Optimizing the inventory management at Aebi Schmidt Nederland B.V. by improving the inventory control policies

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Preface

Dear reader,

You are about to read the master thesis 'Optimizing the inventory management at Aebi Schmidt Nederland B.V. by improving the inventory control policies'. This research has been performed at Aebi Schmidt Nederland B.V., located in Holten, the Netherlands, as the final assignment for the Master Industrial Engineering and Management with a specialization in Production and Logistics Management at the University of Twente.

During my time at Aebi Schmidt Nederland B.V., I have gained valuable insight, learned a lot, and experienced what it is like to work within a company. I am grateful for the opportunity to work on an important topic within the company. I already knew the basics of inventory management but through this thesis, I learned a lot about the subject and how to bring theory to practice. I would like to thank all employees at Aebi Schmidt Nederland B.V. (ASNL) who helped me with my assignment. Their knowledge of the processes and their thoughts about improvements enhanced my understanding of the processes and context. A special thanks to my company supervisors, Ruben Goedhart and Jan Warmelink, who guided me during the research. They gave me a lot of freedom to work on the project independently, provided close guidance, and were always available for questions.

I would also like to express my gratitude to my first supervisor, Engin Topan. His guidance helped me a lot during this research and I enjoyed our meetings in which I got good ideas for the assignment. I would also like to thank my second supervisor Patricia Rogetzer for providing me with new insights and feedback in the final stages of my research.

This master thesis marks the end of study and student life. I am very grateful for the countless fun activities, new and exciting experiences, and personal development during my time in Enschede over the past five and a half years. Lastly, I want to thank my family and friends for their support and interest during my research and my entire study period. Thank you to the girls for sticking with me since the Kick-In, for experiencing countless incredible moments, and for teaching me Dalmuti, to GGD for the many fun activities and days studying together in front of Stress, to the Open Days team for allowing me to organize many open days together of the past five years, and to Thomas for his feedback, valuable support, and the days working on both our researches together. I especially want to thank Emma for providing me with the necessary motivation, new ideas, and feedback, and for making me feel like I was never alone every step of the way, and Mark for his unconditional support and belief in my abilities.

I hope you enjoy reading this master thesis!

Rozan Hopman

Enschede, May 2024

Management summary

This research was conducted at Aebi Schmidt Nederland B.V. (ASNL), located in Holten, the Netherlands. ASNL manufactures products for a wide range of urban and infrastructure needs, such as spreaders, sweepers, and snowploughs. ASNL operates as a mix of the Make-To-Order (MTO) and Engineer-To-Order (ETO) manufacturing settings with a High-Mix, Low-Volume (HMLV) product portfolio. Post COVID-19 pandemic, ASNL noticed a surge in material inventory and total inventory value within its production facility. All inventory-related decisions are Net Working Capital (NWC) driven, limiting the total inventory investment to a certain budget to mitigate high interest rates. The current inventory value lies around € 12 million and the norm is about € 5 to € 6 million. A primary cause of the too-high inventory levels is unstructured ordering due to unclear inventory control policies. Therefore, the core problem that is solved in this research is that 'Aebi Schmidt Nederland B.V. does not have clear inventory control policies for the procurement of materials'. This research aims to develop inventory control policies by answering the following main research question:

'How can the inventory control at Aebi Schmidt Nederland B.V. (ASNL), in terms of inventory control policies, be improved to reduce the raw material inventory, by considering ASNL's manufacturing setting?'

The article scope consists of 108,483 distinct articles. The ABC analysis on inventory value showed that 20% of the articles in inventory account for 87% of the total inventory value. The inventory coverage analysis showed that 63% of the total inventory value remains in inventory for longer than two months, exceeding ASNL target maximum Days-On-Hand (DOH) of two months and indicated excessive inventory levels. The current inventory control policies differentiate the Replenish-To-Stock (RTS) and Replenish-To-Order (RTO) strategies based on whether an article's Supply Lead Time (SLT) falls within the standard Frozen Period (FP) length of ten weeks. Furthermore, the inventory control policies heavily rely on gut feeling and employee expertise, due to a limited degree of internal SAP knowledge, low data quality, and limited data-driven decision-making.

Leveraging the insights gained from the performed literature review covering manufacturing settings, demand and lead time modelling, Kanban, Advance Demand Information (ADI), and Vendor Managed Inventory (VMI), classification methods, and basic inventory control policies, this research developed tailored inventory control policies aligned with ASNL's context. A literature confrontation outlined the academic contribution by determining the gap in literature this research addresses. This research bridges a gap in literature by showing how inventory control policies, including a Stock Keeping Unit (SKU) classification method, statistical distributions and parameters, can be applied in an MTO-ETO manufacturing setting by considering and combining the existing knowledge on the aforementioned inventory management concepts. This research uniquely models both demand and lead times as stochastic variables enhancing the accuracy of inventory control parameters, employs the less commonly used XYZ classification method, and uses the Ready Rate (RR) as the main service measure.

As ASNL's Enterprise Resources Planning (ERP) system, SAP, allows for the continuous review of inventory levels, the proposed control policies are continuous review policies. The control policies classify the SKUs based on their demand coefficient of variation according to the XYZ classification method and select a control policy accordingly. X and Y articles are managed using the (s, Q)-policy and Z articles are managed using the (s, S)-policy. Both demand and SLTs are modelled as stochastic random variables, with the SLT using the Triangular distribution. By combining the mean demand and its standard deviation with the SLT distribution using the 'combining the demand rate per time unit distribution with the lead time distribution' approach by Silver, Pyke, and Thomas (2016, p. 284) and rules of thumb, the proposed policies select the demand during random lead time (RLD) distributions. The RLD distribution selection contains five statistical distributions: Normal, Gamma, Binomial, Poisson, and (Generalized) Negative Binomial. The proposed policies determine the control parameters of the proposed policies using their respective formulas and the historical article usage from 2022 and 2023. We developed a prototype Microsoft Excel inventory management tool

to execute the proposed inventory control policies and determine the new control parameter values. The decision to use Microsoft Excel is based on the existing knowledge base within ASNL and the relatively easy integration of the tool within ASNL's current processes.

To obtain performance metrics to evaluate the performance of the proposed control policies, we developed a simulation model in Python Spyder that simulates the inventory levels using the actual demand over the first three months of 2024 for a sample of 60 articles. The simulation has a time bucket of one day to ensure continuous review and produces Key Performance Indicator (KPI) values for each article, such as the average On-Hand Inventory (OHI) value, the realized RR and realized Fill Rate (FR). Initial simulations indicated that while the proposed policies yield substantially lower inventory levels, they also result in lower service performance. This discrepancy is due to the initial OHI at the start of the simulation and the lack of a warm-up period. Using different initial OHI values demonstrated that a steady state simulation results in a reduction of inventory levels while obtaining similar service levels to those of ASNL in reality. This conclusion is supported by the implementation of Effective Lead Time (ELT), which is the difference between the SLT and Demand Lead Time (DLT) with the latter being equal to the FP. Using the ELT provides insights into the expected policy performance in a steady-state simulation, showing that the proposed policies in a steady-state simulation comply with the objective of reducing inventories while ensuring sufficient inventory for production.

A sensitivity analysis tested the robustness of the proposed control policies. Increasing the target RR resulted, as expected, in higher average inventory levels but not in a substantial change in service performance. Furthermore, the proposed policy performance is most sensitive to a target RR increase from 90% to 95%. Therefore, we recommend ASNL to maintain a RR of 90%. The sensitivity analysis on the SLT bounds showed that performance is highly sensitive to changes in the upper bound of the Triangular distribution interval and to large gaps between the lower and upper bounds. Therefore, eliminating SLT variability has a considerable impact on the inventory levels. The proposed policy performance showed no considerable difference when modifying the holding cost rate but does show substantial differences for different ordering cost rates. Therefore, ASNL should make more effort to precisely determine the ordering cost rate than to determine the holding cost rate. The precise determination of the ordering cost rate (and holding cost rate) starts with a thorough data analysis and can use an Activity-Based Costing approach in which costs are allocated to products and services according to the activities required, ensuring a more accurate representation of the actual inventory management costs. Using the FP length of ten weeks already results in a performance complying with the targets in a steady-state simulation. Therefore, ASNL does not have to shorten or lengthen the FP. Lastly, an implementation plan was formulated to ensure an effective implementation of the proposed control policies.

Based on the results analysis and the insights gained from the performed research, we list the following conclusions for ASNL:

1. Using the proposed inventory control policies and the prototype inventory management tool, we can determine the new control parameters for ASNL's articles. In a steady-state simulation, the overall inventory value is reduced while ensuring sufficient inventory for production. The overall monetary impact of the proposed policies is a reduction in total inventory value of € 2,034,295.55, which is a decrease of about 19%. Implementing the proposed control policies results in not only a reduction of inventory value but also an increase in inventory value as some articles need to maintain higher inventory levels, compared to the current inventory levels, to ensure sufficient inventory to fulfil demand, which causes the inventory values to increase. The proposed policies do not fully solve the action problem and reach the norm of about € 5 to € 6 million, as the € 2 million reduction does not decrease the € 12 million to the norm.

2. When implementing the proposed control policies and the newly determined parameter values, ASNL should increase their OHI levels to equal the average OHI under the new policies. This adjustment helps to stabilize the inventory more quickly.

3. Using the ELT approach by Hariharan and Zipkin (1995) provides insights into the steady-state performance but practical implementation in SAP is not possible due to SAP's SLT configuration.

4. Eliminating SLT variability substantially reduces inventory levels, supporting the statement of Silver et al. (2016, p. 282) that every reasonable effort should be made to eliminate SLT variability. To achieve this, ASNL should consider options such as exploring different transportation modes, implementing Service Level Agreements (SLAs), adopting Vendor Managed Inventory (VMI), and enhancing collaboration with suppliers.

5. To implement the proposed control policies, ASNL can use the proposed implementation plan explained in Section 7.3.

Based on the conclusions and the knowledge gained during the executed research, we provide ASNL with the following recommendations:

1. Implement the proposed inventory control policies using the proposed implementation plan and regularly review and update the inventory parameters.

2. Ensure more data-driven decision-making by implementing and tracking the proposed (simulation) KPIs to gain insight into the inventory performance.

3. Collaborate with suppliers to reduce SLT uncertainty and to ensure that order quantities better accommodate ASNL's needs.

4. Start leveraging VMI for low-valued, regular-usage (Kanban) articles.

5. Improve the degree of internal SAP knowledge and data quality to enhance decision-making speed and visibility of improvement possibilities.

Contents

Reader's guide

In the eight chapters within this thesis, we describe how the research at Aebi Schmidt Nederland B.V. (ASNL) is executed.

Chapter 1: Introduction
The first chapter introduces the research, describes the company and provides the research motivation. Furthermore, using a problem cluster, the core problem causing the observed action problem is identified. Lastly, the research design, including the scope, research questions, and deliverables, is explained.

Chapter 2: Context analysis
The second chapter analyses the current situation at ASNL. The product portfolio is explained, as well as the current supply chain. Furthermore, the available data, demand planning, inventory composition with its characteristics, and the current inventory control policies are analysed.

Chapter 3: Literature review
The literature review consults academic literature to gain insights into relevant inventory management concepts and models applicable to ASNL. The chapter starts by discussing relevant literature concepts. Then, different Stock Keeping Unit (SKU) classification methods, inventory control policies, and the determination of the control parameters are described. Lastly, a literature confrontation between this research and the existing academic literature helps to identify the literature gap in which this research is situated.

Chapter 4: Inventory policy design
The fourth chapter describes the proposed design of the inventory control policies, which are designed using the knowledge gained on classification methods, control policies and parameters from academic literature and taking the context at ASNL into account. Lastly, this chapter provides the modelling assumptions and limitations.

Chapter 5: Tool design
The fifth chapter describes the developed inventory management tool that executes the proposed inventory control policies. This chapter describes the stakeholder requirements as well as the tool's functioning.

Chapter 6: Results analysis
In the sixth chapter, the performance of the proposed inventory control policies is tested using a simulation and is benchmarked against the performance of ASNL's actual inventory during the first three months of 2024. Furthermore, different On-Hand Inventory (OHI) scenarios and setting experiments are tested. Lastly, a sensitivity analysis is performed to evaluate the robustness of the proposed policies.

Chapter 7: Implementation
The seventh chapter details the proposed implementation plan to guide the implementation of the proposed control policies and knowledge gained into ASNL's practices. The implementation plan is based on the concept of change management and details the involved stakeholders, the stepwise implementation approach, and the tool's maintenance challenges.

Chapter 8: Conclusions, recommendation, and further research
The last chapter provides the conclusions and recommendations about the performed research. Moreover, the limitations and potential future research topics are discussed. Lastly, this research's academic and practical contributions are detailed.

List of abbreviations

ADI Advance Demand Information.
AHP Analytic Hierarchy Process.
ASG Aebi Schmidt Group.
ASNL Aebi Schmidt Nederland B.V..
ATO Assemble-To-Order.

BOM Bill of Materials.

CDF Cumulative Distribution Function.
CIM Centralized Inventory Management.
CODP Customer Order Decoupling Point.
CS Consignment Stock.
CSL Cycle Service Level.

DBMS Database Management System.
DLT Demand Lead Time.
DOH Days-On-Hand.

EKCS Extended Kanban Controlled System.
ELT Effective Lead Time.
EOQ Economic Order Quantity.
ERD Entity Relationship Diagram.
ERP Enterprise Resources Planning.
ETO Engineer-To-Order.

FIFO First-In, First Out.
FOQ Fixed Order Quantity.
FP Frozen Period.
FR Fill Rate.

GKCS Generalized Kanban Controlled System.

HMLV High-Mix, Low-Volume.

IBP Integrated Business Planning.
IKCS Independent Kanban Controlled System.
IP Inventory Position.

JIT Just-In-Time.

KCS Kanban-Controlled System.
KPI Key Performance Indicator.

LSO Local Sales Organization.

MaxOQ Maximum Order Quantity.
MCIC Multi-Criterion Inventory Classification.
MGF Moment Generating Function.
MinOQ Minimum Order Quantity.
MTO Make-To-Order.
MTS Make-To-Stock.

NWC Net Working Capital.

OHI	On-Hand Inventory.
OPP	Order Penetration Point.
OVS	Order Volg Systeem.
PDF	Probability Density Function.
PICS	Production and Inventory Control System.
PPE	Product & Production Engineering.
R&D	Research & Development.
RLD	demand during random lead time.
RR	Ready Rate.
RTO	Replenish-To-Order.
RTS	Replenish-To-Stock.
SCIC	Single-Criterion Inventory Classification.
SK	Street King.
SKCS	Simultaneous Kanban Controlled System.
SKU	Stock Keeping Unit.
SLA	Service Level Agreement.
SLT	Supply Lead Time.
SMI	Supplier-Managed Inventory.
SSR	Special Sales Request.
TBR	Time Between Replenishments.
TBS	Time Between Stockouts.
TPS	Toyota Production System.
US	United States.
VMI	Vendor Managed Inventory.
VMR	Vendor Managed Replenishment.
WIP	Work-In-Progress.

1 Introduction

This master's thesis is conducted at ASNL, focusing on the complex inventory management aspects of ASNL's production. Section 1.1 introduces the reader to the company, and Section 1.2 describes the motivation for this research. Section 1.3 addresses the problem identification and describes the core problem within this research. Finally, Section 1.4 explains the research design.

1.1 Company description

This research is conducted at Aebi Schmidt Nederland B.V. (ASNL), located in Holten, the Netherlands. ASNL is part of the Aebi Schmidt Group (ASG). ASG is a global leader in intelligent solutions for customers who care for clean and safe infrastructure and cultivate challenging grounds. ASG produces products for a wide range of urban and infrastructure needs. Such products include spreaders, sweepers, and snowploughs (Figure 1.2). The origin of ASG lies in Burgdorf, Switzerland, where Aebi was founded in 1883. In 1920, Schmidt was founded in St. Blasien, Germany. In 1939, ASNL opened its production facility in Holten as Universal Machines B.V., and in 1983, ASNL acquired the brand Nido. Currently, ASG counts 14 production facilities in Europe (5), the United States (US) (8), and Canada (1), and they are present in 106 countries through their own sales (16) or partnerships with dealers (90). ASG operates within five business areas and has 15 different product groups (Aebi Schmidt Group, n.d.-a). Figure 1.1 provides an overview of these five business areas.

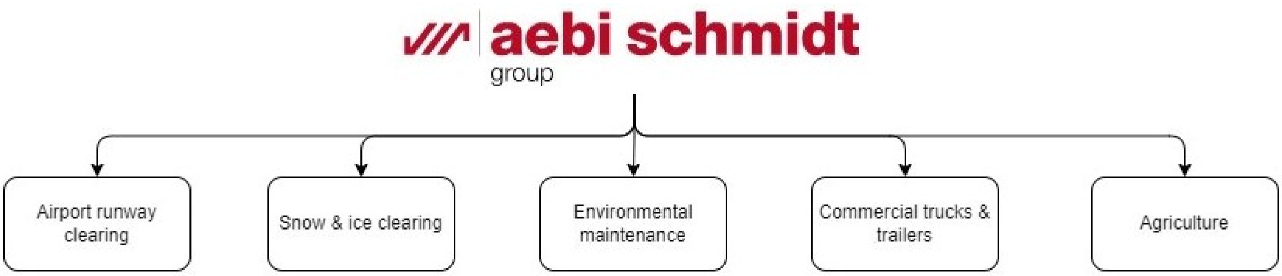


Figure 1.1: ASG business areas

ASNL is a mix of a Make-To-Order (MTO) and a Engineer-To-Order (ETO) manufacturing company with a High-Mix, Low-Volume (HMLV) product portfolio. In MTO and ETO manufacturing, all supply chain tasks, ranging from procurement of materials, parts, and components to fabrication, sub-assembly, and assembly until final delivery, are triggered by receipt of a customer order (Li & Womer, 2012). In 2022, ASG had a sales revenue of € 840 million, of which ASNL contributed about € 80 million. Each year, ASNL produces approximately 1,500 spreaders, and 120 truck-mounted sweepers, and executes approximately 20 big airport projects.

Figure 1.2: ASG product examples - from ASG's internal media library

1.2 Research motivation

This section describes the motivation for this research. As mentioned in Section 1.1, ASNL operates as a mix of MTO and ETO manufacturing with a HMLV product portfolio. In ETO, unique and complex products are designed and produced to the customer's specification, whereas in MTO, products are configured according to standard designs and specifications (Barbosa & Azevedo, 2019). HMLV indicates offering a large variety of products in low batch volumes. Offering many product variants has become a key strategy for many manufacturing companies to stay competitive and to offer customers acceptable delivery schedules, companies may have to store inventory. The amount of inventory for this purpose is a complex trade-off between the negative effect of stockouts and inventory investments (Radke, Tolio, Tseng, & Urgo, 2013).

Inventory management is a critical aspect of supply chain management that involves planning, executing, and controlling the forward and reverse flow and storage of goods, services, and related information between the point of origin and consumption to meet customer demand (Dadaneh, Moradi, & Alizadeh, 2023). Post COVID-19 pandemic, ASNL notices a surge in material inventory within its production facility. The pandemic has caused major shifts in global supply chains, rendering them more global and complex than before (Bier, Lange, & Glock, 2020). As reported by van Hoek (2020), 86% of global supply chains were adversely affected by the COVID-19 pandemic, indicating its impact.

All inventory decisions made by ASG and ASNL are Net Working Capital (NWC) driven, meaning that the total inventory costs cannot exceed a certain budget, as ASG deals with high-interest rates on its inventory. Currently, the NWC problem is a hot topic for all of ASG's manufacturing facilities. Therefore, the main objective is to minimize the total costs invested in inventory. Typically, in MTO-ETO manufacturing, all processes start after the arrival of a customer order. However, the disadvantage of MTO-ETO is that it usually results in long customer lead times (Vidyarthi, Elhedhli, & Jewkes, 2009). To obtain a competitive advantage manufacturing companies maintain inventory to shorten customer lead times. The main motivation for this research is to investigate how ASNL can optimally deal with its complex inventory management to reduce its inventory levels towards pre-pandemic targets and thus decrease the ASNL's inventory costs.

1.3 The research problem

This section takes a closer look at the research problem and provides a better understanding of the problem context. Section 1.3.1 defines the action problem that marks the start of the research. Subsequently, Section 1.3.2 describes the problem identification resulting in a set of potential core problems that cause the action problem. One of these problems is selected as the core problem for this research in Section 1.3.3.

1.3.1 Action problem

Within the ASNL production facility in Holten, problems occur within its inventory management. After the COVID-19 pandemic, ASNL noticed a surge in the inventory of materials within the production facility and a corresponding increase in the total inventory value, causing a surge in inventory costs due to ASNL's high-interest rates on inventory. Despite implementing several measures to rescue inventory levels, including adjustments to safety stocks for certain Stock Keeping Units (SKUs) and modifications to the standard Bill of Materials (BOM) for certain machines, ASNL has not achieved the intended results. These measures have been symptomatic relief instead of addressing the root cause. SKUs refer to inventory items that are specific as to function, style, size, colour, and location (van Kampen, Akkerman, & van Donk, 2012), and a BOM comprises the components required for the total product (Slack, Chambers, & Johnston, 2016, p. 691). The implemented measures lacked a systematic approach and were executed based on intuition. Furthermore, no large fluctuations within the total inventory value are observed. Therefore, the problem is that 'the inventory of materials within the production facility is structurally too high'. This situation is an action problem.

According to Heerkens and van Winden (2017, p. 21), anything or any situation that is not how you want it to be is an action problem, and it is a discrepancy between the norm and the reality as perceived by the problem owner. Within this research, the problem owner is ASNL. In this case, the reality is that the material inventory within the production facility has a structurally too high value of about € 12 million. The norm is that the inventory value should be about € 5 to € 6 million. This norm is derived from the inventory value before the COVID-19 pandemic and a maximum allowable Days-On-Hand (DOH) inventory of at most two months (ten Brinke, 2023). The DOH is the expected time until the current stock level will be depleted. This maximum allowable DOH is an internally agreed measure within ASNL. To summarize, the problem selected to be solved within this research is the following action problem.

'The inventory of materials within the production facility is structurally too high'

1.3.2 Problem identification

In order to identify the root cause of the action problem, problem identification is needed. By means of an observational study and through interviews, a better understanding of the underlying problems related to the action problem is created. We created a problem cluster to visualize the relationships between all identified problems. A problem cluster maps the problems causing the action problem along with their connections and identifies potential core problems (Heerkens & van Winden, 2017, p. 42). Figure 1.3 shows the constructed problem cluster.

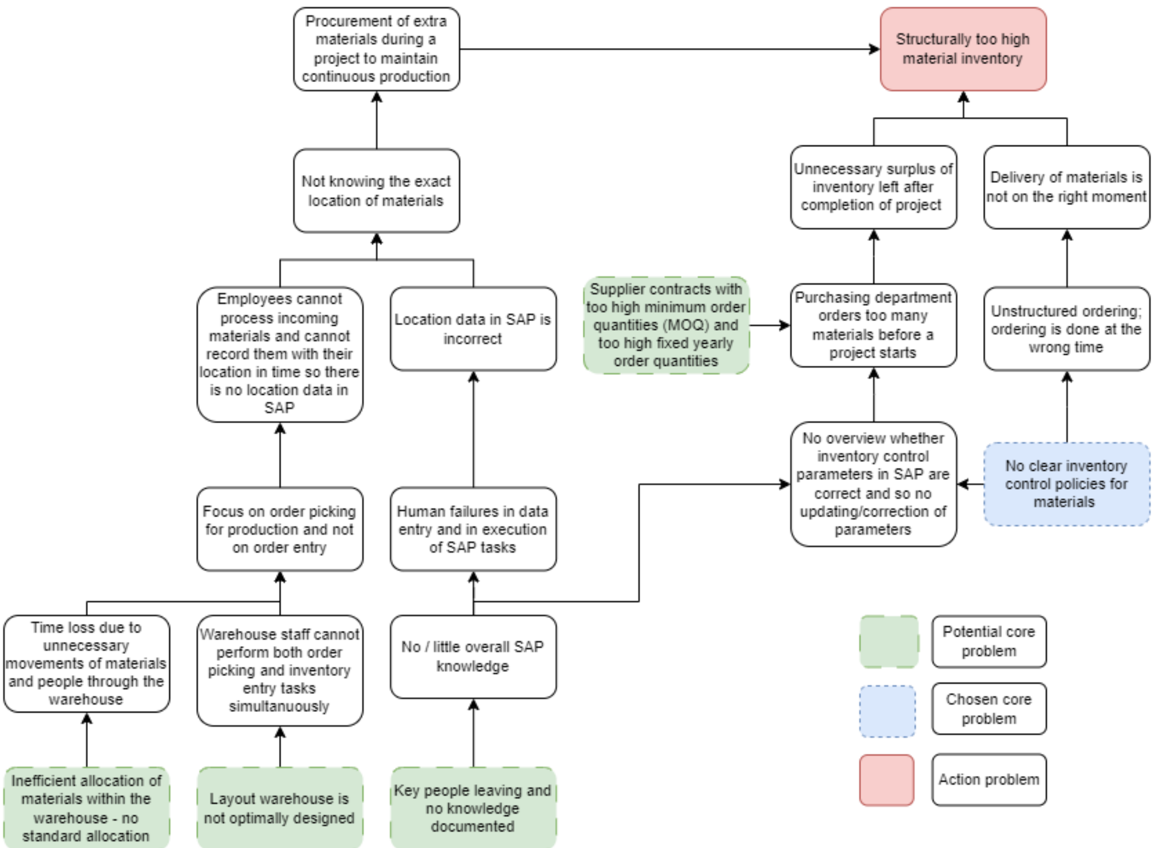


Figure 1.3: Problem cluster

In Figure 1.3, the action problem 'Structurally too high material inventory' is a consequence of three underlying problems. At the time this research is performed, the delivery of materials to the warehouse by suppliers does not align with production needs. This either means that materials are delivered too early or too late. This is caused by the unstructured ordering method used by the Purchasing department. This unstructured ordering results from the Purchasing department does not have clear inventory control policies for the numerous SKUs.

The second problem causing the action problem is the problem that a surplus of unnecessary inventory remains after the completion of a project. ASNL operates on a MTO and ETO basis, producing exclusively for customer orders. Therefore, it quite often occurs that materials are solely purchased for a specific customer order. Because the Purchasing department orders too many materials before a project starts, a surplus of these materials remains in the warehouse after the completion of such a project. This surplus originates from supplier contracts with excessively high Minimum Order Quantities (MinOQs) and too large contractually established fixed yearly order quantities and from a lack of oversight regarding whether the inventory control parameters, such as safety stock and reorder point, in the Enterprise Resources Planning (ERP) system, called SAP, are correct. A MinOQ describes the minimum allowable order quantity of a supplier (Silver et al., 2016, p. 165). The lack of insight into whether the control parameters are correct is caused by the earlier-mentioned lack of inventory control policies and by the little to no overall SAP knowledge of employees within ASNL. The lack of knowledge of whether the control parameters are correct results in no updating or correction of these parameters.

Lastly, the structurally too high material inventory originates from the procurement of extra (unnecessary) materials during a project in order to maintain continuous production because the warehouse employees cannot find the materials. The Purchasing department resorts to these additional material orders as many materials get lost within the warehouse, and thus, their exact location is unknown. This lack of knowledge about material locations is due to two separate problems: (i) the inability of warehouse employees to process incoming goods and, therefore, do not record the materials with their location in SAP, and (ii) the location data in SAP is incorrect. First, we address the incoming material processing problem. The warehouse employees are not able to process all the incoming materials because the picking process to supply the assembly lines of goods has priority over processing the incoming materials. Order picking is the process of extracting the needed materials from the shelves in the warehouse and supplying them to the assembly lines. The focus on supplying the assembly lines, and thus on order picking, is, on the one hand, due to the physical limitations of the warehouse. These limitations prevent employees from simultaneously processing incoming materials and order picking. On the other hand, the focus on order picking is due to a substantial loss of time spent on the movement of materials and people through the warehouse. These movements are due to the inefficient allocation of materials within the warehouse. An example of the inefficient allocation of materials is that materials are not allocated according to their usage. Daily-used materials are often placed at the end of the shelves, materials for a specific assembly line location are scattered, and two batches of materials can be placed at two entirely different locations within the warehouse. So, no standard allocation of materials is used, and therefore, the required materials for one machine may be scattered throughout the warehouse.

The lack of knowledge about material locations within the warehouse is also due to the location data in SAP being incorrect. The incorrect data relates to human failures in data entry and the execution of SAP tasks. In recent years, ASNL experienced a loss of critical SAP knowledge due to a high employee turnover. This resulted in SAP becoming a black box and an overall lack of SAP knowledge within the company and so, many errors in data entry and the execution of SAP tasks occur.

1.3.3 Core problem and motivation

Core problems are problems that do not have a cause. These problems can be found at the edges of the problem cluster. Using the problem cluster (Figure 1.3), we identify five potential core problems. According to Heerkens and van Winden (2017, p. 44), a core problem is selected if it can be influenced. The first potential core problem, the 'loss of critical SAP knowledge due to employee turnover', could be resolved by hiring SAP professionals to train ASNL's employees. However, since ASNL plans to switch to a new version of SAP (SAP HANA) within the upcoming year, they have decided to postpone employee training.

The second potential core problem is the problem that ASNL has several supplier contracts with too high MinOQs and too large fixed yearly order quantities. This issue can be addressed by altering the supplier contracts and lowering the MinOQs and the fixed yearly order quantities. However, higher management within ASG has decided to discontinue these types of supplier contracts. This decision is based on the impending transition towards an SAP Integrated Business Planning (IBP) tool with ASNL's suppliers. The IBP tool is included in SAP HANA and through the IBP tool, ASNL strives to enable suppliers to better anticipate the expected material demand and plan their deliveries accordingly. As the integration of the IBP tool is an ongoing project, this problem will not be chosen as the core problem of this research.

Three potential core problems now remain, (i) the inefficient allocation of materials within the warehouse, (ii) the sub-optimal warehouse layout design, and (iii) the lack of inventory control policies. These three remaining potential core problems are of utmost importance to be solved for ASNL. Together with the stakeholders, it has been decided to focus this research on 'the lack of inventory control policies', which is a pure procurement problem. To solve this selected core problem, inventory control policies are developed and implemented in an inventory management tool, to provide structure in ASNL's inventory management. The inventory management tool is developed as SAP is currently more or less a black box for ASNL's employees and the tool is a workaround to provide a clear inventory overview. Simultaneously, the other two potential core problems will serve as a basis for a new project within ASNL's Continuous Improvement department, as these two problems form a larger project due to their close interrelation, which exceeds the given time frame of an academic semester. The problem cluster shows that the five potential core problems are interrelated, and solving one problem might not fully solve the action problem. To reduce the research complexity, together with the stakeholders, it has been decided to treat the problems as independent problems, even though in reality this is not the case. To conclude, the following problem has been selected as the core problem to solve during this research.

'Aebi Schmidt Nederland B.V. does not have clear inventory control policies for the procurement of materials'

1.4 Research design

This research is structured following the methodology designed by Heerkens and van Winden (2017, p. 22). Their methodology comprises seven distinct steps: (i) Defining the problem, (ii) formulating the approach, (iii) analyzing the problem, (iv) formulating (alternative) solutions, (v) choosing a solution, (vi) implementing and (vii) evaluating the solution. Based on these steps, we formulate the research questions. Section 1.4.1 provides these research questions. Section 1.4.2 provides the overall approach within this research and Section 1.4.3 details the research scope. Section 1.4.4 defines the stakeholders involved in the research. Lastly, Section 1.4.5 describes the intended deliverables.

1.4.1 Research questions

This section provides an overview of the formulated research questions. Based on the problem identification and core problem selection, we formulate the main research question as follows:

'How can the inventory control at Aebi Schmidt Nederland B.V. (ASNL), in terms of inventory control policies, be improved to reduce the raw material inventory, by considering ASNL's manufacturing setting?'

In order to be able to answer the main research question and thus to solve both the action and core problem, research is conducted by answering several research questions. These questions structure the research and are formulated as follows:

1. *What is the current inventory management situation at Aebi Schmidt Nederland B.V.?*
    - What is the current production-inventory supply chain of ASNL?
    - How are the SKUs currently classified?
    - What is the current inventory composition?
    - What is the current demand planning of the SKUs in inventory?
    - What inventory control policies are currently in place, and what parameters (such as reorder level, safety stock, and lead times) are associated with them?
    - How is uncertainty incorporated in the current inventory control policies?
    - Which quantitative data regarding inventory management is available and can be extracted from the ERP system (SAP)?
2. *What inventory management methods from literature apply to the situation at Aebi Schmidt Nederland B.V.?*
    - What literature concepts align with the inventory context at ASNL?
    - What SKU classification methods are available in literature?
    - How are SKU classification methods applied in inventory control?
    - What inventory control policies are available in literature?
    - How can uncertainty be incorporated within the available inventory control policies?
    - How can the theoretical inventory control parameters be determined?
    - In which gap in academic literature is this research situated?
3. *How should the inventory control policies be designed?*
    - How should the SKUs be classified?
    - What inventory control policies are suitable for each SKU class?
    - How should the parameters of the selected control policies be determined?
    - What assumptions must be made to design the control policies?
4. *How should the inventory management tool be designed and developed?*
    - What are the tool requirements from stakeholders?
    - How can the tool incorporate the available data and the designed inventory control policies?
5. *What is the performance of the proposed inventory control policies and management tool?*
    - How can the performance of the proposed inventory control policies and management tool be assessed?
    - What is the effect of using the proposed inventory control policies and management tool compared to the current inventory situation?

- How can the results of the proposed inventory control policies and management tool be validated?
- How sensitive is the performance of the proposed inventory control policies to changes in input parameters?

6. *How can the proposed inventory control policies and management tool be successfully implemented and maintained at Aebi Schmidt Nederland B.V.?*
   - How can the defined stakeholders be integrated within the implementation process?
   - What steps need to be taken in order to implement the proposed inventory control policies and management tool?
   - How can we ensure proper maintenance of the proposed inventory management tool over time?
7. *What conclusions and recommendations can be drawn from the research at Aebi Schmidt Nederland B.V.?*
   - What are the main conclusions resulting from the conducted research?
   - What are the main recommendations resulting from the conducted research?
   - What are the limitations of the conducted research?
   - What areas of future research can be identified from the conducted research?
   - What are the academic and practical contributions of the conducted research?

1.4.2 Approach

In order to solve the action problem, first insights into the current situation are obtained. The context analysis is executed by means of a combination of a descriptive study and data analysis. Interviews with different stakeholders are performed to gain contextual insights. Chapter 2 described the context analysis. Chapter 3 consists of a literature study that provides insights into relevant inventory management literature and control policies. It not only explores the relevant inventory policies for ASNL but also the classification of SKUs, and the determination of the control parameters. With the contextual knowledge from Chapter 2 and the insights gained from the literature review in Chapter 3, we design inventory control policies in Chapter 4. Subsequently, we develop an inventory management tool that executes the design policies. The tool development, as described in Chapter 5, also considers the stakeholder requirements. Chapter 6 focuses on the performance of the proposed inventory control policies and management tool, the effects of the policies and tool in comparison with the current inventory situation, and the validation of the results. Chapter 7 describes the implementation and maintenance of the proposed inventory control policies and management tool. This chapter outlines how the tool can be applied in practice and how the stakeholder can be integrated into the implementation process. Finally, Chapter 8 provides the conclusions and recommendations derived from this research. Moreover, this final chapter discusses the limitations of this research, the identified future research areas, and the academic and practical contributions. Figure 1.4 illustrates the approach in a flowchart.

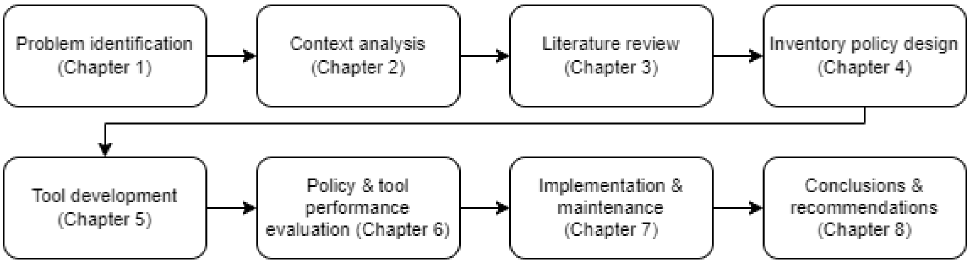


Figure 1.4: Approach flowchart

1.4.3 Scope

As explained in Section 1.2, the inventory management aspects of the MTO and ETO manufacturing setting at ASNL is complex. In order to ensure that this research results in reliable outcomes within the given time frame of an academic semester, a research scope is defined. With the selection of the core problem, this research has already been narrowed down to only include inventory management and not the logistics within the warehouse. Next to that, the following boundaries of the scope are defined:

- The accuracy of the sales forecast is out of scope as this research focuses on the production facility of ASNL and not on the sales facility (Local Sales Organization (LSO)).
- The procurement process of materials is out of scope, as the specific process of purchasing materials from a supplier does not affect the total inventory value. The inventory control policies and parameters are separate from the procurement process and belong to the scope of this research.
- The accuracy of the BOM defined by the Product & Production Engineering (PPE) department does affect the quantity with which materials are ordered. However, this does not belong to the scope of this research.

1.4.4 Stakeholders

The main stakeholder in this research is Aebi Schmidt Nederland B.V. (ASNL). Within ASNL, the Purchasing department, the Inventory Warehouse, and the Continuous Improvement department are defined as key stakeholders for this research.

1.4.5 Deliverables

Together with the defined stakeholders (Section 1.4.4), a set of the following deliverables has been defined. These deliverables will be presented to the stakeholders at the end of this research.

- A (prototype) inventory management tool with which the inventory control policies can easily be reviewed and updated.
- A proposal on implementing and maintaining the developed inventory management tool.
- Recommendations and conclusion in order to reduce the material inventory at Aebi Schmidt Nederland B.V.
- This master thesis to understand how the research has been conducted.

2 Context analysis

This chapter provides a context analysis of the current situation at ASNL and answers the following research question by answering its sub-questions explained in Section 1.4.1.

What is the current inventory management situation at Aebi Schmidt Nederland B.V.?

This chapter is structured as follows. Firstly, Section 2.1 describes the product portfolio manufactured by ASNL. Subsequently, Section 2.2 provides insights into the supply chain of ASNL and Section 2.3 discusses the available data within SAP, which is needed to conduct the context analysis. Section 2.4 describes the ASNL's demand planning. Following that, Sections 2.5 and 2.6 discuss the inventory composition based on several characteristics and the current inventory control policies, respectively. Lastly, this chapter concludes with the answers to the research questions in Section 2.7.

2.1 Product portfolio

To understand the context at ASNL, we first need to gain insight into the different machines that are produced by ASNL, as the research scope includes the inventory at ASNL, containing materials for all different types of machines. Overall, ASNL has four different assembly lines, each dedicated to a specific product category. The four product categories are the Street King (SK) 660, the Wasa 300+, the spreaders, and the airport category. Figure 2.1 shows product examples of the first three categories.

Figure 2.1: ASNL products - Wasa 300+, SK 660, and spreaders - from ASG's internal media library

The SK 660 is a truck-mounted sweeper. In February 2022, the assembly of the SK 660 moved from Aebi Schmidt Germany to ASNL. The SK 660 is capable of sweeping and collecting dirt in a container. Its high suction power, large seven m^3 dirt container, and high water volume (1600 litres) make the SK 660 a suitable machine for long-distance sweeping with maximum efficiency (Aebi Schmidt Group, n.d.-d).

The Wasa 300+ is a towed sweeper and picks up dirt mechanically. This machine is particularly suitable for cleaning streets in small towns and communities, along with industrial and port areas. The sweeping unit consists of two towed disc brushes in front and a rear-mounted roller brush, enabling effective cleaning operations (Aebi Schmidt Group, n.d.-e). The Wasa 300+ is only produced from January until April. During the remaining months, the space of the Wasa assembly line is used for other projects. The relatively short manufacturing period aligns with the needs of Scandinavian customers as they rely on grit alongside salt to de-ice roads and ensure safety when temperatures become too low. Once spring arrives and the temperatures rise, the Wasa 300+ removes the grit from the roads.

Within the spreader product category, there are various specialized spreaders, such as the Stratos, Syntos, Traxos, and Galeox. These machines are used for winter road maintenance, as they distribute salt across the road surface to de-ice the road (Aebi Schmidt Group, n.d.-c). The spreader product category is the biggest group in terms of production numbers and revenue.

The last product category is the airport category, which contains various large machines designed to clean and maintain the airport infrastructure. An example of an airport machine is the ASP Airport Sprayer. This spraying machine ensures a fast and exact application of de-icing agents. The ASP offers a maximum working width of 40 meters and can be used for both preventive and curative de-icing on runways and aprons (Aebi Schmidt Group, n.d.-b). Figure 2.2 shows product examples within the airport category.

Figure 2.2: ASNL airport products - from ASG's internal media library

2.2 Current supply chain

To gain insight into the current inventory management situation at ASNL, a comprehensive understanding of the supply chain of ASNL is required. This section describes the supply chain of ASNL, as illustrated in Figure 2.3. Additionally, Figure A.1 in Appendix A.1 provides a detailed swimlane diagram of the supply chain.

