improvement of 16.8% in fill rate for those SKUs. An important sidenote about using ready rate is that for some SKUs and for some POs long periods of demand information are available (in the simulation only a minimum number of periods are taken into account) which the buyer can use to determine far enough ahead of time what the inventory level is supposed to be. Thus, for these SKUs, when MRP-driven, it would make sense that their inventory level be near zero for some periods if the buyer knows there will be no demand.

The approximate labour costs due to backordering are determined using *eq. 1*, see *Section 2.2.3*. The equation does not take into account what type of SKU is backordered. For some SKUs, in reality, the price of backordering a unit is different. For instance it might be equally labour taxing to replace or wait for one engine, compared to 10 meters of electrical cable. Due to this some approximations may be unreasonably high, compared to others. The approximate labour cost due to backordering is €147.000 of which 75,4% is due to the C-items in class 1. Seven C-items account for roughly 66,7% of this cost, for which these SKUs per unit are supposed to be less labour taxing. For the backordering cost of class 3 and 4, both have one SKU which accounts for all of the backordering cost in the respective classes.

The total average OHI value using the proposed control policies is €46.000 more than that in the current situation. The main difference in these costs is due to the SKUs which are controlled using inventory control policies. The increase in the class 1 SKUs is divided over all the SKUs. However, in class 3 and 4 there are three SKUs which are the cause to the large increase (€65.710) over the current situation. These are expensive SKUs with relatively long SLTs, that are used in uncommon modules, that in the current situation have a longer DLTs than other SKUs from the same production stage. This is due to, as mentioned in *Section 2.3.2*, central planner knowing further in advance that demand for this type of module is required and signals VPM-1 to start up production before a PO is filled into SAP. Meaning that in the current situation there is little to no average OHI for these SKUs.

When reviewing the output data on a SKU-level, certain patterns could be decerned amongst the SKUs with the worst fill rates. *Table 5.4* shows the 19 SKUs with a realised fill rate lower than 90%. There are three patterns which can be decerned as to why the SKUs perform badly, these are explained below. The patterns have been numbered and added to the table. A notable detail is that 17 of the 19 SKUs are C-items. The ordering of class 1 is different to that of class 3, 4 and 5. For class 3, 4 and 5 the safety stock and reorder points is based on Net LT. For class 1 this is based on SLT and safety LT. The reason the available demand information was not included for C-items is that they are the cheaper SKUs for which one would like to spend as little amount of management attention as possible.

Table 5.4: Overview of the 19 SKUs with a realised fill rate < 90%

SKU #	Class	Policy	Realised fill rate	Backordering cost	$\hat{x}_L$	$\bar{x}_L$ in 2021	CV	Pattern
32	1	(s,Q)	55,0%	€ 6.384	9,6	34,4	1,66	**1**
37	1	(s,Q)	88,9%	€ 6.540	48,4	142,3	1,33	**2**
116	1	(s,Q)	86,3%	€ 3.749	46,4	65,1	0,33	**2**
119	1	(s,Q)	63,8%	€ 4.654	4,2	30,9	9,01	**1 & 2**
131	1	(s,Q)	87,2%	€ 17.921	45,7	341,1	3,35	**1 & 2**
260	1	(s,Q)	85,1%	€ 1.153	4,8	16,7	2,14	**1**
266	1	(s,Q)	71,5%	€ 25.914	34,9	224,1	2,86	**1 & 2**
284	1	(s,Q)	88,1%	€ 339	0,1	3,2	85,26	**1**
298	1	(s,Q)	75,5%	€ 2.160	9,9	20,4	1,51	**1**
351	1	(s,Q)	69,0%	€ 9.523	25,9	75,0	1,59	**1 & 2**
352	1	(s,Q)	58,5%	€ 3.284	5,3	18,8	1,59	**1**
353	1	(s,Q)	60,5%	€ 3.419	0,5	18,8	19,16	**1 & 2**

358	3	(s,S)	76,4%	€ 1.928	4,8	11,3	3,03	**1 & 3**
359	1	(s,Q)	82,7%	€ 2.548	14,8	34,4	2,38	**1 & 2**
397	4	(s,Q)	89,0%	€ 36.560	392,5	654,2	0,59	**2 & 3**
423	1	(s,Q)	66,7%	€ 300	0,37	0,9	6,74	**1**
475	1	(s,Q)	84,5%	€ 7.104	23,9	108,8	2,17	**1 & 2**
557	1	(s,Q)	88,5%	€ 2.470	51,8	50,0	0,75	**3**
590	1	(s,Q)	70,0%	€ 1.540	16,2	6,9	2,31	**1 & 3**

The *first pattern* is that for some SKUs the control policy parameters are not sufficient, likely due to the assumption of Normally distributed demand. For most of the SKUs in *Table 5.4* the CV value of their demand during lead time is a lot higher than 1. Dependent on if the $\hat{x}_L > 10$, the demand should have either been modelled as a (compound) Poisson distribution or Gamma distribution. When reviewing the progression of the graphs for the SKUs requiring a (compound) Poisson distribution, the reorder points are not set high enough. Demand during SLT may be a lot larger than the reorder point and safety stock, resulting in a backorder. As many periods during the year have zero demand, they decrease the average demand per period which results in a distorted picture if using a Normal distribution. The reorder point is then set to a level which is not capable of handling the de demand if it occurs.

The *second pattern* that can be discerned is that for some SKUs the average demand per period in 2021 is significantly higher than that of the previous years. This results in backordering as the level of the reorder point cannot cover demand during the respective SLT.

The *third pattern* which is found for two of the SKUs is a few exceptionally large demand occasions in 2021, which resulted in stockout occasions and backordering of SKUs.

The lower fill rates due to the first pattern seem to mainly affect the C-items. To prevent or reduce the backordering due to this first pattern a simple solution could be to increase the Time Between Stockout (TBS) for these SKUs. This should increase the safety stock and therefore the reorder point of the SKU, implying the average OHI is increased and replenishment orders are placed sooner. Besides this, the safety LT of the SKU could be increased. This value virtually increases the SLT of a SKU, thus the demand during LT is calculated over a larger period, increasing the reorder point. Another option for these C-items is to include the known demand information. The reasoning this was not included for C-items in the first place is that they are the cheaper SKUs for which one would like to spend as little amount of management attention as possible. However, in the case of the SKUs with *pattern 1* this might prevent or reduce the backordering to the “unexpected” large demand occasions.

The best way to deal with *pattern 2* is to update the control parameters regularly (every 2 months) with new data. This way the increase or decrease in demand in 2021 can be taken into account. It is unlikely something could be done to prevent *pattern 3,* as the demand is exceptionally large, it could not have been foreseen before determining the policy parameters.

5.4 Sensitivity analysis

In this section sensitivity analyses are performed where input variables are changed and the effects discussed to test how robust the solution is to change. In the analyses, the performance of a change is compared to the performance of the initial solution in *Section 5.3*, resulting in an positive or negative “improvement”. The analyses will show a concise table of results. A more detailed versions of these results, like *Table 5.3*, can be found in *Appendix A.10*.

5.4.1 Minimal DLT of a PO and application of DLT_{extra}

In this experiment the minimal DLT of a PO is varied to see how this affects the results. The DLTs tested are 8, 6 and 5 weeks, see *Table 5.5*.

Table 5.5: Overall improvements of results, varying min. DLT of a PO, taking $safety\ LT = 1\ week$ and without DLT_{extra} into account.

Min. DLT of PO	8 weeks	6 weeks	5 weeks
Improvement in avg. fill rate	0,0%	-10,2%	-14,2%
Improvement in total backordering cost	€ -1.279	€ 375.268	€ 991.360
Improvement in avg. OHI value	€ -28.994	€ 144.784	€ 291.968

Varying the minimal DLT of a PO impacts the number of A-items which can be procured on-order and therefore also their control policies. For instance, applying 8 weeks means that due to the extra week of demand information the number of A-items which can be procured on-order (Class 2) increases from 295 to 313. Applying 6 weeks decreases the number of A-items which can be procured on-order to 194.

When applying 8 weeks of minimal DLT of a PO the total average OHI value improves by €28.994, compared to the solution in *Table 5.3*, just by applying one additional week of DLT. The average fill rate remains roughly the same. The average fill rate of the A-items marginally improve from 99,80% to 99,90%. The large group of C-items is not controlled using available demand information, thus an increase of the minimal DLT has no effect on the performance of these SKUs. When applying 6 or 5 weeks of minimal DLT, less SKUs can be procured on-order, and the average OHI value deteriorates by €144.784 and €291.968 respectively, compared to the initial solution. An additional reason is that on average more inventory needs to be kept to cover the larger Net LTs. When applying 5 or 6 weeks of minimal DLT a large decrease in average fill rate can also be seen. This is due to a group of 150 Class 2 SKUs which are required to be procured on-order because of their volume. Lowering the minimal DLT results in a negative Net LT for these SKUs, meaning there is insufficient time to procure these on-order, thus they will backorder. If assuming that regardless of the minimal DLT, this group of SKUs are always procured and delivered on time and the fill rate of these SKUs is therefore 100%, the average fill rate of the A-items does not change in the case of 6 weeks and reduces by 0,1% in the case of 5 weeks. The backordering cost are then increased by €553 and €30.532 in the respective cases. Interestingly, the total backordering cost of the A-items in the case of 5 weeks is €66.705, of which €58.580 is due to SKU 397, featured in *Table 5.4*. Due to the underestimation of the demand during Net LT the reorder point for this SKU is set to low. Therefore, if the demand information is decreased the backordering for this SKU is increased.

Table 5.6: Overall improvements of results including $\boldsymbol{DLT_{extra}}$, taking $\boldsymbol{min. DLT\ of\ PO = 7\ weeks}$ and safety LT = 0

Improvement in avg. fill rate	0,1%
Improvement in total backordering cost	€ -36.173
Improvement in avg. OHI value	€ -71.241

Lastly, DLT_{extra} is applied, see *Table 5.6*. Extra demand information is applied which is known from the final sales layout in the preliminary stage, as mentioned in *Section 2.3.6*. For SKUs which are consumed in the production of the RC and CT modules this means that 4 more weeks of demand data are available. And for SKUs consumed in the production of Cutting Tables this is 2 more weeks of data. Here the assumption is made that the demand is 100% certain. As mentioned in *Section 2.3.6*, this is not true, however, the demand can be seen as the *upper bound* of SKU consumption. Meaning this will likely overestimate the demand, but backordering should be less of a risk. Almost all the A-items can now be procured on-order. The average fill rate of the A-items has improved to 100%. The total backordering cost has decreased by €36.173, mainly due to SKUs 358 and 397 now being controlled by MRP. Moreover, the total average OHI value has decreased by €71.241, which means the that this is better than the current average OHI value.

What can be concluded from this analysis, is that by changing the minimal DLT, thus the moment information is known about the demand of a PO, the average OHI value is affected significantly. On the other hand, the average fill rate only changes marginally. The average fill rate of the A-items was already high (>99%). The likely reasons for the marginal changes is due to the use of high target fill rates, a safety LT, or the application of undershoot. In the following sub-sections these three reasons are experimented.

5.4.2 Target fill rates

The target fill rate is a variable which can affect the policy parameters of the A-items. More specifically the SKUs in class 3, 4 and 5. Class 2 also contains A-items, however, these are procured on-order and are therefore MRP-driven. *Table 5.7* shows the results of the four tests which were performed. The top left table shows the improvements of results when the target fill rates are increased to 99%. The top right and bottom tables show the results when the target fill rate is decreased by 10% each experiment. The columns only takes into account the 26 SKUs of class 3, 4 and 5. The fill rate is compared to the average fill rate of 98,7% from the initial solution over these SKUs.

Table 5.7: Overall improvements of results for class 3, 4 and 5 compared to initial solution, altering target fill rate. Min. DLT of PO = 7 weeks, safety LT = 1 week and without DLT_{extra}.

Target fill rate	99%	86,5%	76,5%	66,5%
Improvement in avg. fill rate	0,3%	-0,5%	-0,7%	-1,0%
Improvement in total backordering cost	€ -620	€ 3.574	€ 4.106	€ 4.571
Improvement in avg. OHI value	€ 22.827	€ -31.795	€ -41.538	€ -47.431

The analysis shows that the realised fill rate is not very responsive to the large increase or decrease in the target fill rate. The realised fill rate remains relatively high. The total average inventory value, however, is affected by the increase or decrease in target fill rate. Decreasing the average target fill rate from 86%, decreases the average OHI value by €31.795, when the realised fill rate only decreases 0,5%.

A more detailed analysis shows that the change in fill rate only affects 2 to 4 SKUs. The other SKUs have a fill rate of 100%. The SKU most heavily affected and determining of the resulting fill rate is SKU 358, which is featured in *Table 5.4*. This SKU, which is uncommon, has in reality, a larger DLT_{known}, as the central planner signals VPM-1 of demand before it is filled into SAP. When applying the average target fill rates 76,5% and 66,5%, 23 SKUs have had their safety factor set to 0 due to the nonnegativity assumption, as explained in *Section 5.2.4*. This creates a bound which lowering the target fill rate cannot change. Other additional factors likely to cause the low responsiveness of the solution to a change of the target fill rate could be the use of safety LT and the application of undershoot.

5.4.3 Safety LT

The safety LT is an input variable which the user can choose for each SKU. The variable is used to virtually increase the SLT with which the policy parameters are calculated. This variable ensures that the replenishment order arrives a certain amount of weeks before the start of production. In case of an A-item the safety LT also determines if the SKU is procured on-order or that it is controlled by a control policy. *Table 5.8* show the improvements of the simulation over the initial solution when applying a safety LT of 0 and 2 weeks respectively. The results show that the safety LT only has a slight effect on the overall average fill rate. The fill rate of the C-items is slightly affected, but the fill rate of the A-items does not change. However, the safety LT does significantly affect the total average OHI value. In comparison to this the change in total backordering cost is relatively small. Going from 1 to 2 weeks of safety LT increases the total average inventory value by €266.172, while decreasing the total backordering cost by €18.095. The large increase in inventory value is due to 119 A-items, which are moved from class 2 to classes 3, 4 and 5. These SKUs can no longer be procured on-order and are controlled by inventory policies. Analysing the SKUs featured in *Table 5.4* however, it can be found that the impact on improving the backordering of SKUs due to the *first pattern* is minimal. By increasing the safety LT the SKUs which have an underestimated lead time demand (*second pattern*) had a decrease in backordering.

Table 5.8: Overall improvements of results when changing safety LT, min. DLT of PO = 7 weeks and without DLT_{extra}.

Safety LT	0	2
Improvement in avg. fill rate	-0,3%	0,2%
Improvement in total backordering cost	€ 21.509	€ -18.095
Improvement in avg. OHI value	€ -150.632	€ 266.172

Table 5.9 shows the results when the safety LT applied are based on the supplier performances found in *Section 2.4.2*. The safety LTs is chosen such that they cover $\mu_{delivery\ date} + 2 * \sigma_{delivery\ date}$. Larger safety LTs are applied to SKUs which have worse performing suppliers to cover their uncertainty in supplier performance. The resulting average fill rate is marginally higher than the initial solution and the backordering costs are improved. However, the solution does require €49.896 more in average inventory investment. The benefit however of having a safety LT to cover the potential for stockouts and backordering, due to late or incomplete deliveries, cannot be seen, as the simulation model uses deterministic SLTs.

Table 5.9: Overall improvements of results per class applying a safety LT based on supplier performance.

Improvement in avg. fill rate	0,1%
Improvement in total backordering cost	€ -11.161
Improvement in avg. OHI value	€ 49.896

5.4.4 Undershoot

Based on the literature research performed in *Section 3.3.2*, when non-unit sized demand occurs undershoot should be taken into account. This has been taken into account when determining the parameters of the control polices for the SKUs. In this experiment however, the undershoot is excluded from the continuous review policies. *Table 5.10* shows the results of the experiment. The average fill rate of the 25 class 3 and 4 SKUs in the initial solution is 98,6%. Excluding the undershoot has a small impact on the fill rate. The three A-items that backorder in the initial solution are also the SKUs which perform slightly worse when removing the undershoot, all other SKUs still have 100% fill rate. Excluding the undershoot does have an impact on average OHI value, decreasing by €25.063. This would mean that for most of the SKUs taking undershoot into account is not required for them to perform optimally. Thus in the initial solution the control policies have been set too high by including the undershoot.

