Master thesis: Industrial Engineering and Management

"A simulation model to optimise the inventory parameters of Paul Mueller with uncertain supplier lead times and demand variability."

Author:
M.A. Zwiers (Maarten)
s2398168
MSc. Industrial Engineering and Management
m.a.zwiers-1@student.utwente.nl

University of Twente
MSc. Industrial Engineering and Management
Postbus 217
7500 AE Enschede
Tel. (053) 489 9111

Paul Mueller Company
Paul Mueller Company, Noordgang 14
7141 JP Groenlo
Tel. (088) 683 0000

First supervisor University of Twente
Dr D.R.J. Prak (Dennis)
Second supervisor University of Twente
Dr D. Demirtas (Derya)

Supervisor Paul Mueller Company
Maikel-Bastiaan Post (Supply Chain Manager)

Preface

Dear reader,

You are about to read the results of my master's graduation thesis in the field of Industrial Engineering and Management at the University of Twente. This research was conducted for Paul Mueller Company from March 2024 to October 2024. Paul Mueller Company is an international leader in heat transfer and storage solutions, and the research focused on optimizing the company's inventory management processes by addressing lead time variability and demand forecasting challenges. Specifically, I investigated how the company can improve the item fill rate, these insights will contribute to improving the company's OTIF. The item fill rate is enhanced by developing a new inventory model in which deterministic and stochastic demand and lead times are compared.

Throughout this research, I gathered data from internal sources and conducted in-depth discussions with the supply chain team at Paul Mueller. Using this data, I developed a simulation model to evaluate different inventory configurations, leading to insights that will help the company better align stock levels with actual demand.

I would like to extend my gratitude to my supervisor at Paul Mueller Company, Maikel-Bastiaan Post. His guidance and feedback were invaluable throughout the research process, and I appreciate the support and expertise. I also want to thank the employees of Paul Mueller who contributed their time and insights, allowing me to gain a deep understanding of the company's operations.

Additionally, I would like to express my appreciation to my first supervisor from the University of Twente, Dr. Dennis Prak. His continuous support, constructive feedback, and enthusiasm were crucial to the success of this thesis. I also want to thank Dr. Derya Demirtas, my second supervisor, for her insights.

Finally, I would like to thank my family and friends for their unwavering support throughout this journey.

Maarten Zwiers
30-09-2024, Enschede

Management Summary

This research was conducted at Paul Mueller Company and focused on optimizing inventory management to improve On-Time-In-Full (OTIF) performance, which currently falls below the target of 92.5%. The core issues identified include outdated inventory parameters, inaccurate demand forecasting, and unreliable supplier lead times. These factors have contributed to a fill rate of 78.9%, significantly lower than the company's desired levels, which impacts customer satisfaction and leads to operational inefficiencies.

Research Objectives

The research aims to develop an inventory model that addresses the issues of lead time uncertainty, demand variability, and inefficiencies in current stock management practices. To achieve this, a simulation model was built to evaluate three configurations:

1. A model that represents the current situation.
2. A model that considers deterministic lead times.
3. A model that incorporates stochastic lead times.

The simulation was designed to measure the impacts of these models on key performance indicators (KPIs), such as inventory turnover, backorder rate, and fill rate. Additionally, the costs associated with holding inventory, ordering, and backorders were evaluated to determine the overall effectiveness of each configuration.

Key Findings

The results of the simulation revealed that addressing lead time variability and demand uncertainty had a significant impact on improving service levels and reducing costs. Both the deterministic and stochastic models outperformed the current model, with the stochastic model showing the best overall performance in terms of fill rate, service level, and reduction in backorders.

The implementation of stochastic lead times increased service performance, as well as a notable reduction in the number of backorders and related costs. However, this model also resulted in higher holding costs compared to the deterministic model.

Results

KPI	Current	Deterministic	Stochastic
Weighted Average Inventory Turnover	838,4	9,1	5,6
Weighted Average Backorder Rate	47,1%	95,3%	98,8%
Weighted Average Fill Rate	43,1%	93,8%	98,2%

Table 1 Key Performance Indicators for Inventory Models

Costs	Current	Deterministic	Stochastic
Holding costs	€123.065	€720.362	€938.017
Ordering costs	€2.950.013	€ 392.815	€360.353
Total costs	€3.069.274	€1.113.177	€1.298.370

Table 2 Cost Overview

Backorders	Current	Deterministic	Stochastic
Total backorders occurred	247210	18348	6833
Total number of items backordered	17064955	2065298	500558

Table 3 Backorder Details

Discussion
Several key findings of this thesis are discussed next, particularly in relation to inventory management. The current model demonstrated a higher inventory turnover, primarily due to frequent replenishments driven by poor planning rather than actual efficiency. In contrast, both the deterministic and stochastic models exhibited lower turnover rates, indicating a more strategic approach to inventory holding.

Regarding service level and fill rate, the stochastic model showed the best performance, achieving a service level of 98.8% and a fill rate of 98.2%. This highlights its superior ability to meet customer demand without stockouts when compared to both the deterministic and current models.

In terms of costs, both the deterministic and stochastic models had significantly lower total costs than the current model, with the deterministic model having the lowest overall costs. However, the stochastic model, despite its higher holding costs, outperformed the deterministic model in service level and fill rate, making its slightly higher total cost justifiable.

Additionally, both models drastically reduced the number of backorders. The stochastic model, in particular, reduced backorders by 97.2% compared to the current model, leading to enhanced customer satisfaction and greater operational efficiency.

Recommendations
Based on the simulation results, several recommendations are made for Paul Mueller Company. First, the company should implement the stochastic inventory model, as it has shown significant improvements in service level, fill rate, and reduction of backorders. Although the stochastic model incurs higher holding costs than the deterministic model, the overall benefits in terms of customer satisfaction and service efficiency make it the superior choice.

Second, data accuracy, particularly regarding lead times and demand forecasting, must be continuously monitored and improved. Maintaining accurate and up-to-date data is crucial to ensuring the inventory model remains effective and responsive to fluctuations in demand and supply conditions.

Third, optimizing supplier relationships is recommended. Lead time variability has a notable impact on inventory performance, so Paul Mueller Company should work closely with suppliers to reduce lead times where possible or, at the very least, enhance the accuracy of lead time estimates.

Finally, the company should implement key performance indicators (KPIs), such as inventory turnover, backorder rate, and fill rate, to monitor and drive ongoing improvements in the inventory management system. This approach will help sustain performance improvements and allow for adjustments when necessary.

Conclusion
By adopting the proposed stochastic inventory model, Paul Mueller Company can significantly improve its inventory management performance. The improvements in fill rate, service level, and reduction of backorders will help meet the company's OTIF targets and enhance overall customer satisfaction, while also keeping costs at manageable levels. This model aligns the company's inventory strategy with actual market demand and supplier capabilities, making it more agile and responsive to changing conditions in the supply chain.

Table of Contents

Readers Guideline

This research is presented in seven chapters and a structured overview of the work conducted at Mueller is provided.

Chapter 1: Introduction

The first chapter introduces the company. The observed action problem is analysed using a problem cluster and the core problem is selected. Next, the research design is explained determining the scope of the research and listing the research question and deliverables.

Chapter 2: Current Situation

An analysis of Mueller's current operational processes is provided. The production process of Mueller is explained, as well as the Stock Keeping Units (SKUs) in the scope of this research. The demand data is analysed, and the calculations are performed on the reliability suppliers. Lastly, the current inventory policy is described.

Chapter 3: Literature Review

This chapter explores methodologies for managing lead time uncertainty, modelling lead time demand distributions, and fitting demand and lead time data. It identifies different service-level policies and KPIs crucial for optimizing Mueller's inventory management.

Chapter 4: Model Development

The foundational models to optimize the inventory configurations and performance at Mueller are explained here. This includes evaluating service level policies, fitting data distributions, and calculating costs needed as input for the models.

Chapter 5: Result Analysis

Simulation results are presented and analysed in terms of costs, backorders, fill rates, backorder rates, and inventory turnover for different inventory configurations. Each configuration will be compared to determine the most effective model. The chapter also includes a step-by-step calculation for one item, an assessment of excess inventory, and a discussion of model validation and limitations.

Chapter 6: Implementation

This section outlines the steps Mueller needs to take to implement the proposed changes in its inventory management practices.

Chapter 7: Conclusion, Discussion, Future Research

The research concludes with key findings and recommendations, followed by a discussion of the research limitations and suggestions for future work.

List of Figures

List of Tables

List of Abbreviations

APCR = Average Price Criticality Ratio
BOM = Bill Of Materials
DFE = Dairy Farm Equipment
EOQ = Economic Order Quantity
ERP = Enterprise Resource Planning
IP = Inventory Position
KPI = Key Performance Indicator
KPIs = Key Performance Indicators
LTD = Lead Time Demand

MOQ = Minimum order quantity
MRP = Material Resource Planning
SBT = Serving beer tanks

Chapter 1 Introduction

The objective of this research is to improve the On-Time-In-Full (OTIF) delivery of the Paul Mueller Company in Groenlo. This is done by improving the inventory management at Mueller. This chapter provides a global overview of the research. Section 1.1 consists of an introduction to the company. In Section 1.2 the problem studied is identified and the background of the problem is discussed. In Section 1.3 the research approach is mentioned.

1.1 Company Description

The Paul Mueller Company is known as a leader in cooling and heat exchange solutions. The company is headquartered in Springfield, Missouri, U.S.A. and was founded by Paul Mueller in 1940. In 1970 a partnership with Meko Holland was formed and since then managed the sales of milk tanks in the Netherlands. In 1988 a manufacturing company for dairy tanks opened in Lichtenvoorde in the Netherlands. In 2008 Paul Mueller Company acquired Meko, which consists of the production company in Lichtenvoorde, a service company in Wesepe and the Sales & HQ in Assen. From 2008 and onwards Paul Mueller Netherlands would focus on manufacturing dairy farm equipment products, serving beer tanks and a full range of heat transfer and processing equipment for internal markets. In 2015 the implementation of the ERP was completed. On April 9th, 2018, the sites in Lichtenvoorde (Production), Wesepe (Service) and Assen (Sales & HQ) merged and moved into a brand-new building in Groenlo. Nowadays, Paul Mueller Company is stock-listed and has an annual revenue of approximately 200 million US dollars. The Paul Mueller Company employs seven hundred people in the USA and 250 people in Groenlo.

Figure 1 Milk silo.

The company's main product is the stainless-cooled storage solutions, used in a wide variety of products and industries. For example, the Dairy Farm Equipment (DFE), Serving Beer Tanks (SBT), Bakery, Pharmacy and Chemical. The DFE mainly consists of Silo's (See Figure 1) (Paul Mueller, 2024a) and the O&P tanks (see Figure 3) (Paul Mueller, 2024b). For these products base models are created. This is a standard product which can later be specified to customers' preferences. The silos are known in twelve different sizes. Before the production can start a decision has to be made regarding the cooling systems and the final colour of the silo. The decision in the cooling system is either with or without a mantle evaporator and the silos of Mueller are produced in three standard colours. Each base model of a silo consists on average of 240 distinct parts.


Figure 3 Milk cooling tank.

There are forty different types and sizes of O&P milk tanks before customer specification. A base model of an O&P tank on average consists of 140 parts.


Figure 2 Serving beer tank.

In the production of SBT (see Figure 2) (Paul Mueller, 2024c) there is not a lot of variation. Based on eight sub-assemblies, all final products can be made. The products created for all other products are treated as specials. This means that the products are uniquely designed by the engineering department and are not made on a base model. Therefore, the items needed for these products are bought specifically for this product and are not put in stock. In addition to the production of the products, Mueller is offering a highly qualified after-sales service. This includes performing maintenance, reparation, and refurbishing products regardless of the product type or the date of purchase.

1.2 Problem identification.

After the merger into a centralised facility in Groenlo, the communication, operational efficiency, transport arrangement and work order prioritisation improved a lot. However, the On-Time, In-Full (OTIF) delivery rate does not yet meet the company's target. This action problem is described in Section 1.2.1. In Section 1.2.2 the visualised problem cluster is used to identify the core problems.

1.2.1 The action problem

The On-Time, In-Full (OTIF) delivery rate measures the percentage of orders a business can deliver at the time agreed with the customer (on time) and at the volumes expected (in full). An order can be considered as delivered on time, in full if the customer receives exactly what was ordered, in the amount requested, at the correct location, and within the agreed-upon time. Currently, Mueller does not reach the OTIF of 92.5% which is the goal of the company.

Improving OTIF is challenging because multiple departments across the supply chain influence it. Therefore, understanding which departments impact OTIF is crucial. A brief explanation of the product flow from the moment an order is placed is provided below.

When a customer places an order, the sales team receives it. This order may be for a standard existing product, in which case it is entered into the Enterprise Resource Planning (ERP) system and processed accordingly. If the order is for a special product, it requires new drawings from the engineering department. Next, the order entry department ensures that all components required to produce the product are available when needed. The work preparation department then creates the production schedule. Once the production schedule is entered into the ERP system, the system suggests items that must be purchased by the purchasing department. After procurement, the warehouse ensures that the products are logged into the system, and the work orders are picked for production. Once the production department completes the product, it is tested, washed, packed, and sent to the customer. A more detailed overview of the supply chain is available in Appendix A: Product flow.

Based on personal observations and meeting with experts at Mueller we found out that many parts have been in the warehouse for years without future purpose in sight. On the other hand, there are also buy-in products not available at the required time, leading to additional work and more pressure on the production department, a lower OTIF and lower customer satisfaction.

As mentioned previously, the OTIF can be influenced by a lot of departments. Therefore, this research will focus on the fill rate since the most benefits can be gained in the inventory configuration. Which can be captured with the fill rate. Why the OTIF is selected is explained in more detail in Section. 1.2.2.

To summarize, Mueller currently holds stock of items that are not needed, while items that are needed are not sufficiently stocked, leading to a lower OTIF. To improve item availability in the warehouse, the company needs to enhance its fill rate. The fill rate measures the percentage of customer demand that is met without stockouts, indicating the effectiveness of inventory management.

Given the impact of inventory availability on OTIF, improving the fill rate is essential. Therefore, the following action problem is defined:

"The fill rate at Mueller based on the data from 01/01/2022 until 01/07/2024 is 78.9%[1] *while the goal of Mueller is to exceed 92.5%."*

[1] These calculations can be found in Section 5.1.1.

To improve this the most gain can be achieved by adjusting the parameters of the inventory levels. Therefore, this research focuses on designing an inventory management system in which the inventory levels are adjusted to Mueller's needs.

1.2.2 Problem cluster and core problems

The action problem identified is that the lower OTIF at Mueller is caused by discrepancies between the availability of final products and the promised delivery dates to customers. The availability of final products is often because the buy-in products and sub-assemblies are not available at the right time. Therefore, the most significant improvements can be made by adjusting the inventory level configurations. To understand how inventory levels influence OTIF, a problem cluster has been created, which is depicted in Figure 4.

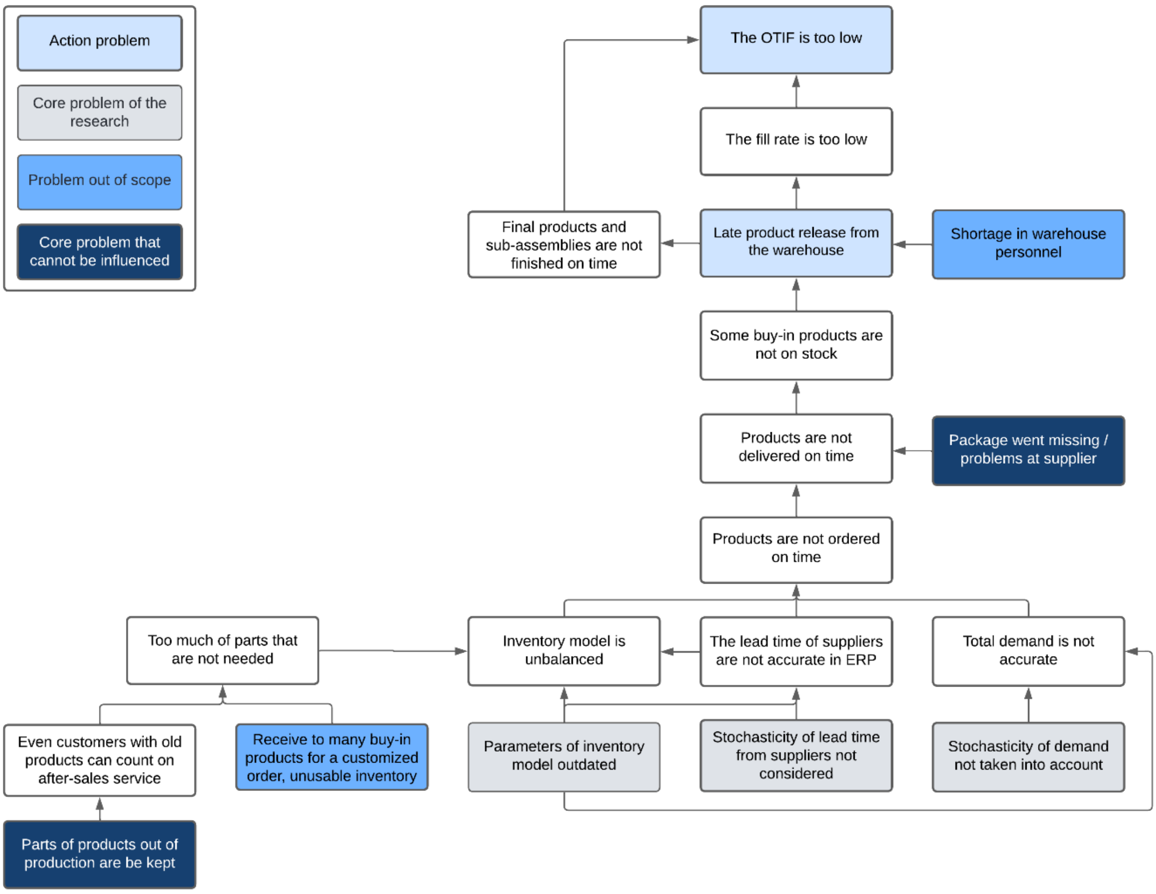


Figure 4 Problem cluster.

The Problem cluster, as illustrated in Figure 4, is designed to address the root causes of the lower OTIF. Based on this problem cluster three core problems can be identified. Core problems represent the root problem that causes the challenges of a company or system. The company needs to address the core problem to effectively resolve related issues and achieve desired outcomes. To ensure a thorough understanding of the core problems, additional explanation is provided.

The OTIF at Mueller is directly impacted by two key factors: delays in the production of final products and sub-assemblies, and the late release of products from the warehouse, which lowers the fill rate and reduces the OTIF. These delays can be traced back to issues within the purchasing and warehouse departments, where problems such as insufficient stock availability and delayed product ordering arise. This research will focus on these departments to identify the core issues and propose solutions that will enhance the OTIF. The final products and sub-assemblies are treated as buy-in products and the production time is considered as the lead time of suppliers. This assumption is made due to time restrictions.

The late release of products from the warehouse can be caused by two things. Historically the late release from the warehouse was caused due to a lack of personnel in the warehouse. This problem has been solved and therefore is outside the scope of this research. Secondly, delays occur due to insufficient stock availability, which is a consequence of products not being delivered on time.

Products delivered on time can be influenced due to two things, either product loss or other transport-related issues, which cannot be influenced by Mueller. The second reason is that the products are not ordered on time. Delayed ordering is caused by insufficient or inaccurate information. This is due to a lack of maintaining the inventory model after the implementation of the ERP system in 2015. The next three causes can be identified. The inventory parameters are outdated and therefore not optimal, the total demand is unknown and the lead times of suppliers are not accurate.

The inventory parameters are outdated:
The first core problem lies in the outdated parameters of the inventory model, which results in an inefficient inventory model. Over time, product demand at Mueller has shifted, particularly due to changes in government subsidies that affect sales. However, the inventory model has not been updated to reflect these changes, leading to excess stock for some items and insufficient stock for others. This misalignment between actual demand and inventory levels is a significant contributor to the OTIF issues. This brings us to the first core problem; the parameters of the inventory model are outdated.

The second reason why the inventory model is no longer optimal is that many products have become obsolete over time. Due to the nature of custom orders and after-sales service, there is inventory that has remained unused for the past two years. This is caused by purchasing and receiving excess products for customized orders, resulting in unusable stock. The company is aware of this, and it is managed by the purchasing department. Secondly, Mueller promises quick after-sales service for all products it has ever produced. This includes tanks manufactured as far back as thirty years ago, which require different components for repairs compared to those used in more recently produced tanks. While this presents a challenge, it also serves as a competitive advantage for Mueller and is therefore not considered within the scope of this research.

The demand forecast is not data-driven:
When a replenishment order is placed, it is typically based on a forecast of the total demand for each item. However, at Mueller, this process does not rely on a data-based forecast but rather on a judgmental forecast made by the order entry department. As a result, the demand generated by after-sales service and emergency orders does not influence the timing of when an order is placed. To account for this, additional safety stock is reserved to cover the demand from after-sales service and emergency orders. In this research a demand forecast is created for each item, to obtain data for the inventory model to work with.

The lead times of suppliers are not accurate:
The lead times of suppliers recorded in the ERP system at Mueller are not in line with the average lead times of the suppliers, leading to delays in product availability. This inaccuracy is due to outdated data and the lack of consideration for the stochastic nature of lead times. This research will update the deterministic lead time parameters and explore whether modelling lead times stochastically could result in a more reliable fill rate and therefore a better OTIF.

In summary, the research identifies three core problems contributing to Mueller's OTIF issues: outdated inventory parameters, inaccurate demand forecasting, and unreliable supplier lead times. By addressing these core problems, the research aims to optimize inventory configurations, this includes calculations for the reorder point and order quantity. This will ensure that the right products are available at the right time, thereby improving the OTIF and overall customer satisfaction. Therefore, the core problem is:

"The current inventory model suffers from inadequate lead time estimations, inaccurate total demand forecasting, and suboptimal inventory parameters in the inventory model, resulting in wrong inventory configuration."

1.3 Research design

In this section, the research design is described. This research is structured using the Managerial Problem-Solving Method (MPSM) by Heerkens & van Winden, 2021. In section 1.3.1 the scope of this research is set. In section 1.3.2 the main research question is split up into smaller sub-questions to ensure clarity and manageability of the research process. Lastly, the deliverables are mentioned in the section 1.3.3.

1.3.1 Scope

The company's On-Time In-Full (OTIF) performance has been identified as suboptimal. A problem cluster is created to identify the root causes in Section 1.2.2. Based on this the conclusion was made that the most significant improvements can be achieved by optimizing the inventory model. The current inventory has three key issues, namely: inadequate lead time estimations, inaccurate total demand forecasting, and outdated inventory parameters.

To effectively measure the performance of the inventory model, some Key Performance Indicators (KPIs) have been established. The KPIs exclusively reflect the impact of the inventory model, unaffected by external factors like production or transport, which are also captured in the OTIF. Why these KPIs are chosen is explained in Section 3.5.

Volume fill rate per item, this represents the percentage of demand satisfied directly from the shelf.
The inventory turnover to ensure the average inventory stock level remains reasonable.

The items in the scope of this research are the items associated with O&P tanks, Silos, SBT, and Phantoms. Phantoms refer to the components required to transform base model products into final products. The products have a standardized production plan, making them ideal for inclusion in the inventory model. Additionally, items necessary for after-sales service are also considered.

For the selected items, an inventory model will be developed and integrated into Mueller's (s, Q) model. To do this the following steps must be taken. First, historical data will be used to classify items and fit appropriate demand distributions. Then, a demand forecast will be created to account for demand uncertainty. Given Mueller's context, the forecast will be simple, avoiding complex models that incorporate trends and seasonality. Finally, the uncertainty in supplier lead times will be incorporated into the model.

In this inventory model, three different inventory configurations will be compared: the current inventory parameters; inventory parameters updated using fitted demand distributions and stochastic lead times; and inventory parameters updated with fitted demand distributions and deterministic lead times, based on the average lead time of the new data. To evaluate the performance of these configurations, a simulation model is developed. In this model, the daily operations over one year are simulated. The demand and lead time of suppliers are generated based on the distributions fitted to the historical demand. This simulation will assess the effectiveness of each inventory configuration using the previously defined KPIs.

It is important to note that this thesis will not consider the multi-indenture product structure due to time constraints. As a result, each sub-component will be treated as a buy-in product, and product dependencies will not be factored into the analysis. Given that the Bill of Materials (BOM) at Mueller typically involves only three levels, this assumption is not expected to have a significant impact on the results.

1.3.2 Research questions

Based on the core problem the following research question is derived:

"How can the inventory model of Paul Mueller be optimised by reevaluating the inventory parameters of all items, while considering stochastic demand and uncertain supplier lead times?"

This leads to the following research objective:

This research develops a new inventory model to address inadequate lead time estimations, inaccurate demand forecasting, and a suboptimal inventory parameter configuration. Subsequently, a simulation model will be developed to evaluate and compare the effectiveness of the updated inventory model in improving the fill rate at Paul Mueller, while considering stochastic demand and uncertain supplier lead times.

1. What is the current situation regarding item availability, forecasting and supplier lead times?
   - 1.1 Which items are in the scope of this research?
   - 1.2 How do the items available correspond to the demand sources and patterns?
   - 1.3 What is the accuracy of current supplier lead times?
   - 1.4 How is the current inventory policy structured within Mueller?
   - 1.5 What is the performance of the current inventory model?

The first question aims to understand the current operational processes at Mueller by analysing order procedures and interactions with production and inventory. This involves interviewing experts and reviewing internal data. The answers to the following questions are presented in Chapter 2 Analysis of the current situation.

2. How does incorporating lead time uncertainty and demand distribution modelling impact the optimization of safety stock levels, reorder points, and service-level policies in inventory management at Mueller?
   - 2.1 How does lead time variability affect safety stock levels, reorder points, and overall inventory costs in stochastic inventory models?
   - 2.2 What are the key factors in accurately modelling the lead time demand (LTD) distribution, and how does the integration of demand and lead time variability impact inventory performance?
   - 2.3 What are the most effective methods for fitting discrete and continuous distributions to historical demand and lead time data in inventory management, and how do these methods influence inventory policy accuracy?
   - 2.4 What different service level policies does the literature prescribe that can be applied at Mueller?

2.5 Which key performance indicators (KPIs) are most effective for evaluating inventory policies and how do they impact the decision-making process in inventory management at Mueller?

The goal of this section is to explore various approaches and methodologies from the literature to address lead time uncertainty, model lead time demand distributions, and fit appropriate demand and lead time data to optimize inventory management at Mueller. Additionally, service level policies and essential KPIs are identified, providing a framework for effectively managing inventory performance and ensuring the continuous improvement of inventory policies.

3. How can different inventory optimization models, service level policies, and cost calculations be effectively integrated to enhance inventory management at Mueller, considering demand and lead time uncertainty?

3.1 How can different inventory models be developed and validated to simulate future demand and optimize inventory configurations at Mueller?
3.2 What impact do different service level policies, such as ABC-XYZ classification and cost-based approaches, have on optimizing stock levels and balancing customer demand at Mueller?
3.3 How can accurate inputs for ordering, backordering, and inventory holding costs be determined to calculate optimal EOQ and set appropriate service level targets?
3.4 What are the most effective methods for fitting demand and lead time distributions, and how do they influence inventory performance and forecasting accuracy?
3.5 How can different inventory configurations, incorporating deterministic and stochastic lead times, improve inventory performance and reduce costs at Mueller?
3.6 What are the most relevant KPIs for evaluating inventory configurations at Mueller, and how can they be used to measure cost efficiency and service levels?

The purpose of this chapter is to establish the foundational models and methodologies necessary for inventory optimization at Mueller. By analysing different service level policies, fitting data distributions, and calculating costs, this chapter lays the groundwork for improving inventory management. The insights provided here will guide the selection of inventory configurations and the use of KPIs to ensure cost efficiency and meet customer demand.

4. How can the performance of different inventory configurations (current, deterministic, and stochastic) be evaluated and compared using simulation models to optimize costs, service levels, and inventory efficiency at Mueller?

4.1 What are the cost, service level, and inventory efficiency metrics generated from the historical and future demand simulation models?
4.2 How are costs, backordered days, total backorders, fill rate, backorder rate, and inventory turnover calculated from the simulation models?
4.3 How do the current, deterministic, and stochastic inventory configurations differ in terms of costs, backorders, and service level metrics, and what are the key differences?
4.4 How much excess inventory and obsolete items does Mueller have, and what strategies can be used to minimize these issues?
4.5 How can the simulation model for inventory management be verified and validated, and what limitations should be considered when interpreting the results?