The process at ASNL starts when a Local Sales Organization (LSO) receives a customer order. LSOs, which are ASG's sales organizations located globally, communicate these orders to ASNL's Product & Production Engineering (PPE) department through a system called 'Sofon'. The end customer only contacts the LSO, making the LSO responsible for converting the customer requirements into an order request. PPE then enters the machine(s) of an order in a system called Order Volg Systeem (OVS) (in English: Order Tracking System), determining the strategic production slot (week X) for the specific machine(s), and communicating the delivery date to the customer. When scheduling the strategic production slot, OVS considers three factors: (i) the production scenario (also known as production plan) within a certain week. This production plan, decided by management, states the number of machines to be produced per assembly line based on the LSO sales forecasts; (ii) the mixing rules, which ensure a balanced workload; and (iii) the technical specifications. A more complex machine will be scheduled at a later point in time than a less complex machine, as more complex machines require more preparations regarding the BOM. OVS and SAP are parallel systems, ensuring that orders entered in OVS are mirrored in SAP. PPE then converts the customer requirements into a BOM using Sofon. Both OVS and Sofon are workaround systems connected to SAP, developed because SAP is more or less a black box for ASNL as explained in Section 1.3.2. Approximately 75% to 80% of the orders contain Special Sales Requests (SSRs) indicating customized customer preferences beyond the standard offerings available in Sofon. Once the BOM is finalized, PPE enters it in SAP and connects it to the corresponding machine. At this point, the machine becomes visible in SAP for the Production Planning and Procurement departments. The Production Planning department then schedules the operational production slot (day Y) for machine assembly. The Demand Lead Time (DLT) denotes the time from SAP visibility until the customer delivery date. Section 2.4 provides a detailed explanation of the materials procurement process.

Ten weeks (= 47 workdays) before the strategic production slot (week X), the Frozen Period (FP) starts. After the start of the FP, it is no longer possible for the customer to change the requirements. So, the BOM is fixed and, therefore, demand is 100% certain at the start of the FP. The standard length of the FP is ten weeks (= 47 workdays). In practice, the length of the FP can vary based on the complexity of the specific machine(s) of an order. The decision whether to shorten or lengthen the FP is based on experience. For the sake of simplicity, during the remainder of this thesis, we use the standard FP length of ten weeks within inventory-related decisions.

Within ASNL, two types of suppliers exist: internal and external. The internal suppliers, namely the Welding and the Part Assembly departments, transform materials sourced from external suppliers, Inventory F (Fremd), into Inventory E (Eigen/Halb) articles. The Procurement department sources all the required materials from external suppliers using the order quantities given by SAP. The order quantities given by SAP are based on several inventory control parameters, like safety stock and MinOQs. Both internal (E) and external (F) suppliers are required to deliver materials seven workdays before Assembly starts production, allowing the final seven workdays for booking inbound materials, releasing the work order, order picking, and processing sub-assemblies. The scope of this research includes both types of supply. It is important to note the difference in reliability of both supply types. Internal suppliers are generally more reliable than external suppliers, as internal suppliers generally deal with fewer types of uncertainty.

To initiate machine production, the Production Planning department releases a work order 72 hours in advance. The Production Planning department conducts a daily meeting with the Procurement department to determine which machines will start production three full workdays from the meeting date. Each machine waiting for production receives a separate work order. Within this meeting, they check whether all materials for a specific machine are present at ASNL. So, the work order can be released when all the required materials of a specific machine are present within the warehouse. Once the work order is released, the materials are dedicated to that specific work order and cannot be used for another work order/machine. The warehouse employees then have 72 hours to deliver the necessary materials to the specific locations within the assembly lines. Situations occur when not all the materials are present in the warehouse due to, for example, delays in deliveries, defective materials, or materials that have not yet been processed at order entry. In such cases, the Production Planning department determines whether it is still possible to release the work order, relying on the technical expertise of the employees involved in this daily meeting to assess the possibility of assembling the machine without the missing materials and adding the materials at a later moment. If a work order cannot be released, the team checks the options of bringing a later-scheduled machine forward. For this newly considered machine, the same steps are followed to check the material availability and technical feasibility when not all required materials are present.

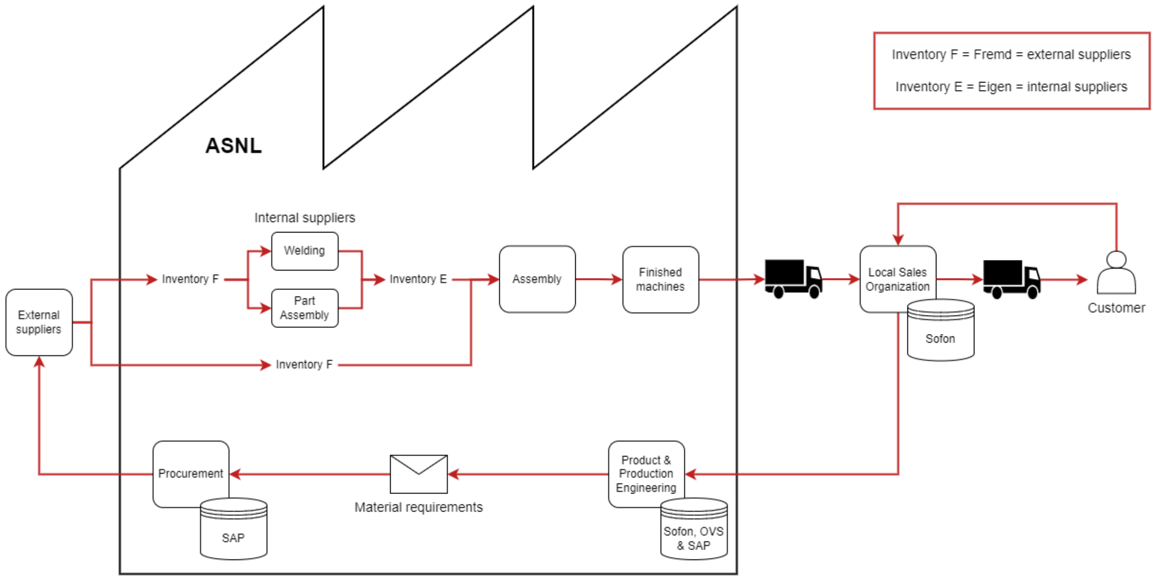


Figure 2.3: ASNL supply chain

2.3 Data availability

As previous explained, ASNL uses an ERP system, called SAP. All data, needed to run different processes, is stored and updated within SAP. Furthermore, it is possible to extract data from SAP, which is essential for executing the contextual analysis of the current situation at ASNL. The following list indicates the data types for all possible articles extracted from SAP, which we thoroughly analyse in the remaining sections of this chapter.

- Data on individual article level including, among other details, descriptions, unit values, and inventory control parameters.
- Historical data on the article usage per month of 2022 and 2023. The end of this period coincides with the end of the COVID-19 pandemic, and the effects of the pandemic may influence the data accuracy. However, using a data timeframe that starts after the conclusion of the pandemic mitigates this influence to some extent.
- Historical and current inventory data, including Key Performance Indicator (KPI) values, and current storage locations of SKUs.

Expected future usage data, in terms of sales forecasts, will not be used. Each machine sold is unique, and the expected sales numbers cannot provide any information as to what materials are exactly needed. Therefore, the sales forecasts do not offer meaningful insights applicable to the inventory decision-making process. The products manufactured by ASNL can be considered to be a family, where each machine is unique. How to leverage the sales forecast to obtain insights on the expected future usage data presents a future research topic.

2.4 Demand planning

Section 2.2 explained the supply chain at ASNL. Planned demand for a SKU arises when the machine becomes visible in SAP for the Production Planning and Procurement departments. This moment occurs before the start of the FP and can range from several months before to a day before. During the time until the start of the FP, demand is known but not with absolute certainty. Only after the start of the FP, demand is 100% certain, and all required materials are known. Figure 2.4 illustrates a schematic overview of the demand planning.

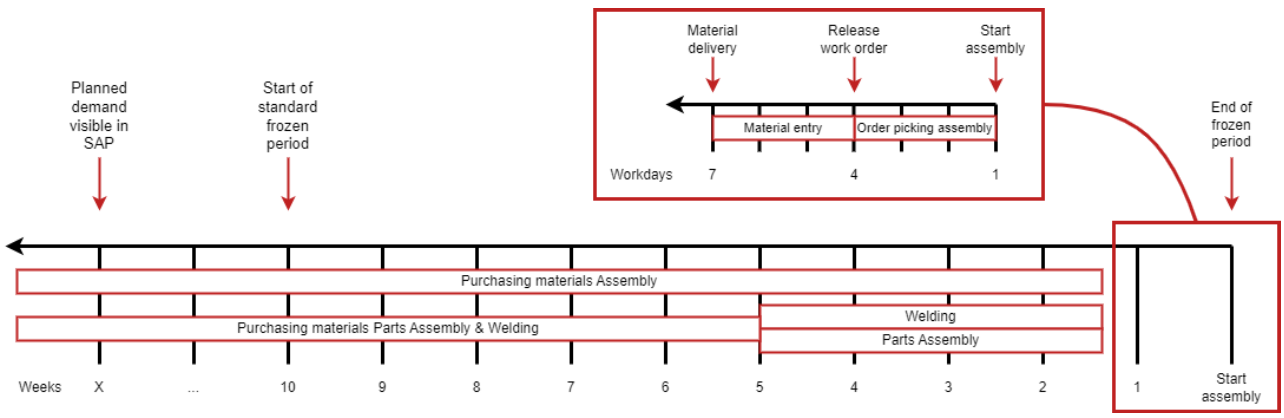


Figure 2.4: Schematic overview SKU demand planning

As soon as planned demand arises, the required materials can be purchased from external suppliers by the Procurement department. However, at this point in time, demand is not absolutely certain, so there is a degree of uncertainty as to whether the materials are actually required. Each material has a distinct Supply Lead Time (SLT) (also known as the replenishment lead time). Sometimes SLTs are shorter or equal to the standard length of the FP. These materials can be purchased within the

FP when demand is absolutely certain. Such materials can be purchased considering a Replenish-To-Order (RTO) strategy. Materials with a longer SLT must be ordered before the start of the FP, so before demand is 100% certain. Situations occur that the SLT is longer than the DLT. Recall that the DLT denotes the time from the moment demand arises until the customer delivery date. To ensure that these materials are available at the right moment, either safety stocks are maintained, or the expected material requirements are determined. The expected material requirements are based on the previous year's usage and the production scenario. Based on the expected material requirements, the Production Planning department can decide to enter a SK 660 dummy machine in SAP. This dummy machine is a standard machine used to generate demand for certain materials manually. Note that this is only possible for the SK 660 and not for the other product categories. The materials purchased to maintain a safety stock are procured using a Replenish-To-Stock (RTS) strategy. RTS and RTO are equivalent to the general manufacturing settings Make-To-Stock (MTS) and MTO-ETO, respectively (Ahmadi, Atan, de Kok, & Adan, 2019; Zhao, Zhang, Ru, & Sutherland, 2018). In a MTS manufacturing system, the operations to produce products start before the receipt of customer demand (Slack et al., 2016, p. 697). Section 2.6 provides more details about the inventory control policies by ASNL used to control the inventories.

All materials from both internal and external suppliers need to be delivered at least seven workdays before assembly starts. That means that at that moment, the processes of the internal suppliers, Welding and Part Assembly, need to be finished. The same mechanism with work order release holds for Part Assembly and Welding, so 72 hours in advance. As the Welding and Part Assembly processes take time, the procurement horizon for the required materials is three weeks (= 15 workdays) of the standard FP length instead of ten weeks. Ensuring that materials are present at the right moment for Part Assembly and Welding works similarly, regarding safety stocks and material expectations, as for Assembly.

There are three situations where the above-explained demand planning is deviated from. Namely, (i) work order postponement due to unavailability of materials, (ii) production postponement due to deviations from the production schedule, and (iii) deviations from the expected production scenario. The last paragraph of Section 2.2 already explained the postponement of work orders due to material unavailability. The postponement of machines can also occur when the Assembly department is behind schedule. When the Assembly department falls behind schedule, machines scheduled on day X move to day X + 1. However, the machines initially scheduled on day X + 1 remain scheduled for that day. This creates a growing backlog of machines awaiting production as additional machines are added daily to a full schedule. Machines are not rescheduled as this is a very time-consuming task within OVS, and this only happens when the backlog of still-to-be-produced machines becomes too big. The management team decides when this is the case. As the machines are not rescheduled, the required materials are not delayed and are delivered on the original date. So, the materials will be delivered too early in comparison with the production schedule. The rescheduling of machines is not part of the research scope, but it can be a future research topic.

The expected material requirements are based on the previous year's usage and the production scenario. Recall that the production scenario states the number of machines that will be produced on a certain assembly line within a specific week and is based on the sales forecasts of the LSOs. The management team decides on the production scenario. Based on the expected material requirements, long SLT materials can be procured. However, uncertainties in the production scenario can lead to deviations in the actual production schedule. These deviations can result in discrepancies in the delivery of long SLT materials and the actual moment the materials are needed.

2.5 Inventory composition

At the moment of conducting this context analysis about the current inventory situation at ASNL, 110,960 distinct article numbers are documented within SAP. Not all of these articles are kept in stock, as some article numbers represent travel time, hotel costs, and travel distance. Next to that, several article numbers no longer correspond to materials but remain within the SAP database. Out of the 110,960 articles, an average of 13,000 are part of ASNL's physical inventory. This section provides a detailed inventory analysis. First, Section 2.5.1 analyses the inventory based on several inventory characteristics. Subsequently, Section 2.5.2 analyses the inventory coverage. Lastly, Section 2.5.3 discusses the inventory performance based on several inventory-related metrics.

2.5.1 Inventory characterization

As previously mentioned, after the COVID-19 pandemic (March 2019 until May 2022 in the Netherlands (Ministerie van Algemene zaken, 2024)), ASNL observed an increase in the inventory of materials within the production facility and a corresponding increase in the total inventory value. Figure 2.5 shows the total inventory value in the warehouse of ASNL from August 2019 onwards. The graph shows an increase in total inventory value after the COVID-19 pandemic. Additionally, in February 2022, the assembly of the SK 660 moved from Aebi Schmidt Germany to ASNL, along with the transfer of inventory. This increase in total inventory value at ASNL is visible in the graph. The relocation of materials from Germany to ASNL took several months, explaining the inventory increase over a longer period.

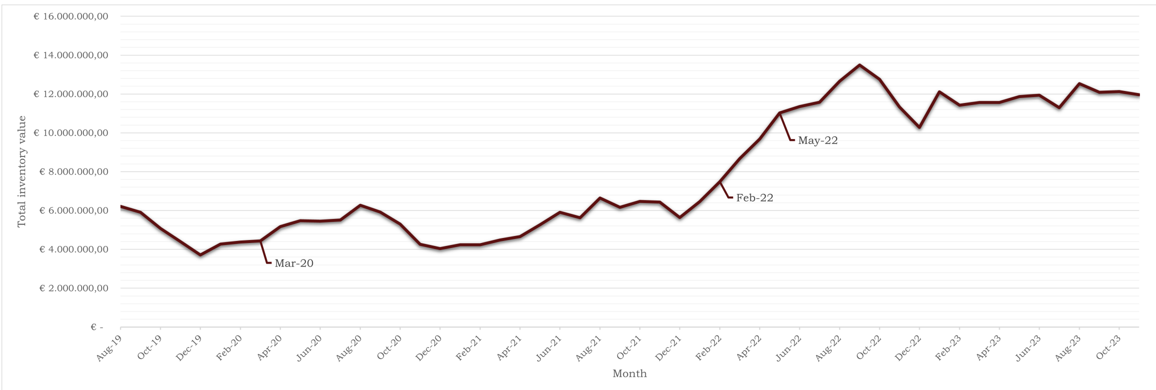


Figure 2.5: Total inventory value over time

The inventory at ASNL can be categorized into four distinct groups: (i) the raw materials, which are the input to the manufacturing system and are consumed within the machine assembly lines, at the Welding department, or at the Part Assembly department; (ii) the semi-finished products, which result from Welding and Part Assembly processes; (iii) the Work-In-Progress (WIP), which are the products within a process waiting to be processed; and (iv) the finished machines, representing the completed machines that are ready to be transported to the customer. Section 2.2 described the supply chain of ASNL. The raw materials are part of Inventory F, and the semi-finished products are part of Inventory E. To recall, the Inventory F materials are sourced from external suppliers, and the Inventory E materials are sourced from internal suppliers. Certain materials belong to both Inventory F and E, and these materials are labelled as Inventory X within SAP. Since the goal of this research is to reduce the inventory within the warehouse of ASNL, the research will focus on Inventory F, E, and X.

As previously mentioned, SAP contains 110,960 distinct article numbers, each characterized by specific attributes describing its function and group classification. Within the remainder of this section, we analyze the inventory based on the following article characteristics: commodity group, article status, inventory group, article usage and value distribution, and storage locations. Understanding these characteristics is important for the development of inventory control policies and the inventory management tool.

Commodity group
Within SAP, each article is part of a commodity group. At ASNL, there are four commodity groups: (i) the manufacturing articles, including all articles used to manufacture the machines; (ii) the operational expenditures, including articles such as electricity, insurance, IT software, and personnel uniforms; (iii) end products; and (iv) services and outsourcing. The commodity group of manufacturing articles contains the most articles (97.39%). These articles are the main focus of this research. However, several operational expenditure articles (423) are also included within the focus of this research, as they are important for production. The exclusion of the remaining articles results in 108,483 distinct articles remaining within the focus of this research. Appendix A.3.1 provides a more detailed analysis of the commodity group distribution.

Article status
Each article has a specific status that denotes whether the article can still be purchased by ASNL. The articles at ASNL can have one of the seven distinct statuses: (i) in development, (ii) prototype, (iii) free to use, (iv) spare part, (v) SSR, (vi) not active, and (vii) blocked. The 'in development' and 'prototype' articles are used by Research & Development (R&D). These articles cannot be freely purchased because they are still in development. The 'free to use' articles denote the standard articles used within the manufacturing process, and the 'SSR' articles denote the non-standard articles. The 'spare part' articles are no longer used in manufacturing but are kept as spare parts for customers. At ASNL, no spare part articles are currently kept in inventory. The 'not active' and 'blocked' articles are no longer used and can no longer be purchased. Lastly, some articles do not have a status within SAP.

The 'free to use' status group is the largest and biggest value-contributing group as it accounts for 92.394% of the articles and 99.384% of the total inventory value. Furthermore, the non-standard SSR articles account for 0.346% of the articles and 0.072% of the total inventory value. Compared to the standard articles, these percentages show that the non-standard articles contribute considerably less to the total inventory value at ASNL. Appendix A.3.2 provides a more detailed analysis of the article status distribution.

Inventory group
As mentioned before, the articles recorded in SAP can be part of Inventory F, E, or X. Additionally, some articles are not recorded to be part of an inventory group. Of the 108,483 distinct articles within the focus of this research, 58% is part of Inventory F, 42% of Inventory E, 0.003% of Inventory X, and 0.176% are blanks. Inventory F and E account for 85% and 15% of the total inventory value, respectively. Inventory X and the blanks do not contribute, as none of these articles are currently in inventory.

Article usage and value distribution
During this inventory analysis, we found that out of the 108,483 articles, around 16,000 have been used in 2022 and 2023, and around 13,000 are currently in inventory. Not all articles with recorded usage are part of the current inventory, and vice versa, not all articles in inventory have recorded usages. Among the articles with recorded usage during 2022 and 2023, approximately 68% are kept in inventory, and 32% are not. Among the 13,000 articles in inventory, approximately 81% have recorded usage during 2022 and 2023, and thus 19% have not. Appendix A.3.3 provides Figure A.2, which illustrates the distribution of articles for each usage frequency category, and Figure A.3 that provides the usage pattern of two randomly chosen articles. Moreover, Appendix A.2 provides several SAP data adjustments executed in order to obtain the usage frequencies. The analysis of the demand patterns (Appendix A.3.3) shows that 258 articles follow an intermittent demand pattern.

Figure 2.6 illustrates the value distribution of the SKUs in inventory at ASNL. As described by Silver et al. (2016, p. 28), this so-called ABC analysis is a useful tool to gain insight into the performance of the inventory and the most important SKUs. The resulting Pareto graph from this analysis illustrates the 80/20 rule, where approximately 20% of the total number of SKUs account for 87% of the total inventory value. Typically, these items belong to the class A items and should receive the most personalized attention from management. The next 30% of SKUs, which account for the next 10% of the inventory value, typically belong to the class B items. The remaining 50% of the SKUs belong to the C class items. These items comprise a minor part of the total inventory investment, and for these items, inventory control must be kept as simple as possible (Silver et al., 2016, p. 29). This ABC analysis shows that the emphasis should lie on targeted and personalized focus on the A items as these articles significantly contribute to the total inventory value.

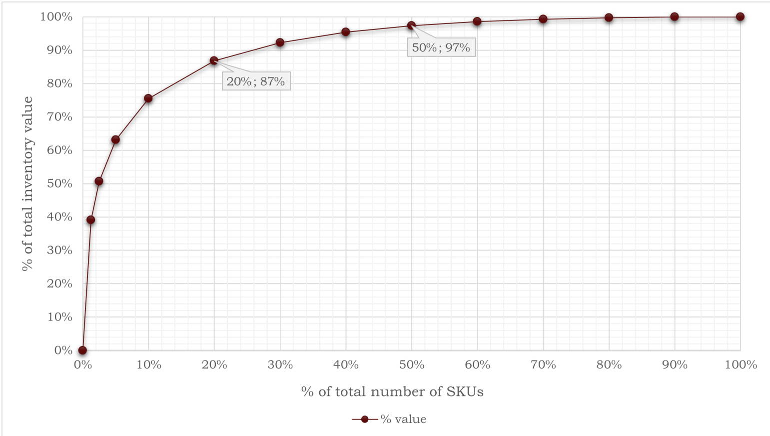


Figure 2.6: SKU value distribution

Storage locations

Within the production facility of ASNL, materials can be stored in the outside area, in the warehouse, and at the different production departments (Part Assembly, Welding, and Assembly). In SAP, each distinct location has a location number. That way, the locations of all the materials inside the production facility are recorded. Recall that sometimes these locations are incorrect due to human failures in data entry and execution of SAP tasks. The materials stored at the different production departments are stored separately or in a Kanban system. In the case of separate storage, warehouse employees more materials to designated locations upon the release of a work order, reflecting a push control system where the work order triggers the movement of materials. Push control is a term to indicate that work is being sent forward to workstations as soon as it is finished on the previous workstation (Slack et al., 2016, p. 340). Kanban is the Japanese word for a card or a signal (Slack et al., 2016, p. 514). Kanban controls the flow of resources by replacing only what has been consumed in a production process (Wang, 2010). This can be considered as a pull control system as the usage of materials triggers the replenishment of the materials. Pull control is a term used to indicate that a workstation requests work from the previous station only when it is required (Slack et al., 2016, p. 340). The Kanban system at ASNL can be divided into pallet and two-bin systems. The pallet system is used for larger materials, and the two-bin system is used for smaller, high-volume articles. The two-bin system consists of two bins for the storage of an article. Demand is satisfied from the first bin until the stock is depleted. In that case, the second bin is opened, and a replenishment is triggered. When the replenishment arrives, the second bin is refilled, and the remainder is added to the first bin (Silver et al., 2016, p. 242). Based on the storage locations of materials in SAP, we know whether an article's inventory is kept in the Kanban system or is stored separately.

2.5.2 Inventory coverage

An inventory coverage analysis assesses the expected time at which the current stock level will be depleted. This analysis can investigate imbalances in inventory such as excess, dead, or very slow-moving inventory (Silver et al., 2016, p. 366). The coverage of a SKU is determined by dividing the On-Hand Inventory (OHI) of a SKU by the expected usage rate per year. At ASNL, the coverage is referred to as the DOH of a SKU. The DOH is calculated, using Equation 2.1, to be the division of the

OHI by the sum of the SKU usage during 2022 and 2023, multiplied by 730 days. The 730 days does not only include business days but all days of 2022 and 2023. Even though ASNL does not produce products during weekends, the inventory interest rates (discussed in Section 1.2) do count for all days of the year. Therefore, we determine the inventory coverage based on 730 days.

$$DOH = \frac{OHI}{Yearly\ SKU\ usage\ 2022 + Yearly\ SKU\ usage\ 2023} * 730\ days \tag{2.1}$$

Figure 2.7 illustrates the inventory coverage of the SKUs currently in inventory at ASNL. This graph shows the number of SKUs, the percentage of articles, and the value percentage corresponding to each DOH range. Figure 2.7 shows that 37% of the total inventory value will be depleted in two months. The remaining 63% of the SKU inventory value will remain in inventory for longer than two months. Section 1.3.1 explained that the total inventory value norm is € 5 to € 6 million and that this norm is based on a maximum allowable DOH of at most two months. Based on the coverage analysis, we conclude that 63% of the inventory value falls outside the maximum allowable DOH. This finding supports the action problem, suggesting that ASNL holds too much inventory. The insights gained from this research contribute to optimizing the inventories at ASNL and mitigating the 63% of the total inventory value that exceeds the recommended DOH.

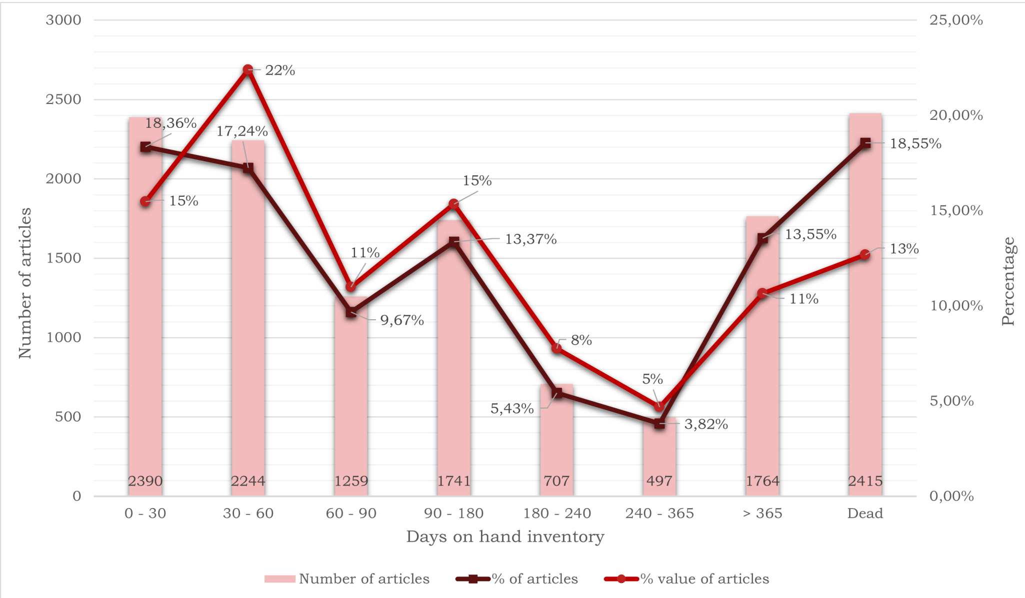


Figure 2.7: Inventory coverage of SKUs in stock at ASNL

As explained in Section 2.5.1, not all SKUs with recorded usage are part of the current inventory, and vice versa, not all SKUs in inventory have recorded usages. In case a SKU has an OHI of zero and positive usage, the DOH becomes zero. Recall that this is the case for approximately 32% of the articles that have recorded usage during 2022 and 2023, which is about 4% of all articles within the research focus. In case a SKU has a positive OHI and a usage of zero, the DOH is said to be an arbitrarily large number. About 18% of the SKUs in inventory has this arbitrarily large DOH, and this group accounts for about 13% of the total inventory value. This indicates that these SKUs are dead/obsolete stock, and will remain in inventory indefinitely. Silver et al. (2016, p. 370) provide several options for the disposal of dead or excess inventory, including repurposing materials, shipping the materials to another location, returning the materials to suppliers at a reduced price, auctions, and disposing for scrap value.

2.5.3 Inventory Key Performance Indicators (KPIs)

Various inventory-related metrics, commonly referred to as Key Performance Indicators (KPIs), provide insight into the current inventory situation at ASNL. Chopra and Meindl (2016, p. 63) explains several inventory-related metrics, such as the average inventory, inventory turnover, DOH, and the

Fill Rate (FR). Section 2.5.2 already discussed the DOH. Data about the KPIs is extracted from SAP. This section focuses on the inventory turnover, the Ready Rate (RR), and the FR.

Inventory turnover
Inventory turnover, also known as stockturns, is a primary KPI for inventory management measuring the number of times the average inventory is turned during some period (Silver et al., 2016, p. 10). SAP calculates the inventory turnover for all distinct articles by dividing the annual usage by the average inventory. The higher the turnover, the faster a company is replacing its inventory. On the other hand, when the turnover ratio is too high, this may lead to stockouts. The average annual total inventory turnover at ASNL is 1.67. This indicates ASNL's inventory is turned over approximately 1.67 times per year (= 218.56 days). The maximum allowable DOH is at most two months, indicating a yearly overall turnover of 6 (*12 months / 2 months*). The relatively low yearly inventory turnover indicates that ASNL holds too much inventory, supporting the action problem explained in Section 1.3.1. As the average annual total inventory turnover considers all the articles, outliers may cause the turnover value to decrease. When excluding the dead/obsolete articles, the overall turnover increases to 3.9. This is higher in comparison to the 1.67 but is still not close to the turnover target of 6.

Ready Rate and Fill Rate
One of the most commonly used performance measures in inventory control is the Fill Rate (FR), defined as the fraction of demand that can be satisfied from inventory without shortages (Silver et al., 2016, p. 249). The Ready Rate (RR) is a lesser-known performance measure and denotes the fraction of time that the OHI of an SKU is positive (Thorstenson & Larsen, 2014). In SAP, the number of times the inventory of an article is zero during a specific period is recorded. With these values, an estimate of the RR can be calculated by one minus the division between the number of times the inventory is zero and the length of the period (Equation 2.2).

$$\textit{Ready Rate} = \textit{1} - \frac{\textit{Number of times zero OHI during period}}{\textit{Length of period}} \tag{2.2}$$

Of the 108,483 articles, about 9% have a 100% RR over 2022 and 2023. These articles have not stockout-out and thus can fulfil demand immediately from inventory. However, about one-third of these articles did not have demand, indicating that these articles are part of dead/obsolete stock. On the other hand, some articles (0.5%) have a 0% RR since they are not kept in inventory but have had demand during 2022 and 2023. Approximately 80% of all articles did not have a positive inventory and did not have demand, and therefore, do not have a RR value. Moreover, the average RR of the remaining articles is 97%. This further provides an indication of excessive inventory levels at ASNL.

2.6 Inventory control policies

For more or less all organizations, the total inventory investment is enormous, and the control of capital tied up in raw materials, WIP, and finished goods offers substantial potential for improvement (Axsäter, 2006, p. 1). Inventory control policies specify when an order for inventory should be placed and what quantity of a specific SKU should be ordered (Silver et al., 2016, p. 242). This section describes the inventory control policies currently used at ASNL. First, Section 2.6.1 explains the classification of the SKUs. Subsequently, Section 2.6.2 explains the current inventory control policies, and Section 2.6.3 describes the corresponding inventory control parameters.

2.6.1 Classification

The classification of articles supports inventory management and assists in determining the material planning strategy of different inventory articles. There are many methods to classify articles, and the main techniques include the ABC classification (classifying SKUs based on value) and the XYZ classification (classifying based on usage regularity), as well as other alternatives (Scholz-Reiter, Heger, Meinecke, & Bergmann, 2012). Section 2.5.1 briefly discussed the ABC classification. SAP allows adding an indicator to classify a SKU within a certain ABC and/or XYZ category. Currently, articles have ABC and/or XYZ indicators, which are inaccurate as employees add indicators without validation. Furthermore, the indicators are also not used in inventory decision-making processes due to their inaccuracies.

2.6.2 Policies

As explained in Section 1.2, all inventory decisions made by ASNL are NWC driven, meaning that the total inventory invested costs cannot exceed a certain budget. Therefore, the main objective is to minimize the total costs invested in inventory.

The control policies used by ASNL differentiate the procurement strategy based on SLT. As explained in Section 2.4, materials are either purchased using a RTO or RTS strategy depending on whether their SLT fits within the standard FP length. Besides for materials with long lead times, ASNL holds safety stock for so-called ”risky” materials. This group of materials is either critical for production, has a high chance of delayed deliveries, or has a high chance of having quality issues. Which materials belong to this group and what safety stock to maintain is based on the gut feeling and experience of the purchasers and the warehouse employees.

Some materials have specific ordering requirements. SKUs can have one of three or a combination of ordering requirements; (i) A Minimum Order Quantity (MinOQ) imposing a minimum allowable order quantity of the supplier (Silver et al., 2016, p. 165). (ii) A Maximum Order Quantity (MaxOQ) specifying that the order quantity cannot exceed this specified amount (Zhu, 2022). (iii) A Fixed Order Quantity (FOQ) ensuring that the quantity of ordered materials is a fixed amount (Kostić, 2009). (iv) A rounding factor ensuring that a material is ordered in a quantity, which is a multiple of the factor. SAP ensures that the inventory levels are constantly known and when demand arises or inventory levels drop below certain thresholds (e.g. reorder point), SAP communicates the order quantity to the operational purchaser. The order quantity is based on several policy parameters, and the following section explains these parameters.

2.6.3 Parameters

The explained inventory policies in Section 2.6.2 are managed through various parameters. These parameters in SAP are: Supply Lead Time (SLT), safety stock, reorder point, Minimum Order Quantity (MinOQ), Maximum Order Quantity (MaxOQ), Fixed Order Quantity (FOQ), and rounding factor. The values for some of these parameters are contractually established with suppliers (MinOQ, MaxOQ, FOQ, and rounding factor), and other parameters are based on experience and gut feeling.

Supply Lead Time
The Supply Lead Time (SLT) is the duration between the moment of ordering replenishments and its arrival (Silver et al., 2016, p. 44). Figure 2.8 shows the SLT distribution of ASNL's 108,483 articles. Approximately 90% of the articles have a SLT that fits within the standard length of the FP (10 weeks = 47 workdays). The remaining 10% have a longer SLT. About 12% of the articles have a have a SLT of zero weeks. These articles are all internally sources materials (Inventory E) that were not used during 2022 and 2023, therefore their SLT was set to zero. In practice, the FP length can vary based on the complexity of the specific machine(s) of an order. The decision whether to shorten or lengthen the FP is based on experience. For the sake of simplicity, during the remainder of this research, the standard FP length of ten weeks will be used within inventory-related decisions. Figure 2.8 shows the SLT distribution, and this shows a peak at eight weeks. Until recently, the standard FP length was eight weeks. ASNL made agreements with its suppliers on whether they could deliver the products in eight weeks, and therefore eight weeks was denoted as the SLT.

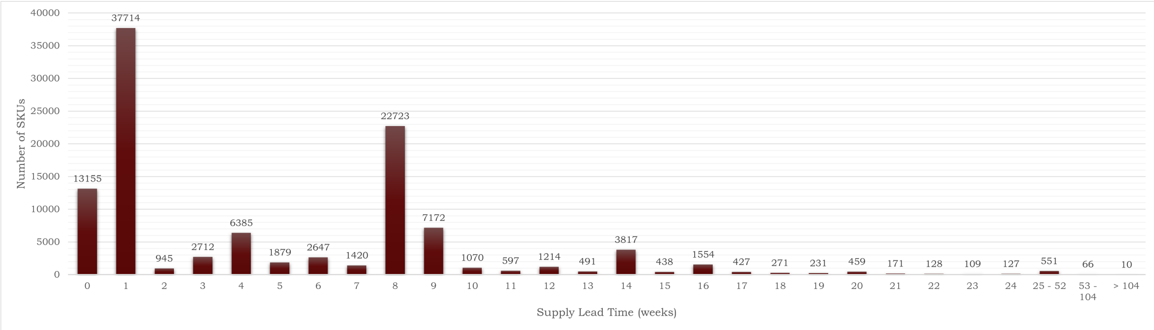


Figure 2.8: Supply Lead Time distribution among SKUs

Ordering requirements
Section 2.6.2 already explained the different ordering requirements. Table 2.1 provides an overview of the number of articles with each ordering requirement. There are 69 articles that both have a MinOQ and a MaxOQ.

Order requirement	Number of articles
Minimum Order Quantity (MinOQ)	14,219
Maximum Order Quantity (MaxOQ)	3,497
Fixed Order Quantity (FOQ)	48
Rounding factor	6,758

Table 2.1: Ordering requirement distribution

Reorder point
The reorder point represents the inventory level at which a replenishment order is placed. This point is calculated in such a way that the inventory does not run out before a replenishment arrives (Slack et al., 2016, p. 700). For seven articles, a reorder point is documented in SAP, and each of these articles also has a safety stock value. As mentioned before, these reorder points are based on experience and gut feeling.

Safety stock
Safety stock represents the amount of inventory kept on hand to allow for the uncertainty of demand and the supply in the short run (Silver et al., 2016, p. 26). In SAP, 1,091 articles at ASNL have a safety stock value in SAP. About half of these articles have a SLT that is shorter or equal to the standard length FP, but a safety stock is maintained because of other reasons. As mentioned before, these safety stock values are based on experience and gut feeling. So, the reasons for maintaining safety stock are not specified. Articles can be labelled as 'risky' articles, but which articles are labelled as risky and how this is translated to a safety stock parameter value is unknown.

To assess the alignment between the safety stock parameter values and ASNL's actual inventory, we calculate the implied safety stock using Equation 2.3. Comparing the parameter values with the implied values reveals that over 3,000 articles have a higher implied safety stock than their parameter value. Notably, this is a higher number of articles than the number of articles that have a safety stock value in SAP. This excess inventory suggests overstocking, supporting the action problem explained in Section 1.3.1. This deviation may be due to the ordering requirement parameters ensuring that more inventory is kept than needed. When examining these articles, for about 1,200 articles, the deviation between the safety stock parameter value in SAP and the implied safety stock may be due to the MinOQ requirement. For 12 articles, the deviation may be caused by the FOQ, and for about 450 articles, the deviation may result from the rounding factor. The implied safety stock shows that the ordering requirement parameter can greatly impact the total inventory.

$$\textit{Implied safety stock} = \textit{Average inventory - (Average usage * SLT)} \tag{2.3}$$

2.7 Conclusions

In this chapter, we investigated the current inventory management situation at ASNL by answering the research question *'What is the current inventory management situation at Aebi Schmidt Nederland B.V.?'* and its sub-questions.

First, we described ASNL's product portfolio and the current supply chain. ASNL's product portfolio consists of four product categories: SK 660, Wasa 300+, spreaders, and the airport category. Figure 2.3 shows an overview of the supply chain, which includes both internal (Welding and Part Assembly departments) and external suppliers. Internal suppliers transform materials sourced from external suppliers, Inventory F (Fremd), into Inventory E (Eigen/Halb) articles. Production Planning initiates the production of a machine by releasing a work order 72 hours in advance, depending on material availability. If not all required materials are present, Production Planning determines whether it is possible to release the work order based on the technical possibility of assembling the machine without the missing materials and adding them later. Secondly, we examined the available data in ASNL's ERP system, SAP. The available data, including article information and usage data, are essential for the contextual analysis. The expected future usage data, such as sales forecasts, cannot be used, as each machine sold is unique, and does not provide any insights on the required materials.

Thirdly, we analyzed the demand planning process. Planned demand for a SKU arises when a machine becomes visible in SAP, which occurs before the start of the FP, ranging from several months to a day before. The FP denotes the time before the strategic production slot that a customer can no longer change the order requirements, with a standard FP length of ten weeks. At the start of the FP, demand is 100% certain. Materials with shorter SLTs than the standard FP length can be procured within the FP using a RTO strategy, while others use a RTS strategy. RTS and RTO are equivalent to the manufacturing setting MTS and MTO-ETO, respecitevly.

Fourthly, we explained the inventory composition, coverage and several KPIs. Post COVID-19, ASNL observed increased inventory levels and total inventory value, as visible in Figure 2.5. Inventory characteristics include commodity group, article status, inventory group, usage and value distribution, and storage location. An ABC analysis showed that about 20% of SKUs account for 87% of the total inventory value. Storage locations vary for each material, including separate storage in the warehouse and Kanban systems (pallet and two-bin). The inventory coverage analysis using the DOH showed that 63% of the inventory value exceeds the maximum allowable DOH of two months, indicating excessive inventory and supporting the action problem addressed in this research. The inventory turnover is approximately 1.67 times per year, which lies considerably below the goal of 6 and further indicates excessive inventories.

Lastly, we reviewed ASNL's current inventory control policies and their parameters. In inventory control, the classification of articles supports determining the materials planning strategy of different inventory articles. Well-known classification methods are the ABC and XYZ methods. SAP allows adding an ABC and/or XYZ indicators to each article. However, these indicators are currently not used in inventory decision-making processes due to inaccuracies in the indicators. Materials are procured using RTS and RTO strategies. Furthermore, ASNL holds safety stock for so-called "risky" materials. Which materials belong to this group and what safety stock to maintain is based on the gut feeling and experience of the purchasers and the warehouse employees. The control policies are managed through parameters, like the SLT, safety stock, reorder point, MinOQ, MaxOQ, FOQ, and rounding factor. The analysis of these parameters showed that about 90% of the articles have a SLT that fits within the standard FP length. Furthermore, the implied safety stock showed that a notably higher number of SKUs has a higher safety stock value in reality than as supposed to according to the parameter value in SAP, indicating excessive inventories at ASNL.

