Optimizing Reactive Strategies for Excess Inventory

TIL5060: Thesis

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TUDelft

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by

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This study examines a use case from a Dutch e-commerce platform. To ensure confidentiality, sensitive information has been anonymized. The company will be referred to as [Company XYZ] and the relevant product category is not specified. Additionally, some parameter values, containing sensitive information, have been altered or approximate ranges are presented instead of exact values. If a parameter value has been anonymized this is denoted as follows: [anonymized value]. These adjustments are limited to the text, the calculations and optimization have been performed with the actual parameter values. The model results stated in this study are based on the actual parameter values. As such, the anonymization does not compromise the validity of the results and conclusions.

Preface

This document presents my graduation research for completing the MSc in Transport, Infrastructure and Logistics at Delft University of Technology. Additionally it marks the end of my days as a student. Looking back on my years in Delft, I am filled with gratitude for the amazing friendships and experiences. I can truly say that I am a proud 'Delftenaar'.

I would like to thank my graduation committee from the TU Delft for their guidance and helpful collaboration throughout my project. Jafar, I have greatly enjoyed our discussions in which we brainstormed about the approach and implications of findings. I have highly valued your supervision, willingness to dedicate extra time beyond the meeting slots, and prompt responses. Alessandro, your expertise on mathematical programming and eye for detail was of great value, elevating my thesis to a higher level. I fondly recall the in-depth explanation of the Gurobi solver, which I found both insightful and engaging. Additionally, I appreciate your visits to TPM for every key meeting.

I want to thank my company commissioner for giving me the opportunity to perform my graduation research at [Company XYZ]. It is worth noting that I had the privilege of being the first official thesis project under your guidance, thank you for your dedication and support. With your positivity, you always managed to energize me. Lastly, I want to thank the entire product team at the company for making me feel so welcome within the organization. I highly enjoyed our lunches, coffee breaks, and various team outings.

The past half-year has been a bit of whirlwind, balancing my research on a short deadline, preparing interviews for a full-time job, and moving to Amsterdam shortly before the green light meeting. Despite some challenges, I am happy with the result and excited to share it with you. Hopefully, you will enjoy reading my master's thesis.

Noa Zijlmans
Delft, January 2025

Summary

E-commerce platforms increasingly compete through broad product offerings and short delivery times, requiring good product availability. Given difficulties in demand forecasting and procurement, this increases the risk of excess stock occurrence for online retailers. Excess stock can negatively impact financial performance through increased holding costs, value depreciation, capital lock-ups, or lost revenue opportunities due to occupied warehouse capacity limiting the storage of other products. For durable finished goods, the issue could be amplified, as targeting more specific customer segments may reduce diverse selling opportunities, while longer lifespans could contribute to larger excess stock accumulation over time. Given the imperfect nature of demand forecasts, supply chain disruptions or other operational issues, excess inventory is likely to persist, underlining the importance of effective reactive control strategies. Therefore, the objective of this research was to help decision-makers within e-commerce platforms improve the financial performance of excess durable finished goods inventory through reactive control strategies. Hereby, the research also aimed to address the identified knowledge gap. Literature is focused on proactive excess stock management, for example through improved forecasting and procurement. Limited research is available on optimization models for reactive strategies, and mainly focuses on optimizing a single reactive strategy, often not including stock retention as control decision.

Specifically, this research addresses the use case of the [Product Category] within [Company XYZ], a large e-commerce platform, managing a broad variety of stock keeping units (SKUs). In 2024, this category held over 88 thousand different SKUs. On average, 25% of stock was considered to be excessive, corresponding to 90 thousand excess items with an estimated value of €1.2 million. This excess stock is expected to remain in inventory for at least 3 months. Currently, [Company XYZ] does not systematically consider financial implications of various control strategies in excess stock management. This underlines the urgency of improving excess stock management using a structured and data-driven approach.

A literature review identified five feasible reactive strategies for managing excess stock: keep in stock, return, liquidate, recycle, discount. Considering the context of the company, recycling was excluded due to the financial superiority of liquidation; discounting was excluded due to the unavailability of price elasticity data on the level of SKU. A binary programming (BP) model was developed for periodic review of reactive control strategies for excess stock. Through optimization, the costs of the three control decisions were minimized. These included holding costs, working capital costs, transport costs for clearing, opportunity costs of clearing, and opportunity costs of keeping in stock. Opportunity costs represent indirect costs from revenue losses compared to regular customer sales or due to occupied storage capacity.

After verification, the model was applied to the excess inventory of the [Product Category] from 27 November 2024. The data set consisted of 19,096 excess SKUs, corresponding to 44,160 excess items. Out of these excess SKUs, 86% was eligible for return, and 65% had zero projected sales for the coming six months (end of forecast period). Under limited warehouse capacity, representing peak seasons, the optimization yielded a 19% retention rate, 67% return rate, and 14% liquidation rate, resulting in total excess stock costs of - €166k (indicating a profit increase), an estimated improvement of €435k over current practices. In an unlimited capacity scenario, eliminating the opportunity costs of keeping in stock, the model suggested a higher retention rate of 31%, with returns and liquidation rates adjusted to 59% and 11%, respectively, yielding total costs of - €215k and estimated improvement of €205k.

These findings highlight that capacity constraints significantly affect excess stock management. Further analysis of results showed that returning excess SKUs is consistently preferred over liquidation, making return eligibility a key consideration. Across sensitivity analyses, the return rate ranged between 45% to 75%, demonstrating the attractiveness of returns as control strategy. This can partially be explained by a relatively high discount rate for excess stock (37% per annum), and the observation that for 36% of the excess SKUs the return prices exceeded the selling prices. This suggests potential misalignment in the pricing strategy of [Company XYZ].

For SKUs eligible for return, the decision of whether to return or keep in stock can be based on the

expected days in stock, and the benefit of return vs. regular sale (defined as return price minus transport costs for return minus selling price). For SKUs not eligible for return, the decision of whether to liquidate or keep in stock can be based on the expected days in stock, and liquidation vs. selling price. Additional to these factors, sensitivity analysis highlighted that control decisions are significantly influenced by the opportunity costs of keeping in stock, particularly the average days in stock and average contribution margin. Financial performance is particularly sensitive to the assumed discount rate of excess stock, which also mainly affects the opportunity costs of keeping in stock. This underscores that indirect costs from revenue losses (opportunity costs) are crucial to consider in managing excess stock, while the daily holding costs, working capital costs and transport costs are typically less significant.

Another key finding was that the assumed stock days for SKUs without sales forecast (65% of total), significantly impacts the excess stock costs. This underscores the dependence of effective excess stock management on accurate sales forecast. Improving the accuracy, or reliably extending the forecast period, could have significant financial benefits. Given the research focus on reactive strategies, this was outside the scope however.

Based on scenario analysis it was found that relatively simple decision rules could present a cost- and time-efficient alternative to exact optimization, closely approximating the optimal solution. This can be attributed to the clear relationships that were observed between the control decisions, expected days in stock and benefit of clearance vs. regular sale (revenue of clearing minus transport costs minus selling price).

The expected improvement in financial performance should be placed into perspective with key limitations of this research. The exclusion of dynamic price changes over the excess stock retention period, possibly due to discounting, presents an important shortcoming. While this affects the financial implications of retention, it also disregards discounting as control strategy. This poses a significant gap as discounting is a common practice at [Company XYZ] and e-commerce platforms in general. Additionally, the reliance on a single dataset, assumptions of defect-free inventory, and immediate revenue generation after clearance, limit the applicability of the findings within a broader context. Finally, the effect of clearance decisions on commercial considerations such as customer satisfaction, and their associated financial implications, were not considered. This limited the research from concluding with reliable recommendations for accurately defining excess stock, and implementing single-item excess stock retention policies.

Future research could address these limitations by accounting for dynamic price changes and incorporating discounting as reactive strategy. This requires research into the price elasticities of demand, and possibly mathematical methods to include multi-period optimization. Repeating the analysis for different data sets within the [Product Category], preferably supplemented with analyses for other product categories or online retailers, could improve the robustness of the findings. Future research could also focus on the inclusion of return eligibility criteria into procurement strategies. Given the financial attractiveness of return, investigating possible synergies from strategy alignment could be interesting.

In conclusion, this research provides a framework for optimizing reactive strategies in excess inventory management, incorporating real-time stock data and warehouse capacity configurations. The potential financial benefits for [Company XYZ] were demonstrated to be substantial. In a broader context, durable finished goods e-commerce platforms can leverage the BP model for systematic decision-making, incorporating operational constraints and financial performance. However, the model's effectiveness relies on the availability of an established definition of excess stock, accurate stock data and reliable demand forecasts. Broader insights from this research suggest that incorporating opportunity costs alongside direct costs, and differentiating excess stock management strategies based on seasonality, can improve the financial performance of excess inventory in e-commerce.

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Nomenclature

Abbreviations

Table 0.1: List of abbrevations

Abbreviation	Definition
APV	Annual Purchase Value
CM	Contribution Margin
EDLSP	Economic Disposal and Lot-Sizing Problem
BP	Binary Programming
MILP	Mixed-Integer Linear Programming
NNPP	Net Net Purchase Price
RoD	Right of Destruction
RoR	Right Of Return
SKU	Stock Keeping Unit

Definitions

Table 0.2: List of definitions

Term	Definition
Benefit of Return vs. Regular Sale	Return price minus transport costs (for return) minus selling price
Contribution Margin (CM)	Selling price (excl. VAT) minus the base cost price
Item	A single product item in stock belonging to a SKU
Liquidation Price vs. Selling Price	Liquidation price minus selling price

1

Introduction

The research topic of excess durable finished goods inventory is introduced in section 1.1. After formulating the problem definition in section 1.2, the research objective and scope are discussed in section 1.3. Based on this, the main and sub research questions are identified in section 1.4. Lastly, the structure of the rest of the document is presented in section 1.5.

1.1. Excessive Inventory of Durable Finished Goods

In the last years, there has been a vast increase in e-commerce sales. Within this growing market, competition has intensified with retailers fighting for market share. E-commerce platforms try to win customers through broad product assortments, competitive pricing and service level improvements, e.g., through shorter lead and delivery times, making accurate inventory management crucial (Tanaka & Sagawa, 2018). Advanced forecasting methods can improve procurement processes and help in matching supply and demand. Optimal inventory levels are however unrealistic due to complexities in predicting demand, supply chain disruptions, or other operational issues (Singh, 2022). As such, both stock-outs and excess inventories are common phenomena in e-commerce, causing a large portion of the retailers losing millions annually (Zaarour et al., 2016).

Whereas stock-outs lead to opportunity costs of lost sales, carrying excessive inventory levels causes slow-moving or even dead stock which leads to increased inventory holding costs, depreciation of stock value, and tied-up working capital (Tangsucheeva & Prabhu, 2013). Additionally, slow-moving stock lowers the available storage space, creating opportunity costs from lost sales of other (more popular) items (Pourhejazy, 2020). A possible solution for handling excess stock, is to clear these items. This enhances inventory management, especially in case of capacity constraints, and allows retailers to hedge inventory risk and profitability (Maggiar & Sadighian, 2017). Possible clearance actions include returns to suppliers, discounting, or recycling. This is however often paired with a reduced sales price and extra incurred costs compared to a 'regular' customer sale. Given the forecasted demand, the question is, how much of the excess inventory should be kept in stock, or cleared? In case of clearance, which strategy is financially the most attractive?

This research will focus on excess inventories of durable, finished goods with a long-tail as these characteristics present interesting dynamics for the dead stock problem. Due to their specific nature, finished goods are more difficult to sell compared to raw materials, further complicating the dead stock problem, especially for a large variety of products that can be stored long-term.

1.2. Problem Definition

At the [Product Category] of [Company XYZ], the issue of excess inventory is actual and complex. Due to its broad product offering, keeping appropriate inventory levels for all product items is challenging. Given the non-perishable nature of the products, long-term storage is common, contributing to the accumulation of dead stock. On average, between 1 January and 16 November 2024, 25% of the [Product Category] inventory was considered to be excessive. This corresponds to 90k excess product items, resulting in

an average excess stock value of €1.2 million. Of the excess SKUs, 65% was expected to have no sales in the coming six months (maximum forecast period), corresponding to 41% of the excess product items. These dynamics illustrate the challenges of excess stock within the [Product Category] of [Company XYZ].

Although the company has detailed quantitative insight into the current and forecasted stock levels and value, there is limited insight into inventory control strategies. What are possible reactive strategies for dealing with excess inventory? What trade-offs arise in selecting a control decision? Following this, what control decision for excess inventory is financially the most attractive, and under what circumstances? Currently, a structured approach, based on detailed quantitative insights, is lacking for these types of decisions. This gives rise to a need for optimizing control decisions for excess inventory using quantitative data such as demand forecasts, stock levels, supplier agreements (including return conditions), holding costs, transport costs and expected revenue from the product sales.

1.3. Research Objective and Scope

The objective of this research is to help decision makers within e-commerce platforms to improve the financial performance of excessive, durable, finished goods inventory. Specifically, this research has the objective to enhance the financial performance of [Company XYZ] by improving the reactive control strategies for excess inventory of the [Product Category].