In this chapter, the performance of different inventory configurations will be evaluated through simulations, presenting detailed metrics such as costs, backorders, fill rates, backorder rate, and inventory turnover. Each configuration will be compared to determine the most effective model. Additionally, the chapter will provide a step-by-step calculation for one item as a showcase, assess excess inventory and obsoletes, and address the verification, validation, and limitations of the models used. This chapter will offer valuable insights into the optimization of inventory management at Mueller.

After the inventory policies are compared the recommendations for Mueller are formulated and the conclusions are written down. Furthermore, a reflection on the research is performed and the limitations and further research are identified in Chapter 7: Conclusion, Discussion and Future .

1.3.3 Deliverables

During the completion of this research, the main research question is answered, leading to the following deliverables:

- Recommendations for the current inventory model, included the parts classification, review period, safety stock and order-up-to-level. This will be based on an analysis of the current situation and solution design.
- A simulation model to assess the performance of the inventory policies using historical lead time and demand data.
- A dashboard evaluating the current inventory model based on the KPIs.
- Recommendations on the implementation and further research.

Chapter 2 Analysis of the current situation

In this chapter, the starting point of the research is described. Section 2.1 presents the exact SKUs in the scope that are identified and analysed. The demand planning and the demand patterns are described in Section 2.2. In Section 2.3, the supply lead times from the suppliers are described. Section 2.4 explains the structure of the current inventory policy. Section 2.5 concludes the chapter.

2.1 The SKUs in Inventory

The current items in the ERP system at Mueller are analysed. In total there are 35027 items in the ERP system. Of these items 29206 items used in the production and 9324 items in the service department, hence, there are 3503 duplicated items used in service and production. The items selected to discuss for this research are all items needed to produce the O&P tanks, silo tanks and SBT tanks, in all configurations and the items needed for after-sales. For the items needed for after-sales, the following separation is made. The products for which there was no demand in the last two years are outside the scope of this thesis.

First, the items used in production are analysed. To create an overview within the 35027 items in the ERP systems, the items are categorised into four distinct groups: the materials required for manufacturing all base models O&P tanks, the items necessary to create all base models Silos, the items needed to transform the base models products into final products, referred to as Phantoms and the materials needed for manufacturing all SBT tanks.

O&P basic models come in forty different versions. To manufacture all these models, 819 distinct pieces are needed in total. These products include materials that are made internally as well as components that are acquired. The base models' bill of materials (BOM) is organized into three echelon levels. Of the 819 goods, 626 are produced internally by Mueller, and the remaining 193 originate from outside purchases. This thesis treats all products as buy-in items and does not account for the multi-echelon level. Therefore, the manufacturing time for manufactured goods is interpreted as the supplier's lead time. To do this, the assumption is made that the items needed for manufacturing are never out of stock.

There are nine distinct sizes of base models available for Silos. Since there is little demand for silos that are not on the list of basic models, these products are handled as special orders. These nine sizes result in 158 distinct silo base models since the buyer can choose from a variety of choices on the silo. Out of these 158 distinct Silos, 486 unique items result, of which 334 are manufactured in-house and 152 are buy-in products.

Silo and O&P base model tanks still need to be converted from base model to finished goods, depending on the customer's selected options. Different items are required for each option. To be able to execute every transition, a total of 722 unique pieces are required. Therefore, these items are also in the scope of this research.

SBT comes in a total of twenty-eight varieties. To produce every possible SBT production type, 232 distinct products are needed. Out of the 232 distinct products needed for SBT manufacture, 127 are sourced externally and 105 are created in-house.

When the SBT, O&P, Silo, and Phantoms are merged, a total of 2258 items are considered. Once the duplicates are eliminated, 1915 unique things remain. Certain items are recently added to the ERP system and do not yet have a demand pattern, or products had no demand in the last two years, or the organization is still missing certain pieces of information. Consequently, certain items are eliminated from the thesis's scope, leaving 1630 elements that are associated with the production section of the organization. Data validation is conducted for these products; for example, demand for some items has to be coupled because they have been replaced in the last two years. Next, the annual consumption value is calculated by multiplying the unit costs by the annual demand. To calculate the percentage utilization value per SKU, the annual usage value of each SKU is divided by the annual usage value of all items. Next, the items are arranged from largest to smallest utilization value and the cumulative usage value is calculated. The items distributed by value are presented in Figure 5. In this figure, we see that only 13% of the items are responsible for 80% of the annual costs.

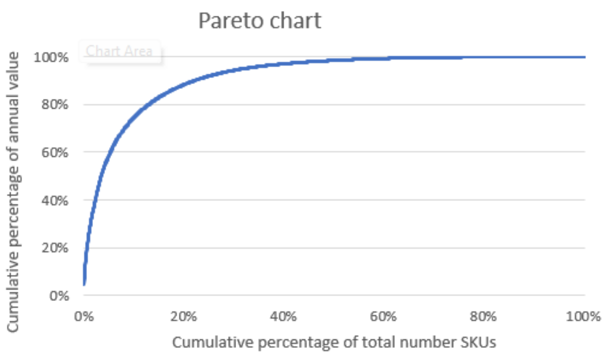


Figure 5 Pareto chart production

All products that have been relocated more than four times in the past two years are considered by the service department. This encompasses every item necessary for both refurbishment and post-purchase service, resulting in a total of 2,652 unique items. Due to their use in refurbishment and post-purchase service, these items do not have an associated Bill of Materials (BOM). The cumulative consumption value for the service department is calculated in the same manner as previously described. Figure 6 presents the distribution by value, demonstrating that 80% of the annual costs are attributed to merely 8% of the items.

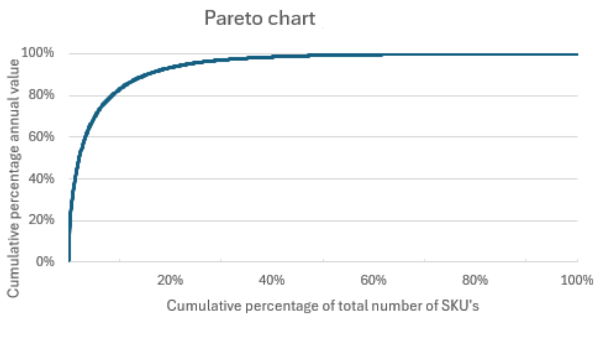


Figure 6 Pareto chart service

2.2 The demand patterns

The total demand encompasses both deterministic elements and stochastic elements. The deterministic part is caused by the production plan. The stochastic part is caused due to rush orders from customers and the service department. The stochastic part introduces uncertainty into the total items needed, therefore a demand forecast is required. In this section a short overview is given, a more elaborate overview can be found in Appendix B: The demand pattern of Mueller.

2.2.1 Deterministic demand

A production plan is created ten weeks in advance once a week the production plan is revised and one more week is added to the production plan. This is done for the O&P production line, the silo production line, and the serving beer production line. To determine which products to produce is done in the same way for each of the production lines, and boils down to the following steps:

1. Yearly sales create a forecast on how many O&P tanks, Silos and serving beer tanks will be sold during the next year.
2. Based on the forecast created by sales the production capacity, in work hours, for each production line is determined.

3. The production planning for the next ten weeks can be created based on the available working hours per production line.
4. The first step is to plan products that are sold to consumers and must be finished in the next 10 weeks.
5. If the production capacity is not filled with the products sold, products are made in advance, called base models.
6. Determining which base models to make is based on the products sold during the last year. Based on this, the expected number of products sold is calculated. The products already created during the last year are subtracted. Based on this a percentage of fulfilled demand is calculated. The product with the lowest fulfilled demand percentage is created.

One of the main differences between the O&P production line and the silo production line is that the O&P products are first made as base models. Once a customer buys one of the O&P tanks, the base model is made customer-specific and can be sent to the customer in a brief period. To produce a silo the customer preferences, have to be determined at an earlier stage of the production process. Therefore, the variety in silos is bigger, hence not all products are made as base models. Therefore, the silos created as base models can be offered to customers who are in a rush. All silo orders which are not needed within ten weeks are not created from a base model but are incorporated into the standard production planning.

Since the suppliers have a lead time of less than ten weeks, the products required to conduct the manufacturing plan can be ordered once the production schedule is established. Since the production plan's demand is deterministic, there should not be any requirement for inventories. However the lead timers are not entirely deterministic, and demand unpredictability also arises from urgent client orders, the maintenance and service department, and other factors. First, let us examine the demand's stochasticity.

2.2.2 Stochastic demand

Urgent customer order:
Products sold to consumers who expect delivery within the next ten weeks. To meet this customer demand, the work preparation department must adjust the production plan as detailed in Section 2.2.1. For these urgent orders, the work preparation department looks if there is a possibility to stop creating a new base model and change an existing base model into the product for the customer in a rush. To do this of course the work preparation department has to check if all products needed are available in stock. Therefore, it is important to model the probability of rush orders into the demand forecast. As a result, the customers' urgent orders are a stochastic component of the demand projection.

After Sales Service:
Mueller offers after-sales service and maintenance on the products sold to the customers and refurbishes old products. Therefore, it occurs that items are needed to repair products at customer locations. These items must also be in stock, and the demand rate is not known on forehand. This component involves fulfilling orders related to after-sales service.

2.2.3 The Demand Forecast

In the current situation at Mueller, no demand forecasting is done. When and how much the purchasing department should buy is determined by the MRP, as explained in Section 1.2.2. The MRP system adds up all the items needed during the lead time. If the amount of stock available, minus what is needed during that time, drops to a certain level, a new order is made to restock. This means that the point at which a new order is made is not fixed but depends on how many items are expected to be needed during the lead time. How long the system looks into the future the demand is determined by how long it takes for suppliers to deliver, highlighting the importance of suppliers giving accurate estimates of delivery times in this system.

Therefore, in the current model, only the current deterministic demand pattern is taken into account. Demand caused by urgent customer orders and after-sales service must be incorporated by the level of the safety stock. In the current situation, there is no forecast for the stochastic demand.

2.2.4 Historical Demand Data

In the historical demand data of Mueller, it is not possible to distinguish between demand that is deterministic and stochastic. The demand distributions are now fitted by assuming that all demand is stochastic, as a result, safety stock levels will be higher than necessary. For instance, consider an item with a weekly demand of eighty units and a standard deviation of 50 units. If it is later revealed that fifty units are planned 25 weeks in advance, this distinction is not reflected in the data. As a result, the existing model accounts for more uncertainty than what is present, potentially leading to excessively high safety stock levels. By accurately identifying and separating deterministic demand, the company can adjust inventory parameters accordingly and optimize safety stock levels.

2.3 The accuracy of current supply lead times

As mentioned in Section 2.2.3 the accurate lead time of suppliers is important to ensure that orders are placed on time. Therefore, an analysis is done to evaluate the supplier reliability of Mueller. For each order, the following information is stored in the ERP system of Mueller:

1. Order date: This denotes the specific date when a purchase order is formally issued to the supplier by Mueller's procurement department.
2. Request date: Signifying the targeted date by which the ordered items are requested to be received.
3. Promised delivery date: This signifies the date on which a supplier commits to delivering the ordered goods.[2]
4. The receipt date, marking the actual reception and logging of the products into the system, is recorded.

Based on this data the lead times in ERP and actual suppliers' lead time are analysed, and the reliability of the supplier's lead time is computed. Furthermore, an estimation is made on how heavily the company relies on the safety stock. To do this, the following assumptions are made:

- Lead time: determined as the time interval between the date of receipt and the order date.
- Supplier reliability: calculated as the difference between the promised delivery date and the date the products are received. This is done for each order and then sorted per supplier. This is an indication of the supplier's dependability. A negative difference implies that the supplier did not deliver the goods by the promised delivery date.
- Accounting for safety stock: When the receipt date is later than the requested date, safety stock must compensate for either delayed orders by the purchasing department or uncertainties in lead times. Analysing the frequency of these occurrences provides valuable insights into whether safety stock levels are appropriately set for each product. Products with

2 The promised delivery date of German suppliers is interpreted as the date the products must be sent from their location towards Mueller. Therefore, an additional 2 to 3 days of delivery time must be factored in. This is due to the agreements made with the supplier based on the International Commercial Terms, known as incoterms.

higher uncertainty may require increased safety stock levels. Frequent delays in receipt relative to the requested date indicate potential issues with product availability and a higher risk of stockouts.

Late deliveries at Mueller:

Each ordered product is analysed to create insights into the reliability of the supplier. This analysis involves comparing the supplier's promised delivery date with the actual receipt date of the product. The results are divided into discrete time frames: deliveries that occur ten days or more ahead of schedule, deliveries that arrive five to ten days early, deliveries that arrive within five days of the scheduled date, deliveries that arrive exactly on the scheduled date, deliveries that arrive within five days late, deliveries that arrive between five and ten days late, and deliveries that arrive more than ten days after the scheduled date. Figure 7 presents the findings. It is important to mention that the promised delivery date is updated by Mueller when a supplier mentions the delivery is delayed. Therefore Figure 7 is optimistic compared to reality. Even in this case, 17% of the deliveries are five or more days too late.

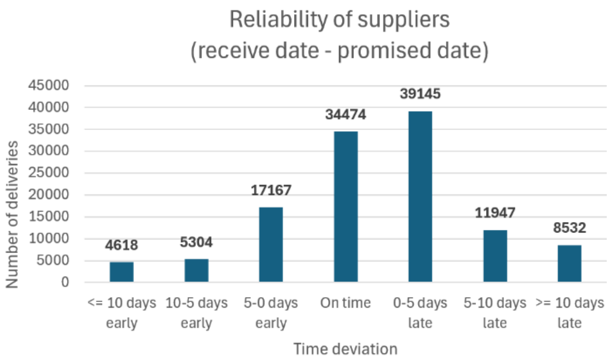


Figure 7 Reliability suppliers

Products delivered ahead of schedule do not cause any issues, as the faculty in Groenlo still has enough storage capacity. Therefore, first, the delayed deliveries are analysed. As previously mentioned, Mueller's suppliers in Germany interpret the promised delivery date differently, which contributes to the late delivery. To better comprehend the percentage of products delivered late, a second study is conducted. Table 4 illustrates the percentage of late deliveries for different periods. For example, 23% of all deliveries are four or more days late. Some insights are created into how often deliveries are late, compared to the agreed delivery date with suppliers. However, in the MRP system, the lead time in the ERP system is taken into consideration. Therefore, in the next section, the accuracy of the lead times mentioned in the ERP systems is analysed.

< 0 days	22.35%
< 1 day	50.80%
< 2 days	67.57%
< 3 days	71.79%
< 4 days	76.88%
< 5 days	83.10%
< 6 days	86.86%
< 10 days	92.96%
< 15 days	95.78%
< 20 days	96.87%
< 25 days	97.71%

Table 4 Late deliveries at Mueller

Accuracy lead time of the ERP system:

As discussed in Section 2.2.3, the lead times in Mueller's ERP systems have a major impact on the inventory policies. Therefore, an examination is conducted to determine whether the lead times present in the ERP system correspond with the actual delivery times of products. The first step in doing this is figuring out the actual delivery time, which is calculated as the interval between the order date and the date of receipt. The real delivery schedules for every article number are then arranged based on all orders placed since January 1, 2021. Next, a comparison is done between the lead times recorded in the ERP system and the actual delivery times. Intervals are set up based on percentage deviations from lead times in the ERP system to generate an analysis.

For example, if the ERP system shows a lead time of 21 days, a lower bound of 18 days can be obtained by deducting 10% (2.1 days) and rounding to the next whole number for the "on-time delivery" benefit. Similarly, adding 10% (2.1 days) to 21 days and rounding to 24 days yields an upper bound. As a result, deliveries that fall between 18 and 24 days are all considered "on-time" with a 10% margin of error. For orders between 10 - 20% and 20 - 40% variations, this method is repeated. Consequently, 47,729 orders are among those that fall outside of the 50% deviation range. To determine if items are delivered early or late, a distinction is made. The detailed outcomes of this analysis are depicted in Figure 8. In total 23.4% of all deliveries are more than 50% later than the lead time represented in the ERP system.

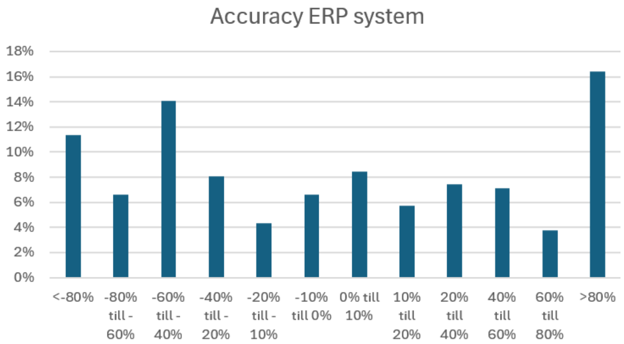


Figure 8 Accuracy lead times in ERP system

A second analysis is done, to evaluate if the average actual lead time per article is in line with the lead time in the ERP system. This is done for all 4,376 different items that were ordered since 01/01/2021. The upper and lower bound as described above were set up for a 50% range. The average lead time was outside the ranges in 32.6% of the cases. Based on this, it can be concluded that the lead times currently in the ERP system are not representative of the actual lead time of the supplier. The next question is, how often is the safety stock high enough to capture all demand in the meantime and how often does the company end up at a stock out?

Possible stockout occasion:

It is now known how frequently the company receives delayed supplies and that the lead time in the ERP system is not in line with the actual lead time. However, knowing how frequently these delays lead to operational problems or backorders is more important. Ideally, orders should be placed with accurate lead times so that deliveries arrive on time. If the agreed lead time is only learned after the order is placed, it is already too late, and the company faces an operational challenge, even if the delivery arrives on the agreed date.

To determine how frequently late deliveries cause issues at Mueller we examine the time interval between the requested date and the receipt date. If the requested date – received date is less than zero, Mueller must rely on safety stock to fulfil demand. Stockouts happen when the safety stock runs out. In addition, the safety stock is used to cover any demand for rush orders and post-purchase servicing during the wait period. To obtain a better understanding of the company's reliance on safety stock. Intervals are created based on the quantity of early deliveries, on-time deliveries, deliveries that are delayed by 1 to 3 days, 3 to 5 days, etcetera. The results are displayed in Figure 9. The received date is later than the requested date in 55% of the orders and in 21% of the cases, the received date is more than 5 days later than the requested date. Based on this, there are three conclusions:

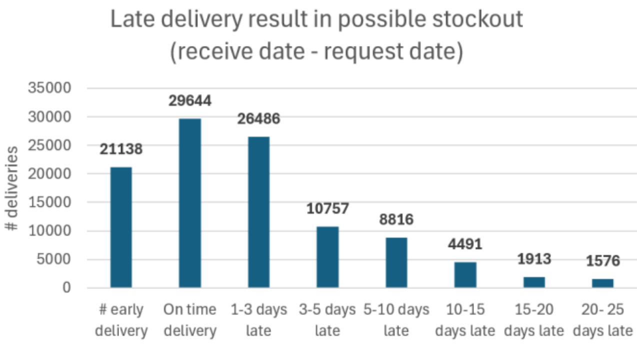


Figure 9 Occurrence possible stockout

1. The safety stock at Mueller is very high.
2. There are a lot of problems regarding the availability of products.
3. The request date already includes a buffer for late deliveries.

After discussing the results with the company, it is mentioned that products are often requested earlier than needed to be used the products are available on time. But there are no guidelines or agreements with suppliers about this.

The products manufactured by Mueller itself in general have a 7-day lead time. Which corresponds to five working days. Therefore, the safety stock must cover the total demand during these five working days. So, to create a better understanding of what these numbers mean in practice we assume that a stockout occurs if the time between receiving an order - the requested date is 5 days or more. Then, the number of items critically delayed per article can be calculated by applying the following formula:

$$Items\ critically\ delayed\ = \left(1 - \frac{\#\ stockout\ occasions}{Total\ number\ of\ orders}\right) * \ 100\%$$

Note: The stockout occasion is counted if the inventory runs out during an order cycle.

The number of items critically delayed is categorised into groups of 10%. However, twenty-seven products have only been ordered once, as a sample product. The delivery times for these products are not representative and therefore are not included in the graph in Figure 10. The graph shows that 793 items are critically delated between 80 and 90%.

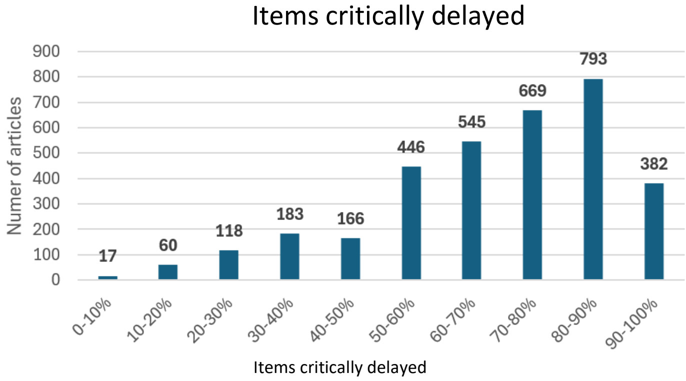


Figure 10 items critically delayed

Note: In this section, the number of items critically delayed is *presented instead of the item fill rate. This choice was made due to limitations in historical data, which does not allow us to accurately track the exact number of out-of-stock items or the specific times when stockouts occurred. To estimate the number of stockout occasions, we had to make a strong assumption: we assume a stockout occurs if the time between receiving an order and the requested delivery date exceeds 5 days.*

2.4 Inventory policies

Inventory control aims to strike a balance between two opposing objectives: reducing stock levels to free up cash and increasing efficiency by using large batches and high inventory to prevent production halts and deliver high levels of customer service (Axsäter, 2015). Three important concerns are answered by replenishment control systems: when to place orders, how big of an order should be, and how frequently should inventory status be checked. Answers to these questions are influenced by how important the item is to the company (E. A. Silver et al., 2016a).

2.4.1 Inventory policy is suitable for each type of classification.

The current inventory model at Mueller can be best compared with an s, Q model. The only difference is that the reorder point and order quantity are solely based on the known demand and no forecast is created. To make sure the suggested changes in the Inventory policy can be implemented by Mueller, we will therefore apply a s, Q model. The s, Q model works as follows: if the inventory level reaches the level "s", a new order is triggered to replenish stock up to the desired level, with the order quantity "Q".

2.5 Chapter conclusion

In this chapter, a clear overview of the status of the inventory policy at Mueller is presented. To do this, first, an overview of the production flow at Mueller is created. Secondly, the SKUs in the scope of this research are determined. This led to a total of 1630 SKUs in the production side of the company, from which only 13% is responsible for 80% of the annual usage value. For the service side of the company a total of 2652 SKUs are included in the research, 8% of these products are responsible for 80% of the annual usage.

Furthermore, an analysis of the lead time of suppliers is conducted. The analyses indicate significant discrepancies between the lead times used in the current ERP system and the actual delivery timelines. These analyses facilitate the establishment of clearer agreements with suppliers, leading to more reliable supplier relationships. Consequently, more accurate estimations of lead times can be made, bringing actual delivery times closer to expected delivery times. This alignment is expected to improve demand forecasts and reduce the occurrence of potential stockouts.

Therefore, there appears to be considerable potential for improvement in gaining a better understanding of the supplier lead times of Mueller. Hence, this research will include a performance evaluation on two different models, in the first model the inventory parameter will be reevaluated and updated to the most accurate information, without stochastic lead times. In the second model, the stochasticity of supplier lead times is included. Then a simulation model is created to evaluate the performance of both inventory models.

Chapter 3 Literature Review

In this chapter, a literature study is performed to find out how to deal with the uncertainty in lead times at Mueller. In Section 3.1 the effect of lead time uncertainty in inventory models is discussed. Section 3.2 approaches on how to model the lead time demand distribution are discussed. Literature on how to fit a distribution to historical data is discussed in Section 3.3. Section 3.4 different service level policies are described to calculate the inventory parameters based on the lead time demand distribution. In Section 3.5 literature research is performed to determine KPIs to actively steer on future demand changes. The chapter conclusion and key findings are presented in Section 3.6.

3.1 Uncertainty in lead time

As shown in the section 2.3, the lead times are uncertain at Mueller. Reducing lead time variability tends to have a greater impact than reducing lead times, especially when lead time variability is large (Song, 1994; Wang & Disney, 2016; Grossj & Sorianof, 1969). Therefore, in this section, extensive literature research is done on what the effects are of lead time uncertainty within inventory models.

Lead time uncertainty plays a significant role in inventory models by introducing variability that affects safety stock levels, reorder points, and overall inventory costs. According to (Chopra et al., 2004), higher lead time variability necessitates increased safety stock to maintain service levels. Similarly, (Eppen & Martin, 1988a) highlight that stochastic lead times may require adjustments to reorder points to accommodate uncertainty in inventory replenishment timing. (Heuts & De Klein, 1993) emphasize the financial implications, noting that variability in lead times can elevate both inventory holding and backlogging costs. The complexity of modelling also increases with stochastic lead times, as traditional models assuming constant lead times may lead to inaccuracies (Conceicąo et al., 2015). Furthermore, (Eppen & Martin, 1988b) discuss the impact on service levels, noting that increased lead time variability heightens the risk of stockouts, potentially compromising service levels. Lastly, (Wang & Disney, 2016) describe the order crossover phenomenon, where replenishments may arrive out of sequence, complicating inventory management.

Based on the information above, we can conclude that incorporating stochastic lead times into inventory models is crucial, as they significantly impact safety stock, reorder points, and overall costs. Therefore, it is essential to accurately consider these factors in the research conducted at Mueller.

In this research, we assume stationary, probabilistic demand coupled with a stationary, probabilistic lead time. Where demand and lead time are statistically independent. Furthermore, the assumption is made that lead times are independent and identically distributed, and deliveries cannot cross. With deliveries cannot cross we mean if multiple orders of an item are outstanding, we assume that they are delivered in the same order as the orders are placed.

The lead time of the supplier can be assumed to be always continuously distributed, as explained in (Hayya et al., 2008). In this research, the lead time distributions considered are the normal and the gamma distribution. The normal distribution is restrictive because of the symmetrical form of the distribution. A further disadvantage is that the range of the distribution also includes negative values, which cannot be the case in lead time. Therefore, the gamma distribution is more desirable, it is defined for nonnegative values. Furthermore, it can easily model the usually encountered positively skewed lead-time data.

3.2 Modelling the lead time demand distribution

As mentioned in Section 2.3 the lead time uncertainty must be considered in the research at Meuller. Therefore, we are not only interested in modelling the variability in the demand of Mueller but also the variability in the lead time. Combining these two gives us the lead time demand distribution. The

Lead Time Demand (LTD) has received continuous attention from researchers and practitioners because the knowledge of the distribution of LTD is essential in the design of inventory management systems. In the literature on stochastic inventory models, much of the previous theoretical research on LTD can be divided into three groups. The first group advocates using various theoretical distributions to represent LTD. Papers that fall into this category include those that discuss specific distributions like Poisson, Gamma (Burgin, 1970), Normal, and others. For example, the work by (E. A. Silver & Pyke, 1998) is mentioned as establishing boundaries between slow-moving and fast-moving items and considering normal distribution for LTD modelling. The second group attempts to fit a member of some flexibly shaped four-parameter family of distributions. An example of this approach is found in the studies by (Kottas & Lau, 1980) and (Shore, 1999), which explore the use of versatile distribution families in stochastic inventory calculations. The third group focuses on deriving the distribution of LTD from the given distributions of demand and lead time. The work by (Bagchi et al., 1984a), (Girlich, 1996) and (M. C. Van Der Heijden & De Kok, 1998) highlighted an example of this approach, where the distribution of LTD is explicitly treated as a compound distribution.

In this research, we are concerned with the last group approach that explicitly treats the distribution of LTD as a compound distribution. The period demand and lead time are assumed to be independently and identically distributed random variables and the distribution of LTD is considered a compound distribution, (Bagchi et al., 1984) formalized the approach of obtaining the distribution of LTD. The order intensity, order size, and lead time are considered primary components. Then it coalesces two of the primary components into the intermediate component (e.g., demand per unit time, see Figure 11, (Park, 2007)), to reduce the analytic task in the characterization of LTD.