3 Literature review

This chapter provides a literature study to gain insights into the relevant literature concepts, SKU classifications, inventory control policies, and the determination of the control parameters. In this chapter, we answer the following research question by answering its sub-questions explained in Section 1.4.1.

What inventory management methods from literature apply to the situation at Aebi Schmidt Nederland B.V.?

Firstly, Section 3.1 discusses several concepts from academic literature that align with the inventory context at ASNL. Sections 3.2 and 3.3 provide insights into SKU classification methods and inventory control policies, respectively. Subsequently, Section 3.4 provides a confrontation between this research and the existing academic literature to identify the literature gap in which this research is situated. Lastly, this chapter concludes with the answers to the research questions in Section 3.5.

3.1 Inventory context versus literature

This section discusses several inventory management concepts from academic literature that align with the inventory context at ASNL. First, Section 3.1.1 provides more insight into the different manufacturing settings in academic literature. The different manufacturing settings form a knowledge foundation for other academic literature concepts. Section 3.1.2 discusses how academic literature views demand and lead times and how inventory systems are classified. Subsequently, Sections 3.1.3 and 3.1.4 provide insights into Kanban and Advance Demand Information (ADI). Lastly, Section 3.1.5 provides insights into Vendor Managed Inventory (VMI).

3.1.1 Manufacturing setting

As explained in Section 1.1, ASNL uses the MTO and ETO manufacturing settings. The difference between these manufacturing settings relates to where the Customer Order Decoupling Point (CODP) or Order Penetration Point (OPP) is situated. The CODP is defined as the point in the value chain where a product is tied to a specific customer order (Olhager, 2010). The four basic choices of manufacturing settings are MTS, Assemble-To-Order (ATO), MTO, and ETO. The CODP divides the manufacturing stages that are forecast-driven from the stages that are customer-order-driven (van Kampen & van Donk, 2014). Figure 3.1 shows the position of the CODP for each of the four basic manufacturing settings.

In MTO manufacturing, products are configured to standard designs and specifications. A customer chooses the product according to limited available standard options. In ETO manufacturing, unique and complex products are designed and produced to the customer's specifications (Barbosa & Azevedo, 2019). In an MTS manufacturing system, the operations to produce products start before the receipt of customer demand (Slack et al., 2016, p. 697). So, the product specifications are set before the customer decides to order products (Barbosa & Azevedo, 2019). The MTO strategy eliminates inventories and reduces financial risks. However, this strategy usually leads to long customer lead times (Shao & Dong, 2012). Having a pure MTS strategy may result in excess inventory. To overcome the disadvantages of the MTS and MTO strategies, companies often tend to adopt the hybrid MTO-MTS strategy (Perona, Saccani, & Zanoni, 2009). This hybrid strategy is one of the most dominant manufacturing settings research in literature. On the other hand, the MTO-ETO setting has received little attention in academic literature (Barbosa & Azevedo, 2019). Lastly, ATO manufacturing includes components that are combined into end products. Demand occurs for the end products, but the system maintains inventory for the components (Song & Zipkin, 2003).

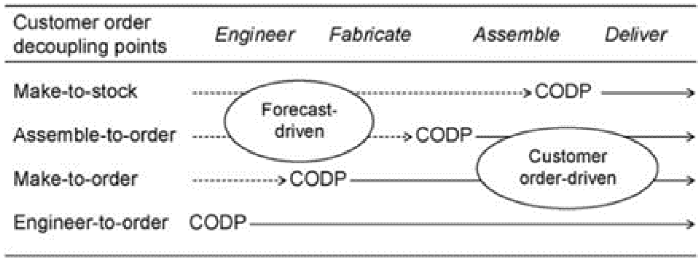


Figure 3.1: Customer Order Decoupling Point - from van Kampen & van Donk (2014)

3.1.2 Frozen Period (FP)

The demand planning at ASNL considers a Frozen Period (FP) with a standard length of ten weeks. At the beginning of this FP, demand is 100% certain, as changes to the BOM are no longer possible. The traditional inventory management models consider the occurrence of demand as entirely exogenous. In order words, there is nothing we can do to control demand. In these models, demand is only certain at the moment it has occurred. According to (Hariharan & Zipkin, 1995), the time from the placement of a customer order until its due date is denoted as the DLT. They denote the time required to receive replenishments as the SLT. Within their proposed model, Hariharan and Zipkin (1995) incorporate advance ordering to create a period within the DLT where demand is certain. This advance ordering creates a FP in which demand is certain. Hariharan and Zipkin (1995) incorporate the FP by using the Effective Lead Time (ELT), which is the difference between the SLT and the DLT. ASNL's FP divides the articles between the RTS and RTO strategies. In a RTO system, the replenishments are based on orders made by customers, and therefore, this system is equivalent to the MTO manufacturing system. On the other hand, in a RTS system, replenishments are placed in advance of customer demand. Therefore, this system is equivalent to the MTS system (Zhao et al., 2018).

Inventory management concerns the control of inventories (Schönsleben, 2003, p. 212). Inventory control studies inventory systems consisting of inventories linked by supply and demand processes (Zipkin, 2000). Numerous complex inventory systems have been identified in the real world (Möllering, 2019, p. 10). In theory, inventory systems/models can be classified based on several factors. According to Shenoy and Rosas (2017, p. 8), such factors include:

- The time of inventory review – continuous or periodic
- The nature of item demand – deterministic, probabilistic, varying by period, etc.
- The nature of replenishment lead time – constant, varying, etc.
- The number of items under management – single- or multi-item
- The number of locations – single- or multi-echelon
- The possibility of repetitive orders – single period or multiple periods

One of the most well-known inventory models is the Newsvendor or Newsboy model. This model refers to the news vendor who each day orders a certain quantity of the newspaper that sells during the day (Möllering, 2019, p. 28). The Newsboy model is a single-period model that determines the optimal order quantity as the trade-off between expected excess inventory and expected shortage costs (Möllering, 2019, p. 28). Another well-known inventory model is the Base Stock (or periodic review, order-up-to-level) model. In this model, each period, a replenishment order is placed to bring the inventory position to the base-stock level or order-up-to-level. The base-stock level must be large enough to cover the demand until the next replenishment and the uncertainties in demand. The advantages of the Base Stock model are its mathematical tractability and the realistic business assumptions involved (Neale, Tomlin, & Willems, 2004).

3.1.3 Kanban

Section 2.5.1 discussed the material storage locations within ASNL's production facility, including separate storage and the Kanban system. Kanban is part of the broader concepts of Lean manufacturing and Just-In-Time (JIT) manufacturing. Lean manufacturing, originating from the Toyota Production System (TPS), focuses on reducing and eliminating waste and non-value-adding activities within production processes (Liker, 2004; Santos, Wysk, & Torres, 2006, p. 8). JIT aims to eliminate waste by ensuring that the right quantity of materials is available at the right place and time (Mukhopadhyay & Shanker, 2005). Kanban is suitable only for specific environments and is not suitable for environments with unstable demand, non-standardized operations, raw materials supply uncertainty, and a great variety of items (Lage Junior & Godinho Filho, 2010). Typically, this does not align with ASNL's HMLV environment. However, Kanban is used for standard articles due to their consistent usage.

Kanban is the Japanese word for a card or a signal (Slack et al., 2016, p. 514). A Kanban-Controlled System (KCS) is a Production and Inventory Control System (PICS) that uses cards to regulate the flow of materials between stages in a manufacturing process (Zipkin, 2000, p. 352). Containers, such as pallets and bins, transport materials between stages in a KCS, with the inventory levels being controlled and limited by the number of Kanban cards. When inventory is consumed, a Kanban signal triggers the replenishment upstream (Claudio & Krishnamurthy, 2009; Silver et al., 2016, p. 664). Similar to the Base Stock model explained in Section 3.1.2, KCS operates as a pull system where demand triggers subsequent events (Zipkin, 2000, p. 353). Typically, KCS is a dual-card system using two communication cards: (i) withdrawal (or move) cards that authorize the transportation of materials to downstream stages, and (ii) production cards that authorize the production of products (Lage Junior & Godinho Filho, 2010; Silver et al., 2016, p. 665). The Kanban card on the container identifies the material, gives the capacity of the container, and where the material is coming from (Yurdakul, İç, & Gulsen, 2020). Every container at a production stage storage location is equipped with a withdrawal card. When the contents are consumers, the empty container is sent to a supplier stage for refilling or the withdrawal card is transferred to another full container. The production card, initially attached to the container, is transferred to a filled container after production (Silver et al., 2016, p. 666). ASNL's Kanban system operates as a single-card system using only withdrawal cards.

In recent years, KCS have gained popularity (Claudio & Krishnamurthy, 2009) for its simplicity, effectiveness, and cost-efficiency in inventory control, and it has proven to help reduce inventory and eliminate stockouts (Mukhopadhyay & Shanker, 2005). Various variations on the KCS exist, developed because of the difficulty of using the original KCS in diverse, company-specific environments. A well-known Kanban application is the two-bin system (Section 2.5.1). Lage Junior and Godinho Filho (2010) provide a literature review on the variations of the original KCS from TPS, such as E-Kanban, Simultaneous Kanban Controlled System (SKCS), Independent Kanban Controlled System (IKCS), Job-Shop Kanban, Generalized Kanban Controlled System (GKCS), and Extended Kanban Controlled System (EKCS). Topan and Avsar (2009) developed an approximation of Kanban-Controlled assembly systems (ATO). They discuss two Kanban signal release mechanisms, the SKCS and IKCS. In SKCS, the signals can only be given when the assembling operation is ready to start, meaning that all materials are available at the stock points. In IKCS, there is no delay in the release of demand as they are released independently of the availability of the other materials at the stock points.

3.1.4 Advance Demand Information (ADI)

Several researchers, including Gallego and Özer (2001), Tan, Güllü, and Erkip (2007), Claudio and Krishnamurthy (2009), and Ahmadi et al. (2019), use the advance ordering concept of Hariharan and Zipkin (1995) to create inventory models that incorporate Advance Demand Information (ADI). An example of ADI is a customer wish list, which can provide organizations with information on what products customers are interested in (Tan et al., 2007). Another example is a preorder strategy where customers place orders ahead of their actual needs, reducing demand uncertainties through longer commitment lead times (Ahmadi et al., 2019).

ADI literature assumes either perfect or imperfect demand information. Perfect ADI involves customers placing orders in advance with fixed quantities and delivery times that do not change over time. Hariharan and Zipkin (1995) are the first researcher to study perfect ADI in a single location, continuous-review setting with deterministic replenishment lead times. Imperfect ADI involves uncertain demand information with estimated quantities and/or due dates (Benbitour & Sahin, 2015; Ahmadi et al., 2019). Ahmadi et al. (2019) provide an overview of the most relevant literature on perfect and imperfect ADI. Claudio and Krishnamurthy (2009) investigate the benefits of integrating ADI with KCS, highlighting the complexity and importance of factors like Kanban card limits, base stock levels, demand information lead times, and ADI quality on performance measures such as throughput, inventory holding costs and customer service levels. High quality ADI can enable manufacturers to shift from MTS to MTO strategies, reducing inventory levels without compromising on service guarantees. However, stochastic inventory models incorporating ADI are rare, making them less applicable to the dynamic and uncertain environments of many organizations (Gallego & Özer, 2001; Claudio & Krishnamurthy, 2009). Currently, ASNL cannot use any form of ADI due to the large variety of products they manufacture and because the sales forecast cannot provide insights on the expected future article usage, as explained in Section 2.3.

3.1.5 Vendor Managed Inventory (VMI)

An application of ADI is Vendor Managed Inventory (VMI) (Tan et al., 2007). Section 1.3.3 explained that ASG decided to discontinue fixed yearly order contracts with suppliers due to the impending transition towards the SAP IBP tool with their suppliers. Through this tool, ASNL strives to enhance supplier anticipation of material demand and plan deliveries accordingly. In VMI, the external supplier manages the required inventory levels based on access to its customers' inventory data (Schönsleben, 2003, p. 191). VMI is a useful strategy for lean supply chains (Vrat, 2014, p. 168), increasing the replenishment frequencies with smaller sizes (Marquès, Thierry, Lamothe, & Gourc, 2010). Other terms for VMI include Vendor Managed Replenishment (VMR), Supplier-Managed Inventory (SMI), and Centralized Inventory Management (CIM) (Marquès et al., 2010; Disney & Towill, 2003). VMI systems raise questions about the customer's motivation to delegate replenishment decisions to its external supplier, as overstocking, to ensure sufficient stock to prevent stock-out, benefits the supplier. VMI with Consignment Stock (CS) resolves this drawback by making the supplier responsible for all replenishment decisions, maintaining continuous stock, and retaining ownership of the materials until consumption by the customer (Çömez Dolgan, Moussawi-Haidar, & Jaber, 2021). Another application is two-bin VMI, where the supplier monitors bins and replenishes when one of the bins is empty (van Driel, 2018). This two-bin-VMI system can also be combined with CS. Currently, ASNL leverages VMI to a limited extent and CS is not leveraged at all.

3.2 Stock Keeping Unit (SKU) classification methods

Manufacturing organisations often deal with many different SKUs, each varying in annual sales volume, demand predictability, product value, or storage specifications, leading to the implementation of different inventory policies. Consequently, organisations dealing with a wide variety of SKUs often struggle with the control of their production and inventory systems (van Kampen et al., 2012). Inventory classification categorizes SKUs based on their characteristics to enable organisations to make decisions for a specific class of SKUs rather than for every individual SKU (Ng, Wang, & Ng, 2018). Classification methods considerably impact cost performance, stocking decisions, and supply chain process design (Svoboda & Minner, 2022), as they simplify inventory management tasks by setting inventory control methods and service-level targets per class (Teunter, Babai, & Syntetos, 2010). In production management, classification methods enable the selection of appropriate production strategies such as MTS and MTO, and in inventory management, classifications enable the selection of inventory control policies. In demand management, these methods enable the selection of the appropriate forecasting methods and demand distributions (Babai, Ladhari, & Lajili, 2015).

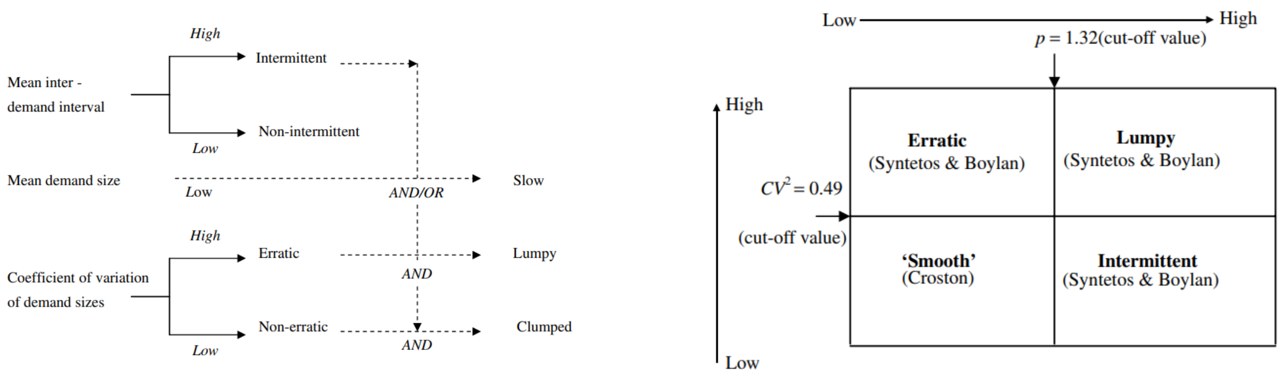
According to van Kampen et al. (2012), most of the SKU classification models are one-dimensional, using traditional criteria such as the demand value or the demand volume of a SKU (Babai et al., 2015). One of the most well-known Single-Criterion Inventory Classification (SCIC) methods is the ABC model, which classifies SKUs based on their demand value (van Kampen et al., 2012). Other SCIC methods include the XYZ, FNS/FSN, SDE, and HML frameworks (Ng et al., 2018; Shenoy & Rosas, 2017, p. 211) consider factors such as unit value, criticality, lead time, variety, and variability (van Kampen et al., 2012). Table 3.1 shows these SCIC methods with their classification characteristics and classes according to Ng et al. (2018).

Method	Characteristic	Classes	Method	Characteristic	Classes
ABC	Demand value	A (high) B (medium) C (low)	SDE	Lead time	S (scarce) D (difficult) E (easy)
XYZ	Demand variability	X (regular) Y (fluctuating) Z (irregular)	HML	Article value	H (high) M (medium) L (low)
FNS	Demand rate	F (fast) N (normal) S (slow)	FSN	Demand rate	F (fast) S (slow) N (non-moving)

Table 3.1: SCIC methods

The main advantage of using SCIC methods is simplicity (Teunter et al., 2010). However, research has shown that these methods can lead to cost-inefficient results because of a lack of consideration of important operational factors such as replenishment patterns, costs or criticality of SKUs (Svoboda & Minner, 2022). To address this limitation, extensive academic literature focuses on Multi-Criterion Inventory Classification (MCIC) methods, which consider multiple criteria simultaneously (Babai et al., 2015). According to the literature review on classification methods by van Kampen et al. (2012), researcher use tables, matrices, or graphical techniques to illustrate their classification. Williams (1984) developed a two-dimensional classification method considering the variabilities in demand size and frequency, resulting in five SKU classes: lumpy, highly lumpy, slow-moving, and two classes for smooth demand. Building on this method, Syntetos, Boylan, and Croston (2005) proposed algorithms using the mean inter-demand interval (p) and the squared coefficient of demand size (CV^2) to quantify the variabilities in demand frequency and demand size, respectively. This resulted in a two-by-two matrix with four categories: smooth, erratic, intermittent, and lumpy. Boylan, Syntetos, and Karakostas (2008) developed a framework, illustrated in Figure 3.2a, linking non-normal demand patterns with factors proposed in academic literature. Furthermore, Boylan et al. (2008) also linked the cutoff values for the categorization, from Syntetos et al. (2005) and Croston (1972), to the factors from literature as shown in Figure 3.2b. Other MCIC methods include the Analytic Hierarchy Process (AHP) method, used for weighing criteria and selecting alternatives (de F.S.M. Russo & Camanho, 2015). Rezaei (2007) and Cakir and Canbolat (2008) use AHP in their MCIC method, with the latter using a web-based decision support system (Rezaei & Dowlatshahi, 2010).

Sections 2.5.1 and 2.6.1 discussed the ABC and XYZ classification methods and their relation with ASNL's ERP system, SAP. The following sections further discuss these two classification methods, as these are the most applicable in the case of ASNL.



(a) Non-normal demand patterns framework (b) Cutoff values

Figure 3.2: Frameworks from Boylan, Syntetos, and Karakostas (2008)

3.2.1 ABC classification

As previously mentioned, the ABC classification method is widely used by companies that deal with a large number of distinct SKUs (Babai et al., 2015). The ABC method classifies SKUs based on their demand value (/sales volume) and generally consists of three classes: A, B, and C. However, the number of classes can be easily extended by simply dividing the ranked SKUs into more groups. The number of classes is usually limited to at most six (Teunter et al., 2010). This classification method has been reported to be the standard approach of many companies to assign the same target service levels to the SKUs in a certain class (Babai et al., 2015).

The classification of items into the A, B, and C classes is based on the 80/20 Pareto-rule, where roughly 20% of the SKUs contribute to 80% of the total inventory value. A items, labelled as the 'critical few', contain the top 20% SKUs and should receive the most personalized attention from management due to their substantial contribution to inventory value. The next 30% of SKUs, accounting for the next 10% of the inventory value, typically belong to the class B items. Finally, the remaining 50% of the SKUs belong to the C class, representing the 'trivial many'. These items comprise a minor part of the total inventory investment, and their decision systems should be as simple as possible. Generally, organizations maintain large inventories for C items to minimize the stockout inconveniences (Silver et al., 2016, p. 29).

Zhang, Hopp, and Supatgiat (2001) and Teunter et al. (2010) are two examples of SCIC methods based on the ABC-analysis that consider stock control. Zhang et al. (2001) specify a SCIC emphasizing holding costs and lead times, excluding back-order costs. They propose the ratio according to Equation 3.1, where D denotes the demand volume, l denotes the replenishment lead time, and c denotes the unit costs. The SKUs are ranked based on the ratio in ascending order, and the service levels are fixed per class. The A items receive the lowest service, the B items a moderate service, and the C items receive the highest service. Unlike the typical ABC classification method that distinguishes SKUs based on criteria that are not relevant to cost optimality, the method proposed by Zhang et al. (2001) suggest inventory theory informed criteria to classify the SKUs (Teunter, Syntetos, & Babai, 2017).

$$\frac{D_i}{l_i c_i^2} \tag{3.1}$$

With their new ABC classification, Teunter et al. (2010) challenges the traditional ABC approach of multiplying the cost characteristics with the demand volume. According to them, the classes should be based on dividing the demand volume by the unit holding costs. They propose the ratio according to Equation 3.2, where b denotes the shortage costs, D denotes the demand volume, h denotes the holding costs, and Q denotes the order size. The SKUs are ranked based on the ratio in descending order, and the cycle service levels are fixed per class. The advantage of this new ABC classification is that this classification takes criticality into account without considering more complex MCIC methods. According to Millstein, Yang, and Li (2014), most ABC classification methods are developed from an inventory value perspective, aiming to maximize performance scores. The ABC classification of Teunter et al. (2010) has been developed from an inventory cost perspective, aiming to minimize total inventory costs. In their paper, Teunter et al. (2010) assessed the performance of their ABC classification method by comparing their method with traditional demand value and demand volume criteria and to the criterion proposed by Zhang et al. (2001). Their method consistently outperforms these other criteria across datasets, target service levels, and types of demand distribution in minimizing the safety stock costs. The criterion proposed by Zhang et al. (2001) performed reasonably well and much better than the two traditional criteria.

$$\frac{b_i D_i}{h_i Q_i} \tag{3.2}$$

Finally, Huiskonen, Niemi, and Pirttilä (2005) used a self-organizing map algorithm to classify C items. The algorithm categorized C items into three groups: slow-response items, service items, and non-important items. Slow-response items are those where customers do not require fast delivery, allowing for a centralized stock policy. Service items have the most regular demand, making local availability policies recommendable. Non-important products are items that can potentially be discarded.

3.2.2 XYZ classification

Another commonly known SCIC method is the XYZ analysis, which classifies SKUs based on their usage regularity. The statistical measure used in the XYZ method is the coefficient of variation (CV^2), calculated as the ratio of the standard deviation of demand and the average demand over a certain period ($\sigma/\overline{X}$). Similar to the ABC classification, the three classes of the XYZ classification are X, Y, and Z. SKUs with a CV^2 smaller than 0.5 are classified as X-items as these items show constant consumption. The Y class contains SKUs with a CV^2 between 0.5 and 1. Such a CV^2 value shows stronger fluctuations in demand, which are usually due to trends or seasonal reasons. In case the CV^2 is greater than 1, the items belong to the Z class, as these items show completely irregular demand (Scholz-Reiter et al., 2012).

3.2.3 ABC-XZY

The ABC classification can be complemented by the XYZ classification, which yields a measure of the continuity of demand (Schönsleben, 2003, p. 318), as both the demand value and the demand uncertainty are taken into account (Reiner & Trcka, 2004). The combined ABC-XYZ classification enables the selection of the appropriate material management methods, tailored to individual items based on service-level targets and inventory control policies. Table 3.2 shows the nine classes of the ABC-XYZ classification (Schönsleben, 2003, p. 566), each with distinct characteristics. For instance, the AX class represents high-value, highly predictable products with continuous demand, while the BZ class indicates medium-value, low-predictable products with irregular demand patterns (Stojanoviç & Regodic, 2017).

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

Table 3.2: ABC-XYZ classification classes

Stojanoviç and Regodic (2017) provides an overview of the target inventory levels for each of the nine classes (Table 3.3). For the relatively more predictable and/or higher-value items, we can maintain lower inventory levels. On the other hand, when demand is less predictable, higher inventory levels need to be maintained to ensure that demand can be met. In order to maintain lower inventory levels, more sophisticated/precise control policies are necessary in comparison to maintaining higher inventory levels. Therefore, more adequate attention should be dedicated towards the AX, AY, BX, and CX items.

	X	**Y**	**Z**
A	Low inventory	Low inventory	Medium inventory
B	Low inventory	Medium inventory	Medium inventory
C	Low inventory	High inventory	High inventory

Table 3.3: Target inventory levels ABC-XYZ classes

3.2.4 Stock Keeping Unit (SKU) classification application in inventory control

In most manufacturing organisations, the number of SKUs is too large to implement specific inventory control policies for each separate SKU. Therefore, a good starting point is to group the SKUs and to determine inventory management guidelines for the SKUs in each group (Larsen, 2021). As mentioned in the previous sections, the ABC classification method is the most common starting point to divide SKUs into classes. The main application of SKU classification methods within inventory control is that companies classify their articles and decide to use similar inventory control policies for the articles in each group (Mohammaditabar, Hassan Ghodsypour, & O'Brien, 2012). So, based on the different classes, inventory management determines the order/production quantities, reorder points, safety stock, etc. (van Kampen et al., 2012).

The typical application of SKU classification suggested in academic literature and commonly used in practice is to give a certain class of SKUs the same service level. The most widely applied service measure is the Fill Rate (FR), which denotes the fraction of demand that is satisfied directly from OHI (Teunter et al., 2017). Other service measures are the Ready Rate (RR) and the Cycle Service Level (CSL). Recall that the RR denotes the fraction of time that the OHI of a SKU is positive. The CSL is defined as the probability that no stockout occurs during a specific time period (Teunter et al., 2010). In inventory control, service levels are used to determine the appropriate reorder point or safety stock values (Axsäter, 2006, p. 96). Within the ABC classification method, service levels are often fixed per class (Teunter et al., 2010). Generally, as the A class contains the most important SKUs, these items receive the highest service levels. The C-items should receive the lowest service levels (Millstein et al., 2014). However, Huiskonen et al. (2005) argue that the C-items deserve more attention, as dealing with stockouts for these items is a waste of effort. Teunter et al. (2017) state that although the service levels are fixed per class, academic literature does not provide guidance on how the service level should be differentiated on an individual SKU basis. They propose a methodology for the specification of the target FR at an individual SKU level using the class target FR and the criticality of the SKU.

3.3 Inventory control policies and parameters

Inventory control policies help to determine when a replenishment order should be placed and how much to order. In general, control policies take the Inventory Position (IP), demand, and different cost factors into account. The IP is different from the inventory level as it also includes outstanding orders (pipeline) and backorders, and is calculated using Equation 3.3 (Axsäter, 2006, p. 46).

$$IP = \textit{Inventory Level} + \textit{Outstanding Orders} - \textit{Backorders} \tag{3.3}$$

Among numerous possible inventory control policies, there are four basic policies regulating order timing and order quantities (Möllering, 2019, p. 22), shown in Table 3.4. These policies are differentiated on two factors: the review frequency and the order size. The review frequency concerns how often the inventory status is reviewed. This frequency can either be periodic or continuous. The order size can be a fixed or variable quantity each time an order is placed.

The review frequency can either be continuous or periodic. The review period (R) specifies the time that elapses between two consecutive moments at which the stock levels are reviewed. With continuous review, the stock level of an SKU is always known. With periodic review, the stock level is only known at a review moment, so every R units of time (Silver et al., 2016, p. 241). An advantage of periodic review is that it enables multi-item coordination. All SKUs ordered from the same supplier can, for example, be reviewed at the same moment. An advantage of continuous review is that less safety inventory is required, as the safety inventory only needs to cover the demand variations during the lead time. In periodic review, the safety inventory must cover the demand variations during the lead time and the review period (Axsäter, 2006, p. 47).

The replenishment size can either be a fixed or variable quantity each time an order is placed. If the order quantity has a fixed size, its size is determined based on the Economic Order Quantity (EOQ) and the order requirements, such as MinOQ and MaxOQ. If the order quantity is variable, the replenishment size ensures that the IP increases to the order-up-to-level (S) (Shenoy & Rosas, 2017, p. 14).

In inventory control, understanding what happens when customer demand cannot be met due to stockouts is crucial. There are two extreme cases: complete backordering and complete lost sales. In complete backordering, any unmet demand is backordered and filled once a sufficient replenishment arrives. This can result in a negative IP when demand occurs during a stockout. In complete lost sales, any unmet demand is lost. The customer will search elsewhere to fulfil his/her demand and the IP will never become negative. In practice, mostly a combination of these extremes is visible. Most inventory control policies are developed for one of the extremes (Silver et al., 2016, p. 239).

	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)

Table 3.4: Inventory control policies

(s, Q)-policy

The (s, Q)-policy is a continuous review policy with a fixed lot size. A fixed quantity (Q) is ordered when the IP drops to or below the reorder point (s). The main advantage of the (s, Q)-policy is its simplicity. The primary disadvantage of this policy is that it may not be able to cope with the situation when individual transactions are large (Silver et al., 2016, p. 242). In such cases, where the IP is sufficiently low, multiples of the fixed order quantity may be necessary. This variation is denoted as an (s, nQ)-policy, where n denotes the number of times the quantity Q is ordered (Axsäter, 2006, p. 48).

The two-bin Kanban system, explained in Section 3.1.3, is the physical implementation of the (s, Q)-policy. In the two-bin system, demand is satisfied from the first (working) bin until its stock is depleted. Upon depletion, the second (reserve) bin is opened, signalling the need for replenishment. When the replenishment arrives, the second bin is refilled, and the remainder is added to the first bin. So, a replenishment of size Q is triggered when the second bin is opened, and the inventory drops below the reorder point (s) (Silver et al., 2016, p. 242). While academic literature describes the two-bin system with unequal-sized bins, practical implementation often involves equal-sized bins, simplifying the system to a single parameter as s and Q are equal. Moreover, the two-bin system facilitates First-In, First Out (FIFO) cycling of inventory. The two-bin system is not necessarily limited to two bins. Such a system is denoted as a n-bin system, where n denotes the number of bins (Kanet & Wells, 2019). Furthermore, according to Silver et al. (2016, p. 667), other forms of Kanban systems are also equivalent to an (s, Q)-policy.

(s, S)-policy
The (s, S)-policy is a continuous review policy with a variable lot size. Similar to the (s, Q)-policy, a replenishment is ordered when the IP declines to or below the reorder point (s). However, the (s, S)-policy uses a variable replenishment quantity, ordering enough to increase the IP to the order-up-to-level (S). The (s, Q) and (s, S) policies are identical when demand transactions are unit-sized. The (s, S)-policy is also known as a min-max system as the IP is always, except for a momentary drop below the reorder point, between a minimum value of s and a maximum value of S (Silver et al., 2016, p. 242). For $s = S - 1$, this policy is known as the one-for-one replenishment policy (Tayebi, Haji, & Ghalebsaz Jeddi, 2018; Möllering, 2019, p. 26).

(R, s, Q)-policy
The (R, s, Q)-policy is a periodic review policy with a fixed lot size. In this control policy, the IP is reviewed every R units of time. If the IP is lower or equal to the reorder point (s), a replenishment quantity of size Q is ordered. In case $R = 0$, then the (R, s, Q)-policy becomes the (s, Q)-policy. Similar to the (s, Q)-policy, it is possible to order a multiple of quantity Q. This policy is denoted as a (R, s, nQ)-policy.

(R, S)- or (R, s, S)-policy
The (R, S)- or (R, s, S)-policies are periodic review policies with variable lot sizes. The (R, S)-policy, commonly used in companies without sophisticated computer control, entails ordering a replenishment every R units of time to raise the IP to the order-up-to-level (S). The (R, s, S)-policy is a combination of the (s, S)- and (R, S)-policies. Every R units of time, the IP is reviewed. If the IP is equal to or lower than the reorder point (s), a replenishment is ordered to raise the IP to the order-up-to-level (S). If the IP is above the reorder point, nothing is done until at least the next review moment. When $R = 0$, the (R, s, S)-policy is equal to the (s, S)-policy and when $s = S - 1$, the (R, s, S)-policy is equal to the (R, S)-policy (Silver et al., 2016, p. 244). Literature often refers to the (R, S)-policy as the base-stock policy and can also be denoted as the (S-1, S)-policy (Möllering, 2019, p. 25).

3.3.1 Policy selection

The most commonly used inventory policies are the (s, Q) and (s, S) policies (Teunter et al., 2010). However, there are no standard procedures to select the appropriate policy for each SKU. Generally, continuous review policies are proposed for the most important items, and periodic review policies are proposed for less important items. Currently, it is more common for companies to use continuous review policies for inventory items due to the development of new technologies in inventory control (Mohammaditabar et al., 2012). Silver et al. (2016, p. 245) propose rules of thumb for selecting inventory control policies for A and B items. Table 3.5 shows these rules of thumb. For C items, companies can use more manual and simple approaches equivalent to simple (s, Q) or (R, S) models. A simple way to control C items is the two-bin system (Arnold, Chapman, & Clive, 2008, p. 318). However, Kanet and Wells (2019) recommend not automatically designating the two-bin system for all C items or limiting the use of the system only to C items. They, as well as Bijvank and Vis (2012), recommend to only use the two-bin system for non-bulky multi-usage disposable items.

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

Table 3.5: ABC rules of thumb for selecting inventory policies

Considering the nature of demand is important when selecting an inventory control policy. Demand can be dependent or independent. Furthermore, demand can be deterministic (constant) or stochastic (variable) (Mohammaditabar et al., 2012). Section 3.2 discussed the non-normal demand patterns classification framework and its cutoff values. This framework provides the classification of non-normal demand but not the appropriate lead time demand distribution. The Normal and Gamma distributions are commonly used to model demand for fast- and slow-moving SKUs (Babai et al., 2015), but especially fast-moving SKUs (Silver & Robb, 2008). According to Silver et al. (2016, p. 275), articles are fast-moving if the mean lead time demand exceeds ten units. They recommend using the Normal distribution when the coefficient of variation is lower or equal to 0.5. Otherwise, they recommend using the Gamma or Lognormal distributions. Articles are slow movers when the mean lead time demand is lower than ten units. For these articles, the Normal and Gamma distributions are not adequate, and thus, the discrete distributions (Poisson, Binomial, Negative Binomial, Geometric) need to be used. Silver et al. (2016, p. 275) recommend using the Poisson distribution in case the variance-to-mean ratio is approximately 1. If this ratio is smaller than 1, then the Binomial distribution is more appropriate, and if the ratio is greater than 1, we must use the Negative Binomial distribution. Similarly to demand, the SLT itself may be deterministic or stochastic. Including SLT variability increases complexity but may have a major impact on service (Möllering, 2019, p. 24). Traditionally, companies incorporated a safety lead time to cope with lead time uncertainties. However, this tactic did not prove to be optimal (Kouvelis & Li, 2011). According to Silver et al. (2016, p. 282), every reasonable effort must be made to eliminate variability in the SLT. This requires close cooperation with suppliers. In case not all SLT variability can be eliminated, there are two approaches to model SLT variability.

1. Measure the SLT and demand distributions separately and then combine the two to obtain the distribution of total demand over the lead time.

2. Measuring or estimating the actual demand during the SLT to obtain its distribution.

Approach 1 is a simple but effective method to measure the total demand over the SLT. Its objective is to find the inventory parameters when the SLT distribution is unknown. In this method, the CSL is the desired performance measure. Silver et al. (2016, p. 283) clearly describes the steps of this approach. Approach 2 assumes that the SLT and the demand are independent random variables which can be measured or estimated. Silver et al. (2016, p. 284) provide two formulas to determine the total demand during the SLT. This approach does not necessarily assume a Normal distribution. As mentioned before, other distributions can be applicable to model demand, but this is also the case for the SLT itself. Most researchers assume that the demand and SLT distributions are given, even if it is unknown. Zipkin (2000, p. 295) gives an example where the mean SLT and its standard deviation are given, Piplani, Wang, Xia, and Bhullar (2012) model the SLT using a triangular distribution, and Tomlin and Wang (2009) model the SLT as a standard lead time with a stochastic non-negative delay. So, stochastic inventory control models can include one of the following three settings: (i) variable demand with constant SLT, (ii) constant demand with variable SLT, and (iii) variable demand with variable SLT (Shenoy & Rosas, 2017, p. 146). When the demand and the SLT are deterministic, continuous and period policies lead to similar outcomes in terms of order quantity, reorder level, etc. The only difference can be found in the managerial complexity of both systems. A continuous review system is more complex to manage than a periodic review system. However, as mentioned before, the development of new technologies rapidly decreases this managerial complexity. When the demand and/or the SLT are stochastic, continuous review generally leads to less safety stock than periodic review (Mohammaditabar et al., 2012).

3.3.2 Parameter determination

This section discusses the different inventory control parameters associated with the previously discussed control policies and the formulas with which the values of these parameters can be determined.

Order quantity (Q) and ordering requirements
For policies with fixed order quantities, the order quantity is determined with the EOQ formula (Equation 3.4). The EOQ is the foundation of all inventory models and uses quite strong and limiting assumptions, but the most important one is that demand needs to be constant and deterministic (Neale et al., 2004). However, research has shown that the EOQ does not perform substantially worse than

more complex, but optimal, order quantities (Silver et al., 2016, p. 146). The objective of the EOQ is to minimize the sum of the annual costs (Brown, 1967). Within the EOQ formula, A denotes the fixed ordering costs of an article, D denotes the demand of an article (in units/unit time), v denotes the value of the article (in price/unit), and r denotes the holding cost rate. Another derivation of the EOQ uses the holding cost (h) per unit and time unit (Axsäter, 2006, p. 52).

$$EOQ = Q^* = \sqrt{\frac{2AD}{vr}} = \sqrt{\frac{2AD}{h}} \tag{3.4}$$

Section 2.6.3 discussed the ordering requirements (MinOQ, MaxOQ, FOQ, and rounding factor). When an article has a MinOQ, the order quantity (Q) should either be the EOQ or the MinOQ, whichever is higher. So, in case the EOQ is lower than the MinOQ, the order quantity becomes equal to the MinOQ (Silver et al., 2016, p. 165). When an article has a MaxOQ, we take the minimum of the EOQ or the MaxOQ. With a FOQ, the order quantity is always equal to the FOQ regardless of the EOQ. Lastly, in case of a rounding factor, the order quantity should be rounded up towards that value.

Review period (R)
In periodic review policies, inventory levels are reviewed once every R units of time. R denotes the length of the review period (Sezen, 2006) and is also known as the Time Between Replenishments (TBR) or cycle time (T). The review period can be determined by dividing an article's EOQ by its demand (D) (Equation 3.5) (Axsäter, 2006, p. 53).

$$R = T^* = \frac{Q^*}{D} \tag{3.5}$$

According to Sezen (2006), periodic control policies are controlled by two parameters: (i) how often to review inventory levels (the size of R), and (ii) how much to raise the inventory levels at each review period (the size of Q). These parameters are influenced by demand variability, where high demand fluctuations necessitate larger safety inventories to avoid shortages. Sezen (2006) conclude that shorter review periods are advisable for highly variable demand compared to more stable demand situations.

Undershoot (Z)
When the IP is at or below the reorder point (s), a replenishment order is placed to raise the IP to the order-up-to-level (S). In reality, it rarely occurs that the IP is exactly equal to the reorder point when a replenishment is triggered. The amount that the IP is below the reorder point is called the undershoot (Z) (Baganha, Pyke, & Ferrer, 1996). Neglecting the undershoot reduces the mathematical complexity, but can also reduce the service levels (Babiloni, Guijarro, & Trapero, 2023). Two factors cause the undershoot: (i) the waiting time until the next review moment in periodic review systems (Silver, Naseraldin, & Bischak, 2009), and (ii) non-unit size demand in continuous review systems (Silver et al., 2016, p. 327). The undershoot can be modelled as random variables with a mean and variance. In case the demand distribution is a discrete distribution, Equations 3.6 and 3.7 calculate the mean and variance of the undershoot, respectively. When the demand distribution follows a continuous distribution, Equations 3.8 and 3.9 calculate the mean and variance of the undershoot, respectively.

Discrete demand distribution

$$E(Z) = \frac{E(Y^2)}{2E(Y)} - \frac{1}{2} \tag{3.6}$$

$$Var(Z) = \frac{E(Y^3)}{3E(Y)} - \frac{1}{4}\left(\frac{E(Y^2)}{E(Y)}\right)^2 - \frac{1}{12} \tag{3.7}$$

Continuous demand distribution

$$E(Z) = \frac{E(Y^2)}{2E(Y)} \tag{3.8}$$

$$Var(Z) = \frac{E(Y^3)}{3E(Y)} - \frac{1}{4}\left(\frac{E(Y^2)}{E(Y)}\right)^2 \tag{3.9}$$

Within the equations above, Y denotes the demand size, $E(Y^2)$ denotes the second moment of demand, and $E(Y^3)$ denotes the third moment. Equations 3.10 and 3.11 calculate the second and third moments of a random variable, respectively (Marx & Larsen, 2011). Calculating the third moment is done with the Moment Generating Function (MGF), which needs to be integrated three times. In a periodic review system, the calculation of the undershoot is based on the demand during the review period D_R instead of Y.