Table 5.10: Overall improvements of results for the 25 SKUs in class 3 and 4, without taking undershoot into account.

Improvement in avg. fill rate	-0,9%
Improvement in total backordering cost	€ 4.029
Improvement in avg. OHI value	€ -25.063

Table 5.11 shows the results when reperforming the tests from *Table 5.2*, including the use of undershoot for continuous review policies. The table also shows the improvement of the fill rate over the realised fill rates in *Table 5.2*. The results from the table show that applying undershoot to the continuous review policies increases the fill rate beyond the target. Especially when the target fill rate is set low and the nonnegativity constraint of the safety factor is removed. From this a conclusion can be drawn that undershoot for the continuous review policies, even though non-unit sized demand is in play, is not necessary.

Table 5.11: Target and realised fill rate of 168 A-items, allowing negative safety factors vs. not allowing them and without undershoot vs. with undershoot for continuous review policies. Min. DLT of PO =4, Safety LT=0

Negative safety factor	Target fill rate	Realised fill rate	Improvement over *Table 5.2*
Not allowed	95%	97,8%	3,3%
Not allowed	85%	95,5%	4,2%
Not allowed	75%	95,0%	4,5%
Not allowed	65%	94,8%	4,5%
Allowed	95%	97,7%	3,5%
Allowed	85%	92,6%	6,3%
Allowed	75%	86,8%	11,4%
Allowed	65%	78,8%	13,1%

5.4.5 Time Between Stockout occasions

An input variable which can be adapted for the C-items is the Time Between Stockout occasions (TBS). The variable is used in *eq. 17* to determine the safety factor. By increasing the TBS the safety factor is increased, which in turn increases the safety stock level. *Table 5.12* shows the results of the simulation for the C-items with varying TBS values. The initial solution was made with a TBS of 5 years. As the overall average fill rate of the C-items is already very high, improvements to this fill rate using larger values of TBS are marginal. However, the results do show a considerable decrease in backordering cost against a relatively small increase in average inventory value. The largest performance increases can be found in the C-items featured in *Table 5.4*. The results of these C-items can be found in *Appendix A.10*. When increasing the TBS the reorder points and safety stocks are also increased to levels at which the sudden large consumption of SKUs is covered better. However, for some of the C-items this is still not enough to cover the large consumptions completely. As mentioned previously, using the known demand information for these SKUs is likely more beneficial.

Table 5.12: Improvements of results varying the Time Between Stockout occasions for the C-items

TBS	3	10	50	100
Improvement in avg. fill rate	-0,6%	0,6%	1,2%	1,3%
Improvement in total backordering cost	€ 14.236	€ -22.784	€ -67.469	€ -78.512
Improvement in avg. OHI value	€ -7.746	€ 11.471	€ 28.621	€ 36.053

The results can be further optimised by determining the best performing TBS for each C-item individually. *Table 5.13* shows the results after optimizing the TBS per SKU, this was done by incrementally increasing TBS by 10 years if fill rate is unequal to 100%. Increasing TBS past 100 years does have a limited improvement potential. The overall average fill rate for C-items is increased by 1,3%, the backordering costs decreased by €78.512 and the average inventory value only increase by €3.285.

Table 5.13: Improvements of results when optimising the TBS for C-items

Improvement in avg. fill rate	1,3%
Improvement in total backordering cost	€ -78.512
Improvement in avg. OHI value	€ 3.285

5.4.6 Include demand information for C-items

As mentioned in *Section 5.3* and the previous sub-sections it may be beneficial to take demand information into account for the C-items. The main reasoning this was not done in the design was to make the control of these SKUs as simple as possible. However, as can be seen in *Table 5.4*, there are SKUs for which the initial solution does not work due to the *first pattern* identified in *Section 5.3*. Some SKUs have a high CV, meaning the demand distribution have been modelled incorrectly, these SKUs may have a (compound) Poisson or even intermittent demand. *Table 5.14* shows the results of including demand information for those C-items of *Table 5.4* with a high CV, by applying A-item policies. By moving them from C to A-items most can be controlled by MRP.

Table 5.14: Results of the simulation excluding and including demand information for the C-items featured in Table 5.4 with a high CV.

	Excluding demand information	Including demand information
Avg. fill rate	75,4%	94,6%
Total backordering cost	€ 98.999	€ 23.176
Total avg. OHI value	€ 5.426	€ 2.263

The results show an overall increase in performance. The average fill rate increases by 19,2% and the average OHI value decreases by €3.163. By moving those C-items to A-items and seeing how well they perform a case could be made as to why not control all C-items with the available demand information. This would mean complicating the control policies for these SKUs and increasing the ordering frequency and therefore, ordering cost. For C-items, the least important SKUs, typically one would like to keep a relatively large number of units on hand to minimize the inconvenience caused by stockouts (Silver, Pyke, & Thomas, 2017).

5.4.7 Policy selection per class

To test if the policies chosen in *Chapter 4* are the most optimal for the respective classes, a sensitivity analysis is performed. In which, for each class, the policies found in *Chapter 3* are varied. To ensure the policies are tested over a larger set of SKUs the testing is done with a minimal DLT of a PO of 5 weeks with a safety LT of 1 week. This classifies more A-items under classes 3 to 5. *Appendix A.10.6* shows the results of the sensitivity analysis for each policy. The results of the analyses are compared to the results from *Table 5.5.*

The results showed that the policies used in the initial solution, in most classes, are the best performing. However, a large improvement can be made by changing the periodic review policies of class 5 to the same continuous review policies of class 3 and 4. Improving the avg. fill rate for class 5 by 0,1% and the avg. OHI by €49.737. The sensitivity analysis did show that a larger improvement of the fill rate (+0,8%) of class 5 is possible with an (R, s, S)-policy, however this does increase the average inventory value by €8.272 over the initial solution. As the target fill rate is already achieved with the (s, S) & (s, nQ)-policy, the difference of €58.464 between the two policies seems too large of an investment.

5.4.8 Best solution

Based on the experiments performed in the previous sub-sections the best settings of the model are given. This best solution is based on the currently available demand information, thus not including DLT_{extra}. A safety LT of one week is applied as this is the minimum amount of safety LT that VPM-1 would like to use. From the sensitivity analysis it was found that the undershoot in the case of continuous review policies is not required. Meaning this can be ignored when determining the policy parameters. From the last sensitivity analysis it was found that for class 5 the continuous review policies perform better than the periodic review policy as initially designed. *Table 5.15* shows the solution of the simulation using the improved settings. Moreover, it shows the improvement over the initial solution and compares it to the current situation. The solution satisfies all the target fill rates which were initially set with the stakeholders, moreover it requires €26.251 less average OHI compared to the initial solution. The solution however does require €19.941 more average OHI over the current situation. However, when the fill rate of the class 1, 3, 4 and 5 SKUs (98,2%) is compared to the ready rate of the same SKUs in the current situation (81,5%), the improvement is 16,7%. This should significantly reduce the unavailability of SKUs for production. If DLT_{extra} is included, then the average OHI investment of the solution is €31.828 less than the current situation, maintaining the high overall fill rate.

Table 5.15: Results of best solution, taking $\boldsymbol{min.\,DLT\ of\ PO = 7\ weeks}$, $\boldsymbol{safety\ LT\ = 1\ week}$ and without $\boldsymbol{DLT_{extra}}$ into account.

Avg. fill rate (Improvement over initial solution)	99,1% (0,0%)
Total backordering cost (Improvement over initial solution)	€ 147.099 (€ 4.029)
Total avg. OHI value (Improvement over initial solution)	€ 455.327 (€ -26.251)
Improvement of avg. OHI value over current situation	€ 19.941

There are some practical adjustments which could be made on a SKU level, which could further improve the performance: (1) Move badly performing C-items, due to a high CV, to A-item classes, to ensure these are controlled using demand information. (2) The TBS for C-items can be optimized for each SKU individually. (3) To further decrease the chances of stockout due to supplier performance, the safety LT can be based on the their current delivery date performance, see *Section 2.4.2*.

5.5 Conclusion

In this chapter a simulation study was performed to provide an answer to the fourth research question: *"What is the performance of the inventory when applying the proposed inventory management tool?"*. In this section the answer is given by answering corresponding the sub-questions.

How can the performance of the proposed inventory management tool be best simulated?
To test the performance of the inventory management tool and the ensuing control policies a stochastic and discreet simulation model was built using Excel VBA. The model simulates the performance of the policies over 2021, applying historical demand data, and comparing that to the current situation. The two main KPIs to measure performance are the realised fill rate and the average OHI value. In addition, to give management an indication, the model also outputs the expected labour cost due to backordering.

Are the results from the simulation study valid and verifiable?
To verify the simulation a "trace" was performed, examining the state of the simulated system after each event and checking if it works as intended compared to the hand calculations. In the current situation there are no defined inventory control policies in place to manage the SKUs. Which makes validating the simulation model by comparing it to reality impossible. As an alternative, separate aspects have been validated by the stakeholders, reviewing if the simulation results are reasonable and consistent with the perceived system behaviour.

What is the performance of the inventory using the proposed inventory management tool in comparison with the current inventory performance?
The average OHI value in the current situation is approximately €435.000 with a ready rate of 81,5% over the SKUs which according to the proposed model should be controlled by inventory policies. The ready rate is taken,

assuming this is a good indication of the fill rate over this period, as the fill rate is not a KPI that is currently measured at VPM-1. The proposed policies from *Chapter 4* achieve a fill rate of 98,3% over the same SKUs against an increase of average OHI value of approximately €46.000. Thus the proposed policies potentially increase the SKU availability by 16,7%. The proposed policies have, however, been further optimized after the sensitivity analysis. The proposed periodic review policies for the class 5 SKUs do not work as well as the continuous review policies. Moreover, the sensitivity analysis showed that taking undershoot into account for the continuous review policies, even though the demand is not unit-sized, is not necessarily required to achieve the target fill rates. The improved policies achieve the same potential increase in SKU availability against an average OHI value increase of approximately €20.000. If demand information from the final sales layout *is* included then the average OHI value of the solution is approximately €403.000, which is an improvement of €32.000, while maintaining the high overall fill rate.

How robust is the proposed tool to discrepancies in input settings and relaxations of constraints?
To analyse how the proposed inventory management tool and the ensuing policies react to changes a sensitivity analysis was performed. In which various input settings and relaxations of constraints were tested. Changing the *minimal DLT of a PO* has a significant impact on the average OHI value, as this results in the SKUs being re-classified into different classes. However, it only marginally impacts the overall fill rate. Similar results were found when changing the *safety LT.* Adapting the *target fill rates* has little impact on the realised fill rate due to the nonnegativity constraint of the safety factor and the use of undershoot. Following this, *undershoot for continuous review polices* was analysed. This showed that undershoot increased the fill rate beyond the target against a significant increase in average OHI value. Thereafter, possible improvements to the C-items by changing the *Time Between Stockout* (TBS) and *including demand information* is analysed. Changing the TBS to larger values has only a marginal impact on the overall fill rate of the C-items, however, the results do show a considerable decrease in backordering cost against a relatively small increase in average OHI value. By moving these badly performing C-items to A-items classes they can be controlled using known demand information, reducing the amount of average OHI value required and reducing stockouts and backordering of these SKUs. Lastly, the *policies per class* are altered, analysing which policy performs best for the individual classes compared to the proposed policies. For class 1 to 4 the proposed policies perform the best. However, for the class 5 SKUs it is found that the continuous review policies, used on class 3 and 4, perform better than the periodic review policies.

6 Implementation

Table 6.1: Stakeholders of implementation

Department	Stakeholder
VPM	Group leader
	Senior operational buyer
	Planner
	Team leader Handling
	Warehouse employee
VSM	Operations manager
	Materials management specialist
	Purchasing manager
	Functional manager SAP
	Business controller

As concluded in the previous chapter the proposed policies should reduce the stockout occasions and backordering considerably. This chapter concisely provides an answer to the following research question: "*How can the proposed inventory management tool be implemented into practice?*". *Table 6.1* shows the stakeholders for the implementation. The project owners are the Operations manager of VSM and the Group leader of VPM. The project leader is the Materials management specialist. They will perform most of the implementation and are responsible for monitoring and analyzing the results. The remaining stakeholders are part of the project team and will provide data and feedback and assist in the implementation of the policies into SAP.

This research and Excel model are based on the SKUs of VPM-1. To determine the efficacy of the proposed policy and to determine if the model can be applied more widely in the company it is necessary to *perform a pilot with a small group of SKUs*. Selecting the SKUs for this small group is the first step of the implementation. This group should consist of the SKUs which are currently found to perform badly and some SKUs from each class. The selection should be made by the Materials management specialist and be reviewed by the Group leader. The pilot should be run for at least 4 months.

The second step, which is reiterative, is to run the model with the most up to date (demand) data and SKU characteristics. Ensuring that also all the resulting policy parameters are up to date. As a guideline use at least 2 year of demand data. The stakeholders responsible for this should be the Materials management specialist and the Senior operational buyer. The Purchasing manager and Business controller should be kept informed.

The third step is to determine and implement the best way to measure the fill rate. During this research an Excel tool was implemented where the warehouse employee is responsible to keep track of the fill rate of the SKUs. The measurement, is therefore, completely dependent on the employee and if they use it when required. The measurement system works, however, due to the dependability on the employee it might be key to discuss other ways of measuring the KPI or making sure it is part of their routine. For instance, using Power BI, as currently being tested, combining planned pick dates and the available stock information from SAP. If an order cannot be picked due to missing SKUs, there is a backorder. The stakeholders required for this step are the: Materials management specialist, Group leader, Team leader Handling, Warehouse employee and the Business controller.

The fourth step, is to implement the policies for this small group of SKUs into SAP and use the testing environment to determine if the system places purchasing requests on the correct dates. According to the SAP consultants of VSM it is relatively simple to implement the designed policies. The Material management specialist is responsible for this. If this testing is successful, implement this into practice and monitor and observe over time if the implementation has the desired effect. The results should be analysed by the Materials management specialist and be reviewed by the other stakeholders.

If after 4 months the pilot is deemed successful by the stakeholders then the fifth step is to enlarge the set of SKUs. If the pilot is not yet deemed successful, iterate back to step four and analyse what the issues may be. The Materials management specialist is responsible for this.

The last step is to research the other manufacturing departments of VSM and find how the inventory management tool can be applied here to improve their inventory management.

7 Conclusions

This thesis constructed a model which can help Voortman Parts Manufacturing 1 (VPM-1) improve their inventory management and reduce backordering and overall stockout occasions of components (SKUs) consumed in the production processes of the handling modules. VPM-1 is a department of Voortman Steel Machinery (VSM) that manufactures the roller conveyors (RC), cross transports (CT) and Cutting Tables. These are used for the handling of material past the advanced machining solutions that VSM develop. By reviewing the SKUs in inventory and the current practices at VPM-1, and combining this practical knowledge with theoretical knowledge from literature, an opportunity was identified to improve the inventory management by taking the available demand information and incorporating it into the determination of inventory control policies. In *Chapter 4* the model was designed to classify the SKUs based on their various characteristics and user input variables and determine appropriated inventory control policies and corresponding parameters to attain a target fill rate. In *Chapter 5* the inventory control policies, following from the model, were tested using a stochastic and discrete simulation model, using actual demand data of 2021. In a sensitivity analysis the input parameters and certain constraints were changed to research how robust the solution is. Subsequently, in *Chapter 6*, the implementation of the inventory control policies into the ERP-system of VSM is described.

This chapter provides the conclusions of the thesis (*Section 7.1*) by answering the main research question and sub-questions from *Section 1.4*. Based on these conclusions, *Section 7.2* gives recommendations to VPM-1 and VSM. *Section 7.3* briefly discusses practical and scientific contributions of this research and is followed by a discussion (*Section 7.4*) on the limitations of the study. Lastly, *Section 7.5* provides suggestions for future research areas.

7.1 Conclusion

This research was initiated because VPM-1 have a gut feeling that the unavailability of stocks is a large and frequent disturbance to the flow of production orders (POs). Moreover, that the current way of ordering and managing inventory is insufficient to prevent this unavailability, which results in 'firefighting' for office and production staff and an inflexibility of the production planning. The goal of this research is to gain knowledge in inventory management techniques and propose a solution which will reduce the backordering and stockout occasions of SKUs, such that the flow of POs is not impeded. The main research question used to achieve this goal is:

"How can the inventory management of SKUs at VPM-1 be improved, to reduce the frequency of stockout occasions in production?"