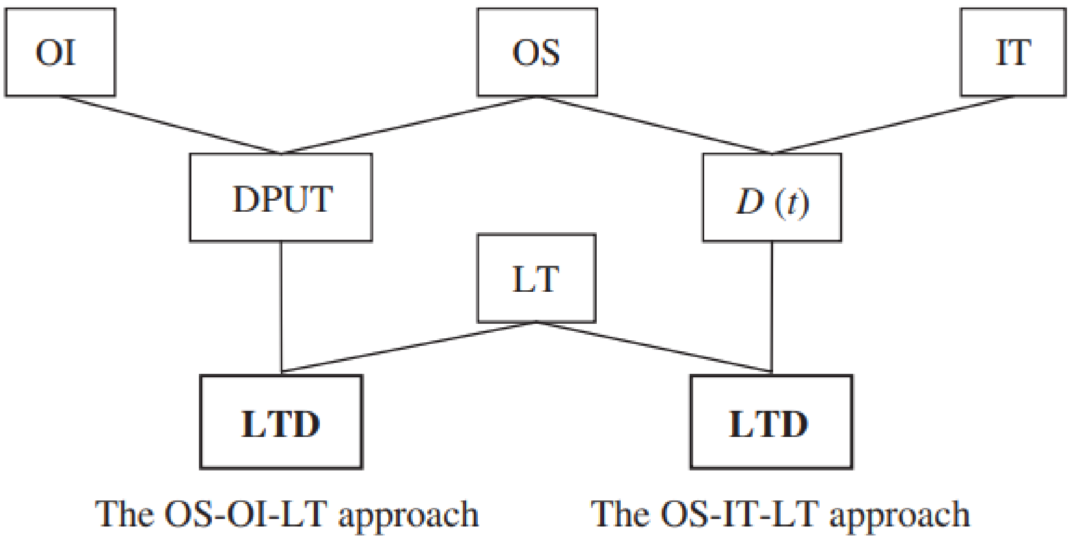


Figure 11 Approach to lead time demand.

In general, the Order Intensity (OI) is a discrete random variable. The Lead Time (LT) appears to be continuous (but may be recorded in days or weeks, because of replenishment policies). The Order Size (OS) is discrete, but continuous approximations may be considered appropriate (for high lead time variability).

The approach on the right-hand side is the OS-IT-LT approach which is often utilized to investigate the behaviour of stochastic inventory systems (Girlich, 1996); (M. C. Van Der Heijden & De Kok, 1998)). The OS-IT-LT approach is also the approach performed in this research. First, the D(t) is derived using information on OS and inter-arrival time (IT), the time duration between consecutive customer orders. Then LTD is generated by joining D(t) and LT.

To perform the OS-OI-LT approach the demand distribution and a lead time distribution must be known. Therefore, a distribution must be fit based on historical data. How this is done is explained in the section 3.3.

3.3 Methods for fitting distributions to demand and lead time distribution.

Fitting distributions to demand data is a well-established practice in inventory management, with various methods available to model several types of demand distributions. A simple, widely supported method in literature is fitting discrete distribution of the first two moments of a random variable, as mentioned in (Adan et al., 1995). This method is robust and versatile for slow-moving items, which are items with a lead time demand of less than 10. For fast-moving items, a demand during a lead time above 10, a continuous distribution is fitted based on the method described by (Bagchi et al., 1984b) and (M. Van der Heijden, 2021c).

Fitting a discrete distribution on the first two moments of a random variable:

The fitting of discrete distributions based on the first two moments of a random variable, specifically the mean (EX) and the coefficient of variation (CV), has been extensively studied. A random variable X on the non-negative integers can be defined with mean EX and coefficient of variation CV if and only if the following condition holds:

$$CV^2 \geq \frac{2k + 1}{EX} - \frac{k(k+1)}{(EX)^2} - 1$$

With k is the unique integer satisfying $k \leq EX \leq k + 1$

This condition delineates the feasible pairs of (EX, CV) for discrete distributions. The exclusion of certain items, particularly those with low mean and high coefficient of variation, is supported by theoretical considerations. These items, represented in Figure X with the symbol (Ø), typically do not fit well within standard discrete distributions due to their atypical characteristics.

The literature classifies distributions into several categories, the Poisson distribution, mixtures of binomial distributions, mixtures of negative-binomial distributions, and mixtures of geometric distributions with balanced means. The classification is determined using the variable defined as $a := CV^2 - \frac{1}{EX}$, which helps in appropriately categorizing items into these distribution classes. This is visualized in Figure 12 ((Adan et al., 1995)).

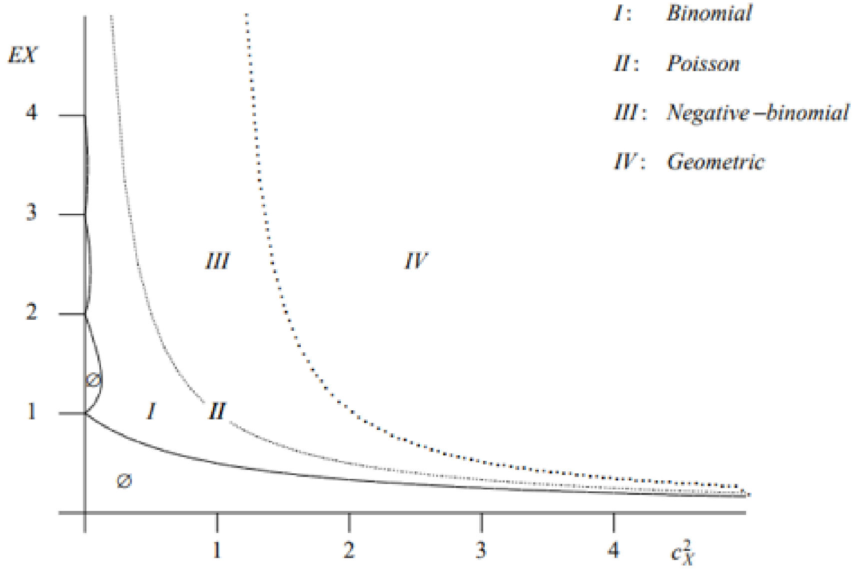


Figure 12 Fitting discrete distributions

Fitting a continuous distribution on the covariance of each SKU:

As previously mentioned, for the fast-moving items continuous distributions are considered. In this research, the normal and gamma distributions are considered as explained by (Bagchi et al., 1984b) and (M. Van der Heijden, 2021c).

The selection between these distributions is guided by the coefficient of variation (CV), calculated using the formula $CV = \frac{\sigma_L}{\hat{x}_L}$. Items with a CV lower than 0.5 are best modelled by a normal distribution, while those with a CV greater than 0.5 are better approximated by a gamma distribution.

The covariance of each SKU is assessed. This is done by calculating the following formula, If the covariance of the item is lower than 0.5 the SKU can be best approximated by the normal distribution. A low CV indicates that the standard deviation is relatively small compared to the mean, resulting in a less skewed and more symmetric distribution, which aligns well with the properties of the normal distribution. If the covariance is greater than 0.5 the SKU can be best approximated by the gamma distribution. A higher CV indicates that the standard deviation is large relative to the mean, which often corresponds to a right-skewed distribution, a characteristic that the gamma distribution can model effectively.

Two items were categorized as "not feasible" due to low average demand and high demand variability. Additionally, these items were inexpensive. In the current MRP model, both items had a safety stock level of one and did not trigger any expedited notifications. After consulting with the supply chain manager, it was concluded that the original parameters for these items are appropriate, and thus, they fall outside the scope of this research.

Fitting a distribution on the lead time for each item:

The lead time of the supplier can be assumed to be always continuously distributed, as explained in Hayya et al., 2008. Therefore, distribution fit for the lead time of suppliers is done in the same way as explained in *continuous distribution on the covariance of each SKU.*

3.4 Determination of service level policy

After the lead time demand is found, we still must determine a service level goal for the company. In the end, inventory management choices must be decided at the individual item or product (SKU) level (E. A. Silver et al., 2016b). To improve supply and demand dynamics and address inventory imbalances, the literature describes two types of models that exist and deal with the trade-off between the inventory levels and the fill rates (van Donselaar et al., 2021): models which minimize inventory holding costs subject to a fill rate constraint and models which assign a backorder cost to out-of-stock situations and then minimize inventory holding costs plus backorder costs (also known as penalty or shortage costs). Managers often prefer to set a service constraint (like a target fill rate) rather than to specify the backorder costs since those costs can be difficult to specify (Gardner & Dannenbringf, 1979), (Schneider, 1981) and (Hopp et al., 1996). In this thesis, a comparison of three different service settings is compared. The first one is based on classifying the products based on their value or demand variability, and different service levels are assigned accordingly (Dhoka, 2013) (Nallusamy et al., 2017). Secondly, the service level goals are based on a cost-based method. This method involves calculating the service level based on the trade-off between back-ordering costs and holding costs. The last method discussed is based on a target fill rate, this involves setting a specific target fill rate and adjusting inventory policies to achieve that target (Teunter et al., 2017).

3.4.1 Fill rate based on ABC, XYZ classification.

At Mueller, SKUs are not currently classified. Therefore, we will adopt a well-known and straightforward approach, as the concept is new to the company.

ABC Classification

Based on Pareto analysis, which indicates that a tiny percentage of inventory goods contribute to overall sales, the most popular classification method is the ABC analysis (Dhoka, 2013). The ABC analysis is sometimes criticized for considering just one criterion, despite its simplicity. Sometimes, more criteria are applied to make it better (Ding & Sun, 2011). For instance, because they are essential to operations, some low-cost SKUs might be rated as "A" (E. A. Silver et al., 2016b). Usually, a matrix with two criteria is employed, and the analysis can be manually modified to take certain considerations, such as procurement concerns, into consideration (Flores & Whybark, 1986)

XYZ classification

The XYZ analysis is a dynamic extension of the static ABC analysis (Stojanović & Regodić, 2017). It categorizes items based on fluctuations in consumption, like the fast, normal, and slow-moving technique (Stojanović & Regodić, 2017). Class X items have a constant demand, Y items exhibit stronger fluctuations, and class Z items show high variation. This division is based on the coefficient of variation, calculated using the following formula, coefficient of variation $= CV = \frac{\sigma}{\bar{x}}$.

Combining ABC and XYZ Classification

By integrating ABC and XYZ classifications, a more nuanced approach to inventory management can be achieved. This combined classification helps determine the target fill rate for each item. High-priority items (A) with stable demand (X) have higher target fill rates compared to lower-priority items (C) with highly variable demand (Z). This classification system ensures that inventory levels are optimized based on the criticality and demand variability of each SKU.

Therefore, the literature review into SKU classification is performed to provide a structured approach for managing inventory at Mueller. Understanding and applying these classification methods allow for better alignment of inventory policies with the characteristics of each SKU, leading to improved inventory management and optimized stock levels.

3.4.2 Fill rate based on a cost-based method.

The method to determine the target fill rate on a cost-based approach is to set the target fill rate for each item based on the following formula (A. E. Silver et al., 2016):

$$Fill\ rate = \frac{B_3}{B_3 + r}$$

where B_3 represents the fractional charge per unit short per unit time, and r denotes the holding costs. A method to determine the Backorder costs (B_3) is set up in Section 4.3. The fill rate, which is the fraction of customer demand met without backorders or lost sales, is an important metric in inventory management. This service level metric is particularly appealing to practitioners in contexts where a significant portion of the replenishment lead time is unchangeable, such as in a branch warehouse scenario where transit time constitutes a major part of the lead time. The use of the B_3 shortage-costing measure in this formula provides a means to balance the costs of holding inventory against the costs associated with stockouts, thereby setting an appropriate target fill rate under certain conditions.

3.4.3 Item fill rate based on assortment fill rate.

Different methods can be used for this method. A well-known method is described by (Teunter et al., 2017). The OFR is used as a service level requirement, by using it as input in setting the Target Fill Rates (TFRs) of the individual SKUs. A benefit of this method is that the target fill rates are executed on individual SKU levels. Therefore, the multi-echelon levels within the BOM do not have to be considered, while still having a target system fill rate for the end products.

Solving the original multi-item problem and finding the optimal fill rates (and related reorder levels) per individual SKU is more complex to solve. However, the rewards are also higher (van Donselaar et al., 2021). Furthermore, the master thesis of E. Vlaswinkel, 2024, shows this method works well. Hence, this method is also used in this research.

3.5 Determine the KPIs

To ensure the company can keep the inventory model up to date the goal is to implement some Key Performance Indicators (KPIs) that are crucial for evaluating the effectiveness of inventory policies at Mueller. These KPIs provide valuable insights into various aspects of inventory management, aiding in decision-making and performance monitoring.

<u>Fill rate:</u>

In general, the fill rate is the fraction of customer demand that is met routinely, without backorders or lost sales (Silver et al., 2017, p.249). There are several types of fill rates, difference of the fill rates are explained by Van der Heijden, 2021a, in this thesis we will work with the:

The Volume Fill Rate (VFR): Represents the proportion of total units ordered that are delivered on time. It assesses the efficiency of inventory management in meeting overall demand within the specified period.

<u>The inventory turnover</u>

The Inventory Turnover is the financial ratio showing how many times a company has sold/replaced inventory during a given period (Van der Heijden, 2021c). Inventory turnover is a valuable tool for evaluating inventory policy, as it provides a measure of efficiency and can uncover potential issues such as slacking sales or theft (Reynolds, 1999). This measure can be particularly useful for comparing same-store activity and similar operations within a segment (Reynolds, 1999). Inventory turnover is a simple yet powerful tool for evaluating inventory management performance (Ballou, 2000).

Cycle Service Level

Cycle Service Level measures the probability or frequency that demand for a specific item will be fully met from the available inventory during a particular replenishment cycle. This metric is crucial for assessing the effectiveness of inventory policies, as it reflects the ability of a stock system to satisfy customer demands without encountering stockouts.

Ready Rate

Ready Rate denotes the proportion of time or instances an item is immediately available for fulfilment relative to the total demand. The ready rate emphasizes the availability of items on hand when demand arises. This KPI is important in scenarios where quick response times are critical, such as in just-in-time manufacturing or service-oriented industries.

3.6 Chapter conclusion

In this chapter, a comprehensive literature review has been conducted to address the challenges of lead time uncertainty within inventory management at Mueller. First, the impact of lead time variability on inventory models is examined. This highlights that stochastic lead times introduce significant complexity into inventory management, affecting safety stock levels, reorder points, and overall inventory costs. The literature emphasizes that accurately incorporating lead time uncertainty is crucial to avoid inaccuracies and optimize inventory performance.

Next literature review is performed on different methods to model the lead time demand distribution. In this research, the demand and lead time distributions are integrated to capture the demand during lead time. To do this, first the demand and lead time distributions must be known. Therefore, a method is discussed to fit distributions based on historical data, addressing both discrete and continuous distributions. Furthermore, the impact of selecting appropriate distributions is highlighted.

Additionally, the chapter reviews different service-level policies and their impact on inventory management. Three main methods are analysed: fill rate based on ABC and XYZ classifications, cost-based methods, and assortment fill rates. Each method offers a unique approach to balancing inventory levels and service constraints, tailored to the specific needs and characteristics of Mueller's inventory.

Lastly, the KPIs essential for evaluating inventory policies are identified.

Chapter 4 Model Development

This chapter presents the theoretical and mathematical foundation of the models, offering detailed mathematical explanations as well as general descriptions of the simulation models. Additionally, key terminologies and concepts essential for conducting the models are introduced, as these are critical to the research. Section 4.1 outlines the models used in this research. Section 4.2 discusses the different service level policies. In Section 4.3 the necessary information to perform the methods is discussed. In Section 4.4, the fitting of distributions on data is explained. The calculations for the costs and the KPIs of the company are described in Section 4.5. The key findings are presented in Section 4.6.

4.1 Models' explanation

In this section, we introduce and explain the different models developed for this thesis. The flow chart Figure 13 provides a global overview of how the models work together to simulate future demand and calculate costs and KPIs for various inventory configurations. These models serve as the basis for evaluating different warehouse settings and implementing improved inventory configurations at the company.

In total four models are created. The first model is based on historical data. This model calculates the company's current performance, providing a benchmark for evaluating future models. This also helps validate the future demand simulation model.

The second model generates the demand during lead time. This is done by drawing from the fitted demand and lead time distributions, as described in Section 4.4. This is done in the fourth step of the general overview.

In the third model, inventory configurations are determined based on these fitted distributions and chosen service-level policies. Three configurations are compared: the current setup, a configuration assuming deterministic lead times, and one where stochastic lead times are considered. This is done in step 6 of Figure 13.

Finally, the fourth model compares these inventory configurations by simulating future demand. This simulation evaluates the configurations based on the costs associated with each inventory model and the KPIs, both at the individual SKU level and as weighted averages. This model is represented in step 7 of Figure 13.

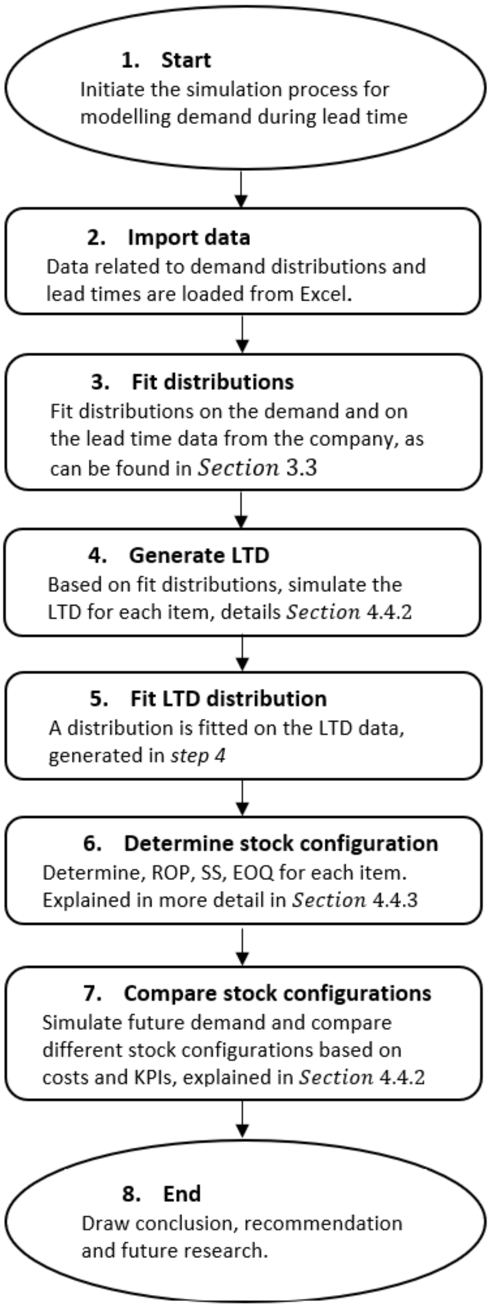


Figure 13 Total overview models

4.1.1 Historical Data Analysis

In this model, historical data is used to create an overview of the company's current performance. Only the current inventory levels and the inventory level on the first day of each year are available for all items. Hence, currently, there is no data on how often backorders occur, how often products must be expedited or when creative solutions had to be used due to a lack of inventory. To get a better understanding of how this occurs the steps are shown in Figure 14. Furthermore, this model creates a benchmark for evaluating future models and helps to validate the future demand simulation model. This model analyses the data from 01/01/2022 to 01/07/2024.

The model takes the following data as input:

- Starting inventory levels of all items as of 01/01/2022.
- Daily historical demand per item.
- Daily receipts of incoming products per item.

This input is uploaded into the Python model the entire model can be found in Appendix H**: Pipeline simulation historical data:** The key steps of the model are outlined in the flowchart as represented in Figure 14.

The model generates the following outputs:

- overview showing the on-hand inventory at the start of each day.
- The daily demand for each item.
- The number of items received that day.
- The on-hand inventory at the end of the day, calculated by subtracting daily demand and adding received items to the starting inventory.
- A backorder flag to indicate whether an item is backordered for the next day.
- The amount the items are backordered.

Additionally, the model calculates the number of backorder rate, FR and their weighted averages of these KPIs across all items.

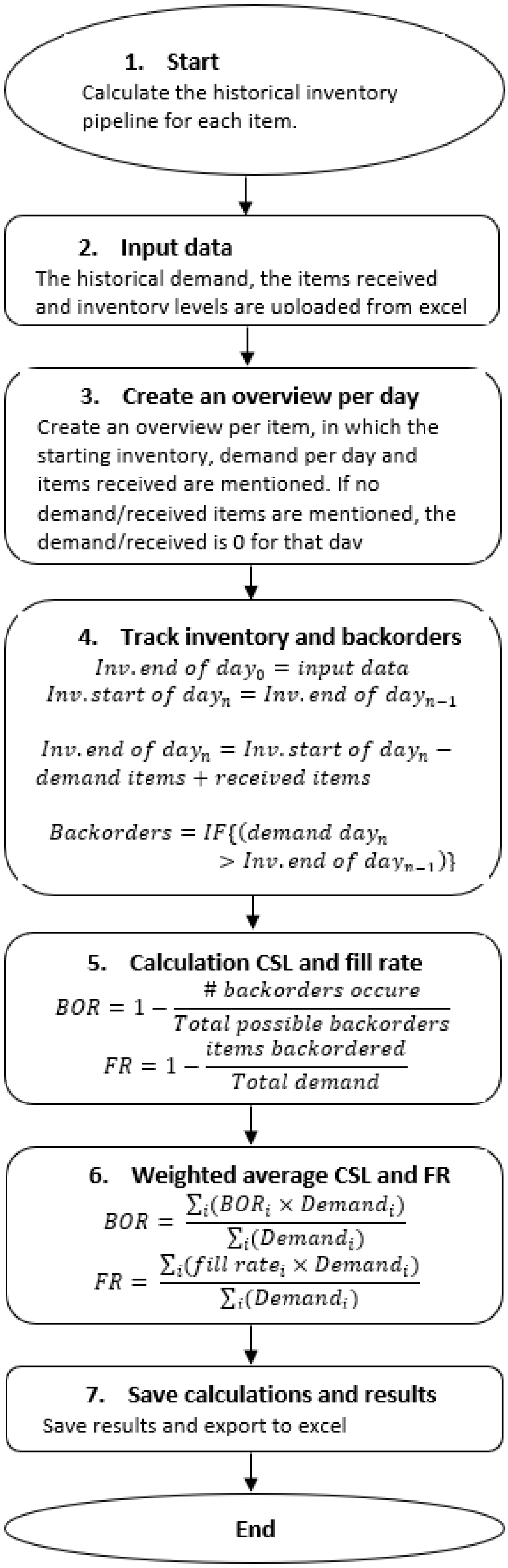


Figure 14 Flowchart historical model

Key assumptions made in this model:
A backorder occurs if the demand for the next day is greater than the inventory level at the end of the previous day.

The backordered quantity is the difference between the ending inventory and the next day's demand if the inventory is insufficient.

4.1.2 Lead time demand distribution.

In this subsection a flowchart is created that explains the simulation model for the demand during lead time. This model plays a vital role in calculating the various inventory configurations, which are based on the demand during lead time.

Input data:
The model uses the fitted demand and lead time distribution, which is covered in more detail in Section 4.4.

The model:
The flowchart, in Figure 15, systematically explains the simulation process. In this thesis the lead time for each item is drawn 100.000 to ensure statistical significance in the results, capturing the variability in both demand and lead time. For example, if the draw from the lead time is eighteen, it means that we draw eighteen times out of the demand function. The demand during lead time is the sum of all draws from the daily demand function.

The output:
As an output, the 100.000 simulations of the demand during lead time for each item are given. These outputs are also visualized as the empirical distribution of the total demand during the lead time of the items to provide deeper insights into the potential variability in demand. Next, the average and the variance of each item are calculated. Based on the average and the variance during the distribution can be fitted again, represented in step 7 of the flowchart. This is done in the same way as the daily demand distributions are fitted, as explained in Section 4.4.

The outputs are verified by checking if the average daily demand and lead time of the 100.000 simulation runs align with the historical values, confirming the accuracy of our model.

Assumptions made:
The model assumes that demand and lead time follow the fitted distributions which were fitted based on historical data. Additionally, it assumes that lead time and demand are independent and that lead times are positive.

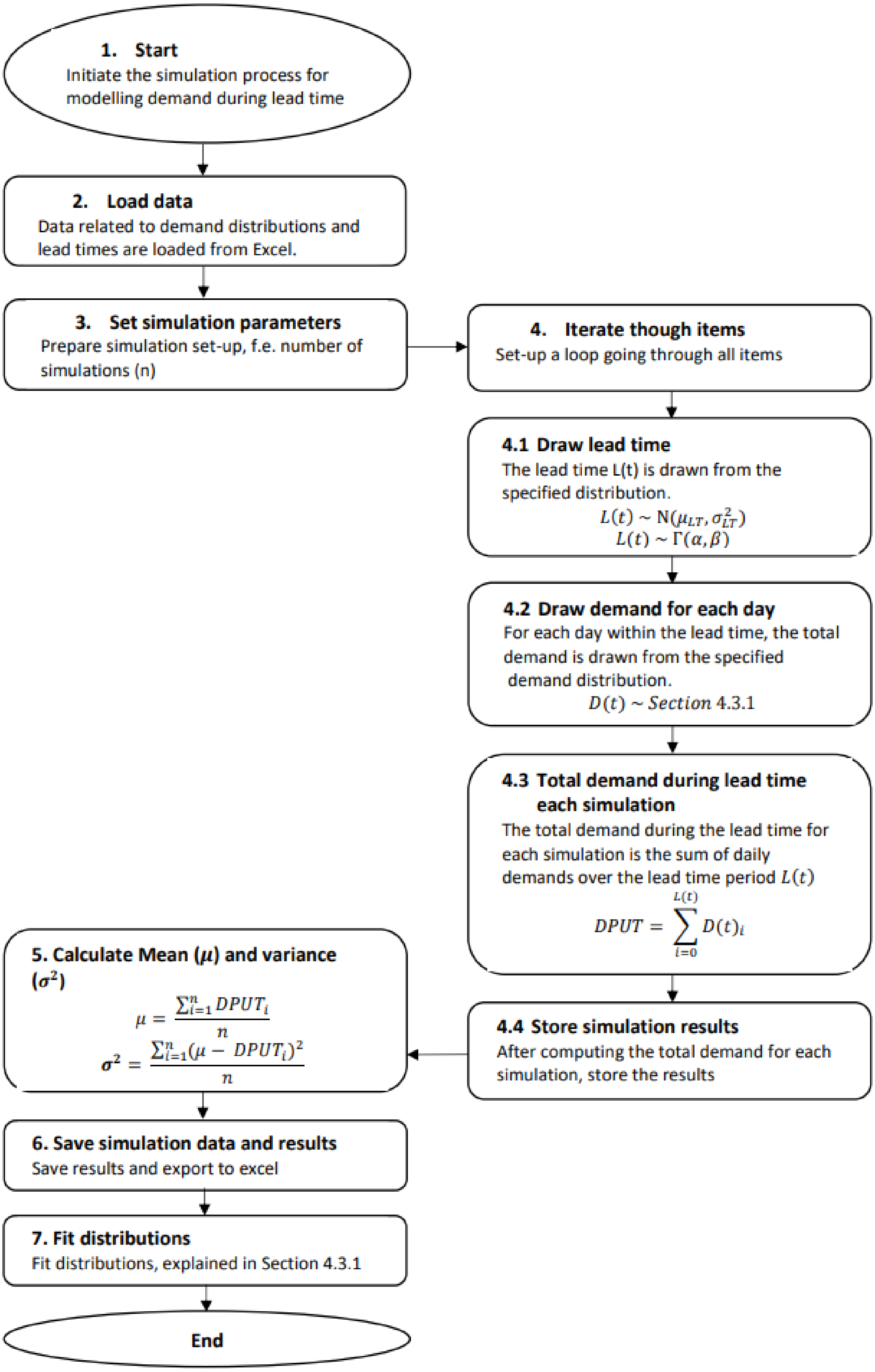


Figure 15 Flowchart Lead time demand distribution.

4.1.3 Inventory Configuration Model

In this section, a framework is created to calculate the safety stock, the ROP and the order quantity. This is done based on the three different Service-level policies, which are explained in more detail in Section 4.2. The general steps that are performed in each of the policies are the same. Only the way the target fill rate is determined is adapted, these changes are explained in this section. To explain the general steps a flowchart is created, which can be found in Figure 16. Furthermore, the entire Python code to execute these calculations can be found in Appendix G**: Determine Safety Stock, Reorder Point and EOQ:**.

Input data:
The input for this simulation consists of distribution fitted to the demand during lead time, as explained in Section 4.1.2. Furthermore, some item-specific inputs, such as the classification of items, holding and ordering costs.