Second and third moments

$$E(Y^2) = Var(Y) + E(Y)^2 \tag{3.10}$$

$$E(Y^3) = M_Y^{(3)}(0) \tag{3.11}$$

Reorder point (s)

The reorder point (s) represents the inventory level at which a replenishment order is placed. In a continuous review system, the reorder point should cover demand during the SLT ($\hat{x}_L$) and is determined as the expected SLT demand plus the safety stock (ss) (Equation 3.12). The safety stock in a continuous review system is a safety factor (k) multiplied by the standard deviation of SLT demand (σ_L). In a periodic review system, the reorder point should cover the demand during the SLT plus the review period ($\hat{x}_{R+L}$) (Equation 3.13) (Silver et al., 2016).

$$s = \hat{x}_L + ss = \hat{x}_L + k\sigma_L \tag{3.12}$$

$$s = \hat{x}_{R+L} + k\sigma_{R+L} = \hat{x}_{R+L} + ss \tag{3.13}$$

Equations 3.12 and 3.13 neglect the undershoot. When including the undershoot, the reorder point can be calculated with Equations 3.14 and 3.15 for the continuous and periodic review systems, respectively (Silver et al., 2016).

$$s = \hat{x}_L + E(Z) + k\sqrt{Var(x_L) + Var(Z)} \tag{3.14}$$

$$s = \hat{x}_{R+L} + E(Z) + k\sqrt{Var(x_{R+L}) + Var(Z)} \tag{3.15}$$

Safety factor (k) and service measures

The safety factor (k) relates to several service measures, such as the CSL (P_1), FR (P_2), RR (P_3), and Time Between Stockouts (TBS). For the CSL, see Equation 3.16 (Silver et al., 2016, p. 269). Within this equation, Φ denotes the Standard Normal distribution function and Φ^{-1} denotes its inverse.

$$P_1 = \Phi(k) = \Phi\left(\frac{s - \hat{x}_L}{\sigma_L}\right) \rightarrow k = \Phi^{-1}(P_1) = \Phi^{-1}\left(\frac{s - \hat{x}_L}{\sigma_L}\right) \tag{3.16}$$

For the Fill Rate, see Equation 3.17, in which $G(k)$ denotes the Normal loss function. $G(k)$ can be determined using Equation 3.18, in which ϕ denotes the Standard Normal density function. Equation 3.17 holds for a complete backordering situation. In case of complete lost sales $1 - P_2$ is replaced with $(1 - P_2)/P_2$ (Silver et al., 2016, p. 271). The (R, s, S)- and (R, s, Q)-policies use a different equation to determine the value of k (Equation 3.19), where $J(k)$ is calculated with Equation 3.20. In a (R, s, S)-policy, the order quantity (Q) can be calculated using Equations 3.23 or 3.24. In a (R, s, Q)-policy, the value of Q is a fixed value.

$$G(k) = \frac{Q(1 - P_2)}{\sigma_L} \tag{3.17}$$

$$G(k) = \phi(k) - k * (1 - \Phi(k)) \tag{3.18}$$

$$J(k) = \frac{2\hat{x}_R * Q(1 - P_2)}{\sigma_{R+L}^2} \tag{3.19}$$

$$J(k) = (1 - k^2)(1 - \Phi(k)) - k\phi(k) \tag{3.20}$$

For the RR, we can use Equation 3.21. The FR and the RR are equal in inventory systems with continuous Normally distributed demand (Thorstenson & Larsen, 2014; Axsäter, 2006, p. 98).

$$P_3 = 1 - \frac{\sigma_L}{Q}\left(G(k) - G\left(k + \frac{Q}{\sigma_L}\right)\right) \tag{3.21}$$

Silver et al. (2016, p. 360) recommend to base the safety factor on the TBS for C-items, which can be done using Equation 3.22. They recommend using large TBS values of between 5 and 100 years, as the extra costs of high safety stocks for these items are relatively low.

$$TBS = \frac{Q}{D} * \frac{1}{1 - \Phi(k)} \rightarrow k = \Phi^{-1}\left(1 - \frac{Q}{D * TBS}\right) \tag{3.22}$$

Order-up-to-level (S)
In control policies with variable lot sizing, the order-up-to-level (S) denotes the level to which the IP needs to rise when a replenishment is ordered. When we choose to neglect the undershoot and/or when demand is unit-sized, the order-up-to-level can be calculated with Equation 3.23, where Q can be calculated with the EOQ (Equation 3.4), and s can be calculated using Equations 3.12 and 3.13 (Silver et al., 2016, p. 328). When demand is not unit-sized, the undershoot should be taken into account. In this case, Equation 3.24 holds (Silver et al., 2009).

$$S = s + (S - s) = s + Q \tag{3.23}$$

$$S = s + (S - s) - E(Z) \tag{3.24}$$

In the case of an (R, S)-policy, the order-up-to-level should be calculated differently. This is only the case for periodic review systems, and therefore, the replenishment order should cover the demand during $R + L$. In case we neglect the undershoot, we can use Equation 3.13 and change the s to S. Otherwise, we use Equation 3.15 and change the s to S.

Kanban
The Kanban and two-bin systems are equivalent to a (s, Q)-system, as explained in Section 3.3. Therefore, we can use the same formulas to determine the values for s and Q. If the two bins are of unequal size, a replenishment of Q is triggered when the second bin is opened as the inventory drops below the reorder point (s). If the two bins are of equal size, the values for s and Q are also equal.

3.4 Literature confrontation

In this chapter, we explained multiple theoretical inventory management concepts, such as manufacturing setting, SKU classification methods, demand distribution, lead time distribution, and Kanban. To identify the literature gap addressed by this research, we perform a confrontation between academic literature and this research. Table 3.6 and its continuation (Table 3.7) provide an overview of various academic papers and the concepts they consider. The confrontation table shows that the majority of papers focus on either MTS or ATO, with fewer addressing the MTO and ETO manufacturing settings in combination with the other concepts. This aligns with Barbosa and Azevedo (2019), who note the limited attention given to MTO-ETO settings in academic literature. Additionally, most papers focus on single inventory management concepts or the combination of a few concepts. For example, Table 3.6 shows that when a paper focuses on the manufacturing setting combined with inventory control, it does not include SKU classification methods. Regarding inventory control policies, the demand distribution is often modelled stochastically, while the lead time distribution is modelled deterministically. Moreover, the CSL and the FR are commonly used service measures.

This research shows how inventory control policies, including a SKU classification method, statistical distributions and parameters, can be applied in an MTO-ETO manufacturing setting by considering and combining the existing knowledge on the discussed inventory management concepts. Chapter 4 discusses the designed inventory control policies for ASNL. We use the XYZ classification method to categorise articles into different classes, although it is less commonly used than the well-known ABC classification method. Section 6.5.2 shows the value of using the XYZ classification. Additionally, we model both demand and lead times as stochastic random variables, in contrast to the common practice of modelling demand stochastically while treating lead times as deterministic or fixed variables. Only two papers in Table 3.6 consider stochastic lead time. This research fills a gap by modelling both variables stochastically, using a selection of five statistical distributions to model demand and a Triangular distribution to model the lead time variability. To model the demand, the standard distribution is the Normal distribution. Using multiple demand distributions allows more accurate modelling of demand variability and more precisely determining the control parameters. Incorporating SLT randomness creates a more realistic representation of supply chain dynamics and enhances the determination of control parameters, allowing better resilience to supply chain disruptions. The selected inventory control policies use a target RR to determine the reorder point, deviating from the general approach in literature to use the FR. Furthermore, the simulation model explained in Section 6.2 yields the FR and RR performance. All selected control policies are continuous review policies with fixed and variable order quantities, as SAP allows for the continuous review of the inventory levels.

While this research explains VMI, it is not incorporated with the proposed inventory control policies due to ASNL's impending transition towards the SAP IBP tool. The article storage type is incorporated within the SKU classification, as ASNL already uses a Kanban system for specific articles. We, therefore, only differentiate the already implemented two-bin and pallet Kanban systems of ASNL. Other types of Kanban systems from academic literature are not included in this research. ADI cannot be leveraged as the sales forecasts cannot provide meaningful insight into the expected article demand. However, the approach of Hariharan and Zipkin (1995) to use the Effective Lead Time (ELT), explained in Section 3.1.2, to incorporate a form of ADI is tested within Section 6.5.3.

Paper	Manufacturing setting	Classification method	Demand distribution	Lead time distribution	VMI	Kanban	ADI	Policies		
								Service measures	Review frequency	Replenishment size
Ahmadi et al. (2019)	ATO - two components & single end product	Not mentioned	Deterministic (single-unit)	Deterministic	Not mentioned	Not mentioned	Perfect ADI	Not mentioned	Continuous	Variable
Atan, Ahmadi, Stegehuis, de Kok, and Adan (2017)	ATO - multiple components and end-products	Not mentioned	Deterministic	Deterministic	Not mentioned	Not mentioned	Not mentioned	(Order) FR	Periodic & Continuous	Fixed & Variable
Claudio and Krishnamurthy (2009)	MTS-MTO	Not mentioned	Not mentioned	Not mentioned	Not mentioned	KCS	ADI (perfect & imperfect) integration	CSL	Not mentioned	Not mentioned
He, Jewkes, and Buzacott (2002)	MTO	Not mentioned	Stochastic (Poisson)	No lead time (zero)	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Continuous	Variable
Hill (2007)	Not mentioned	Not mentioned	Stochastic (Poisson)	Deterministic (fixed)	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Continuous	Variable
Kanet and Wells (2019)	Not mentioned	ABC	Stochastic (Normal)	Deterministic (constant)	Not mentioned	Two-bin system	Not mentioned	CSL	Continuous	Fixed
Karaarslan, Atan, de Kok, and Kiesmüller (2018)	ATO - two components & single end product	Not mentioned	Stochastic	Deterministic (given)	Not mentioned	Not mentioned	Not mentioned	CSL	Periodic	Variable
Larsen (2021)	Not mentioned	ABC	Stochastic (Normal)	Deterministic (constant)	Not mentioned	Not mentioned	Not mentioned	FR	Continuous	Fixed
Liberopoulos (2008)	MTS	Not mentioned	Deterministic	Stochastic	Not mentioned	Not mentioned	Perfect ADI	Not mentioned	Continuous	Variable
Piplani et al. (2012)	MTS-MTO	Not mentioned	Stochastic (Poisson)	Stochastic (Triangular distribution)	Not mentioned	Not mentioned	Not mentioned	FR	Continuous	Variable

Table 3.6: Literature confrontation

Paper	Manufacturing setting	Classification	Demand distribution	Lead time distribution	VMI	Kanban	ADI	Policies		
								Service measures	Review frequency	Replenishment size
Sezen (2006)	Not mentioned	ABC	Stochastic (Normal)	No lead time	Not mentioned	Not mentioned	Not mentioned	CSL	Periodic	Variable
Silver and Robb (2008)	Not mentioned	Not mentioned	Stochastic (Normal & Gamma)	Stochastic	Not mentioned	Not mentioned	Not mentioned	CSL & FR	Periodic	Fixed
Silver et al. (2009)	Not mentioned	Not mentioned	Stochastic (Normal)	Deterministic (constant)	Not mentioned	Not mentioned	Not mentioned	FR	Periodic	Variable
Tayebi et al. (2018)	Not mentioned	Not mentioned	Stochastic (Poisson)	Deterministic (constant)	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Periodic	Fixed
Teunter et al. (2017)	Not mentioned	ABC	Stochastic (Normal)	Deterministic (constant)	Not mentioned	Not mentioned	Not mentioned	FR & RR	Continuous	Fixed
Topan and Avsar (2009)	ATO	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Kanban - SKCS & IKCS	Not mentioned	CSL & FR	Not mentioned	Not mentioned
van Driel (2018)	ATO	Not mentioned	Not mentioned	Not mentioned	VMI	two-bin-VMI	Not mentioned	Not mentioned	Not mentioned	Not mentioned
This research	MTO-ETO with RTO-RTS strategies	XYZ classification method	Stochastic (Normal, Gamma, Binomial, Poisson & (Generalized) Negative Binomial)	Stochastic (Triangular distribution)	Explained but not leveraged	Storage location incorporated in SKU classification	Tested the application of ELT	Target RR & FR and RR performance	Continuous	Fixed & variable

Table 3.7: Literature confrontation - continued

3.5 Conclusions

In this chapter, we performed a literature review on inventory management methods by answering the research question *'What inventory management methods from literature apply to the situation at Aebi Schmidt Nederland B.V.?'* and its sub-questions. First, we gained insights into several inventory management concepts from academic literature that align with the inventory context at ASNL. These concepts are the manufacturing setting, demand and lead times, Kanban, ADI, and VMI. The knowledge gained on the CODP helps to understand the manufacturing setting in academic literature. There are four basic manufacturing settings: MTS, ATO, MTO, and ETO. Material demand at ASNL is 100% certain at the start of the FP. The incorporation of advance ordering, as introduced by Hariharan and Zipkin (1995), formed the foundation for research on ADI. We also reviewed VMI as this is an application of ADI which can be valuable for ASNL. VMI also relates to the KCS, which is a popular PICS of which many variants exist in both literature and practice.

In the literature, we have seen a wide variety of different inventory classification methods. Inventory classification is the process of placing SKUs into classes and distinguishing them based on their characteristics to enable organisations to make decisions for a specific class of SKUs rather than for every individual SKU. So, based on the different SKU classes, inventory management determines the order quantities, reorder points, safety stocks, etc. The typical application of SKU classification suggested in academic literature and commonly used in practice is to give a certain class of SKUs the same service level. Most classification methods used in the literature are one-dimensional, so-called SCIC methods, meaning they classify SKUs based on a single criterion. The most well-known SCIC methods are the ABC and/or XYZ methods. The ABC method classifies SKUs into three classes based on their demand value, where the A class contains the articles that account for the highest demand value. Zhang et al. (2001) and Teunter et al. (2010) developed variations on the classical ABC methods that consider stock control, and these variations outperform the classical method in minimizing safety stock costs. The XYZ method classifies SKUs into three classes based on their demand variability, and the ABC-XYZ method is a combination of both methods. Opposed to SCIC methods, MCIC methods take a combination of criteria into account. Examples of such MCIC methods are the framework of Boylan et al. (2008) and AHP.

Next to the inventory classification methods, inventory management comprises numerous inventory control policies with different control parameters. Inventory control policies help to determine when a replenishment order should be placed and how much to order, and generally, take the IP into account. There are four basic policies that regulate order timing and order quantities; the (s, Q), (s, S), (R, s, Q), and (R, s, S) policies. These policies are differentiated on two factors: the review frequency (continuous or periodic) and the order size (fixed or variable). There are no standard procedures to select the appropriate policy for each SKU. However, Silver et al. (2016) provided some rules of thumb for the ABC classes. When selecting an inventory control policy, it is also important to consider the nature of demand and SLT, as both can be modelled deterministically or stochastically. Several guidelines exist to select the appropriate demand and SLT distributions. Each control policy manages its own parameters, and formulas exist to determine the values for these parameters.

Lastly, we developed a confrontation between academic literature and this research to identify the gap in academic literature addressed by this research. This research shows how inventory control policies, including a SKU classification method, statistical distributions and parameters, can be applied in an MTO-ETO manufacturing setting by considering and combining the existing knowledge on the discussed inventory management concepts. This research considers the less commonly used XYZ classification method, models the lead time as a stochastic variable with a Triangular distribution, and uses a target RR as the service measure instead of the CSL or FR. To conclude, this research fills a literature gap by deviating from the common approaches suggested in academic literature and combining multiple inventory management concepts instead of focusing on single concepts.

4 Inventory policy design

This chapter describes the proposed inventory control policies, which are designed using the knowledge gained from academic literature and taking ASNL's context into account. In this chapter, we answer the following research question by answering its sub-questions explained in Section 1.4.1.

How should the inventory control policies be designed?

This chapter starts with describing the chosen SKU classification method in Section 4.1. Sections 4.2 and 4.3 describe the selected policies for each class of SKUs and the corresponding control parameters, respectively. Subsequently, Section 4.4 provides an overview of the modelling assumptions made to design the control policies and the limitations of the modelling approach. Lastly, this chapter concludes with the answers to the research questions in Section 4.5.

4.1 Stock Keeping Unit (SKU) classification

To be able to make appropriate inventory decisions for the articles, we conduct an XYZ analysis, as discussed in Section 3.2.2, to divide the articles into three different classes based on the demand variability. The coefficient of variation (CV) is the measure that determines the demand variability as the ratio of the standard deviation of demand and the average demand over 2022 and 2023 ($\sigma/\overline{X}$). The three classes are further divided among the different inventory storage types (Kanban, pick, partial Kanban and pick, and no inventory), and replenishment strategies (RTO and RTS). Recall that articles not stored in a Kanban system are picked from the warehouse when needed for production.

The most well-known classification method, the ABC method, cannot provide more extensive insights into demand patterns than the XYZ classification method and is therefore not included in inventory control policy selection because not all articles kept in inventory are used and vice versa. However, this method can provide insights into which articles in inventory ASNL have to prioritise attention in terms of inventory value. Therefore, the ABC classification method based on inventory value is executed. This is different from the ABC method as described in Section 3.2.1, which explains that the classification used the demand value as its criteria. Using the inventory value, as opposed to the demand value, as the criteria for the article classification creates classes based on which articles contribute the most to the total inventory value to contributing the least. As ASNL's main focus is the total inventory value, this ABC classification helps to provide an overview into which articles need to receive attention from management to reduce the inventories.

4.2 Inventory control policy selection

The literature review in Section 3.3 explained that there are four basic inventory control policies and that the nature of demand and lead times are important to consider. This section first discusses the inventory control policies chosen for each article class. After that, more insights are provided into the demand and lead time distributions. Lastly, the demand and lead time distributions are combined to model the demand during random lead time.

4.2.1 Policies per Stock Keeping Unit (SKU) class

As explained in Section 3.3.1, there are no guidelines as to what inventory control policy to use for which group of articles. Silver et al. (2016) provide rules of thumb for the ABC classification method in combination with the four basic inventory control policies. These rules of thumb and the reasoning behind these guidelines form the foundation for the policies used for each class in this research. Table 4.1 provides the chosen inventory control policies for each class of articles.

ASNL's ERP system, SAP, enables the continuous review of inventory levels, so the chosen inventory policies are all continuous review policies. X articles have relatively constant demand, so more static inventory policies can be used. Policies that use variable lot sizes are more dynamic than policies with fixed lot sizes, as with variable lot sizes, the order quantity is determined based on the inventory levels. Therefore, the (s, Q)-policy is chosen for X articles. Z articles experience high variability in demand, making the dynamic (s, S)-policy appropriate. The (s, Q)-policy is chosen for Y articles, as these articles show moderately fluctuating demand patterns. This selection of control policies per SKU class differs from the rules of thumb proposed by Silver et al. (2016) as they use the ABC classification method rather than the XYZ method. Within academic literature, the XYZ classification method is less commonly used in inventory control. Furthermore, this selection of control policies per SKU class is specific for ASNL as it focuses on demand variability and not on inventory value to accommodate ASNL's MTO-ETO manufacturing setting with a HMLV product portfolio.

Class	X	Y	Z
Policy	(s, Q)	(s, Q)	(s, S)

Table 4.1: Chosen policies per class

4.2.2 Supply Lead Time (SLT) distribution

The SLT may be deterministic or stochastic. The literature review in Section 3.4 showed that the lead time is often modelled deterministically. The data available in SAP lacks insights into the current SLTs uncertainties, making the SLTs stochastic (random) variables. Section 3.1.2 explained incorporating the FP into the SLT using the ELT from Hariharan and Zipkin (1995). However, SAP uses the full SLT to be able to generate order incentives at the right moment and for the right quantity. Therefore, the SLTs are incorporated within the inventory control policies by using a Triangular distribution, taking inspiration from Piplani et al. (2012). A Triangular distribution is denoted as $Triangular(a, b, c)$, where a denotes the lower limit, b denotes the upper limit, and c denotes the mode (Kissell & Poserina, 2017). In this instance, the value of c is equal to the article's SLT, as denoted in SAP. The lower limit (a) is $100\% - x\%$ of the SLT denoted in SAP, and the upper limit (b) is $100\% + y\%$ of the SLT. Since there is no data to determine the values of a and b, we rely on the expertise of the Supply Chain Manager to estimate these values. The values of x and y are 10% and 30%, respectively (Lindenburg, 2023), and this interval is denoted as $(-10\%; +30\%)$. We do not differentiate between F and E articles concerning the bounds of the SLT distribution. One might argue that internal suppliers (E) are more reliable than external suppliers (F) and that, therefore, the bounds of the SLT distribution should be different. However, we assume these values to be the same for all articles at ASNL. With the values of a, b, and c, the mean SLT and its variance can be determined. Appendix B provides a more detailed explanation of the Triangular distribution and its properties.

4.2.3 Demand during random lead time distribution

Similarly to the SLT, demand can either be deterministic or stochastic. To obtain the values for the inventory control parameters, academic literature uses the demand during lead time, with its mean ($\hat{x}_L$) and standard deviation (σ_L). However, academic literature suggests a fixed SLT for the demand during lead time. In this instance, it is necessary to determine the demand during random lead time (RLD), with its mean ($\hat{x}_{RLD}$) and standard deviation (σ_{RLD}). Obtaining the RLD distribution follows the 'combining the demand rate per time unit distribution with the lead time distribution' approach (Approach 2) from Silver et al. (2016, p. 284), as described in Section 3.3.1, and uses Equations 4.1 and 4.2 to determine the RLD mean and standard deviation. This method explicitly assumes that the SLT and demand are independent random variables. As none of the chosen inventory control policies use periodic review, the review period (R) is not included within these equations.

$$E(X_{RLD}) = \hat{x}_{RLD} = E(L)E(D) \tag{4.1}$$

$$\sigma_{RLD} = \sqrt{E(L)Var(D) + (E(D))^2 Var(L)} \tag{4.2}$$

The mean RLD and its standard deviation do not specify the exact distribution. Therefore, the exact distribution is selected based on the rules of thumb from Silver et al. (2016, p. 275) described in

Section 3.3.1. Table 4.2 shows these rules, and Appendix C provides the properties of these different RLD distributions.

Mean random lead time demand ($\hat{x}_{RLD}$)	**Coefficient of variation (CV)**	**Variance-to-Mean ratio (V/M)**	**RLD distribution**
$\hat{x}_{RLD} \geq 10$	$CV \leq 0.5$	-	Normal(μ, σ)
	$CV > 0.5$	-	Gamma(α, β)
$\hat{x}_{RLD} < 10$	-	$V/M < 1$	Binomial(n, p)
	-	$V/M \approx 1$	Poisson(λ)
	-	$V/M > 1$	Negative Binomial(r, p)

Table 4.2: RLD distribution rules of thumb

4.3 Inventory control parameter determination

The two different inventory control policies, (s, Q) and (s, S), use three different parameters. Table 4.3 provides an overview of the formulas used to determine the control parameter values. The value for the reorder point (s) is obtained through $P(s > X_{RLD}) \geq RR$, as the probability that the size of the reorder point covers demand during random lead time should be at least the Ready Rate (RR). The RR is used as the performance measure, as this performance measure is the most intuitive in an MTO-ETO setting. The RR denotes the fraction of the time an article's OHI is positive, and for an MTO-ETO manufacturer, this measure provides more insights, in comparison with the FR, into whether production is possible once a customer order is received. The reorder point denotes the point where the cumulative probability of X_{RLD} is greater or equal to the RR, and the inverse of the cumulative distribution provides the value for the reorder point. For the Normal, Gamma, and Binomial distributions, the provided Excel functions for the inverse of the cumulative distribution can be used to determine the value of s. For the Poisson and Negative Binomial distributions, such functions do not exist (in Excel), and therefore, we developed four Excel VBA functions to determine the reorder point value for these distributions. Appendix D includes the algorithms of these four VBA functions. Algorithms D.1 and D.3 determine the cumulative value at a specific point for both the Poisson and Negative Binomial distributions, respectively. Algorithms D.2 and D.4 determine the inverse of the cumulative distributions by summing the cumulative values until reaching the RR value, with the number of additions equating to the reorder point value. Notably, the Negative Binomial VBA function handles a real-valued number of successes (r), also known as the Generalized Negative Binomial distribution (Consul & Famoye, 1995).

The order quantity (Q) is calculated using the EOQ-formula, but depends on the existing ordering requirements as well. In case an article has an MinOQ, the value of Q is determined by taking the maximum of the EOQ and MinOQ. Similarly, when an article has an MaxOQ, the value of Q is the minimum of the EOQ and MaxOQ. With an FOQ, the value of Q is always equal to the FOQ regardless of the EOQ value. When a rounding factor is involved, the value of Q should be rounded up to the nearest multiple of the rounding factor. Lastly, the value of Q must be an integer, and in the case of a real value, it is rounded up towards the first integer. The order-up-to-level (S) for the (s, S)-policy is determined by adding the reorder point and the order quantity. The order quantity within the (s, S)-policy is similarly determined as explained above for the order quantity in the (s, Q)-policy.

Notably, the formulas to determine the control parameters do not consider the undershoot. Recall, that two factors cause the undershoot: (i) the waiting time until the next review moment in periodic review systems (Silver et al., 2009), and (ii) non-unit size demand in continuous review systems (Silver et al., 2016, p. 327). As we are not dealing with a periodic review system, the first factor does not apply. However, the second factor is relevant because several articles show non-unit size demand as their units are measured in meters, kilograms, etc. However, ASNL orders such articles in whole units. Furthermore, neglecting the undershoot reduces the mathematical complexity (Babiloni et al., 2023). Therefore, the undershoot is not included in the control parameter determination.

<table>
<tr><th>(s, Q)</th><th>(s, S)</th></tr>
<tr><td colspan="2">Reorder point (s):
$P(s > X_{RLD}) \geq RR$</td></tr>
<tr><td colspan="2">Normal: s = NORM.INV(RR; $\hat{x}_{RLD}$; σ_{RLD})
Gamma: s = GAMMA.INV(RR; α; θ) = GAMMA.INV(RR; α; $1/\beta$)
Binomial: s = BINOM.INV(n; p; RR)
Poisson & Negative Binomial: obtain s using the Excel VBA functions in Appendix D</td></tr>
<tr><td colspan="2">Safety stock (ss):
$ss = s - \hat{x}_{RLD}$</td></tr>
<tr><td>Order quantity (Q):
$EOQ = \sqrt{\frac{2AD}{h}}$
If $FOQ > 0$: $Q = FOQ$
If MinOQ ≤ 0 and MaxOQ ≤ 0: $Q = EOQ$
If MinOQ > 0 and MaxOQ ≤ 0:
$Q = \max\{MinOQ; EOQ\}$
If MinOQ ≤ 0 and MaxOQ > 0:
$Q = \min\{MaxOQ; EOQ\}$
If MinOQ > 0 and MaxOQ > 0:
$MinOQ \leq Q \leq MaxOQ$
If Rounding factor (w) > 0: $Q = w * \lceil \frac{Q}{w} \rceil$</td><td>Order-up-to-level (S):
$S = s + Q$</td></tr>
</table>

Table 4.3: Parameter determination

4.4 Modelling assumptions and limitations

The design of the proposed inventory control policies includes several assumptions. These assumptions and the scope of the research cause several limitations which impact the performance of the proposed inventory control policies. In order to ensure a comprehensive understanding of the context in which the inventory control policies operate and the constraints of the policies, this section provides a summary of the assumptions and limitations.

4.4.1 Assumptions

The following list provides an overview of the different assumptions made within this chapter.

1. Demand for separate articles is assumed to be independent as the usage relations between separate articles are not included within the research scope. Section 4.4.2 further explains the usage relations.

2. The percentage with which the values for the lower and upper bounds of the Triangular SLT distribution are assumed to be the same for all articles at ASNL.

3. The demand and the SLT are assumed to be independent random variables.

4.4.2 Limitations

The assumptions and the research scope impose several limitations on the performance of the proposed inventory control policies. Firstly, these policies do not consider usage relations between different articles. For instance, if article A is always used with 2 units of article B, optimizing the inventory policy of article A alone may lead to suboptimal inventory levels for both articles. So, when only optimising the inventories of article A, article B is not automatically considered. Consequently, the policies may not yield accurate results for E inventory articles. When optimising inventory levels for an E article, the inventories of the corresponding other E articles and related F articles are not optimised. This may result in strong deviations and stockouts, causing the production of the E article to come to a halt.

Secondly, limitations exist regarding the selection and modelling of the RLD and SLT distributions. The policies rely on a limited set of five RLD distributions, selected based on rules of thumb, which may not always accurately represent ASNL's reality. Similarly, the Triangular distribution is used for the SLT. This distribution's lower and upper limits are based on expert opinion but may vary in reality. Moreover, assuming uniform limits for all articles may not represent the diverse behaviours of suppliers, resulting in deviations from ASNL's reality.

Lastly, the proposed inventory control policies do not incorporate forecasted future demands due to ASNL's HMLV environment as each machine is unique. The lack of leveraging ADI limits the ability of the control policies to accurately predict future demand and optimize inventory levels accordingly.

4.5 Conclusions

In this chapter, we designed inventory control policies for ASNL's specific needs by answering the research question *'How should the inventory control policies be designed?'* and its sub-questions.

First, we selected the XYZ classification method to categorize SKUs based on demand variability, using the coefficient of variation of demand. The three XYZ classes are further subdivided based on inventory storage types (Kanban, pick, partial Kanban and pick, and no inventory), and replenishment strategies (RTO and RTS).

Secondly, we explained the control policy selection, including the SLT and RLD distributions. Different policies were chosen based on the SKU class: (s, Q)-policy for X and Y articles, and (s, S)-policy for Z articles. The Triangular distribution was selected to model SLT variability due to the lack of data on the supplier delivery performance. Furthermore, the ELT method of Hariharan and Zipkin (1995) is not used as SAP uses the full SLT to be able to generate order incentives at the right moment and for the right quantity. For the RLD distributions, we applied the 'combining the demand rate per time unit distribution with the lead time distribution' approach from Silver et al. (2016, p. 284) to obtain the mean and standard deviation of the RLD. Based on the rules of thumb, each article is assigned a statistical distribution (Normal, Gamma, Binomial, Poisson, and (Generalized) Negative Binomial).

Thirdly, we provided an overview of the formulas used to calculate the control parameter values has been provided. The control parameters are determined based on the RR service measure, as this is the most intuitive service measure to use for a MTO-ETO manufacturer. Lastly, the proposed policies are constrained by not being able to consider the usage relations between articles, the limited selection of statistical distributions, and the inability to leverage ADI.

5 Tool design

This chapter describes the inventory management tool developed to execute the designed inventory control policies of Chapter 4 and determine the new control parameter values. In this chapter, we answer the following research question by answering its sub-questions explained in Section 1.4.1.

How should the inventory management tool be designed and developed?

Section 5.1 discusses the stakeholder requirements for the tool, and Section 5.2 provides a detailed description of the tool's functioning using an Entity Relationship Diagram. This chapter concludes with the answers to the research questions in Section 5.3.

5.1 Tool motivation and stakeholder requirements

Several stakeholder requirements must be considered in the development of the inventory management tool. This section explains the stakeholder requirements and the different decisions made in order to comply with these requirements.

The two most important requirements are that the tool should be user-friendly and that it can be used within the currently existing IT system at ASNL so that the tool can be easily incorporated within current processes and no new skills are needed to use the tool. SAP can potentially execute the proposed inventory control policies and determine the new control parameter values. However, as explained in Section 1.3.2 due to the overall lack of SAP knowledge at ASNL, SAP is a black box within ASNL. Most employees know their tasks within SAP, but the oversight is missing. Therefore, the decision was made to develop the tool in Microsoft Excel, as this is the main tool, next to SAP, that supports current processes. Next to that, all employees at ASNL have a basic understanding of Microsoft Excel. The decision to use Microsoft Excel to develop the tool ensures that when certain functionalities cease to work due to updates, the tool can easily be adjusted, as no extensive programming skills are required from the stakeholders. Another program that has been considered for the tool is Python Spyder. However, due to the lack of Python knowledge present at ASNL, this program is not suitable for the development of the tool. Note that the simulation model explained in Section 6.2 is implemented in Python Spyder, due to Excel's limited computational speed. The simulation model only supports the evaluation of the results and is therefore not a research deliverable.

Another important requirement is the integration of real-time data, as up-to-date data needs to be incorporated within the tool to ensure accurate results. The automation of the policy calculations through an integration of the Excel tool in SAP is not part of the research scope. Therefore, the tool uses data exported from SAP to Excel. This exported data can be pasted into the right workbooks of the Excel tool. This ensures up-to-date data integration within the policy calculations and that the newly determined control parameters fit with ASNL's inventory needs. The integration of real-time data also ensures that maintaining the tool is relatively straightforward, as new data can be pasted into the tool.

The last requirement is that the calculation results must provide clear actions for users on how to improve the inventories at ASNL. If an article's control parameters should be updated, the tool must provide the user with the action on how to alter the specific parameters. For example, when the reorder point of an article needs to be updated, the tool provides the user with the action to change the reorder point parameter from the old value to the new value. When an article is part of dead inventory, the action should state that the stakeholder should determine whether the article can be thrown away, can be used for other orders/machines, or can be sold to, for example, other branches of ASG or to the original supplier, following the disposal options from Silver et al. (2016, p. 370) explained in Section 2.5.2. Lastly, the tool should notify the user that nothing needs to change when the parameters are still correct according to the proposed policies.

5.2 Tool description

Based on the stakeholder requirements, the chosen programme to develop the tool is Microsoft Excel. The inventory management tool comprises seven interconnected workbooks, as Microsoft Excel has limited computational power. Each workbook serves a unique purpose. Figure 5.1 provides a flowchart showing the steps the tool takes to obtain its results, and Figure 5.2 provides an overview of the relations between each of the seven workbooks using an Entity Relationship Diagram (ERD). Most relations between the workbooks are one-to-one relations, except for a few relations. Many-to-one relations exist between the different sheets in the workbooks as the article inventory and usage data from SAP contains data for all ASNL's articles.

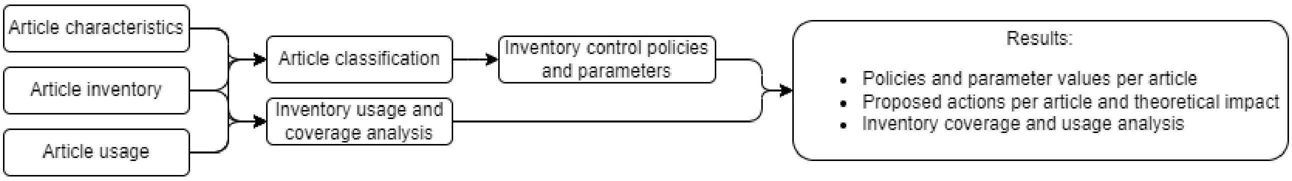


Figure 5.1: Flowchart functioning inventory management tool

The 'Tool input + results' workbook is at the core of the tool. Users can enter up to 100 article numbers into the input sheet, for which the tool executes the calculations. As the tool contains the data on all 108,484 identified articles in Section 2.5.1 and needs to cross-reference many data types for all these articles, this limited number of articles ensures that the calculations remain within Excel's computational bounds and that the running time to perform the calculations does not become exceptionally long. Next to that, the control parameters need to be manually updated in SAP, when alterations are required. Therefore, the tool article limit of 100 articles ensures that the user maintains oversight. In case a user wants to review more than 100 articles, the user must enter the articles in batches into the tool. Next to the article input, the values of the input parameters, such as the FP length, the lower and upper bounds for the SLT distribution, and the target RR value, can be altered according to the wishes of the user. With this information, the other underlying workbooks execute different calculations, and the results are visible in the results sheet. The results contain the actions suggested to be executed based on the deviations between the current situation and the newly determined control parameter values, and the potential monetary impact of these proposed actions. Furthermore, the tool also proposed whether an article can be placed in a Kanban system or should be taken out of the Kanban system based on its demand. This advice does not consider factors such as the size and weight of the articles. Lastly, the 'Tool input + results' workbook contains a comprehensive user manual and a dashboard with the updated versions of the inventory coverage (Figure 2.7) and usage frequency (Figure A.2 in Appendix A.3.3) graphs.

Three workbooks contain the source data for the inventory control policies, these are the 'Article characteristics', the 'Article inventory', and the 'Article usages' workbooks. The 'Article characteristics' workbook contains the essential article characteristics, including, among others, current control parameters values and order requirements from SAP, article value, inventory type and status, and the SLT. The 'Article inventory' workbook evaluates the inventory locations, storage types, and inventory value for the input article selection. This workbook contains two sheets. One with the inventory export from SAP and one with the analysis of the exported data for the input articles. Lastly, the 'Article usages' workbook works similarly to the 'Article inventory' workbook and (i) evaluates the historical article usage over 2022 and 2023, (ii) combines the demand data with the SLT distribution to obtain the RLD distribution, and (iii) calculates the distribution parameters for the RLD distributions. The search ranges within the tool to extract data from these three workbooks are set to a larger value than the current size of the source data. This ensures that the tool can handle larger quantities of source data, such as newly added articles, without the need to update the tool.

The 'Inventory usage and coverage analysis' and the 'Article classification' workbooks both use the article, inventory, and usage characteristics of the articles to execute their specific analyses. Furthermore, both workbooks focus on the entire article population at ASNL, encompassing all 108,484 identified articles in Section 2.5.1. The 'Inventory usage and coverage analysis' workbook is a standalone workbook that executes the inventory usage and coverage analysis explained in Appendix A.3.3 and Section 2.5.2, respectively. The resulting graphs (Figure A.2 in Appendix A.3.3 and Figure 2.7 in Section 2.5.2), provide ASNL with useful inventory insights. The 'Article classification' workbook executes the article classification as described in Section 4.1. The workbook first determines whether an article is part of dead inventory or not. After that, articles are classified based on five characteristics, specifically RTO versus RTS, XYZ, ABC, ABC-XYZ, and Kanban versus Pick versus Partially. Recall that the ABC classification is based on inventory value instead of demand value.

Lastly, based on the article classification, the 'Policies and parameters' workbook assigns the appropriate control policies to the selected articles and executes the policies to determine the corresponding control parameter values. The parameter values are used in the results sheets of the 'Tool input + results' workbook to determine the actions that need to be taken for each selected article and the theoretical impact of the proposed actions.

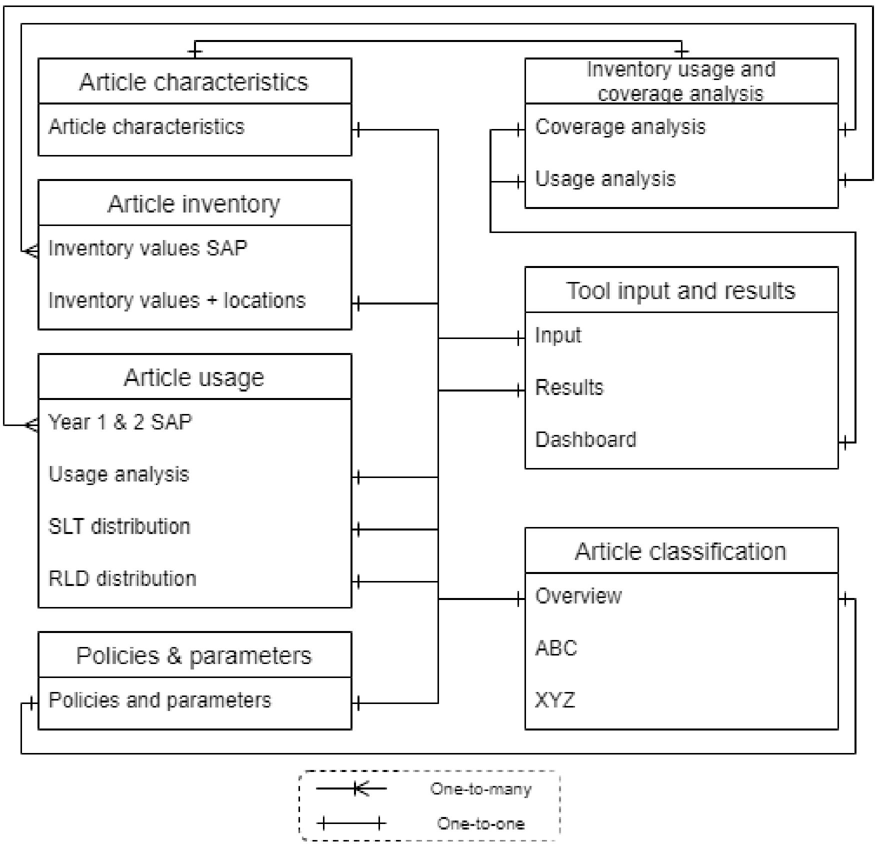


Figure 5.2: Inventory management tool ERD

5.3 Conclusions

In this chapter, we developed the inventory management tool by answering the research question *'How should the inventory management tool be designed and developed?'* and its sub-questions. The tool design considers several stakeholder requirements. The tool must be user-friendly and fit with the currently existing IT system at ASNL. As SAP is a black box within ASNL, due to an overall lack of SAP knowledge, we selected Microsoft Excel as the software for the tool development. The familiarity with Excel among ASNL's employees reduced the need for employee training.

The Excel tool consists of seven interconnected workbooks that execute the proposed control policies and determine the new control parameter values. To ensure real-time data integration, data exports from SAP can be uploaded in the designated Excel workbooks and the tool uses this updated data within the calculations. The tool design allows the data exports from SAP to be directly copied into the tool, minimizing manual data adjustments. Users can enter up to 100 article numbers into the tool at once, for which the tool executes the calculations. This limited number of articles ensures that the calculations remain within Excel's computational bounds and that the running time to perform the calculations does not become exceptionally long. Furthermore, the article limit ensures that users maintain oversight of the necessary parameter updates. In case a user wants to review more than 100 articles, the user must enter the articles in batches into the tool.

The tool's calculations result in the newly determined control parameter values for the inputted articles and the potential monetary impact of the parameter changes. Furthermore, the tool provides advice on whether an article should be stored in a Kanban system or be taken out of the Kanban system based on the article's demand. This advice does not consider factors such as the size and weight of the articles. Lastly, the tool also provides ASNL with updated versions of the inventory coverage (Figure 2.7) and usage frequency (Figure A.2) graphs to ensure up-to-date insights into ASNL's inventory performance.