To improve the inventory management, this research proposes a solution using inventory control policies. With these policies clear decisions can be made when to and how much to order of a certain SKU instead of basing these decisions purely on the experience of the senior operational buyer. As there are a large number of SKUs, they are classified using an adapted process from Hautaniemi & Pirttilä (1999), in which the SKUs are classified based on distribution by value, net lead time (LT) and their CV of demand during LT. Inventory control policies are chosen per classification class. Overall, the simulation model shows overall promising performance for the proposed policies considering the average on-hand inventory (OHI) value. The sub-questions are answered below:

"What is the current situation, regarding inventory management of the SKUs and what are the causes of the stockout of SKUs?"

VPM-1 use an assemble-to-order (ATO) policy for their production-inventory model. The handling modules are produced according to a production order, however, to reduce the total LT, VPM-1 produce the sub-weldments and sub-assemblies to stock. The focus of this research is placed on the SKUs directly consumed in the production of the handling modules. These are the supplier-bought and internally produced components. The average inventory investment of these SKUs is approximately €435.000. The main replenishment strategy used is a demand strategy, also known as MRP-driven ordering: replenishments are based on known demand (reservations), reordering what is needed to fill POs, taking into account ordering requirements. Replenishment orders are placed based on the experience and intuition of the buyer. There are lot-sizing procedures implemented for the SKUs, however, due to a lack of maintenance these are often ignored. VPM-1 do not use any other control policy or any kind of classification method. Only 14,9% of the 601 SKUs have safety stocks in place, for which the level is based on the experience and intuition of the buyer and planner. Demand of a PO is known at least 7 weeks before the loading date (shipping date), also known as the due date of a PO. Based on this LT and the production stage in which the SKU is consumed the due dates of the SKUs can be determined and therefore the available demand lead time (DLT). A potential was found to improve the current demand planning considerably by taking demand information from the final sales layout into account. Increasing the DLT for RC and CT SKUs by 4 weeks and Cutting Table SKUs by 2 weeks. Solely based on the confrontation between the current demand planning of a least 7 weeks and supply lead times (SLT), 57,5% of the SKUs can be procured on-order. And the average OHI value of these SKUs (€261.482) can be significantly reduced. The fill rate of the SKUs in inventory has not been measured. To get an indication of the fill rate, the ready rate is used. The average ready rate of the SKUs which cannot be procured on-order is 81,5%. The causes to the stockout occasions were found to be likely due to a small group of SKUs, which in-turn is caused by the current way of ordering and the lack of inventory control policies for these SKUs. Other causes that were found were: (1) the current demand planning, movement of POs over the time horizon and the sequentiality of filling POs. (2) the unexpected demand due to incorrect BOMs and consumption of spare parts and (3) the delivery performance of suppliers.

"What inventory management methods are proposed in literature, that suit the situation at VPM-1, with which the backordering of SKUs can be reduced?"

From literature VPM-1's production system can be described as a multi-item, multi-stage ATO-system with multiple end products. If it is assumed that demand for a SKU is certain for the DLT then this period should be taken into account when determining inventory control policies. This results in a Net LT with which the policy parameters are determined. To more easily control the large number of SKUs, various classification methods are suggested. A structured stepwise classification methodology of Hautaniemi & Pirttilä (1999) is found to be the most applicable when combined with the XYZ-classification of Dhoka & Choudary (2013). Four common inventory control policies were found in the literature. These policies ensure that procurement is carried out according to a clear procedure, where little experience is required. The most suitable control policy is dependent on the SKU and the class in which it is categorized.

"What inventory management methods are most applicable for the SKUs and what should the design of the inventory management tool be?"

Based on the input parameters, especially the known DLT of the loading date and the characteristics of the SKUs, the 601 SKUs are classified using the designed classification method. Subsequently, based on suggestions in literature, inventory control policies were chosen for each classification class. *Table 7.1* shows an overview of the classification types per class, the number of SKUs and the proposed policies. For class 3 to 5 one of the proposed policies is chosen based on the ordering requirements of a SKU.

Table 7.1: Number of SKUs per class, the classification type and the proposed policies, taking current minimal DLT of a PO and safety LT into account

	Class 1	Class 2	Class 3	Class 4	Class 5
# SKUs	280	295	11	14	1
Classification type	C-item	A-item $Net\ LT \leq 0$ OR SKU required on-order	A-item $Net\ LT > 0$ $CV > 1$	A-item $Net\ LT > 0$ $0{,}5 \leq CV \leq 1$	A-item $Net\ LT > 0$ $0{,}5 < CV$
Proposed policies	(s, Q)	MRP	(s, S) & (s, nQ)	(s, S) & (s, nQ)	(R, s, S) & (R, s, nQ)

"What is the performance of the inventory when applying the proposed inventory management tool?"

To test the performance of the inventory management tool and the ensuing inventory control policies a simulation model was built using Excel VBA. The model simulates the performance of the policies over 2021, applying historical demand data. The model is stochastic and discreet, in each period of one week a decision is made on the size of the replenishment order. The results of the simulation showed that the initial solution with the proposed policies shows a significant improvement of the fill rate over the current situation. The fill rate of the inventory can be improved to 99,1% over all SKUs. When comparing the ready rate of the SKUs in class 1, 3, 4 and 5 to the fill rate of the same SKUs, the proposed policies can lead to an improvement of 16,7%. The average OHI value, however, does increase by approximately €46.000. The proposed policies from the initial solution have however been further optimized after analysing the results of the sensitivity analyses. The analyses showed that the proposed periodic review policies for the class 5 SKUs do not work as well as the continuous review policies. Moreover, the analyses showed that taking undershoot into account for the continuous review policies, even though the demand is non-unit sized, is not necessarily required to achieve the target fill rates. The improved policies achieve the same potential increase of the SKU availability against an average OHI value increase of approximately €20.000. There is however a potential for a further increase of performance. If demand information from the final sales layout *is* included then the average OHI value of the solution is approximately €403.000, which is an improvement of €32.000 over the current situation, while maintaining the high overall fill rate. Although the results of the simulation are promising, there are some C-items that underperform due to their demand distributions and due to the recommended policies not taking into account known demand information. During this research it was assumed that all demand is Normally distributed. However, there are SKUs with high CVs and intermittent demand, indicating their demand should have been modelled with a (compound) Poisson distribution. There are some practical adjustments which could be made on a SKU level, which could further improve the performance: (1) Move poorly performing C-items, due to a high CV, to A-item classes, to ensure these are controlled using demand information. (2) The TBS for C-items can be optimized for each SKU individually, to increase the reorder points and safety stocks to better cover sudden large consumptions of SKUs. (3) To further decrease the chances of stockout due to supplier performance, the safety LT can be based on the current supplier performance.

"How can the proposed inventory management tool be implemented into practice?"

The proposed control policies should reduce the unavailability of SKUs due to stockouts and backordering considerably. However, this has only be proven in a simulation study, for which some aspects were difficult to compare to the current situation due to a lack of KPIs being measured. A six step plan is recommended for the implementation of the proposed inventory management tool. The first four steps are for a pilot. Testing the proposed policies on a small group of SKUs in practice and determining the efficacy in reducing the unavailability of SKUs required for production. According to the SAP consultant implementation of the proposed policies into the ERP-system is relatively simple. If after four months of testing, the pilot is deemed successful by the stakeholders the next step is to implement the policies for all the 601 SKUs in this research. The last step is to research the remaining SKUs of VPM-1, which were excluded during this study, and the other manufacturing departments of VSM and investigate how the inventory management tool can be applied to improve their performance.

Besides the potential to significantly reduce the unavailability of SKUs by 16,7%, implementing the inventory management tool will: (1) increase purchasing control, (2) decrease the firefighting in the office and on the production floor, (3) create the possibility to increase the flexibility of the production planning and (4) provide VPM-1 the opportunity to understand the implications that longer supply LTs may have on the inventory.

7.2 Recommendations

Based on the conclusions and results from this research, this section provides some recommendations to VPM-1.

Use tool and implement subsequent inventory control policies
The results from the analyses performed in *Chapter 5,* show that by applying the tool, the inventory fill rate will significantly increase. The recommendation is to implement the inventory management tool, using the implementation plan of *Chapter 6*. Starting with a small set of SKUs, take the worst performing SKUs from the fill rate analyses in *Section 2.2.3* and a couple SKUs which in this research are categorized in class 3, 4 or 5. When performing the pilot ensure that for these SKUs the characteristics, i.e. SLT, in SAP are correct and verified with supplier. It is also recommended that for the SKUs which were found to have unexpected demand due to incorrect BOMs or required spare parts the safety stocks should be increased to cover these. Reservations for spare parts should also be added to the safety stocks. Furthermore, it is recommended to re-determine the control policies with a frequency of one month based on the two most recent years of available data. This to ensure that the control policies cover certain trends in demand as much as possible without applying forecasting. Without forecasting the policies will always show a lagged response to a significant change in demand.

Increase DLT with demand information from final sales layout
As found in *Section 2.3.6* the current DLT can be extended with the demand known from the final sales layout. Added benefit, as shown in the sensitivity analysis of *Section 5.4.1*, is that more SKUs can then be procured on-order using an MRP policy, meaning their average OHI can be considerably reduced, while keeping a high fill rate. To increase the DLT, the demand information from the final sales layout needs to be filled into SAP once available. This demand, however, should be clearly marked as “preliminary”, such that a distinction can be made between the demand that is known with 100% certainty, and demand from sales layouts. As module demand from the final sales layout may be altered slightly and customer specific components may be added before the final design is completed, as mentioned in *Section 2.3.6.*

Implement ways to measure the performance KPIs and improve and invest in reliable data
As found during this research, VPM-1 and by extension VSM, do not currently measure many performance metrics for their inventory. When stockouts are encountered they are dealt with in a firefighting manner. For instance, calling suppliers to bring replenishment orders forward in time, or to find alternative suppliers who can deliver at short notice. However, after a stockout event there is little to no review as to what actually happened and how this could be prevented in the future. A recommendation therefore would be to implement performance KPIs, like for instance item and order fill rate, to track the performance of the inventory. Review the fill rate measuring tool that was made during this research and investigate if it needs improvement, and if so, how this could be done. For instance, using Power BI, as currently being tested, combining planned pick dates and the available stock information from SAP. If an order cannot be picked due to missing SKUs, there is a backorder. The current tool is used by the warehouse employee, with which they can make a notification of missing materials when picking SKUs from inventory for a PO. However, as it requires manual registration of missing orders and it is not (yet) part of their day to day activities, the feeling is that this data is not yet totally reliable and they sometimes forget to fill it. Moreover, to get a sense of the costs involved with the stockouts occasions, find a method to measure or estimate the labour cost attached to the stockout event and possibly even the transportation costs if incurred. Another performance metric which could influence the amount of safety LT taken into account in the control policies is the supplier delivery date performance. In *Section 2.4.2* an analysis was performed on this. However, this analysis is also dependent on when inbound orders are booked into stock by the warehouse employee. Currently, it occurs that the warehouse employee does not have enough time to replenish the storage locations immediately when a delivery from a supplier comes in. Sometimes inbound shipments may sit idle for multiple days. All this time decreasing the supplier’s apparent performance, due to internal processes. Thus, investigate a way in which the performance is less dependent on the in-house goods receipt. A possibility could be to ask the suppliers for an advanced shipping notice to confirm a shipment is delivered and making a daily list of expected shipment arrivals.

To further improve future analyses over the inventory it is necessary to improve historical demand data. Especially in the case when new SKUs phase out an older SKUs. In that instance there is little to no connection in SAP between the new and old SKU. Meaning there is also no demand data available of the new SKU. Even though the new SKU should have a similar demand pattern.
Investigate the use of a database in which faults, that may occur in production, are registered and analysed. For instance the stockout of a SKU from inventory or missing SKUs during production. Furthermore, giving a possible root cause to the issue. By giving more basic root causes, you are able to generate a pareto of the most common faults and improve these. The database will then also give a better indication to the severity of the problem. Moreover, having a database will require encouraging production employees to register the faults made in production.

In SAP: check and verify the MRP-data (i.e. SLTs, cost prices and ordering requirements) of SKUs with the suppliers. During this research it was found that for many SKUs the SLT in SAP is not equal to the SLT that the buyer currently takes into account. In fact, many were still set to the default 7 days, implying that a signal from SAP to the buyer would come too late and components might be ordered too late. If this data is not corrected then the implementation of the inventory control policies will fail.

Improve overview of rescheduling orders in SAP
A current issue which the buyer, planner and production engineer at VPM-1 consistently mention, is that in SAP there is no clear overview of notifications for rescheduling purchase orders. The causes for rescheduling is often due to the movement of POs in the timeline, due to customers delaying the project for instance, or that another PO has precedence. This causes the already planned shipments to be insufficient and to be rescheduled. However, when no notification is made or it is unclear, this might leads to stocking out. The rescheduling of projects has a large effect, as the amount and type of RC modules and the amount, type and length of CT modules is very customer dependent. If a change in planning is made, or projects are swapped in the timeline it will have a bullwhip effect on the POs at VPM-1. The swapping and moving of POs often occurs past the fixed period of 7 weeks as taken into account in this research. Thus, if an improvement or use of the known demand information past these 7 weeks is desired, the overview of rescheduling purchase orders needs to be improved. Another added benefit to an improved overview is that the planner could get an indication as to the ramifications of bringing a PO forward in time.

Improve warehouse management and warehouse design
The current picking and booking process of material in and out of inventory is in need of improvement. Currently, the picking is done manually and in such a way that the list of SKUs which have been picked are only booked out of inventory at the end of the day, or whenever is most convenient to the employee. SKUs could have physically left the warehouse in the morning and only have been booked to the production stage in the late afternoon or following morning. The best course of action is to perform a booking each time a movement has been made. A recommendation is to investigate the use of a barcode scanning system. This ensures immediate booking and reduces the risk of picking errors. Moreover, a recommendation is to re-evaluate the current movement types in use for booking and moving stock in, out and between storage locations, keeping data analysis in an external program, like Excel, in mind. During the research data was sometimes difficult to collect as it was uncertain which movement type(s) were strictly relevant to the analysis. And some movement types were used for different cases.

The warehouse at VPM-1, seems to be overflowing. For the larger components, pallets and pallet racks are used for storage, as these are easily moved with a forklift truck from storage location to the production stage. However, due to the overflowing warehouse, there are not enough locations on the pallet racks and many of the pallets are stacked on the production floor next to the warehouse. Besides, loss of overview the implications of the stacked pallets is that finding the right pallet of SKUs might entail many movements with the forklift truck.

Automize purchasing

As mentioned in *Chapter 2* only a small part of the inventory is managed by the vendor. These are mainly floor stock and some more simple turning and milling components. For the remaining inventory the purchasing is done manually and is time consuming. A recommendation is to investigate the opportunities within SAP to automate purchasing for certain SKUs. In this research an automized purchasing strategy was not researched, however, the clear policies proposed in this research, in combination with an improved warehouse management could help in the decision-making process and decrease purchasing effort.

Improve production planning

The planner uses time buckets of a week to define production LTs. Currently, each production stage takes one week to perform. However in reality, it might only take one or two days to finish a PO per production stage. Meaning that each stage may have a lot of WIP. The planner mentioned at the start of the research that one of the restraining factors to reducing the LT of production stages is material supply and the accompanying SLT. This research needs to be implemented and trailed for several months, however, if it is found to solve most of the material supply issues, it should be researched how the throughput time can be reduced. The planner mentioned that if material is available it should be possible to reduce the throughput time of a PO from 4 weeks to 1,5 to 2 weeks. If the throughput time is reduced, research using the tool, what the implications are for average inventory levels of SKUs. As a decrease in overall LT means a decrease of DLT_{known} and an increase of Net LT over which the policy parameters are calculated.

7.3 Discussion

Although the designed tool and proposed polices show promising performances, this research still contains some limitations. These are discussed below.

The results of the proposed policies are only telling of the performance for the 601 SKUs that are consumed in the production process of the handling modules. As the components in inventory which supply the production of the internally produced components (sub-weldments and sub-assemblies) were excluded to simplify the problem to a single-level inventory problem. The assumption was that there is always sufficient stock to produce these internally produced components. This research will need to be extended to investigate the best inventory management strategy for these SKUs. For these SKUs, the period of known demand is shorter and dependent on the period of known demand of the production stage in which the parent-part is consumed.