The model:
The reorder point is calculated by the z-value. The safety stock is equal to the $ROP - \mu_{LTD}$, this covers the variability in demand and lead time. The order quantity is calculated for each item using the classic EOQ formula, which determines the optimal order quantity that balances the holding costs and the ordering costs.

$$EOQ = \sqrt{\frac{2 * D * S}{H}}$$

Where:
D = the annual demand
S = ordering costs
H = holding costs, H = Cost per units * holding cost (%)

Note: Assumptions regarding holding and ordering costs at Mueller are made and substantiated in Appendix C: **Ordering** .

The difference in the target fill rate based on the different models:

Method 1. The ABC, XYZ classification
In this method, a target fill rate is linked to each of the classes of the ABC, XYZ. The classification is covered in more detail in Section 4.3.

The target fill rates for C-class items are set higher than those for B-class items despite their lower economic value. This is because C-class items are typically low-cost, and their absence can disproportionately impact production processes. The cost of production delays due to stockouts of these inexpensive items can exceed the costs of maintaining a higher inventory level. Therefore, a higher target fill rate for C-class items minimizes the risk of production downtime and its associated costs. This strategic inventory management approach balances the cost of holding stock against the potential costs of stockouts, optimizing overall operational efficiency.

Method 2, Fill rate based on a cost-based method
In this method, the target fill rate for each SKU is not based on the ABC-XYZ classification but rather on the cost-based approach. So, the target fill rate $= \frac{B_3}{B_3 + r}$

The rest of the steps follow those in the ABC-XYZ classification approach.

Method 3, Fill rate-based target fill rate
For the third method, the calculation to determine the target fill rate is based on the APCR and is calculated as follows:

$$APCR = \frac{\sum_{i=1}^{n}(\frac{p_i}{c_i} D_i)}{\sum_{i=1}^{N} D_i}$$

The individual fill rate for each SKU denoted as FR_i, is approximated using the formula:

$$1 - FR_i \approx (1 - FR_T) \frac{PCR_i}{APCR}$$

A more detailed explanation of the method is covered in Section 4.2.3. A lower bound for the fill rates is implemented for all individual SKUs. In the Python code used for this research, the lower bound was equal to 70%. The next steps are executed in the same way as explained in the Fill rate based on the ABC, XYZ classification approach.

The output:
The outputs generated by this model include the safety stock, ROP and EOQ for each product in the dataset. This model ensures that products are available to meet customer demand during lead times, while also minimizing costs associated with excess inventory.

The assumption:
The model assumes that demand and lead time follow the fitted distributions derived from historical data. Furthermore, the model assumes that lead times and demand are independent of each other and that lead times are always positive. These assumptions allow the model to calculate the necessary inventory levels based on statistical methods for continuous and discrete demand distributions.

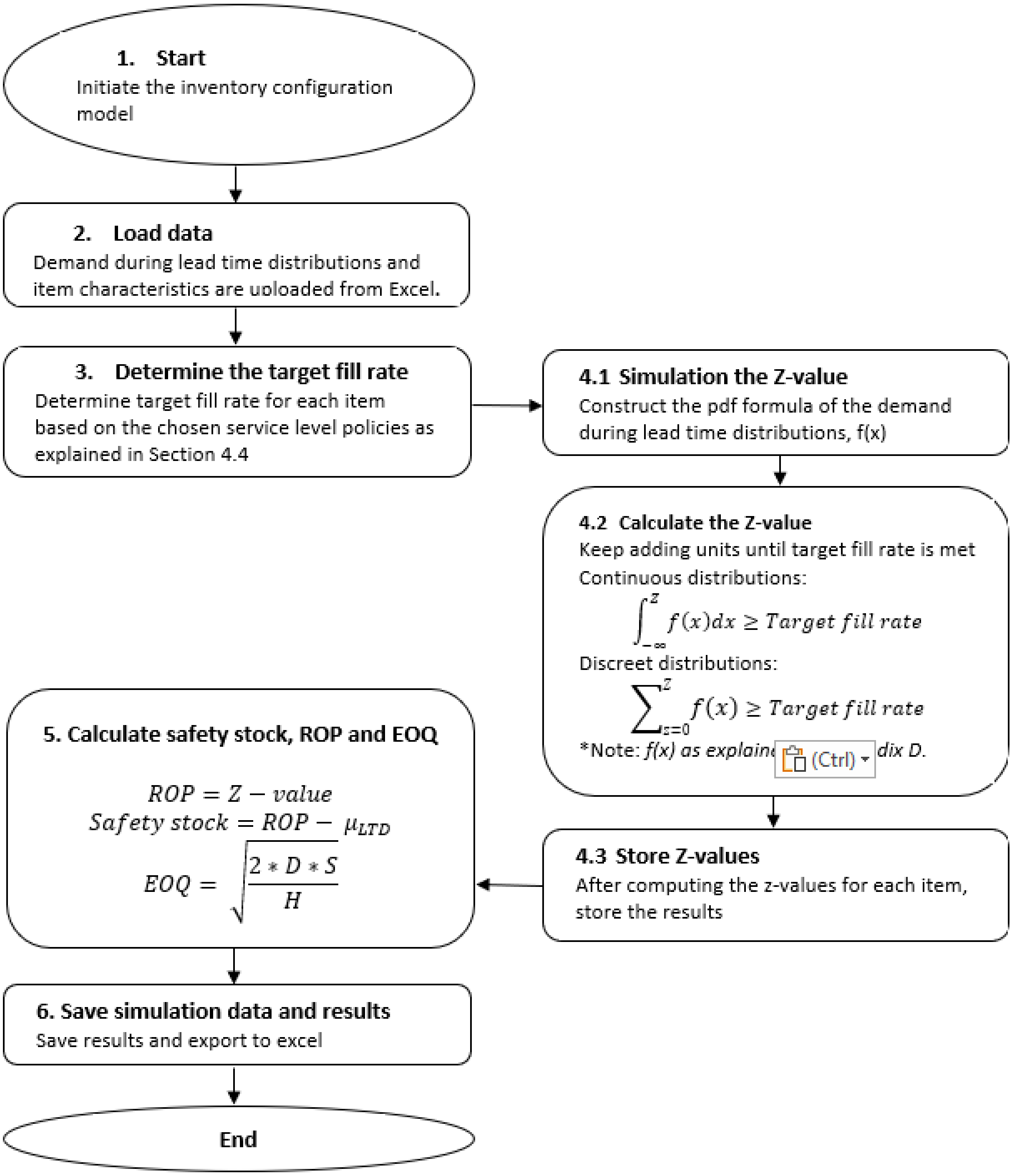


Figure 16 Flowchart inventory configuration.

4.1.4 Simulation model

In this section, different inventory configurations are compared based on future demand forecasts. To provide a clear overview of how the model works, a flowchart has been created, which can be found in Figure 17. This simulation gives an evaluation of effectiveness in meeting customer demand and the associated costs minimizing costs.

Input data of the simulation:
The model uses the following key input data:

- Demand and lead-time distributions, derived from historical data.
- Inventory levels as of 01/07/2024.
- The ROP, EOQ, and safety stock level for each item
- Item-specific inputs are considered, such as item classifications, units, holding and ordering costs.

The model:
The simulation covers one year from July 1, 2024, to 1 January, 2026. It simulates daily operations within this time to assess the performance of each inventory configuration over time. The same daily demand is used to compare the different inventory configurations. The steps in the model are presented in Figure 17.

In our model, the simulation begins on 01/07/2024, with inventory levels reflecting the company's actual stock as of that date. As a result, during the initial phase, inventory levels may not yet align with the calculated configurations, potentially leading to an inflated number of backorders due to early adjustments. These early imbalances are part of the system's natural progression toward stability. Therefore, the first six months are used as the start-up period and are excluded from the analysis to focus on a more stable inventory period, offering a clearer view of long-term performance. So, the results, as shown in Section 5.1.2, are based on the simulation from 01/01/2025 until 01/01/2026.

Output of the model:
The output of the model is an overview in which the following information for each item per day is represented per day:

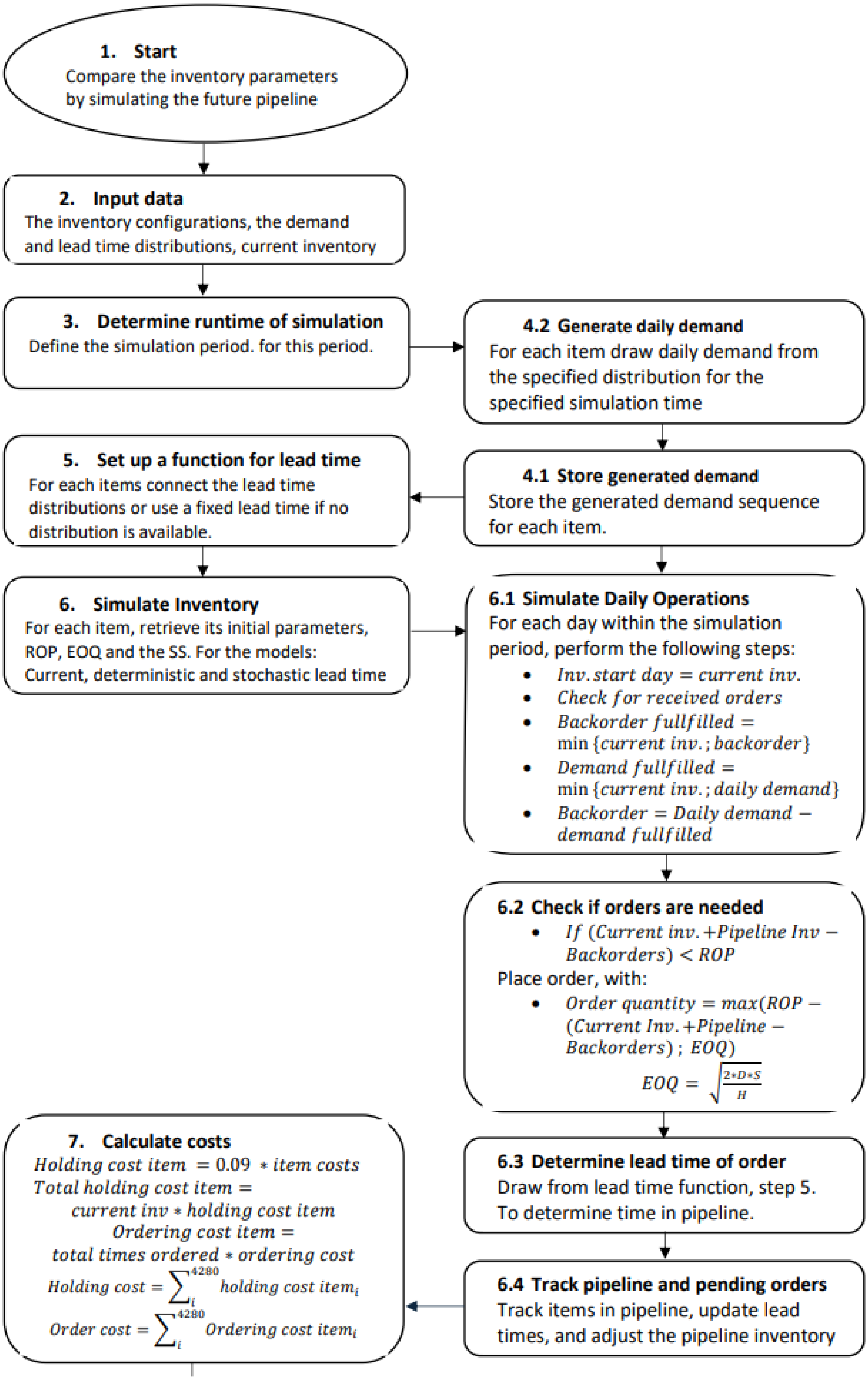
- On-hand inventory start of day
- Received items.
- Demand per day.
- Demand fulfilled from stock.
- Demand back ordered.
- The number of items pipeline
- On-hand inventory end of day

To evaluate the inventory performance the model calculates the following cost parameters, the (total) holding costs and (total) ordering costs. Next, the following KPIs are calculated, the inventory turnover rates, the fill rate and the backorder

rate are calculated. The actual calculations can be found in Section 4.6. Based on this information we can balance inventory costs with service levels, offering insights into how well various inventory policies satisfy customer demand while efficiently managing stock levels. Furthermore, the total costs can be compared against the total number of backorders.

Assumptions:

The following assumptions are made in the model. The demand and lead times are assumed to follow specific probabilistic distributions based on historical data. A fixed daily holding cost is used, calculated as a percentage of the item's unit cost. When no lead time data is unavailable, the model defaults to a lead time of 7 days. Which is based on the production time of the products at Mueller.



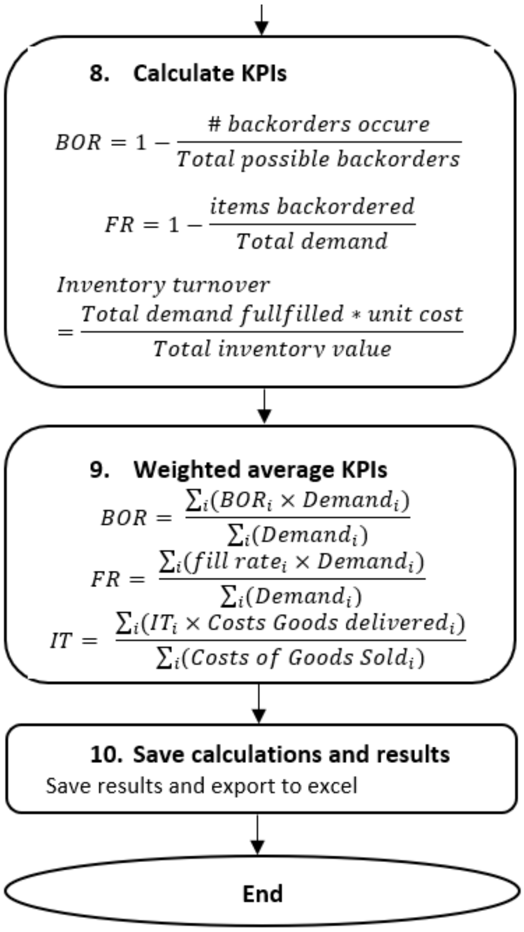


Figure 17 Flowchart future simulation.

4.2 Service level policies.

Here, the various service-level policies are explored to optimize inventory management. The discussion focuses on three key approaches, as discussed in Section 3.4. Each method offers a unique perspective on managing stock levels, balancing inventory costs, and meeting customer demand. Additionally, we aim to offset these three service-level policies and compare the models based on the results to identify the most effective strategy.

4.2.1 Fill rate based on ABC, XYZ classification.

The number of items in each section at Mueller is distributed across different classifications as shown in Table 5. In this section all the formulas are given in generic form, the specific values used in this research can be found in Section 0.

All items								
Classification	# items	Target fill rate	Classification	# items	Target fill rate	Classification	# items	Target fill rate
AX	1	D	BX	0	G	CX	0	J
AY	24	E	BY	25	H	CY	45	K
AZ	380	F	BZ	604	I	CZ	3201	L

Table 5 Item classification

Based on the classification data, a significant portion of inventory items at Mueller fall under the Z category, indicating high demand uncertainty. This uncertainty makes it difficult to predict the demand for these items.

Using the target fill rates and the number of items in each classification, the minimum average target fill rate at Mueller can be calculated as follows:

$$Minimum\ average\ target\ fill\ rate = \frac{\sum_i \#\ items_i * Target\ fill\ rate_i}{Number\ of\ items\ items}\ with\ i = AX, AY, \dots\ , CY, CZ$$

4.2.2 Fill rate based on a cost-based method.

In the method discussed in Section 3.4.2, the target fill rate is determined for each SKU using a cost-based approach, as outlined by (A. E. Silver et al., 2016). The target fill rate is calculated using the formula:

$$Fill\ rate = \frac{B_3}{B_3 + r}$$

where B_3 represents the fractional charge per unit short per unit time, and r denotes the holding costs.

The inclusion of the B_3 shortage-costing measure enables a balanced approach to managing the trade-off between holding costs and the costs associated with stockouts, allowing for an optimal target fill rate under specified conditions.

Holding Costs:
The holding cost is established at 9% of the purchase price of the products. The 9% is based on a discussion with the CEO of the company and is based on the cost of capital of the company. This percentage reflects the costs associated with storing inventory, including warehousing expenses, insurance, and the opportunity cost of capital.

Backorder Costs:
A method for estimating backorder costs is discussed in Section 4.3. In this method, both holding, and penalty costs are incorporated. This method ensures a balanced consideration of inventory management costs and operational disruptions, leading to a more rational determination of target fill rates. By factoring in the criticality of each SKU as in the next model, the model enhances decision-making for inventory optimization.

4.2.3 Fill rate-based target fill rate

In the third inventory model, the method described by (Teunter et al., 2017) set Target Fill Rates (TFRs) for individual SKUs based on a system-wide Order Fill Rate (OFR) requirement. This approach, also validated in the master's thesis of E. Vlaswinkel, 2024 has proven effective.

The methodology begins with defining the OFR as the primary service level metric, as explained in Section 3.4.3. The OFR is used to derive individual fill rates for each SKU. To do this the calculations as explained in Section 4.1.3 must be applied.

The criticality c_i reflects the impact of a backlog of SKU i on the system's OFR. In this study, criticality is represented by the number of final products involving the SKU, indicating its importance in meeting customer demand.

The individual fill rate for each SKU denoted as FR_i, is approximated using the formula:

$$1 - FR_i \approx (1 - FR_T)\frac{PCR_i}{APCR}$$

Where:
FR_T is the target system fill rate
PCR is the Price Criticality Ratio for SKU i

This formula ensures that SKUs with higher price and criticality ratios are prioritized, aligning the inventory levels with their relative importance in the order fulfilment process.

As mentioned in (Teunter et al., 2010), a potential issue arises when the calculated fill rate FR_i becomes negative for certain SKUs, particularly expensive ones. To address this, a positive lower bound on the fill rate can be imposed. This constraint prevents unrealistic scenarios where the inventory model suggests a negative fill rate, which would imply a planned stockout. By setting minimum fill rates, such as 50%, 70%, or 90%, we ensure a minimum level of availability for all SKUs, even at the risk of exceeding the target system fill rate. (Teunter et al., 2017) found that applying these minimum fill rate thresholds still led to reductions in system stock value, highlighting the method's efficiency in balancing stock levels and service quality.

4.3 Input for the service level policies and EOQ

To accurately calculate the fill rate using the different service rate approaches, as explained in 4.2, the costs associated with ordering and backorder costs must be determined. Currently, the company lacks historical data on the frequency of backorders and the associated costs. Therefore, this section presents an alternative approach to estimating these costs.

To perform the ABC, XYZ classification
The ABC-XYZ classification of the items must be conducted to perform the fill rate as explained in Section 3.4.1.

ABC Classification
First, all SKUs need to be classified. A combination of the ABC and XYZ classification is used for this. In ABC classification, the A items are the items that combine make (the first) 80% of the total annual usage value. Normally, it is expected that this approximates 20% of the SKUs considered. At Mueller, the first 80% was governed by only 11% of the SKU’s. Meaning a few items are responsible for a substantial percentage of the annual revenue at Mueller. The A items are classified as the items that combined make up the first 80% of the total annual usage value, the B items are the items that combined make up the next 15%, and the C items the remaining 5%.

XYZ Classification
The XYZ classification method is classified based on demand uncertainty, which is measured as the coefficient of variation of lead time demand. First, this value was computed for all SKUs. Based on the distribution of these values, we determined the two boundary values: Lower bound = 25% and middle bound = 50%. X items have a coefficient of variation below the lower boundary, Y items are in between the boundaries and Z items are above the larger boundary.

Combining ABC, XYZ Classification
Eventually, the AX items are considered the “most valuable, easy to predict SKUs.” This means that investing time in providing sophisticated means to forecast these items is justified. The CZ class, on the other hand, should receive less attention. These items are the “least valuable, hardest to predict SKU’s.”

Backordering costs
The backorder costs are needed to perform Service level policy cost-based approach as explained in Section 3.4.2.

Calculating the backorder costs is challenging due to the lack of specific data on past backorders and the associated costs at the company. Therefore, an alternative method is developed to estimate these costs. The underlying assumption is that the unavailability of a single component prevents the assembly of the final product. Given that the average final product consists of approximately three hundred components, the absence of one item renders the other 299 items temporarily useless. Consequently, the backorder cost includes:

1. Holding Costs of Available Components: These costs reflect the total holding expenses for components already in stock but unusable due to the missing part.

To calculate the excess inventory costs first need to know how often the number of backorders occurs, this is done based on historical data, as explained in the section. 4.1.1. The next step is to gather information about the individual items and quantities that constitute each final product, as well as the sales frequency of these final products. With this information, the probability of not being able to finish a final product due to a stock out of each item can be calculated. Hence, the probability of the excess items if a backorder occurs is also known. Hence, the holding costs of these items can be calculated, which in turn can be factored into the back ordering costs. Based on this we could calculate that if a backorder occurred the probability of which items excess items on stock and therefore the holding of these items can be applied as back ordering costs. Based on this data, we can accurately determine the excess inventory costs.

2. Penalty Costs: A penalty cost is applied to account for additional expenses and operational disruptions caused by stockouts. This includes:

    - Extra order processing costs, including rush orders or alternative supplier arrangements.
    - The involvement of the supply chain manager in expediting the replenishment process.
    - Potential inefficiencies in production due to the need to switch to other projects, leading to reduced productivity.

After discussing with experts of the company we decided to set a minimum penalty cost of one hundred euros per stockout event in the model. These costs reflect the various disruptions and additional expenses. This penalty is a conservative estimate designed to capture the broader impact of stockouts on operational efficiency and costs.

The Backordering costs can now be calculated by simply adding the holding costs and the penalty costs.

$$Backordering\ cost\ = \sum_{i=1}^{n} Holdingcost_i + €100$$

With n = of all other components incorporated in the BOM.

By incorporating these elements, the model effectively balances the costs of holding inventory against the costs incurred when stock is unavailable, ensuring an economically rational determination of the target fill rate for each SKU.

Criticality:
For the calculation of the fill rate-based target fill rate method, the criticality of an item must be

known, as explained in Section 3.4.3. The criticality is represented by the number of final products involving the SKU, indicating its importance in meeting customer demand.

Ordering costs
The ordering costs are needed to perform the EOQ calculations and are used in the cost calculation. In the absence of specific ordering costs at the company, an analysis was conducted to determine these costs. Ordering costs are defined as the expenses incurred when placing an order for inventory or materials. These include:

- Administrative Costs: These are expenses related to the paperwork and personnel involved in placing and processing orders. This includes the procurements costs, so the costs associated with researching suppliers, negotiating contracts, and ensuring compliance with regulations.
- Transportation and Freight Costs: Costs associated with the delivery of goods.
- Inspection and quality control costs: Some products need to be inspected to ensure they meet agreed criteria when the products arrive at Mueller.

The breakdown of these costs resulting from a single order is described in Appendix C**: Ordering** . Based on the values found a formula can be created to estimate the ordering costs.

$$Ordering\ costs\ = \text{€}33{,}92\ +\ 4\%\ \text{unit costs}$$

This information in needed for to perform the calculations of the order quantity.

4.4 Fitting distributions

In this section, an explanation is given to fit distributions based on the first two moments of a random variable, the mean (EX) and the coefficient of variation (CV). This can be done to accurately predict the demand during lead time. This is crucial for ensuring high service levels. The assumption is made that crossing of orders is not permitted, implying that lead times are correlated, however, this correlation is ignored for simplification. To determine the demand during lead time distribution, we first fit probability distributions to historical daily demand data and historical lead time data. We then combine these distributions using simulation, as explained in Section 4.1.2.

4.4.1 Fitting daily Demand distributions

The historical data is analysed to determine the best-fitting distribution for each item's demand pattern, as explained in Section 3.3. Based on the historical data the items are divided into two groups, fast movers, and slow movers. For the fast movers, the continuous distributions are considered. As explained by (Bagchi et al., 1984b) and (M. Van der Heijden, 2021c). For the slow movers, the discrete distributions are calculated based on the first two moments of a random variable, the mean (EX) and the coefficient of variation (CV), as explained by (Adan et al., 1995).

A clear overview of which distribution best described the demand pattern of each item can be found in Figure 18. The formula used to calculate the parameters for each distribution is described in Appendix E**: Distributions** .

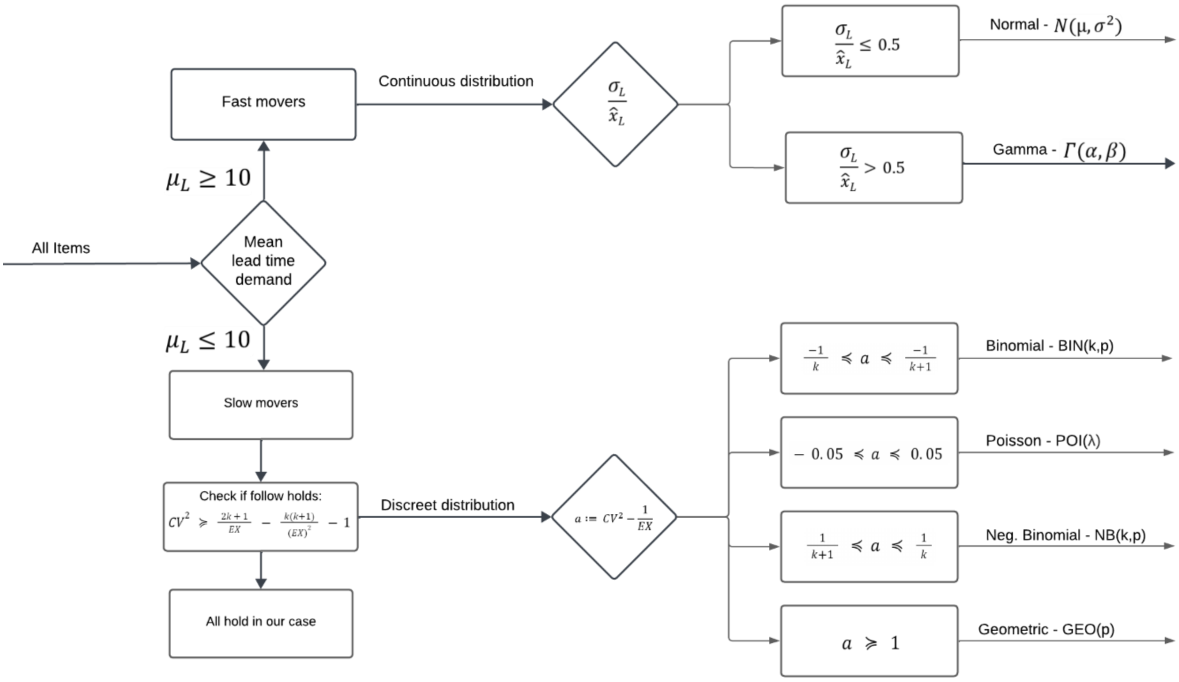


Figure 18 Fitting demand distributions.

4.4.2 Fitting Lead Time Distributions

The SKUs in which the lead time variability is considered is explained in Section 2.1, treating lead time as a random variable. The lead time of the supplier can be assumed to be always continuously distributed, as explained by Bagchi et al. (1984). Therefore, the lead time distributions assigned to the SKUs are done in the same way as the demand distribution for fast-moving SKUs, as shown in Figure 19. The formula used to calculate the parameters for each distribution is described in Appendix E: **Distributions** .

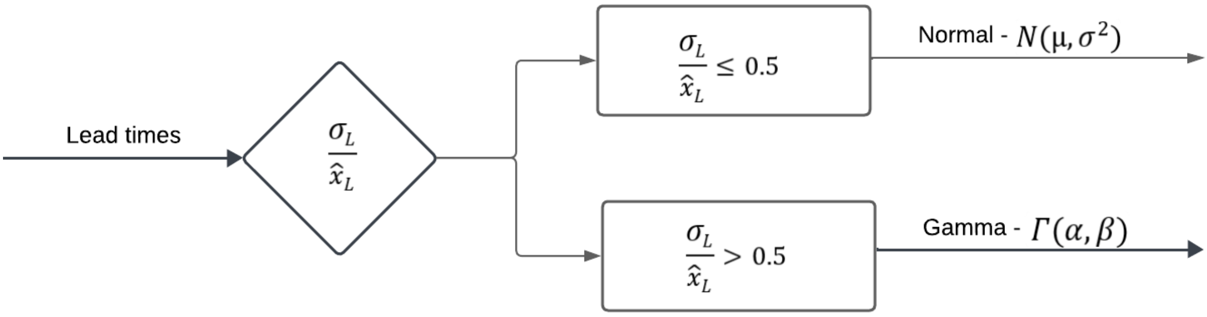


Figure 19 Fitting lead time distribution.