The optimization of control decisions for excess inventory will be based on cost minimization. Therefore, as part of the research, the relevant costs will be identified. This likely includes variable costs such as the in-stock costs, transport costs, return costs, and opportunity costs of lost sales. In the optimization, only reactive strategies for excess inventory are considered. Proactive strategies such as improvements in demand forecasting, optimizing procurement, or refining the product assortment fall outside the scope. The rationale behind this is that, even in (nearly) perfect systems with accurate demand forecasting, procurement processes and inventory control, excess inventories occur. Hence, a quantitative decision strategy for controlling this excess inventory is needed. The optimization will address the question what control decisions (e.g., clear or keep in stock) should be taken at a specific moment in time. In other words, the model can be deployed for a periodic review. This corresponds to the intended use at the company, where it is not feasible to control excess inventory continuously.

With excess inventory as core problem, the warehouse is the system under consideration. In modeling the stock, individual warehouses are not considered and stock is not distinguished across warehouses. As will be outlined in chapter 4, the company has various business models. Since the objective is to improve the performance of [Company XYZ], products sold by external partners fall outside the scope.

As will be discussed in the literature review in chapter 2, there is little scientific research on the optimization of reactive strategies for excess inventory control, using mathematical models. Models often focus on one type of inventory control decision, with a predetermined set of to-be cleared inventory. This research will develop a decision model for cost optimization of excess inventory through reactive strategies, including the control decision to retain excess products in stock. Thereby, this research aims to address the knowledge gap and contribute to the current body of knowledge. The results of the use case of the [Product Category] of [Company XYZ] will be applicable to a broader context - specifically, for excess inventory of durable, finished goods within the business-to-customer e-commerce environment. Thereby, this research also aims to make a practical contribution.

1.4. Research Questions

Based on the problem definition, the main research question is:

> *To what extent can reactive strategies improve the financial performance of managing excess inventories in an e-commerce platform?*

To answer the main research question, the following sub questions have been identified:

1. How can excess inventory be defined?
2. What reactive strategies available in literature can be leveraged in the context of this work?
3. How can a mathematical model be developed to improve control decisions for excess inventory?

4. Considering the level of complexity and size of the mathematical model, what is a suitable solution method?

5. How do various factors, such as right of return and expected stock days, affect excess inventory control decisions and financial performance?

6. What are successful reactive control strategies for improving financial performance of excess inventory, and how can these be implemented?

1.5. Structure of the Document

The rest of the document is structured as follows.

First, a literature review is performed in chapter 2, discussing four components of excess inventory: definition and identification, root causes, mitigation strategies, and quantitative models. Hereby, insight into the current state of knowledge is generated, and the knowledge gap is identified. Following this, the research methodology is presented in chapter 3.

The specific use case of the [Product Category] of [Company XYZ] is introduced in chapter 4. The business model and management of excess inventory are discussed. Subsequently, the binary programming (BP) model, as presented in the methodology, is tailored to the use case of the company. Lastly, the relevant data is collected and analyzed. In chapter 5, the BP model is verified, and the excess stock from 27 November 2024 is optimized. After analyzing the results, a sensitivity and scenario analysis are performed.

Lastly, the research is concluded in chapter 6 by answering the research questions. Additionally, the key limitations of the research are discussed. Subsequently, recommendations are provided for effective excess inventory management through reactive control strategies. Finally, interesting areas for future research are discussed.

2

Literature

This section presents the results of the literature review based on four pillars. The aim of the literature review is to understand the current body of knowledge and subsequent knowledge gap. Section 2.1 is focused on establishing a scientific definition of excess inventory. In a later stage of the research, this definition will be applied to the context of [Company XYZ], and used to identify excessive inventory. Section 2.2 identifies possible causes of excess inventory and dead stock accumulation. After understanding the causes of the problem, section 2.3 explores potential solutions in the form of mitigation strategies. Lastly, section 2.4 aims to understand the current state-of-the-art of optimization models for excessive inventory.

2.1. Defining and Identifying Excess Inventory

Li et al. (2022) argue that due to ambiguity in the definition, companies tend to delay classifying inventories as dead stocks, thereby resulting in accumulation. Correctly and timely identifying slow-moving stock, also known as potential dead stock, is important for reducing opportunity losses, unnecessary storage and stock-out costs, and frozen capital (Chodak, 2020; Relph & Barrar, 2003). This underlines the importance of establishing a clear definition based on science, that can be applied throughout this research.

Dead or non-moving stock is considered to have no selling opportunity in the future (Hastings, 2021; Singh, 2022). Additional to 'dead stock', literature uses multiple related terms: overstock, slow-moving, excessive, overage or obsolete inventory. Slow-moving inventories are defined as inventories that travel, sell, and replenish slower than other inventories. According to Hastings (2021), slow-moving items have a mean time between demands that is ten times larger than the average supply lead time. However, the threshold values for these categories are often based on the retailer's or industry's turnover ratio standards (Li, Chiu, & Seva, 2023). 'Excessive' and 'overstock' are general terms for inventory levels that exceed the desired quantity, whereas 'overage' is used to describe excess inventory in the context of planned inventory levels (Relph & Barrar, 2003). A related term is obsolete inventory, indicating items that have reached their definite end-of-life and demand completely diminishes, for example due to the employment of new technologies, or market changes (Persona et al., 2005; Pinçe & Dekker, 2011). Since this research is focused on durable goods that are non-perishable, identifying the definite end-of-life is challenging. As such, the term 'dead stock' is preferred over obsolete stock. Figure 2.1 illustrates the inventory terminology that will be used in this research.

Various inventory classification frameworks for (potential) dead stock identification are available in literature (Li, Seva, & Chiu, 2023). A widely recognized inventory categorization method is FSN analysis (Fast-, Slow-, Non-Moving). Another well-known classification method is ABC analysis, which categorizes inventory based on annual dollar value calculated as annual demand and cost per unit (Ivanov et al., 2021). Combining or tailoring these inventory classification frameworks for (potential) dead stock identification is common in literature. Li, Seva, and Chiu (2023) propose a potential dead stock classification and prioritization framework, using KPIs for identification (Actual Remaining Life, Turnover Ratio, Inven-
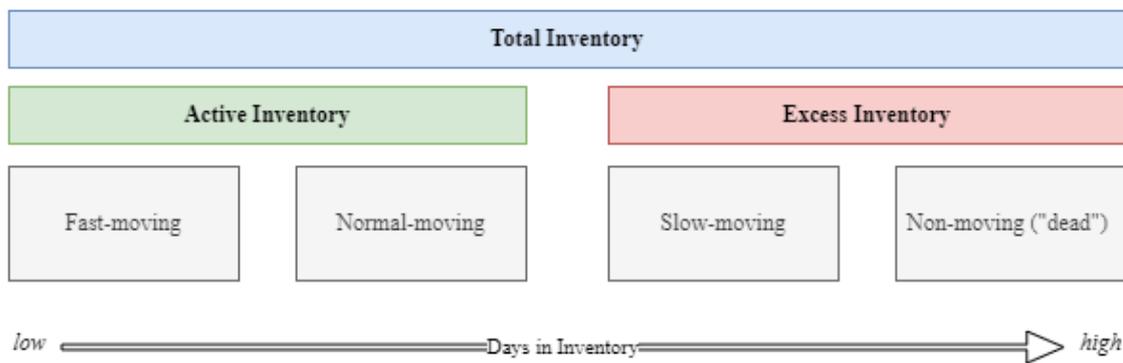
Figure 2.1: Inventory classification

tory Level), and (financial) risks calculations for prioritization of potential dead stock. Including both the speed of product movement and stock levels are essential for effective dead stock identification (Chodak, 2020).

Contrasting to these traditional inventory classification frameworks, Jollyta et al. (2019) use the Random Forest and Naïve Bayes classification algorithm to identify slow-moving inventory based on patterns in product data (e.g., item code, name and category). Machine learning approaches such as Naïve Bayes, neural networks, and k-means clustering are growing areas of interest for classifying dead stock (Gul et al., 2009; Khan et al., 2009; Sugumaran & Sukumaran, 2019).

2.2. Root Causes of Slow-Moving and Dead Stock Accumulation

Identifying possible causes of excess stock accumulation will help in understanding and formulating reduction strategies. Root causes of excess inventories in the e-commerce environment can be split into three categories: supply and demand imbalance, product characteristics, and e-commerce specific dynamics.

Firstly, imbalance between supply and demand could lead to a surplus of supply, and thus inventory. This can be caused by demand forecast inaccuracy, inappropriate inventory control, incorrect product assortment planning, sudden changes in demand, or setting prices too high (Chodak, 2020; Li et al., 2022; Zaarour et al., 2016). Over-ordering due to bulk discounts or long lead times, and the bullwhip effect also contribute to excess inventory (Lamzaouek et al., 2021; Vahdani et al., 2022). Considering this amplification of demand variability, the problems of excess inventories can become larger when moving up the supply chain (Tangsucheeva & Prabhu, 2013).

Secondly, product specifics such as product expiration, seasonality, and product damages can increase the potential of dead stock accumulation (Li et al., 2022). As priorly mentioned, product expiration is not relevant in this research due to the focus on durable finished goods. Other characteristics contributing to the dead stock problem are products with short life cycles, recent design changes, or a high degree of specialization. If a product's design has recently been updated, the old products could become obsolete. The more specialized a product, the narrower the potential customer base, increasing the risk of dead stock accumulation.

Thirdly, compared to traditional bricks-and-mortar, the e-commerce environment has some specific dynamics and complexities that contribute to dead stock accumulation. Higher volumes and larger product assortments complicate monitoring and managing the dead stock problem (Honjo et al., 2022). Also the large number of customer returns adds to the complexity. Additionally, due to increased competition, combined with the ease of price comparison due to lower search costs, online customers have a higher price elasticity of demand making appropriate pricing even more important (Chodak, 2020; Hinz & Eckert, 2010; Tanaka & Sagawa, 2018). Chodak (2020) argues that the lack of costly exhibition space, compared to traditional trade, lowers pressure on efficient inventory control in e-commerce. Lastly, online retailers are often more inclined to focus on best-selling inventories instead of optimizing dead stock management (Chodak, 2020; Li, Chiu, & Seva, 2023).

Although excess inventories are not preferred, there are various reasons why retailers might decide to hold on to these inventories once dead stock accumulation occurs. First of all, it could be that demand is expected to grow in the future, or that inventory clearance is more expensive than storage. One of the main reasons however is customer service: increasing customer satisfaction by ensuring product availability (Riza et al., 2018).

2.3. Mitigation Strategies for Excess Inventory

For reducing the problems related to excess inventories, a distinction between proactive and reactive strategies can be made. Proactive strategies focus on reducing the inflow of excess inventories, e.g., by improving demand forecasts, keeping accurate stock levels and re-order points (Li, Seva, & Chiu, 2023). Reactive strategies on the other hand, focus on increasing the outflow of slow-moving and dead stock once accumulation has occurred. Possible reactive strategies are price discounts, product bundling, additional promotions (e.g., using social media, recommendation systems, search engines), selling to a liquidator, returning to suppliers, recycling, disposal, donation or gifting (Chodak, 2020; Pourhejazy, 2020; Zaarour et al., 2016). Lastly, moving excess stock to higher demand markets, geographies or customer segments, could help for reducing excess stock in a financially viable manner. Table 2.1 shows an overview of the identified control strategies, their operational feasibility and financial attractiveness. Below, the more complex reactive strategies are elaborated upon in more detail.

Excess Stock Discounts

In case of discounting to reduce excess inventory, key considerations are timing, discount level and quantity (Gupta et al., 2006). Various discounting strategies can be identified: continuous or periodic pricing with a variable or fixed discount (Adomavicius et al., 2015). Maggiar and Sadighian (2017) recognize the significant potential of dynamic pricing for strategically influencing inventory levels. Supporting this view, Adomavicius et al. (2015) found that the often deployed fixed-price and fixed-quantity strategies do not yield optimal results in terms of revenue. Given unknown customer demand, revenue could be increased through sophisticated pricing policies involving dynamic adjustment of discount prices to customer behaviour. Since customer behavior is dependent on the price elasticity of demand, this is important to consider in discount strategies (Tanaka & Sagawa, 2018; Zaarour et al., 2016). In addition to boosting sales of excess stock, discounting could enhance overall revenues by attracting new customers, who may purchase higher-margin products as well (Adomavicius et al., 2015).

Recommendation Systems for Excess Stock

Through interactive features and data connectivity, e-commerce platforms can use data analytics to influence purchasing decisions and formulate customer-centered marketing strategies (Rosário & Raimundo, 2021). Aiming to increase user satisfaction and revenues, recommendation systems often deploy (user) data to recommend products that are likely to be bought by the customer, e.g., bestsellers, novelties, complements or substitutes (Valcarce et al., 2016). These systems typically recommend products based on similarity metrics, often deploying content-based methods (similar product properties) or collaborative filtering techniques (user-product interactions) (Hinz & Eckert, 2010; Valcarce et al., 2016). Hereby, recommendation systems can generate additional sales, or initiate a shift in demand through product substitution. In light of this research, recommendation systems could prove particularly valuable by increasing or shifting demand towards slow-moving or excessive products.