The tool assumes Normally distributed demand. In general this approach does not lead to bad performances, although most SKUs, according to rules of thumb, found in literature, should not have been modelled as Normal. In some instances it would have been better to model demand with either a Gamma distribution if the CV is too high or with a (compound) Poisson distribution if the demand during (Net) LT is low. The results showed that for a handful of SKUs, the policy parameters were too low to accommodate a consumption of a PO, resulting in a bad realised fill rate. Demand for those SKUs were too intermittent and often larger than unit sized. Taking Normally distributed demand would level out the demand occasions with all the zero demand occasions and this would result in a low average demand during LT, subsequently resulting in low policy parameters that cannot account for large demand occurrences.

The simulation model simulates the progression of the inventory for 2021 with time buckets of a week. After each week the model decides if it needs to place an order, and if so, how much to order. The decision for the time bucket was based on available data and due to the planner planning POs with time buckets of a week. However, this does not exactly reflect reality, where the buyer can view and order stock on any day of the week. And on any day of the week a replenishment shipment may come in. Moreover, the POs may have one week LT per production stage, however, part of that LT is safety LT, which the planner uses to absorb possible delays. In addition, a production stage may produce multiple POs in each week and due to this, POs may also start on other days of the week. The implications of these differences between the simulation and reality are that, the inventory will likely show a slightly better performance with the proposed policies in reality compared to the simulation. As the buyer can order a replenishment in a shorter interval.

The comparison between the current and simulated performance. In *Chapter 2* it was found to be difficult to determine the desired performance metrics, especially fill rate, given the available data. Therefore, there was no possibility to compare the true performance of the current situation to that of the simulation. Moreover, as there is no clear inventory control policy currently in-place it was not possible to model the current performance in the simulation and improve on the validity of the simulation. Furthermore, time between stockout occasions (for C-items) and fill rates (for A-items) are inputs for the control parameters. However, the values for these inputs in the current situation are unknown.

The omission of constraints to the storage capacity of SKUs. In this research an underlying assumption which was made is an infinite storage capacity. In a practical setting, however, this can never be true, storage locations have a limited capacity. These capacities per SKU, per storage location have not been investigated at VPM-1 and are currently unknown. Thus these could not be taken into account. It could be possible that the inventory, using the proposed policies, will exceed the capacity.

7.4 Practical and scientific contributions

The practical contribution of this thesis is that the tool designed in *Chapter 4* provides inventory control policies and the accompanying parameters which in-turn can be implemented in SAP. The expectation, based on the testing performed in *Chapter 5* is that these proposed policies should reduce the stockout occasions and backordering significantly. Moreover, these control policies will likely reduce the ordering frequencies amongst the C-items and improve the planning flexibility for the planner. Another practical contribution lies within the generalisability of the model for VPM-1. The model can be easily adapted if more or less demand information becomes available. In addition, it can be adapted to suit other stock streams at VPM-1, for instance the SKUs required in the internally produced components or it can be used as the basis for a similar tool for the other production departments of VSM.

Although, the use of control policies and designing a tool which can determine these is not new, the scientific contribution of this tool is applying the known control policies to a practical production-inventory model. Moreover, the model makes use of a Net LT to take into account the known demand information. Ensuring that the correct control policy is used based on the available information. If there is sufficient demand information, $Net\ LT \leq 0$, then the SKU should be controlled using MRP.

7.5 Future research

Based on some practical and theoretical findings gained in this research, this sub-section presents some suggestions for future research.

Use of other demand distributions to determine control policies

Future research could investigate what the effect of applying the Gamma and (compound) Poisson distribution is to the performance of the inventory and the accompanying average inventory investment.

Inventory control policies for SKUs consumed in internally produced components

The current solution and research is based on a single-level inventory problem, only taking into account the SKUs directly consumed in the production of handling modules. A suggestion in the previous sub-section is to extend the current research and applying the single-level inventory problem approach to the SKUs consumed in the internally produced components. Another option for future research is to investigate how the inventory management could be improved by taking into account the multi-level aspect of the inventory. Moreover taking into account the dependence that some SKUs have with one-another.

Taking into account stochasticity of supply lead time and delivery quantities
The proposed policies and simulation model disregard the stochasticity of SLTs and delivery quantities. It might be an interesting avenue to investigate how the performance can be increased by taking these into account and how this might affect the proposed policies. However, before this can happen, it is key for VPM-1 and VSM to improve their measurements and to keep track of the KPIs involved.

Use of more accurate time buckets
Future research could investigate what the effect of applying smaller time buckets (one day) would be on the performance of the inventory in the simulation. This would then more accurately simulate what happens to the inventory on a day-to-day basis once stock is consumed from inventory and used in production. The expectation is that the performance of the inventory would be better than currently simulated. As the smaller time bucket also allows for a more rapid response with the replenishment orders.

Forecasting
In this research the main focus was placed on the use of inventory control policies in combination with the known demand information. The forecasting was not heavily researched due to time restrictions. Forecasting may be an interesting direction for future research to increase the performance of the inventory further, by being able to anticipate increases or decreases in demand for certain SKUs before demand has even occurred. The proposed policies, without forecasting, will always lag behind events which have already occurred, and only change based on those. Meaning an increase in demand for a SKU might not be caught in the policies and stockouts and backordering may still occur. The contrary might also occur in which a decrease or a sudden stop in usage is not foreseen. Keeping unnecessary inventory. Furthermore, forecasting might also open up another future research avenue: *dynamic inventory control policies*. In which certain policy parameters are adapted dynamically, based on the forecasted demand during LT. Forecasting in the case of VPM-1, is expected to be difficult due to the complexity of certain interdependencies. The demand of SKUs is dependent on the demand for parent modules (RCs and CTs). Which in-turn are dependent on the system which the individual customers design with the sales engineers. In the organisation there is a rolling-horizon forecast available for the machines which are expected to be built. However, the relation between this forecast and the demand for handling modules is small. A recommendation would be to research if handling modules, independent of the machine forecast, can be properly forecasted.

Applying an optimization model
The model designed in this research, in its current state, does not use the simulation model to find the most optimal input settings with which the SKUs satisfy a specified fill rate and that minimizes the total average inventory value. It could be an interesting future research avenue, especially to research if and how the average inventory value resulting from the use of the proposed policies can be reduced, while maintaining the desired fill rate. An option could be to apply a heuristic, which varies the input variables and determines based the output of the simulation model if the policy parameters are optimal or not.

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A.1 Demand process SKUs for handling systems

Figure A-1 shows the demand process of SKUs for the handling systems. The demand for SKUs starts at sales, where they receive a customer order for a production line. Using VSM's custom configuration tool, project engineering, in close contact with the customer, can design the production line using building blocks. Once the primary design is made, a downpayment on the project is paid by the customer and the LT begins. Following this, the design it is sent to the Worksoffice department who design the production line using the various modules for the handling systems. All specification of a customer order, e.g. testing documentation and modules used to build the production line, are saved centrally in the DNA of that customer order. The final design is then approved by the customer, at which time the LT for the production of the handling systems at VPM-1 starts. When approved, the modules in the customer order are converted into production orders (POs) in SAP. The planner of VPM-1 plans the POs into production based on the current capacity of resources and the delivery date of the customer order. SAP generates demand for SKUs based on the POs and the current inventory position. The buyer orders SKUs from the supplier, using his intuition and experience to determine the order quantities. Lastly, the SKUs are delivered and stored in inventory before use in production.

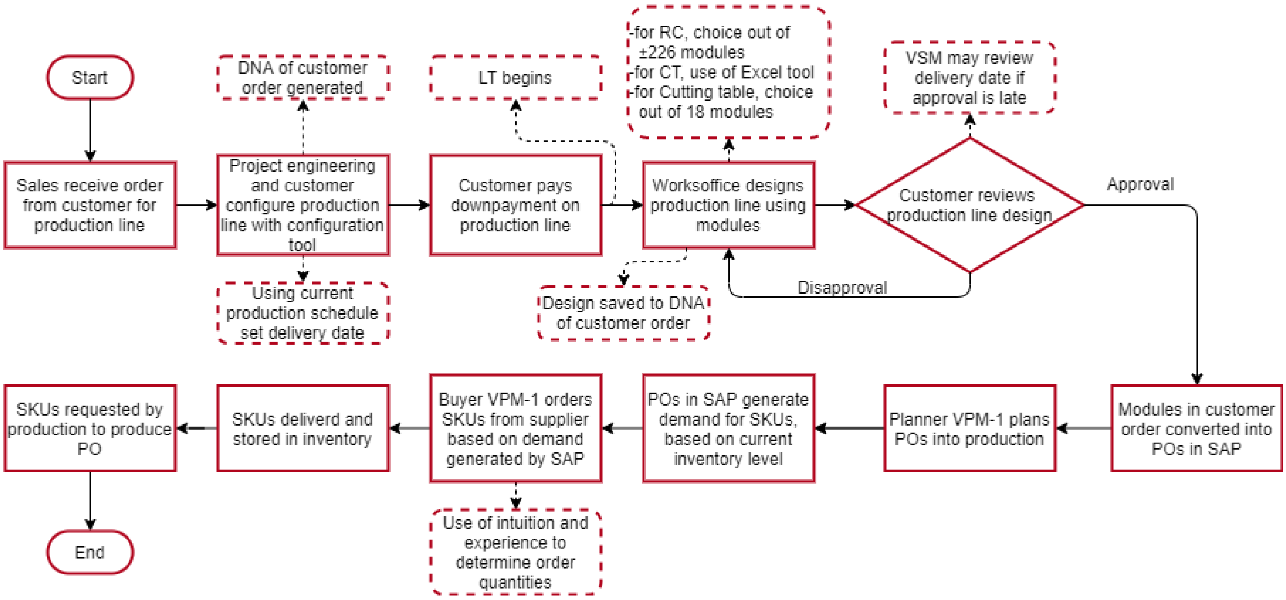

Figure A-1: Demand process for VPM-1

A.2 Problem cluster

To get further insight into the problem context, and to find what is known within the organisation about the issue of inventory stockout, the planner and buyer of VPM-1 were consulted. Based on their knowledge about the issue, the following problem cluster was constructed, see *Figure A-2*. Orange shows the current problem of stockout and red, the consequences of that problem, as experienced in production. The causes to the stockout are colour coded to give an indication as to where and how the causes arise. Causes surrounded in a red dotted line are causes to which we expect to have no influence.

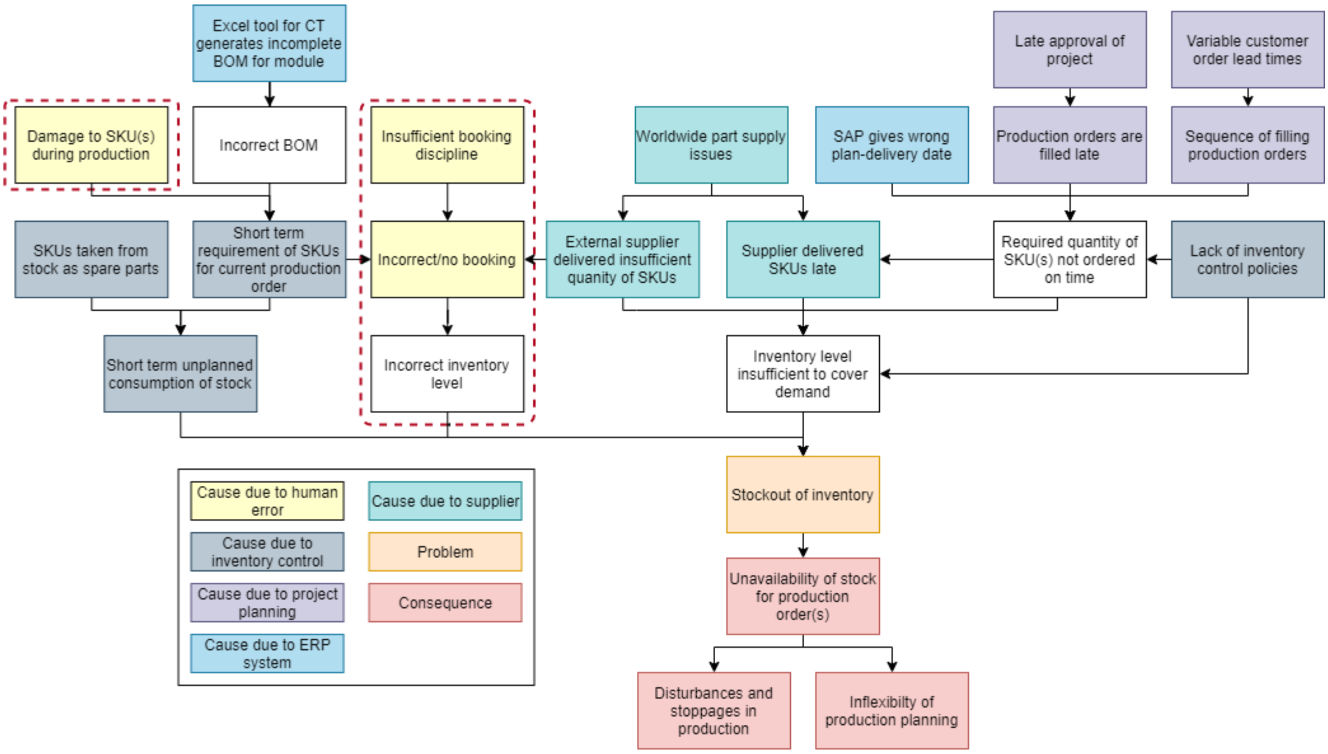

Figure A-2: Problem cluster showing related causes and consequences of stockout of SKUs in inventory.

A.3 Handling systems

As mentioned in *Section 1.1,* VPM-1 produces three types of handling systems, namely: the Roller Conveyor (RC), the Cross Transport (CT) and the Cutting Table. The first two systems can be used in conjunction with one another to create an integrated production line that is capable of transporting the steel beams past multiple beam-processing machines, see *Figure A-3* for an example. The Cutting Tables have a different purpose. They are used in the plate cutting and drilling machines that VSM manufactures. VSM uses standardised components to design and build their handling system modules. Similar modules share roughly 90-95% of their components, i.e. a one-way CT of 5m would use many of the same components as a one-way CT of 10m only the length dependent components and amounts would vary.

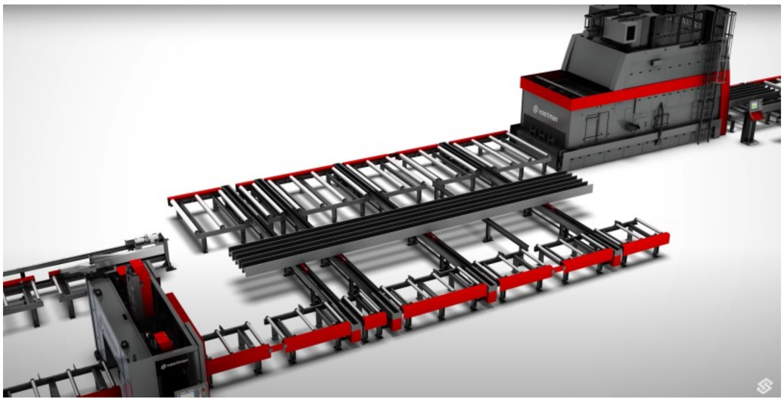

Figure A-3: Integrated production line for steel beams in which, the RCs and CTs are connecting a VSB2500 shotblasting machine (top right) and a V630M drilling machine (bottom left) (Voortman Steel Machinery, 2014).

Roller Conveyors

The RCs can be used as infeed and outfeed for the beam and some plate processing machines. For VSM to create a tailor-made solution for their customers, using for instance Multi System Integration, they require a high level of flexibility and configurability of the RCs and the CTs for the solution to fit into the customer's facility. To enable this, VSM have designed approximately 226 variations of the RC, also known as modules. The variations encompass length, width, roller size, roller distance, (non-)driven rollers, working temperatures and if they are in combination with a CTs or not.