The lead time distributions considered are the normal and the gamma distribution. The normal distribution is restrictive because of the symmetrical form of the distribution. A further disadvantage is that the range of the distribution also includes negative values, which cannot be the case in lead time. Therefore, the gamma distribution is more desirable, it is defined for nonnegative values. Furthermore, it can easily model the usually encountered positively skewed lead-time data.

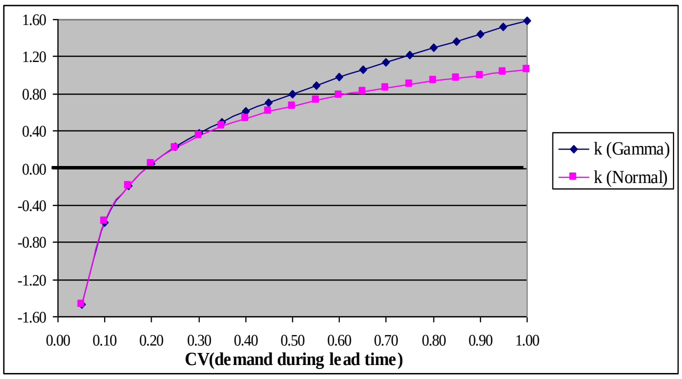


Figure 20 Difference between normal and gamma distribution

The influence of the normal or gamma distribution on the safety factor in calculating the safety stock can be found in Figure 20 (M. Van der Heijden, 2021c).

4.5 Inventory Configurations

This section introduces three different inventory configurations that are used in each of the service-level policies. Each configuration is used in the simulation model as explained in Section 4.1.4. The different configurations reflect different approaches to managing inventory, incorporating variations in demand and lead time uncertainties.

4.5.1 The current inventory configuration

The first inventory configuration represents the current inventory levels, as they are currently mentioned in Mueller's ERP system. This configuration creates a baseline, allowing for an assessment of how the current system performs relative to the other two models.

4.5.2 The inventory configurations are based on stochastic lead time.

The second inventory configurations are calculated as described in Section 4.1.3, incorporating stochastic lead times where both demand and lead time uncertainties are considered. The input for the model is the fitted demand and lead time distribution, as explained in Section 4.4. The demand and lead time distributions are fitted on the data between 01/01/2022 and 01/01/2024.

For items manufactured by Mueller or for those with no available lead time data between 01/01/2022 and 01/01/2024, we assume that the lead time recorded in the ERP system is accurate and that no lead time variation is considered.

To conclude, this configuration models inventory using ROP, safety stock, and order quantity parameters, with the stochastic lead time contributing to the variability. It allows the company to account for risks associated with unpredictable lead times and assess how this affects inventory levels and service levels.

4.5.3 The inventory configurations are based on deterministic lead time.

The third inventory configuration assumes that lead times are deterministic, meaning no lead time variability is considered in this model. As in the second configuration, the demand distribution is fitted to data between 01/01/2022 and 01/01/2024. The lead times are treated as a fixed average, rather than a distribution.

This approach is taken because Mueller's ERP system is not currently set up to handle lead time distributions or complex calculations for lead time variability. For products manufactured by Mueller or items without historical lead time data from the past two years, the lead time in the ERP system is assumed to be accurate, and no variation is introduced.

Like the second configuration, this model calculates the inventory using ROP, ss, and order quantity parameters, but with deterministic lead times. This configuration isolates demand variability as the sole source of uncertainty in the model.

4.6 Calculation of KPIs

In this section, the generic calculations for costs and KPIs are given, these calculations are crucial to balance operational costs and customer satisfaction by meeting demand agreements. The two primary costs analysed in the model are holding costs and ordering costs. Holding costs refer to the expenses associated with storing inventory over time while ordering costs encompass the expenses incurred from placing replenishment orders. Additionally, several KPIs, including the backorder rate, Fill Rate, and Inventory Turnover are explained. These KPIs provide real-time insights into inventory performance, identifying potential inefficiencies and can be ran in the background. The detailed calculations for both costs and KPIs are provided in the following sections.

4.6.1 Costs Analysis

Holding costs:

The holding costs are calculated based on the value of the inventory being held over time. For each item, the holding cost per unit is determined using the annual holding cost rate, which is typically a percentage of the item’s unit cost. In this case, the annual holding cost rate is 9%, which is applied to the item's cost:

$$Holding\ cost\ per\ item\ = \text{annual holding cost rate} * item\ costs$$

Next,

$$Holding\ cost\ per\ item\ per\ day = \ Current\ inventory\ * \frac{Holding\ cost\ per\ item}{365}$$

These daily holding costs are accumulated over the simulation period to determine the total holding cost per item per year:

$$Holding\ cost\ per\ item\ per\ year = \sum_{n=1}^{365} Holding\ cost\ per\ item\ per\ day_n$$

Finally, the total holding cost for all items in the inventory is calculated by summing the holding costs for each item over the entire simulation:

$$Total\ Holding\ cost = \sum_{i}^{4280} Holding\ cost\ per\ item\ per\ year_i$$

Ordering Costs

The second important cost metric is the total ordering cost, which represents the expenses incurred from placing replenishment orders. This is calculated by multiplying the number of orders placed during the simulation by the cost per order, the ordering costs are determined in Section 4.3:

$$Ordering\ cost\ per\ item = Total\ times\ ordered * ordering\ cost$$

The total ordering cost for all items in the inventory is calculated by summing the holding costs for each item over the entire simulation:

$$Total\ order\ cost = \sum_{i}^{4280} Ordering\ cost\ per\ item_i$$

The total costs are the sum of the total holding costs and total ordering costs for each item, reflecting the overall expense associated with managing inventory during the simulation.

4.6.2 Key Performance Indicators (KPIs)

Volume Fill Rate (VFR)

The VFR measures the proportion of total units ordered that are delivered on time. It reflects the efficiency of the inventory system in meeting demand within the expected time. In this research, this KPI is not focused on assessing the timely delivery of products to customers but focuses on ensuring that production lines receive the necessary components without delay. Therefore, a high VFR means minimizing production disruptions and therefore a better configuration of inventory parameters. The VFR is calculated in the following way:

$$Volume\ fill\ rate = 1 - \frac{\sigma_L * G(k)}{Q}$$

Where:

Q is the order quantity or batch size.
σ_L is the standard deviation of demand during the lead time.
$G(k)$ is a function that depends on the safety factor k.

k is the safety factor, which indicates how many standard deviations the safety stock is above the expected demand during the lead time.

$$G(k) = \emptyset(k) - k[1 - \Phi(k)]$$

Where:

$\emptyset(k)$ is the probability density function (PDF) of the fitted distribution evaluated at k.
$\Phi(k)$ is the cumulative distribution function (CDF) of the fitted distribution evaluated at k.
How the PDF and CDF evaluated at k are found is explained in Section 4.1.3.

The weighted average fill rate is calculated in the following way:

$$Weighted\ Average\ fill\ rate = \frac{\sum_i (fill\ rate_i \times Demand_i)}{\sum_i (Demand_i)}$$

Inventory Turnover Ratio

This financial metric indicates how often inventory is sold and replaced over a given period. A high turnover ratio indicates efficient inventory management and reduced holding costs. Monitoring this ratio helps the company prevent overstocking and indicates obsolete products based on actual demand patterns. The inventory turnover is calculated as follows:

$$Inventory\ turnover = \frac{Annual\ Sales}{Average\ inventory\ value}$$

Where:

The annual sales represent the total revenue generated from selling the inventory over a year. The average inventory value is the average value of the inventory held by the company during the year.

The weighted average inventory turnover is calculated in the following way:

$$Weighted\ Average\ Inventory\ Turnover = \frac{\sum_i (Inventory\ Turnover_i \times Costs\ of\ Goods\ delivered_i)}{\sum_i (Costs\ of\ Goods\ Sold_i)}$$

The Cycle Service Level

The Cycle Service Level (CSL) measures the fraction of cycles where the inventory level does not reach zero before the next replenishment arrives. The Cycle Service Level is defined as the cumulative probability that demand during the lead time will not exceed the available inventory. In other words, it represents the probability that a stockout will not occur during a replenishment cycle. The CSL can be represented by the function $\Phi(k)$.

$\Phi(k)$ is the cumulative distribution function (CDF) of the fitted distribution evaluated at k. With k is the safety factor, which indicates how many standard deviations the safety stock is above the expected demand during the lead time.

The Ready Rate:

The ready rate measure quantifies the proportion of time an item is immediately available to meet demand. The ready rate is calculated as:

$$Ready\ Rate = 1 - F_{NS}(0) = 1 - \frac{\sigma_L}{Q}[G(k) - G(k + \frac{Q}{\sigma_L})]$$

Where:

$F_{NS}(0)$ represents the probability that there is no stock available when demand occurs (a stockout).
σ_L is the standard deviation of demand during lead time
Q is the order quantity
$G(k)$and $G(k + \frac{Q}{\sigma_L})$ are functions that take into account the probability distribution of demand relative to the safety stock level k.

4.7 Summary Chapter

This chapter explains the foundational models relevant to the research, establishing the basis for the development of inventory optimization models. The focus is on understanding the various service level policies, methods for calculating ordering and back ordering costs, and fitting data distributions, all of which are essential for accurately simulating future demand and optimizing inventory levels.

The research compares three different service level policies, each offering unique approaches to managing stock levels and balancing inventory costs with customer demand. The ABC-XYZ classification system revealed that most inventory items at the company fall into the Z category, indicating high demand uncertainty. In the absence of historical backorder data, an alternative method was developed to estimate backorder costs, while ordering costs were derived from procurement and administrative activities.

To improve decision-making, appropriate distributions are fit to historical data on demand and lead time, which are critical for forecasting and setting appropriate inventory levels. Finally, the key performance indicators (KPIs) such as the fill rate, backorder rate, and inventory turnover were calculated, providing valuable insights into how different inventory configurations perform in terms of cost efficiency and customer service.

Chapter 5 Simulation Results and Analysis

In this chapter, we will apply the theoretical models from Chapter 4 to real-world data, present the outcomes and derive conclusions based on these results. Three different inventory configurations are compared, and the model results are presented. The results of the models are presented in Section 5.1. Section 0 discusses how the results of the simulation model are calculated. In Section 5.3 the different inventory configurations are compared. The obsolete items of the company are discussed in Section 5.4. In Section 5.5 the validation and verification of the models is done. The key findings of the chapter are presented in Section 5.6.

5.1 Results

In this Section, the results of the simulations are given. First, the results of the historical model are presented, as explained in Section 4.1.1. Next, the simulation results of the further demand model, as explained in Section 4.1.4, are given.

The models are analysed based on the cost components and the KPIs. Additionally, the KPIs are determined in such a way that the company can effectively adjust parameter configurations at the SKU level. These KPIs are crucial for preventing an inventory configuration that may become outdated in the coming years. The methodology for these calculations is outlined in Section 4.6, the actual calculations are described in Section 0. The results are based on these calculated costs and KPIs, providing a framework for optimizing future inventory management strategies.

5.1.1 Results Historical Simulation

The following results present the historical data analysis from 01/01/2022 to 01/07/2024. The model serves as a benchmark for evaluating future models and helps validate future demand simulation models. In total 11,539 items were analysed, in this period a total of 513,012 backorders occurred. 509,686 of these backorders were caused by only 948 items.

In this model the KPIs, so the inventory turnover, the fill rate, the backorder rate, but also the costs, so the holding costs and the ordering costs are calculated for each SKU. Based on this the Weighted average of the KPIs and the total costs are calculated. The results are shown underneath:

The weighted average inventory turnover = 25.72
The weighted average fill rate = 0.789 = 78.9%
The weighed average backorder rate = 0.951 = 95.1%
The total holding costs = €6.501.652,78
The total ordering costs = €4.341.965,47

For the subset of 4,280 items within the scope of the analysis, the total number of backorders that occurred was 88,148, with 87,009 backorders attributed to only 169 items. This led to the following results:

The weighted average inventory turnover = 23.65
The weighted average fill rate = 0.845 = 84.5%
The weighed average backorder rate = 0.880 = 87.96%
The total holding costs = €3.331.069,23
The total ordering costs = €3.002.286,55

These results provide a comprehensive overview of the historical performance of the company.

5.1.2 Results Future Simulation

In this section the results of the future simulation model, as explained in Section 4.1.4 are shown for the different inventory configurations, as explained in Section 4.5. In total each of the three models are run three times. The averages of the three runs are shown in this section. The results of the exact runs can be found in Appendix D: **Individual simulation**

Note: Only Method 1 (ABC, XYZ classification) could be executed. Methods 2 and 3 could not be performed due to a lack of critical data, as explained in Section 5.5.

Therefore, the results are based on method one, the ABC, XZY classification.

	Currently	Deterministic	Stochastic
KPIs			
Weighted Average Inventory Turnover	838,4	9,1	5,6
Weighted Average Backorder Rate	47,1%	95,3%	98,8%
Weighted Average Fill Rate	43,1%	93,8%	98,2%
Costs			
Holding costs	€123.065	€720.362	€938.017
Ordering costs	€2.950.013	€392.815	€360.353
Total costs	€3.069.274	€1.113.177	€1.298.370
Backorders			
The total number of backorders that occurred	17.064.955	2.065.298	500.558
Total times an item went out of stock	247.210	18.348	6.833

Table 6 Results future simulation

The results demonstrate the differences between the current, deterministic, and stochastic models on the performance of the KPIs, costs and backorders. Regarding the KPIs, the current model performs poorly with a high backorder occurrence and low fill rate. This reflects the inefficiency of the company's current inventory model, in which frequent stockouts and unsatisfied demand or late start of production occur. The deterministic model improves significantly, but the stochastic model shows the most balanced and efficient performance. It achieves the highest fill rate of 98.2% and the lowest backorder occurrence of 6.8%, indicating superior performance in demand fulfilment and operational efficiency.

In terms of costs, the current model incurs significantly higher total costs, almost fully driven by ordering costs. This can be explained since the company currently does not calculate the ordering costs. Hence, this is not taken into account in the current inventory model. In the calculation of the order quantity in the deterministic and the stochastic model the order costs are considered, leading to lower total costs. The deterministic model achieves the lowest total costs overall. However, the stochastic model is slightly more expensive than the deterministic in terms of holding costs but offers an inventory configuration that optimizes the service level, leading to more consistent inventory availability.

Regarding the backorders, the current system experiences a large number of backorders, reflecting its poor capability in managing stockouts. The deterministic model reduces backorders drastically compared to the current setup, but the stochastic model outperforms both by reducing backorders to only a fraction of the current model. This improvement not only enhances customer satisfaction but also mitigates the operational disruptions associated with stockouts. The marginally higher cost of the stochastic model is justified by the significant reduction in backorders, thus achieving a more efficient and reliable system.

5.2 Calculations Results

This section provides a detailed overview of the calculations behind both the historical and future simulation results. These calculations are essential for understanding the performance of the models, offering a deeper understanding on which the inventory management system is based. Lastly, the calculations are shown for one individual SKU.

5.2.1 Historical Simulation

Total Costs are a combination of holding and ordering costs, providing insight into the operational costs of the inventory system. This is important since Paul Mueller Netherlands has a debt at the mother company in America. Therefore, it is important that the total cost of the inventory model are known at Mueller. In this thesis this is calculated as follows:

$$Total\ Ordering\ Costs = \sum_i (Ordering\ Costs_i \times Number\ of\ Orders_i)$$

$$Total\ Holding\ Costs = \sum_i (Inventory\ level_i \times Daily\ holding\ costs_i)$$

With:

$$Daily\ holding\ costs_i = \frac{Holding\ costs\ \times Unit\ Costs}{365}$$

$$Total\ Costs = Total\ Ordering\ Costs + Total\ Holding\ Costs$$

Backorders represent a critical measure of service performance. The total number of backorders reflects how often demand could not be met immediately.

- The Total Backorder is the cumulative number of units that could not be fulfilled on time during the given period.
- The Backordered Days is the number of days when backorders occurred. Backorders are calculated daily based on inventory shortfalls.

<u>The calculation of the KPI's:</u>

In this research two KPIS are selected to ensure the configuration of the inventory parameters are set in such a way that the demand is satisfied. The first KPI is the item fill rate. In the historical simulation, the fill rate is a critical indicator of how well customer demand was met directly from available inventory, without the need for backordering. This an KPI that is often use in practice. The fill rate is calculated using the following formula:

$$Fill\ rate\ = 1 - \frac{Total\ Backordered\ Units}{Total\ demand\ for\ SKU}$$

$$Weighted\ Average\ fill\ rate = \frac{\sum_i (fill\ rate_i \times Total\ Demand_i)}{\sum_i (\ Total\ Demand_i)}$$

Ideally, the fill rate calculation would also consider lead time variations, lost sales, and backorder penalties. But due to a lack of data, on lost sales and backorder costs these calculations could not be performed.

The second KPI that is calculated in the research is often used in academic research. This KPI is calculated using the following formula:

$$backorder\ occurrence\ rate\ = \frac{Number\ of\ days\ without\ backerders}{Total\ number\ of\ days}$$

$$Weighted\ Cycle\ Service\ Level\ = \frac{\sum_i (CSL_i \times Demand_i)}{\sum_i (Demand_i)}$$

In an ideal scenario, backorder rate should account for the replenishment lead time and variability in both demand and supply. The replenishment cycles unfortunately cannot be determined due to corrupted lead time data.

Lastly, a KPI is selected to ensure that not a lot of inventory is currently in stock at the warehouse without any future demand insight. This KPI is called the Inventory Turnover and is calculated in the following way:

$$Inventory\ Turnover = \frac{Total\ demand\ per\ SKU}{Average\ Inventory\ Level\ of\ SKU}$$

$$Weighted\ Average\ Inventory\ Turnover = \frac{\sum_i (Inventory\ Turnover_i \times Total\ demand_i)}{\sum_i Total\ demand_i}$$

5.2.2 Future simulation

The future simulation applies the same fill rate and cost calculations to three different inventory configurations: the Stochastic Model, the Deterministic Model, and the Current Parameters Model. The total costs for each model are the sum of the holding costs and ordering costs, which are derived from inventory levels, order quantities, and replenishment frequencies.

The target fill rates are set as follows. The set actual values set as target fill rate as based in such a way that the average target fill rate reaches the goal of the company of 92.5%.

All items								
Classification	# items	Target fill rate	Classification	# items	Target fill rate	Classification	# items	Target fill rate
AX	1	0,98	BX	0	0,96	CX	0	0,94
AY	24	0,94	BY	25	0,92	CY	45	0,9
AZ	380	0,96	BZ	604	0,94	CZ	3201	0,92

For C-class items, despite their lower economic value, higher target fill rates are applied. This strategy ensures that the impact of stockouts on production is minimized, as the costs of delays often outweigh the costs of maintaining inventory. The objective is to reduce the risk of production downtime by balancing inventory costs against the risk of shortages.

Using the target fill rates and the number of items in each classification, the minimum average target fill rate at Mueller can be calculated as follows:

$$Minimum\ average\ target\ fill\ rate = \frac{\sum_i \#items_i * Target\ fill\ rate_i}{4279}\ with\ i = AX, AY, \dots\ , CY, CZ$$

Substituting the values from the table into the formula:

$$The\ minimum\ average\ target\ fill\ rate\ = 0{,}9263$$

This calculated minimum average target fill rate of 0.9263 reflects the baseline performance goal for item availability at Mueller, balancing the inventory levels and operational needs across different classifications.

The calculations of the costs and KPIs of the future simulation are the same as mentioned in Section 5.2.1.

5.2.3 Item example

This section provides a detailed comparison of the three inventory models: Current Parameters, Deterministic, and Stochastic for a single item. First, the input variables used in the inventory model are discussed, followed by the output results and an explanation of how the calculations were performed. A graph illustrating the demand and lead time distributions will be included to enhance clarity.

Input variables for the Python Model:

The first step is to define the input variables that drive the inventory model. These include the unit costs, ordering costs, lead time, and demand distribution. The following example showcases the input parameters for a specific item:

- Unit costs: 0.31
- Ordering costs: 33.93
- Lead time:

In the current situation the ERP give a lead time of 14 days.
Based on historical data an average lead time of 29 days is found, this is used in the current and deterministic model
For the stochastic model, a lead time distribution is applied, as explained in Section 4.4.2. The lead time distribution found is: Normal(29; 13.21). The distribution is plotted in Figure 21.

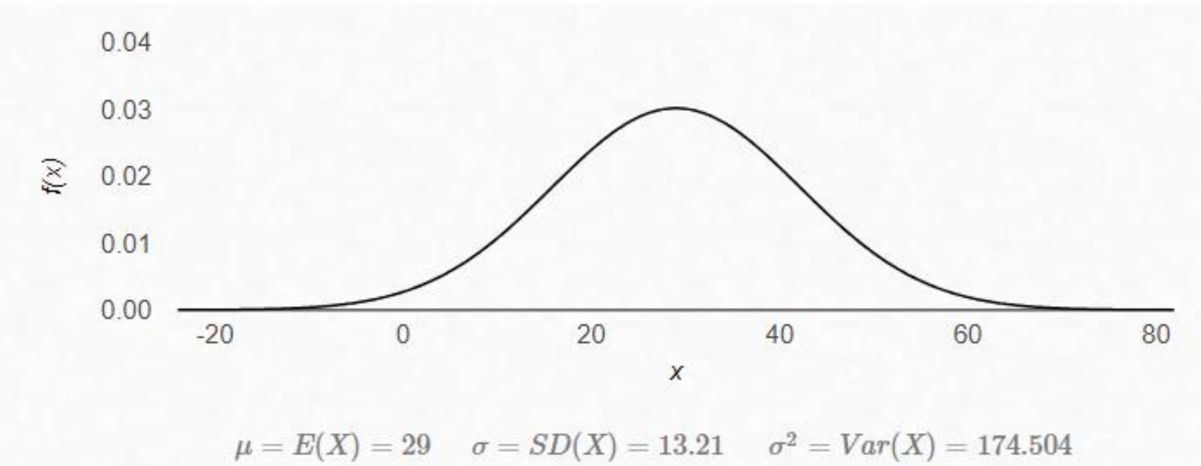


Figure 21 Lead time distribution item 135629

- The demand

For the demand the demand distribution is found, as explained in Section 4.4.1. In this case the demand in the simulation follows two geometric distribution, with certain probability, with a probability of 15.22% we draw from Geometric(0.059912) as represented in Figure 22 , and with probability of 84.78% we draw from Geometric(0.261961), as represented in Figure 23.

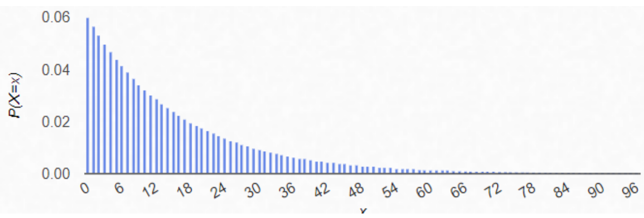


Figure 22 Geometric(0.059912)

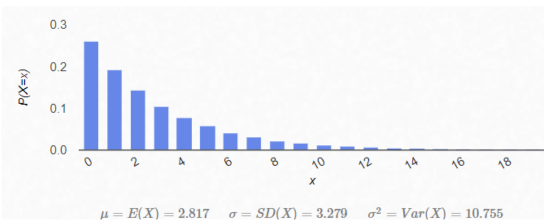


Figure 23 Geometric(0.261961)

Results of the Python Model:

The results generated by the Python model are detailed in an Excel file, displaying various metrics over time. An example of the output for item 135629 is shown below:

Item Number	Metric	1-7-2024	2-7-2024	...	29-12-2025	30-12-2025
135629	On-hand inventory start of day	28	23		0	0
135629	Received items	0	0		0	5
135629	Demand	5	0		1	6
135629	Demand fulfilled from stock	5	0	...	0	0
135629	Demand back ordered	0	0		95	96
135629	Pipeline	0	0		95	91

Table 7 Result metric Python model, Currently

These results reflect the evolution of inventory, demand, and orders over time.

Explanation of the Calculations

Each of the rows in Table 7 above is derived using specific formulas, as detailed below:

- On-hand inventory start of day:

$$I_t = I_{t-1} + R_t - D_t$$

where I_t is the on-hand inventory at the start of day t, I_{t-1} is the inventory at the end of the previous day, R_t is the received items on day t, and D_t is the demand fulfilled from stock on day t.

- Received items:

The number of items received from pending orders is calculated by checking if any lead time has finished. For each pending order:

$$R_t = \sum_{i=1}^{n} qty_i \qquad if\ lead\ time_i = 1$$

where n is the number of pending orders and qty_i is the quantity for the i-th order whose lead time is completed, based on the fitted lead time distribution as explained in Section 4.4.2.

- Demand:

The daily demand is drawn from a pre-defined distribution using the draw_demand() function, which simulates the demand for each item on a given day. The actual demand D_t is stochastic and depends on the distribution used, as explained in Section 4.4.1.

- Demand fulfilled from stock:

This is the amount of demand that can be satisfied from the current inventory:

$$D_{fulfilled,t} = min\ (I_t, D_t)$$

- Demand backordered:

Any unsatisfied demand is backordered:

$$B_t = B_{t-1} + (D_t - D_{fulfilled,t})$$

Where B_t is the total backordered demand at the end of day t, and B_{t-1} is the backordered demand carried over from the previous day.

- Pipeline (pending orders):

The pipeline represents items that have been ordered but not yet received:

$$P_t = \sum_{i=1}^{n} qty_i$$

where qty_i is the quantity of each order still pending (lead time greater than 1 day).

Consistency across models

To ensure a fair comparison between the different simulation models (currently, deterministic and stochastic), the same daily demand values for each item are used across all models. This allows for a direct evaluation of the impact of using different lead time and demand distributions.

5.3 Analysis Results

5.3.1 Comparison Inventory Configurations

This section provides a detailed comparison of the three inventory models: Current Parameters, Deterministic, and Stochastic. The comparison highlights the significant differences in both cost structure and performance across these models, based on the KPIs and the number of backorders. Table 8 presents an overview of the different inventory configurations.

Total overview			
	Current	Deterministic	Stochastic
KPIs			
Weighted Average Inventory Turnover	838,4	9,1	5,6
Weighted Average Backorder Rate	47,1%	95,3%	98,8%
Weighted Average Fill Rate	43,1%	93,8%	98,2%
Costs			
Holding costs	€123.065	€720.362	€938.017
Ordering costs	€2.950.013	€392.815	€360.353
Total costs	€3.069.274	€1.113.177	€1.298.370
Backorders:			
The total number of backorders that occurred	17.064.955	2.065.298	500.558
Total times an item went out of stock	247.210	18.348	6.833

Table 8 Overview inventory configurations

Important to notice based on the information mentioned in Table 8 is that both the Deterministic, as well as the stochastic model score better than the current inventory configurations in all aspects. Additionally, it is worth mentioning that while the holding costs in the current model are low, this is achieved by frequently placing orders for small quantities. Consequently, this strategy results in significantly higher ordering costs, highlighting a trade-off between inventory holding and ordering expenses in the current system.

<u>Detailed model comparison:</u>

	Total costs (€)	**Total number of backorders**	**Difference in backorders**	**Difference in total costs (€)**
Current Parameters	€3.069.274	247.210	n.v.t.	n.v.t.

Deterministic Model	€1.113.177	18.348	-228.862	- €1.956.097
Stochastic model	€1.298.370	6.833	-240.377	- €1.770.904

Table 9 Model comparison

The Current Parameters Model results in the highest number of backorders, with 247.210 occurrences. This is significantly more than both the Stochastic and Deterministic Models. The Stochastic Model reduces backorders by 240.377, and the Deterministic Model reduces them by 228.862 compared to the Current Model. Next to that the current inventory parameters also have the highest total costs.

<u>Comparison of the Stochastic & Deterministic model:</u>
The Current Parameters Model results in the highest number of backorders, totalling 226,137, which is significantly more than both the Stochastic Model and the Deterministic Model. The Stochastic Model reduces backorders by 213,147, while the Deterministic Model decreases backorders by 203,266, compared to the current system.

<u>Comparing the Stochastic Model and the Deterministic Model:</u>

	Total costs (€)	**Total number of backorders**	**Cost per backorder (€)**
Stochastic Model	€1.298.370	6.833	190,01
Deterministic Model	€1.113.177	18.348	60,67

Table 10 Comparison backorders

While the Stochastic Model incurs higher total costs compared to the Deterministic Model, it achieves fewer backorders. Although the Deterministic Model is more cost-effective per backorder, the Stochastic Model offers significantly better performance in reducing stockouts and improving service levels.

You can also see it as that the costs to reduce the backorder from 18.348 to 6.833 are €185.193. So, the costs associate to reduce the backorder from 18.348 to 6.833 are €16,08 per backorder.