In literature, two key approaches can be found: direct and indirect excess stock recommendation systems. In the direct approach of Agarwal and Vijayalakshmi (2019), the set of to-be recommended items is based on prioritizing products with the highest accumulation and need to be cleared. To ensure an effective system, recommendations are generated using the Pearson similarity metric for item-item collaborative filtering. For liquidating excess stock items, Valcarce et al. (2016) recommend the best users for each long tail product, even if the product is not among the most preferred items. Due to a lack of data on inventory metrics, three strategies are used for identifying long-tail products: the least rated, lowest rated, and least recommended products. Using Item Relevance Modeling with conditional sampling (IRM2), the best users for each long-tail product are identified. Experiments show that, for the task of recommending users to long-tail items, the model outperforms traditional user- and item-based algorithms.

Table 2.1: Overview of reactive strategies for excess inventory management

	Strategy	Operationally Feasible?	Financially Attractive?	Argumentation
Increase Regular Customer Sales	Discount	✓	✓	Pourhejazy (2020) considers discounting the economically most viable control strategy. Dynamic discounting strategies considered to be most effective (Adomavicius et al., 2015; Maggiar & Sadighian, 2017). E-commerce platforms can relatively easily update prices following any discounts.
	Recommendation System	✓	?	Accuracy and effectiveness of recommendation system highly dependent on data availability and quality (Agarwal & Vijayalakshmi, 2019). Expected to be operationally feasible since many large e-commerce platforms already deploy recommendation systems, and have access to customer data. However, literature offers a lack of insight into financial improvements excess stock recommendation models. Additional demand from recommendation systems always yields positive financial impact, but demand shift could deteriorate financial performance if high margin products are substituted with low margin products (Hinz & Eckert, 2010).
	Product Bundling	✓	?	Operationally feasible as product bundling is common for large e-commerce platforms (albeit not excess stock specific). Potential financial benefits recognized in literature, but quantification of expected benefits unclear (Franco et al., 2017).
	Allocate Stock to Higher Demand[1]	?	?	Operational feasibility dependent on market accessibility and demand. Financial attractiveness dependent on transport costs, competition, and customer's willingness to pay.
Alternative Revenue	Return to Supplier	✓	✓	Operationally feasible due to relatively simple process but dependent on supplier agreements related to the right of return, and the allowed return period. Financial attractiveness dependent on the refund amounts, as well as return costs (e.g., transport costs).
	Liquidation Recycling	✓ ✓	✓ ✓	Liquidation and recycling parties generally accept all goods. Operationally feasible due to relatively simple process. Despite very low (possibly zero) revenues, liquidation and recycling could be financially attractive to prevent further losses from holding costs (Pourhejazy, 2020)
Other	Keep in Stock	✓	✓	Operationally feasible, financial attractiveness depends on profit margin (lower margin decreases financial attractiveness of keeping items in stock (Pourhejazy, 2020)).
	Donation	✓	✗	Operationally feasible but logistics can be challenging[2]; No direct financial benefits, possible long-term benefits from improved partnerships or reputation (Pourhejazy, 2020).
	Disposal	✓	✗	Operationally feasible due to its simplicity. However, recycling considered to always be preferred over disposal due to negative indirect costs associated with disposal (reputation damage, negative effects on health and environment) (Pourhejazy, 2020).

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[1]This could involve a different market, geography or customer segment.
[2]In the case of large volumes, parties could show unwillingness or incapacity to accept the large bulk of donated goods.

In contrast, Chodak and Suchacka (2012) take an indirect approach, basing product recommendations on the predicted degree of meeting a customer's needs, and product costs. The authors argue that, in order to optimize profits, retailers should focus on selling items associated with the highest cost in inventory. These are defined as the purchase cost - serving as a proxy for the amount of frozen capital - and the inventory costs (depreciation and storage costs). It is concluded that, although literature highlights the potential of recommendation systems for reducing excess stock, there is a gap in understanding the associated financial benefits. No quantitative insight is given into the profit improvements from implementing such a system.

Bundling of Excess Stock Products
Product bundling refers to the practice of selling multiple products combined into one unit, at a relatively lower price than buying the products individually (Rosário & Raimundo, 2021). For reducing excess inventory, slow-moving product sales could be increased through bundling with more attractive products, thereby increasing business profits (Franco et al., 2017). In deciding whether and which products to bundle, the expected revenue and costs (including storage costs) should be considered. Also the degree of contingency is important: with increasingly complementary products, the bundle is more likely to sell. As such, recommendation systems can be valuable for identifying product bundles based on similarity metrics. Using machine learning, Sugumaran and Sukumaran (2019) classify moving and dead stock using a hybrid classifier (Adaboost with ID3). Subsequently, dead stock is bundled with fast-moving stock using the UCB algorithm. Lastly, linear programming is performed to determine the number of product to be sold. The mathematical model for profit maximization is relatively simple, using a fixed and known bundle price, with profit defined as the difference between selling price and purchase cost per product. Despite the highlighted potential of bundling, the associated financial benefits remain unquantified.

2.4. Quantitative Models for Excess Inventory
Most literature is focused on developing models for proactive dead stock reduction. This includes research aiming to improve demand forecasts (Honjo et al., 2022; Tanaka & Sagawa, 2018), optimize lot-sizing (Persona et al., 2005), and inventory policies (Kourentzes et al., 2019; Thevenin et al., 2024). Recent developments in the field include better demand prediction for slow-moving items using machine learning techniques (Thevenin et al., 2024).

Maggiar and Sadighian (2017) develop a decision model that includes both proactive and reactive strategies, jointly determining replenishment, pricing and disposal decisions. The proposed inventory management framework deploys discrete convex analysis in which the following decisions are made at the beginning of each time step: (i) purchasing quantity, (ii) return and liquidation quantities, and (iii) selling price. Demand is assumed to be stochastic, dependent on price. A limitation of the research is the single-supplier and single-product item consideration, posing a signification simplification of reality.

A stream in literature that focuses on reactive strategies are excess stock disposal models. In these, the economic retention or disposal quantity is decided, when there is an excess stock of an item (Pinçe & Dekker, 2011). Although related to this research, it does not optimize the decision between various reactive strategies (e.g., discount, return to supplier, recycle). Çetinkaya and Parlar (2010) have developed a single-product, periodic review model for a one-time disposal opportunity, optimizing the expected discounted profit. The expected revenue, procurement costs, inventory holding costs and back order costs are considered. The mathematical model computes the optimal amount of excess inventory to dispose at a discounted price. The importance of including this price elasticity of demand, as well as its stochastic nature, is widely recognized in literature (Tanaka & Sagawa, 2018). To address the economic disposal and lot-sizing problem (EDLSP) for perishable goods, Vahdani et al. (2022) have developed a mixed-integer linear programming (MILP) model. Due to significant differences in the objective and scope, this model cannot be applied to the problem stated in this research. First of all, the EDLSP optimizes disposal quantity and timing, other excess inventory control decisions are out of scope. Furthermore, the optimization is based on holding and disposal costs, revenues are not considered. Lastly, the EDLSP considers single-item inventory of perishable products with a fixed lifetime and deterministic demand. Nevertheless, the research gives useful insights into the development of the MILP, as well as its solution methods. The authors use linearization techniques, as well as the dragonfly and genetic algorithm, to solve the model efficiently. It is concluded that both algorithms are suitable for small-sized problems;

however, for larger problems, the genetic algorithm performs best.

Another stream in literature that focuses on reactive strategies, are pricing models for clearing inventory. The objective is to establish optimal pricing in order to clear obsolete stock. However, compared to this research, these models have a fundamentally different basis: the set of to-be-cleared inventory is known (i.e., the decision to retain inventory is not considered). Nevertheless, insights from these optimization models can be valuable. Zaarour et al. (2016) use the following approach: First, the optimal price is determined with a multi-period nonlinear programming model; Second, the timing and duration of the discount is optimized with a linear programming model, using a set of predetermined prices. Price elasticity of demand is incorporated using cluster analysis and a nonlinear power regression model.

2.5. Conclusion Literature Review

It is concluded that the topic of excess inventories is relatively mature with a significant body of scientific research. The definitions of excess, slow-moving and dead stock are straightforward, but to ensure relevance, the threshold values should be based on the specific context. Additional to traditional approaches for dead stock identification, using the speed of product movement and inventory levels, machine learning approaches are increasingly deployed. By recognizing patterns in data, clustering of inventories can be useful for identifying slow-moving and dead stock.

Within the field, research is mainly focused on understanding the causes of excess inventories, and proposing methods to reduce the accumulation of dead stock. This focus on proactive reduction strategies primarily includes mathematical models for improved demand forecasts, re-order points or inventory policies in general. The focus on proactive strategies aiming to reduce the accumulation of dead stock is sensible, as it addresses the problem at its source. However, this focus has resulted in missed opportunities to optimize excess inventory management once accumulation has occurred. This is important, as imperfect demand forecasts and thus dead stock accumulation are likely to persist despite improvements in proactive reduction strategies - particularly for the dynamic e-commerce environment.

The existing body of research on the optimization of reactive strategy for excess inventory is limited. Models focus on one type of inventory control decision, and the set of to-be cleared inventory is often known. This leads to a research gap on optimization models that incorporate a broader range of control decisions, including the decision to retain excess products in stock. By developing a decision model for the cost optimization of reactive strategies for excess inventory, this research aims to address the knowledge gap and contribute to the existing scientific knowledge.

3

Methodology

The research methodology is shown in Figure 3.1 below. For answering the first research question, focused on defining excess inventory, a literature review is performed. The excess stock definition determines the subset of inventory for which the control decision are optimized. Thereby, this first question scopes the research. Literature review is also used for the second research question, identifying possible reactive strategies for managing excess inventory.

The third research question is focused on developing a mathematical model suitable for optimizing reactive control decisions for excess inventory. The model formulation incorporates the excess stock definition and feasible reactive control strategies identified in the previous research questions. The fourth research question is aimed at identifying a suitable technique for solving the mathematical model. This might involve problem relaxation or the use of heuristics. After solving the model, verification is performed.

Following this, the excess stock optimization model is specified for the use case of this research: [Product Category] of [Company XYZ]. Data is collected and analyzed, which is used for optimization. Subsequently, the fifth research question is focused at understanding the relationship between model parameters (such as expected days in stock), excess inventory control and financial performance. This will be done on the basis of sensitivity analyses. Lastly, the final research question will use scenario analysis to evaluate specific excess inventory management policies for e-commerce platforms.
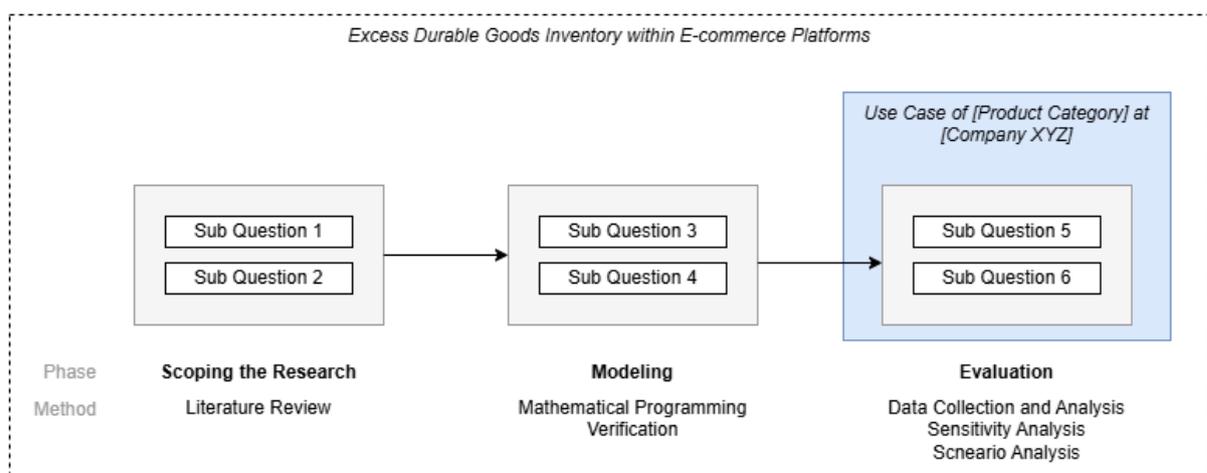
Figure 3.1: Research methods

The mathematical model is discussed below by stating the model assumptions (section 3.1), presenting

the model formulation (section 3.2), and defining the model KPIs (section 3.3). Further in the research (subsection 4.3.2) the model is tailored to the specific use case. This iterative approach in which a more generic model for excess stock optimization is developed first, ensures that scientific value is added by addressing the knowledge gap, whilst adding practical value for [Company XYZ].

3.1. Model Assumptions

A BP model is developed for optimizing excess stock at a given moment in time (periodic review), based on cost minimization. The assumptions related to the scope, modeling logic, and structure are stated below. Note that these relate to the model itself, assumptions about data will be discussed in section 4.4.

Reactive Control Strategy Optimization for Excess Stock, through Periodic Review
- The model can be deployed for periodic review of excess stock management. Periodic use is likely more practical and cost-effective than continuous operation. Due to economies of scale, continuously optimizing excess stock is likely not financially or operationally feasible. After the analysis of the results, a recommendation is provided on the periodic interval.
- The model is aimed at optimizing only that subset of inventory that is considered to be excessive.
- Only reactive control strategies are considered, aligning with the scope of the research.
- The optimization is performed at the item level. The control decisions, and thus costs, are evaluated for each individual product item in stock, rather than for the entire stock keeping unit (SKU) as a whole.
- The demand forecast is assumed to be deterministic. The sales forecast for an item is reflected in the metric 'expected days in stock'. This forward-looking measure expresses, from the moment of optimization, how many days the item is expected to remain in stock until being sold to a customer.