6 Results analysis

This chapter provides an analysis of the performance of the proposed inventory control policies to show their performance in comparison with the current situation at ASNL. In this chapter, we answer the following research question by answering its sub-questions explained in Section 1.4.1.

What is the performance of the proposed inventory control policies and management tool?

Section 6.1 explains the experimental design, including how the proposed inventory control policies described in Chapter 4 are applied. Subsequently, Section 6.2 describes the simulation model that is used to evaluate the performance of the proposed control policies and Section 6.3 describes the performance of the proposed control policies applied to reality and benchmarks this performance against what happened in reality at ASNL during the first three months of 2024. Section 6.4 provides the performance results of the proposed control policies when we alter the initial OHI at the start of the simulation. Subsequently, Section 6.5 provides the performance results in case we alter several decisions we made in Chapter 4 and Section 6.6 examines the impact of modifying the input parameters of the proposed control policies using a sensitivity analysis. This chapter concludes with the answers to the research questions in Section 6.7.

6.1 Experimental design

The inventory control policies described in Chapter 4 are designed to solve ASNL's inventory problem. We must obtain performance metrics to evaluate whether the proposed control policies help to solve ASNL's inventory problem. For this purpose, we designed a simulation model that simulates the inventory levels of a randomly selected article sample of 60 existing articles over the first three months of 2024 using the article's actual usage data and through the simulation model results we obtain the performance metrics for five specific KPIs. Section 6.2 provides a detailed description of the simulation model and the designed KPIs. The simulation results enable performing experiments on the proposed policy performance with which we evaluate the behaviour of the proposed policies under different circumstances. Table 6.1 provides an overview of the performed experiments in this chapter. Note, that in this chapter the term 'experiment' is used as an umbrella term encompassing various scenarios or setting changes. Setting changes entail modifications made to the proposed control policy design and scenarios entail the specific configuration under which the policies are tested.

Experiment 1 entails a comparison between the proposed policies applied to reality and ASNL's reality in the first three months of 2024, to gain insights into the relative performance of the proposed control policies. In the evaluation of the proposed policy performance, we notice that the initial OHI at the start of the simulation majorly impacts the performance results due to the lack of a warm-up period at the start of the simulation. Therefore, Experiment 2 evaluates the proposed policy performance when the simulation starts with different OHI scenarios to determine the expected performance of a steady-state simulation. Experiments 3, 4, and 5 investigate the effects of changing several decisions, such as the selection of control policy per XYZ class or using the Effective Lead Time (ELT). Experiment 4 evaluates the effects of using the EOQ as the replenishment size instead of the order quantities (Q) set by the order quantity rules in Table 4.3 in Section 4.3, as multiple articles show considerable differences between the EOQ and order quantity (Q). Experiment 5 evaluates the impacts of selecting different control policies, regardless of XYZ class, to assess whether the policy selection could be enhanced. Experiment 6 assesses the effects of using the Effective Lead Time (ELT) and whether this method of modelling the lead time yields different results.

The final four experiments are part of the sensitivity analysis. Experiment 6 performs a sensitivity analysis on the target RR to evaluate the impact on proposed policy performance when ASNL desires another RR than 90%. Experiment 7 analyzes the effect of differentiating the bounds for the Triangular distribution with which we model the SLT in the proposed control policies. Silver et al. (2016) state that every reasonable action must be taken to eliminate variability in the SLT and this experiment helps to determine whether taking effort would yield differences in performance. Experiment 8 examines the effects of different holding and ordering cost rates, as the values used for these cost rates are based on expert opinion. This experiment helps to determine whether ASNL must make an effort to precisely determine these cost rate values. Lastly, Experiment 9 evaluates whether different Frozen Period (FP) lengths impact the performance results. The FP length denotes the period in which article demand is 100% certain and a longer FP, which indicates a longer period of certainty, can be crucial in optimizing inventory levels. The subsequent sections within the experimental design provide a detailed explanation of how the proposed control policies are applied to the sample articles.

Number	Experiment	Goal
1	Proposed control policies applied to reality versus reality	Gain insight into the relative performance of the proposed control policies applied to reality against ASNL's reality.
2	Scenario experimentation - Initial OHI differentiation	Evaluate the proposed policy performance under a steady-state simulation.
3	Setting experimentation - Order quantity (Q) versus EOQ	Evaluate the performance impact of using the EOQ instead of the order quantities proposed by the design rules in Chapter 4.
4	Setting experimentation - Class policy selection	Gain insight into whether the design policy selection could be enhanced.
5	Setting experimentation - Effective Lead Time (ELT)	Gain insight into whether using the Effective Lead Time (ELT) yields different results than using the regular Supply Lead Time (SLT).
6	Sensitivity analysis - Target Ready Rate (RR)	Investigate what happens in terms of performance when ASNL desires a different target RR.
7	Sensitivity analysis - Supply Lead Time (SLT) bounds Triangular distribution	Determine whether taking action in eliminating SLT variability is worth the effort.
8	Sensitivity analysis - Holding and ordering cost rates	Determining whether ASNL must make an effort in the precise determination of the holding and ordering cost rate values.
9	Sensitivity analysis - Frozen Period (FP) length	Investigate the effects of creating a longer period on demand certainty.

Table 6.1: Experiment overview

6.1.1 Training data

To determine the new control parameter values, the proposed inventory control policies designed in Chapter 4 must be trained using historical demand data. The historical demand data used to train the control policies contains data from 2022 and 2023. The data from these two years ensures accurate demand representation, encompassing data from after the arrival of the SK 660 assembly line and from the final months and aftermath of the COVID-19 pandemic. The two-year data interval length ensures the inclusion of a sufficient number of data points to model demand accurately.

6.1.2 Classification and article sample

In Chapter 2, we identified 108,484 articles relevant to this research. Approximately 80% of these articles are either part of dead inventory or did not show demand during 2022 and 2023. Therefore, these articles do not require analysis and are excluded from the scope. The Excel tool provides suggestions for handling dead inventory following the options from Silver et al. (2016, p. 370) explained in Section 2.5.2. Thus, about 18,000 remain within the analysis scope for this research, to which we apply the XYZ classification method (as described in Section 4.1). Table 6.2 shows the distribution of the articles per XYZ class. Most articles are part of the X class, and these articles show relatively constant demand patterns. The least articles are part of the Z class, including articles with irregular demand patterns. Some articles from the excluded 80% might have been part of the Z class due to the lack of demand during 2022 and 2023. However, analyzing control policies for these items does not provide relevant insights given ASNL's current situation. Table 6.2 also includes the distribution of the XYZ classes among different inventory storage types (Kanban, pick, partial Kanban and pick, and no inventory) and replenishment strategies (RTO and RTS). Recall that articles not stored in a Kanban system are picked from the warehouse when needed within production. The article distribution shows that most articles are either 'pick' articles or do not have any inventory, regardless of their class. Furthermore, most Kanban-stored articles are part of the X class, aligning with the Kanban guidelines that state Kanban articles should show relatively stable demand patterns. However, 127 Z articles are Kanban articles. These articles are used in the production of the Wasa 300+, which is only produced from January until April. This relatively short production period results in fluctuating demand patterns; hence, these articles are classified as Z articles. Furthermore, some articles are Kanban and Pick articles, as these articles are Kanban articles at one point in the assembly line and Pick articles at another point. Lastly, the distribution between the two replenishment strategies indicates that most articles should be procured using the RTS strategy due to their SLT being longer than the standard FP length.

Class	X	Y	Z	Total
Total	13,129 *(20)*	3,745 *(20)*	1,201 *(20)*	18,075 *(60)*
Kanban	1,795 *(5)*	748 *(5)*	127 *(5)*	2,670 *(15)*
Pick	4,736 *(5)*	1,912 *(5)*	760 *(5)*	7,408 *(15)*
Partial Kanban & Pick	652 *(5)*	320 *(5)*	120 *(5)*	1,092 *(15)*
No inventory	5,946 *(5)*	765 *(5)*	194 *(5)*	6,905 *(15)*
RTO	3,348 *(10)*	1,081 *(10)*	283 *(10)*	4,712 *(30)*
RTS	9,781 *(10)*	2,664 *(10)*	918 *(10)*	13,363 *(30)*

Table 6.2: XYZ article classification and class distribution article sample

To further narrow the experiment article scope, we draw a sample of 60 random articles, with each class containing an equal number of articles in the sample. The italic values in parenthesis in Table 6.2 show the number of articles per class included in the article sample. The sample excludes any E articles as this type of article consists of multiple F articles and relations between E and F articles are not included in the scope of the research, as explained to be a limitation of the proposed policies in Section 4.4.2. So, it is unknown which and how many F articles are needed to produce a specific E article. Optimising the inventory policies for E articles may cause a shift in inventory policies for the related F articles. So, the joint inventory optimisation between E articles and its related F articles is not possible with the proposed control policies and one of the main limitations of the proposed policies. Nevertheless, the policies and the inventory tool can analyse E articles individually.

6.1.3 Supply Lead Time (SLT) and demand during random lead time distributions

Section 4.2.2 explains how we incorporate the SLTs within the inventory control policies using the Triangular distribution. The lower limit (a) of the Triangular distribution is $100\% - x\%$ of the article's SLT denoted in SAP, and the upper limit (b) is $100\% + y\%$ of the SLT. The values of x and y are estimated to be 10% and 30%, respectively (Lindenburg, 2023). Section 4.2.3 describes the guidelines on which RLD distribution to select for each article and Table 6.3 shows the distribution of the RLD distributions among the articles within the sample, which aligns with the nature of inventory and demand patterns at ASNL. The higher number of articles with a Normal RLD distribution reflects ASNL's many articles used regularly in stable quantities with a relatively high mean demand size. These consistent demand patterns result in a Normal RLD distribution, even if the articles do not belong to the X class, which typically indicates stable demand. These articles can still have a Normal distribution when the demand size remains approximately the same every time demand occurs. The high number of articles with a Binomial RLD distribution is also a result of the large part of the article population being regularly used, but in smaller quantities, characteristic of ASNL's HMLV environment. The distribution of RLD distributions may vary with different settings for the lower and upper SLT bounds. Changing these limits alters the mean RLD and its standard deviation, potentially shifting the RLD distribution.

Normal	Gamma	Binomial	Poisson	Negative Binomial	Total
35	2	20	2	1	60

Table 6.3: RLD distributions article sample

6.1.4 Input parameters

To determine the parameter values, several variables are set to a fixed value when applying the proposed policies to reality. Firstly, the holding cost rate (r) is estimated to be 15% for all articles (ten Brinke, 2024), covering both the interest rate on the inventory funds and employee inventory management costs. Secondly, the ordering costs (A) per article are estimated at 5% of an article's value (ten Brinke, 2024). For example, an article valued at € 10 would have an ordering cost of € 0.50. These costs are proportional to the article's value. Both holding and rates are estimated because of a lack of data and are assumed to be the same for all articles, regardless of article characteristics. Note that the holding cost rate and ordering cost rate, separately, can be two different values. For instance, a holding cost rate of 15% indicates that all articles use a holding cost rate of 15%, but next to that the ordering cost rate can be 5% for all articles. Lastly, the target RR is equal to 0.9, ensuring a positive OHI 90% of the time. This RR value is decided upon with the stakeholders of this research.

6.2 Simulation

To validate the effectiveness of the proposed control policies and their parameter values in reducing ASNL's inventory levels and to evaluate their relative performance, we developed a simulation model using Python Spyder which simulates the inventory levels of the sample articles over the first three months of 2024 using the article's actual usage data. This section describes the simulation model and the experiments performed in the remainder of this chapter use the simulation to obtain the performance of the experiment instances.

The simulation model applies the proposed inventory control policies and their control parameter values to the usage data of the sample articles. This simulation has time buckets of one day. So, the simulation checks the inventory levels for each day and decides whether a replenishment must be ordered. The one-day time bucket is chosen as SAP relies on a continuous review system and purchasers make the decisions for replenishment orders daily. Additionally, this time bucket ensures an accurate representation of reality, allowing for the flexibility of articles being ordered or used on any given day. Thus, using a larger time bucket, such as a week or month, would fail to accurately represent reality.

The decision on whether a replenishment must be ordered, depends on the IP. For both selected control policies ((s, Q) and (s, S)), the simulation initiates a replenishment order when the IP drops below the reorder point (s). The replenishment size equals the order quantity (Q) for the (s, Q)-policy and equals $Q = S - IP$) for the (s, S)-policy. The IP depends on the OHI after demand, the pipeline inventory, the previously backordered demand, and the size of a received replenishment. Equation 6.1 provides the formula the simulation uses to determine the IP.

$$IP = \max\{0; OHI_{Start} + Pipeline - Demand_{Backordered} + Received_{Replenishment} \\ - Demand_{Realized}\} \tag{6.1}$$

The simulation model requires input data to perform the calculations and to evaluate the performance of the proposed inventory control policies, the simulation must generate output in terms of KPIs. The input data includes article characteristics, proposed control parameters, the daily article usage data and received replenishments from the first three months of 2024, and the actual inventory levels on January 1, 2024. The simulation generates several KPI values: the 'number of replenishments', the 'average OHI value', the 'number of stockout days', the 'realized RR', and the 'realized FR'. The 'average OHI value' is the summation of the ending OHI on each day, divided by the total number of days (= 90 days) times the article's value. The 'realized RR' is the number of days the ending

OHI is positive, divided by the total number of days, and the 'realized FR' is the summation of the demand directly fulfilled from stock, divided by the total realized demand. To determine the aggregate performance of the proposed control policies, we average the 'realized RR' and 'realized FR' of each SKU. In other words, the aggregated 'realized RR' is the average of all articles separate 'realized RRs' and the aggregated 'realized FR' is the average of all articles separate 'realized FR'. Furthermore, we sum the other KPIs to obtain their aggregate performance. In other words, to obtain, for example, the aggregated 'average OHI value', we sum all articles separate 'average OHI values'. We compare the resulting KPI values to the real inventory performance, as after the simulation of the proposed inventory control policies, the simulation model evaluates the real inventory performance of the first three months of 2024. Appendix E provides the Python Spyder code of the simulation model.

6.2.1 Visualisation - case example

This section provides an example of the simulation for a specific SKU. This SKU is classified as a Y-article and is managed using an (s, Q)-policy, with a Binomial RLD distribution. Its reorder point (s) is 10, its order quantity (Q) is 14, and its SLT is 18 days. Table 6.4 provides the simulation values per day for the first 30 days and Figure 6.1 graphically visualizes these results.

Day	1	2	3	4	5	6	7	8	9	...	22	23	24	25	26	27	28	29	30
OHI start	13	13	10	10	10	5	4	4	1	...	0	0	0	12	12	12	8	7	7
Realized demand	0	-3	0	0	-5	-1	0	-3	-1	...	-1	-1	0	0	0	-4	-1	0	-2
Received replenishment	0	0	0	0	0	0	0	0	0	...	0	0	14	0	0	0	0	0	0
Demand satisfied from stock	0	3	0	0	5	1	0	3	1	...	0	0	0	0	0	4	1	0	2
Demand backordered	0	0	0	0	0	0	0	0	0	...	1	2	0	0	0	0	0	0	0
OHI end	13	10	10	10	5	4	4	1	0	...	0	0	12	12	12	8	7	7	5
Total pipeline	0	0	0	0	14	14	14	14	14	...	14	14	0	0	0	14	14	14	14
IP	13	10	10	10	19	18	18	15	14	...	13	12	12	12	12	22	21	21	19
Placed replenishment	0	0	0	0	14	0	0	0	0	...	0	0	0	0	0	14	0	0	0

Table 6.4: Simulation case example

The simulation for this SKU starts with an OHI of 13 units. During the day, two changes in inventory can occur. These are demand and/or the arrival of replenishments. When demand arises, individual articles are either fulfilled from stock if sufficient inventory is available or backordered if inventory levels are insufficient. For instance, when there is demand for 5 units and the OHI is 3, then 3 units are fulfilled from stock, and the remaining 2 units are backordered. At the end of a day, the simulation updates the OHI by subtracting the occurred demand and the previous backordered demand from the OHI at the start of the day and then adding any received replenishment. To update the IP, the simulation adds the total pipeline to the end OHI. When the IP drops below the reorder point (s), a replenishment order is placed to increase the IP.

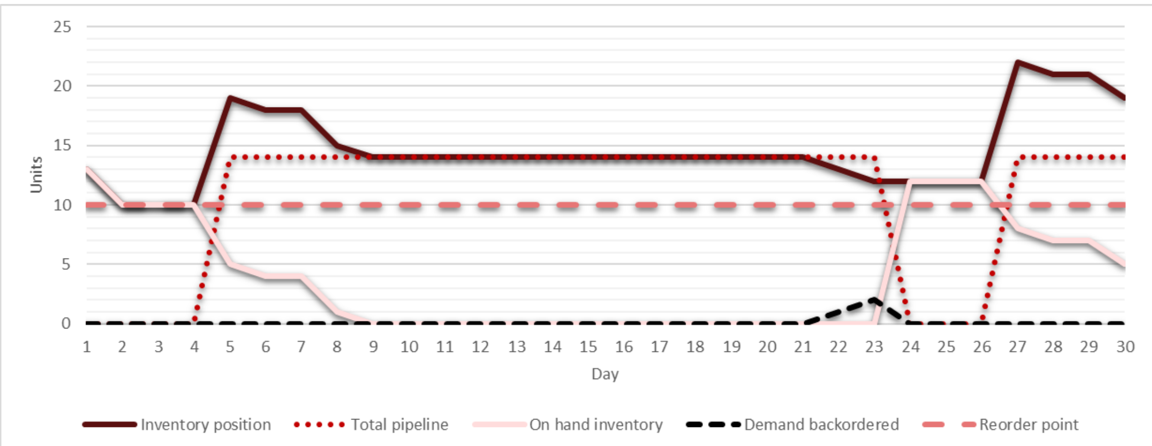


Figure 6.1: Simulation case example

6.2.2 Verification and validation

According to Vrat (2014, p. 144), the last step in developing simulation models is the model validation and analysis of the results. The validation includes verification of the simulation logic, and determining whether the developed simulation model accurately represents reality (Law, 2015, p. 246). This section discusses the verification and validation of the simulation model and the subsequent section analyses the simulation results.

Verification

Verfication, as described by Kleijnen (1995), concerns determining whether the simulation performs as intended. In other words, verification concerns resolving errors in the simulation (Law, 2015, p. 246). Kleijnen (1995) discusses several verification techniques, including tracing and debugging the simulation results. Tracing verifies whether the intermediate simulation results are correct and this can either be done through manual calculations or eyeballing. We thoroughly debugged the simulation by tracing several SKUs to test whether the simulation uses the correct control policies and places replenishment orders of the correct size at the right moment.

Validition

Validity is defined as the extent to which a test measures what we wish to measure (Cooper & Schindler, 2014, p. 257), and validation concerns determining whether the conceptual simulation model is an accurate representation of the system under study (Kleijnen, 1995). It is important to note that validation cannot yield a perfect model, since the perfect model is the real system itself and each model, by definition, is a simplification of reality (Kleijnen, 1995; Law, 2015, p. 247). The best method to establish validity is to input the current inventory control policies and the accompanying parameter values into the simulation and evaluate whether the simulation results resemble the actual system results. Section 2.6.2 explained that the current inventory control policies do not follow clear rules and are mainly based on gut feeling. Therefore, these policies cannot be implemented into the simulation model, making direct comparison with reality impossible.

To obtain a valid simulation model, the simulation model uses the article's usage data over the first three months of 2024, as Kleijnen (1995) recommend that analysts should try to obtain real-world data. Furthermore, the simulation model also provides ASNL's actual inventory performance by using the actual article usage data and the actual received replenishments. The received replenishment data and quantities are validated against the data denoted in SAP.

According to Kleijnen (1995), validity also entails determining whether the model's behaviour agrees with the judgements of experts. Therefore, several simulation aspects have been discussed with internal experts to determine the simulation's validity. The internal stakeholders confirmed the suitability of using the day-sized simulation time buckets, as this matches SAP's continuous review system. Furthermore, the usage data incorporated in the simulation model has been checked with the Logistics and Procurement departments on the accuracy of this data. Lastly, the case example in Section 6.2.1 further enhances the credibility of the simulation model.

6.3 Proposed policies performance

To effectively assess the performance of the proposed control policies, we apply them to the reality of ASNL and compare them to ASNL's real inventory performance over the first three months of 2024. In other words, we take the actual OHI on January 1st, 2024, and the realized article demand during the first three months of 2024 and execute the policies using the simulation model. First, the Excel tool developed in Chapter 5 determines the new control parameter values for the articles in the sample. Table F.1 in Appendix F presents the current parameter values extracted from SAP, the newly updated parameter values according to the proposed policies, and the theoretical monetary impact of these new parameter values. The monetary impact is based on the difference between the current inventory value and the average inventory under the new control policies. Recall that the objective of this research is optimizing the inventory control policies to decrease inventory levels (and thus inventory value) while ensuring sufficient inventory to fulfil demand. The overall monetary impact, which denotes the difference between the current inventory value and the average inventory value under the new control policies, of the article sample amounts to a decrease in inventory value of € 54,499.96 (Table F.1 in Appendix F). This is a decrease of about 45% compared to the overall current inventory value of the article sample. Note that the overall monetary impact is a different performance measure than the 'average OHI value' resulting from the simulation. Several articles have an increase in inventory value, which indicates that the control policies increase the inventory levels to ensure a 90% RR. This is mainly the case for the 'no inventory' articles, as the RR results in higher inventory levels than currently maintained. The 'no inventory' articles are currently not kept in inventory, but based on historical demand the inventory control policies recommend to maintain inventory for these articles. The XYZ article classification in Table 6.2 shows that most 'no inventory' articles are part of the X class and a regularly used. Therefore, maintaining inventory for these articles ensures that demand for these articles can be filled more effectively.

Second, we use the simulation model to evaluate what would have happened if the proposed inventory control policies had been used during the first three months of 2024. The simulation starts with the actual OHI on January 1st, 2024, and loops over each day in the first three months. As explained in Section 6.2, the simulation results in several KPI values. Table 6.5 shows the KPI results for the proposed control policies applied to reality in comparison to the KPI results of what ASNL did in reality. To determine the KPI results for reality the simulation uses the actual OHI on January 1st, 2024, the actual realized demand, and the received replenishments during the first three months of 2024 and calculates the inventory position on each day.

Simulation variable	**Proposed policies applied to reality**	**Reality**
Average OHI value	€ 81,969.27	€ 136,118.12
Realized ready rate	71.13%	87.33%
Realized fill rate	63.18%	87.03%
Number of replenishments	123	36
Number of stockout days	1,577	693

Table 6.5: Proposed policies applied to reality versus reality

Let's first explore the comparison of the KPI results for reality with the proposed policies applied to reality. This comparison shows several notable differences. Firstly, the proposed control policies result in a considerably lower average OHI value, indicating a substantial reduction in inventory compared to reality. Secondly, the proposed policies lead to a higher number of replenishments, as well as a higher number of stockout days. Lastly, the proposed policies lead to a lower realized RR and a lower realized FR. The higher number of replenishments aligns with the objective of reducing inventory while ensuring sufficient inventory to meet demand. Consequently, given the reduction in average inventory levels, the observed increase in stockout days is a logical outcome. Moreover, the realized RR decreases due to the increase in stockout days, as the RR denotes the fraction of time the OHI is positive. Additionally, the realized FR, which denotes the fraction of demand fulfilled directly from inventory, decreases. So, the relations between the different KPI values result in logical outcomes.

The lower realized RR and realized FR indicate that the proposed inventory control policies fulfil less demand from stock than what occurred in reality over the first three months of 2024. Additionally, there is a considerable gap between the target RR (90%) and the realized RR of the proposed policies, where we expect a realized RR close to the target. This gap raises questions about whether the proposed inventory control policies actually optimize ASNL's inventory. However, we see a substantial decrease in inventory value of € 54,499.96 (Table F.1 in Appendix F) when we look at the overall monetary impact. So, the simulation results and the overall impact seem to contradict each other. The difference between these two results is that the overall monetary impact is based on the average inventory values under the new policies, but the simulation model starts with the actual OHI on

January 1st, 2024. When the OHI on January 1st, 2024 is insufficient to cover demand until the next replenishment arrives, demand is backordered. These backorders, due to the low initial OHI, decrease the realized RR and realized FR and as the simulation only simulates three months, there is not enough time to recover from the first performance setback. We visualize this performance setback in Figure 6.2 using the relation between the performance and the initial OHI by looking at the difference between the initial OHI minus the reorder point (s). We call this difference the '$OHI - s$'-difference and a negative difference indicates that the initial OHI lies below the proposed reorder point which means that the initial OHI is not sufficient to cover demand until the next replenishment arrives and demand is backordered. Figure 6.2 shows that when the '$OHI - s$'-difference lies below zero, there is a corresponding drop in realized RR. Figure G.1 in Appendix G shows a similar relation between the '$OHI - s$'-difference and the realized FR.

A way to reduce the impact of the initial OHI is to use a warm-up period at the start of the simulation. Such a warm-up period ensures that the simulation results do not depend on its initial state and that simulation results are measured over a steady state simulation (Robinson, 2007). Given the limited amount of data, it is not possible to establish a warm-up period in our simulation model. Another option to deal with the lack of a warm-up period is to ignore the first points in the results. However, several articles have a SLT closely equal to the simulation length, indicating that the performance does not recover the first backlogs due to the initial OHI within the simulation time frame. Therefore, Section 6.4 investigates the performance of the proposed inventory control policies in case the initial OHI is set to different values to simulate the proposed policy performance in a steady-state simulation.

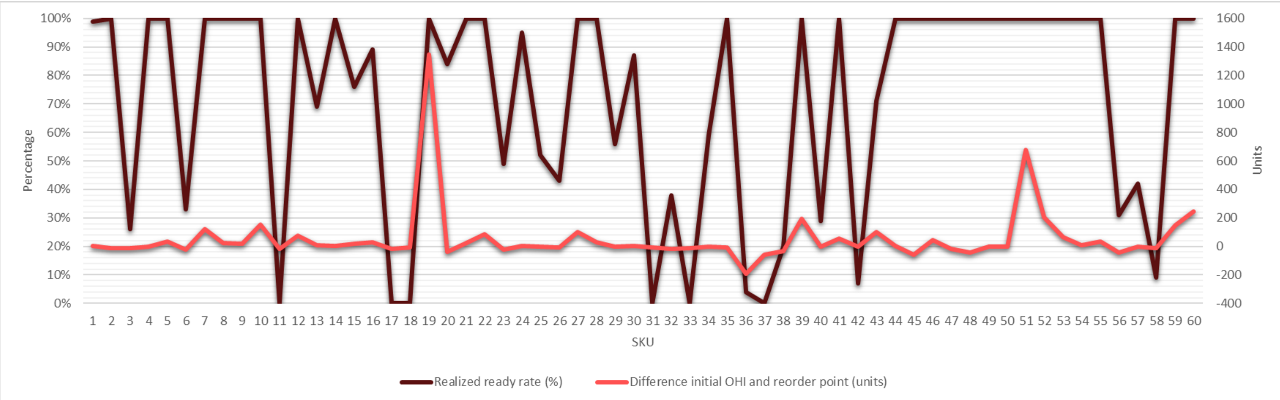


Figure 6.2: Relation realized RR with the difference between initial OHI and proposed reorder point

Examining the proposed control policies in Table F.1 in Appendix F shows that the proposed control policies result in relatively small EOQ values. Given ASNL's MTO-ETO setting and HMLV portfolio, smaller EOQs are logical due to the low volumes of most SKUs. Furthermore, Table F.1 in Appendix F shows that multiple SKUs have a considerable difference between their order quantities (Q), set by the order requirements (Order quantity rules Table 4.3 in Section 4.3), and the EOQ value. For instance, SKU 1 has an order quantity (Q) of 60 units because its MinOQ is 60 units, but this article has an EOQ value of 16 units. We see a notable difference between these two values (Q versus EOQ). Using the EOQ instead of the specified order quantity (Q) within the inventory control policies might result in better inventory levels, as the EOQ is not bound by order requirements. To investigate the impact of using the EOQ instead of the order quantity (Q), set by the order requirements, Section 6.5.1 provides an analysis of the simulation results in case we use the EOQ as the replenishment size.

At the beginning of this section, we stated that the overall monetary impact of the article sample amounts to a decrease in inventory value of € 54,499.96. However, the article population at ASNL is bigger than the selected sample. To determine the impact of the new inventory control policies for the entire article population at ASNL, we developed an Excel VBA code (Algorithm F.1 in Appendix F) to run the Excel tool for all articles. This results in a decrease in inventory value of € 2,034,295.55, which is composed of a € 3,597,387.32 decrease in inventory value and a € 1,563,091.77 increase in inventory value. The overall impact corresponds to a decrease in inventory value of about 19%, compared to ASNL's current total inventory value.

6.4 Scenario experiment - Initial On-Hand Inventory (OHI)

Section 6.3 showed that the simulation results highly depend on the simulation's initial OHI and that using a warm-up period at the start of the simulation is not possible due to the limited amount of data available for the simulation. To evaluate the performance of the proposed inventory control policies in case the initial OHI is set to different levels, we set the initial OHI equal to three values: a minimum value (pessimistic), a maximum value (optimistic), and a value equal to the average of the minimum and maximum value. In the pessimistic scenario, the initial OHI equals the reorder point (s). In the optimistic scenario, we alter the initial OHI to equal the highest possible value according to the respective article's control policy. For the (s, Q)-policy, this corresponds to an initial OHI equal to the order quantity (Q) added to the reorder point (s) (thus: initial OHI = $s + Q$), while for the (s, S)-policy, it equals the order-up-t-level (thus: initial OHI = S). For the average scenario, the initial OHI equals the average of the minimum and maximum values. For the (s, Q)-policy, the initial OHI equals $\frac{s+(s+Q)}{2}$, and for the (s, S)-policy, the initial OHI equals $\frac{s+S}{2}$. We rerun the simulation with these altered initial OHI values to obtain the KPI results for each OHI scenario. Table 6.6 provides these results. Furthermore, we take the average of the three OHI scenario results to obtain what the expected proposed policy performance would be when the inventories enter a steady state. The comparison between the scenarios with different initial OHIs and reality is not an entirely fair comparison as reality starts with the actual OHI on January 1, 2024, and the other scenarios do not. However, due to the lack of current inventory control policies at ASNL, another performance benchmark does not exist. Therefore, we compare the OHI scenarios with the reality, keeping the difference between the scenarios and reality in mind.

Simulation variable	Reality	Pessimistic OHI	Average OHI	Optimistic OHI	Three scenario average
Average OHI value	€ 136,118.12	€ 108,225.16	€ 150,903.96	€ 200,493.40	€ 153,207.50
Realized ready rate	87.33%	80.15%	87.47%	93.63%	87.08%
Realized fill rate	87.03%	68.65%	78.82%	84.17%	77.21%
Number of replenishments	36	137	114	85	122
Number of stockout days	693	1,083	685	349	706
Without SKU 6:					
Average OHI value	€ 110,278.50	€ 40,578.12	€ 61,782.92	€ 89,898.36	€ 64,086.47
Realized ready rate	87.12%	79.81%	87.25%	93.53%	86.86%
Realized fill rate	86.81%	68.12%	78.46%	83.90%	76.83%
Number of replenishments	36	134	112	83	110
Number of stockout days	693	1,083	685	349	706

Table 6.6: Initial OHI scenario experiment results

The performance results of the different OHI scenarios provide several noteworthy insights. The first insight we obtain from the results is that when we start the simulation with the pessimistic OHI, we do not reach the desired target RR. However, the realized RR and realized FR of the pessimistic OHI scenario considerably improved compared to the proposed control policies applied to reality in Section 6.3. When the initial OHI is equal to the average of the pessimistic and optimistic OHI values or equal to the optimistic OHI value, the realized RR and realized FR do not substantially differ from the realized RR and realized FR of reality. This is also visible in the average of the three OHI scenario results.

Table 6.6 shows that the average OHI value for the average OHI and optimistic OHI scenarios lie higher than the average OHI value of reality. Figure 6.3 shows the average OHI value for each separate SKU for the three scenarios and this figure shows one major outlier, SKU 6. SKU 6 is an X item with a relatively long SLT and a relatively high item price. Due to its relatively high item value, increasing the initial OHI results in a substantially higher average OHI value. Table 6.6 also shows what happens to the KPI results when removing SKU 6 from the results. Leaving out SKU

6 does not majorly affect the realized RR, realized FR, number of replenishments, and number of stockout days. However, the average OHI value does decrease and lies below reality's average OHI value for each OHI scenario. Based on these insights, we conclude that the proposed control policies in a steady-state simulation substantially reduce inventory value while reaching similar performance on the service measures compared to reality. Furthermore, we advise ASNL to increase the OHI levels when implementing the new control policies and its parameters to equal at least the average OHI scenario to ensure that the inventories faster reach a steady state so that the performance effects are visible on a shorter time horizon. To ensure a fairer comparison of the proposed policies results of the settings modifications and sensitivity analysis results with reality, we do not use a modified initial OHI level in the subsequent experiments.

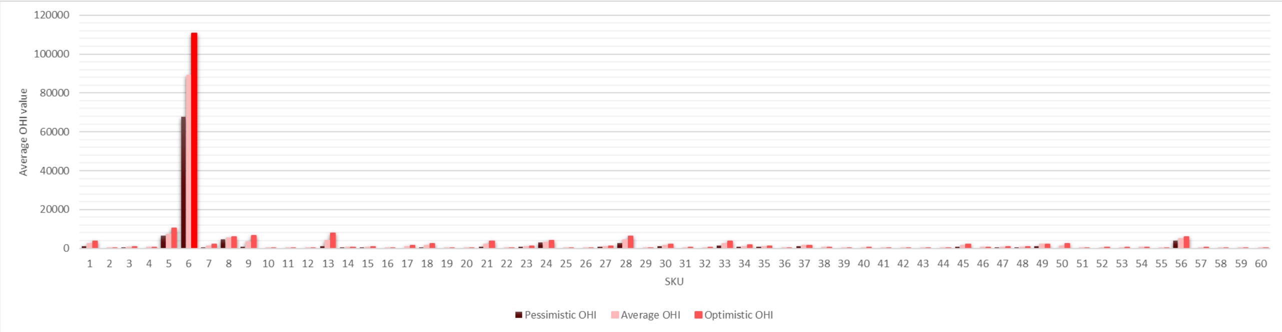


Figure 6.3: Average OHI value for each OHI scenario

6.5 Setting experimentation

Within Chapter 4 several decisions regarding the settings of the control policies were made. For instance, we decided to select specific inventory control policies for each XYZ class and we decided not to use the ELT. To test whether these decisions were correct, this section provides the result analysis of the experiments where we alter several settings. Section 6.5.1 discusses the insights gained from using the article's EOQ as the replenishment size. Subsequently, Section 6.5.2 provides insights into the selection of different control policies, regardless of XYZ class. Lastly, Section 6.5.3 discusses what happens to the control policy performance when we use the ELT instead of the SLT denoted in SAP.

6.5.1 Order quantity (Q) versus Economic Order Quantity (EOQ)

Section 6.3 showed that multiple SKUs have a considerable difference between their order quantities (Q), set by the order requirements (order quantity rules Table 4.3 in Section 4.3), and their EOQ value. Using the EOQ instead of the specified order quantity (Q) within the inventory control policies might result in more optimal inventory levels, as the EOQ is not bound by order requirements. Let's first look at the overall monetary impact when using the EOQ for all articles. We determine this impact similarly to the overall monetary impact described at the end of Section 6.3. When using the EOQ, the overall decrease in total inventory value is € 3,239,710.81, which is composed of a € 4,592,962.83 decrease in inventory value and a € 1,353,252.02 increase in inventory value. The impact of using the EOQ instead of the order requirements-based order quantity (Q) leads to a considerably bigger reduction in inventory value. The monetary impact for the article sample amounts to a decrease in total inventory value of € 71,433.36 (Table F.1 in Appendix F). Recall that the overall monetary impact is a different performance measure than the 'average OHI value' resulting from the simulation.

To further evaluate the performance impact of using the EOQ, we alter the replenishment size to equal the EOQ and run the simulation model. For instance, SKU 1 has an order quantity (Q) of 60 units and an EOQ value of 16 units. Within this experiment, we alter the replenishment size of SKU 1 to equal 16 units. Table 6.7 presents the KPI results for the control policies using the 'regular' order quantity and the EOQ as the replenishment size.

Simulation variable	Proposed policies applied to reality	EOQ
Average OHI value	€ 81,969.27	€ 79,208.79
Realized ready rate	71.13%	70.42%
Realized fill rate	63.18%	62.80%
Number of replenishments	123	166
Number of stockout days	1,577	1,616

Table 6.7: Order quantity (Q) versus EOQ

The KPI results in Table 6.7 do not show considerable differences in the average OHI value, number of stockout days, realized RR, and realized FR. However, the number of replenishments lies substantially higher when using the EOQ as order quantity, indicating a corresponding increase in ordering costs. The lack of considerable KPI differences contradicts the bigger overall monetary decrease of € 3,239,710.81 when using the EOQ. The lack of differences in the simulation results is due to the characteristics, such as item value, of the selected articles within the sample. Figure G.2 in Appendix G shows the average OHI value results for the proposed policies applied to reality and for the EOQ setting. This graph does not show considerable differences in OHI value on individual article level. The only article that shows a reduction in average OHI value bigger than € 500 is SKU 5, with a reduction of about € 1,500. Furthermore, several SKUs show a relatively small reduction in average OHI value. Due to these relatively small reductions, we do not see substantial changes in the overall average OHI value of the article sample. Based on the considerably bigger reduction in article population-wide inventory value when using the EOQ, we advise ASNL to talk to their suppliers about whether their order requirements can be altered to better accommodate ASNL's needs for specific articles so that the overall inventory value can be decreased.

6.5.2 Class policy selection

Section 4.2.1 explains that the (s, Q)-policy is selected for X and Y articles, while for Z articles, we use the (s, S)-policy. While the (s, Q)-policy is less dynamic than the (s, S)-policy because it uses a fixed replenishment size regardless of the IP, the (s, S)-policy is more complex to implement in SAP and requires additional manual effort for the purchasers than the (s, Q)-policy. In this section, we evaluate the performance of selecting a specific control policy regardless of SKU class to assess whether the policy selection in Section 4.2.1 could be enhanced. To obtain the KPI results, we implement either the (s, Q)-policy or the (s, S)-policy for all sample articles, regardless of their respective XYZ class, and rerun the simulation. Table 6.8 provides the simulation KPI results for the proposed policies applied to reality, the (s, Q)-policy setting, and (s, S)-policy setting.

Simulation variable	Proposed policies applied to reality	(s, Q)-policy	(s, S)-policy
Average OHI value	€ 81,969.27	€ 80,863.71	€ 82,526.61
Realized ready rate	71.13%	70.32%	72.68%
Realized fill rate	63.18%	62.62%	64.26%
Number of replenishments	123	130	90
Number of stockout days	1,577	1,621	1,493

Table 6.8: Policy selection scenario results

When we select the (s, Q)-policy for all articles, the average OHI value is slightly lower compared to the proposed policies applied to reality. Conversely, using the (s, S)-policy for all articles results in a slightly higher average OHI value. The minor differences in average OHI value are caused by the article characteristics similar to those we encountered in Section 6.5.1. Furthermore, the number of replenishments is considerably higher with the (s, Q)-policy and the realized RR and FR are higher with the (s, S)-policy. Comparing these results shows that using the (s, S)-policy for all articles, regardless of their respective class, results in more effective fulfilment of demand from stock, less replenishment and thus less ordering costs, against a slightly higher average OHI value. The slightly higher average OHI value is due to the generally bigger replenishment size produced by the (s, S)-

policy. This experiment shows the minor impact of these bigger replenishment sizes. Nonetheless, despite the minor differences between the experiment settings and given that the (s, S)-policy takes more effort, we advise ASNL to implement the proposed policy selection among the XYZ classes.

6.5.3 Effective lead time

In their paper, Hariharan and Zipkin (1995) model the lead time as the difference between the SLT and the DLT, as their analysis shows that DLTs are, in a precise sense, the opposite of SLTs. Recall, that the difference between the SLT and the DLT is defined as the ELT. Section 4.2.2 explained we decided to use the SLT instead of the ELT. However, to validate this decision and to evaluate the impact of using the ELT, this section experiments with the SLT setting. In ASNL's case, the DLT equals the FP length with a standard length of ten weeks (= 47 workdays). Equation 6.2 provides the formula of the ELT as the maximum of either seven days or the SLT minus the FP. The lower bound of the ELT must be seven days, as ASNL's demand planning requires all materials to be delivered at least seven workdays before assembly starts (Section 2.4). To implement the ELT within the proposed inventory control policies and in the developed inventory management tool, only the calculation of the SLT needs to be updated with Equation 6.2. Furthermore, all rules in terms of classification, RLD distributions, and parameter determination remain unchanged.

$$ELT = \max\{SLT - FP; 7\} \tag{6.2}$$

Implementing the ELT effects the selected RLD distributions for each article in the sample, as the SLT becomes the ELT changes the period length over which the $\hat{x}_{RLD}$ and σ_{RLD} are calculated. Table 6.9 shows the differences in the distributions of RLD distributions between the proposed policies and using the ELT setting. The RLD distributions show a lower number of SKUs with a Normal RLD distribution and a higher number of SKUs with a Binomial RLD distribution in the ELT setting. Section 4.2.3 explained that the Binomial distribution is used when the mean RLD demand ($\hat{x}_{RLD}$) is lower than ten units. As the SLT decreases and becomes the ELT, the mean demand size during the SLT decreases as well. Therefore, the Binomial RLD distribution is selected more often over the Normal RLD distribution when using the ELT.