<u>Difference in inventory holding costs per classification type:</u>
In this section, we will explore the increase in holding costs across different item classifications. The rise in holding costs aligns with our expectations based on the number of articles in each classification. It is important to note that an increase in the ROP for items in classification A will have a much greater impact on total holding costs compared to a similar increase in classification C. This is because classification A typically contains higher-value or higher-demand items, and changes in stock parameters for these items result in more significant cost variations.

	Currently	Deterministic	Stochastic
AX	€ 4.226,8	€ 8.718,4	€ 11.678,3
AY	€ 10.726,6	€ 27.143,4	€ 67.532,5
AZ	€ 33.251,0	€ 466.103,7	€ 600.532,3
BX	€ 402,0	€ 1.116,3	€ 822,4
BY	€ 4.735,1	€ 10.804,4	€ 12.771,0
BZ	€ 28.450,0	€ 104.850,3	€ 128.944,3

CX	€ 23,4	€ 34,6	€ 31,2
CY	€ 556,8	€ 2.112,4	€ 2.287,4
CZ	€ 36.890,3	€ 102.113,5	€ 113.999,1

Table 11 Holding costs per classification

The differences in inventory holding costs between the current, deterministic, and stochastic models highlight this trend. For instance, while the increase in holding costs for classification A items is substantial across all models, the changes for classification C items are relatively small, especially if we take into account how many items are C classified. This demonstrates that managing the ROP for high-impact classifications like A is crucial for optimizing holding costs.

<u>Which items are responsible for the biggest differences in costs:</u>
Next an analysis is done on which specific items are responsible for the largest differences in holding costs. This was done to identify potential areas where the company could explore agreements with suppliers, especially for the top 200 items, regarding lead time or the possibility of maintaining a safety stock at the supplier's location. Implementing such agreements could significantly reduce the capital tied up in stock at Mueller while maintaining service levels.

	Currently	Deterministic	Stochastic
100 items	€ 67.558	€ 352.932	€ 483.886
200 items	€ 83.892	€ 452.290	€ 615.556
300 items	€ 93.302	€ 504.912	€ 685.001
400 items	€ 99.533	€ 539.685	€ 729.246
500 items	€ 103.982	€ 565.972	€ 760.536

Table 12 Important items costs difference

<u>Comparison between the current inventory configuration and proposed options :</u>

	Deterministic compared to Currently	Stochastic compared to Currently
100 items	€ 342.625	€ 473.381
200 items	€ 429.903	€ 591.504
300 items	€ 473.079	€ 651.718
400 items	€ 500.799	€ 688.112
500 items	€ 521.755	€ 713.886

Table 13 Comparison current model and proposed models

Based on the data in the table, we can conclude that 65% of the holding costs in the deterministic model are generated by just 300 items, which represent only 7% of the total items. In the stochastic model, even 69% of the holding costs are attributed to these same 300 items. Therefore, it may be beneficial to focus on these 300 items and apply the proposed solutions to the remaining items.

Additionally, some items may have predictable demand since they are only used in large projects. This allows for better planning and can reduce the need for high safety stock levels, ultimately lowering cash outflow while maintaining high fill rates. Although this is accounted for in the current model, it is not reflected in the proposed solutions. As a result, the differences between the results presented in this chapter may appear more pronounced than they would be in practice.

Lastly, we observed that in the current model, some items are assigned a safety stock of 0 and a reorder point of 0. These items are treated differently by the MRP system, where they are ordered every time they are used. This approach, however, provides an unrealistic view of holding costs, as it affects 1,082 items within the scope of our research. This issue needs to be addressed to ensure more accurate inventory and cost analysis.

5.3.2 Item example

In this section, the examination of item 135629 across the three different models is continued. Each model applies different inventory control policies, specifically regarding safety stock, reorder points, and order quantities. We will explore the simulation results, highlighting the impact of each model on inventory levels, backorders, and operational costs. Additionally, we will incorporate graphical representations of the results to visualize the differences between the models.

Input parameters for each model:

Model	Safety Stock	Reorder Point	EOQ
Currently	0	0	0
Deterministic	49	116	2050
Stochastic	117	253	2050

Table 14 Input parameters for each model

In the current model, no safety stock is set. As a result, the ERP system forecasts demand for the lead time plus an additional week, since orders at Mueller are only placed on Tuesdays. When the inventory level reaches zero, all items needed within this time frame are ordered. In this case, with a lead time of 14 days in the ERP system, all items required over the next 21 days are ordered if the inventory level is expected to drop to zero.

The current and deterministic model follows fixed lead times, as explained in Section 5.2.3. Therefore, in this model, only variability in demand is considered.

In the stochastic model, both variability in demand and lead times is incorporated, accounting for more uncertainties in the supply chain.

Results and Observations

The following results are derived from the simulation of 529 days with a startup period of 181 days, for all three models:

135629	**Currently**	**Deterministic**	**Stochastic**
Total Demand	1655	1655	1655
Total Backorders	1655	56	0
Average Inventory Level	0	941	1110
Total Sales Value	€518.02	€518.02	€518.02
Inventory Turnover	0.00	1.75	1.49
Cycle Service Level	0.00	0.97	1.00
Fill Rate	0.00	0.97	1.00
Total Holding Cost	€0, -	€26,73	€31,52
Total Ordering Cost	€7.770,55	€33,93	€33,93

Table 15 Results item 135629

Graphical Analysis

- Number of Items on Hand

Figure 24 illustrates the inventory levels over the simulation period for the current, deterministic, and stochastic models:

In the current model, the inventory remains at zero throughout the simulation, which is because if the safety stock is 0 and the item get in backorder, the simulation model cannot determine to order an additional x units. Which an employee at the purchasing department could do.

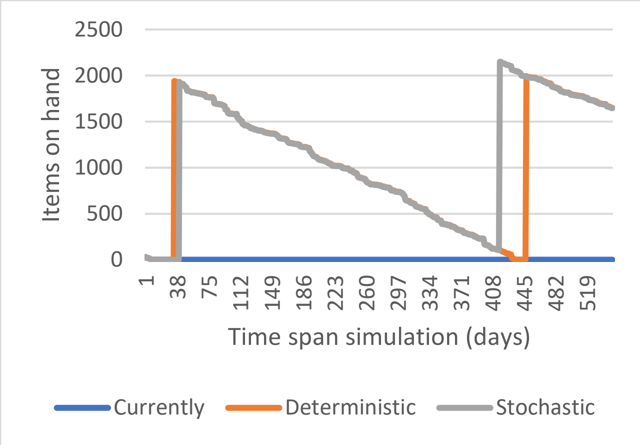


Figure 24 Items on hand

The deterministic model shows a substantial increase in inventory levels after the reorder point is reached, stabilizing until a large order is placed again.

The stochastic model reflects a more gradual decline in inventory due to variable lead times and demand fluctuations, but it maintains a higher overall inventory than the deterministic model.

- Items Backordered

Figure 25 represents the number of backorders throughout the simulation period:

The current model experiences continuous backorders, as already explained in the Items on hand part.

the deterministic model, backorders only appear briefly, reflecting better control over inventory with fewer shortages.

The stochastic model successfully eliminates backorders due to more flexible inventory policies that account for demand variability.

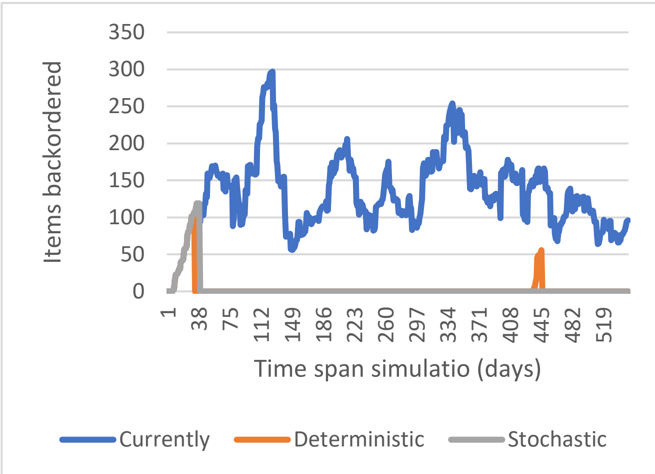


Figure 25 Items backordered

Conclusion

This analysis demonstrates the significant differences in inventory management between the current, deterministic, and stochastic models. The current model leads to persistent stockouts and high backorders, as expected from its "order-on-demand" configuration. The deterministic model offers a much-improved performance with relatively low backorders and reasonable inventory levels. However, the stochastic model performs the best, eliminating backorders and maintaining a higher service level, albeit with slightly higher holding costs.

It is important to note that in reality, human intervention from the purchasing team would likely prevent the extreme backordering seen in the current model. This limitation emphasizes the need for adaptive models like the stochastic one, which can adjust to real-world uncertainties in demand and lead time.

5.4 Excess inventory / obsoletes.

Lastly, an analysis is conducted to assess the proportion of obsolete items in Mueller's current inventory, defined as items without any recorded movement over specific periods. By identifying these items, the company can take steps to optimize inventory levels by scrapping or removing products that no longer contribute to operational efficiency. This process is critical for improving inventory management and compensating for the increases in inventory levels that result from implementing the new inventory configurations.

The analysis focused on three key periods: items that had no movement in the past six months, one year, and two years. Table 16 summarizes the values associated with these time periods, along with the percentage of total inventory value that these obsolete items represent.

Date	Value	Percentage inventory value
<01/04/2024	€ 4.842.373,54	53.8%
< 01/01/2024	€ 1.676.293,31	18.6%
<01/01/2023	€ 657.141,81	7.3%

Table 16 Obsolete values at Mueller

The total inventory at Mueller at this moment is €8.996.536,80.

This suggests a considerable proportion of stock that may no longer be necessary for future operations. Items that have not moved in the past year and two years account for 18.6% and 7.3% of the total inventory value. Eliminating these obsolete items can lead to a more streamlined, inventory system, that better align with future demand and operational needs.

5.5 Verifications, Validations, and Limitations

5.5.1 Verification of Simulations Analysis

Verification involves ensuring that the assumptions have been accurately implemented in the computer program (Law, 2015). To verify this, the model must be carefully traced and debugged to confirm that the correct logical sequences are followed. Several SKUs were tracked to validate that the simulation operated as expected.

5.5.2 Validations of Simulations Analysis

Validation is the process of determining whether a simulation model is an accurate representation of the system for the objects of the study (Law, 2015). This means the model should enable decision-making as if experiments were being conducted on the real system. However, it is important to mention that the model will always remain an approximation of the actual system. The most effective way to validate a model is by ensuring that its output closely mirrors the outcomes observed in the real system.

Validation of historical model:

The results of the output data were cross-verified with the on-hand inventory recorded at the start of 01/06/2024. In most cases a match was found, hovering for some items errors were noticed. The errors were caused by two things, first error is that received items are recorded in the ERP system in bulk quantities, such as boxes or pallets, whereas demand is assessed in individual units. This could lead to quite big negative values in the inventory level. Therefore, these items are excluded from the remainder of the analysis. Second, small errors may occur due to inventory adjustments, which result from discrepancies during cycle counts or inaccuracies in delivered quantities.

Validation of future model:

In our case, this means making sure the results of the historical simulation, 5.1.1 are in line with the number of backorders that are experienced in the simulation model, where the ROP and EOQ are based on the current values presented in the ERP system. Unfortunately, there is quite a discrepancy between the simulated backorders under the current inventory parameters (247.210) and the historically expected backorders (88,148). This can be partially explained by the fixed-order quantity (EOQ) assumption in the model. In practice, the purchasing department frequently adjusts the order size for 25% to 30% of the orders, which is not accounted for in the model. This real-world flexibility in order sizing results in higher actual inventory levels, leading to increased holding costs and reduced ordering costs in comparison to the rigid EOQ framework modelled in the simulation. Unfortunately, due to the lack of detailed data on these adaptive purchasing decisions, this behaviour could not be fully integrated into the simulation, potentially explaining the disparity in backorder figures.

In the simulation model of the current inventory system, when a new order is placed, it is based on the EOQ, and not necessarily in multiples of the EOQ. Therefore, if a large order is needed, the model will continue to place new orders, as necessary. The order quantity is determined by the following equation:

$$Order\ quantity = Max\{(ROP - current\ inventory + pipeline - backorders)\ ; EOQ\}$$

If the system encounters a backorder and the EOQ is too low, the model struggles to catch up with demand. This leads to repeated orders, resulting in higher ordering costs and an increase in backorders compared to the actual performance of the system. Where the purchasing department can ensure that the ordered quantity is sufficient to avoid placing another order the next day.

5.5.3 Limitations of the model

One of the primary limitations encountered during this research was the inability to perform the cost-based fill rate method and the target fill rate method due to the lack of data.

The costs-based fill rate could not be executed due to the unavailability of essential data at Mueller. Specifically, the company lacks information regarding which individual items are incorporated into final products. This absence of Bill of Materials (BOM) data meant that the criticality levels of the items could not be determined. Without knowing the role each item plays in the production process, it is impossible to assess their impact on overall product availability, which is crucial for implementing this method. However, the Python code necessary to run this method has already been developed. If Mueller can obtain the required BOM data in the future, the company can easily implement the method.

Similarly, the target fill rate method, could not be performed due to the absence of data on backorder costs. A potential workaround, which involved estimating backorder costs based on excess inventory costs as explained in Section 4.2.3, also proved infeasible. This was because the necessary data on specific SKUs and Line Replaceable Units (LRUs) that form part of the final items were not available. As a result, the back ordering costs could not be calculated, making it impossible to determine the target fill rate as described by Teunter et al., 2017.

5.6 Chapter Conclusion

In this chapter, the theoretical models from Chapter 4 are applied to the data from Mueller. The historical simulation, covering a period from January 2022 to July 2024, serves as a benchmark, showing high backorder rates concentrated in a small fraction of items. This highlights inefficiencies in the current inventory model. The future simulation, based on the ABC XYZ service policy classifications, analyses three inventory configurations, the current parameters, deterministic, and stochastic,. The results are based on the inventory turnover, costs, service levels, and backorder occurrences. The stochastic and deterministic models demonstrate superior performance across all metrics compared to the current system, particularly in reducing backorders and overall costs. Additionally, the analysis of obsolete inventory underscores the necessity for better stock management, with significant portions of inventory value tied to items that may no longer be needed.

Lastly, the verification and validation process reveal some discrepancies between the simulated and actual performance, largely attributable to data limitations, such as incomplete order quantity information and the absence of backorder cost data. These insights highlight the need for refining the company's inventory management strategies, with specific recommendations focused on implementing more robust data collection and storage at Mueller.

Chapter 6: Implementation

This chapter describes how the proposed inventory model for Paul Mueller can be effectively implemented in the company's operations. It addresses both technical and organizational steps necessary to ensure successful adoption. The implementation steps will be guided by the findings from the research and simulation models developed in this thesis. Section 6.1 introduces some theory on the implementation of changes in a business environment. The stakeholders that er involved in the implementation process are identified in Section 6.2. In Section 6.3 the theory is applied to Mueller and concrete steps are identified. Section 6.4 discusses some main challenges and considerations regarding the implementation. The chapter is concluded in Section 0.

6.1 Implementation Approach

The proposed inventory model incorporates demand uncertainty and lead time variability to optimize stock levels. Implementing this change represents a shift in the company’s current inventory policy, requiring both a technical solution and stakeholder involvement. Successful change management, as described by (Kotter, 1995), will be crucial to mitigate resistance and ensure alignment.

6.2 Stakeholder Involvement

To ensure the successful implementation of the new inventory policies, the initial coalition of stakeholders includes the supply chain manager, production manager, purchasing team, and the ERP system implementation consultant. Their role is crucial in transitioning the new inventory policies from a strategic to an operational level.

The supply chain manager will oversee the overall transition, ensuring alignment with company goals and improvements in on-time and in-full (OTIF) performance. The production manager is responsible for optimizing production schedules according to the new inventory levels and lead times. The purchasing team will update order quantities and lead time parameters in the ERP system, while the ERP consultant will make the necessary changes in the system and ensure correct integration of data collection and calculation.

As the implementation progresses, more stakeholders from the operational teams, including warehouse staff, will become involved.

The company is aware of the out-date inventory parameters, and this has been the motive for this research. The stakeholders mentioned above have a shared commitment to implement the new policies created. The main stakeholder is the supply chain manager and company supervisor of this thesis. During semi-weekly meetings, he has been kept up to date on the progress of the research as well as the direction, ensuring that the solution is fitted to the company.

6.3 Steps for Implementation

Step 1: Arrange ERP system and greenlight Management Team (MT)

The first step is to bring the Management Team (MT) up to speed and secure their approval for the additional cash required to support higher safety stock levels. This is crucial to avoid cash flow issues while maintaining improved service levels. Next, ensure that the ERP system is capable of storing and processing the data required for the new inventory calculations, including accurate updates for lead times and demand patterns. In addition, all relevant departments must undergo training to ensure consistent data interpretation. This will help prevent any misunderstandings and ensure smooth collaboration as the new model is implemented across the company.

Step 2: Data Integration

The first step in implementing the new inventory policies is to update the ERP system with the new lead time and demand parameters identified in the simulation. These parameters must be kept up-to-date regularly, incorporating new demand patterns and supplier lead times to avoid data obsolescence. Historical data for lead times and demand will be used to recalibrate the system.

Step 3: Small-Scale Pilot

A small-scale pilot will be conducted to test the implementation of the new inventory policies. Selected SKUs will be updated in the ERP system with the new policy configurations. This pilot will focus on measuring the fill rate, inventory turnover, and backorder rate. A three-month pilot period will be set, after which an evaluation will take place.

The stakeholders will be trained to understand how the updated model impacts ordering processes, production, and stock levels.

Step 4: Pilot Evaluation

After the three-month pilot, a review will take place with key stakeholders. The performance of the new model will be evaluated using the KPIs outlined in the thesis (fill rate, total costs, inventory turnover). Feedback from operational staff will be considered to identify any operational challenges.

Step 5: Full-Scale Implementation

If the pilot is successful, the model will be rolled out to all relevant SKUs in the ERP system. This phase will include updating the entire inventory database and training staff across departments on the changes. Regular audits will be performed to ensure that the model is operating as expected and that parameters are continually updated.

Step 6: Continuous Monitoring

Once the new model is implemented company-wide, continuous monitoring of lead times and demand patterns is necessary. KPIs such as fill rate, backorders, and inventory turnover should be tracked to ensure sustained improvements in OTIF and operational efficiency. Further adjustments to the inventory model can be made as new data becomes available or if operational priorities change.

6.4 Challenges and Considerations

The successful implementation of this inventory model will depend on several key factors. First, data accuracy is critical, as the model’s effectiveness relies on up-to-date lead time and demand data, which must be regularly updated. Second, change management is essential, as resistance to the new system may arise from staff unfamiliar with it. Clear communication of the benefits, along with adequate training, will help mitigate this resistance. Finally, the success of a small-scale pilot will be crucial in determining how quickly the full-scale implementation can proceed.

6.5 Chapter Conclusion

This chapter outlines the practical steps to implement the proposed inventory model, starting with data integration, a small-scale pilot, and scaling up to a full implementation. Regular updates and stakeholder involvement are essential for maintaining the model's effectiveness.

Chapter 7: Conclusion, Discussion and Future Research

In this chapter, the findings of the research are presented. This includes the recommendations, the limitations, and potential future directions. Section 7.1 Presents the conclusions drawn from the research. In Section 7.2, the implications of the research are discussed, including recommendations for implementation at Mueller, as well as the limitations of the study. Finally, Section 7.3 Outlines suggestions for future research, highlighting areas that could benefit from further investigation to enhance inventory management practices.

7.1 Conclusions

This thesis focused on optimizing inventory parameters at Paul Mueller by developing a simulation model that accounts for uncertain supplier lead times and demand variability. The goal was to enhance OTIF (On-Time, In-Full) performance by improving item availability at the warehouse, expressed through the fill rate. Improved fill rates will lead to a smoother production flow and increase the company's resilience to supply chain uncertainties.

The current inventory model at Paul Mueller suffers from several inefficiencies, primarily due to outdated inventory parameters, inaccurate demand forecasting, and unreliable supplier lead times. These issues have contributed to excess inventory for some items and stockouts for others, leading to suboptimal customer service levels and increased costs.

Therefore the inventory parameters of all items were reevaluated using more accurate data inputs. This resulted in significant improvements in the inventory performance at Paul Mueller Company when switching from the current model to the proposed models. The comparison of deterministic and stochastic models demonstrated clear advantages in terms of KPIs such as the fill rate, inventory turnover, backorders, and overall costs. The stochastic model accounts for both demand variability and lead time uncertainty. Whereas the deterministic model only updates the lead times based on more recent data and is then based on the demand variability. A simulation model resulted in the following results:

The weighted average fill rate for the current model was 43.1%, while the deterministic model achieved a fill rate of 93.8%, and the stochastic model reached an even higher rate of 98.2%.

In terms of backorders, there was a dramatic reduction, with the current model registering 247,210 backorders, which decreased substantially to 6,833 in the stochastic model.

The comparison of total costs also shows a notable improvement. The current model incurred a total cost of €3,069,274, whereas the deterministic model resulted in a cost of €1,113,177, and the stochastic model demonstrated a slightly higher cost at €1,298,370.

Based on this we can conclude that the stochastic model performed best in terms of balancing higher service levels with acceptable holding costs, but the deterministic model was more cost-effective overall. These differences highlight the critical role that uncertainty in both lead time and demand plays in inventory optimization.

7.2 Discussion

The models developed in this thesis demonstrate substantial improvements in inventory management; however, there are important considerations regarding their applicability and limitations. First, the challenges encountered during this research will be discussed, as well as their impact on the study.

A significant challenge encountered during this research was data limitations. The available data did not allow for a clear separation between demand that was known far in advance and uncertain demand. This limitation made it difficult to estimate demand uncertainty or detect patterns accurately. As a result, in calculating key parameters such as safety stock, ROP and order quantities, it was necessary to assume that all demand was uncertain. This assumption may have skewed the results, as the actual situation likely involves more predictable demand for certain items. The inability to account for these differences limits the fairness of comparing the model to the real-world scenario.

Another issue was the inconsistency in the existing data at Paul Mueller. Different departments interpreted information from the ERP system in varying ways, leading to polluted data. For example, suppliers' promised delivery dates were frequently adjusted whenever new information became available, which distorted reliability measurements. This inconsistency created challenges in achieving accurate and reliable inventory analyses. Additionally, the absence of comprehensive backorder data made it difficult to precisely simulate the current state of operations. Although I made every effort to approximate the real situation, the lack of complete information about backorders limits the accuracy of the simulation results.

Furthermore, the absence of Bill of Materials (BOM) data hindered the assessment of the criticality of specific items. Without this information, it was not possible to evaluate the full cost implications of backorders, and therefore, a detailed comparison between different fill rate methods could not be conducted as intended. This shortcoming represents a significant gap in the research, as the criticality of certain components could greatly influence inventory policies and overall costs.

Secondly, a reflection on the research process reveals several areas where improvements could have been made. Greater emphasis could have been placed on ensuring data accuracy and consistency across all departments from the outset. A more proactive approach in verifying data availability and aligning data preparation with the research requirements would likely have prevented some of the challenges encountered. For example, relying on assurances from others regarding the availability of necessary data, rather than directly verifying it, contributed to delays and complications during the research.

Moreover, the choice to fit a distribution to the lead-time demand data, rather than using simulated empirical data, might have influenced the model's accuracy. A deeper investigation into alternative methods for handling empirical data would have provided more robust simulation results. Similarly, better alignment between the data and the model design could have enhanced the overall applicability and reliability of the findings.

Despite these challenges, the research offers several key recommendations for Paul Mueller to optimize its inventory management practices. Accurate and consistent data collection, particularly regarding demand forecasts, supplier lead times, and item criticality, should be prioritized. By ensuring reliable data, the company will be able to set more appropriate reorder points, safety stock levels, and economic order quantities, reducing both stockouts and excess inventory. Additionally, upgrading the current ERP system to support dynamic inventory management methodologies, such as ROP, order quantity, and safety stock calculations, is essential to improving inventory control. The implementation of stochastic inventory models, as developed in this thesis, can further enhance performance by accounting for variability in demand and lead times.

One critical factor involves the potential introduction of safety stock at the supplier level, particularly for high-cost items. By doing so, lead-time variability could be reduced, lowering the need for excess stock on-site at Paul Mueller. This strategy may enhance overall inventory efficiency but requires careful consideration of supplier dynamics and cost implications.

Finally, the research has several limitations that should be addressed in future work. One major limitation is the unavailability of critical data, such as item criticality, backorder costs and detailed BOM information. The lack of this data restricted the ability to fully assess the financial impact of various inventory policies. Additionally, the simulation model relied on several assumptions regarding lead times and demand patterns, which may not fully reflect real-world conditions. Future studies should prioritize collecting more comprehensive data to enable more accurate and actionable analyses.

In conclusion, while the research presented here provides a solid foundation for improving inventory management at Paul Mueller, future research and implementation should address these limitations to further enhance operational efficiency and decision-making capability.

7.3 Future research

There are several promising directions for future academic research that can build upon the findings of this thesis. One important area is the exploration of inventory optimization within multi-echelon systems, where optimization occurs across various levels of the supply chain, including manufacturing, distribution, and retail. This approach would offer a more comprehensive view of inventory management, as it considers the interdependencies between different supply chain stages and allows for better coordination of stock levels across the entire network.

Additionally, there is substantial potential in applying machine learning techniques to improve demand forecasting. Machine learning models could be used to predict demand more accurately, thereby reducing the uncertainty that often complicates inventory management. By enhancing demand accuracy, companies can optimize reorder points, safety stock levels, and order quantities to achieve higher service levels with lower inventory costs.

Another critical area for future research is the handling of uncertainty in supply chains, particularly regarding supplier reliability. Supplier performance plays a crucial role in inventory outcomes, and future studies could investigate how supplier relationships might be strengthened through contractual agreements. For example, incorporating penalty clauses for late deliveries or other performance optimization mechanisms could help reduce lead-time variability, minimizing the risk of backorders and improving overall service levels.

Within the context of Paul Mueller, future research should prioritize the restructuring of its current ERP system to better support inventory management methodologies, such as ROP, safety stock, and order quantity. The company's existing system, which is primarily designed for MRP, lacks the necessary functionalities to manage inventory dynamically and in response to fluctuating demand patterns. By updating the ERP system so it supports these methodologies, Paul Mueller would be able to manage inventory with greater precision and agility, optimizing stock levels while minimizing excess inventory.

A related focus should be on refining data collection processes to better differentiate between deterministic demand, driven by planned production orders, and stochastic demand, which is triggered by unplanned or urgent customer orders. This improved segmentation of demand would enable the company to adjust its inventory policies more accurately, reducing unnecessary safety stocks and aligning inventory parameters with actual demand variability.

Ensuring consistent data interpretation across all departments is another vital area for future work. Standardizing data collection and analysis within the ERP system would help guarantee that each department is working with the same definitions, metrics, and objectives. Developing KPIs for each department would guide these efforts and ensure alignment across the organization. These KPIs would also support the recalculation of inventory parameters such as safety stocks, reorder points, and EOQ, allowing the inventory model to remain responsive to evolving business conditions.

Another important aspect to consider for future research is increasing the transparency around the costs of backorders. Currently, Paul Mueller lacks clear insight into the financial implications of backorders for individual items. Future research could investigate methods for quantifying these costs, which could include lost sales, production delays, and customer dissatisfaction. A better understanding of backorder costs would allow the company to refine its reorder points, safety stocks, and order quantity more effectively, balancing the costs of carrying inventory against the risks and financial impact of stockouts. This would lead to a better inventory configuration that reflect both demand patterns and the economic trade-offs involved in inventory management.

In conclusion, future research should concentrate on restructuring the ERP system, improving data collection methods to differentiate between known and uncertain demand, and ensuring uniform data interpretation across the organization. These advancements will further optimize inventory management at Paul Mueller and lay the groundwork for sustained operational efficiency.

In the academic field, future studies could delve deeper into two key areas. First, inventory optimization could be expanded to include multi-echelon systems, where optimization happens simultaneously across multiple levels of the supply chain, providing a more holistic view of inventory control. Second, further research could focus on addressing uncertainty in supply chains by examining supplier reliability and exploring how to improve supplier relationships. This could be achieved through contracts that reduce lead-time variability or through the inclusion of performance-enhancing clauses, such as penalties for late deliveries. By addressing these key areas, future research can significantly contribute to advancing inventory management practices and supply chain efficiency.