Cross Transports

The CTs are used as transport between two RCs or to buffer material before or after they have been processed. Just as the RCs, the CTs have many variations, however, these are generated differently. There are 28 variations of the CTs consisting of three types: one-way, two-way and liftables. The latter being able to lift a batch of beams on to a RC instead of pushing them on, which reduces noise. Besides this, the CTs are configurable into any length as required by the customer. In order to determine the BOM for a CT module, a calculation is made based on a standard 6m long CT using an Excel tool. The tool determines for instance: the required number of legs, the cutting lengths of the profiles and the length of the drive chain.

Cutting Tables

Figure 1.2 shows a plasma cutting and drilling machine. The setup consists of one or multiple cutting and drilling gantries and Cutting Tables on which the plates are placed. The length of a Cutting Table is a standard 2 meters and the total length for a cutting system could be increased by placing multiple tables in-line and increasing the tracks on which the gantry move. Due to this modularity the Cutting Tables have a lower configurability compared to the RCs and CTs. There are approximately 18 variations, which differ in width and top deck.

A.4 SAP data corrections

Data corrections for some SKUs with certain characteristics

In *Section 2.2.2* an analysis was performed on the ordering requirements of the SKUs in the selection. Based this analysis, there are a few recommendations. The main recommendation is to review the ordering requirements placed on the internally produced components. There are many instances where an IOQ is placed on an internally produced component for which a FOQ could be more effective. Or that when an IOQ is placed on a component a MOQ is no longer required if the IOQ is greater than the MOQ.

In *Section 2.2.3* some more in-depth analyses of the inventory is performed. However, there is an issue with the data that is exported from SAP when using transaction MB51. The transaction does not track SKUs correctly with a F22 procurement type and when SKUs are booked in different units of measure.

F22 means that the SKUs are purchased on-order. However, it is not possible to use the MB51 transaction on a large group of components if one or some of them has this F22 procurement type. It is not possible to easily distinguish between the components. And when using the data, the received goods and issued goods are no longer distinguishable. All components have the movement type 101, but are never stored in inventory. They are immediately sent to and stored at the production stage. And this does make sense. However, it is not reflected in the data once extracted and used for monitoring. A recommendation is to change the movement type, or alter the system that when an components is booked in under 101 it is automatically booked out under 261 with the production order. This way monitoring a large data set of components is easier and does not require many different rules for different component types.

When large data sets are exported from MB51 it is not distinguishable which SKUs use consistent units of measure and which do not. When, for example, the inventory level is monitored in an external program, like Excel, the inventory level of the components does not make sense and could be far off of the actual inventory level.

Moreover, using MB51 users must be made aware that “transfer posting” movement types should not be taken into account when using the data for monitoring.

For *Section 2.2.3* these issues have been found rather late in the analysis stage. To improve the data quality for some of the analyses, the following action have been performed:

- Movement type 641 and 642 have been ignored as “incoming goods” as they are just transfer postings, in many cases they do not change anything about the physical inventory.
- For SKUs with F22, the demand data has been altered to look at movement type 101 as demand. Moreover, the components with F22 are not taken into account when doing the analysis of coverage and ready rate.
- For the SKUs with alternative units of measure, the following is done: for most SKUs MM have been changed to M. However, there are components where M need to be converted into PC or vice versa. For most SKUs this has been done, however, some might have been missed.

Data corrections of SLT of SKUs

As mentioned in *Section 2.4.1*, for this research other SLTs for the SKUs were taken into account than are filled into SAP. This is due to the SLTs in SAP not matching up with the LTs that are taken into account in practice and which have been agreed upon with the suppliers. When comparing the MRP LTs of the supplier components with the LTs given in the interview with the senior operational buyer, 83,7% have longer LTs than stored in SAP.

The discrepancy in the SLTs of the supplier components has two underlying reasons. The first being, that the MRP-data in is not updated frequently enough with the current LTs by the buyer. In SAP there are two SLTs, one stored in the “Purchasing Inforecords” of a component. And one stored in the MRP-data of the component. These are independent inputs. Changing the one does not change the other. In the Purchasing Inforecords the purchasing department can store the current and past suppliers of a component their pricing and the SLT. The main problem is that the MRP-data are not updated once a change occurs. Secondly, due to procedural difficulties with the MRP-data and SAP, for most supplier components the SLT is set to a default 7 days. The situation as is explained by the production engineer, planner and buyer is as follows: When the SLT of a component is set to the time agreed upon with the supplier, say 4 weeks, it is not possible to plan production of a production order in for over 3 weeks, if the OHI is not sufficient. Even if this is a required starting date for production to achieve the loading date. And even if, by calling the supplier they are able to deliver an urgent order in 2 weeks (van Dijk, Ros, & Schreurs, 2021).

To find the SLT used in practice for the internally produced components, the planner was interviewed. As compared to the supplier-bought components the SLT of internally produced components is not updated in the MRP-data. However, this could be done with the input “in-house production time”. Currently SAP can give suggestions to the planner on when to start production orders of a internally produced components. However, the underlying data and how the estimations of the production stage durations where determined are unknown to the planner. And are often incorrect. The registered LT of a PO in SAP is different to the actual LT. The planner uses a program “ROB-EX” in parallel to SAP, to plan production orders in production (Schreurs, 2021).

For the delivery date performance analysis, the delta between the confirmed delivery date and the actual delivery date is taken. In most instances the senior buyer will issue an expected delivery date to the supplier and the supplier will accept. The reason we take the confirmed delivery date (confirmed by the supplier) is that, it may occur that the buyer will issue unrealistic delivery times to its suppliers, which are shorter than agreed upon. In those instances it is then unfair to penalize the delivery performance of a supplier.

A.5 In-depth analyses

A.5.1 Determining labour cost of backordering

To determine an approximate labour cost for backordering, a practical example in which multiple SKUs were unavailable for a PO was analysed. The situation is detailed here below.

Date: 2-12-2021
Order 3009706

- Missing 4x component 005-1909. The assembly of the PO is planned to start 2-12-2021 and the missing SKUs are required. The next delivery of 005-1909 is 22-12-2021. The loading date of the PO is 15-12-2021.
- As the loading date is before the next delivery of SKUs the assembly operators need to alter their assembly procedure and work around the missing components. Extra actions need to be performed, such as measuring out cables and hoses that would need to connect to the missing SKUs.
- The analysis of the situation took roughly 1 hr. of the assembly operator and 0,5 hr. for the office personnel. The workaround is roughly 2 x 0,5 hr. (assembly operator) per frame. Totalling 4 hrs.
- The missing SKUs will need to be sent to the customer and the assembly of the missing SKUs will need to be performed by a field engineer. Roughly 1 hr. per SKU.

Additional information:
The SKUs have a delivery issue from the supplier. The impact of the issue could have possibly been prevented or reduced with better inventory management or by finding alternative options. The SKU price is €462 per unit and the current safety stock level was 5 units. The safety stock level was not enough to cover a single PO in which 7 units where required.
In normal circumstances the SLT of the component is between 4 to 8 weeks.

Based on the example, a formula for the labour costing has been determined, see *eq.27* . The formula comprises of a fixed labour cost per stockout occasion and a variable labour cost per backordered SKU. X being the number of stockout occasions and Y the number of backordered SKUs. As the scenario in the example does not apply to all SKUs, two variations of the costing have been made. The first scenario applies if the SKUs arrive before the loading date of the PO and the second scenario applies if the SKUs need to be delivered to the customer and installed by a field engineer. The expectation is that scenario 1 occurs 75% of the time and scenario 2 occurs 25% of the time. An overview of the costing can be found in *Table A-1* to *Table A-4*.

$$Fixed\ cost/stockout\ occasion = 0{,}75 * 105 + 0{,}25 * 265 = €145$$
$$Variable\ cost/backordered\ SKU = 0{,}75 * 32{,}50 + 0{,}25 * 57{,}50 = €38{,}75$$
$$Labour\ cost\ due\ to\ backordering = 145X + 38{,}75Y \tag{27}$$

Table A-1: fixed labour costing per stockout occasion (scenario 1)

Activity	# Hrs.	Hourly rate	Cost
Office FTE for analysing backordered SKU	0,5	€80,00	€40,00
Assembly FTE for workaround during main assembly	1	€65,00	€65,00
Total cost			**€105,00**

Table A-2: fixed labour costing per stockout occasion (scenario 2)

Activity	# Hrs.	Hourly rate	Cost
Office FTE for analysing backordered SKU	0,5	€80,00	€40,00
Assembly FTE for workaround during main assembly	1	€65,00	€65,00
Office FTE for arranging transport	2	€80,00	€160,00
Total cost			**€265,00**

Table A-3: Variable labour costing per backordered SKU (scenario 1)

Activity	# Hrs.	Hourly rate	Cost
Assembly FTE for workaround during main assembly	0,25	€65,00	€16,25
Assembly FTE for assembly of SKU on completed module	0,25	€65,00	€16,25
Total cost			**€32,50**

Table A-4: Variable labour costing per backordered SKU (scenario 2)

Activity	# Hrs.	Hourly rate	Cost
Assembly FTE for workaround during main assembly	0,25	€65,00	€16,25
Assembly FTE for assembly of SKU on completed module	0,25	€65,00	€16,25
Field engineer FTE for assembly of SKU	0.25	€100,00	€25,00
Total cost			**€57,50**

A.5.2 Inventory turnover rate

Table A-5: Inventory turnover rate, shown annually

Year	Inventory turnover rate	Inventory turnover (days)
2017	7,46	48,94
2018	14,06	25,95
2019	10,79	33,82
2020	11,74	31,10
2021	14,40	25,36

According to Silver, Pyke and Thomas (2017) a primary aggregate performance indicator for inventory management is the inventory turnover rate (ITR), also known as stockturns. It is a measure to see how much time passes between when inventory is bought and consumed. The higher the inventory turnover, the faster a company is replacing their stock and the less financial resources they have tied up in inventory. However, the flip side to this is when the turnover rate is too high, this can lead to stockouts and create massive and expensive expediting (Silver, Pyke, & Thomas, Inventory and Production Management in Supply chains, 2017, p. 10). *Table A-5* shows the ITR for the last five years, for the SKUs in the selection. When comparing this to the manufacturing industry of commercial machinery, in the U.S., the turnover rate is high. The industry median, for 229 companies, is an ITR of 3,8 (ReadyRatios, 2021). This equates to an turnover rate of 96 days. This could be an indicator as to why stockouts occur at VPM-1. *Figure A-4* shows the ITR on SKU-level for 2021. The 10% of SKUs with the highest turnover rates are internally produced components with a high annual usage and some supplier-bought components which are commonly used in POs, such as beams and geared motors. In the case where VPM-1 would consider an ITR > 10 to be too high, then 40,2% of SKUs would have a high likelihood of frequent stockouts. The last 25% of SKUs, not shown in the graph, have an ITR of 0 as they have not been stocked in 2021, due to being purchased on-order, or they have had no usage. By increasing inventory levels for the SKUs the ITR would decrease, which by extension would decrease the frequency of stockout occasions.

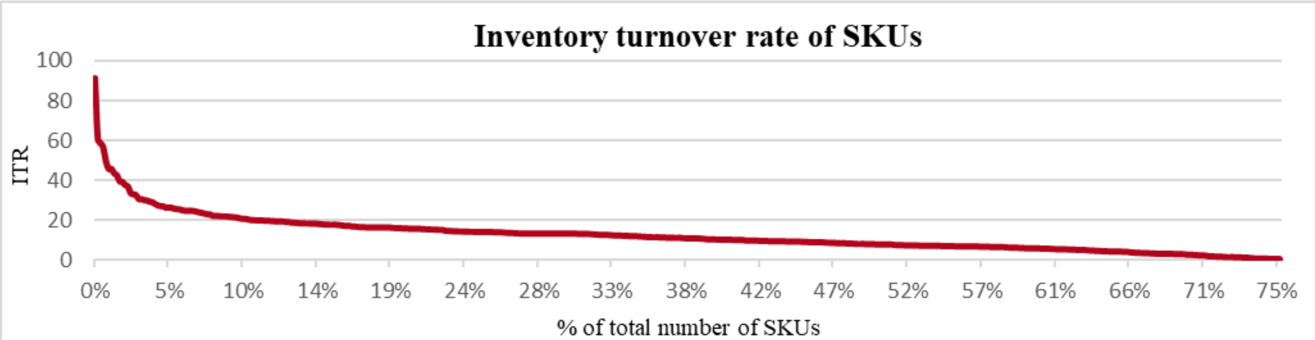

Figure A-4: Inventory turnover rate of SKUs in 2021

A.5.3 Inventory coverage

A useful analysis to review the OHI is the inventory coverage for each SKU. It is the expected time till the current stock level is depleted. This could be used as an indicator to find imbalances in stock, knowing which SKUs have a high OHI and a low usage, indicating excess or even dead stock (Silver, Pyke, & Thomas, 2017, p. 366). As the expectation is that the current OHI is not a true depiction of what is usually in stock, the average OHI of 2021 was taken as an input for the analysis. In *Appendix A.4* some details and recommendations regarding the data from SAP are given. In *Figure A-5* the inventory coverage is illustrated. The 96 SKUs which are purchased on-order have been removed from the analysis. Following from the analysis it can be found that 2,7% of the SKUs, which equates to 1,6% of the total average inventory value is dead stock. And that in total 9,8% of the SKUs are zero-movers, they have not had demand over the last year. Furthermore, 13,3% of SKUs, which equates to 4,6% of the total inventory value, had a coverage of 1 year (52 weeks) or more. The median stock coverage over all the SKUs was 5,2 weeks, which is an acceptable level. The analysis also shows that 14,9% of the SKUs (26,2% of the total inventory value) has, on average, a stock coverage of 3 weeks or less. Dependent on the SKU this could be considered too low in case a supplier cannot deliver on time or that a larger PO consumes more stock than anticipated, this could lead to stockout. The SKUs with the lowest coverage are internally produced components, components with infrequent demand patterns, some SKUs with frequent demand that do not have any (high) order requirements.

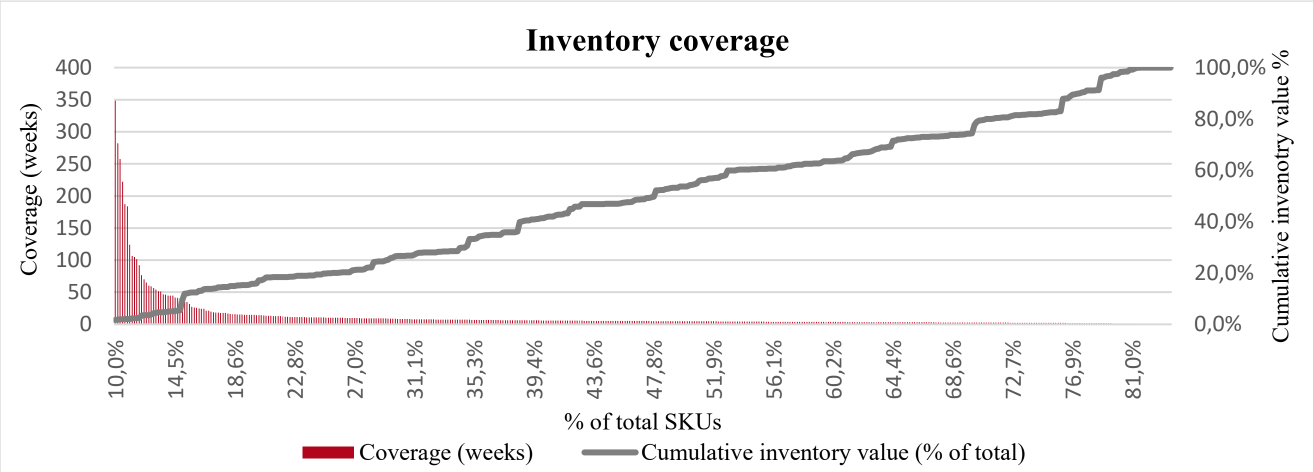

Figure A-5: Inventory coverage of average OHI of SKUs in 2021.

A.5.4 Ready rate analysis

In this appendix the details of the ready rate analysis in *Section 2.2.3* are given. The analysis uses inventory level data of 2020 and 2021, where the ready rate is determined over the period where stock was first kept till it was last kept. To ensure sufficient observations, the analysis excludes SKUs with periods < 300 days. For the analysis roughly 25% of SKUs have been removed as their data gave inaccurate ready rates. Further exclusions are listed below:

- Of the 601 SKUs, 92 have been removed due to F22 and F70.
- Of the remaining 509 SKUs, 8 have negative average inventories for either 2020, 2021 or both. For these SKUs this is due to the way these are backflushed. Or that their stock levels were inaccurate and were corrected later in the year. In any case the ready rates for these SKUs are inaccurate.
- A further 20 SKUs have never been stocked and have never had demand in the two years being researched.