Inclusion of Four Reactive Control Strategies: Keep-In Stock, Return, Liquidate, Recycle
- The literature review in section 2.3, identified five feasible reactive control decisions for excess stock: discount, return to supplier, liquidate, recycle, keep in stock. Price elasticities of demand are crucial for considering the effect of discounting on demand and stock levels (Tanaka & Sagawa, 2018). Due to a lack of reliable data on these elasticities, discounting has been excluded as control strategy.
- The strategy 'keep in stock' is considered to be the base alternative ('do nothing').
- If the item is cleared (returned, liquidated, or recycled), this is assumed to occur immediately, yielding immediate revenues and costs.
- For the control decision 'keep in stock', the revenues (selling price) and costs are evaluated over the expected days in stock (remaining holding period). This approach ensures that trade-offs between control strategies are accurately accounted for, incorporating long-term financial effects of holding inventory while optimizing single-time-step control decisions through periodic review (at t=0).
- For the control decision 'return':
  - Items are only eligible for return if the supplier offers the right of return (RoR), and if the minimum and maximum return periods are adhered to.
  - Maximum return values or quantities, which could be included in supplier agreements, are not incorporated in the model.
  - In case of product returns, no differentiation is made between credit and cash refunds. These are assumed to be equally attractive. Hence, there is no supplier preference based on the type of refund offered.
- Products are assumed not to expire, aligning with scope of research: excessive inventory of durable finished goods. Furthermore, products are assumed to be of sufficient quality for sale (no defects). As such, for each item in stock, the full range of control decisions is feasible. In practice, if a product is defective, returning to a supplier is not possible, and the product is either discounted, liquidated or recycled (dependent on the nature of defect).

Minimize Costs of the Reactive Control Strategies for Full Excess Stock
- The objective of the model is to minimize the total costs of reactive control strategies over all items in the excess stock. To keep the model comprehensible, only costs that differ across control decisions are included.

    – Picking, packing, outbound, and inbound costs are excluded. These costs are incurred for all control decisions, and assumed to be equal. This implicitly assumes that a product kept in stock will be sold at some point in the future.

    – Transport costs are included only for clearing decisions. For 'keep in stock' it is assumed that these costs are paid for by the customer purchasing the product.

- The total costs of the reactive control decisions consist of direct costs and opportunity costs. The direct costs are the sum of the in-stock costs and transport costs for clearing (return, liquidate, recycle). The opportunity costs are considered to be indirect costs resulting from a loss in revenue. The opportunity costs are the sum of the opportunity costs of clearing and opportunity costs of keeping in stock.

    – In-stock costs are the sum of the **inventory holding costs** and the **working capital costs** (Tangsucheeva & Prabhu, 2013). Both are evaluated over the expected remaining holding period of the item ('expected days in stock'). Working capital costs are only incurred if the product is financed by the retailer.

    – **Transport costs for clearing**: these are specified for each clearing decision (liquidation, return, liquidation, recycle) to account for costs differences (e.g., due to distance, or transport mode).

    – **Opportunity costs of clearing**: if an item is cleared, the opportunity for a 'regular' customer sale is lost. However, by clearing the item, some other revenue could be generated (e.g., refund from supplier, revenue from liquidation or recycling). The opportunity costs of clearing are defined as the difference between the expected revenue if kept in stock and the revenue from the clearance decision. Revenue from clearing would be generated immediately (assumption), whereas revenue from regular sale would be generated after the expected days in stock. The time value of money is included using discounting.

    Opportunity costs for clearing can be both positive and negative. A negative value indicates that clearing the item is financially more attractive than retention (from a revenue perspective).

    – **Opportunity costs of keeping in stock**: if warehouse capacity is limited, retaining an item lowers the available storage space, creating opportunity costs of lost sales from other (more popular) product items (Maggiar & Sadighian, 2017; Pourhejazy, 2020). These costs are valued by calculating per excess item that is retained, how many average products could be sold during the expected days in stock and multiplying this figure with the average contribution margin.

    Should warehouse capacity be unlimited, the opportunity costs of keeping in stock are zero. To this end, the parameter α is introduced: $\alpha = 0$ for unlimited warehouse capacity, $\alpha = 1$ for limited warehouse capacity.

- Labor and administrative costs associated with executing control decisions, such as the employee time spent arranging returns, are excluded from the model.

- Export tariffs are excluded from the model. If required, these could be included as part of the transport costs per item.

3.2. Model Formulation

The notation of sets, parameters and decision variables is shown in Table 3.1. The set of items in the excessive stock $\mathcal{E}$, indexed by j, is defined so that: $\mathcal{E}_r \cap \mathcal{E}_{nr} = \emptyset$ and $\mathcal{E}_r \cup \mathcal{E}_{nr} = \mathcal{E}$. The set of excess items that are eligible and not eligible for return are mutually exclusive and collectively exhaustive. For each item j, the set $\mathcal{I}_j$ is defined by listing the days where the item is expected to be in stock (until regular customer sale). Day = 0 denotes the moment that optimization is performed.

$$\mathcal{I}_j = \{0, 1, .., D_j^e\} \qquad\qquad \forall j \in \mathcal{E} \qquad\qquad (3.1)$$

For each item j, the set $\mathcal{F}_j$ is defined by listing the expected stock days where the item is financed by the retailer. This number of days is dependent on whether an item is currently or future financed (F_j^c, F_j^f). This set is required to accurately account for the working capital costs related to keeping an item in stock. The set $\mathcal{F}_j$ is defined as follows:

$$\mathcal{F}_j = \{0, 1, .., D_j^e\} \qquad \forall j \in \mathcal{E} \mid F_j^c = 1 \tag{3.2}$$

$$\mathcal{F}_j = \{P_j - D_j^c, P_j - D_j^c + 1, ..., D_j^e\} \qquad \forall j \in \mathcal{E} \mid F_j^f = 1 \tag{3.3}$$

$$\mathcal{F}_j = \{0\} \qquad \forall j \in \mathcal{E} \mid F_j^c = 0 \wedge F_j^f = 0 \tag{3.4}$$

This definition of the set $\mathcal{F}_j$ is feasible under the assumption in Equation 3.5. By definition of F_j^c and F_j^f, items are either currently financed by the retailer, in the future, or never (in case the product is sold before the payment period has been reached).

$$F_j^f + F_j^c \leq 1 \qquad \forall j \in \mathcal{E} \tag{3.5}$$

The objective function for minimizing excess stock costs is denoted in Equation 3.6 below. The costs are calculated for every item j, and minimized over all items j in the excess stock $\mathcal{E}$. The total excess stock costs consist of inventory holding costs, working capital costs, transport costs for clearing (return, liquidate, recycle), opportunity costs of clearing, and opportunity costs of keeping in stock. The costs associated with the control decision 'keep in stock' are generated over the holding period (the expected remaining days until sale). Therefore, these costs are discounted to the present value.

$$\min \sum_{j \in \mathcal{E}} \left(\left(\underbrace{\sum_{d \in \mathcal{I}_j} \frac{C_j^s}{(1+R^e)^d}}_{\text{inventory holding costs}} + \underbrace{(F_j^f + F_j^c)C^w N_j \sum_{d \in \mathcal{F}_j} \frac{1}{(1+R^e)^d}}_{\text{working capital costs}} \right) w_j + \underbrace{C_j^r x_j + C_j^l y_j + C_j^d z_j}_{\text{transport costs for clearing}} \right.$$

$$\left. + \underbrace{\frac{P_j^s (x_j + y_j + z_j)}{(1+R^e)^{D_j^e}} - \left(P_j^r x_j + P_j^l y_j + P_j^d z_j \right)}_{\text{opportunity costs of clearing}} + \underbrace{\alpha \left(\frac{D_j^e}{D+L} \frac{M}{(1+R^o)^D} w_j \right)}_{\text{opportunity costs of keeping in stock}} \right) \tag{3.6}$$

The constraints are described below. Firstly, Equation 3.7 ensures that for every item in stock, exactly one control action must be taken. Equation 3.8 ensures that excess SKUs not eligible for return, can not be returned.

$$w_j + x_j + y_j + z_j = 1 \qquad \forall j \in \mathcal{E} \tag{3.7}$$

$$x_j = 0 \qquad \forall j \in \mathcal{E}_{nr} \tag{3.8}$$

$$w_j, x_j, y_j, z_j \in \{0, 1\} \qquad \forall j \in \mathcal{E} \tag{3.9}$$

Sets and Indices		
$\mathcal{E}$	Set of items in excess stock	$\mathcal{E}$
$\mathcal{E}_r$	Set of items in excess stock that are eligible for return	$\mathcal{E}_r \subseteq \mathcal{E}$
$\mathcal{E}_{nr}$	Set of items in excess stock that are not eligible for return	$\mathcal{E}_{nr} \subseteq \mathcal{E}$
$\mathcal{I}_j$	Set of days that item j is expected to be in stock	
$\mathcal{F}_j$	Set of days that item j is expected to be financed by retailer	

Parameters		
In Stock		
D_j^c	Current days in stock of item j	[days]
D_j^e	Expected remaining days in stock until sale of item j	[days]
N_j	NNPP of item j	[€ / item]
Revenue		
P_j^d	Price (revenue) in case of recycling item j	[€ / item]
P_j^l	Price (revenue) in case of liquidating item j	[€ / item]
P_j^r	Refund price in case of returning item j to supplier	[€ / item]
P_j^s	Current selling price of item j	[€ / item]
Costs		
C_j^d	Transport costs for recycling item j	[€ / item]
C_j^l	Transport cost for liquidating item j	[€ / item]
C_j^r	Transport costs for returning item j to supplier	[€ / item]
C_j^s	Daily inventory holding costs for item j	[€ / (item·day)]
C^w	Daily working capital costs	[% of NNPP / day]
Other		
α	Warehouse capacity is limited (1) or unlimited (0)	[binary]
M	Average contribution margin per item[3]	[€ / item]
D	Average days in stock per item[3]	[days]
L	Average lead time per item[3]	[days]
F_j^c	Item j is currently financed by retailer (1) or not (0)	[binary]
F_j^f	Item j is financed by retailer in future (1) or not (0)	[binary]
P_j	Payment period for item j	[days]
R^e	Discount rate excess stock value	[% / day]
R^o	Discount rate overall stock value	[% / day]

Decision Variables		
w_j	Item j kept in stock (1) or not (0)	[binary]
x_j	Item j returned to supplier (1) or not (0)	[binary]
y_j	Item j liquidated (1) or not (0)	[binary]
z_j	Item j recycled (1) or not (0)	[binary]

3.3. Model KPIs

The performance of the model is assessed using the following KPIs: share of control decisions (return rate, keep in stock rate, liquidation rate, recycle rate), total excess stock costs, total expected model benefit, and expected model benefit per item.

The total excess stock costs equal the value of objective function. Subsequently, the total expected model benefit is calculated as the difference between the optimized excess stock costs and the current excess stock costs. This number is divided by the number of excess stock items (number of items included in the optimization) to obtain the total expected model benefit per item. This metric could be considered a measure of model efficiency.

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[3]Average represents the full inventory, i.e., non-excess and excess stock.

<div style="text-align: right; font-size: 4em;">4</div>

Use Case of the Product Category at Company XYZ

This section introduces the use case of the [Product Category] of [Company XYZ], on the basis of its supply chain and operations in section 4.1. Afterwards, section 4.2 is focused on excess inventory specifically. First, the definition of excess stock within [Company XYZ] is discussed (subsection 4.2.1). Second, the occurrence of excess stock within the [Product Category] is analyzed (subsection 4.2.2). Third, the current strategies for dealing with excess inventory are described (subsection 4.2.3). Following this, the BP model from section 3.2 is tailored for the use case in section 4.3. Lastly, the required data is collected, processed and analyzed in section 4.4.

4.1. Supply Chain and Operations at Company XYZ

In deciding upon its product offering of the [Product Category] on its platform, [Company XYZ] makes a selection out of 17 million different products. These products are either sourced and fulfilled by the company itself as internal retailer, or sold by external suppliers. As internal retailer, the company sells products via two distinct propositions: the traditional and cross-dock method. In the traditional method, it orders the products at suppliers, stores these in its warehouse, and sells these to customers through its platform. Products are ordered using an order-up-to model. The desired order quantity for each SKU is based on the current inventory level, demand forecast (output from an advanced algorithm), and expected lead time. Orders are placed at specific suppliers, which are selected based on attractiveness of their offer feed. This includes the purchase price, available stock and lead time. In total, [Company XYZ] has 22 different suppliers of the [Product Category]. The top 5 suppliers account for a prominent share of the annual purchase value (APV).

If a product is not in stock at warehouses of [Company XYZ], it can be offered through the cross-dock proposition (given availability at the supplier). This method deploys a so-called 'pull-system' in which the demand is directly driven by the customers. When a customer orders such a product, it is ordered directly at the supplier and transported to the distribution center of [Company XYZ]. From there, the item is shipped to the customer. Although the cross-dock method is effective for increasing product availability and lowering inventory costs, the company prefers selling products through its traditional proposition. This is due to its strategy to retain market share by offering short delivery times. In practice, the company decides to offer a product solely through cross-dock if it is currently not in stock at its warehouse. Should the product not be available through cross-dock, the customer order is lost (no back orders).