Scenario	**Normal**	**Gamma**	**Binomial**	**Poisson**	**Negative Binomial**	Total
Proposed policies	35	2	20	2	1	60
ELT setting	20	1	33	2	4	60

Table 6.9: RLD distributions article sample base scenario and ELT scenario

After implementing the ELT within the inventory control policies and the developed inventory management tool, the tool provides the updated control parameter values and the overall monetary impact. Table G.1 in Appendix G provides the updated RLD distributions, parameters values, and monetary impact for the sample articles when using the ELT. The overall monetary impact of the article sample amounts to a decrease in inventory value of € 51,166.70, which is a slightly smaller reduction in inventory value than the impact of the proposed control policies without the ELT (decrease of € 54,499.96). Recall that the overall monetary impact is a different performance measure than the 'average OHI value' resulting from the simulation. The next step is to rerun the simulation model with the new control parameter values. Table 6.10 provides the simulation KPI results for reality, the proposed control policies applied to reality, and the ELT setting. Similarly to Section 6.4, Table 6.10 also provides the KPI results when SKU 6 is removed from the selection, as this SKU is an outlier and distorts the performance results.

Simulation variable	Proposed policies applied to reality	Reality	ELT setting
Average OHI value	€ 81,969.27	€ 136,118.12	€ 104,798.37
Realized ready rate	71.13%	87.33%	85.90%
Realized fill rate	63.18%	87.03%	78.92%
Number of replenishments	123	36	87
Number of stockout days	1,577	693	772
Without SKU 6:			
Average OHI value	€ 77,761.00	€ 110,278.53	€ 92,173.54
Realized ready rate	71.78%	87.12%	86.02%
Realized fill rate	63.99%	86.81%	78.89%
Number of replenishments	118	36	84
Number of stockout days	1,516	693	753

Table 6.10: Proposed control policies applied to reality versus ELT setting

The implementation of the ELT results in a performance that lies in between the performance of reality and the proposed control policies and using the ELT considerably reduces the average OHI value, while maintaining a relatively high realized RR and realized FR. The higher realized RR and realized FR are due to the effects of the ELT. In the simulation, the ELT ensures that the time it takes for replenishments to arrive after initiating the replenishment order is shorter. As the simulation only simulates three months, having a shorter lead time until arrival improves the performance of the control policies. Furthermore, the ELT also reduces the effect of the initial OHI at the start of the simulation, as backorders due to the initial OHI and the corresponding drop in performance measures are faster resolved compared to the simulation with the regular SLT because the ELT is shorter than the SLT. This is also visible in that the performance under the ELT setting is similar to the performance of the three OHI scenario average in Section 6.4, except for the average OHI value. The difference in average OHI value makes sense as the ELT setting uses a shorter lead time until the arrival of replenishment, resulting in smaller bounds in the Triangular SLT distribution and less lead time variability. This means that lower inventory levels are sufficient to fulfil demand until the next replenishment arrives.

In Section 6.4, we concluded that SKU 6 results in an average OHI value outlier. Therefore, we removed the performance measures of SKU 6 from the ELT setting performance to evaluate the impact of this outlier. Table 6.10 also shows the ELT setting performance without including the performance of SKU 6. Excluding SKU 6 in the ELT setting does not result in different conclusions, except the drop in average OHI value. This is similar to the conclusions we made in Section 6.4.

As the ELT setting performance is similar to the performance of the three OHI scenario average in Section 6.4, we can use the ELT setting to faster obtain a steady state simulation with the proposed policies without using a warm-up period. However, while using the ELT setting demonstrates that the steady-state inventory performance aligns with ASNL's objectives, SAP uses the regular SLT to generate order triggers at the right moment and of the right size. Therefore, the proposed control policies and their corresponding parameter values must be implemented within SAP to obtain the performance improvements resulting from the analysis in this chapter.

To validate whether the performance effect of the ELT setting does not solely result from the change in RLD distributions, we plug the article's new RLD distributions under the ELT scenario into the proposed policies without using the ELT. This action results in a decrease in inventory value of € 42,796.96. Furthermore, the KPI results are shown below. These results show that solely changing the RLD distributions does not yield the same effect as using the ELT and that other RLD distributions result in worse performance within the proposed inventory control policies.

Average OHI value = € 88,894.25	Number of replenishments = 122	Number of stockout days = 1,587
Realized RR = 70.95%	Realized FR = 62.83%	

To conclude, implementing the ELT in inventory control policies results in simulation results that provide more insights into what the inventory performance is expected to become once the inventories at ASNL enter a steady state. Furthermore, SAP requires the regular SLT and the corresponding control policies and parameter values to generate accurate replenishment triggers. As the implementation of the ELT provides useful insights, we use this setting to perform a sensitivity analysis on the FP length in Section 6.6.4 to investigate how sensitive the performance is to changes in the FP length.

6.6 Sensitivity analysis

To evaluate the robustness of the proposed inventory control policies, we execute a sensitivity analysis in which we modify the input parameters of the proposed policies. These modifications include adjusting the target RR, the SLT bounds of the Triangular distribution, the holding and ordering costs, and the FP length. We compare the changes in performance when executing the modifications to the performance of the proposed control policies applied to reality. The subsequent sections each discuss the input parameter modifications and the results.

6.6.1 Target Ready Rate (RR)

The target RR input parameter of the proposed policies is set to 90% (Section 6.1.4), indicating that an article's OHI must be positive for 90% of the time. This target RR value has been decided by the stakeholders of this research to be an acceptable target. To evaluate what happens when different target RR values are desired, we modify the target RR and execute the sensitivity analysis with six different target RR values: 70%, 75%, 80%, 85%, 95%, and 99%. Table G.2 in Appendix G provides the simulation KPI results for each target RR setting.

Figure 6.4 shows the average OHI value, realized RR, and realized FR for the different target RR settings. Comparing the results of each target RR value provides several noteworthy insights. The most striking observation is that as the target RR increases, the average OHI value increases as well. This relationship is logical since a higher target RR indicates that we want to obtain a larger fraction of time in which the OHI is positive, needing a higher average inventory level. Furthermore, between the target RR values 90% and 95%, we see a substantial increase in the average OHI value, while there are no substantial changes in the realized RR and the realized FR. This increase in the average OHI value indicates that the proposed control policies are most sensitive to the change in target RR from 90% to 95%. Figure G.3 in Appendix G shows the changes in average OHI value for each article for the target RRs of 90% and 95%. Comparing the individual article average OHI values shows that the change from 90% to 95% mainly affects the Y and Z class articles with an RTO replenishment strategy. This makes sense as a higher target RR indicates higher inventory levels and as the Y and Z classes have more irregular demand patterns, we need more inventory to ensure that we cover this irregular demand. Next to that, the RTO replenishment strategy indicates a relatively long SLT which results in higher inventory levels when the desired fraction of time with a positive OHI increases. In other words, due to the long SLT higher inventory levels are needed to both ensure sufficient inventory to meet demand and also ensure that stockouts occur at most 5% (100% − 95%) of the time. At last, another noteworthy observation is the gap between the target RR and the realized RR. As explained in Section 6.3, this gap is due to the initial OHI at the start of the simulation.

As the proposed policy performance is most sensitive to the target RR change from 90% to 95%, while no substantial differences are visible in the realized RR and realized FR, we advise ASNL to maintain a target RR of at most 90%. Furthermore, we advise ASNL to not only consider the inventory value objective and drop the target RR to the lowest possible value but also to take the realized RR and realized FR into account. Figure 6.4 does not show considerable differences in the realized RR and realized FR. However, this may be due to the article characteristics and specific demand patterns of the sample articles. Therefore, we advise ASNL to be cautious when using a different target RR.

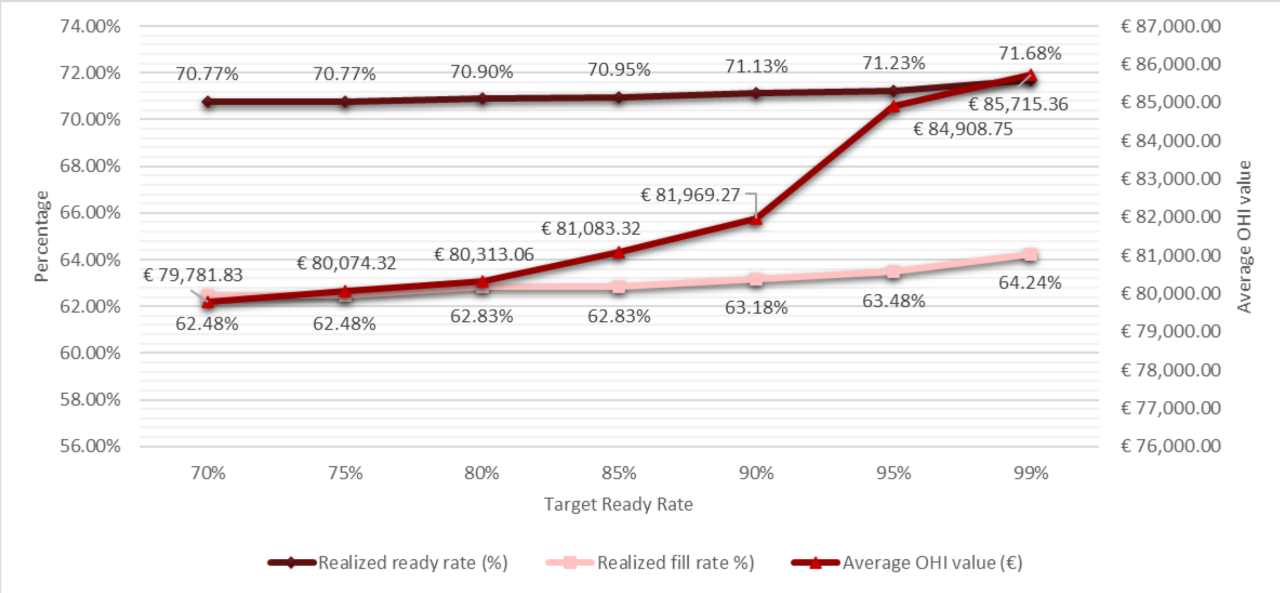


Figure 6.4: Sensitivity analysis on target RR

6.6.2 Supply Lead Time (SLT) bounds Triangular distribution

Recall from Section 6.1.3, that we use the Triangular distribution to model the uncertainty in the SLT. The bounds of the Triangular distribution within the proposed control policies are $a = 100\% - x\%$ and $b = 100\% + y\%$, where $x = 10\%$ and $y = 30\%$ (Lindenburg, 2023). According to Silver et al. (2016, p. 282), every reasonable effort must be made to eliminate variability in the SLT. To investigate whether eliminating variability in the SLT yields substantial performance differences and to evaluate the performance sensitivity, we modify the bounds of the Triangular distribution. We perform the sensitivity analysis with 13 different SLT intervals. Table G.3 in Appendix G provides the KPI results for each SLT bounds interval. Additionally, Figure 6.5 shows the average OHI value, realized RR, and realized FR for each SLT bounds interval.

Comparing the KPI results provides several noteworthy insights. The most striking observation is that the proposed policy performance is more sensitive to changes in the upper bound of the Triangular distribution than to changes in the lower bound of the distribution. The first seven SLT interval settings show that the average OHI value remains relatively stable when we alter the lower bound. As soon as the upper bound changes, we observe a surge in the average OHI value. Throughout the different SLT bound settings the other KPIs remain relatively the same. This indicates the surge in average OHI value is necessary to reach similar service performance when the control parameter values and/or RLD distributions change due to the changes in SLT bounds.

The differentiation of the lower bound while we keep the upper bound on 30%, shows that having a broader SLT interval results in higher average OHI values than when the SLT bounds lie closer together. For instance, the average OHI value for the $(-30\%; 30\%)$ interval is higher than the average OHI value for the smaller $(0\%; 10\%)$ interval. This indicates that a bigger gap between the lower and upper SLT bounds results in the need for higher inventory levels to cope with the big uncertainty range in deliveries. This is logical, as when the range of days in which we can expect a delivery is broad we need more inventory to ensure that we can still cover demand when a delivery arrives, for example, later than anticipated. So, when the gap between the lower and upper SLT bounds is bigger, we need more inventory to ensure the same service levels compared to when the gap is smaller.

The differentiation of the upper bound, while we keep the lower bound at -10%, shows a substantial surge in average OHI value. This is due to the combined sensitivities to the bounds gap and the upper bound. The two types of bounds sensitivities complement each other in these last three SLT bound settings, resulting in the surge in inventory levels.

Based on the insights gained from the different SLT setting results, we advise ASNL to take every reasonable action to eliminate the variation in the upper bound of the SLT. In other words, having a greater uncertainty in terms of suppliers delivering later than the agreed upon SLT, denoted in SAP, has a substantial negative impact on the average OHI value performance of the proposed policies. Furthermore, when the gap between the lower and upper SLT bounds is big, the average OHI value is generally higher than for a smaller bounds gap. Therefore, eliminating uncertainty as much as possible ensures lower inventory levels than when the SLTs are uncertain, supporting the claim from Silver et al. (2016, p. 282) that every reasonable effort must be made to eliminate variability in the SLT. A key component causing lead time variability exists in the shipping time from the supplier to its customer. Choices among transportation modes can affect variability, as well as the average duration, of the SLT (Silver et al., 2016, p. 282). Other options to eliminate SLT variability include, among many options, using Service Level Agreements (SLAs), using VMI, and collaborating with suppliers.

As explained in Section 6.1.3, the Triangular SLT distribution was used to incorporate the SLT variability due to the lack of supplier delivery data. This lack of data presents a future research topic to determine the actual supplier delivery performance per article and a complementary research topic is to investigate how the SLT variability can be eliminated.

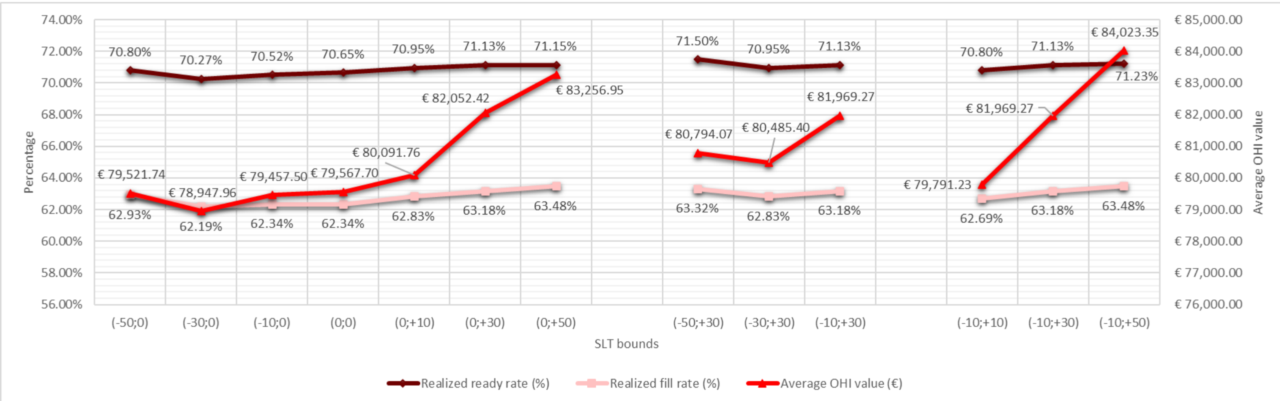


Figure 6.5: Sensitivity analysis on SLT bounds

6.6.3 Holding cost and ordering costs

For the holding and ordering cost rates, we use 15% and 5% of the article's value, respectively. As explained in Section 6.1.4, these values are assumed based on the expertise of the stakeholders. As we are unsure what the actual holding and ordering cost rates are, we perform a sensitivity analysis on these parameters to investigate how sensitive the policies' performance is to changes in these parameters and whether we must try to precisely determine the values for these parameters. First, we perform the sensitivity analysis with nine different holding cost rates. Second, we execute the sensitivity analysis with ten different ordering cost percentages.

Figure 6.6 shows the number of replenishments and the average OHI value for each different holding cost rate. As the holding cost rate increases, the number of replenishments increases and the average OHI value decreases. This relation is logical and can be explained with the EOQ model. When the holding cost increases relative to the ordering costs, the optimal order quantity decreases, resulting in more frequent orders of smaller quantities to minimize the total costs. Therefore, as the holding cost rate increases, we tend to order more frequently to ensure that demand can be met. Note, that the order quantity does not only depend on the EOQ, but also on the supplier order requirements, such as the MinOQ and MaxOQ. Therefore, several articles have an order quantity equal to the EOQ and several articles have an order quantity bound by the order requirements, depending on the specific SAP parameters for the sample articles. Furthermore, we see that the average OHI value remains relatively stable from 10% and above. Additionally, Table G.4 in Appendix G provides the precise KPI results of the different holding cost rate settings. This table shows that next to the average OHI value, the other KPI values also do not show considerable differences for the different holding cost rate settings. Given this relative stability in KPI performance around the holding cost rate of 15% used in the proposed control policies and that 15% is based on stakeholder expertise, we advise ASNL not to make a major effort to determine the precise holding cost rate as it will not result in considerable differences in terms of average OHI value.

Figure 6.7 shows the same KPIs but for each different ordering cost rate. This figure shows the opposite relation that when the ordering costs increase, we tend to order less frequently and hold more inventory to be able to meet demand. This behaviour is consistent with the EOQ model, which indicates that as ordering costs increase relative to holding costs, the optimal order quantity increases. This results in fewer orders of larger quantities, leading to higher average inventory levels. Therefore, an increase in ordering costs results in less frequent replenishments and higher average OHI values. Opposite to the different holding cost rates, the average OHI value shows bigger differences with the different ordering cost rates. This indicates that the proposed policy performance is more sensitive to changes in the ordering cost rate than to changes in the holding cost rate. The bigger sensitivity is due to the fact that several articles have an order quantity equal to the EOQ and several articles have an order quantity bound by the supplier order requirements, depending on the specific SAP parameters for the sample articles. This causes non-linear sensitivities between the holding and ordering cost rates. Additionally, Table G.5 in Appendix G provides the precise KPI results of the different ordering cost rate settings. This table shows that the other KPI values do not show considerable differences for the different holding cost rate settings. As changing the ordering cost rate setting only impacts the average OHI value, while showing stable performance on the other KPIs, we advise ASNL to try to more accurately determine the ordering cost rate.

Lastly, the proposed control policies do not differentiate the holding and ordering cost rate for each article. Instead, Section 4.4.1 explained that the holding and ordering cost rates are the same for all articles, regardless of article characteristics. In reality, this may not be the case, as characteristics like item value, size, and weight can impact both cost rates. For instance, when an article is bigger, its transportation costs may be larger than a smaller article, resulting in higher ordering costs. Differentiating the holding and ordering cost rates for each article presents an area for further research. Chopra and Meindl (2016, p. 282) provide an overview of the cost components in the holding and ordering costs. The first step to determine the holding and ordering cost rates is to perform a detailed cost analysis and convert the overall holding and ordering costs into costs per item. This conversion can be achieved using an Activity-Based Costing approach (Moradi, Ghezel Arsalan, Naimi Sadigh, & Ghalb, 2011). By allocating costs to products and services according to the required activities, this approach ensures a more accurate representation of the actual costs associated with inventory management.

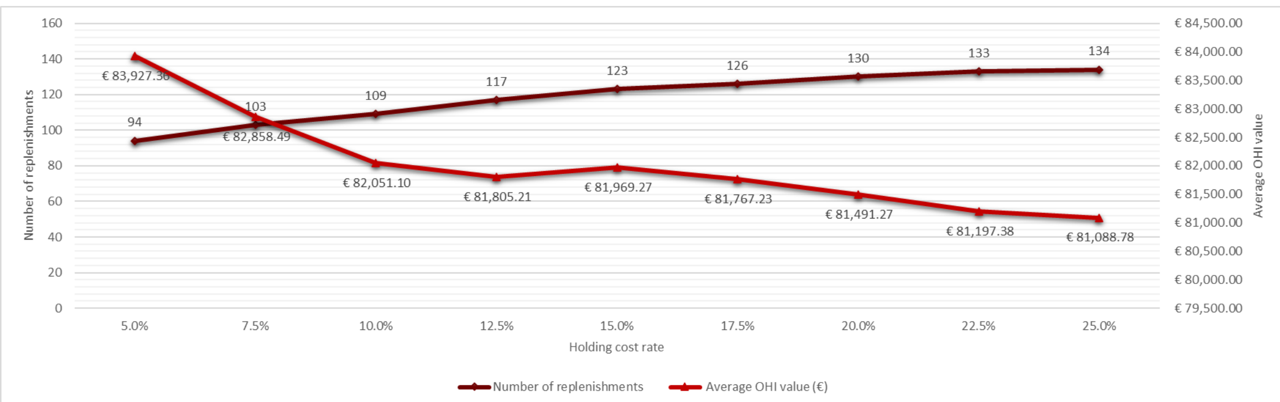


Figure 6.6: Sensitivity analysis on holding cost rate

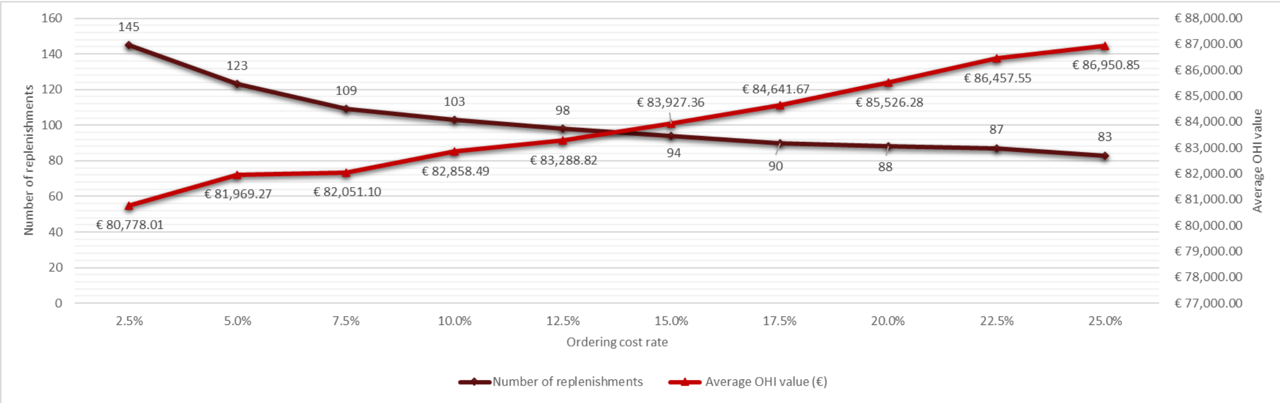


Figure 6.7: Sensitivity analysis on ordering cost rate

6.6.4 Frozen Period (FP) length

Section 6.5.3 explained that using the ELT shows the expected inventory performance in a steady state simulation. The ELT is calculated as the SLT minus the FP length. At ASNL, the standard FP length is ten weeks. However, as explained in Section 2.2, the length of the FP can vary based on the complexity of the specific machine(s) of an order. Furthermore, a longer FP decreases the ELT and might mean that the inventory to cover demand until the next replenishment arrives can be lower. To test whether this hypothesis is correct and to evaluate how sensitive the policies' performance is to different FP length settings, we perform a sensitivity analysis on the FP length using the ELT scenario from Section 6.5.3. Table G.6 in Appendix G provides the KPI results of the different FP lengths.

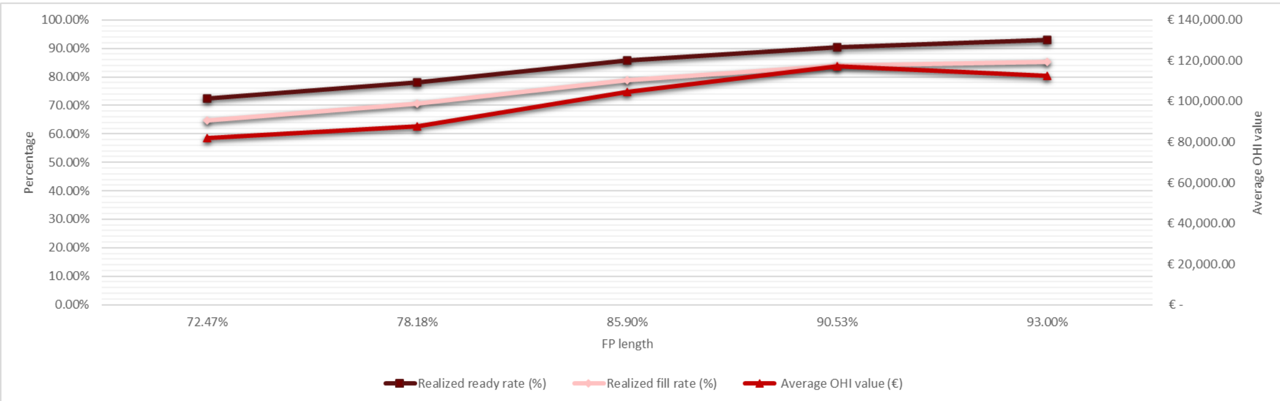


Figure 6.8: Sensitivity on FP length

Figure 6.8 shows the average OHI value, realized RR, and realized FR for the different FP lengths. Contrary to expectations, all three KPI results increase as the FP length increases. This is counter-intuitive because a longer FP decreases the ELT and typically results in lower inventory levels. Decreasing the ELT impacts the determination of the mean and standard deviation of the RLD, affecting the selected RLD distribution. One possible explanation for this observation lies in the shift from Normal to Binomial RLD distributions as the FP length increases, as shown in Table 6.11. Specifically, there is a notable decrease in the number of articles with a Normal RLD distribution and a corresponding increase in the number of articles with a Binomial RLD distribution. This shift suggests that the reduced ELT allows a more accurate determination of control parameter values, enhancing the average OHI value and service (RR and FR) performance. Additionally, the increased accuracy in control parameters leads to more efficient replenishments, resulting in a decrease in the number of replenishments and stockout days. This improved efficiency might explain why, despite the expectation of lower inventory levels with longer FP, the OHI increases. Therefore, the counter-intuitive increase in this KPI, with longer FP lengths, can be attributed to the enhanced efficiency in inventory management resulting from the distribution shift and more accurate parameter determination.

It is important to consider the FP from a customer perspective, as a longer FP means that customers have to wait longer until their orders start production. As explained in Section 1.2, the disadvantage of MTO-ETO is that it usually results in long customer lead times (Vidyarthi et al., 2009). since the RR performance with a FP length of ten weeks lies close to the target RR, we advise ASNL not to alter the FP length.

FP length	**1**	**5**	**10**	**15**	**20**
Normal	33	26	20	12	9
Binomial	22	29	33	38	40

Table 6.11: RLD distribution for different FP lengths

6.7 Conclusions

In this chapter, we analyzed the performance of the proposed inventory control policies by answering the research question *'What is the performance of the proposed inventory control policies and management tool?'* and its sub-questions. The experimental design explains the experiments, the motivation behind the experiments, and the application of the proposed inventory control policies to the sample articles. We performed in total nine experiments of which one compares the performance of the proposed policies with reality, one experiment with different initial OHI scenarios, three experiments with setting changes, and four experiments to test the performance sensitivity. To obtain the performance of the proposed policies, we developed a simulation model in Python Spyder. The simulation simulates demand daily and determines whether a replenishment order must be placed based on the IP on a specific day using the actual demand data from the first three months of 2024. The proposed policy performance is expressed using several KPIs, among which the number of replenishments, average OHI value, number of stockout days, realized RR, and realized FR. This section provides a summary of the key findings and recommendations from each experiment:

1. Proposed policies applied to reality compared to reality: The overall monetary impact of the entire article population amounts to a decrease in total inventory value of € 2,034,295.55, which is a decrease of about 19%, and to a decrease of € 54,499.96 for the article sample, which is a decrease of about 45% compared to the current sample inventory value. The simulation results show a substantial decrease in the average OHI value, but also a decrease in realized RR and realized FR, mainly due to the initial OHI leading to backorders at the start of the simulation. A warm-up period could mitigate this issue, but given the limited data available, this is not possible.

2. Initial OHI scenario: The three initial OHI scenarios (pessimistic, average, and optimistic) show that the pessimistic OHI fails to achieve the desired target RR, but shows a considerable improvement compared to the proposed policies applied to reality. Removing outlier SKU 6 shows no substantial differences in all KPIs, except the average OHI value which substantially decreases. We conclude that a steady state performance considerably improves the ASNL's inventory performance in terms of reduced inventory levels while reaching a high service performance. We recommend ASNL to increase the OHI levels when implementing the new control policies and their parameters to at least match the average OHI scenario to catalyze the process of reaching a steady state, allowing the performance effects to become visible within a shorter time frame.

3. Order quantity (Q) versus EOQ: Using the EOQ results in an overall decrease in inventory value is € 3,239,710.81, which is a considerably bigger reduction than the inventory decrease when using the order quantity (Q). The simulation results do not show considerable differences in KPIs, except that the number of replenishments lies higher. Nonetheless, we advise ASNL to talk to their suppliers about whether their order requirements can be altered to better accommodate ASNL's needs for specific articles so that the overall inventory value can be decreased.

4. Class policy selection: Using the (s, S)-policy results in a slightly higher average OHI value and more effective fulfilment of demand from stock due to a bigger replenishment size produced by this policy. This experiment shows the minor impact of these bigger replenishment sizes and that the value of using the XYZ classes is small. However, this minor impact may be due to the specific characteristics of the sample articles. Nonetheless, based on the insights gained from this experiment, we advise ASNL to implement the proposed policy selection among the XYZ classes.

5. ELT implementation: Implementing the ELT provides more insights into the expected policy performance once the simulation enters a steady state, which yields similar service performance, compared to reality, with a lower average OHI value. This means that lower inventory levels are sufficient to fulfil demand until the next replenishment arrives. However, implementing the ELT in SAP is not possible due to SAP's configuration. Therefore, the ELT implementation only yields insights into the expected steady-state performance.

6. Target RR: As the target RR increases, the average OHI value increases while the service performance remains relatively the same. The proposed policy performance is most sensitive to the target RR change from 90% to 95%. We advise ASNL to maintain a target RR of at most 90% and to not only consider the inventory value but also consider the service performance.

7. SLT bounds: The proposed policy performance is most sensitive to change in the SLT upper bound. Furthermore, when the gap between the lower and upper SLT bounds is big, the average OHI value is generally higher than for a smaller bounds gap. Therefore, eliminating uncertainty as much as possible ensures generally lower inventory levels and we advise ASNL to take every reasonable action to eliminate the variation in SLT. Options to eliminate SLT variability include looking at transportation mode options, using Service Level Agreement (SLA), using Vendor Managed Inventory (VMI), and collaborating with suppliers.

8. Holding and order cost rates: The proposed policy performance is relatively stable around the 15% holding cost rate. Given this stability and that this rate is based on expert opinions, we advise ASNL not to make a major effort to determine the precise holding cost rate as it will not result in considerable differences in average OHI value. The proposed policy performance is more sensitive to changes in the ordering cost rate due to the fact that several articles have an order quantity equal to the EOQ and several articles have an order quantity bound by the supplier order requirements, depending on the specific SAP parameters for the sample articles. This causes non-linear sensitivities between the holding and ordering cost rates. Therefore, we advise ASNL to determine the ordering cost rate more accurately. The precise determination of the ordering cost rate (and holding cost rate) starts with a thorough data analysis and can use an Activity-Based Costing approach in which costs are allocated to products and services according to the activities required, ensuring a more accurate representation of the actual inventory management costs.

9. FP length: The FP length sensitivity analysis greatly affects the selected RLD distributions per article as more articles receive the Binomial RLD distribution with a longer FP, indicating a more accurate determination of control parameter values, enhancing the average OHI value and service (RR and FR) performance. On the other hand, a longer FP poses a disadvantage from a customer perspective. We advise ASNL to keep using a FP of ten weeks.

To conclude, the proposed control policies can substantially reduce ASNL's inventory while reaching high service levels, as shown by the steady-state simulation and the overall monetary impact of the control policies. However, the proposed inventory control policies do not fully solve the action problem and reach the norm of about € 5 to € 6 million. The problem identification identified multiple core problems causing the action problem and this research solves one of these core problems. The remaining core problems are still to be solved to some extent. Therefore, this research cannot solve the entire action problem.

7 Implementation

This seventh chapter describes the implementation and maintenance of the proposed inventory control policies and management tool. In this chapter, we answer the following research question by answering its sub-questions explained in Section 1.4.1.

How can the proposed inventory control policies and management tool be successfully implemented and maintained at Aebi Schmidt Nederland B.V.?

Section 7.1 describes change management, providing insights into the topic to ensure a structured formulation of the implementation plan. Subsequently, Sections 7.2 and 7.3 detail the guiding coalition of the implementation project and the implementation project timeline, respectively. Section 7.4 describes the overall maintenance of the tool and the potential challenges users might face during updates and when handling larger datasets. This chapter concludes with the answers to the research questions in Section 7.5.

7.1 Change management

To formulate an implementation plan for the developed inventory control policies, the inventory management tool, and the knowledge gained from the results, a comprehensive understanding of change management is essential. This knowledge ensures the effective integration of the research outcomes into the current processes at ASNL, allowing them to fulfil their intended purpose. Change management is defined as 'the continuous process of consistently renewing an organization's direction, structure, and capabilities to meet the evolving needs of both internal and external customers' (Todnem By, 2005). Despite the significance of change management, a widely acknowledged fact within research is that numerous change initiatives fail to achieve their intended outcomes and do not result in sustained change (Choi, 2011). More specifically, the fact is that about 70% of all change initiatives fail (Nohria & Beer, 2000). One primary cause is that in their eagerness to change, managers become entangled in initiatives and lose their focus (Nohria & Beer, 2000). Moreover, many change leaders underestimate the pivotal role of individuals within the change process (Choi, 2011). Kotter's (1996) 'Eight-Stage process' is, among many approaches, a well-known approach for organizational change, enhancing the likelihood of successful change by establishing a good understanding of the flow of change and the pitfalls associated with each stage (Kotter & Cohen, 2002). The eight stages of Kotter (1996) are:

1. Establish a sense of urgency
2. Forming a powerful guiding coalition
3. Develop a vision
4. Communicate the vision
5. Empower others to act on the vision
6. Plan for and create short-term wins
7. Consolidate improvements and produce more change
8. Institutionalize new approaches

Amid these stages, it is not uncommon for managers to underestimate the challenges of driving individuals out of their comfort zones (Kotter, 1996). During the change process, managers may be met with resistance from employees. Effective communication, highlighted as a key success factor, plays a crucial role in mitigating resistance and resolving conflicts (Lauer, 2021). Therefore, employee involvement is essential in the change process. The next section provides an overview of the guiding coalition of the implementation project.

7.2 Guiding coalition

To effectively implement the developed inventory control policies, the inventory management tool, and the knowledge gained from the results, we must establish a guiding coalition. We specifically establish a guiding coalition to ensure that the implementation process is not isolated or driven by one individual. Instead, the guiding coalition represents a diverse group of stakeholders who can contribute their expertise, perspective, and resources to the implementation project and this fosters a sense of ownership and commitment which increases the likelihood of successful implementation. The guiding coalition mainly comprises the stakeholders of this research. Nevertheless, we divide more detailed roles among the project members. Table 7.1 provides an overview of the members involved in the implementation process and their respective roles.

Department	Project member	Project role
Continuous Improvement	Continuous improvement engineer	Project leader
Management	Plant manager	Strategic oversight & alignment
Procurement	Procurement manager Operational buyer	Strategic procurement alignment Implementation & operational compliance
Logistics	Logistics manager Material specialist	Logistics alignment Inventory accuracy & operational support
Production planning	Planner	Production planning & forecasting oversight
Finance	Financial controller	Financial & KPI oversight
IT	Internal SAP consultant	SAP support

Table 7.1: Implementation guiding coalition

The Continuous Improvement Engineer assumes leadership of the coalition, facilitates communication and collaboration among project members to ensure seamless integration of the change initiative, and is responsible for the tool management and its maintenance. Even though this research focuses on a purchasing problem, a Continuous Improvement Engineer is best suited within ASNL to assume leadership. Within ASNL, Continuous Improvement Engineers lead all optimization projects. Therefore, their expertise in identifying inefficiencies and driving ongoing improvement is crucial for successful implementation. Furthermore, this implementation project extends beyond the bounds of one department alone as it involves multiple facets, including procurement, operations, logistics, and financial management. As Continuous Improvement Engineers are involved in all of ASNL's improvement projects, they have the knowledge and capabilities to ensure a holistic approach across departments. The Plant Manager ensures alignment of the change initiative with the overall strategic objectives of ASNL and fosters interdepartmental collaboration and resource allocation. The Procurement Manager oversees that the procurement strategies align with the new control policies and coordinates with suppliers to ensure supply chain alignment. The Operational Buyer is responsible for implementing the new procurement procedures and ensuring operational compliance with these new procedures.

The Logistics Manager aligns the logistics strategies with the new inventory management principles, manages challenges that may arise from changes in inventory levels and procurement procedures, and coordinates with the Material Specialist and Operational Buyer to ensure smooth material flows through the manufacturing facility. The Material Specialist ensures inventory data accuracy and contributes to operation decision-making regarding new inventory levels and procurement procedures. The Planner ensures that the inventory management strategies align with the production forecasts and monitors the impact of the inventory policies on the production planning.

The Financial Controller and the Internal SAP Consultant have supporting roles within the guiding coalition. The Financial Controller tracks the financial impact of the change initiative and monitors the KPIs to identify optimization areas. The Internal SAP Consultant provides SAP support for implementing the new inventory control policies.

7.3 Implementation timeline

This section outlines the overall implementation timeline, depicted in the Gantt chart in Figure 7.1, using the insights gained on change management in Section 7.1. Following Kotter's (1996) eight stages, the implementation process starts with creating a sense of urgency. The NWC project commands a substantial sense of urgency within both ASG and ASNL. Given the close relationship between this research project and the NWC project, we conclude that the sense of urgency to implement the outcomes of this research is sufficiently established. The second step entails forming the guiding coalition, comprising the earlier identified employees in Section 7.2, who will meet biweekly to discuss the progress and arisen challenges. As highlighted by Kotter and Cohen (2002, p. 57), a well-defined meeting structure ensures trust and minimizes frustration among team members. This entails focussing on one topic per meeting, ensuring that tasks are finished before the meeting, ensuring that the next steps are clear, and appointing a credible leader.

The subsequent two steps are developing and communicating a transformation vision. Every change initiative must have a vision for the future that is easy to communicate, goes beyond the number from five-year plans, clarifies the organization's intended direction, and appeals to employees, customers, and stakeholders. The key principle for communicating the vision involves using every available communication channel, especially those currently wasted on nonessential information. To a certain extent, the guiding coalition enables others to act by simply effectively communicating the new direction. Nonetheless, empowering others to act also requires the removal of obstacles (Kotter, 1996). The first five stages are part of the pre-pilot phase visible in Figure 7.1, which has an expected duration of one month.

Following Kotter's (1996) first five stages, the practical implementation of the control policies and inventory management tool in practice starts. Before full-scale implementation, a pilot with a limited selection of articles is conducted to assess the efficiency of the proposed control policies and the inventory tool. The pilot starts with an SAP testing phase in the SAP testing environment to evaluate the impact of parameter changes on procurement requests. This phase, crucial due to the limited SAP knowledge at ASNL, involves the Operational Buyer and the Continuous Improvement engineer with the support of the Internal SAP Consultant and takes about one month. Furthermore, the testing phase occurs in the same month as the pre-pilot phase, but the pre-pilot phase precedes the pilot testing phase. After the testing phase, the pilot proceeds with policy implementation, managed by the Operational Buyer and the Continuous Improvement engineer, and data collection on performance metrics, managed by the Planner and Material Specialist. The collected data includes KPIs, like inventory levels, inventory turnover, and stockout occurrences for the selected articles. Furthermore, the KPIs used as performance measures of the simulation model explained in Section 6.2 can be used. The guiding coalition determines the selection size and specific articles. The data collection serves to quantify the impact of the implemented decisions and how well the implemented changes align with the intended outcomes. Next to that, data collection supports continuously monitoring performance metrics and identifying areas for improvement, ensuring responsiveness to evolving operational needs. After three months, the pilot is evaluated based on collected data. If the pilot successfully reduces the inventory values of the pilot articles without major stockout occasions or disruptions to operations, it can be deemed a success. Subsequently, the control policies are gradually implemented for all articles over the course of three months. However, if the pilot is unsuccessful, i.e. not reducing inventory levels or if it causes major stockout occasions and disrupts operations, the project team returns to the testing phase to analyze the issues.

After the initial policy implementation, the control parameters for all articles are iteratively updated based on new usage and inventory data every three months. As the tool also indicates whether articles are part of dead inventory, we recommend checking for and disposing of dead inventory every three months with the parameter updates. Furthermore, complementary projects are initiated to address user feedback and eliminate the inventory policies' limitations mentioned in Section 4.4.2. Additionally, it is possible to research whether the Excel tool can be incorporated within SAP's functionalities or whether SAP can update the source data in Excel automatically. As these complementary projects are new change initiatives, each project needs to go through Kotter's (1996) eight stages on its own.