The duration over which the ready rates are determined:

- If a fixed period of two years is used, there might be components which "unfairly" have a lower ready rate as they have been stocked later than other components. E.g. say a SKUs was only introduced into inventory in 2021 and has never stocked-out, then its ready rate would be 50%. Which is an "unfair" indication of its current ready rate. For 17 SKUs this is the case.
- Same goes for SKUs which have been taken out of inventory at the start of 2021. There is no current list of components which are no longer in use. For 20 SKUs this is the case.
- The ready rate has been taken over the duration of which the SKUs had any movement in inventory. Thus from the moment they were stocked, to the moment they were not stocked any longer. That an SKU was no longer stocked, could indicate a stockout if demand where still to come in for the item. This would be missed in the analysis.
- Some SKUs do not have a very long duration over which the ready rate is determined.
    - 19 SKUs ≤ 100 days
    - 25 SKUs ≤ 150 days

  - 27 SKUs ≤ 200 days
  - 35 SKUs ≤ 300 days
  - 53 SKUs ≤ 400 days
  - 98 SKUs ≤ 500 days
- Taking ≥ 300 days the following observations are made:
  - 446 SKUs
  - There are SKUs in inventory which have 0 demand over the two years, however, have a ready rate of 100% meaning the inventory of this stock is dead stock.
  - Conclude that if the ready rate is equal to the fill rate in this case, it does not seem too bad for most components. There is however a tail of components for which the fill rate is low. If not these are components for which the inventory levels must be improved.
  - Investigated the SKUs with a low average demand (≤ 100) and low ready rate. These components have intermittent demand. For the most part VPM-1 already account for this type of behaviour of some of the SKUs by only ordering these when demand occurs. For the most part demand is known longer than the SLT. It is unknown if these components have had stockout occasions due to suppliers being later than expected.

A.6 Demand side analyses

A.6.1 Unexpected demand analysis

Besides the *planned demand*, discussed in the previous sub-section, some of the SKUs do experience *unexpected demand*, which is taken out of stock on short notice. This demand has two causes, namely: (1) due to incomplete BOMs of the handling modules (mainly CTs) and (2) due to service and spare parts. Combining the fact that in the current situation most SKUs in the inventory are reserved for a certain PO, this could mean that unexpected consumption of the stock would result in future POs missing SKUs if no intervention occurs. For most of the SKUs in the selection no safety stocks have been determined to be able to handle this unexpected demand. And for the few SKUs which do have safety stocks, these may potentially be insufficient to cover the volume of unexpected demand.

As mentioned *Section 2.1.1* for CTs modules the BOMs are created using an Excel tool. In some instances, the resulting BOMs are incorrect as the quantity of some SKUs is insufficient or missing. As the data for the demand due to service and spare parts is only available over 2021, the analysis only shows this one year of data. *Figure A-6* shows the unexpected demand occurrences and total quantities per SKU, in which the two aforementioned demand streams have been combined. The SKUs have been ordered in sequence of number of demand occurrences. In total 70 (11,6%) of the SKUs in the selection had unexpected demand, totalling 226 unexpected demand occurrences in 2021. 61,9% was due to incomplete BOMs and 38,1% due to service and spare parts. The usage value of 2021 for this demand was €42.709, which is 0,73% of the total usage value. A total of 1053 units of SKUs were demanded in 2021 (excluding the two outliers marked in yellow). Of the 70 SKUs only 30 have a set safety stock level. The top 10 SKUs with a higher frequency of unexpected demand, do have safety stocks in place, however, these are in most instances relatively low and potentially insufficient. 8 of those SKUs have a safety stock level set equal or slightly higher than the largest demand occurrence. Of the data that is available, only 36 SKUs had reoccurring unexpected demand. Thus potential stockouts due to unexpected demand only applies to a small percentage of SKUs. For these SKUs it would be beneficial to take the unexpected demand into account in the safety stock levels.

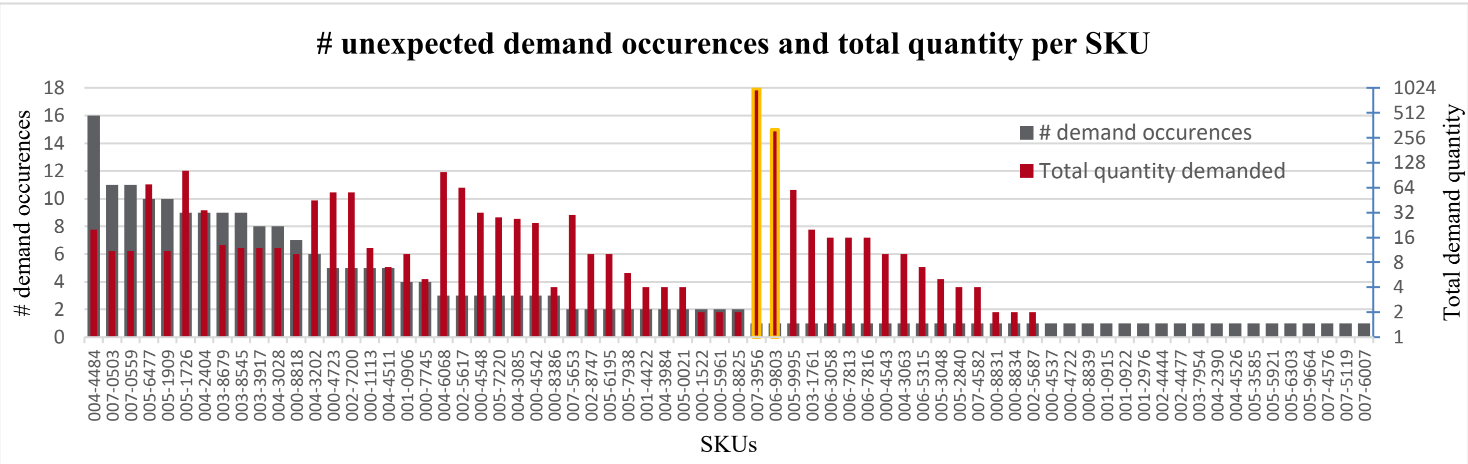

Figure A-6: Number of unexpected demand occurrences and quantity in 2021, due to incomplete BOMs or service and spare parts. The secondary y-axis a logarithmic scale with base 2. In yellow the two outliers have been marked.

A.6.2 Intermittent demand analysis

In this appendix the intermittent demand analysis is performed. For the analysis the demand data of 2020 and 2021 is used. From the data the length of periods between demand occasions are determined and the averages of these periods analysed. 74 SKUs had no demand during this period and have been excluded from the data set. *Figure A-7* shows a histogram of the average time between demand occasions for the SKUs.

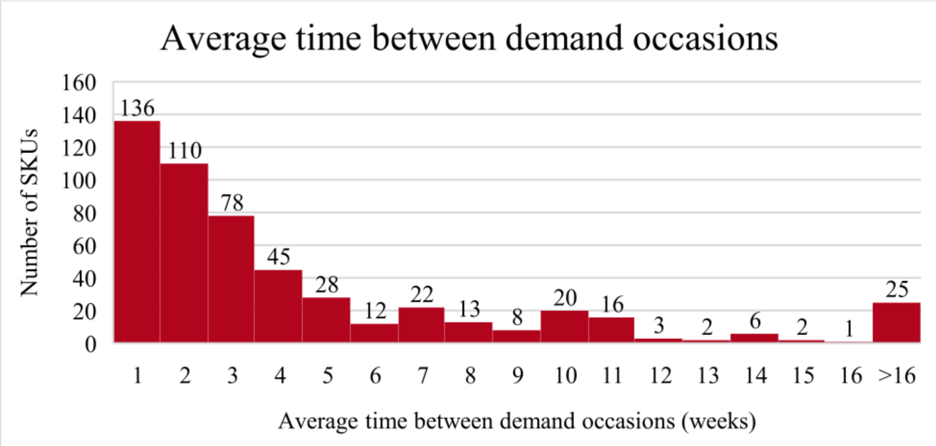

Figure A-7: Average time between demand occasions of SKUs.

The histogram shows there are a large number of SKUs in inventory with on average long periods between demand occasions. When taking 5 weeks or more of time between demand occasions as SKUs with intermittent demand one can conclude from the graph that 133 SKUs have intermittent demand. Moreover, the data shows that for most of these SKUs the demand sizes, when they occur, are non-unit sized.

A.6.3 Demand for handling modules in the preliminary stage

To gain insight into what is known about the demand for handling modules in the preliminary stage, mentioned in *Section 2.3.1*, interviews have been held with: (1) the teamleader of sales support, (2) a project engineer of Worksoffice and (3) the mechanical engineer who designed the type 3 handling systems and the configuration tool which is used by sales.

Sales engineering design a system layout with the customer using the configuration tool and performance specifications. The preliminary stage starts after the downpayment, which occurs when the sales layout is finalized and approved by the customer. Subsequently, the project is kicked-off with a project team. The Projects department reviews and further details the sales layout, taking into account the environment in which the system is placed. The configuration tool uses the standardised modules as building blocks to design the sales layout, including the processing machines and the handling. Hence, after downpayment there is a design of the system available with the required handling modules. However, these are modules with their respective "standard BOMs". The BOMs lack customer specific components like (motor) cables, which are added in the latter detailing stages by Projects. There is a lot of back and forth between the customer and sales before downpayment, the design of the layout may change a lot, or might not even be accepted. Therefore, the teamleader of sales support stated that *before* downpayment there is "*no real certainty about the final design.*" (Oude Avenhuis, 2021).

Projects start by reviewing the system design as a whole, checking if all the modules are used correctly or if there are some which should be added or could be swapped out for other, better fitting modules. In the case of RCs the latter does frequently occur. The same type of RC module is used, so with similar SKU requirements, however, the overall quantity of SKUs is less. E.g. two driven RC modules, *both with 2 rollers*, have been placed in-line with one another in the sales layout. If the project engineer deems this to be over-engineered, he may swap the two RC modules out for a single, longer driven RC module with *3 rollers*. For CT modules hardly any impactful changes are made to the sales layout. The amount and type of modules will remain the same, however, the length of the CT might be altered slightly. The same applies to the Cutting Tables, hardly any changes are made. The project engineer indicated that for SKU consumption the sales layout is a good forecast of what eventually will be required for production. The sales layout could be seen as an upper bound of the size of SKU demand (ten Bolscher, 2021).

The interviewees were asked to what degree (percentage) demand for the underlying SKUs (in the "standard BOM" modules), in the sales layout, concurs with that required in the finalized system design. Thus, to what extent can the sales layout be used as information on upcoming demand for SKUs. *Figure A-8* shows a complete overview on when information on demand is known during the LT of a project and to what degree this information is certain. In the Figure it is referred to as the "degree of certainty" (DoC). A distinction is made between various DoC, as they are different for RC, CT, Cutting Tables and customer specific components (CSC in Figure). Furthermore, the number of SKUs for which that DoC applies are shown.

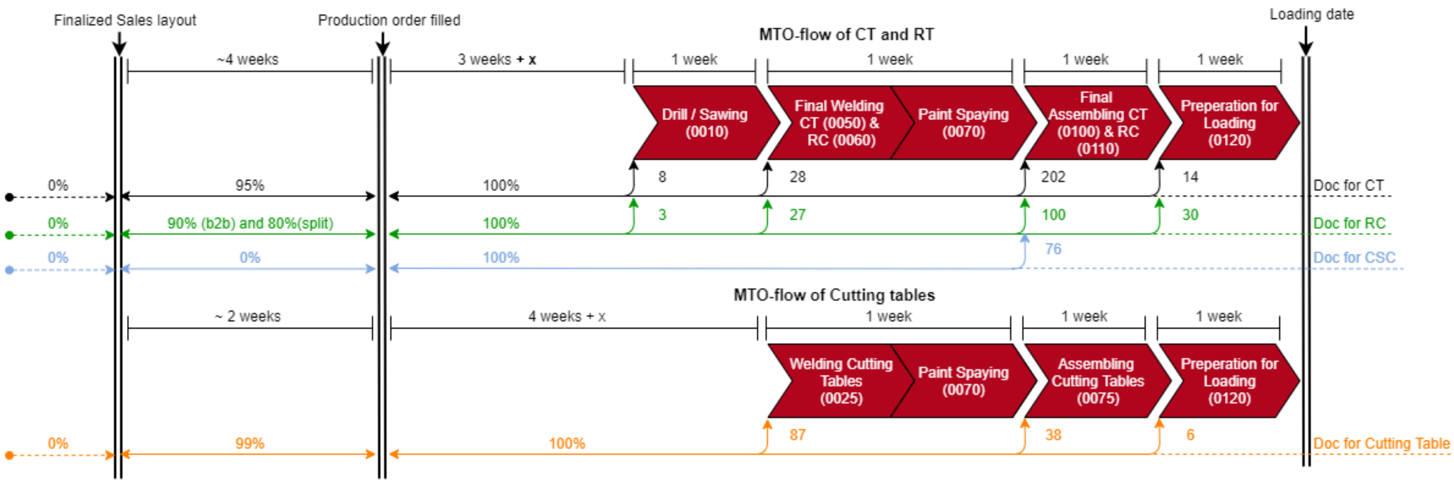

Figure A-8: Overview of degree of certainty (DoC), during the LT of a customer project, per module type. The Figure includes the number of SKUs which are required at a production stage per DoC.

For RCs a slight distinction is made based on the complexity of the total system: (1) "back-to-back" (b2b) systems, with one processing machine and simple in- and outfeed handling changes to the sales layout are less frequent than compared to (2) 'split' systems. These are systems where multiple processing machines are connected using the handling modules.

The project engineer could *not* give a clear estimation as to how much the deviation in SKU demand could be between the sales layout and the final design, as this is heavily dependent on the SKU and its usage in a certain module. In most cases the project engineer will try and adapt a design to reduce overall component usage, without compromising the system design.