The products are stored across three warehouses, where capacity is split across various product categories. Warehouse capacity is only a limiting factor during peak season: the period between half November and half December. During this period, efficient use of the warehouse space is crucial for maximizing revenues. Therefore, excess inventory should be avoided, especially during peak season.

4.2. Excess Inventory at Company XYZ

First, the definition of excess inventory is discussed in subsection 4.2.1. To understand the scale and impact of excess stock, some key metrics on excess stock levels and values are described in subsection 4.2.2. [Company XYZ's] current way of dealing with excess inventory is elaborated upon in subsection 4.2.3.

4.2.1. Inventory Classification

To determine whether a SKU is excessive, [Company XYZ] uses a forward-looking metric: projected stock days. This expresses how many days the SKU will still remain in stock (today until the expected customer sale), using the forecasted demand and current stock level. The forecast period spans the coming 26 weeks. Should a SKU have no projected sales within this half-year, it is labeled 'no sales' and is considered to be non-moving.

Based on the projected stock days, the company categorizes its inventory (Table 4.1). If a SKU is expected to be in stock for more than 12 weeks (84 days), it is considered 'excessive'. The literature review emphasized the importance of tailoring the excess stock definition to the specific business context (Li, Chiu, & Seva, 2023). It is decided to adopt the excess stock definition of [Company XYZ], which considers very-slow moving stock as excessive (potential dead stock) (Chodak, 2020). As such, excess stock is defined as follows: a **SKU is considered to be excessive if its projected stock days exceed 84 days (12 weeks).** The excess stock level, belonging to the excess SKU, is that number of items expected to be sold only after 84 days. This is thus different from total stock level.

The threshold for projected stock days, used to define excess stock, affects the set of SKUs for which reactive control decisions are optimized, and thus the set of SKUs that is potentially cleared. Hereby, the threshold value directly affects product assortment, availability and customer service (Riza et al., 2018). Without detailed research into the impact on market share, revenue and profitability, radically changing the threshold value from the current 12-weeks could disrupt the strategy and business model of [Company XYZ].

Table 4.1: Inventory classification based on projected stock days, used by [Company XYZ]

	Product Movement	Projected Stock Days
Non-Excess Inventory	Fast-moving	< 29 days
	Normal-moving	29-56 days
	Slow-moving	57-84 das
Excess Inventory	Very slow-moving	84-182 days
	Non-moving	> 182 days

4.2.2. Analysis of Excess Stock Occurrence

To gain an understanding of excess stock performance within the [Product Category] of [Company XYZ], Table 4.2 has been established. Data prior to 2023 has been excluded due to incomplete return and liquidation data.

In 2023, the excess stock level of the [Product Category] amounted to 60k items on average. In 2024 YTD[4], this increased to 90k items, corresponding to a value of €1.2 million. In 2024, the average excess stock level was significantly higher compared to 2023. Nevertheless, the relative share of excess stock level and value (as % of total) remained stable over 2023 and 2024. The increase in excess stock is therefore caused by a growing overall stock level. Over the course of 2024 YTD, the net excess stock level decreased with 43k. This was driven by the large number of excess items returned or liquidated (51k). When excluding these, the gross excess stock level increased with 7k items. Compared to 2023, with a gross excess stock build-up of 38k, this is a significant improvement.

To gain better insight into the historic clearance decisions, Table 4.3 has been established. It shows data on the number of excess items that was returned or liquidated by [Company XYZ]. This data reflects the irregularity in the clearance process. In 2024, more than twice the amount of excess items was returned

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[4]2024 YTD: 1 January until 16 November 2024.

Table 4.2: Excess stock of the [Product Category] at [Company XYZ]

	2023	2024 YTD[5]
Average Excess Stock Value [€]	813,391	1,164,569
Average Excess Stock Value [% of total stock value]	24%	24%
Average Excess Stock Level [items]	60,085	89,752
Average Excess Stock Level [% of total stock level]	24%	25%
Δ Net Excess Stock Level (end vs. start of period) [items]	13,815	-43,201
Total Returned and Liquidated [items]	24,180	50,679
Δ Gross Excess Stock Level (end vs. start of period) [items]	37,995	7,478

compared to 2023. In these years, returns were made to 8 different suppliers while over [11][5] suppliers actually offer a RoR (will be shown in subsection 4.4.1). Interestingly, in 2023, no returns were made to one of the top four suppliers, even though this supplier offers a RoR. These observations highlight the untapped potential for making returns.

Using the 2024 average excess stock level (Table 4.2), return and liquidation data (Table 4.3), yields a 53.2% return rate, 45.2% keep in stock rate and 1.6% liquidation rate for excess stock. It is assumed that all returns and liquidations were made at the same moment in time, supported by the fact that, on average, [Company XYZ] executed one return per supplier in 2024.

Table 4.3: Historic returns and liquidations at the [Product Category] of [Company XYZ]

		2023		2024 YTD[5]	
		# of Shipments	Total Quantity	# of Shipments	Total Quantity
Return	Supplier A	2	13,897	1	26,660
	Supplier B	2	3,206	1	4,455
	Supplier C	1	917	1	2,192
	Supplier D	1	1,338	1	4,641
	Supplier E	1	7	-	-
	Supplier F	-	-	2	2,432
	Supplier G	-	-	1	824
	Supplier H	-	-	1	8,000
	Total Returned	7	19,365	8	49,204
Liquidation	*Total Liquidated*	3	4,815	2	1,475
Cleared	*Total Cleared*	10	24,180	10	50,679

4.2.3. Current Reactive Strategies

Currently at [Company XYZ], if the inventory level of a SKU exceeds the desired quantity, the standard procedure is to apply discounting. This excess stock is discounted using a pricing model which updates the selling prices three times a week. This is explained in more detail below. Before applying discounting, it is not assessed whether other control decisions (e.g., return, liquidation) would be more financially attractive. Whereas discounting is applied throughout the year, the other control actions for excess stock are not executed regularly. In theory, these decisions should be made twice a year after sales season, using the process outlined in Figure 4.1. In practice, these process guidelines are not closely followed.

First, it should be checked whether the product is considered to be excessive (first three criteria). Second, it should be assessed if it still meets the criteria to be sold (e.g., safety), and if the product content on the website is sufficient. Then, if the product season does not start within 6 months, the product should be returned or sold to a liquidator. The last option would be to re-evaluate pricing. In practice, these decisions are made once or sometimes twice a year, in an unstructured manner, not using the process in Figure 4.1. Due to this infrequency in large-scale evaluation of excess inventory, return periods may

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[5]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

[6]2024 YTD: 1 January until 16 November 2024.

have already expired, resulting in missed revenue opportunities. Additionally, it contributes to increased inventory holding costs.
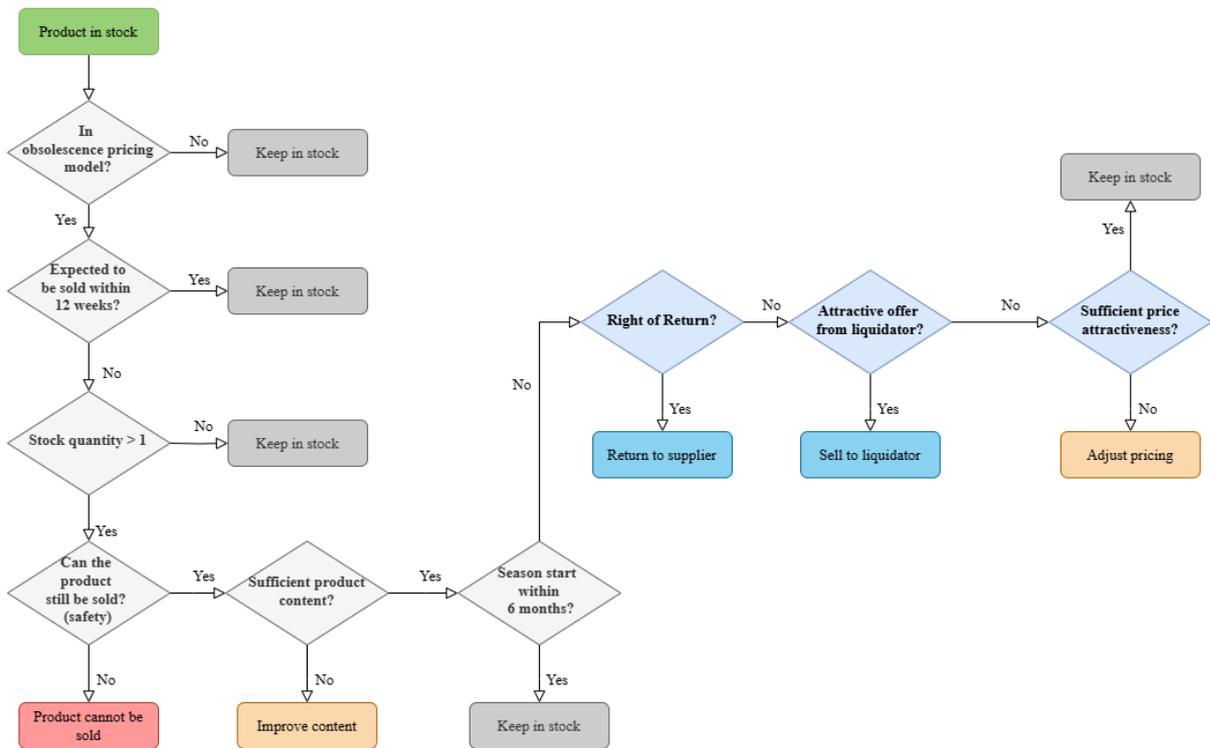
Figure 4.1: Theoretical flow chart for excess stock management at [Company XYZ]

Discount
The retail division of [Company XYZ] deploys the pricing model to set product prices. Appropriate pricing is important for ensuring product rotation, thereby reducing the risk of excess inventory. Besides prevention, the pricing model is also used as reactive strategy, discounting inventory once it is considered to be 'excessive'. A product is included in the obsolescence pricing model if it meets a set of criteria: the product is not new, and the (fashion) season has not yet started. Additionally, it should not already be in the obsolescence pricing model, be in promotion, or be excluded explicitly. Furthermore, the item should be expected to depreciate in value due to obsolescence. Lastly, criteria related to product movement and forecasted stock levels are incorporated.

The pricing model evaluates the prices three times a week; should the desired stock level not yet be reached, the current price is discounted with [5-20%][7]. Discounting will continue until the desired stock level is reached. Additionally, a maximum discount is determined based on a threshold for CM. On September 7, 2024, 37k obsolete items were offered at a discount using the obsolescence pricing model (out of a total of 43k obsolete items).

Return to Supplier
Dependent on the supplier contract, a RoR is available for [Company XYZ]. The contract could also include a minimum and maximum return period. All suppliers of the [Product Category] that offer a RoR, give a [80-100%][7] refund of the net net purchase price (NNPP). If a product is returned to a supplier, the transport costs are paid by [Company XYZ]. Since returning a product will only generate a small profit loss, return rights can considered to be an insurance against low sales (Maggiar & Sadighian, 2017). For optimizing the control decisions of excess stock, it is essential to incorporate the supplier-specific agreements related to returns.

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[7]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

Right of Destruction
Instead of offering a RoR, suppliers can also offer a Right of Destruction (RoD). Under this arrangement, [Company XYZ] receives a refund for destroying the products. Hereby, the company avoids costs for transporting the goods back to the supplier.

Sell to Liquidator
Liquidation is characterized by selling items to a third party willing to take any amount of inventory for a fraction of the price (Maggiar & Sadighian, 2017). Currently at [Company XYZ], a differentiation between liquidation of excess stock and returned goods is made. Whereas returned goods are sold to a liquidation party specialized in the [Product Category], excess stock is sold to general liquidators. The specialized liquidator offers a higher price compared to general liquidators, presenting an interesting revenue opportunity for excess stock liquidation. Desk research showed that [Company XYZ] was unaware of this, and employees agreed with the potential of this initiative. It should be noted that liquidation to a specialized party would require that products are not liquidated in batches with other product types (which is often the case). This could lead to increased transport costs for delivering the excess goods to the liquidator.

Donate
Although not a standard option in Figure 4.1, [Company XYZ] also donates excess stock. Since liquidation generates such low revenues, donation could be an attractive alternative, contributing to society. Currently, if the quality of a product is insufficient for a firsthand sale, and the selling price is below a certain threshold, it can be donated. Donation is quite complicated in terms of logistics and agreements; transport and labor are some of the key cost drivers.

Recycle
Although not included in Figure 4.1, [Company XYZ] also recycles excess stock. Recycling is not financially attractive, as revenues are low and barely outweigh the costs. Compared to donation and liquidation, recycling is a relatively simple process, reducing search and labor costs.

4.3. Mathematical Model for Use Case of Company XYZ
This section describes the mathematical model for optimizing reactive strategies of excess stock, specifically tailored for the [Product Category] of [Company XYZ]. This formulation will serve as the basis for data collection, and will be implemented into Python.

4.3.1. Assumptions
Based on the desk research that was presented in section 4.1 and 4.2, the existing model assumptions of section 3.1 are extended for the specific use case of [Company XYZ].