Finally, the proposed inventory optimization approach and knowledge gained are implemented at other ASG manufacturing locations, institutionalizing the change initiative within the entirety of ASG. Each location forms its project team, including implementation experts from ASNL. This ensures that the newly transformed processes do not differ between different locations. A prerequisite for a successful implementation process at other ASG locations is the comprehensive documentation of the implementation process at ASNL. Figure 7.1 shows that the complementary projects and the ASG wide implementation conclude 18 months after the implementation starts. However, since these projects are separate change initiatives, they need to go through Kotter's (1996) eight stages individually, which may require a longer time horizon than the 18-month period. Considering the NWC project as an ASG wide initiative and the substantial decrease in total inventory value resulting from the results analysis in Chapter 6, implementing the proposed inventory optimization approach and knowledge gained is expected to result in a substantial impact ASG wide.

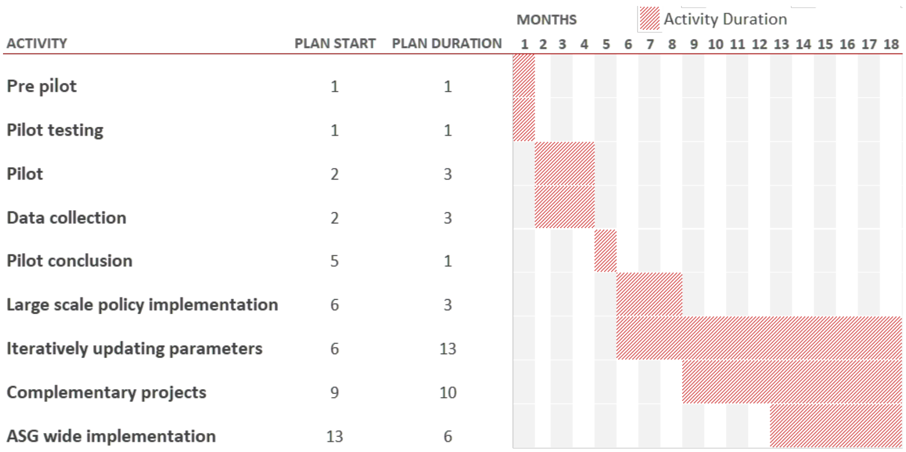


Figure 7.1: Implementation timeline

At the moment of finalising this research, the first steps to implement the proposed inventory optimization approach and knowledge gained have been taken. We are currently waiting for the decision of higher ASG management on whether to start with the pilot implementation for a selection of 15 articles. This shows ASG's urgency to implement measures to reduce its inventories.

7.4 Tool maintenance

This section describes the tool maintenance, a separate key part of the implementation plan to ensure to tool's sustained functionality over time. The Excel tool design focuses on user-friendliness and compatibility with ASNL's existing IT infrastructure. This approach emphasizes the importance of tool design that fits into existing workflows, minimizes the learning curve and leverages familiar platforms to ensure easy tool maintenance. This approach coincides with the stakeholder requirements discussed in Section 5.1. The tool's design allows for real-time data integration of source data (article characteristics, usage, and inventory) to ensure accurate results. However, the integration of real-time data relies on manual SAP data exports to Excel. A complementary project possibility involves the feasibility of establishing an automatic connection between Excel and SAP. Regardless of the automatic connection, one of the maintenance challenges regards changes/updates in the technological ecosystem of both systems, which could disrupt functionality. Mitigating these risks involves regular updates and testing to ensure compatibility with external systems.

As explained in Section 5.2, the search ranges within the tool are set to a larger value than the current size of the source data. This ensures that the tool can handle larger quantities of source data, such as newly added articles, without the need for an update. When the source data reaches the range limits, the tool must be updated or obsolete data should be removed. We provided an extensive internal tool manual that provides a step-by-step approach that explains how to deal with this situation when it arises. The second major maintenance challenge includes the scalability and computational constraints of the tool. As the size of data can grow rapidly, Excel's computational constraints are quickly reached. Handling large datasets requires computational effort, affecting performance and decreasing the tool's responsiveness. Therefore, planning for scalability and preparing for the computational demand of growing datasets are crucial for maintaining the tool's performance. A suggestion to plan for scalability and prepare for growing datasets is to explore alternative platforms. This could involve migrating the Excel tool to a Database Management System (DBMS) or a specialized inventory management software that offers better scalability and performance. Examples of specialized inventory management software are Slimstock's Slim4 or the aforementioned (Section 1.3.3) SAP IBP software. Given ASG's impending transition towards SAP HANA, which includes the IBP software, SAP's IBP software would be the most straightforward software option. However, due to the lack of knowledge regarding SAP at ASNL, we advise ASNL to extensively research whether this software matches the intended purpose before transitioning to this software package. Complementary, we advise ASNL to research whether other software platforms may be a better fit than SAP's IBP. This area presents a potential future research topic.

7.5 Conclusions

In this chapter, we developed an implementation and maintenance plan by answering the following research question '*How can the proposed inventory control policies and management tool be successfully implemented and maintained at Aebi Schmidt Nederland B.V.?*' and its sub-questions. By gaining insights and Kotter's (1996) 'Eight-Stage process', we established a guiding coalition comprising diverse stakeholders, each contributing their expertise, perspective, and resources, to drive the implementation project collaboratively. Table 7.1 provides an overview of the role division within the guiding coalition, with the Continuous Improvement Engineer leading the coalition due to their expertise in identifying inefficiencies and driving ongoing improvement within ASNL.

Following Kotter's (1996) eight stages, we developed the implementation plan. The NWC project commands a substantial sense of urgency within both ASG and ASNL. We initiated the practical implementation of the control policies and inventory management tool with a pilot phase involving a limited selection of articles. In case the pilot successfully reduces the inventory values of the pilot articles without major stockout occasions and disruptions to operations, the pilot can be deemed a success and the control policies are gradually implemented for all articles. Subsequently, the control parameters for all articles are iteratively updated based on new usage and inventory data every three months. Additionally, we initiate complementary projects to address user feedback and eliminate the inventory policies' limitations mentioned in Section 4.4.2. Finally, the proposed inventory optimization approach and knowledge gained are extended to other ASG manufacturing locations, ensuring institutionalization of the change initiative. As the NWC project is an ASG wide project and given the major decrease in total inventory value resulting from the results analysis in Chapter 6, implementing the proposed inventory optimization approach and knowledge gained is expected to result in a substantial impact ASG wide. The first steps to implement the proposed inventory optimization approach and knowledge gained have been taken at the moment of finalising this research.

Lastly, we identified potential maintenance challenges. Firstly, changes/updates in the technological ecosystem of both Excel and SAP may cause the tool to stop functioning properly, needing regular updates and testing to ensure compatibility. Secondly, the scalability and computational constraints of the tool pose challenges. A suggestion to plan for scalability and prepare for growing datasets is to explore alternative platforms, such as a DBMS, Slimstock's Slim4 or SAP's IBP software. The latter is the most straightforward software option. However, due to the lack of knowledge regarding SAP at ASNL, we advise ASNL to extensively research whether this software matches the intended purpose before transitioning to this software package.

8 Conclusions and recommendations

Within this thesis, new inventory control policies have been designed and a prototype Microsoft Excel inventory management tool has been developed. Using the insights gained from performing a context analysis and literature study, the control policies were designed to be suitable to ASNL's situation. The performance of these control policies was tested using a simulation model and several modifications in experiments and a sensitivity analysis were executed to evaluate the effects of these modifications on the performance of the control policies. Lastly, an implementation plan was written. This final chapter answers the following research question and its sub-questions.

What conclusions and recommendations can be drawn from the research at Aebi Schmidt Nederland B.V.?

Section 8.1 provides an overview of the conclusions. Section 8.2 lists the recommendations for ASNL and Section 8.3 explains the limitations of this research and outline potential future research topics. Finally, Section 8.4 provides the academic and practical contributions of this research.

8.1 Conclusions

This research solves the core problem 'ASNL does not have clear inventory control policies for the procurement of materials'. The analysis of ASNL's current situation showed unstructured ordering policies, that a small share (20%) of SKUs accounts for the majority of inventory value (87%) and that 63% of the total inventory value has an inventory coverage longer than two months. The literature review provided knowledge to design the proposed inventory control policies. Based on this knowledge, we implemented the XYZ classification, the Triangular SLT distribution, and the Normal, Gamma, Binomial, Poisson, and (Generalized) Negative Binomial RLD distributions in the proposed control policies. Furthermore, SAP allows for the continuous review of ASNL's inventories and therefore continuous review policies are used. The control parameters of the proposed policies are calculated using their respective formulas and the historical article usage from 2022 and 2023.

The developed simulation model helps to determine the performance of the proposed policies in several experiments. Comparing the proposed policy performance with ASNL's actual inventory performance shows that proposed policies yield substantially lower inventory levels, but also lower service performance. This lower service performance is due to the initial OHI at the start of the simulation and the lack of a warm-up period. Using different initial OHI values shows that a steady-state simulation results in a reduction of inventory levels while maintaining high service levels. This conclusion is supported by the ELT implementation results. Implementing the ELT provides more insights into the expected policy performance once we have a steady-state simulation. The steady-state simulation yields similar service levels compared to ASNL's reality while maintaining a lower average inventory. This shows that the proposed policies in a steady-state simulation comply with the objective of reducing inventories while ensuring sufficient inventory for production.

A sensitivity analysis tests the robustness of the proposed control policies. As expected, having a higher target RR results in higher average inventory levels but as the different target RRs do not considerably change the service performance, we recommend ASNL to maintain a RR of 90%. The sensitivity analysis on the SLT bounds shows that performance is highly sensitive to changes in the upper bound of the Triangular distribution interval and to large gaps between the lower and upper bounds. Therefore, eliminating SLT variability has a substantial impact on the inventory levels.

After this research, we conclude that we solved the core problem 'ASNL does not have clear inventory control policies for the procurement of materials' and partially solved the action problem 'The inventory of materials within the production facility is structurally too high'. This research did not fully reduce the inventory value to the norm of € 5 to € 6 million, as it solves one of the core problems causing the action problem. We formulated an implementation plan to bridge the gap between the core problem and the action problem. Based on this research, we conclude the following for ASNL:

- Using the proposed inventory control policies and the prototype inventory management tool, we can determine the new control parameters for ASNL's articles. In a steady-state simulation, the overall inventory value is reduced while ensuring sufficient inventory for production. The overall monetary impact of the proposed policies is a reduction in total inventory value of € 2,034,295.55, which is a decrease of about 19%. Implementing the proposed control policies results in not only a reduction of inventory value but also an increase in inventory value as some articles need to maintain higher inventory levels, compared to the current inventory levels, to ensure sufficient inventory to fulfil demand, which causes the inventory values to increase. The proposed policies do not fully solve the action problem and reach the norm of about € 5 to € 6 million, as the € 2 million reduction does not decrease the € 12 million to the norm.
- When implementing the proposed control policies and the newly determined parameter values, ASNL should increase their OHI levels to equal the average OHI under the new policies. This adjustment helps to stabilize the inventory more quickly.
- Using the ELT approach by Hariharan and Zipkin (1995) provides insights into the steady-state performance but practical implementation in SAP is not possible due to SAP's SLT configuration.
- Eliminating SLT variability substantially reduces inventory levels, supporting the statement of Silver et al. (2016, p. 282) that every reasonable effort should be made to eliminate SLT variability. To achieve this, ASNL should consider options such as exploring different transportation modes, implementing SLAs, adopting VMI, and enhancing collaboration with suppliers.
- To implement the proposed control policies, ASNL can use the proposed implementation plan explained in Section 7.3.

8.2 Recommendations

The insights gained from the execution of this research provide ASNL with several recommendations. This section lists these recommendations.

1. Implement the proposed inventory control policies using the proposed implementation plan and regularly review and update the inventory parameters.

The proposed inventory control policies should be implemented in SAP using the proposed implementation plan to reduce the total inventory value. Additionally, removing dead inventory, which refers to inventory that has not been used in at least two years, will further decrease on-shelf inventory and reduce interest costs for non-moving articles. We recommend checking for and disposing of dead inventory every three months together with the iterative updating of the parameter values, as the inventory management tool can identify dead inventory.

2. Ensure more data-driven decision-making by implementing and tracking the proposed (simulation) KPIs to gain insight into the inventory performance.

Currently, most decisions made at ASNL are based on gut feeling as most employees do not know how to access and handle specific performance data. This results in a lack of insight into the impact of certain decisions and how to manage certain processes. Therefore, we recommend ASNL to implement the proposed KPIs used in the simulation model and track the performance of these KPIs. The most useful way to visualize the KPI performance is through a data dashboard. This recommendation not only applies to ASNL's Purchasing department and other departments using other KPIs.

3. Collaborate with suppliers to reduce SLT uncertainty and to ensure that order quantities better accommodate ASNL's needs.

The experiment in Section 6.5.1 showed that using the EOQ instead of the order quantity (Q) set by supplier order requirement rules, such as the MinOQ or MaxOQ, results in a larger decrease in inventory value (€ 3,239,710.81 compared to € 2,034,295.55). Furthermore, the sensitivity analysis of the SLT bounds in Section 6.6.2 showed that ASNL should take every reasonable action to eliminate variation in SLTs. Therefore, we recommend ASNL to collaborate with their supplier to reduce SLT uncertainty and to ensure that order quantities better accommodate ASNL's needs.

4. Start leveraging VMI (with CS) for low-valued, regular-usage (Kanban) articles.

Currently, ASNL manages all inventory items internally, including approximately 18,000 of the 108,484 distinct articles that showed demand during 2022 and 2023. Managing all articles internally requires substantial effort from both purchasing and logistics employees. To enhance operational efficiency, it is recommended that ASNL utilizes VMI (with CS) for low-valued, regular-usage (Kanban) articles, ensuring that ASNL's can focus on managing non-standard, higher-value articles that require more specialized handling.

5. Improve the degree of internal SAP knowledge and data quality to enhance decision-making speed and visibility of improvement possibilities.

Currently, SAP is a black box for most of ASNL's employees resulting in inefficient data handling and decision-making based on gut feeling. Enhancing internal SAP knowledge will improve the understanding of ASNL's processes and enable more data-driven decision-making. To achieve this, it is advisable to offer general SAP training to employees and appoint an internal SAP specialist. This specialist can be an existing employee trained for the role, rather than a new hire. Additionally, the data quality in SAP, including lead times, item values, and ABC/XYZ indicators, is crucial for effective operations. Employees are unsure about the accuracy of SAP data, leading to workaround solutions for certain problems that decrease the decision-making speed and the visibility of improvement possibilities. Due to limited in-house SAP knowledge, data must be gathered using various SAP transactions, and while we have connected different data types to the best of our abilities, there is room for improvement.

8.3 Limitations and future research

This research has some limitations, resulting from the research scope and the complexity of ASNL's context. These limitations form a basis for potential future research topics.

- The SLT variability is modelled using the Triangular distribution within the proposed inventory control policies due to the lack of supplier delivery performance data. The bounds of the Triangular distribution are based on the expertise of the Supply Chain Manager and are assumed to be the same for all articles, which may result in deviations from ASNL's reality. Future research can investigate the supplier delivery performance to obtain more accurate SLT distributions for the articles and identify areas for improvement regarding supplier performance.
- Currently ADI is not leveraged within the proposed control policies as the sales forecasts do not provide meaningful insights into the expected article demand. To enhance the performance of the proposed control policies, future research can investigate how the sales forecasts can be translated into a form of ADI using the BOMs of historically produced machines.
- The proposed control policies rely on a limited selection of RLD distributions and the selection of the distribution relies on rules of thumb. The selected distributions may not always be the most accurate distribution for specific articles. Therefore, future research can identify the best-fitting RLD distributions by, for instance, performing goodness-of-fit tests and incorporating different statistical distributions such as the Lognormal or Exponential distribution.
- Section 2.4 explained that rescheduling of machines does not take place when the Assembly department is behind schedule. This rescheduling is not part of this research. A potential

future research topic concerns how the proposed control policies can deal with the rescheduling of machines.

- The holding and ordering cost rates used in the proposed control policies are not differentiated per separate article. This limitation poses a potential future research topic, as using different inventory holding and ordering cost rates results in different control parameter values.
- Chapter 7 discussed several complementary projects next to the implementation of the proposed policies. One of which entails the real-time data connection between the developed Microsoft Excel tool and SAP. This would eliminate the step to export data from SAP and copy it into Excel, which makes using the tool more time-efficient. Furthermore, the fit between ASNL and SAP HANA is also proposed as a future research topic, as SAP is currently a black box for ASNL it is important to research the company fit with the new software. Using SAP HANA also provides new opportunities to migrate the tool's functionalities to SAP.
- The designed inventory control policies do not consider usage relations between different articles when determining the control parameters. Therefore, when optimising the parameters for an E article, the proposed policies cannot optimise inventory levels for the related F articles. Future research entails investigating which articles have usage relations and how these relations can be incorporated into the proposed control policies.

8.4 Academic and practical contributions

This section describes both the academic contributions (Section 8.4.1) and practical contributions (Section 8.4.2) of this research.

8.4.1 Academic contribution

The academic contribution of this research consists of multiple facets. Firstly, this research shows how inventory control policies, including a SKU classification method, statistical distributions and parameters, can be applied in an MTO-ETO manufacturing setting by considering and combining the existing knowledge on the discussed inventory management concepts. Furthermore, the literature confrontation in Section 3.4 shows that this research contributes to academic literature by particularly combining several theoretical inventory management concepts. This research uses the XYZ classification method, instead of the most well-known ABC method, to categorize SKUs into classes. Furthermore, both demand and SLTs are modelled as stochastic random variables, which is uncommon as demand is often modelled as a stochastic variable while treating the SLT as deterministic or fixed. Additionally, we use five statistical distributions to model demand and a Triangular distribution to model SLT variability. Instead of the regular Negative Binomial demand distribution, we applied the Generalized Negative Binomial distribution to enable working with real-valued success rates. Lastly, we tested the performance of using the approach by Hariharan and Zipkin (1995) to use the ELT to incorporate a form of ADI within the proposed control policies. Using the ELT enables the determination of the expected performance resulting from a steady-state simulation.

8.4.2 Practical contribution

The practical contribution of this research comprises multiple facets. Firstly, this thesis contains a thorough analysis of ASNL's current situation, providing valuable insights regarding potential improvement areas. A prototype Microsoft Excel tool has been created with which the parameter values of the inventory control policies can be determined based on historical demand. This tool supports the Procurement department in working with up-to-date inventory control parameters. Furthermore, Section 1.2 explained that the NWC problem is a hot topic for all of ASG's manufacturing facilities. This research shows that the proposed control policy implementation can substantially decrease the total inventory value and thus the NWC at ASNL. This reduction in inventory value and the applicability of the designed solutions to other ASG locations shows that this research has a great added value to the entirety of ASG.

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A Inventory context analysis

A.1 ASNL's supply chain

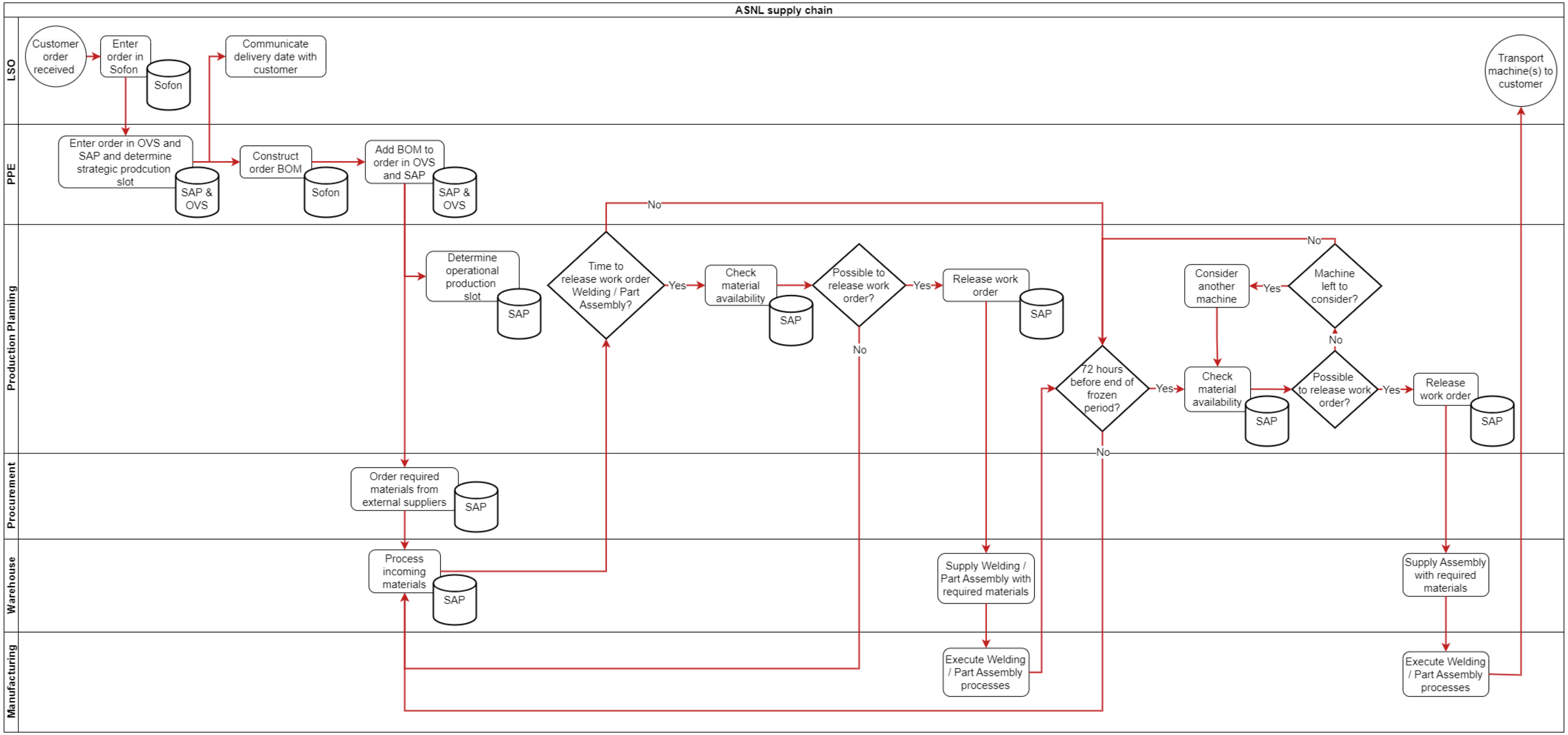

Figure A.1: Supply chain swimlane diagram

A.2 SAP data adjustments

To execute the context analysis of Chapter 2, and develop the inventory control policies (Chapter 4) and the inventory management tool (Chapter 5), several SAP data adjustments need to be executed. The main SAP data adjustments concern the SLT, total inventories including storage types, and usage frequency and article usage.

SKU SLT adjustments
The SLT of each SKU is recorded in SAP. There is a discrepancy between the SLT denoted in SAP and the SLT in reality. The underlying reason for this discrepancy is that the SLT is not updated frequently enough with the current supplier SLT, as this is a time-consuming task. To model the deviations and uncertainties in SLTs, the Triangular distribution is used (see Section 4.2.2). Internally manufactured articles (inventory E) do not have a SLT in SAP. These articles have a so-called 'own production time', which denotes the time it takes to manufacture the article. Similar to the SLT. the 'own production time' is not updated regularly. So, for an F article, the SLT is used within the inventory control policies and for E articles, the 'own production time' is used. In case an article has a black or X label, the shortest recording lead time is used.

Total inventory per SKU and storage types
SAP only provides the SKU inventories per separate location. So to retrieve the total inventory per SKU, all separate inventories need to be added. Furthermore, due to articles being stored in different locations, one article may be a Kanban article on one location and a pick article on another. Therefore, similar to the total inventory values, the storage types also need to be combined for each article. For each distinct article, we summed the inventories from different locations and recorded the storage type of each different location. When an article is a pick article, it has a distinct indicator included in its location code. With this distinct indicator, the pick and Kanban articles can be separated. In case an article is both a pick and a Kanban article on different locations, it receives the label 'partially'. This distinction is particularly important for the classification of the articles.

Usage frequency and article usage
SAP does not provide the usage frequency and Ready Rate for articles. Furthermore, SAP only provides the article usage per month and not per day. Therefore, determining the usage frequency is not straightforward. To determine the usage frequency, the number of months with zero demand is counted. When the number of months is equal to 24, the article did not have any demand during 2022 and 2023. If the number of months is equal to 23 or 22, the article usage is 'less than once a year' or 'once a year', respectively. When the number of months lies between 10 and 21, the article usage is denoted as 'yearly'. Yearly means that the article is used multiple times a year but not every month. Once the number of months lies between 0 and 10, the usage frequency is estimated to be the total usage divided by the time period. When the size of demand divided by 730 days is greater than one, the article is used on a daily basis. A similar method is used for weekly (dividing by 104) and monthly (dividing by 24). For some articles, demand is not unit-sized but per meters, kilograms, or litres. For such articles, it is not possible to make a differentiation between daily, weekly, and monthly. This is due to the limitation that the usage data from SAP only contains the monthly data. For these articles, the usage frequency is always set to 'monthly' usage.

A.3 Inventory characterization

This appendix provides detailed analyses of several inventory characteristics. These characteristics are the commodity group, article status, article usage and intermittent demand, and inventory turnover.

A.3.1 Commodity group

Within SAP, each article is part of a commodity group. At ASNL, there are four commodity groups: (i) the manufacturing articles, including all articles used to manufacture the machines; (ii) the operational expenditures, including articles such as electricity, insurance, liquid fuels, security, IT software, and personnel uniforms; (iii) end products; and (iv) services and outsourcing. Table A.1 shows the distribution of articles among these commodity groups. The commodity group of manufacturing articles contains the most articles (97.39%). As this research focuses on reducing the inventory within the warehouse of ASNL, manufacturing articles are the most important commodity group. However, the operational expenditure group also contains 423 articles that are of importance for production. These 423 articles, in addition to the manufacturing articles, are the focus of this research. When excluding the other articles, 108,483 distinct articles remain within the focus of this research.

Commodity group	Number of articles	Percentage of articles
Manufacturing articles	108,483	97.39
Operational expenditures	1,926	2.21
End products	542	0.49
Services and outsourcing	9	0.01

Table A.1: Commodity group distribution

A.3.2 Article status

Each article has a specific status that denotes whether the article can still be purchased by ASNL. The articles at ASNL can have one of the seven distinct statuses: (i) in development, (ii) prototype, (iii) free to use, (iv) spare part, (v) SSR, (vi) not active, and (vii) blocked. The 'in development' and 'prototype' articles are used by R&D. These articles cannot be freely purchased because they are still in development. The 'free to use' articles denote the standard articles used within the manufacturing process, and the 'SSR' articles denote the non-standard articles. The 'spare part' articles are no longer used in manufacturing but are kept as spare parts for customers. At ASNL, no spare part articles are currently kept in inventory. The 'not active' and 'blocked' articles are no longer used and can no longer be purchased. At ASNL, no articles with a 'not active' status are recorded in SAP. Lastly, some articles do not have a status within SAP.

Overall, the 'free to use' status group is the largest and biggest value-contributing group as it accounts for 92.394% of the articles and 99.384% of the total inventory value. Table A.2 shows the status distribution of the manufacturing articles. Not all articles recorded in specific commodity and status groups are kept in inventory. The 'free to use' status group accounts for 92.390% of the articles within the manufacturing articles commodity group and 99.044% of the total inventory value. Furthermore, the non-standard SSR articles account for 0.072% of the total inventory value. Compared to the standard articles, the non-standard articles contribute considerably less to the total inventory value at ASNL.

Article status	Number of articles	Percentage of articles	Percentage of inventory value
In development	3	0.003	0
Prototype	626	0.579	0.251
Free to use	99,837	92.390	99.044
Spare part	18	0.017	0
SSR	374	0.346	0.072
Not active	0	0	0
Blocked	1,818	1.682	0.010
Blank status	5,384	4.982	0.044

Table A.2: Status distribution of the manufacturing articles

When looking at the 423 'operational expenditure' articles included within this research's focus, we see that most of these articles (98.109%) are part of the 'free to use' status group. Not all 423 articles are kept in inventory, but the articles kept in inventory account for 0.340% of the total inventory value at ASNL. The other 1.891% of these articles are part of the 'blocked' status group, but currently, none of them have a positive inventory level. Within the 423 'operational expenditure' articles, no articles are recorded as SSR articles. At last, a part of the 'operational expenditure' articles that are not included within the focus of this research contribute to 0.237% of the total inventory value.

A.3.3 Article usage and intermittent demand

Figure A.2 illustrates the usage frequency of the articles in SAP, and Figure A.3 illustrates the usage pattern of two randomly chosen articles. Appendix A.2 discussed how the usage frequency of each article is determined. Figure A.2 shows that most articles are used every year. As explained in Appendix A.2, yearly means that an article is used multiple times per year but not every month. Furthermore, the article usage shows that ASNL operates in a high-variety environment and shows the complexity of the inventory problem at ASNL.

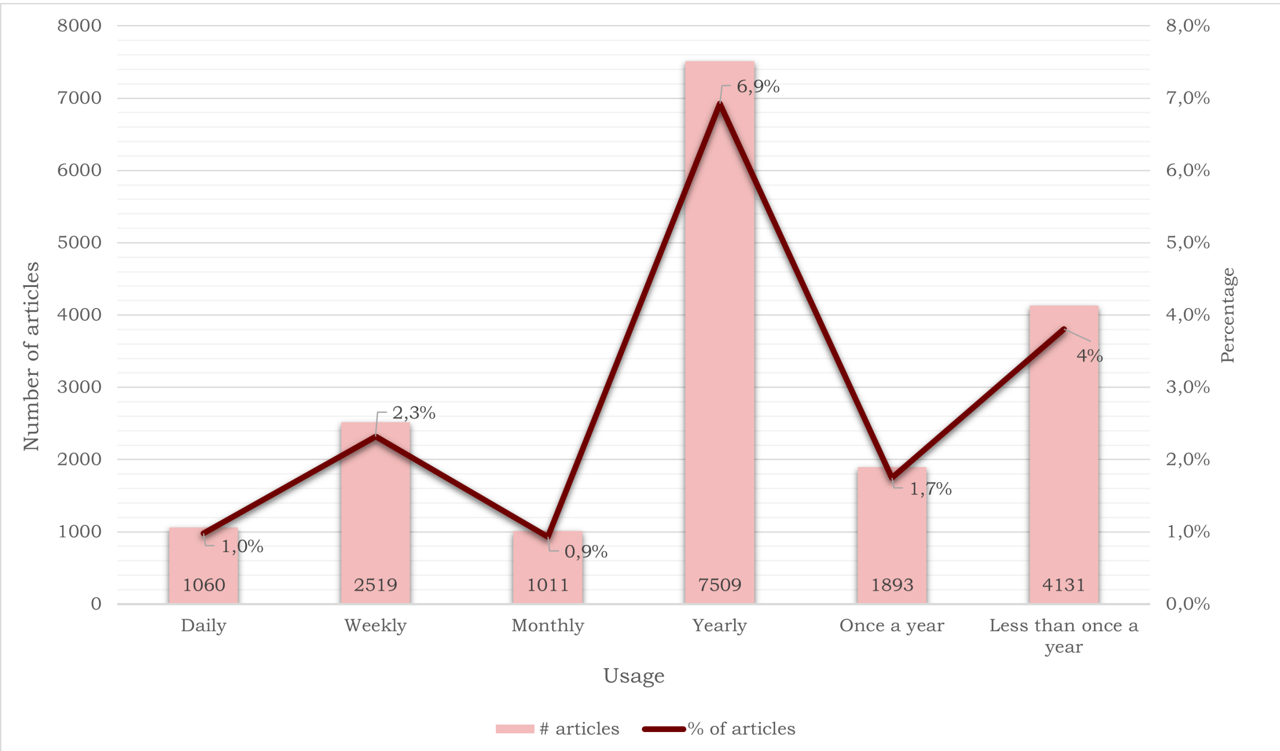

Figure A.2: Article usage frequency

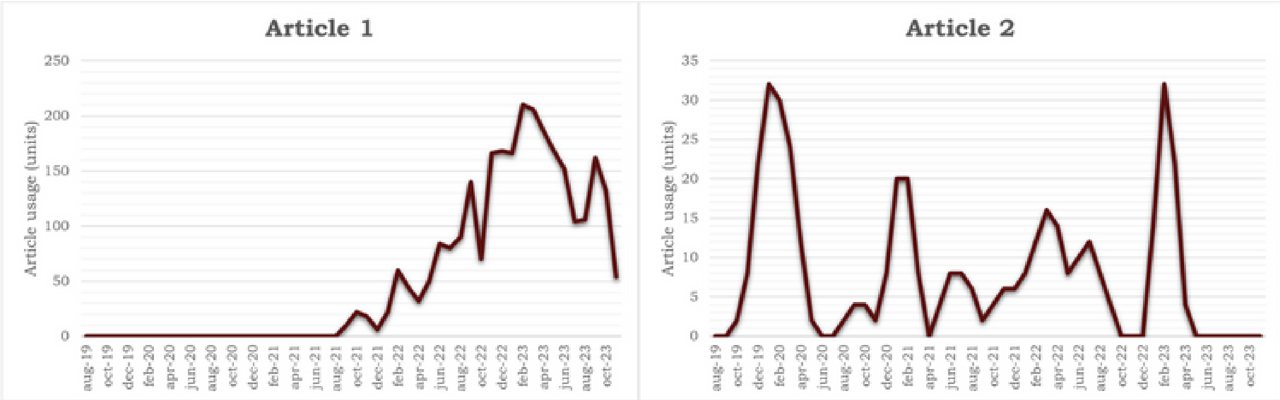

Figure A.3: Article usage examples

To investigate whether articles show intermittent demand patterns, it is necessary to determine the average time between demand occasions and the mean demand size. Based on the historical monthly demand data from the past two years, we counted the lengths of the no-demand intervals and took the average of these lengths to obtain the average time between demand occasions. Figure A.4 shows the distributions of articles among the different average inter-demand intervals. To obtain the mean demand size, we calculated the average of all non-zero demand sizes. An article shows an intermittent demand pattern when the average time between demand occasions is greater than 3 months and the means demand size is bigger than 30 units. The threshold of 30 units is chosen as this is approximately equal to the overall average demand size of all articles at ASNL. This approach results in 258 articles showing intermittent demand patterns. Furthermore, 16,865 articles show more regular demand patterns and 91,360 articles have no recorded usage during the past two years. The articles that show more regular demand patterns can have a high average time between demand occasions, these articles are slow movers instead of intermittent articles.

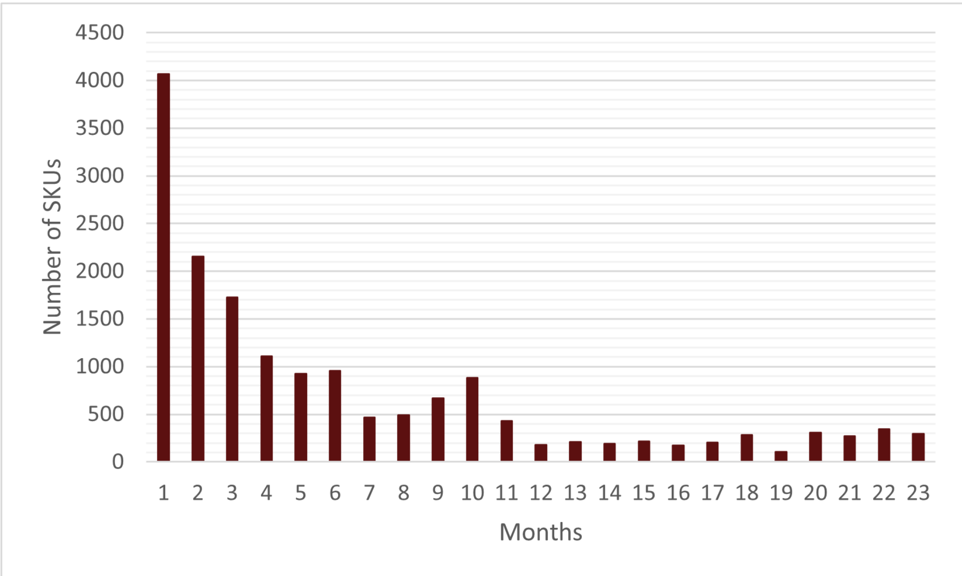

Figure A.4: Average time between demand occasions

B Triangular distribution

The Triangular distribution is used when there is a known relationship between the variable data but when there is relatively little to no data available to conduct a statistical analysis. This distribution is often referred to as the 'lack of knowledge' distribution. The Triangular distribution is a continuous distribution and is denoted as $Triangular(a, b, c)$, where a denotes the lower limit, b denotes the upper limit, and c denotes the mode (Kissell & Poserina, 2017). Equation B.1 provides the limits of a, b, and c. Equations B.2 and B.3 provide the Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of the Triangular distribution, respectively. At last, Equations B.4, B.5, B.6, and B.7 provide the relations between the parameters and the different moments of the Triangular distribution.

$$\begin{gathered} -\infty \leq a \leq \infty \\ b > a \\ a < c < b \end{gathered} \tag{B.1}$$

$$f(x) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}, & a \leq x \leq c \\ \frac{2(b-x)}{(b-a)(b-c)}, & c < x \leq b \end{cases} \tag{B.2}$$

$$F(x) = \begin{cases} \frac{2(x-a)^2}{(b-a)(c-a)}, & a \leq x \leq c \\ 1 - \frac{(b-x)^2}{(b-a)(b-c)}, & c < x \leq b \end{cases} \tag{B.3}$$

$$E(X) = \frac{a+b+c}{3} \tag{B.4}$$

$$Var(X) = \frac{a^2+b^2+c^2-ab-ac-bc}{18} \tag{B.5}$$

$$Skewness = \frac{\sqrt{2}(a+b-2c)(2a-b-c)(a-2b+c)}{5(a^2+b^2+c^2-ab-ac-bc)^{1/2}} \tag{B.6}$$

$$Kurtosis = -\frac{3}{5} \tag{B.7}$$

C RLD distributions

This appendix provides an overview of the different RLD distributions and their properties.