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A.7 Pseudo code Simulation model

```
Sub ReplenishmentOrder(SKU As Long, week As Long)

    If Class(SKU) = 1 Then
        If Policy(SKU) = "(s,Q)" Then
            If IP(SKU, week) <= RP(SKU) Then 'If IP hits s then order Q
                RepOrder(SKU, week) = Lotsize(SKU)
            Else
                RepOrder(SKU, week) = 0
            End If
        ElseIf Policy(SKU) = "(R,S)" Then 'If review period then order up to S
            If (week - 1) Mod ReviewPeriod(SKU) = 0 Then
                RepOrder(SKU, week) = OUTL(SKU) - (IP(SKU, week) - DemandDLT_known(SKU,
                week) - DemandDLT_extra(SKU, week))
            Else
                RepOrder(SKU, week) = 0
            End If
        End If

    ElseIf Class(SKU) = 2 Then
        If (DLT_known(SKU) + DLT_extra(SKU)) > (SLT(SKU) + SafetyLT) Then 'Check if SKU is
        driven by MRP data
            Calculate DemandSLTandSafetyLT
            RequiredAmount = DemandSLTandSafetyLT - (IP(SKU, week) - SafetyStock(SKU))
            'Some Class 2 SKUs may have a safety stock level
        Else
            RequiredAmount = DemandDLT_known(SKU, week) + DemandDLT_extra(SKU, week) -
            (IP(SKU, week) - SafetyStock(SKU))
        End If

        'Replenishment order dependent on lot-sizing procedure and THEN on ordering
        requirement to fulfill lot-sizing procedure
        If RequiredAmount > 0 Then
            'If lot-for-lot or By Weekly or Fixed lotsize then order RequiredAmount
            If LotSizingStrategy(SKU) = "BI" Then 'Bi-weekly lot-sizing
                If week + 1 - SLT(SKU) > 0 Then
                    RequiredAmount = RequiredAmount + max(0, Demand(SKU, week + 1) -
                    RepOrder(SKU, week + 1 - SLT(SKU)))
                Else
                    RequiredAmount = RequiredAmount + Demand(SKU, week + 1)
                End If
            ElseIf LotSizingStrategy(SKU) = "MB" Then 'Monthly lot-sizing
                For i = 1 to 3
                    If week + i - SLT(SKU) > 0 Then
                        RequiredAmount = RequiredAmount + max(0, Demand(SKU, week + i) -
                        RepOrder(SKU, week + i - SLT(SKU)))
                    Else
                        RequiredAmount = RequiredAmount + Demand(SKU, week + i)
                    End If
                Next i
            End If

            If IOQ(SKU) > 0 Then 'In case SKU has an IOQ
                If MOQ(SKU) > 0 Then 'In case SKU has an IOQ and MOQ, order at least
                MOQ and multiple of IOQ
                    If RequiredAmount <= MOQ(SKU) Then
                        RepOrder(SKU, week) = MOQ(SKU)
                    Else
                        RepOrder(SKU, week) = Ceiling(RequiredAmount, IOQ(SKU))
                    End If
                Else 'Order multiple of IOQ
                    RepOrder(SKU, week) = Ceiling(RequiredAmount, IOQ(SKU))
                End If
            ElseIf MOQ(SKU) > 0 Then 'In case SKU has an MOQ, order at least MOQ
                If RequiredAmount <= MOQ(SKU) Then
                    RepOrder(SKU, week) = MOQ(SKU)
                Else
                    RepOrder(SKU, week) = RequiredAmount
                End If
            ElseIf FOQ(SKU) > 0 Then 'In case SKU has an FOQ, order multiple of FOQ
                RepOrder(SKU, week) = Ceiling(RequiredAmount, FOQ(SKU))
            Else 'if no order requirement
                RepOrder(SKU, week) = RequiredAmount
            End If
```

```
        Else
            RepOrder(SKU, week) = 0
        End If

    ElseIf Class(SKU) = 3 Or Class(SKU) = 4 Or Class(SKU) = 5 Then

        If Policy(SKU) = "(s,Q)" Then
            'if inventory position hits s then order Q
            If IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week) <= RP(SKU) Then
                CurrentUndershoot = Abs(RP(SKU) - (IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week)))
                'check if Undershoot > Q -> if true, order multiple of Q to increase Economic IP above s
                n = 1 'init
                Do While n * Lotsize(SKU) < CurrentUndershoot
                    n = n + 1
                Loop
                RepOrder(SKU, week) = n * Lotsize(SKU)
            Else
                RepOrder(SKU, week) = 0
            End If

        ElseIf Policy(SKU) = "(s,S)" Then
            'if inventory position hits s then order up to S
            If IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week) <= RP(SKU) Then
                RequiredAmount = OUTL(SKU) - (IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week))

                'Check if RepOrder is more than MOQ
                If RequiredAmount < MOQ(SKU) Then 'Check if RepOrder is more than MOQ
                    RequiredAmount = MOQ(SKU)
                End If
                RepOrder(SKU, week) = RequiredAmount
            Else
                RepOrder(SKU, week) = 0
            End If

        ElseIf Policy(SKU) = "(R,s,S)" Then
            'if R then check if IP < RP, if true order S-IP
            If (week - 1) Mod ReviewPeriod(SKU) = 0 Then
                If IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week) <= RP(SKU) Then
                    RequiredAmount = OUTL(SKU) - (IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week))

                    'Check if RepOrder is more than MOQ
                    If RequiredAmount < MOQ(SKU) Then
                        RequiredAmount = MOQ(SKU)
                    End If
                    RepOrder(SKU, week) = RequiredAmount
                Else
                    RepOrder(SKU, week) = 0
                End If
            Else
                RepOrder(SKU, week) = 0
            End If

        ElseIf Policy(SKU) = "(R,s,Q)" Then
            'if R then check if IP < RP, if true order nQ
            If (week - 1) Mod ReviewPeriod(SKU) = 0 Then
                If IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week) <= RP(SKU) Then
                    CurrentUndershoot = Abs(RP(SKU) - (IP(SKU, week) - DemandDLT_known(SKU, week) - DemandDLT_extra(SKU, week)))
                    'check if Undershoot > Q -> if true, order multiple of Q to increase Economic IP above s
                    n = 1 'init
                    Do While n * Lotsize(SKU) < CurrentUndershoot
                        n = n + 1
                    Loop
                    RepOrder(SKU, week) = n * Lotsize(SKU)
```

```
                    Else
                        RepOrder(SKU, week) = 0
                    End If
                Else
                    RepOrder(SKU, week) = 0
                End If
            End If
        End If

    End Sub
```

A.8 Example of non-multiplicative FOQ

Below (*Figure A-9* to *Figure A-11*) show the results of the simulation for SKU 201 in the case FOQ is non-multiplicative. The min. DLT of PO (from filling PO to the loading date) is 7 weeks, no DLT_{extra} is applied and the safety LT is 1 week. In each period if a replenishment order is required it may not be larger than FOQ. In the case of SKU 201 the average demand per period in 2021 is 732,7 units. Meaning that the FOQ cannot keep up with demand even when in each period a replenishment order is placed. Which leads to all the demand being backordered and resulting in a realised fill rate of 0%.

SKU Info	
SKU ID	**201**
SKU Class	2
SKU Policy	MRP
Supply LT (weeks)	1
DLT_known (weeks)	3
DLT_extra (weeks)	0
Initial pipeline stock	0
Initial on-hand inventory	0
Initial demand backordered	3017,14
Review period (weeks)	0
Target fill rate	100,0%
Realized fill rate	0,0%
Average on-hand inventory	0,000
Lotsize	624
Safety Stock	0
Reorder point	0
Order-up-to-level	0
Total demand	38834,07
Nr. of orders placed	52

Figure A-9: Simulation information of SKU 201, taking $\text{min. } DLT\ of\ PO\ = 7\ weeks,\ safety\ LT\ = 1\ week\ and\ DLT_{extra}\ = 0$ *into account.*

Weeknumber	1	2	3	4	5	6	7	8	9	10	11	12
Beginning on-hand inventory	0	0	0	0	0	0	0	0	0	0	0	0
Received replenishment order	624	624	624	624	624	624	624	624	624	624	624	624
Realized demand	**0**	**0**	**1813,62**	**900,58**	**180,88**	**1125,63**	**176,53**	**1395,32**	**95,3**	**1426,64**	**633,55**	**916,67**
Demand fullfilled from stock	0	0	0	0	0	0	0	0	0	0	0	0
Demand backordered	2393,14	1769,14	2958,76	3235,34	2792,22	3293,85	2846,38	3617,7	3089	3891,64	3901,19	4193,86
Ending on-hand inventory	0	0	0	0	0	0	0	0	0	0	0	0
Total pipeline	0	0	0	0	0	0	0	0	0	0	0	0
Inventory position	-2393,14	-1769,14	-2958,76	-3235,34	-2792,22	-3293,85	-2846,38	-3617,7	-3089	-3891,64	-3901,19	-4193,86
Demand during DLT_known	2714,2	2895,08	2207,09	1483,04	2697,48	1667,15	2917,26	2155,49	2976,86	2403,36	3048,13	2144,46
Demand during DLT_extra	0	0	0	0	0	0	0	0	0	0	0	0
Economic inventory position	-5107,34	-4664,22	-5165,85	-4718,38	-5489,7	-4961	-5763,64	-5773,19	-6065,86	-6295	-6949,32	-6338,32
Replenishment order	624	624	624	624	624	624	624	624	624	624	624	624

Figure A-10: First 12 periods of the simulation of SKU 201.

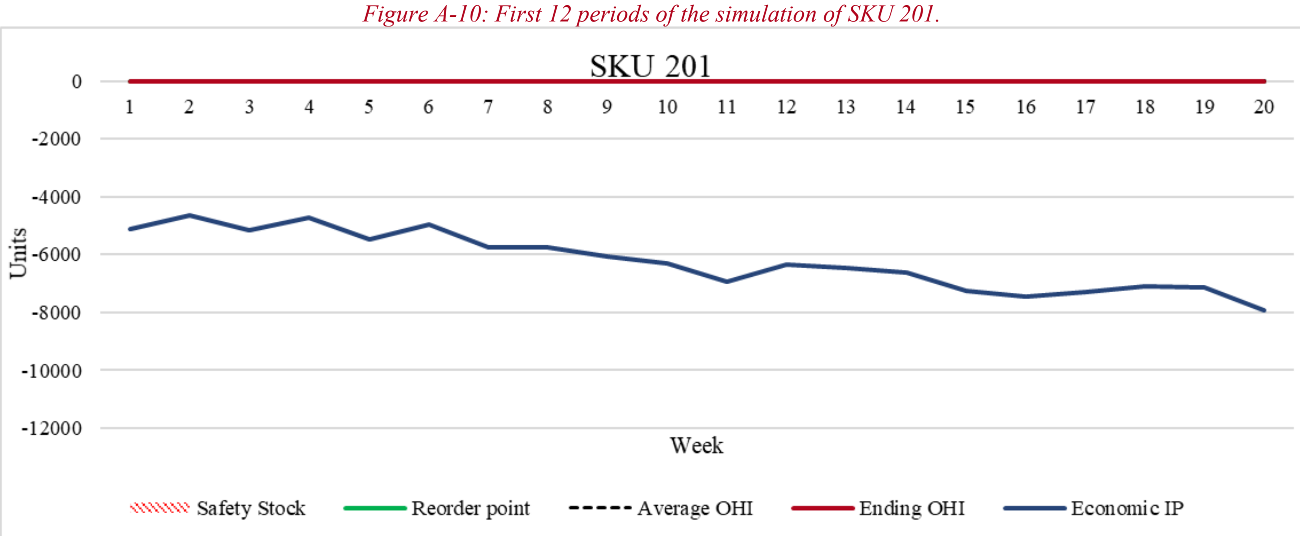

Figure A-11: Graphical visualisation of the simulation in Figure A-10 of SKU 201.

A.9 Results of simulation without vs. with warm-up period

This appendix shows the results of the simulation without a warm-up period compared to with a warm-up period of one year. The control policy parameters are based on the input data in *Table 5.1*. *Table A-6* shows the division of the SKUs over the classes.

Table A-6: Number of SKUs per class, taking min. $DLT\ of\ PO\ = 7\ weeks$, $safety\ LT\ = 1\ week$ and $DLT_{extra} = 0$ into account.

Class 1	Class 2	Class 3	Class 4	Class 5
280	295	11	14	1

Table A-7 shows the results from the simulation without a warm-up period. The simulation is started on 1-1-2021 using the actual OHI on 1-1-2021 as starting inventory. *Figure A-12* to *Figure A-14* show the results and the first 15 periods of the simulation for SKU 235.

Table A-7: Results of simulation without warm-up period, taking min. $DLT\ of\ PO = 7\ weeks$, $safety\ LT = 1\ week$ and DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
Avg. fill rate	96,1%	96,8%	93,8%	94,1%	81,7%	96,3%
Total backordering cost	€ 17.545	€ 16.530	€ 725	€ 1.885	€ 145,00	€ 36.830
Total avg. OHI value	€ 105.485	€ 217.873	€ 44.801	€ 84.269	€ 2.355	€ 454.783
Current avg. OHI value	€ 42.620	€ 338.908	€ 22.777	€ 30.266	€ 816	€ 435.386
Difference in OHI value	€ -62.866	€ 121.035	€ -22.025	€ -54.003	€ -1.539	€ -19.397

SKU Info	
SKU ID	235
SKU Class	4
SKU Policy	(s,Q)
Supply LT (weeks)	6
DLT_known (weeks)	5
DLT_extra (weeks)	0
Initial pipeline stock	0
Initial on-hand inventory	0
Initial demand backordered	0
Review period (weeks)	3
Target fill rate	97,5%
Realized fill rate	90,5%
Average on-hand inventory	32,481
Lotsize	40
Safety Stock	10
Reorder point	29
Order-up-to-level	0
Total demand	618
Nr. of orders placed	15

Figure A-12: Simulation information of SKU 235, without warm-up period.

Weeknumber	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Beginning on-hand inventory	0	0	0	0	0	0	0	53	29	56	37	22	52	36	0
Received replenishment order	0	0	0	0	0	0	120	0	40	0	0	40	0	0	40
Realized demand	**0**	**8**	**12**	**10**	**9**	**15**	**13**	**24**	**13**	**19**	**15**	**10**	**16**	**40**	**0**
Demand fullfilled from stock	0	0	0	0	0	0	13	24	13	19	15	10	16	36	0
Demand backordered	0	8	20	30	39	54	0	0	0	0	0	0	0	4	0
Ending on-hand inventory	0	0	0	0	0	0	53	29	56	37	22	52	36	0	36
Total pipeline	0	120	120	160	160	160	80	80	40	80	80	80	80	80	80
Inventory position	0	112	100	130	121	106	133	109	96	117	102	132	116	76	116
Demand during DLT_known	54	59	71	74	84	84	81	73	100	81	78	75	85	77	86
Demand during DLT_extra	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Economic inventory position	-54	53	29	56	37	22	52	36	-4	36	24	57	31	-1	30
Replenishment order	120	0	40	0	0	40	0	0	40	0	40	0	0	40	0

Figure A-13: First 15 periods of the simulation of SKU 235, without warm-up period.

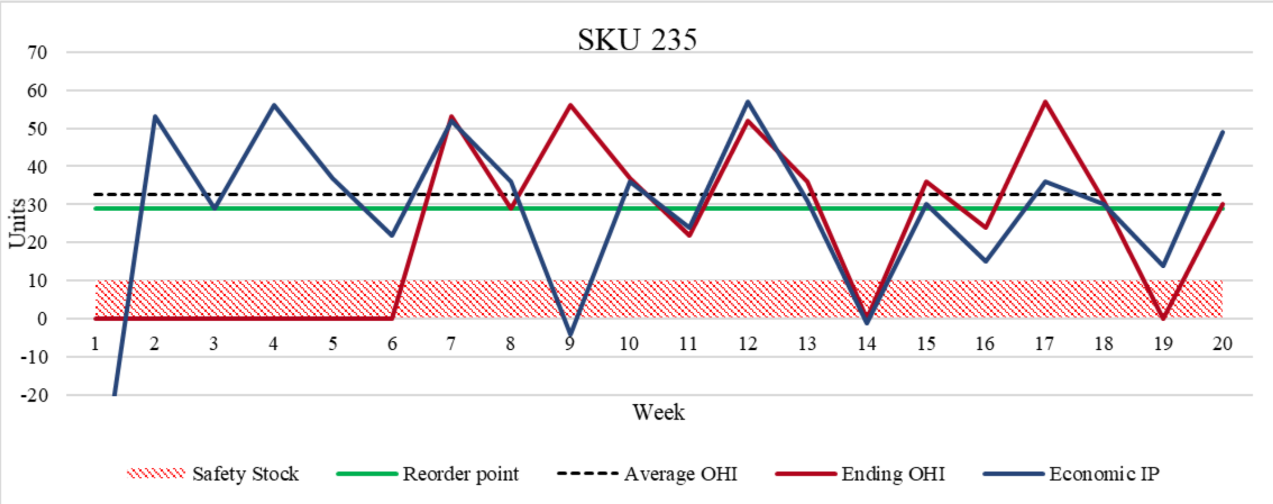

Figure A-14: Graphical visualisation of the simulation in Figure A-13 of SKU 235, without warm-up period.

Table A-8 shows the results from the simulation with a warm-up period. The simulation is started on 1-1-2020 using the actual OHI on 1-1-2020 as starting inventory. The first year (2020) is used as a warm-up period and the KPIs are measured over 2021. *Figure A-15* to *Figure A-17* show the results and the first 15 periods of the simulation for SKU 235.

Table A-8: Results of simulation with warm-up period, taking min. $DLT\ of\ PO = 7\ weeks$, $safety\ LT\ = 1\ week$ and DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
Avg. fill rate	**98,2%**	**100,0%**	**97,9%**	**99,3%**	**100,0%**	**99,1%**
Total backordering cost	€ 110.927	€ -	€ 1.928	€ 34.245	€ -	€ 147.099
Total avg. OHI value	€ 111.138	€ 220.792	€ 49.298	€ 96.983	€ 3.366	€ 481.578
Current avg. OHI value	€ 42.620	€ 338.908	€ 22.777	€ 30.266	€ 816	€ 435.386
Difference in OHI value	€ -68.518	€ 118.116	€ -26.522	€ -66.717	€ -2.551	€ -46.192

SKU Info	
SKU ID	235
SKU Class	4
SKU Policy	(s,Q)
Supply LT (weeks)	6
DLT_known (weeks)	5
DLT_extra (weeks)	0
Initial pipeline stock	40
Initial on-hand inventory	45
Initial demand backordered	0
Review period (weeks)	3
Target fill rate	97,5%
Realized fill rate	100,0%
Average on-hand inventory	36,019
Lotsize	40
Safety Stock	10
Reorder point	29
Order-up-to-level	0
Total demand	618
Nr. of orders placed	15

Figure A-15: Simulation information of SKU 235, with warm-up period.