Optimization at the Level of SKU instead of Item.
It is decided to alter the mathematical model such that control decisions are optimized at the level of SKU, instead of item.

- At [Company XYZ], stock data, such as the supplier, purchase price and order date, is only available on the level of SKU. It is unknown which supplier delivered what exact item, and how long each individual item has been in stock. Also, for returning individual items, it is not checked which supplier delivered that specific item, the company checks which suppliers delivered the related SKU and if they accept a return.

- Modeling the excess stock on SKU level is possible due to the (relatively) homogeneity of individual items belonging to the same SKU. The products are durable finished goods and item-specific characteristics such as defects, quality or expiry date are not considered.

- Optimizing at the level of SKU increases the practical value for [Company XYZ] as it involves significantly less data processing (no need to transfer data from SKU to item level), and reduces the dimensionality of the problem by reducing the number of decision variables.

- By changing the optimization level to SKU, this adapted model will not be applicable for retailers with heterogeneous product items within a specific SKU (e.g., perishable or highly customized goods).

Exclusion of Discounting
- For incorporating discounting as reactive strategy, the effect of price changes on the demand is required (Tanaka & Sagawa, 2018). Price elasticities of demand vary highly across different the product items, and no reliable data on these values is available. Including discounting as control strategy would therefore result in unreliable recommendations.

- The exclusion of discounting also aligns with the research scope to solely focus on reactive strategies. Discounting is part of the pricing strategy at [Company XYZ], which is both a proactive and reactive strategy.

Exclusion of Recycling due to Superiority of Liquidation.
- Desk research revealed that recycling products does not generate profit (revenues approximately equal costs). Due to the assumption that liquidators accept all products, liquidation will always be preferred over recycling. Hence, the 'recycle' control decision is excluded from the model.

No Transport Costs for Liquidation and Return to Suppliers with Right of Destruction.
- For liquidation, products are transported from the company's warehouses to national liquidator parties. Desk research revealed that these transport costs are incorporated into an existing contract. Thereby, [Company XYZ] does not pay additional fees for a liquidation transport request. Hence, the transport cost for liquidation are excluded from the mathematical model.

- Desk research revealed that some suppliers offer a Right of Destruction (RoD) instead of RoR. For these products, [Company XYZ] receives a full refund without incurring any transport costs. Due to its similarity with return, this RoD is incorporated as 'return' with zero transport costs.

4.3.2. Formulation

The BP model for optimizing reactive strategies of excess stock, described in section 3.2, is updated for the extended model assumptions.

The updated definitions and notations are shown in Table 4.4. Whereas sets, parameters and decision variables were previously defined on item level (j), these are now defined on SKU level (g). Parameter values specific to a SKU g, are defined as the average value for an item with SKU g. To accurately account for costs, the objective function (Equation 4.6) multiplies the costs per item with the excess stock level of a SKU (S_g).

The new set of SKUs in the excessive stock $\mathcal{G}$, indexed by g, is defined so that: $\mathcal{G}_r \cap \mathcal{G}_{nr} = \emptyset$ and $\mathcal{G}_r \cup \mathcal{G}_{nr} = \mathcal{G}$. The sets $\mathcal{I}_g$ and $\mathcal{F}_g$ are defined as follows:

$$\mathcal{I}_g = \{0, 1, .., D_g^e\} \qquad\qquad \forall g \in \mathcal{G} \qquad (4.1)$$

$$\mathcal{F}_g = \{0, 1, .., D_g^e\} \qquad\qquad \forall g \in \mathcal{G} \mid F_g^c = 1 \qquad (4.2)$$

$$\mathcal{F}_g = \{P_g - D_g^c, P_g - D_g^c + 1, ..., D_g^e\} \qquad \forall g \in \mathcal{G} \mid F_g^f = 1 \qquad (4.3)$$

$$\mathcal{F}_g = \{0\} \qquad\qquad \forall g \in \mathcal{G} \mid F_g^c = 0 \wedge F_g^f = 0 \qquad (4.4)$$

This definition of the set $\mathcal{F}_g$ is feasible since the following condition holds:

$$F_g^f + F_g^c \leq 1 \qquad \forall g \in \mathcal{G} \qquad (4.5)$$

The objective function optimizes the control decision on the level of a SKU by minimizing the costs per item, multiplied with the stock level of that SKU (S_g). The objective function comprises the inventory holding costs, working capital costs, transport costs for returning, opportunity costs of clearing, opportunity cost of keeping in stock. Due to the optimization at level of SKU, exactly one control decision is executed for the entire excess stock of that SKU. This is ensured by the binary nature of the decision variables, supplemented by constraint 4.7. Constraint 4.8 ensures that SKUs that are not eligible for return, can not be returned.

$$\min \sum_{g \in \mathcal{G}} S_g \left(\left(\left(\underbrace{\sum_{d \in \mathcal{I}_g} \frac{C_g^s}{(1+R^e)^d}}_{\text{inventory holding costs}} + \underbrace{(F_g^c + F_g^f)C^w N_g \sum_{d \in \mathcal{F}_g} \frac{1}{(1+R^e)^d}}_{\text{working capital costs}} \right) w_g + \underbrace{C_g^r x_g}_{\text{transport costs for returning}} \right. \right.$$

$$\left. \left. + \underbrace{\frac{P_g^s(x_g + y_g)}{(1+R^e)^{D_g^e}} - \left(P_g^r x_g + P_g^l \, y_g\right)}_{\text{opportunity costs of clearing}} \right) + \underbrace{\alpha \left(\frac{D_g^e}{D+L} \frac{M}{(1+R^o)^D} w_g \right)}_{\text{opportunity costs of keeping in stock}} \right) \quad (4.6)$$

Subject to:

$$w_g + x_g + y_g = 1 \qquad \forall g \in \mathcal{G} \qquad (4.7)$$

$$x_g = 0 \qquad \forall g \in \mathcal{G}_{nr} \qquad (4.8)$$

$$w_g, x_g, y_g \in \{0,1\} \qquad \forall g \in \mathcal{G} \qquad (4.9)$$

4.4. Data

This section describes the data collection, processing and analysis, required for optimizing excess stock using the BP model outlined in the previous section. The data comprises both time-independent and time-dependent parameters. Section 4.4.1 collects time-independent data such as supplier return agreements, inventory carrying costs, and discount rates. The value of parameters with sensitive information are anonymized, denoted with: [anonymized value].

Subsection 4.4.2 describes the collection and processing of real-time stock data. The set of excess SKUs is determined based on the definition found in subsection 4.2.1: projected stock days $\geq$ 12 weeks. Subsequently, relevant stock performance parameters such as excess stock level and selling price are collected. Additionally, an algorithm is developed to identify the most attractive return offers per SKU. For each SKU eligible for return, the average return price and transport costs are calculated. After collection and processing, the real-time stock data is analyzed. Given the sensitivity of the information, the code for the algorithm and data processing is not included in this document.

It is important to note that there are dependencies between the real-time and time-independent data. For example, time-independent supplier agreements determine which suppliers offer a return within a specific time period, thereby affecting which excess SKUs are eligible for return (reflected in the real-time stock data). Each parameter value or set that will be directly used in the mathematical model, is denoted in **bold blue** font. For running the model at a specific point in time, only the real-time stock data requires updating.

4.4.1. Time-Independent Data

The time-independent data can be divided into: supplier data, inventory carrying costs, liquidation price, opportunity costs of keeping an item in stock, and daily discount rates. Each of these is discussed in the subsections below.

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[8] Average represents the full inventory, i.e., non-excess and excess stock.

Table 4.4: Notation of sets, parameters, and decision variables, revised for the use case of the [Product Category] of [Company XYZ]

	Sets and Indices	
$\mathcal{G}$	Set of SKUs in excess stock	$\mathcal{G}$
$\mathcal{G}_r$	Set of SKUs in excess stock that are eligible for return	$\mathcal{G}_r \subseteq \mathcal{G}$
$\mathcal{G}_{nr}$	Set of SKUs in excess stock that are not eligible for return	$\mathcal{G}_{nr} \subseteq \mathcal{G}$
$\mathcal{I}_g$	Set of days that an average item with SKU g is expected to be in stock	
$\mathcal{F}_g$	Set of days that an average item with SKU g is financed by [Company XYZ]	

	Parameters	
Stock		
D_g^c	Average current days in stock of item with SKU g	[days]
D_g^e	Average expected remaining days in stock of item with SKU g	[days]
N_g	Average NNPP of item with SKU g	[€ / item]
S_g	Excess stock level of SKU g	[items]
Revenue		
P_g^l	Price (revenue) in case of liquidating item with SKU g	[€ / item]
P_g^r	Average refund price in case of returning item with SKU g	[€ / item]
P_g^s	Current selling price of item with SKU g	[€ / item]
Costs		
C_g^r	Average transport costs of item with SKU g in case of return to supplier	[€ / item]
C_g^s	Daily inventory holding costs for item with SKU g	[€ / (item·day)]
C^w	Daily working capital costs	[% of NNPP / day]
Other		
α	Warehouse capacity is limited (1) or unlimited (0)	[binary]
M	Average contribution margin per item[8]	[€ / item]
D	Average days in stock per item[8]	[days]
L	Average lead time per item[8]	[days]
F_g^c	Average item with SKU g is currently financed by [Company XYZ] (1) or not (0)	[binary]
F_g^f	Average item with SKU g is financed by [Company XYZ] in future (1) or not (0)	[binary]
P_g	Average payment period for item with SKU g	[days]
R^e	Discount rate excess stock value	[% / day]
R^o	Discount rate overall stock value	[% / day]

	Decision Variables	
w_g	Excess stock of SKU g kept in stock (1) or not (0)	[binary]
x_g	Excess stock of SKU g returned to supplier (1) or not (0)	[binary]
y_g	Excess stock of SKU g liquidated (1) or not (0)	[binary]

Supplier Data

In total, the [Product Category] of [Company XYZ] has 22 suppliers. Given the sensitivity of supplier information, ranges of parameter values are provided instead of exact figures. The payment period for products ranges from [15 to 100][9] days. Over 50% of the suppliers offer a RoR where the refund equals [80% to 100%][9] of the NNPP. The minimum return period ranges from [0 to 548][9] days and the maximum return period from [90 days to infinity][9]. As discussed in subsection 4.2.3, some suppliers actually offer a RoD instead of RoR. This is incorporated by setting the transport costs to €0 per item. Consequently, the transport costs for return vary between [€0 to €2 per item][9].

The transport costs are based on historic invoices for transport requests from [Company XYZ's] warehouse to suppliers. Returns within Europe are transported by road, while returns to the US are shipped by air. For calculating the cost per item, full pallet loads are assumed (load of 600 items[10]). Due to this assumption, the transport costs could be over- or underestimated dependent on the actual batch size.

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[9] For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

[10] Based on data of [Company XYZ].

The difference in transport costs affects the attractiveness of returns, and should be taken into account when selecting a supplier for making a return.

For three suppliers, the supplier agreement was outdated or not available. Hence, it is assumed that products cannot be returned. One supplier only offers a RoR for specific product items. This level of granularity is not included in the model. Therefore, it is assumed that no RoR is offered - this simplification affects only 1% of the [Product Category]. Note that, should a supplier not have specified a minimum return period, this value is set to 0. For suppliers without maximum return period, this value is set to M (10^6). By using these minimum and maximum values, the return period is not constrained for these suppliers.

Inventory Carrying Cost

The holding costs of a product are dependent on its size. The holding costs vary between [€0.002 to €0.05][11] per item per day. However, a significant majority of the product items has holding costs below €0.02 per day. For calculating the working capital costs of items that are financed by [Company XYZ], the annual working capital costs are assumed to be 5% of the NNPP. This yields daily working capital costs (C^w) of 0.014%.

Liquidation Price

Currently, [Company XYZ] sells excess products to a so-called 'general liquidator'. The general liquidator offers an average liquidation price between [5% to 20%][11] of the selling price. For liquidating inventory that has been returned by customers, the company partners with a liquidator specialized in the [Product Category]. This party offers higher liquidation prices that depend on the selling price. These prices range between [10% to 30%][11] of the selling price excluding VAT. The specialized party only buys products with a selling price higher than [€12][11].

The base model will deploy the 'general liquidator' price equaling [5-20%][11] of the selling price, as this corresponds to the company's current scenario. However, a scenario analysis is performed using a specialized liquidation policy in subsection 5.5.1.

Opportunity Costs of Keeping Item in Stock

Table 4.5 shows the anonymized parameter values related to the opportunity costs of keeping an item in stock. The method for obtaining the parameter value is described as well. Note that, M, L and D are calculated over the total inventory within the inventory of the [Product Category], not merely the excess stock. Thereby, these metrics reflect an average product of the [Product Category], ensuring that the opportunity cost of keeping an excess item are accurately accounted for. The average contribution margin M denotes how much additional profit the sale of an average item would generate (after covering the fixed costs). The average lead time L denotes the average time between the order placement and delivery to the warehouse. The average days in stock D denotes how long it takes for an average product to be sold.