References

Adan, I., Van Eenige, M., & Resing, J. (1995). *Fitting discrete distributions on the first two moments*.

Axsäter, S. (2015). *Inventory Control* (Vol. 225). Springer International Publishing. https://doi.org/10.1007/978-3-319-15729-0

Bagchi, U., Hayya, J. C., & Ord, J. K. (1984a). MODELING DEMAND DURING LEAD TIME. *Decision Sciences*, *15*(2), 157–176. https://doi.org/10.1111/j.1540-5915.1984.tb01207.x

Bagchi, U., Hayya, J. C., & Ord, J. K. (1984b). Modeling demand during lead time. *Decision Sciences*, *15*(2), 157–176. https://doi.org/10.1111/j.1540-5915.1984.tb01207.x

Ballou, R. H. (2000). Evaluating inventory management performance using a turnover curve. In *International Journal of Physical Distribution & Logistics Management* (Vol. 30, Issue 1). # MCB University Press. http://www.emerald-library.com

Burgin, T. A. (1970). The Gamma Distribution and Inventory Control. In *Source: Operational Research Quarterly* (Vol. 26, Issue 3). https://www.jstor.org/stable/3008211

Chopra, S., Reinhardt, G., & Dada, M. (2004). The effect of lead time uncertainty on safety stocks. In *Decision Sciences* (Vol. 35, Issue 1, pp. 1–24). Blackwell Publishing Ltd. https://doi.org/10.1111/j.1540-5414.2004.02332.x

Conceicąo, S. V., Da Silva, G. L. C., Lu, D., Nunes, N. T. R., & Pedrosa, G. C. (2015). A demand classification scheme for spare part inventory model subject to stochastic demand and lead time. *Production Planning and Control*, *26*(16), 1318–1331. https://doi.org/10.1080/09537287.2015.1033497

Dhoka, D. K. (2013). “XYZ” Inventory Classification & Challenges. *IOSR Journal of Economics and Finance*, *2*(2), 23–26. https://doi.org/10.9790/5933-0222326

Ding, B., & Sun, L. (2011). An inventory classification model for multiple criteria ABC analysis. *ICSSSM11*, 1–6. https://doi.org/10.1109/ICSSSM.2011.5959351

Eppen, G. D., & Martin, R. K. (1988a). *Determining safety stock in the presence of stochastic lead time and demand* (Vol. 34, Issue 11).

Eppen, G. D., & Martin, R. K. (1988b). *DETERMINING SAFETY STOCK IN THE PRESENCE OF STOCHASTIC LEAD TIME AND DEMAND** (Vol. 34, Issue 11).

Flores, B. E., & Clay Whybark, D. (1986). Multiple Criteria ABC Analysis. *International Journal of Operations & Production Management*, *6*(3), 38–46. https://doi.org/10.1108/eb054765

Gardner, E. S., & Dannenbringf, D. G. (1979). *Using optimal policy surfaces to analyze aggregate inventory tradeoffs* (Vol. 23).

Girlich, H.-J. (1996). international journal of production economics ELSEVIER Some comments on normal approximation for stochastic demand processes. In *Int. J. Production Economics* (Vol. 45).

Hayya, J. C., Bagchi, U., Kim, J. G., & Sun, D. (2008). On static stochastic order crossover. *International Journal of Production Economics*, *114*(1), 404–413. https://doi.org/10.1016/j.ijpe.2008.03.007

Heerkens, H., & van Winden, A. (2021). *Solving Managerial Problems Systematically*. Routledge. https://doi.org/10.4324/9781003186038

Heuts, R., & De Klein, J. (1993). *An (s, q) Inventory Model with Stochastic and Interrelated Lead Times*.

Hopp, J. W., Sprearman, L. M., & Zhang, Q. R. (1996). *Easily implementable inventory control policies*.

Kottas, J. F., & Lau, H.-S. (1980). The Use of Versatile Distribution Families in Some Stochastic Inventory Calculations. In *Source: The Journal of the Operational Research Society* (Vol. 31, Issue 5). https://about.jstor.org/terms

Kotter, J. P. (1995). *Leading Change Why Transformation Efforts Fail*. www.hbr.org

Law, A. M. . (2015). *Simulation modelling and analysis*. McGraw-Hill Education.

Nallusamy, S., Balaji, R., & Sundar, S. (2017). Proposed model for inventory review policy through ABC analysis in an automotive manufacturing industry. In *International Journal of Engineering Research in Africa* (Vol. 29, pp. 165–174). Trans Tech Publications Ltd. https://doi.org/10.4028/www.scientific.net/JERA.29.165

Park, C. (2007). An analysis of the lead time demand distribution derivation in stochastic inventory systems. *International Journal of Production Economics*, *105*(1), 263–272. https://doi.org/10.1016/j.ijpe.2006.04.017

Paul Mueller. (2024a). *Paul Mueller Company*. Https://Nl.Paulmueller.Com/Melk-Koelen-En-Opslag/Melktanks/Mueller-Silotank/.

Paul Mueller. (2024b). *Paul Mueller Company*. Https://Www.Paulmueller.Com/Dairy-Processing-Equipment/Tanks/Horizontal-Storage-Tank.

Paul Mueller. (2024c). *Paul Mueller Company*. Https://Nl.Paulmueller.Com/Professioneel-Bierbrouw-Apparatuur/Tankbier/.

Reynolds, D. (1999). *Inventory-turnover-analysis*.

Schneider, H. (1981). *Effect of service-levels on order-points or order-levels in inventory models*.

Shore, H. (1999). Optimal solutions for stochastic inventory models when the lead-time demand distribution is partially specified. In *Int. J. Production Economics* (Vol. 59).

Silver, A. E., Pyke, F. D., & Thomas, J. D. (2016). *Inventory and Production Management in Supply Chains Fourth Edition*.

Silver, E. A., & Pyke, D. F. (1998). *Inventory Management and Production Scheduling*. http://mba.tuck.dartmouth.edu/pages/faculty/dave.pyke/inventory_management/submit_error.htm

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2016a). *Inventory and Production Management in Supply Chains*. CRC Press. https://doi.org/10.1201/9781315374406

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2016b). *Inventory and Production Management in Supply Chains*. CRC Press. https://doi.org/10.1201/9781315374406

Song, J.-S. (1994). *The Effect of Leadtime Uncertainty in a Simple Stochastic Inventory Model*.

Stojanović, M., & Regodić, D. (2017). The Significance of the Integrated Multicriteria ABC-XYZ Method for the Inventory Management Process. In *Acta Polytechnica Hungarica* (Vol. 14, Issue 5).

Teunter, R. H., Syntetos, A. A., & Babai, M. Z. (2017). Stock keeping unit fill rate specification. *European Journal of Operational Research*, *259*(3), 917–925. https://doi.org/10.1016/j.ejor.2016.11.017

Teunter, R. H., Zied Babai, M., & Syntetos, A. A. (2010). *ABC Classification: Service Levels and Inventory Costs*. https://doi.org/10.3401/poms.1080.01098

Van der Heijden, M. (2021a). Costs and service levels for order (life) fill rates. In *https://utwente.yuja.com/V/Video?v=511067&node=&a=172325200&autoPlay=1*. University of Twente.

Van der Heijden, M. (2021b). Functional classification of inventories. In *https://utwente.yuja.com/V/Video?v=511065&node=&a=771883505&autoPlay=1*. University of Twente.

Van der Heijden, M. (2021c). Standard deviaton of forecast error over lead time. In *https://utwente.yuja.com/V/Video?v=511058&node=&a=1089812815&autoPlay=1*. University of Twente.

Van Der Heijden, M. C., & De Kok, T. (1998). Estimating stock levels in periodic review inventory systems. In *Operations Research Letters* (Vol. 22).

van Donselaar, K., Broekmeulen, R., & de Kok, T. (2021). Heuristics for setting reorder levels in periodic review inventory systems with an aggregate service constraint. *International Journal of Production Economics*, *237*. https://doi.org/10.1016/j.ijpe.2021.108137

Vlaswinkel, E. A. (2024). *Improving the inventory management of parts using an order-based performance approach at Fluiten*. https://purl.utwente.nl/essays/98604

Wang, X., & Disney, S. M. (2016). Reducing order and inventory variability under stochastic lead-time and correlated demand. *Proceedings of 2015 International Conference on Industrial Engineering and Systems Management, IEEE IESM 2015*, 312–321. https://doi.org/10.1109/IESM.2015.7380177

Appendix A: Product flow

An overview of the simplified product flow of Mueller Groenlo is given. In this product flow, certain details in some steps are not represented, such as product certificates and the engineering departments. This Section is only meant to provide a better understanding of the current way of working at Mueller Groenlo and to understand why certain decisions are made. Therefore, the department that is encountered when one standard product goes through the organisation is shortly introduced.

The first step in the product flow is selling the product. In general, the goal is to first find a customer for the product. In this way the customer can specify the tank to its preferences and the company can include this from the start of the project.

After a product is sold to a customer the sales department forwards the sale to the order entry department. The order entry department connects the right Bill of Material (BOM) to the order sold. In the BOM the items needed at which date, based on the delivery date to the customers, are automatically filled into the ERP systems. Based on this the order entry department checks if all products should be available at the right time. If this is not the case the order entry department can check the status of specific items with the purchasing department.

In the third step, the work preparation department makes a production plan. This production plan is always finished ten weeks in advance. This means that in week one, the production plan for week eleven is made. In this production plan, the deadline of all sub-assemblies and final products are incorporated. This production planning is based on the products sold. But if the production department can create more than the amount currently sold, the production planning will include making base models. base models are products that are not sold to a customer yet. Which products are made in advance is based on the demand forecast. This step is explained in more detail in Appendix B.

When all products are planned in the ERP system the items of which the available stock will drop below safety stock are immediately identified by the ERP system. These products are ordered once a week by the purchasing department. The lead times of suppliers are in general less than ten weeks. Therefore, the products brought should be available on time.

The products purchased by the purchasing department will arrive at the warehouse. The warehouse department will book the products into the ERP system and ensure each product is placed at the predetermined location. Furthermore, the warehouse department makes sure all products needed for the production lines are picked and grouped per sub-assembly. Which items must be picked is determined by the work preparation department. Lastly, once a week all the service engineers that provide service to the products sold by Mueller are supplied by the warehouse.

Once the products are picked by the warehouse the production lines can start making the sub-assemblies or final products. This is done in four different production lines. One production line specialises in the production of O&P milk tanks. One production line is focussed on the production of Silo's. One product line is creating all specials and serving beer tanks. The last production line is creating the sub-assemblies needed by the other product lines. How each specific production line is operating is outside the scope of this thesis.

Once the products are finished the products are sent to the customer. This can either be done via the transport of Mueller or by transport organised by the consumer itself. Once the products arrive at the consumer the products are installed and made sure the products are working as they are supposed to.

Since the vision of Mueller is: "The only quality that matters is quality that works for life" this product line is not finished after successfully implementing the products at the consumer's location. The last step in the product flow is to ensure the customer remains happy. This includes after-sales services, such as performing maintenance and the reparation of errors.

Appendix B: The demand pattern of Mueller

For the inventory model, it is important to be able to make a good estimate of the demand uncertainty. To understand the demand uncertainty, it is important to first understand how the demand rate is determined. The demand rate can be caused by the production plan, rush orders from customers or the service department within Mueller Groenlo, which will now be discussed in more detail:

The production planning:

A production plan is created ten weeks in advance once a week the production plan is revised and one more week is added to the production plan. This is done for the O&P production line, the silo production line, and the serving beer production line. To determine which products to produce is done in the same way for each of the production lines, and boils down to the following steps:

1. Once year sales create a forecast on how many O&P tanks, Silos and serving beer tanks will be sold during the next year.
2. Based on the forecast created by sales the production capacity, in work hours, for each production line is determined.
3. The production planning for the next ten weeks can be created based on the available working hours per production line.
4. The first step is to plan products that are sold to consumers and must be finished in the next 10 weeks.
5. If the production capacity is not filled with the products sold, products are made in advance, this is called base models.
6. Determining which base models to make is based on the products sold during the last year. Based on this, the expected number of products sold is calculated. The number of products already created during the last year is subtracted. Based on this a percentage of fulfilled demand is calculated. The product with the lowest fulfilled demand percentage is created.

One of the main differences between the O&P production line and the silo production line is that all the O&P products are first made as base models. Once a customer buys one of the O&P tanks, the base model product is made customer-specific and can be sent to the customer in a brief period. To produce a silo the customer preferences, have to be determined at an earlier stage of the production process. Therefore, the variety in silos is bigger, hence not all products are made as base models. Therefore, the silos created as base models can be offered to customers who are in a rush. All silo orders which are not needed within ten weeks are not created from a base model but are incorporated into the standard production planning.

The lead time of the suppliers is less than ten weeks, therefore the products needed to execute the production plan can be ordered after the production schedule is known. The demand from the production plan is deterministic and in theory, there is no inventory needed.

Urgent Orders from customers:

Urgent customer orders consist of products sold to consumers who want to receive the product within the next ten weeks. To meet the demand of the customer the work preparation department must change the production plan, as explained in Section 2.1.1. Based on this new urgent order the work preparation department looks if there is a possibility to stop creating a new base model and change an existing base model into the product for the customer in a rush. To do this of course the work preparation department has to check if all products needed are available in stock. Therefore, it is important to model the probability of this occurrence into the demand forecast. Therefore, urgent orders from customers introduce a stochastic element into the demand forecast.

After Sales Service:

Mueller offers after-sales service and maintenance on the products sold to the customers. Therefore, it occurs that items are needed to repair products at customer locations. These items must also be in stock, and the demand rate is not known on forehand. This component involves fulfilling orders related to after-sales service.

Overall, the demand forecast encompasses both deterministic elements and stochastic elements, which introduce uncertainty into the forecast. To determine the input parameters for the inventory model it is important to create insight into the total demand pattern.

Appendix C: Ordering costs.

There is no specific cost of the order at the company, therefore the individual events are analysed to determine the ordering costs.

In this research, the ordering costs are seen as the expenses incurred when a company places an order for inventory or materials. These costs typically involve the administrative and logistical processes associated with ordering goods. To come up with the ordering cost we include the administrative Costs; These are expenses related to the paperwork and personnel involved in placing and processing orders. This included the procurements costs, so the costs associated with researching suppliers, negotiating contracts, and ensuring compliance with regulations. Secondly Transportation and Freight Costs: The transportation costs are associated with the delivery of goods. Lastly, some products need to be inspected upon arrival at Mueller. For these products, the Inspection and Quality Control Costs are considered.

To give a monetary value to the labour of a backorder, the previously mentioned actions have been timed and quantified, as visualised in Tables A, B and C. With these numbers, a formula can be created to estimate the impact of a backorder.

In a year on average, there are 10.000 orders placed at Mueller. Furthermore, we assume that employees work approximately 40 full weeks per year. Therefore, we assume that 250 orders are placed per week.

Costs per hour	€82,50 in production €62,50 at the office
Costs per minute	€1.375 in production €1.042 at the office

Table A: Labour costs administration and purchasing team.

<u>Administrative Costs</u>

Procurements costs 8 hours per week	Researching suppliers, negotiating contracts, and ensuring compliance with regulations	2 min/ order	€2,08
Purchasing department 40 hours per week	Placing an order at the suppliers	9.6 min/ order	€10,-
Processing orders 34 hours per week	Processing the order in the financial department	8.2 min/ order	€8.54

<u>Transportation and freight Costs</u>

In the company, the transportation and freight costs are different per article. Sometimes the costs are expressed as a percentage of the buy-in products and for some suppliers this is a fixed number. After an interview with an expert, we have concluded that a lending cost of 4% of the buy-in price is reasonable. Therefore, this is implemented in the calculation of the ordering costs.

Warehouse moving items 50 hours per week	Getting items to quality control	9.6 min/ order	€10,-
Quality control 10 hours per week	Products get tested to check if all items satisfy all agreed criteria. (costs production per item)	2.4 min/ order	€3,30

Total ordering costs = €33,92 + 4%-unit costs

Appendix D: Individual simulation runs.

The first run:

KPI	Current model	Deterministic	Stochastic
Weighted Average Inventory Turnover	753,3	9,1	5,5
Weighted Average Backorder Rate	47,5%	95,0%	98,7%
Weighted Average Fill Rate	42,7%	93,4%	97,8%
Holding costs	€ 130.675	€ 722.997	€ 938.598
Ordering costs	€ 2.968.295	€ 389.916	€ 358.077
Total costs	€ 3.087.557	€ 1.112.913	€ 1.296.675
Total backorders occurred	248.842	18.633	7.136
Total number of items backordered	17.726.403	1.688.174	515.340

The second run:

KPI	Current model	Deterministic	Stochastic
Weighted Average Inventory Turnover	605,3	9,0	5,3
Weighted Average Backorder Rate	47,4%	96,5%	99,0%
Weighted Average Fill Rate	43,4%	95,0%	98,4%
Holding costs	€ 122.209	€ 728.015	€ 944.720
Ordering costs	€ 2.943.735	€ 389.913	€ 351.293
Total costs	€ 3.065.944	€ 1.117.928	€ 1.296.013
Total backorders occurred	245845	17907	7051
Total number of items backordered	16376036	1500626	480284

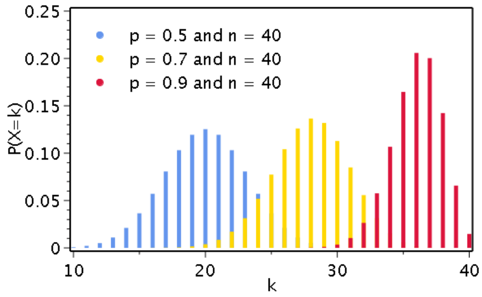
The third run:

KPI	Current model	Deterministic	Stochastic
Weighted Average Inventory Turnover	1156,7	9,2	5,9
Weighted Average Backorder Rate	46,5%	94,4%	98,8%
Weighted Average Fill Rate	43,0%	92,9%	98,4%
Holding costs	€ 116.312	€ 710.075	€ 930.732
Ordering costs	€ 2.938.011	€ 398.614	€ 371.691
Total costs	€ 3.054.323	€ 1.108.690	€ 1.302.423
Total backorders occurred	246942	18504	6312
Total number of items backordered	17092425	3007094	506049

Appendix E: Distributions explained.

Explanation of discreet distribution:

Binomial Distribution:



1. The binomial distribution:

- Describes the number of successes in a fixed number of independent Bernoulli trials, where each trial has only two outcomes (success or failure).
- It is characterized by two parameters: the probability of success on each trial (denoted as p) and the number of trials (denoted as n).

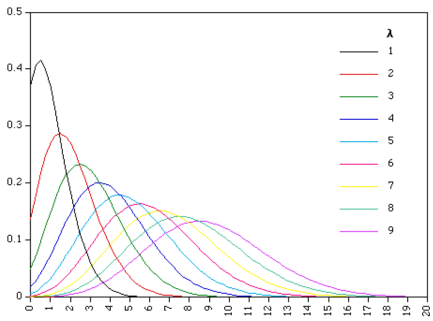
Calculating the input parameters:

$$Y = \begin{cases} BIN(k,P) & w.p.\ q \\ BIN(k+1,P) & w.p.\ 1-q \end{cases}$$

Where:

$$q = \frac{1+a(1+k)+\sqrt{-ak(1+k)-k}}{1-a} ;\ p = \frac{EX}{k+1-q}$$

2. Negative Binomial Distribution:



- The negative binomial distribution models the number of successes (or trials) until a specified number of failures occurs in a sequence of independent Bernoulli trials.
- It is characterised by two parameters: the number of failures (denoted as r) and the probability of success on each trial (denoted as p).

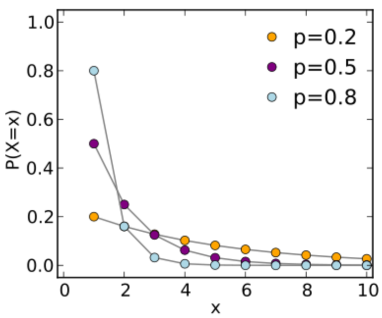
Calculating the input parameters:

$$Y = \begin{cases} NB(k,P) & w.p.\ q \\ NB(k+1,P) & w.p.\ 1-q \end{cases}$$

Where:

$$q = \frac{(1+k)a-\sqrt{(1+k)(1-ak)}}{1-a} ;\ p = \frac{EX}{k+1-q+EX}$$

3. Geometric Distribution:



- The geometric distribution is a special case of the negative binomial distribution where the number of failures r is fixed at 1.
- It models the number of independent trials needed until the first success occurs.

Calculating the input parameters:

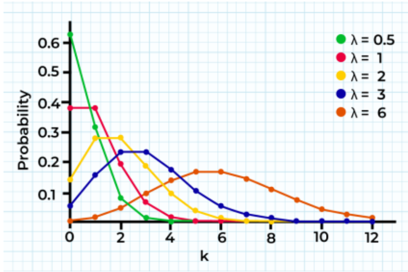
$$Y = \begin{cases} GEO(p_1) & w.p.\ q_1 \\ GEO(p_2) & w.p.\ q_2 \end{cases}$$

Where:

$$p_1 = \frac{EX[1+a+\sqrt{a^2-1}]}{2+EX[1+a+\sqrt{a^2-1}]} ;\ q_1 = \frac{1}{1+a+\sqrt{a^2-1}}$$

$$p_2 = \frac{EX[1+a-\sqrt{a^2-1}]}{2+EX[1+a-\sqrt{a^2-1}]}\,;\ q_2 = \frac{1}{1+a-\sqrt{a^2-1}}$$

4. Poisson Distribution:



- The Poisson distribution models the number of events occurring in a fixed interval of time or space, given that these events occur with a known average rate and independently of the time since the last event.
- It is characterised by a single parameter: the average rate of occurrence (denoted as λ).

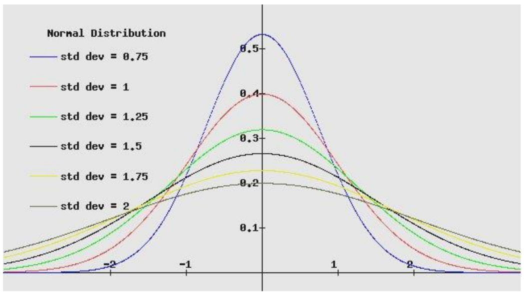
Calculating the input parameters:

$$Y = POIS(\lambda)$$

Where:

$$\lambda = EX$$

Explanation of continuous distribution:



1. The Normal distribution

- The normal distribution also known as the Gaussian distribution, models continuous data that clusters around a mean or average. It is used in situations where data naturally tends to have a central value with symmetric variation on either side.
- It is characterized by two parameters: the mean (μ) and the standard deviation (σ). The mean determines the location of the centre of the distribution, and the standard deviation determines the spread or width of the distribution.

Calculating the input parameters:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

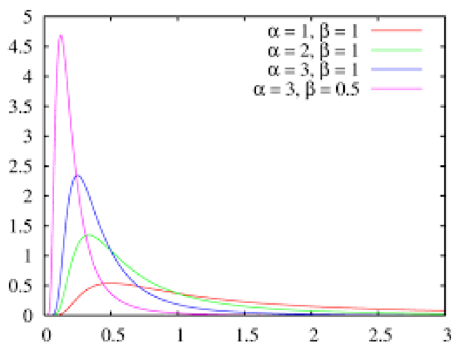
Where:

N = number of data points

x_i = each data point

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

2. The gamma distribution



- The Gamma distribution is a two-parameter family of continuous probability distributions. It models the time until an event occurs a certain number of times, given a known average rate of occurrence.
- It is characterized by two parameters: the shape parameter (α) and the scale parameter (θ). Alternatively, it can be parameterized by the shape parameter and the rate parameter (β), where β=1/θ

Calculating the input parameters:

The density function of gamma:

$$f_{\alpha,\beta}(x) = \frac{y^{\alpha-1}e^{-\frac{\alpha}{\beta}}}{\beta^{\alpha}\Gamma(\alpha)}\ , \qquad y\ \geq 0$$

Where:

$$\bar{y}_k = \frac{1}{N}\sum_{i=1}^{N} y^k$$

$$\bar{y}_1 = \alpha * \beta \qquad \Rightarrow \qquad \bar{y}_2 = \frac{\alpha(\alpha+1)\bar{y}_1{}^{-2}}{\alpha^2} \qquad \Rightarrow \qquad \alpha = \frac{\hat{\mu}^2}{\hat{\sigma}^2}$$

$$\bar{y}_2 = \alpha(\alpha+1)\beta^2 \qquad \alpha = \frac{\bar{y}_1{}^2}{\bar{y}_2 - \bar{y}_1{}^2} \qquad \beta = \frac{\hat{\sigma}^2}{\hat{\mu}}$$

Appendix F: Demand during lead time, python

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.optimize import bisect

# Load data from Excel
df = pd.read_excel('input_python_distributions.xlsx', sheet_name='lead_time_demand')

# Number of simulations
num_simulations = 100000

# List to store total demand during lead time for each item
num_items = df.shape[0]
total_demand_during_lead_time = np.zeros((num_items, num_simulations))

def draw_demand(demand_dist, k, q1, p1, q2=None, p2=None):
    rand_num = np.random.rand()
    if demand_dist == 'Negative Binomial':
        if rand_num < q1:
            return np.random.negative_binomial(k, 1-p1)
        else:
            return np.random.negative_binomial(k + 1, 1-p1)
    elif demand_dist == 'Geometric':
        if rand_num < q1:
            return np.random.geometric(1-p1) - 1
        else:
            return np.random.geometric(1-p2) - 1
    elif demand_dist == 'Binomial':
        if rand_num < q1:
            return np.random.binomial(k, p1)
        else:
            return np.random.binomial(k + 1, p1)
    elif demand_dist == 'Poisson':
        return np.random.poisson(q1)
    elif demand_dist == 'Normal':
        return np.random.normal(q1, p1)
    elif demand_dist == 'Gamma':
        return np.random.gamma(q1, p1)
    else:
        print(f"Unsupported demand distribution type encountered: {demand_dist}")
        raise ValueError(f"Unsupported demand distribution type: {demand_dist}")

def draw_lead_time(lead_time_dist, param1, param2):
    if lead_time_dist == 'Normal':
        return max(1, int(np.random.normal(param1, param2)))
    elif lead_time_dist == 'Gamma':
        return max(1, int(np.random.gamma(param1, param2)))
    else:
        print(f"Unsupported lead time distribution type encountered: {lead_time_dist}")
        raise ValueError(f"Unsupported lead time distribution type: {lead_time_dist}")

# Simulation
for i, row in df.iterrows():
    demand_dist = row['demand_dist']
    k = row.get('k', 0)
    q1 = row['q.1']
    p1 = row['p.1']
    q2 = row.get('q.2', None)
    p2 = row.get('p.2', None)
    lead_time_dist = row.get('lead_time_type', 'Normal')
    lead_time_param1 = float(row.get('lead_time_param1', 1))
    lead_time_param2 = float(row.get('lead_time_param2', 0))

    for j in range(num_simulations):
        # Draw a lead time from the lead time distribution for the i-th item
        lead_time = draw_lead_time(lead_time_dist, lead_time_param1, lead_time_param2)

        # Draw total demand during the lead time period for the i-th item
        total_demand = sum(draw_demand(demand_dist, k, q1, p1, q2, p2) for _ in range(lead_time))

        # Store the result
        total_demand_during_lead_time[i, j] = total_demand

```

```
# Verify the existence of the 'item_id' column
if 'item_id' not in df.columns:
    raise KeyError("Column 'item_id' not found in the DataFrame.")