Weeknumber	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Beginning on-hand inventory	45	45	37	25	55	46	31	18	34	21	42	27	57	41	1
Received replenishment order	0	0	0	40	0	0	0	40	0	40	0	40	0	0	40
Realized demand	**0**	**8**	**12**	**10**	**9**	**15**	**13**	**24**	**13**	**19**	**15**	**10**	**16**	**40**	**0**
Demand fullfilled from stock	0	8	12	10	9	15	13	24	13	19	15	10	16	40	0
Demand backordered	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ending on-hand inventory	45	37	25	55	46	31	18	34	21	42	27	57	41	1	41
Total pipeline	40	40	80	40	80	80	120	80	80	80	80	80	80	80	80
Inventory position	85	77	105	95	126	111	138	114	101	122	107	137	121	81	121
Demand during DLT_known	54	59	71	74	84	84	81	73	100	81	78	75	85	77	86
Demand during DLT_extra	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Economic inventory position	31	18	34	21	42	27	57	41	1	41	29	62	36	4	35
Replenishment order	0	40	0	40	0	40	0	0	40	0	40	0	0	40	0

Figure A-16: First 15 periods of the simulation of SKU 235, with warm-up period.

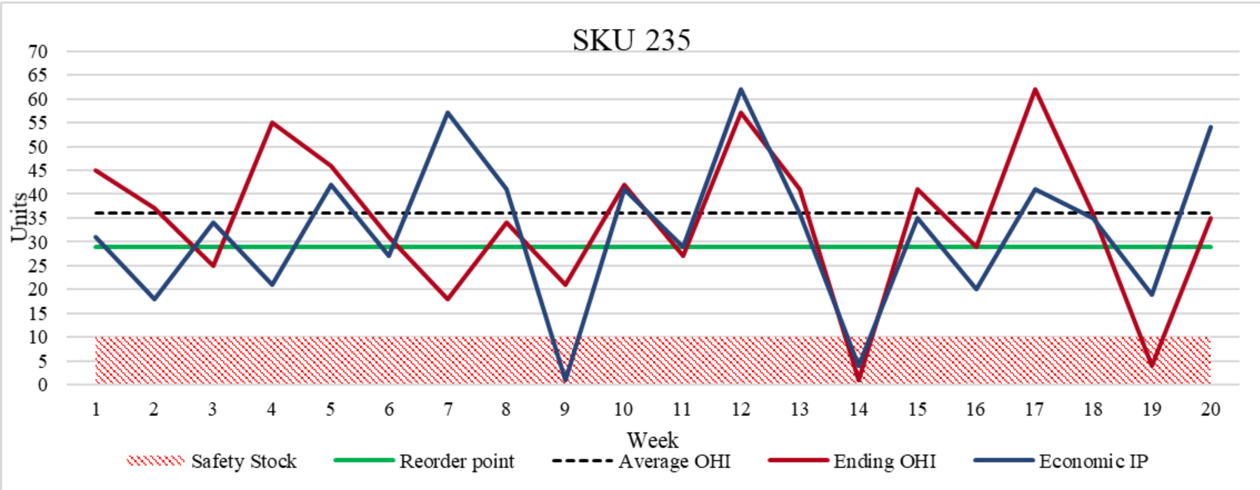

Figure A-17: Graphical visualisation of the simulation in Figure A-16 of SKU 235.

When comparing *Table A-7* and *Table A-8* one can see that the overall fill rate of the simulation is drastically improved from an average 95,9% to an average 98,9%. The improvement is especially noticeable when reviewing the SKUs with inventory policies other than MRP: Class 1, 3, 4 and 5. In the case where no warm-up period is applied the system is not in a steady state. The systems starting inventory OHI is not sufficient to cover demand during the initial SLT. This has as an effect that the initial periods of many SKUs are stocked-out and backordering occurs. An example of this can be seen when comparing the results of SKU 235, in particular *Figure A-14* and *Figure A-17*, where in the case without warm-up period the backordering due to the initial OHI not covering initial demand only stops in period 7. In total 54 units are backordered during this period. In the case where a warm-up period is used the system is in a steady state at the start of the simulation. No stockouts or backordering occur in this case in 2021. By doing this, the results are not negatively influenced by the excessive backordering that occur due to initialisation problems.

A.10 Detailed sensitivity analysis results

A.10.1 Minimal DLT of a PO and application of DLT_{extra}

Table A-9: Improvements of results per class, taking $min. DLT\ of\ PO = 8\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	**280**	**313**	**3**	**4**	**1**	**601**
Improvement in avg. fill rate	0,0%	0,0%	-0,1%	-1,8%	0,0%	0,0%
Improvement in total backordering cost	€ -	€ -	€ -1.279	€ -	€ -	€ -1.279
Improvement in avg. OHI value	€ -	€ -24.040	€ -1.107	€ -3.524	€ -321	€ -28.994

Table A-10: Improvements of results per class compared to initial solution, taking $min. DLT\ of\ PO = 6\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	**280**	**194**	**60**	**63**	**4**	**601**
Improvement in avg. fill rate	0,0%	-31,4%	1,7%	0,6%	0,0%	-10,2%
Improvement in total backordering cost	€ -	€ 374.735	€ 533	€ -	€ -	€ 375.268
Improvement in avg. OHI value	€ -	€ -3.769	€ 77.907	€ 53.730	€ 16.915	€ 144.784

Table A-11: Improvements of results per class compared to initial solution, taking $min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	**280**	**158**	**42**	**100**	**21**	**601**
Improvement in avg. fill rate	0,0%	-53,8%	1,4%	0,7%	-0,8%	-14,2%
Improvement in total backordering cost	€ -	€ 960.828	€ 833	€ -28.880	€ 58.580	€ 991.360
Improvement in avg. OHI value	€ -	€ -3.500	€ 81.428	€ 133.224	€ 80.816	€ 291.968

Table A-12: Improvements of results per class compared to initial solution, taking $min. DLT\ of\ PO = 7\ weeks$, $safety\ LT\ = 1\ week$ and with DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	**280**	**318**	**2**	**0**	**1**	**601**
Improvement in avg. fill rate	0,0%	0,0%	2,1%	-99,3%	0,0%	0,1%
Improvement in total backordering cost	€ -	€ -	€ -1.928	€ -34.245	€ -	€ -36.173
Improvement in avg. OHI value	€ -	€ -47.797	€ -23.380	€ -	€ -64	€ -71.241

A.10.2 Target fill rates

Table A-13: Improvements of results for class 3, 4 and 5 compared to initial solution, altering target fill rate. $Min. DLT\ of\ PO = 7\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 3	Class 4	Class 5	Overall	Class 3	Class 4	Class 5	Overall
# SKUs	**11**	**14**	**1**	**26**	**11**	**14**	**1**	**26**
Target fill rate	**99%**	**99%**	**99%**	**99%**	**85%**	**87,5%**	**89%**	**86,5%**
Improvement in avg. fill rate	0,7%	0,0%	0,0%	0,3%	-0,9%	-0,2%	0,0%	-0,5%
Improvement in total backordering cost	€ -620	€ -	€ -	€ -620	€ 775	€ 2.799	€ -	€ 3.574
Improvement in avg. OHI value	€ 12.184	€ 10.643	€ -	€ 22.827	€ -9.744	€ -20.509	€ -1.541	€ -31.795

	Class 3	Class 4	Class 5	Overall	Class 3	Class 4	Class 5	Overall
# SKUs	**11**	**14**	**1**	**26**	**11**	**14**	**1**	**26**
Target fill rate	**75%**	**77,5%**	**79%**	**76,5%**	**65%**	**67,5%**	**69%**	**66,5%**
Improvement in avg. fill rate	-1,3%	-0,3%	0,0%	-0,7%	-1,8%	-0,4%	0,0%	-1,0%
Improvement in total backordering cost	€ 1.230	€ 2.876	€ -	€ 4.106	€ 1.618	€ 2.954	€ -	€ 4.571
Improvement in avg. OHI value	€ -13.310	€ -26.558	€ -1.670	€ -41.538	€ -16.090	€ -29.670	€ -1.670	€ -47.431

A.10.3 Safety LT

Table A-14: Improvements of results per class, $min. DLT\ of\ PO = 7\ weeks$, $safety\ LT\ = 0$ and without DLT_{extra}.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall

# SKUs	280	313	3	4	1	601
Improvement in avg. fill rate	-0,5%	0,0%	-7,4%	-2,2%	0,0%	-0,3%
Improvement in total backordering cost	€ 18.506	€ -	€ 388	€ 2.615	€ -	€ 21.509
Improvement in avg. OHI value	€ -9.265	€ -129.321	€ -3.076	€ -8.520	€ -449	€ -150.632

Table A-15: Improvements of results per class, $min. DLT\ of\ PO = 7\ weeks$, $safety\ LT\ = 2$ and without DLT_{extra}.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	280	194	60	63	4	601
Improvement in avg. fill rate	0,4%	0,0%	1,8%	0,6%	0,0%	0,2%
Improvement in total backordering cost	€ -17.746	€ -	€ -349	€ -	€ -	€ -18.095
Improvement in avg. OHI value	€ 10.829	€ 51.360	€ 99.556	€ 84.412	€ 20.015	€ 266.172

Table A-16: Improvements of results per class applying a safety LT based on supplier performance.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	280	39	73	58	1	601
Improvement in avg. fill rate	0,2%	0,0%	1,3%	0,5%	0,0%	0,1%
Improvement in total backordering cost	€ -11.849	€ -	€ 388	€ 300	€ -	€ -11.161
Improvement in avg. OHI value	€ 5.279	€ -29.986	€ 31.261	€ 41.763	€ 1.579	€ 49.896

A.10.4 Undershoot

Table A-17: Improvements of results for class 3 and 4, without taking undershoot into account.

	Class 3	Class 4	Overall
# SKUs	11	14	25
Improvement in avg. fill rate	-2,2%	0,0%	-0,9%
Improvement in total backordering cost	€ 1.714	€ 2.315	€ 4.029
Improvement in avg. OHI value	€ -10.487	€ -14.576	€ -25.063

A.10.5 Time between stockout occasions

Table A-18: Fill rates of C-items mention in Table 5.4 using varying TBS. Each improvement over the last is marked in green.

SKU ID	TBS=3	TBS=5	TBS=10	TBS=50	TBS=100
32	55,0%	55,0%	55,0%	76,8%	76,8%
37	88,9%	88,9%	88,9%	88,9%	88,9%
116	86,3%	86,3%	86,3%	100,0%	100,0%
119	60,9%	63,8%	63,8%	99,3%	99,3%
131	87,2%	87,2%	90,0%	93,9%	99,6%
260	85,1%	85,1%	85,1%	95,4%	95,4%
266	71,5%	71,5%	71,5%	93,8%	93,8%
284	88,1%	88,1%	88,1%	88,1%	88,1%
298	75,5%	75,5%	75,5%	75,5%	100,0%
351	69,0%	69,0%	69,0%	69,7%	69,7%
352	58,5%	58,5%	80,0%	80,0%	80,0%
353	60,5%	60,5%	75,4%	75,4%	75,4%
359	82,7%	82,7%	82,7%	100,0%	100,0%
423	66,7%	66,7%	100,0%	100,0%	100,0%
475	84,5%	84,5%	100,0%	100,0%	100,0%
557	88,5%	88,5%	100,0%	100,0%	100,0%
590	70,0%	70,0%	100,0%	100,0%	100,0%
Backorder cost	€ 99.505	€98.999	€ 80.813	€ 40.573	€ 30.479
Average OHI value	€ 5.077	€ 5.426	€ 6.801	€ 7.599	€ 7.729

A.10.6 Policy selection per class

Table A-19: Improvements of results for C-items, taking a (R,S)-policy with a 95% target fill rate. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 1
# SKUs	280
Improvement in avg. fill rate	-2,0%
Improvement in total backordering cost	€ 88.922
Improvement in avg. OHI value	€ 26.886

Table A-20: Improvements of results for 163 A-items, taking a (R,S)-policy. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 3	Class 4	Class 5
# SKUs	42	100	21
Improvement in avg. fill rate	-2,0%	-0,6%	0,4%
Improvement in total backordering cost	€ 38.270	€ 27.989	€ -24.335
Improvement in avg. OHI value	€ 27.334	€ 67.847	€ -22.057

Table A-21: Improvements of results for C-items, taking a (s,Q)-policy with a 95% target fill rate. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 1
# SKUs	280
Improvement in avg. fill rate	-0,8%
Improvement in total backordering cost	€ 50.808
Improvement in avg. OHI value	€ -15.925

Table A-22: Improvements of results for 163 A-items, taking a (s,Q)-policy. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 3	Class 4	Class 5
# SKUs	42	100	21
Improvement in avg. fill rate	0,0%	0,0%	0,1%
Improvement in total backordering cost	€ 745	€ 6.968	€ -7.411
Improvement in avg. OHI value	€ 9.782	€ 2.224	€ -48.064

Table A-23: Improvements of results for 163 A-items, taking a (s,S)-policy. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 3	Class 4	Class 5
# SKUs	42	100	21
Improvement in avg. fill rate	0,0%	0,0%	0,1%
Improvement in total backordering cost	€ 378	€ -359	€ -7.411
Improvement in avg. OHI value	€ 2.658	€ 23.401	€ -38.926

Table A-24: Improvements of results for 163 A-items, taking a (R,s,S)-policy. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 3	Class 4	Class 5
# SKUs	42	100	21
Improvement in avg. fill rate	-0,8%	-0,1%	0,8%
Improvement in total backordering cost	€ 11.439	€ -49	€ -58.580
Improvement in avg. OHI value	€ 54.084	€ 152.814	€ 8.273

Table A-25: Improvements of results for 163 A-items, taking a (R,s,Q)-policy. $Min. DLT\ of\ PO = 5\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra}.

	Class 3	Class 4	Class 5
# SKUs	42	100	21
Improvement in avg. fill rate	-1,7%	-0,1%	0,0%
Improvement in total backordering cost	€ 15.971	€ 8.468	€ -
Improvement in avg. OHI value	€ 57.920	€ 143.492	€ 3.837

Table A-26: Improvements of results per class applying a safety LT based on supplier performance.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
Policy	(s, Q) *with TBS*	*MRP*	(s, nQ) & (s, S)	(s, nQ) & (s, S)	(s, nQ) & (s, S)	
# SKUs	280	158	42	100	21	601
Improvement in avg. fill rate	0,0%	0,0%	0,0%	0,0%	0,1%	0,0%
Improvement in total backordering cost	€ -	€ -	€ -	€ -	€ -7.411	€ -7.411
Improvement in avg. inventory value	€ -	€ -	€ -	€ -	€ -49.737	€ -49.737

A.10.7 Best solution

Table A-27: Results of the simulation per class, taking $min. DLT\ of\ PO = 7\ weeks$, $safety\ LT\ = 1\ week$ and without DLT_{extra} into account.

	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
# SKUs	280	295	11	14	1	601
Avg. fill rate (Improvement over initial solution)	98,2% (0,0%)	100,0% (0,0%)	95,7% (-2,2%)	99,2% (0,0%)	100,0% (0,0%)	99,1% (0,0%)

Total backordering cost (Improvement over initial solution)	€ 110.927 (€ -)	€ - (€ -)	€ 1.928 (€ 1.714)	€ 34.245 (€ 2.315)	€ - (€ -)	€ 147.099 (€ 4.029)
Total avg. OHI value (Improvement over initial solution)	€ 111.138 (€ -)	€ 220.792 (€ -)	€ 38.811 (€ -10.487)	€ 82.407 (€ -14.576)	€ 2.178 (€ -1.189)	€ 455.327 (€ -26.251)
Improvement total avg. OHI value over current situation	€ 68.518	€ -118.116	€ 16.034	€ 52.141	€ 1362	€ 19.941