Table 4.5: Parameter values for the opportunity costs of keeping in stock, specific to the [Product Category] of [Company XYZ]

Parameter		Value	Method
M	Average contribution margin per item	[2.20 €/item][11]	Average value of CM for [Company XYZ], based on data from 1 January to 4 November 2024.
L	Average lead time per item	[7.0 days][11]	Weighted average calculated using lead time per supplier, and annual quantities delivered per supplier. Based on data from last 12 months on 1 October 2024.
D	Average days in stock per item	[60 days][11]	Calculation based on stock quantity and sales forecast (exclusion of SKUs with no forecast). Obtained on 12 November 2024.

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[11] For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

Daily Discount Rate

The daily discount rate of excess stock value is required to account for the time value of money. [Company XYZ] uses inventory reserves to account for the potential financial loss on excess inventory. The inventory is categorized using two metrics: Age Group (current days in stock) and Stock Days (expected days until current inventory is fully sold). For each combination of these metrics, a percentage is specified, indicating the depreciation % of inventory value. These values are shown in Figure 4.2.

Stock Days	Inventory Age					
	<= 28 days	29-56 days	57-84 days	84-182 days	183-365 days	> 365 days
<= 28 days	0%	0%	0%	0%	0%	0%
29-56 days	0%	0%	6%	12%	35%	50%
57-84 days	0%	2%	10%	27%	50%	75%
> 84 days	0%	4%	18%	32%	65%	90%

Figure 4.2: Risk profile stock depreciation

Since excess stock is considered to be in stock for at least 12 weeks, only the category with >84 Stock Days is considered for calculating the discount rate of excess stock. Using a midpoint of 590 days (shown in Table 4.6), the average depreciation per day is calculated for all Inventory Age categories within the Stock Days category '> 84 days'. The weighted average of these values is calculated using the distribution of the age of excessive inventory of the [Product Category] on November 4, 2024 (8%, 14% , 7%, 14%, 27%, 30%, in the same order of categories as Figure 4.2). This leads to a daily discount rate of excess stock value: $R^e = 0.086\%$.

To calculate the depreciation of the full stock, all Stock Days categories are considered. Using the midpoint of the number of days (shown in Table 4.6), the average depreciation per day is calculated for all categories. The weighted average of these values is calculated using the distribution of the age of the full inventory of [Product Category] on November 4, 2024 (39%, 16% , 11%, 14%, 11%, 8%, in same order of categories as Figure 4.2). This leads to a daily discount rate of overall stock value $R^o = 0.023\%$.

Table 4.6: Distribution of stock days

Stock Days	Midpoint (days)	Distribution
<= 28 days	14	81%
29-56 days	42.5	5%
57-84 days	70.5	3%
> 84 days	590[12]	10%

4.4.2. Time-Dependent Data

The goal of the model is to optimize reactive control decisions for excess inventory at a given moment in time. Therefore, real-time excess stock data is required, which was collected on November 27th, 2024. This section describes the collection and processing, as well as the data analysis. The real-time stock parameters are denoted in **bold blue** font.

Collection and Processing of Real-Time Stock Data

Firstly, the set of excess SKUs $\mathcal{G}$ is selected based on the projected days in stock, and relevant threshold of 12 weeks. If the projected stock days exceeds the 12-week threshold, the SKU g is considered 'excessive', meaning that in 12 weeks, SKU g is still expected to be in stock. The excess stock level of SKU g (S_g) equals the number of items that is expected to still be present in 12 weeks.

For each SKU g, the average expected days in stock (D_g^e) is calculated as the average between the 12-week threshold and the projected stock days (resembling the out-of-stock date). Calculating this average is required because the optimization is performed at the level of SKU, but the control decisions apply to the entire stock level of that SKU. Simply using the out-of-stock date would not account for the variation

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[12]Maximum stock days assumed to be 1,095 days, corresponding to 3 years.

in expected days in stock across different items of the same SKU, as some items may sell sooner than others. If no demand forecast is available, indicating that no sales are expected in the coming 26 weeks, D_g^e is assumed to be 3 years (1,095 days). This assumption has been checked with employees of [Company XYZ].

For each excess SKU g, the daily inventory holding costs (C_g^s) are assigned based on its size. The latest retail price of SKU g is assumed to equal the current selling price (P_g^s). Subsequently, the liquidation price (P_g^l) equals [5-20%][13] of the selling price.

Assuming a FIFO principle, the excess stock will consist of the items that have been in stock for the shortest duration. Therefore, the most recently delivered orders of SKU g across suppliers, summing up to the total excess stock level S_g, are used to calculate the average NNPP (N_g), average payment period (P_g), and average current days in stock (D_g^c). The values for P_g, D_g^c and D_g^e are then used to determine whether the excess stock of SKU g is, on average, currently or future financed by [Company XYZ] (F_g^c, F_g^f).

Lastly, an algorithm has been developed to identify possible return options for every SKU that is considered 'excessive' (i.e., belonging to set $\mathcal{G}$). All historic orders of the excess SKUs are collected. Per order, it is assessed whether the items can be returned, based on the order date and the relevant supplier agreement conditions (i.e., does the supplier offer a RoR, and is the allowed return period adhered to). A new table is created (called 'Allowed Returns'), showing a ranked overview of the preferred return offers per SKU. The higher the profit of a return offer, defined as the return price minus transport costs, the higher the ranking of this return option. Based on this table, the weighted average return price (P_g^r) and weighted average return costs (C_g^r) are determined for each SKU g. Per SKU, this average is calculated over the top-preferred return options that sum up to the excess stock level S_g. Additionally, the sets of SKUs eligible for return $\mathcal{G}_r$ and not eligible for return $\mathcal{G}_{nr}$ are determined based on the 'Allowed Returns' table.

Table 4.7 below includes details on the relevance of the calculated real-time stock parameters.

Table 4.7: Relevance of real-time stock parameters

Parameter	Relevance
Sets	
$\mathcal{G}$	Determines set of excess SKUs to be optimized
$\mathcal{G}_r$, $\mathcal{G}_{nr}$	Determine for which SKUs returning is allowed
Revenue and Costs	
P_g^s	Affects opportunity costs of clearing
P_g^l	Affects opportunity costs of clearing
P_g^r	Affects opportunity costs of clearing
C_g^r	Determines transport costs for return
C_g^s	Determines inventory holding costs
In-Stock Metrics	
S_g	Number of items affected by the control decision of excess SKU g
D_g^e	Affects inventory holding costs, working capital costs, opportunity cost of keeping in stock and clearing
Financing	
N_g, P_g, D_g^c	Affect working capital costs
F_g^c, F_g^f	Affect working capital costs

Analysis of Real-Time Stock Data
The results of the data analysis, performed with the excess stock data set of 27 November 2024, are shown in Table 4.8. Some key takeaways are discussed below.

The excess stock data set consists of 19,096 SKUs, corresponding to 44,160 items. Suggesting that, for SKUs with excess stock, on average 2.3 items are actually 'excessive'. Out of the excess SKUs,

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[13]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

a substantial share is eligible for return: 86%. This implies that for 86% of the SKUs, all three control decisions are feasible: keep in stock, return, liquidate.

On average, the excess stock of a SKU is expected to be in stock for 767 days. The weighted average is slightly lower: 605 days. It should be noted that the average is significantly affected by SKUs without sales forecast. In total, 12,403 SKUs (65%) do not have a sales forecast (zero sales in coming half-year), corresponding to 41% of the excess items having no sales forecast. As priorly mentioned, these are assumed to be in stock for 3 years on average, thereby skewing the average D_g^e for excess stock.

Looking at the total excess stock on average in Table 4.8, shows that the selling price exceeds the return price. However, when considering individual products, the average return price actually exceeds the selling price for 36% of the excess SKUs (or 29% of the excess items). This suggests that returning these SKUs is beneficial - even without considering the savings in holding and working capital costs. The fact that the return price exceeds the selling price can be explained by two factors. First of all, [Company XYZ] discounts stock if the actual stock level exceeds the desired stock level using the pricing model (described in subsection 4.2.3), possibly leading to selling prices below the NNPP (which is correlated with return price). Additionally, the return price is based on the most attractive return offers, these could be higher than the NNPP and related selling price of the current products in stock.

Over 76% of the excess SKUs is financed by [Company XYZ], explained by the high average current stock days compared to the payment period. If these SKUs are kept in stock, working capital costs are incurred.

Table 4.8: Key metrics of excess stock within the [Product Category], data from 27 November 2024

	Metric	Value	Simple Mean	Weighted Mean[14]
Sets	$\lvert \mathcal{G} \rvert$	19,096	-	-
	$\lvert \mathcal{G}_r \rvert$	16,336	-	-
	$\lvert \mathcal{G}_{nr} \rvert$	2,760	-	-
	$\lvert \mathcal{G} \rvert$ with $F_g^c = 1$	14,542	-	-
	$\lvert \mathcal{G} \rvert$ with $F_g^f = 1$	4,554	-	-
items	Total excess items	44,160	-	-
	S_g	-	2.3	-
Financials	N_g	-	€20.98	€19.59
	P_g^s	-	€21.93	€22.76
	P_g^{r} [15]	-	€20.06	€17.70
	C_g^s	-	€0.0059	€0.0059
Time Period	D_g^c	-	305 days	235 days
	D_g^e	-	767 days	605 days
	P_g	-	48 days	48 days

Below, some key distributions of excess stock metrics are plotted. Figure 4.3 shows that the excess inventory of the [Product Category] consists of a large selection of SKUs with a low excess stock level. This is also underpinned by the average 2.3 excess items per SKU. The histogram shows that 90% of the SKUs has an excess stock level equal to or less than 4 items. Additionally, 12,655 of the SKUs (65%) have an excess stock level of one single item. Further analysis showed that out of these SKUs with a single item in stock, 9,955 SKUs actually only have one item in the entire stock (excess and non-excess). Clearing these SKUs affects product assortment and availability which may not be desired from a commercial standpoint (Tanaka & Sagawa, 2018). Scenario analysis is performed in subsection 5.5.2 where single-item excess SKUs are forced to be retained.

Since the SKUs without sales forecast significantly affect the calculated average expected days in stock, Figure 4.4 has been created, representing all excess SKUs with projected sales in the coming half-year (35% of the total excess SKUs). This shows that, when excluding the SKUs without sales forecast, the average expected days in stock is 160 days. The minimum value of 85 days results from the selected

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[14]Weighted by the excess stock level.
[15]Averaged over SKUs eligible for return only.
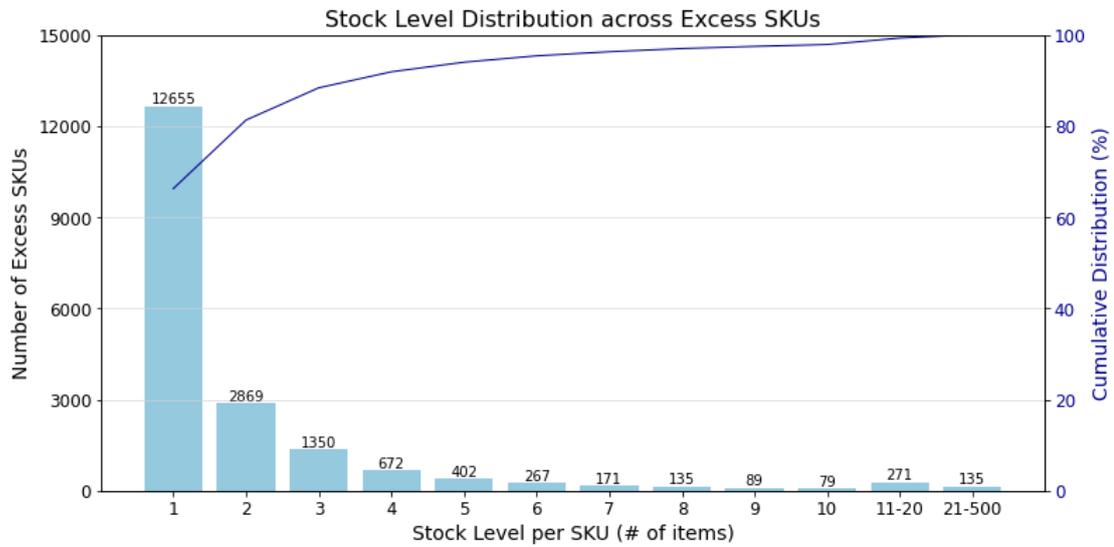
Figure 4.3: Histogram of excess stock level distribution within the [Product Category], data from 27 November 2024

excess stock threshold of 84 days. The maximum value of 15,299 expected days in stock is caused by a daily sales forecast approximating zero.