# Convert simulation results to a DataFrame
simulation_results = pd.DataFrame(total_demand_during_lead_time.T, columns=df['item_id'])

# Calculate the average total demand during lead time for each item
average_demand_daily = simulation_results.mean(axis=0)
# Calculate the standard deviation during lead time for each item
st_deviation = simulation_results.std(axis=0)

# Replace dots with commas and commas with dots in numeric columns of final output
def replace_decimal_separators(value):
    value_str = str(value)
    value_str = value_str.replace('.', 'TEMP_REPLACE').replace(',', '.').replace('TEMP_REPLACE', ',')
    return value_str

simulation_results = simulation_results.apply(replace_decimal_separators)
average_demand_daily = average_demand_daily.apply(replace_decimal_separators)
st_deviation = st_deviation.apply(replace_decimal_separators)

# Save the simulation results to a CSV file
simulation_results.to_csv('simulation_results_vraaglevertijd.csv', index=False)
average_demand_daily.to_csv('average_vraaglevertijd.csv', index=False)
st_deviation.to_csv('st_deviation_vraaglevertijd.csv', index=False)

# Plotting the empirical distribution of total demand during lead time for a few items
num_items_to_plot = 5
fig, axes = plt.subplots(num_items_to_plot, 1, figsize=(10, 15))

for i in range(num_items_to_plot):
    # Debugging: print summary statistics
    print(f"Item {df.loc[i, 'item_id']}: Mean={np.mean(total_demand_during_lead_time[i])}, Std={np.std(total_demand_during_lead_time[i])}")

    axes[i].hist(total_demand_during_lead_time[i], bins=30, density=True, alpha=0.6, color='g')
    axes[i].set_title(f'Item {df.loc[i, "item_id"]}: Empirical Lead Time Demand Distribution')
    axes[i].set_xlabel('Total Demand During Lead Time')
    axes[i].set_ylabel('Frequency')

plt.tight_layout()
plt.show()
```

Appendix G: Determine Safety Stock, Reorder Point and EOQ:

```
import pandas as pd
import numpy as np
import scipy.stats as stats

# Load data from Excel
product_data = pd.read_excel('input_data.xlsx', sheet_name='Sheet1')

# Print column names to check for 'Item_id'
print("Product data columns:", product_data.columns)

# Determine fill rate goals based on classification
def get_fill_rate_goal(abc_xyz_class):
    fill_rate_goals = {
        'AX': 0.98, 'AY': 0.96, 'AZ': 0.94,
        'BX': 0.94, 'BY': 0.92, 'BZ': 0.90,
        'CX': 0.96, 'CY': 0.94, 'CZ': 0.92
    }
    return fill_rate_goals.get(abc_xyz_class, 0.9)  # Default to 0.9 if not found

# Distribution functions
def gamma_pdf(x, alpha, beta):
    return stats.gamma.pdf(x, alpha, scale=beta)

def gamma_cdf(x, alpha, beta):
    return stats.gamma.cdf(x, alpha, scale=beta)

def normal_pdf(x, mu, sigma):
    return stats.norm.pdf(x, mu, sigma)

def normal_cdf(x, mu, sigma):
    return stats.norm.cdf(x, mu, sigma)

def binomial_pmf(x, n, p):
    return stats.binom.pmf(x, n, p)

def binomial_cdf(x, n, p):
    return stats.binom.cdf(x, n, p)

def poisson_pmf(x, lam):
    return stats.poisson.pmf(x, lam)

def poisson_cdf(x, lam):
    return stats.poisson.cdf(x, lam)

def negbinom_pmf(x, r, p):
    return stats.nbinom.pmf(x, r, p)

def negbinom_cdf(x, r, p):
    return stats.nbinom.cdf(x, r, p)

def geometric_pmf(x, p):
    return stats.geom.pmf(x, p)

def geometric_cdf(x, p):
    return stats.geom.cdf(x, p)

# Finding z-values for different distributions
def find_z_normal(service_level, mu, sigma):
    return stats.norm.ppf(service_level, mu, sigma)

def find_z_gamma(service_level, alpha, beta):
    return stats.gamma.ppf(service_level, alpha, scale=beta)

def find_z_geometric(service_level, p):
    cumulative_prob = 0
    x = 0
    while cumulative_prob < service_level:
        cumulative_prob += q1 * geometric_pmf(x, (1-p1)) + q2 * geometric_pmf(x, (1-p2))
        if cumulative_prob >= service_level:
            return x
        x += 1

def find_z_binomial(service_level, n, p):
    cumulative_prob = 0
```

```
    x = 0
    while cumulative_prob < service_level:
        cumulative_prob += q1 * binomial_pmf(x, n, p1) + (1-q1) * binomial_pmf(x, n+1, p1)
        if cumulative_prob >= service_level:
            return x
        x += 1

def find_z_negative_binomial(service_level, r, p):
    cumulative_prob = 0
    x = 0
    while cumulative_prob < service_level:
        cumulative_prob += q1 * negbinom_pmf(x, r, (1-p1)) + (1-q1) * negbinom_pmf(x, r+1, (1-p1))
        if cumulative_prob >= service_level:
            return x
        x += 1

def find_z_poisson(service_level, lam):
    cumulative_prob = 0
    x = 0
    while cumulative_prob < service_level:
        cumulative_prob += poisson_pmf(x, lam)
        if cumulative_prob >= service_level:
            return x
        x += 1

# Calculate z-value for each item in the product data
z_values = []
reorder_points = []
eoqs = []

for index, row in product_data.iterrows():
    classification = row['Classification_ABC_XYZ']
    distribution_type = row['Fitted_Distribution_Type']
    k = row['k']
    q1 = row['q1']
    p1 = row['p1']
    q2 = row['q2']
    p2 = row['p2']

    mean_demand = row['Average_Demand_During_Lead_Time']
    std_demand = row['Std_Dev_Demand_During_Lead_Time']
    average_lead_time = row['Average_Lead_Time']
    std_lead_time = row['St_Dev_Lead_Time']
    fill_rate = get_fill_rate_goal(classification)

    if distribution_type == 'Normal':
        z_value = find_z_normal(fill_rate, mean_demand, std_demand) - mean_demand
    elif distribution_type == 'Gamma':
        z_value = find_z_gamma(fill_rate, q1, p1) - mean_demand
    elif distribution_type == 'Geometric':
        z_value = q1 * find_z_geometric(fill_rate, (1 - p1)) + q2 * find_z_geometric(fill_rate, (1 - p2))
    elif distribution_type == 'Binomial':
        z_value = q1 * find_z_binomial(fill_rate, k, p1) + (1 - q1) * find_z_binomial(fill_rate, k + 1, p1)
    elif distribution_type == 'Negative Binomial':
        z_value = q1 * find_z_negative_binomial(fill_rate, k, (1 - p1)) + (1 - q1) * find_z_negative_binomial(fill_rate, k + 1, (1 - p1)) - mean_demand
    elif distribution_type == 'Poisson':
        z_value = find_z_poisson(fill_rate, mean_demand)
    else:
        z_value = None

    z_values.append(z_value)

    if z_value is not None:
        reorder_point = mean_demand + z_value
    else:
        reorder_point = None

    reorder_points.append(reorder_point)

    # Calculate annual demand
    annual_demand = mean_demand * 365 / average_lead_time

    # Calculate EOQ
```

```
    holding_cost = row['Holding_Costs']
    ordering_cost = row['Ordering_Costs']

    if annual_demand > 0 and holding_cost > 0 and ordering_cost > 0:
        eoq = np.sqrt((2 * annual_demand * ordering_cost) / holding_cost)
    else:
        eoq = None

    eoqs.append(eoq)

# Add the calculated values to the product data
product_data['SafetyStock'] = z_values
product_data['ReorderPoint'] = reorder_points
product_data['EOQ'] = eoqs

# Save the updated data to a new Excel file
product_data.to_excel('updated_inventory_data_variable_lead_time.xlsx', index=False)
```

Appendix H: Pipeline simulation historical data:

```
import pandas as pd

# Load your Excel file and sheets
demand_df = pd.read_excel('overview itemledger.xlsx', sheet_name='Demand items')
received_df = pd.read_excel('overview itemledger.xlsx', sheet_name='Received')
inventory_df = pd.read_excel('overview itemledger.xlsx', sheet_name='Inventory level')
ItemInfo_df = pd.read_excel('overview itemledger.xlsx', sheet_name='Item info')

# Ensure columns with dates are treated as datetime
date_columns = demand_df.columns[1:]
demand_df[date_columns] = demand_df[date_columns].apply(pd.to_datetime, errors='coerce')

# Convert non-date columns to numeric
def to_numeric(df):
    for col in df.columns[1:]:
        df[col] = pd.to_numeric(df[col], errors='coerce')
    return df

demand_df = to_numeric(demand_df)
received_df = to_numeric(received_df)
inventory_df = to_numeric(inventory_df)

# Get the list of items
items = demand_df['Item Number'].unique()

# Split the items into chunks (batch size), e.g., every 200 items
chunk_size = 11540
chunks = [items[i:i + chunk_size] for i in range(0, len(items), chunk_size)]

# Process each chunk separately
for chunk_idx, chunk in enumerate(chunks):
    overview_data = []  # Initialize overview_data for each chunk
    metrics_data = []   # To store metrics for "Sheet2"

    # Initialize variables for weighted average calculations
    weighted_inventory_turnover_sum = 0
    weighted_fill_rate_sum = 0
    weighted_csl_sum = 0
    total_demand_sum = 0
    total_cogs_sum = 0
    valid_demand_sum = 0  # To accumulate demand for valid items
    total_holding_cost_all_items = 0
    total_ordering_cost_all_items = 0

    # Iterate over each item in the chunk
    for item in chunk:
        # Get initial inventory level from the inventory sheet
        if item in inventory_df['Item Number'].values:
            initial_inventory = inventory_df[inventory_df['Item Number'] == item]['On hand inventory'].values[0]
        else:
            initial_inventory = 0

        # Get the corresponding unit costs and ordering costs from the ItemInfo sheet
        item_info = ItemInfo_df[ItemInfo_df['Item Number'] == item]
        unit_cost = item_info['Unit costs'].values[0] if not item_info.empty else 0
        order_cost = item_info['Ordering costs'].values[0] if not item_info.empty else 0

        # Calculate holding cost rate
        holding_cost_per_day = unit_cost * 0.09 / 365

        # Get daily demand and received quantities
        demand = demand_df[demand_df['Item Number'] == item].iloc[:, 1:].values.flatten()
        received = received_df[received_df['Item Number'] == item].iloc[:, 1:].values.flatten()

        # Initialize variables for tracking inventory, costs, backorders, and metrics
        current_inventory = initial_inventory
        total_ordering_cost = 0
        total_holding_cost = 0
        total_backordered_units = 0
        total_demand_item = 0
        backordered_days = 0
        no_backorder_days = 0
```

```
        start_day_inventory_total = 0
        end_day_inventory_total = 0
        cogs_item = 0  # Cost of Goods Sold for current item

        # Iterate over each day
        for day in range(len(demand)):
            if day + 1 < len(demand_df.columns):  # Ensure the date index is within bounds
                date = demand_df.columns[day + 1]

                # On hand inventory at the start of the day
                overview_data.append([item, date, 'On hand inventory start day', current_inventory])
                start_day_inventory_total += current_inventory

                # Demand for the day
                daily_demand = demand[day]
                total_demand_item += daily_demand
                overview_data.append([item, date, 'Demand', daily_demand])

                # Received items for the day
                daily_received = received[day] if day < len(received) else 0
                overview_data.append([item, date, 'Deliveries', daily_received])

                # Add ordering cost every time items are received
                if daily_received > 0:
                    total_ordering_cost += order_cost

                current_inventory = current_inventory - daily_demand + daily_received

                # On hand inventory at the end of the day
                overview_data.append([item, date, 'On hand inventory end of day', current_inventory])
                end_day_inventory_total += current_inventory

                # Calculate backorders
                if daily_demand > current_inventory:
                    backordered_units = daily_demand - current_inventory
                    total_backordered_units += backordered_units
                    backordered_days += 1
                else:
                    no_backorder_days += 1
                    cogs_item += daily_demand * unit_cost  # Cost of goods delivered without backorders

                # Add holding cost for the day
                # Ensure holding cost is 0 if inventory is negative
                daily_holding_cost = max(current_inventory, 0) * holding_cost_per_day
                total_holding_cost += daily_holding_cost

        # Calculate metrics
        avg_inventory_level = (start_day_inventory_total + end_day_inventory_total) / (2 * len(demand))
        inventory_turnover = total_demand_item / avg_inventory_level if avg_inventory_level != 0 else 0
        fill_rate = 1 - (total_backordered_units / total_demand_item) if total_demand_item != 0 else 0
        cycle_service_level = no_backorder_days / len(demand) if len(demand) != 0 else 0

        # Set metrics to 0 if they are negative
        inventory_turnover = max(inventory_turnover, 0)
        fill_rate = max(fill_rate, 0)

        # Store the final calculated metrics for "Sheet2"
        metrics_data.append([item, inventory_turnover, fill_rate, cycle_service_level, total_holding_cost, total_ordering_cost])

        # Exclude zero values from weighted averages
        if inventory_turnover > 0 and total_demand_item > 0:
            weighted_inventory_turnover_sum += inventory_turnover * total_demand_item
            valid_demand_sum += total_demand_item

        if fill_rate > 0 and total_demand_item > 0:
            weighted_fill_rate_sum += fill_rate * total_demand_item

        if cycle_service_level > 0 and total_demand_item > 0:
            weighted_csl_sum += cycle_service_level * total_demand_item

```

```
        total_demand_sum += total_demand_item
        total_cogs_sum += cogs_item
        total_holding_cost_all_items += total_holding_cost
        total_ordering_cost_all_items += total_ordering_cost

    # Calculate weighted averages excluding zeros
    weighted_inventory_turnover = weighted_inventory_turnover_sum / valid_demand_sum if valid_demand_sum != 0 else 0
    weighted_fill_rate = weighted_fill_rate_sum / total_demand_sum if total_demand_sum != 0 else 0
    weighted_csl = weighted_csl_sum / total_demand_sum if total_demand_sum != 0 else 0

    # Convert the overview_data to a DataFrame for "Sheet1"
    overview_df = pd.DataFrame(overview_data, columns=['Item Number', 'Date', 'Metric', 'Value'])

    # Convert the metrics_data to a DataFrame for "Sheet2"
    metrics_df = pd.DataFrame(metrics_data, columns=['Item Number', 'Inventory Turnover', 'Fill Rate', 'Cycle Service Level', 'Total Holding Cost', 'Total Ordering Cost'])

    # Create DataFrame for weighted averages and total costs
    weighted_averages_df = pd.DataFrame([{
        'Weighted Inventory Turnover': weighted_inventory_turnover,
        'Weighted Fill Rate': weighted_fill_rate,
        'Weighted Cycle Service Level': weighted_csl,
        'Total Holding Cost (All Items)': total_holding_cost_all_items,
        'Total Ordering Cost (All Items)': total_ordering_cost_all_items
    }])

    # Save the DataFrames to Excel file with three sheets
    output_file = f'C:/Users/mzwiers/.spyder-py3/Mueller/Pipeline history + costs/overview_output_history_item_ledger_chunk_{chunk_idx + 1}.xlsx'
    with pd.ExcelWriter(output_file, engine='xlsxwriter') as writer:
        overview_df.to_excel(writer, sheet_name='Sheet1', index=False)
        metrics_df.to_excel(writer, sheet_name='Sheet2', index=False)
        weighted_averages_df.to_excel(writer, sheet_name='Sheet3', index=False)

    print(f"Overview for chunk {chunk_idx + 1} saved to '{output_file}'")
```

Appendix I: Pipeline simulation future:

```python
import pandas as pd
import numpy as np

# Load the data from the Excel files
voorraad = pd.read_excel('voorraad.xlsx', sheet_name='Sheet1')
input_inventory_params_calculated = pd.read_excel('Input_inventory_parameters.xlsx', sheet_name='Calculated')
input_inventory_params_deterministic = pd.read_excel('Input_inventory_parameters.xlsx', sheet_name='Deterministic')
input_inventory_params_currently = pd.read_excel('Input_inventory_parameters.xlsx', sheet_name='Currently')
demand_distributions = pd.read_excel('input distributions.xlsx', sheet_name='Demand')
lead_time_distributions = pd.read_excel('input distributions.xlsx', sheet_name='Lead time')
fixed_lead_time_distributions = pd.read_excel('input distributions.xlsx', sheet_name='Fixed lead time')
unit_costs = pd.read_excel('unit_costs.xlsx', sheet_name='Unit costs')
fitted_distributions = pd.read_excel('Fitted_distributions_demand_during_lead_time.xlsx')

# Set the date range for the simulation
simulation_start_date = pd.to_datetime('2024-07-01')
simulation_end_date = pd.to_datetime('2025-07-01')
simulation_dates = pd.date_range(simulation_start_date, simulation_end_date, freq='D')

# Function to draw daily demand based on the distribution
def draw_demand(demand_dist, k, q1, p1, q2=None, p2=None):
    rand_num = np.random.rand()
    if demand_dist == 'Negative Binomial':
        if rand_num < q1:
            return np.random.negative_binomial(k, 1-p1)
        else:
            return np.random.negative_binomial(k + 1, 1-p1)
    elif demand_dist == 'Geometric':
        if rand_num < q1:
            return np.random.geometric(1-p1) - 1
        else:
            return np.random.geometric(1-p2) - 1
    elif demand_dist == 'Binomial':
        if rand_num < q1:
            return np.random.binomial(k, p1)
        else:
            return np.random.binomial(k + 1, p1)
    elif demand_dist == 'Poisson':
        return np.random.poisson(q1)
    elif demand_dist == 'Normal':
        return max(0, int(np.random.normal(q1, p1)))  # Ensure demand is non-negative
    elif demand_dist == 'Gamma':
        return max(0, int(np.random.gamma(q1, p1)))  # Ensure demand is non-negative
    else:
        raise ValueError(f"Unsupported demand distribution type: {demand_dist}")

# Function to generate and store the demand sequences for all items
def generate_demand_sequences():
    demand_sequences = {}
    for item in demand_distributions['Item Number']:
        demand_params = demand_distributions[demand_distributions['Item Number'] == item]

        # Generate the demand sequence for this item over the entire simulation period
        if not demand_params.empty:
            item_demand_sequence = [
                draw_demand(demand_params['demand_dist'].values[0],
                            demand_params['k'].values[0],
                            demand_params['q1'].values[0],
                            demand_params['p1'].values[0],
                            demand_params['q2'].values[0] if 'q2' in demand_params else None,
                            demand_params['p2'].values[0] if 'p2' in demand_params else None)
                for _ in simulation_dates
            ]
        else:
            item_demand_sequence = [0] * len(simulation_dates)  # No demand if parameters are missing

```

```
        # Store the demand sequence
        demand_sequences[item] = item_demand_sequence
    return demand_sequences

# Function to draw lead time based on the distribution or fallback to fixed lead time if not found
def draw_lead_time(item, lead_time_distributions, fixed_lead_time_distributions):
    lead_time_params = lead_time_distributions[lead_time_distributions['Item Number'] == item]

    # Check if there are valid lead time parameters
    if not lead_time_params.empty:
        lead_time_dist = lead_time_params['lead_time_dist'].values[0]
        param1 = lead_time_params['param1'].values[0]
        param2 = lead_time_params['param2'].values[0]

        if lead_time_dist == 'Normal':
            return max(1, int(np.random.normal(param1, param2)))
        elif lead_time_dist == 'Gamma':
            return max(1, int(np.random.gamma(param1, param2)))
        else:
            return None  # Add a return to handle unsupported distributions
    else:
        # Try to retrieve the fixed lead time for the item
        fixed_lead_time_params = fixed_lead_time_distributions[fixed_lead_time_distributions['Item Number'] == item]

        if not fixed_lead_time_params.empty:
            return fixed_lead_time_params['Lead_Time'].values[0]
        else:
            return 7  # Default to 7 days if no distribution or fixed lead time is found

def run_simulation(input_inventory_params, unit_costs, demand_sequences):
    # Prepare a list to store results in the required format
    rows = []

    # Prepare lists to store the total inventory cost, total ordering cost, total costs, and total backorders
    total_inventory_costs = []
    total_ordering_costs = []
    total_costs_summary = []

    # Variables for weighted average calculations
    weighted_inventory_turnover_numerator = 0
    weighted_inventory_turnover_denominator = 0
    weighted_fill_rate_numerator = 0
    weighted_fill_rate_denominator = 0

    # Simulate the inventory process for each item
    for item in input_inventory_params['Item Number']:
        # Extract item-specific parameters
        rop = input_inventory_params.loc[input_inventory_params['Item Number'] == item, 'Reorder Point'].values[0]
        eoq = input_inventory_params.loc[input_inventory_params['Item Number'] == item, 'EOQ'].values[0]
        safety_stock = input_inventory_params.loc[input_inventory_params['Item Number'] == item, 'Safety Stock'].values[0]

        # Get the initial inventory from the 'voorraad' DataFrame
        initial_inventory_series = voorraad.loc[voorraad['Item Number'] == item, 'Aantal On Hand']

        if not initial_inventory_series.empty:
            current_inventory = initial_inventory_series.values[0]
        else:
            current_inventory = 0  # Or some default value if the item is not found

        # Retrieve the lead time parameters for the item
        lead_time_params = lead_time_distributions[lead_time_distributions['Item Number'] == item]

        # Retrieve the unit cost and ordering cost for the item
        unit_cost = unit_costs.loc[unit_costs['Item Number'] == item, 'unit_costs'].values[0]
        ordering_cost = unit_costs.loc[unit_costs['Item Number'] == item, 'ordering_costs'].values[0]

```

```python
        # Calculate the daily holding cost (9% per year, divided by 365)
        holding_cost_per_unit_per_day = (0.09 * unit_cost) / 365

        # Retrieve the safety factor and calculate k
        classification = fitted_distributions['Classification_ABC_XYZ'].values[0]
        safety_factor_k = {
            'AX': 0.98, 'AY': 0.96, 'AZ': 0.94,
            'BX': 0.94, 'BY': 0.92, 'BZ': 0.90,
            'CX': 0.96, 'CY': 0.94, 'CZ': 0.92
        }
        k = safety_factor_k[classification]

        # Initialize metrics for the item
        metrics = {
            'On-hand inventory start of day': [],
            'Received items': [],
            'Demand': [],
            'Demand fulfilled from stock': [],
            'Demand backordered': [],
            'Pipeline': []
        }
        backorders = 0
        total_backorders = 0  # Initialize total backorders
        total_backorder_days = 0  # Initialize total backorder days
        orders_pending = []
        pipeline = 0  # Initialize pipeline

        total_inventory_cost = 0  # To accumulate inventory holding costs
        total_ordering_cost = 0  # To accumulate ordering costs
        num_orders = 0  # To count the number of orders

        # Variables for new calculations
        total_demand = 0
        total_inventory_level = 0

        # Get the pre-generated demand sequence for this item
        item_demand_sequence = demand_sequences.get(item, [0] * len(simulation_dates))


        for day_index, date in enumerate(simulation_dates):
            # Log the starting inventory for the day
            metrics['On-hand inventory start of day'].append(current_inventory)

            # Use the pre-generated demand for this day
            demand = item_demand_sequence[day_index]
            metrics['Demand'].append(demand)
            total_demand += demand  # Accumulate total demand

            # Check for received orders
            deliveries = 0
            orders_pending_updated = []
            for (lt, qty) in orders_pending:
                if lt == 1:
                    deliveries += qty
                else:
                    orders_pending_updated.append((lt - 1, qty))
            orders_pending = orders_pending_updated
            current_inventory += deliveries  # Add all deliveries to inventory at once
            metrics['Received items'].append(deliveries)

            # Fulfill backorders first
            fulfilled_from_inventory = min(current_inventory, backorders)
            current_inventory -= fulfilled_from_inventory
            backorders -= fulfilled_from_inventory

            # Fulfill today's demand
            fulfilled_today = min(current_inventory, demand)
            metrics['Demand fulfilled from stock'].append(fulfilled_today)
            current_inventory -= fulfilled_today
            backorders += (demand - fulfilled_today)  # Any unfulfilled demand adds to backorders

            # Update total backorders
            total_backorders += backorders
            metrics['Demand backordered'].append(backorders)

            # Track backorder days
```

```
            if backorders > 0:
                total_backorder_days += 1

            # Place new order if needed
            ordered = 0
            if current_inventory + pipeline - backorders < rop:
                lead_time = draw_lead_time(item, lead_time_distributions, fixed_lead_time_distributions)

                # Ensure lead_time is valid
                if lead_time is None:
                    lead_time = 7  # Fallback to default

                order_quantity = max(rop - (current_inventory + pipeline - backorders), eoq)
                orders_pending.append((lead_time, order_quantity))
                ordered = order_quantity
                num_orders += 1

            pipeline += ordered
            pipeline -= deliveries  # Remove delivered items from the pipeline
            metrics['Pipeline'].append(pipeline)


            # Calculate inventory level after fulfilling demand (for averaging purposes)
            inventory_level_today = max(current_inventory, 0)  # Ensure non-negative inventory level
            total_inventory_level += inventory_level_today

            # Update inventory costs and ordering costs
            total_inventory_cost += inventory_level_today * holding_cost_per_unit_per_day
            total_ordering_cost += ordered * ordering_cost  # Add ordering cost for each order placed

        # Calculate the Volume Fill Rate (VFR)
        demand_sum = sum(metrics['Demand'])
        if demand_sum > 0:
            vfr = 1 - total_backorder_days / len(simulation_dates)
        else:
            vfr = 0

        # Calculate summary metrics for this item
        total_cost = total_inventory_cost + total_ordering_cost
        average_inventory_level = total_inventory_level / len(simulation_dates)
        total_sales_value = total_demand * unit_cost
        total_inventory_cost_value = average_inventory_level * unit_cost
        inventory_turnover = total_sales_value / total_inventory_cost_value if total_inventory_cost_value != 0 else 0

        # Update the weighted average calculations
        total_demand_fulfilled = sum(metrics['Demand fulfilled from stock'])
        weighted_inventory_turnover_numerator += inventory_turnover * total_demand_fulfilled * unit_cost
        weighted_inventory_turnover_denominator += total_sales_value

        weighted_fill_rate_numerator += vfr * total_demand
        weighted_fill_rate_denominator += total_demand

        # Store the result for this item in the summary table (combine all 10 columns in a single append call)
        total_costs_summary.append([
            item, total_inventory_cost, total_ordering_cost, total_cost,
            total_backorders, total_demand, average_inventory_level,
            total_sales_value, total_inventory_cost_value, inventory_turnover, vfr
        ])

        # Append results for this item to the rows list
        for metric, values in metrics.items():
            rows.append([item, metric] + values)

        # Append an empty row after each item's metrics
        rows.append([])

        # Calculate the weighted averages
    weighted_average_inventory_turnover = weighted_inventory_turnover_numerator / weighted_inventory_turnover_denominator if weighted_inventory_turnover_denominator != 0 else 0
```

```
    weighted_average_fill_rate = weighted_fill_rate_numerator / weighted_fill_rate_denominator if weighted_fill_rate_denominator != 0 else 0

    print(f"Weighted Average Inventory Turnover: {weighted_average_inventory_turnover}")
    print(f"Weighted Average Fill Rate: {weighted_average_fill_rate}")

    # Convert the rows list to a DataFrame with dates as columns
    columns = ['Item Number', 'Metric'] + list(simulation_dates)
    structured_results = pd.DataFrame(rows, columns=columns)

    # Create the DataFrame from the summary results
    total_costs_df = pd.DataFrame(total_costs_summary, columns=[
        'Item Number', 'Total Holding Cost', 'Total Ordering Cost', 'Total Cost',
        'Total Backorders', 'Total Demand', 'Average Inventory Level',
        'Total Sales Value', 'Total Inventory Cost', 'Inventory Turnover', 'Fill Rate'
    ])

    return structured_results, total_costs_df, total_costs_df  # Return total_costs_df instead of total_costs_summary

# Function to save results to Excel files for each model
def save_simulation_results(model_name, results_df, summary_df, total_costs_df):
    results_filename = f'{model_name}_results.xlsx'
    summary_filename = f'{model_name}_costs.xlsx'
    turnover_filename = f'{model_name}_turnover.xlsx'

    # Save detailed results
    results_df.to_excel(results_filename, sheet_name='Results', index=False)

    # Save summary costs
    summary_df.to_excel(summary_filename, sheet_name='Costs', index=False)

    # Save total_costs costs
    total_costs_df.to_excel(turnover_filename, sheet_name='turnover', index=False)

# Generate demand sequences for all items
demand_sequences = generate_demand_sequences()

# Run the simulation for 'Calculated' parameters using the same demand sequences
calculated_results, calculated_summary_costs, calculated_total_costs = run_simulation(input_inventory_params_calculated, unit_costs, demand_sequences)
save_simulation_results('Calculated', calculated_results, calculated_summary_costs, calculated_total_costs)

# Run the simulation for 'Deterministic' parameters using the same demand sequences
deterministic_results, deterministic_summary_costs, deterministic_total_costs = run_simulation(input_inventory_params_deterministic, unit_costs, demand_sequences)
save_simulation_results('Deterministic', deterministic_results, deterministic_summary_costs, deterministic_total_costs)

# Run the simulation for 'Currently' parameters using the same demand sequences
currently_results, currently_summary_costs, currently_total_costs = run_simulation(input_inventory_params_currently, unit_costs, demand_sequences)
save_simulation_results('Currently', currently_results, currently_summary_costs, currently_total_costs)

print("Simulation complete. Results saved to separate Excel files.")
```