C.1 Normal distribution

Normal (or Gaussian) distributions are the most important probability distributions in statistics. The Normal distribution is a 'bell-shaped' continuous distribution denoted as $N(\mu, \sigma^2)$, where μ denotes the mean and σ^2 the variance. The Standard Normal distribution is a special form of the Normal distribution with $\mu = 0$ and $\sigma^2 = 1$ (Loftus, 2022). Equation C.1 provides the PDF of the Normal distribution (Kissell & Poserina, 2017). Equations C.2 and C.3 provide the first (mean) and second (variance) moments of the Normal distribution. The third (skewness) and the fourth (kurtosis) moments are equal to zero.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{C.1}$$

$$\mu = E(X) \tag{C.2}$$

$$\sigma^2 = Var(X) \tag{C.3}$$

C.2 Gamma distribution

The Gamma distribution is a continuous distribution and is denoted as $\Gamma(\alpha, \beta) = Gamma(\alpha, \beta)$, where α is the shape parameter and β the inverse scale parameter. The Gamma distribution can also be denoted as $\Gamma(k, \theta)$, where $k = \alpha$ and $\theta = 1/\beta$. Equations C.4 and C.5 provide the PDF and CDF of the Gamma distribution, respectively. Equations C.6, C.7, C.8, and C.9 provide the first four moments of the Gamma distribution.

$$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-x\beta} \tag{C.4}$$

$$F(x) = \frac{1}{\Gamma(\alpha)} \gamma(\alpha, \beta x) \tag{C.5}$$

$$E(X) = \frac{\alpha}{\beta} \tag{C.6}$$

$$Var(X) = \frac{\alpha}{\beta^2} \tag{C.7}$$

$$Skewness = \frac{2}{\sqrt{\alpha}} \tag{C.8}$$

$$Kurtosis = \frac{6}{\alpha} \tag{C.9}$$

To determine the values for α and β, we can use the method of moments, resulting in Equations C.10 and C.11.

$$\alpha = \frac{E(X)^2}{Var(X)} \tag{C.10}$$

$$\beta = \frac{E(X)}{Var(X)} \tag{C.11}$$

C.3 Binomial distribution

The Binomial distribution is a discrete distribution used for sampling trials and is denoted as $B(n, p)$, where n denotes the number of trials and p denotes the success probability for each trial (Kissell & Poserina, 2017). Equations C.12 and C.13 provide the PDF and CDF of the Binomial distribution, respectively.

$$f(x) = \binom{n}{k} p^k (1-p)^{(n-k)} = \frac{n!}{k!(n-k!)} p^k (1-p)^{(n-k)} \tag{C.12}$$

$$F(x) = \sum_{i=0}^{k} \left(\binom{n}{i} p^i (1-p)^{n-i} \right) \tag{C.13}$$

Equations C.14, C.15, C.16, and C.17 provide the relations between the parameters and the different moments of the Binomial distribution.

$$E(X) = np \rightarrow n = \frac{E(X)}{p} \tag{C.14}$$

$$Var(X) = np(1-p) \rightarrow n = \frac{Var(X)}{p(1-p)} \tag{C.15}$$

$$Skewness = \frac{1-2p}{\sqrt{np(1-p)}} \tag{C.16}$$

$$Kurtosis = \frac{1-6p(1-p)}{np(1-p)} \tag{C.17}$$

By substituting the righthand side of Equations C.14 and C.15 into each other and using the derivation in Equation C.18, we obtain the formula to determine the value of p. With the value of p, we can calculate the value for n.

$$\begin{aligned} \frac{E(X)}{p} &= \frac{Var(X)}{p(1-p)} \\ \frac{p(1-p)E(X)}{p} &= Var(X) \\ \frac{p(1-p)}{p} &= \frac{Var(X)}{E(X)} \\ 1-p &= \frac{Var(X)}{E(X)} \\ p &= 1 - \frac{Var(X)}{E(X)} \end{aligned} \tag{C.18}$$

C.4 Negative Binomial distribution

The Negative Binomial distribution is a discrete distribution that measures the number of failures before the nth success in a sequence of trials. The Negative Binomial distribution is denoted as $NB(r, p)$, where r denotes the number of successes until the experiment stops and p denotes the success probability in each experiment (Sinharay, 2010). Equations C.19 and C.20 provide the PDF and CDF of the Negative Binomial distribution, respectively.

$$f(x) = \binom{k+r-1}{k} (1-p)^k p^r \tag{C.19}$$

$$F(x) = \sum_{i=0}^{k} \left(\binom{k+r-1}{r-1} p^r (1-p)^i \right) \tag{C.20}$$

Equations C.21, C.22, C.23, and C.24 provide the relations between the parameters and the different moments of the Binomial distribution.

$$E(X) = \frac{r(1-p)}{p} \tag{C.21}$$

$$Var(X) = \frac{r(1-p)}{p^2} \tag{C.22}$$

$$Skewness = \frac{2-p}{\sqrt{(1-p)r}} \tag{C.23}$$

$$Kurtosis = \frac{6}{r} + \frac{p^2}{(1-p)r} \tag{C.24}$$

To determine the values for r and p, we can use the method of moments, resulting in Equations C.25 and C.26.

$$r = \frac{E(X)^2}{Var(X) - E(X)} \tag{C.25}$$

$$p = \frac{E(X)}{Var(X)} \tag{C.26}$$

C.5 Poisson distribution

The Poisson distribution is a discrete distribution that measures the probability of a given number of events occurring in a specified time period. The Poisson distribution is denoted as $Poi(\lambda)$, where λ denotes both the mean and variance (Kissell & Poserina, 2017). Equations C.27 and C.28 provide the PDF and CDF of the Poisson distribution, respectively.

$$f(x) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{C.27}$$

$$F(x) = \sum_{i=1}^{k} \left(\frac{\lambda^k e^{-\lambda}}{k!} \right) \tag{C.28}$$

Equations C.29, C.30, and C.31 provide the relation between the relations between λ and the moments of the Poisson distribution.

$$E(X) = Var(X) = \lambda \tag{C.29}$$

$$Skewness = \lambda^{-1/2} \tag{C.30}$$

$$Kurtosis = \lambda^{-1} \tag{C.31}$$

D Poisson and Negative Binomial Excel VBA functions

Algorithm D.1 Cumulative Poisson Distribution

```
Function CumulativePoissonDist (x As Long, λ As Double) As Double

Dim distr As Double
Dim k As Long

distr = 0

for k= 0 to x do
    distr = distr + (λ^k * e^−λ)/k!
end for

CumulativePoissonDist = distr

End Function
```

Algorithm D.2 Inverse Cumulative Poisson Distribution

```
Function InverseThresholdPoissonDist (x As Long, lambda As Double, threshold As Double) As Double

Dim distr As Double
Dim k As Long

distr = 0

for k = 0 to x do
    distr = distr + (λ^k * e^−λ)/k!
    if distr ≥ threshold then
        InverseThresholdPoissonDist = k
        Exit Function
    end if
end for

InverseThresholdPoissonDist = CVErr(xlErrValue)

End Function
```

Algorithm D.3 Cumulative Negative Binomial Distribution

```
Function CumulativeNegBinDist (n As Long, r As Double, p As Double) As Double

Dim dens, distr As Double
Dim k As Long

dens = e^(r*log(1−p))
distr = dens

for k = 0 to n do
    dens = dens * p * (k + r - 1) / k
    distr = distr + dens
end for

CumulativeNegBinDist = distr

End Function
```

Algorithm D.4 Inverse Cumulative Negative Binomial Distribution

```
Function InverseThresholdNegBinDist (n As Long, r As Double, p As Double, threshold As Double) As Double

Dim dens, distr As Double
Dim k As Long

dens = e^(r*log(1−p))
distr = dens

for k = 0 to n do
    dens = dens * p * (k + r - 1) / k
    distr = distr + dens
    if distr ≥ threshold then
        InverseThresholdNegBinDist = k
        Exit Function
    end if
end for

InverseThresholdNegBinDist = CVErr(xlErrValue)

End Function
```

E Simulation Python code

```
import pandas as pd
import numpy as np
from datetime import datetime, timedelta
import xlsxwriter

# function to determine the reorder policy
def ReorderPolicy(Inventory_Position, day, article, sim_name):
    Order_Policy = Sim_Article_Info.iat[article, 3]
    SLT = Sim_Article_Info.iat[article, 4]
    Order_Quantity = Sim_Article_Info.iat[article, 6]
    Reorder_Point = Sim_Article_Info.iat[article, 8]
    Order_UpTo_Level = Sim_Article_Info.iat[article, 9]
    EOQ = Sim_Article_Info.iat[article, 14]

    # initialize variables
    Replenishment = 0
    Receive_Day = 0

    # check if inventory position is below reorder point
    if Inventory_Position < Reorder_Point:
        # determine replenishment strategy based on simulation name
        if (sim_name == "EOQ based") or (sim_name == "EOQ pessimistic") or (sim_name
        ↪   == "EOQ optimistic"):
            if Order_Policy == "(s, Q)":
                Replenishment = EOQ
                Inventory_Position = Inventory_Position + Replenishment
                Receive_Day = day + SLT
            elif Order_Policy == "(s, S)":
                Replenishment = Order_UpTo_Level - Inventory_Position
                Inventory_Position = Inventory_Position + Replenishment
                Receive_Day = day + SLT
        elif (sim_name == "(s, Q)-policy"):
            Replenishment = Order_Quantity
            Inventory_Position = Inventory_Position + Replenishment
            Receive_Day = day + SLT
        elif (sim_name == "(s, S)-policy"):
            if (Order_Policy == "(s, Q)"):
                Order_UpTo_Level = Reorder_Point + Order_Quantity
            Replenishment = Order_UpTo_Level - Inventory_Position
            Inventory_Position = Inventory_Position + Replenishment
            Receive_Day = day + SLT
        else:
            if (Order_Policy == "(s, Q)"):
                Replenishment = Order_Quantity
                Inventory_Position = Inventory_Position + Replenishment
                Receive_Day = day + SLT
            elif (Order_Policy == "(s, S)"):
                Replenishment = Order_UpTo_Level - Inventory_Position
                Inventory_Position = Inventory_Position + Replenishment
                Receive_Day = day + SLT
```

```
    # update inventory position
    Inventory_Position = Inventory_Position

    return Replenishment, Inventory_Position, Receive_Day

# import simulation article information
Sim_Article_Info = pd.read_excel("D:\Simulation source data.xlsx", sheet_name = 0)
Article_Info_cols = Sim_Article_Info.columns.tolist()

# import usage data article including OHI values on a specific date
Sim_Usage_Info = pd.read_excel("D:\Simulation source data.xlsx", sheet_name = 1)

# import incoming goods quantities
Sim_Incoming_Info = pd.read_excel("D:\Simulation source data.xlsx", sheet_name = 2)

# initialize variables
start_date = datetime(2024, 1, 1)
end_date = datetime(2024, 3, 31)

sim_names = ["Proposed policies", "Reality", "EOQ based", "Pessimistic",
↪  "Optimistic", "EOQ pessimistic", "EOQ optimistic", "(s, Q)-policy", "(s,
↪  S)-policy"]
sim_variable_names = ["Date", "Realized demand", "Begin OHI", "Received
↪  replenishement", "Demand satisfied from stock",
                      "Demand backordered", "Ending OHI", "Total pipeline",
                      ↪  "Inventory position", "Replenishment"]
sim_results_variables = ["Article", "Number of replenishments", "Avergage OHI",
↪  "Number of stockout days", "Total demand",
                         'Realized ready rate', "Average OHI value", 'Realized fill
                         ↪  rate']

#initalize array lengths
num_articles = 60
num_days = (end_date - start_date).days + 1
num_sim__input_variables = len(sim_variable_names)
num_sim_output_variables = len(sim_results_variables)
num_sims = len(sim_names)

# make simulation array to fill in the results
simulation = np.zeros((num_articles, num_sim__input_variables, num_days + 1), dtype
↪  = object)
sim_results = np.zeros((num_articles + 1, num_sim_output_variables), dtype = object)

# create Excel workbook
workbook = xlsxwriter.Workbook("D:\Simulation results.xlsx")
new_worksheet = workbook.add_worksheet('Results overview')

# write simulation results variables to the Excel worksheet
column = 2
for i in range(len(sim_results_variables)):
    sim_results[0][i] = sim_results_variables[i]
    if i > 0:
        new_worksheet.write(0, 0, "Article")
```

```
        new_worksheet.write(0, 1, "Simulation")
        new_worksheet.write(0, column, sim_results_variables[i])
        new_worksheet.write(0, column + 11, sim_results_variables[i])
        column += 1

for i in range(num_sims):
    new_worksheet.write(i + 1, 12, sim_names[i])

# simulation
for sim in range(num_sims):
    sim_name = sim_names[sim]

    simulation = np.zeros_like(simulation)

    # loop over the articles
    for article in range(num_articles):
        current_date = start_date.date()

        # determine initial OHI values based on simulation name
        if (sim_name == "Proposed policies") or (sim_name == "EOQ based") or
        ↪  (sim_name == "Reality") or (sim_name == "(s, Q)-policy") or (sim_name ==
        ↪  "(s, S)-policy"):
            simulation[article][2][1] = Sim_Usage_Info.iat[article, 1]
        elif (sim_name == "Pessimistic") or (sim_name == "EOQ pessimistic"):
            Reorder_Point = Sim_Article_Info.iat[article, 8]
            simulation[article][2][1] = Reorder_Point
        elif (sim_name == "Optimistic") or (sim_name == "EOQ optimistic"):
            Order_Policy = Sim_Article_Info.iat[article, 3]
            Order_Quantity = Sim_Article_Info.iat[article, 6]
            Reorder_Point = Sim_Article_Info.iat[article, 8]
            Order_UpTo_Level = Sim_Article_Info.iat[article, 9]
            if Order_Policy == "(s, Q)":
                simulation[article][2][1] = Reorder_Point + Order_Quantity
            elif Order_Policy == "(s, S)":
                simulation[article][2][1] = Order_UpTo_Level

        # initialize variable for each article
        Total_Pipeline = 0
        Demand_Backorder = 0
        Number_Replenishments = 0
        Realized_RR = 0
        Realized_FR = 0
        Average_OHI = 0
        Number_Stockouts = 0
        Positive_OHI = 0
        Sum_OHI = 0
        Sum_Demand_from_Stock = 0
        Count_Replenishments = 0

        # initialize simulation array
        for i in range(len(sim_variable_names)):
            simulation[article][i][0] = sim_variable_names[i]
```

```
# loop over the days
for day in range(1, num_days + 1):

    if sim_name == "Reality":
        Order_Day = 0

        # fill simulation array
        simulation[article][0][day] = current_date # write day dates in the
        ↪  top row
        simulation[article][1][day] = Sim_Usage_Info.iat[article, day + 1] #
        ↪  write usage data per day
        simulation[article][3][day] = Sim_Incoming_Info.iat[article, day] #
        ↪  write received goods per day

        # initialize variables
        OHI_Start = simulation[article][2][day]
        Received_Replenishment = simulation[article][3][day]
        Realized_Demand = simulation[article][1][day]

        # simulate for article using all the data
        OHI_End = max(0, OHI_Start + Received_Replenishment - (-
        ↪  Realized_Demand) - Demand_Backorder) # Ending OHI
        simulation[article][6][day] = OHI_End
        if day < num_days:
            simulation[article][2][day + 1] = OHI_End
        if OHI_End <= 0:
            Number_Stockouts += 1
        elif OHI_End > 0:
            Positive_OHI += 1

        Sum_OHI = Sum_OHI + OHI_End

        Demand_from_Stock = min(- Realized_Demand, max(0, OHI_Start +
        ↪  Received_Replenishment - Demand_Backorder))
        simulation[article][4][day] = Demand_from_Stock
        Sum_Demand_from_Stock = Sum_Demand_from_Stock + Demand_from_Stock

        Demand_Backorder = max(0, - Realized_Demand + Demand_Backorder -
        ↪  OHI_Start - Received_Replenishment)
        simulation[article][5][day] = Demand_Backorder

        # determine the original order day of a received replenishment
        if Received_Replenishment > 0:
            SLT = Sim_Article_Info.iat[article, 4]
            Order_Day = day - SLT
            Count_Replenishments += 1

            # if replenishment placed in simultion period, add it as real
            ↪  replenishment to specific day and update pipeline
            ↪  accordingly
            if Order_Day > 0:
                simulation[article][9][Order_Day] = Received_Replenishment
                Number_Replenishments += 1
```

```
                for k in range(Order_Day, day):
                    if Count_Replenishments > 1:
                        Total_Pipeline = simulation[article][7][k] +
                         ↪  Received_Replenishment
                    else:
                        Total_Pipeline = Received_Replenishment
                    simulation[article][7][k] = Total_Pipeline
                    simulation[article][8][k] += Received_Replenishment

            # if replenishment placed before simulation period, only update
            ↪  pipeline accordingly
            elif Order_Day <= 0:
                for k in range(1, day):
                    if Count_Replenishments > 1:
                        Total_Pipeline = simulation[article][7][k] +
                         ↪  Received_Replenishment
                    else:
                        Total_Pipeline = Received_Replenishment
                    simulation[article][7][k] = Total_Pipeline
                    simulation[article][8][k] += Received_Replenishment

        Total_Pipeline = max(0, Total_Pipeline - Received_Replenishment)

        Inventory_Position = OHI_End + Total_Pipeline - Demand_Backorder
        simulation[article][8][day] = Inventory_Position

        current_date += timedelta(days = 1) # update current date

    else:

        # fill simulation array
        simulation[article][0][day] = current_date # write day dates in the
        ↪  top row
        simulation[article][1][day] = Sim_Usage_Info.iat[article, day + 1] #
        ↪  write usage data per day

        # initialize variables
        OHI_Start = simulation[article][2][day]
        Received_Replenishment = simulation[article][3][day]
        Realized_Demand = simulation[article][1][day]

        # simulate for article using all the data
        OHI_End = max(0, OHI_Start + Received_Replenishment - (-
        ↪  Realized_Demand) - Demand_Backorder)
        simulation[article][6][day] = OHI_End
        if day < num_days:
            simulation[article][2][day + 1] = OHI_End
        if OHI_End <= 0:
            Number_Stockouts += 1
        elif OHI_End > 0:
            Positive_OHI += 1

        Sum_OHI = Sum_OHI + OHI_End
```

```
            Demand_from_Stock = min(- Realized_Demand, max(0, OHI_Start +
            ↪ Received_Replenishment - Demand_Backorder))
            simulation[article][4][day] = Demand_from_Stock
            Sum_Demand_from_Stock = Sum_Demand_from_Stock + Demand_from_Stock

            Demand_Backorder = max(0, - Realized_Demand + Demand_Backorder -
            ↪ OHI_Start - Received_Replenishment)
            simulation[article][5][day] = Demand_Backorder

            Inventory_Position = OHI_End + Total_Pipeline - Demand_Backorder -
            ↪ Received_Replenishment
            simulation[article][8][day] = Inventory_Position

            # call ReorderPolicy function to determine whether replenishment is
            ↪ ordered
            Replenishment, Inventory_Position, Receive_Day =
            ↪ ReorderPolicy(Inventory_Position, day, article , sim_name)

            # if replenishment is placed, update the simulation array
            if Replenishment > 0:
                simulation[article][9][day] = Replenishment
                simulation[article][8][day] = Inventory_Position
                Number_Replenishments += 1
                if (Receive_Day > day) and (Receive_Day < num_days):
                    simulation[article][3][Receive_Day] = Replenishment

            Total_Pipeline = Total_Pipeline + Replenishment -
            ↪ Received_Replenishment
            simulation[article][7][day] = Total_Pipeline

            current_date += timedelta(days = 1) # update current date

        # calculate and store results
        sim_results[article + 1][0] = Sim_Article_Info.iat[article, 0]
        sim_results[article + 1][1] = Number_Replenishments
        Average_OHI = Sum_OHI / num_days
        sim_results[article + 1][2] = round(Average_OHI, 2)
        sim_results[article + 1][3] = Number_Stockouts
        sim_results[article + 1][4] = - Sim_Usage_Info.iloc[article,-1]
        Realized_RR = Positive_OHI / num_days
        sim_results[article + 1][5] = round(Realized_RR, 2)
        sim_results[article + 1][6] =  Average_OHI *
        ↪ Sim_Article_Info.iat[article, 17]
        if Sum_Demand_from_Stock == 0:
            Realized_FR = 0
        else:
            Realized_FR = Sum_Demand_from_Stock / - Sim_Usage_Info.iat[article,
            ↪ -1]
        sim_results[article + 1][7] = Realized_FR

    # write results to Excel
    worksheet = workbook.add_worksheet(sim_name)
```

```
center_bold_format = workbook.add_format({'align' : 'center', 'valign' :
↪  'vcenter', 'bold' : True})
center_format = workbook.add_format({'align' : 'center', 'valign' : 'vcenter'})
date_format = workbook.add_format({'num_format': 'dd-mm-yyyy'})
merge_format = workbook.add_format({'rotation': 90, 'align': 'center', 'valign':
↪  'vcenter'})

# initialize variables
row = 0
new_row = 0
col = 0

# loop over articles
for article in range(num_articles):

    # write article name to results overview sheet
    new_worksheet.write(new_row + 1, col, Sim_Article_Info.iat[article, 0])

    i = sim

    # write simulation names to results overview sheet
    new_worksheet.write(new_row + 1 + i, col + 1, sim_names[i])

    # loop over simulation outpurt variables and write values to results
    ↪  overview sheet
    for j in range(2, num_sim_output_variables + 1):
        new_worksheet.write(new_row + 1 + i, col + j, sim_results[article + 1, j
        ↪  - 1])

    worksheet.merge_range(f'A{row+1}:D{row+1}', "Article information",
    ↪  center_bold_format)
    midpoint = len(Article_Info_cols) // 2

    # loop over first half of article information columns and write article
    ↪  information to each new simulation sheet
    for i in range(midpoint):
        worksheet.write(row + 1 + i, col, Article_Info_cols[i], center_format)
        worksheet.write(row + 1 + i, col + 1, Sim_Article_Info.iat[article, i],
        ↪  center_format)

    # loop over second half of article information columns and write article
    ↪  information to each new simulation sheet
    for i in range(midpoint, len(Article_Info_cols)):
        worksheet.write(row + 1 + i - midpoint, col + 2, Article_Info_cols[i],
        ↪  center_format)
        worksheet.write(row + 1 + i - midpoint, col + 3,
        ↪  Sim_Article_Info.iat[article, i], center_format)

    # write simulation results to each new simulation sheet
    for i in range(len(Article_Info_cols) - len(sim_results_variables) + 2,
    ↪  len(Article_Info_cols) + 1):
```

```
            worksheet.write(row + i - midpoint, col + 3, sim_results[article + 1][i
            ↪   - (len(Article_Info_cols) - len(sim_results_variables) + 1)],
            ↪   center_format)

        # loop over simulation variables and days to write results
        for variable in range(num_sim__input_variables):
            for day in range(num_days + 1):
                if variable == 0:
                    worksheet.write(row + variable, col + 6 + day,
                    ↪   simulation[article][variable][day], date_format)
                else:
                    worksheet.write(row + variable, col + 6 + day,
                    ↪   simulation[article][variable][day])

        # update row counters
        row += max(midpoint, num_sim__input_variables) + 4
        new_row += num_sims

for i in range(num_sims):
    new_worksheet.write_array_formula(f'N{2+i}',f
        '=SUMIFS($C$2:$C$541,$B$2:$B$541,$M{2+i})')
    new_worksheet.write_array_formula(f'O{2+i}',f
        '=SUMIFS($H$2:$H$541,$B$2:$B$541,$M{2+i})')
    new_worksheet.write_array_formula(f'P{2+i}',f
        '=SUMIFS($E$2:$E$541,$B$2:$B$541,$M{2+i})')
    new_worksheet.write_array_formula(f'Q{2+i}',f
        '=AVERAGEIFS($G$2:$G$541,$B$2:$B$541,$M{2+i})')
    new_worksheet.write_array_formula(f'R{2+i}',f
        '=AVERAGEIFS($I$2:$I$541,$B$2:$B$541,$M{2+i})')

# close workbook
workbook.close()
```

F Propsed policy results

SKU	Class	Distribution	SAP reorder point	New reorder point	SAP safety stock	New safety stock	Order quantity	EOQ	Impact	EOQ impact
1	X-Kanban-RTS	Normal	0	42	0	5	60	16	€ -21.45	€ -965.25
2	X-Kanban-RTS	Normal	0	40	0	6	20	12	€ -113.40	€ -135.00
3	X-Kanban-RTS	Normal	0	18	0	3	10	9	€ -186.03	€ -206.70
4	X-Kanban-RTO	Binomial	0	11	0	2	10	10	€ -47.92	€ -47.92
5	X-Kanban-RTO	Normal	0	107	0	15	100	34	€ -2,299.34	€ -5,274.95
6	X-Pick-RTS	Normal	0	29	0	4	12	12	€ 14,316.00	€ 14,316.00
7	X-Pick-RTS	Gamma	0	124.62	0	54.06	210	21.60	€ -716.24	€ -1,313.46
8	X-Pick-RTS	Normal	0	58	0	7	12	12	€ -7,157.50	€ -7,157.50
9	X-Pick-RTO	Binomial	0	2	0	1	12	4	€ -4,397.05	€ -6,466.25
10	X-Pick-RTO	Normal	0	28	0	5	100	27	€ 1.96	€ -6.44
11	X-Partially-RTS	Normal	0	16	0	5	25	9	€ -265.14	€ -343.70
12	X-Partially-RTS	Normal	0	28	0	4	11	11	€ -101.36	€ -101.36
13	X-Partially-RTS	Normal	0	12	0	2	20	8	€ -14,544.75	€ -17,189.25
14	X-Partially-RTO	Normal	0	15	0	3	50	18	€ -337.88	€ -549.88
15	X-Partially-RTO	Normal	0	41	0	10	50	28	€ -1,676.08	€ -1,900.92
16	X-No inventory-RTS	Normal	0	47	0	6	100	16	€ 42.93	€ 8.91
17	X-No inventory-RTS	Normal	0	16	0	4	20	8	€ 921.84	€ 460.92
18	X-No inventory-RTS	Binomial	0	9	0	3	10	6	€ 1,370.98	€ 949.14
19	X-No inventory-RTO	Normal	0	1639	0	209	121	121	€ 0.61	€ 0.61
20	X-No inventory-RTO	Normal	0	38	0	7	100	31	€ 7.49	€ 2.66
21	Y-Kanban-RTS	Binomial	0	8	0	3	10	6	€ -8,482.18	€ -9,271.22
22	Y-Kanban-RTS	Normal	0	13	0	3	10	7	€ -203.22	€ -209.50
23	Y-Kanban-RTS	Normal	0	46	0	7	20	15	€ -701.24	€ -775.84
24	Y-Kanban-RTO	Binomial	0	10	0	3	14	14	€ -748.78	€ -748.78
25	Y-Kanban-RTO	Binomial	0	6	0	2	8	8	€ -266.00	€ -266.00
26	Y-Pick-RTS	Poisson	0	9	0	3	8	8	€ -179.66	€ -179.66
27	Y-Pick-RTS	Normal	0	211	10	41	100	38	€ -1,880.33	€ -2,050.52
28	Y-Pick-RTS	Normal	0	129	0	20	100	25	€ -1,897.93	€ -3,240.81
29	Y-Pick-RTO	Binomial	0	4	0	2	6	6	€ 33.14	€ 33.14
30	Y-Pick-RTO	Normal	0	25	6	7	50	16	€ -1,640.21	€ -2,525.40
31	Y-Partially-RTS	Poisson	0	7	0	3	7	7	€ -294.68	€ -294.68
32	Y-Partially-RTS	Normal	0	20	0	3	10	10	€ 42.35	€ 42.35
33	Y-Partially-RTS	Binomial	0	10	0	4	7	7	€ -3,313.20	€ - 3,313.20
34	Y-Partially-RTO	Binomial	0	2	0	1	10	5	€ -691.11	€ -1,075.06
35	Y-Partially-RTO	Normal	0	21	0	5	15	15	€ -927.52	€ -927.52
36	Y-No inventory-RTS	Normal	0	194.31	0	47.99	40	28.05	€ 46.19	€ 39.92
37	Y-No inventory-RTS	Normal	0	56	0	10	15	14	€ 321.50	€ 308.64
38	Y-No inventory-RTS	Normal	0	35	2	6	20	14	€ 211.90	€ 163.00
39	Y-No inventory-RTO	Normal	0	17	0	6	25	13	€ 49.60	€ 30.40
40	Y-No inventory-RTO	Binomial	0	1	0	1	3	3	€ 401.06	€ 401.06
41	Z-Kanban-RTS	Normal	0	27	60	6	20	10	€ -62.04	€ -66.74
42	Z-Kanban-RTS	Binomial	0	3	0	2	4	4	€ -84.86	€ -84.86
43	Z-Kanban-RTS	Normal	0	59	0	13	100	18	€ -29.03	€ -46.66
44	Z-Kanban-RTO	Binomial	0	2	0	2	5	4	€ 13.33	€ 0.0
45	Z-Kanban-RTO	Normal	0	63	0	13	100	25	€ -46.45	€ -544.07
46	Z-Pick-RTS	Binomial	0	8	0	2	5	5	€ -5,589.68	€ -5,589.68
47	Z-Pick-RTS	Normal	0	147	0	29	200	28	€ -650.37	€ -879.13
48	Z-Pick-RTS	Gamma	0	46	0	20	20	15	€ 195.50	€ 166.75
49	Z-Pick-RTO	Binomial	0	3	0	2	10	7	€ 229.39	€ -114.70
50	Z-Pick-RTO	Binomial	0	6	0	3	80	7	€ 569.75	€ -397.50
51	Z-PartiallZ-RTS	Normal	0	77	0	13	100	14	€ -327.60	€ -348.24
52	Z-PartiallZ-RTS	Binomial	0	7	0	2	10	5	€ -12,168.54	€ -12,319.89
53	Z-PartiallZ-RTS	Binomial	0	9	0	3	10	8	€ -2,895.75	€ -2,945.25
54	Z-PartiallZ-RTO	Binomial	0	12	0	4	11	11	€ -121.10	€ -121.10
55	Z-PartiallZ-RTO	Normal	0	22	0	6	25	17	€ -61.31	€ -69.35
56	Z-No inventorZ-RTS	Normal	0	43	0	10	20	16	€ 1,457.85	€ 1,263.47
57	Z-No inventorZ-RTS	Binomial	0	3	0	2	4	4	€ 348.48	€ 348.48
58	Z-No inventorZ-RTS	Normal	0	22	0	6	10	10	€ 78.32	€ 78.32
59	Z-No inventorZ-RTO	Negative Binomial	0	157	0	155	8	8	€ 16.30	€ 16.30
60	Z-No inventorZ-RTO	Binomial	0	9	0	3	15	15	€ 0.45	€ 0.45
								Total	€ -54,499.96	€ -71,433.36

Table F.1: Proposed policy article parameters

Algorithm F.1 Overall impact Excel VBA code

```
Sub InsertArticles()

Dim W, i, k, j as Integer

W = ThisWorkbook.Sheets("Overall result").Range("C2").Value

for i = 1 to W do
    ThisWorkbook.Sheets("Overall result").Cells(i + 1, 5) = i
end for

for k = 1 to W do
    for j = 1 to 101 do
        ThisWorkbook.Sheets("Input").Cells(j, 1) = ThisWorkbook.Sheets("Overall result").Cells((k - 1) * 100 + j, 1)
    end for

    ThisWorkbook.Sheets("Overall result").Cells(k + 1, 6) = ThisWorkbook.Sheets("Results").Cells(2, 31)
    ThisWorkbook.Sheets("Overall result").Cells(k + 1, 7) = ThisWorkbook.Sheets("Results").Cells(2, 33)
end for

End Function
```

G Experiments and sensitivity analysis

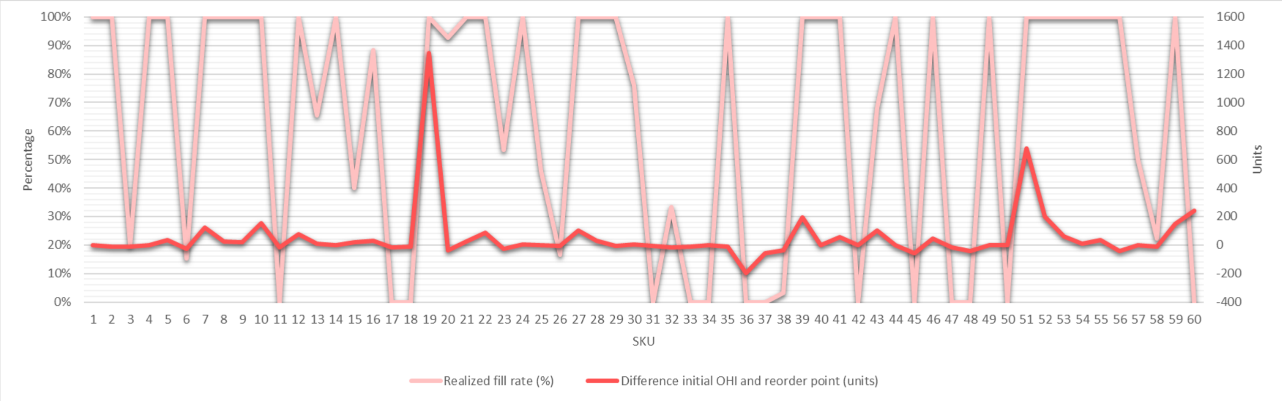

Figure G.1: Relation realized fill rate with the difference between initial OHI and proposed reorder point

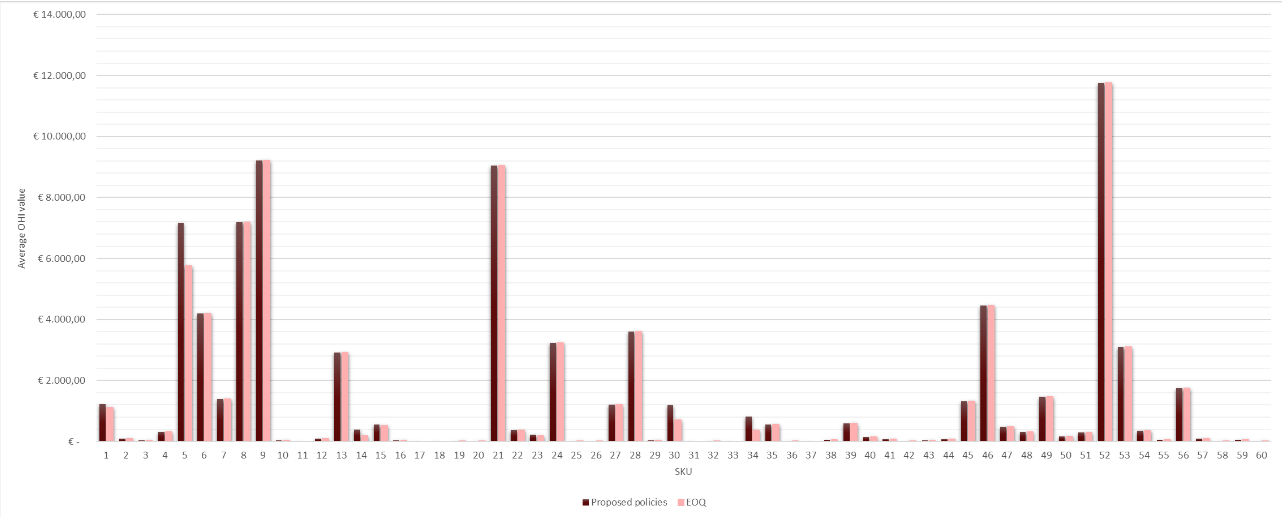

Figure G.2: Article's average OHI value of proposed policies applied to reality versus EOQ setting

SKU	Distribution	ELT reorder point	ELT order quantity	Impact
1	Normal	3	60	€ -64.35
2	Normal	4	20	€ -118.80
3	Binomial	2	10	€ -206.70
4	Binomial	1	10	€ -59.90
5	Normal	6	100	€ -2,705.10
6	Normal	3	12	€ 12,526.50
7	Gamma	28.06	210	€ -798.65
8	Normal	6	12	€ -7,214.76
9	Binomial	1	12	€ -4,397.05
10	Normal	4	100	€ 1.84
11	Binomial	2	25	€ -279.87
12	Normal	3	11	€ -101.92
13	Binomial	2	20	€ -14,544.75
14	Binomial	3	50	€ -337.88
15	Normal	7	50	€ -1,706.74
16	Normal	4	100	€ 42.12
17	Binomial	3	20	€ 883.43
18	Binomial	2	10	€ 1,265.52
19	Normal	72	121	€ 0.36
20	Normal	6	100	€ 7.42
21	Binomial	2	10	€ -8,679.44
22	Binomial	1	10	€ -207.41
23	Normal	4	20	€ -746.00
24	Binomial	2	14	€ -898.53
25	Binomial	2	8	€ -266.00
26	Poisson	2	8	€ -185.85
27	Normal	15	100	€ -1,951.70
28	Normal	12	100	€ -2,041.17
29	Binomial	1	6	€ 24.86
30	Binomial	3	50	€ -1,744.35
31	Binomial	2	7	€ -331.52
32	Binomial	3	10	€ 42.35
33	Binomial	3	7	€ -3,534.08
34	Binomial	1	10	€ -691.11
35	Binomial	2	15	€ -1,014.48
36	Normal	29.93	40	€ 36.71
37	Normal	7	15	€ 282.92
38	Binomial	3	20	€ 187.45
39	Binomial	2	25	€ 43.20
40	Binomial	1	3	€ 401.06
41	Normal	5	20	€ -62.51
42	Binomial	1	4	€ -106.08
43	Negative Binomial	10	100	€ -29.67
44	Binomial	1	5	€ 0.00
45	Normal	6	100	€ -92.89
46	Binomial	2	5	€ -5,589.68
47	Normal	15	200	€ -668.99
48	Negative Binomial	1	20	€ 69.00
49	Binomial	1	10	€ 114.70
50	Binomial	2	80	€ 556.50
51	Normal	10	100	€ -328.32
52	Binomial	2	10	€ -12,168.54
53	Binomial	2	10	€ -2,920.50
54	Binomial	2	11	€ -148.01
55	Poisson	4	25	€ -63.32
56	Negative Binomial	165	20	€ 8,990.08
57	Binomial	1	4	€ 290.40
58	Binomial	3	10	€ 63.64
59	Negative Binomial	86	8	€ 9.40
60	Binomial	2	15	€ 0.43
			Total	€ -51,16670

Table G.1: ELT SKU distributions, parameters, and impact

Target ready rate	Number of replenishments	Average OHI value	Number of stockout days	Realized ready rate	Realized fill rate
70%	120	€ 79,781.83	1,596	70.77%	62.48%
75%	121	€ 80,074.32	1,596	70.77%	62.48%
80%	122	€ 80,313.06	1,589	70.90%	62.83%
85%	122	€ 81,083.32	1,587	70.95%	62.83%
90%	123	€ 81,969.27	1,577	71.13%	63.18%
95%	127	€ 84,908.75	1,571	71.23%	63.48%
99%	131	€ 85,715.36	1,546	71.68%	64.24%

Table G.2: Target RR sensitivity results

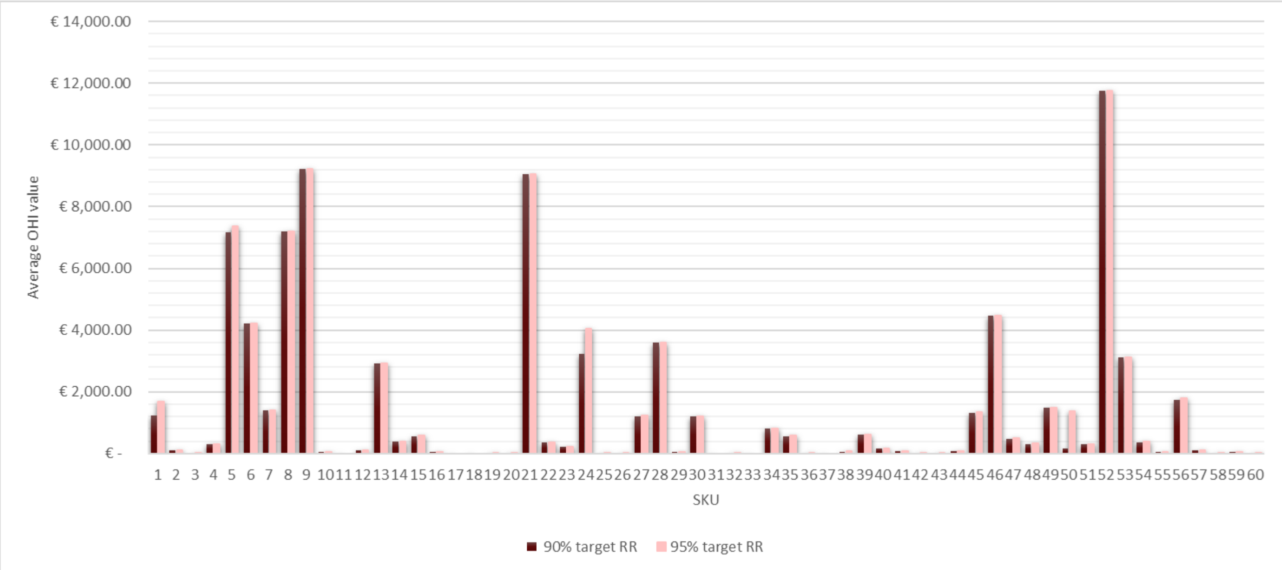

Figure G.3: Average OHI value target RRs values 90% and 95%

SLT bounds	Number of replenishments	Average OHI value	Number of stockout days	Realized ready rate	Realized fill rate
(-50;0)	111	€ 79,521.74	1,595	70.80%	62.93%
(-30;0)	114	€ 78,947.96	1,623	70.27%	62.19%
(-10;0)	116	€ 79,457.50	1,609	70.52%	62.34%
(0;0)	117	€ 79,567.70	1,602	70.65%	62.34%
(0;+10)	120	€ 80,091.76	1,587	70.95%	62.83%
(0;+30)	124	€ 82,052.42	1,577	71.13%	63.18%
(0;+50)	128	€ 83,256.95	1,576	71.15%	63.48%
(-50;+30)	147	€ 80,794.07	1,556	71.50%	63.32%
(-30;+30)	121	€ 80,485.40	1,587	70.95%	62.83%
(-10;+30)	123	€ 81,969.27	1,577	71.13%	63.18%
(-10;+10)	117	€ 79,791.23	1,594	70.80%	62.69%
(-10;+30)	123	€ 81,969.27	1,577	71.13%	63.18%
(-10;+50)	128	€ 84,023.35	1,571	71.23%	63.48%

Table G.3: SLT bounds sensitivity results

Holding cost rate	Number of replenishments	Average OHI value	Number of stockout days	Realized ready rate	Realized fill rate
5.0%	94	€ 83,927.36	1,520	72.18%	64.06%
7.5%	103	€ 82,858.49	1,531	71.97%	63.63%
10.0%	109	€ 82,051.10	1,535	71.88%	63.39%
12.5%	117	€ 81,805.21	1,572	71.22%	63.25%
15.0%	123	€ 81,969.27	1,577	71.13%	63.18%
17.5%	126	€ 81,767.23	1,580	71.07%	63.11%
20.0%	130	€ 81,491.27	1,575	71.17%	63.11%
22.5%	133	€ 81,197.38	1,575	71.17%	63.04%
25.0%	134	€ 81,088.78	1,593	70.82%	62.48%

Table G.4: Holding cost rate sensitivity results

Ordering cost rate	Number of replenishments	Average OHI value	Number of stockout days	Realized ready rate	Realized fill rate
2.5%	145	€ 80,778.01	1,605	70.62%	62.41%
5.0%	123	€ 81,969.27	1,577	71.13%	63.18%
7.5%	109	€ 82,051.10	1,535	71.88%	63.39%
10.0%	103	€ 82,858.49	1,531	71.97%	63.63%
12.5%	98	€ 83,288.82	1,525	72.07%	63.92%
15.0%	94	€ 83,927.36	1,520	72.18%	64.06%
17.5%	90	€ 84,641.67	1,491	72.72%	64.41%
20.0%	88	€ 85,526.28	1,489	72.75%	64.60%
22.5%	87	€ 86,457.55	1,482	72.88%	64.72%
25.0%	83	€ 86,950.85	1,447	73.52%	65.04%

Table G.5: Ordering cost rate sensitivity results

FP length	Number of replenishments	Average OHI value	Number of stockout days	Realized ready rate	Realized fill rate
1	119	€ 81,954.45	1,503	72.47%	64.74%
5	98	€ 87,712.42	1,191	78.18%	70.51%
10	87	€ 104,798.37	772	85.90%	78.92%
15	79	€ 117,110.69	517	90.53%	84.06%
20	79	€ 112,499.51	382	93.00%	85.18%

Table G.6: FP length sensitivity results