In Appendix A, Figure A.1 illustrates the distribution of the expected days in stock for the entire excess stock (including SKUs without sales forecast). The minimum and maximum value are unaffected by the inclusion of SKUs without sales forecast. This is sensible since the additionally included SKUs all have expected stock days of 1,095. As a result, the median value for expected days in stock is 1,095 days (3 years).
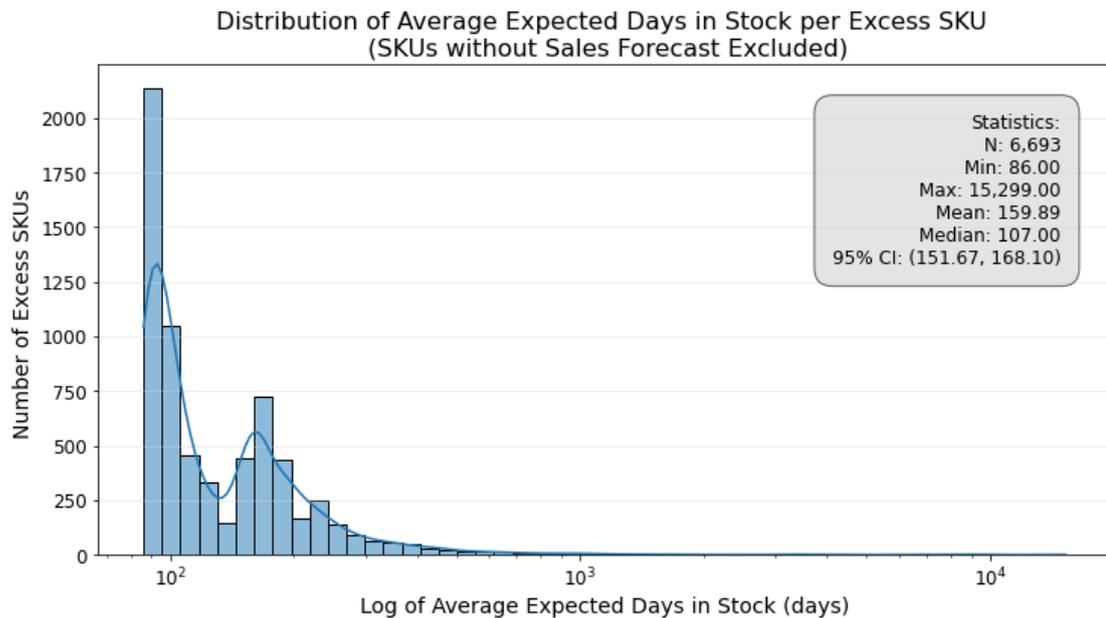
Figure 4.4: Histogram of expected days in stock distribution of excess products in [Product Category]. Data from 27 November 2024, excluded 12,403 SKUs without sales forecast.

Figure 4.5 shows that the average gross margin[16] of excess products in the [Product Category] is only €0.95 per item (based on data from 27 November 2024). The median value is slightly higher: €1.11 per

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[16]Defined as: gross margin = selling price - NNPP.

item. Additionally, the cumulative distribution function shows that nearly 50% of the SKUs with excess stock actually has a negative margin. These low gross margins can be explained by two factors. Firstly, [Company XYZ] is highly focused on winning or maintaining market share in the market, as such the company is willing to maintain low to negative margins on individual product items. Secondly, products that are considered to be 'excessive' are frequently discounted using the pricing model, resulting in lower selling prices and thus margins. The observed low gross margins support the finding that, for 36% of the excess SKUs, the return price actually exceeds the current selling price.
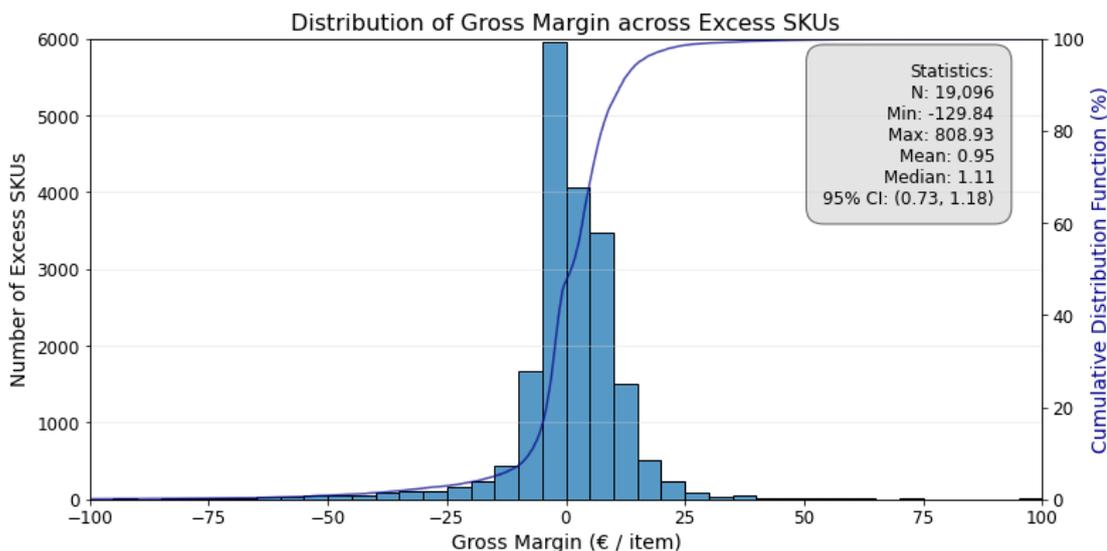
Figure 4.5: Histogram of gross margin distribution for excess SKUs within the [Product Category], data from 27 November 2024

4.5. Conclusion

This chapter provided an analysis of the [Product Category] at [Company XYZ], focusing on its operations, and the challenges posed by excess inventory. A SKU is considered 'excessive' if its projected stock days exceed 84 days, or 12 weeks. Using this definition ensures alignment with the specific business context of the use case, and recognizes slow-moving stock as potential dead stock - important considerations according to the performed literature review. Given this definition, 25% of the category's inventory qualifies as excessive, corresponding to an average of 90k excess items with an estimated total value of €1.2 million. Among the excess stock, 65% of the SKUs are projected to have no sales within the next six months (or 41% of the excess items). This underlines the urgency of effective excess stock management strategies. Currently, reactive strategies for excess inventory are lacking a systematic and data-driven approach, leading to suboptimal financial outcomes.

Excess inventory in the [Product Category] is characterized by its long-tail distribution, comprising a large variety of SKUs with relatively low levels of excess stock, averaging at just 2.3 items. Additionally, gross margins are typically low - €0.95 per excess item - and 36% of the excess SKUs even has return price exceeding the current selling price. This highlights the complexities of excess stock management within the category, where financial implications of control decisions must be carefully evaluated for each SKU.

The BP model, tailored to the use case, integrates characteristics of reactive strategies with real-time and forecasted stock data to enhance excess stock management. The model can be deployed for periodic optimization of reactive strategies for excess stock. Optimization is performed through cost minimization, consisting of direct costs (holding, working capital costs, transport costs) and indirect costs from loss of revenues. These comprise opportunity costs of clearing, representing the revenue difference between a customer sale and clearance action, and opportunity costs of keeping in stock, representing potential revenue losses from other (faster-selling) items due to limited warehouse capacity. By incorporating three reactive strategies with proven feasibility in literature and practice (keep in stock, return, liquidate), the model aims to generate quantitative insights into the effectiveness of various strategies, and subsequently improve the financial performance of excess stock.

Results

This chapter describes the results of excess stock optimization using the BP model, specified for the use case of the [Product Category] at [Company XYZ]. First, the model is implemented into Python in section 5.1. Subsequently, the model is verified in section 5.2. After verification, optimization is performed for the excess stock data set of 27 November 2024. The results are interpreted in section 5.3. The situation of limited and unlimited warehouse capacity are analyzed in more detail in subsection 5.3.1 and 5.3.2. Lastly, sensitivity and scenario analyses are performed in section 5.4 and 5.5.

5.1. Model Implementation

The BP model of section 4.3 was implemented in Python, using the Gurobi solver deploying a brand-and-bound algorithm (version 9.5.2). The optimization was performed on a mobile workstation with Windows 11 and 16GB RAM. The Python code is included in Appendix B. The code specifies the time-independent parameters corresponding to the values in subsection 4.4.1. Additionally, the code processes the real-time stock data collected on 27 November 2024, as described in subsection 4.4.2. Based on this real-time stock data, the relevant sets are determined: $\mathcal{G}_r$, $\mathcal{G}_{nr}$, $\mathcal{F}_g$, $\mathcal{I}_g$. Following this, the decision variables, model objective and constraints are defined.

The allowed tolerance ('MIPGap') was set to 0, resulting in an effective optimality gap of 0% for every model run (precisely, the gap was smaller than 1×10^{-325}). The model consisted of nearly 60,000 integer decision variables. Despite the large dimensionality of the problem, the model was solved in the pre-solve phase with a computational time of only 0.05 seconds (excluding data analysis and plotting). This is likely due to the fact that the model is formulated such that the optimal control decision of a SKU is independent of the decisions for other SKUs. Given the short computational time, it was not required to apply additional heuristics or simplifications to the mathematical model.

5.2. Model Verification

Model verification is performed by checking the overall consistency of the model's structure. Additionally, its response to changes in decision variables and parameter values has been tested. To assess model behavior, extreme values are applied. To ensure that the opportunity costs of keeping in stock are included in the verification, $\alpha = 1$ is used across experiments.

5.2.1. Model Consistency

First, the code is verified by checking that the decision variables, objective function and constraints are correctly implemented according to the mathematical model. Additionally, it is checked that the definition of the sets $\mathcal{F}_g$ and $\mathcal{I}_g$ correspond to the mathematical model (Equation 4.1, 4.2, 4.3, 4.4). The correctness of these sets is also checked manually for a subset of SKUs.

An optimization gap smaller than 1×10^{-325} implies that the model very closely approximates the global minimum. The objective function is manually computed by decomposing the objective function into the

following elements: inventory holding costs, working capital costs, return costs, opportunity costs of clearing, opportunity costs of keeping in stock. In every model run, it is confirmed that the manual cost calculation coincides with the value of the objective function. Additionally, it is checked that the constraints are adhered to: for each SKU exactly one decision is made: return, liquidate, or keep in stock. Also, only SKUs that are eligible are actually returned.

5.2.2. Behavioral Testing: Decision Variables

Model behavior related to control decisions is verified by fixing the values of the binary decision variables one by one and assessing whether the model responds as expected. This verification is performed with the excess stock data set of 27 November 2024, the experiments and results are shown in Table C.1 in Appendix C. Some key insights and conclusions are discussed below.

Per experiment, one of the decision variables (w_g, x_g, y_g) is fixed at 0 or 1, for all SKUs within a specific set ($\mathcal{G}$, $\mathcal{G}_r$ or $\mathcal{G}_{nr}$). This test is repeated for all sets and decision variables, resulting in a total of 18 experiments (3 sets, 3 decision variables, 2 values per decision variable), and one base scenario where no additional constraints are added.

Each run resulted in an effective optimality gap of 0% and the manual cost calculation coinciding with the value of the objective function. Across runs, the total number of SKUs, and number (not) eligible for return, correspond to $\mid \mathcal{G} \mid$, $\mid \mathcal{G}_r \mid$ and $\mid \mathcal{G}_{nr} \mid$. This suggests correct formulation of the sets. Additionally, it has been verified that costs are only incurred if the related control decision is executed (e.g., return costs are zero if no returns are made).

In the base scenario, the value of the objective function is - €165.5k. As the objective function expresses costs, this negative value denotes a profit increase. This is driven by the negative opportunity costs of clearing: more revenue is generated by clearing than retaining stock. Each experiment constrains one of the decision variables, reducing the solution space, thereby yielding a less optimal values of the objective function compared to the base case. The deterioration, thus cost increase, is largest for experiments that prohibit returns for SKUs eligible for return ($g \in \mathcal{G}_r$), even yielding a positive objective function value. The least optimal objective function value (€781.3k) occurs when all SKUs are forced to be kept in stock - increasing the total costs with €946.8k compared to the base case optimization.

The value of the objective function is minimally affected in the following two cases: all SKUs not eligible for return are liquidated; all SKUs eligible for return can not be liquidated. The first experiment affects the optimal control decision for only 159 SKUs (0.8% of total), leading to a small deterioration in the value of the objective function (+ €5.7k). The second experiment only affects one SKU, leading to a negligible total cost increase of €0.05.

One experiment yields the same objective function value as the base case: $x_g = 0 \; \forall g \in \mathcal{G}_{nr}$. This is sensible, the condition was already ensured by constraint 4.8: SKUs not eligible for return cannot be returned.

It is concluded that the model behaves as expected in relation to changes in decision variables.

5.2.3. Behavioral Testing: Parameter Values

In this section, the model is verified by setting extreme values for model parameters one by one. In total 11 different parameters are included, using a minimum and maximum value of 0 and 100,000 (except for C^w where 0% and 100%, and D_g^e where 85 and 100k are used). In each experiment, an extreme value is applied to one model parameter for a set of eight SKUs with different characteristics (return eligibility, financing status, expected days in stock, etc.). The experiments and key findings are included in Table 5.1; the set of SKUs is shown in Table C.2 in Appendix C. Since only one parameter is varied per experiment, the other parameter values equal the base case mentioned in Table C.2.

Through experiments, it has been verified that all constraints are adhered to: for each SKU exactly one control decision is taken, a SKU can only be returned if eligible, and decision variables are binary.

Additionally, it was shown that if the price of a certain control decision equals €100k (selling price, return price, liquidation price), this is the optimal decision for all (eligible) SKUs. Moreover, it was found that control decisions are significantly influenced by the expected days in stock. This is sensible as D_g^e affects all cost components in the objective function, except for the return costs. Across experiments, control

decisions are independent of the financing status (current/future) of a SKU. This hypothesis is specific for the values selected in Table C.2 and will be further tested in section 5.3.

Table 5.1: Results of verification experiments

Exp. #	Parameter	Values		Key Insights
1	P_g^s	€0	€100k	$P_g^s = 0$: all SKUs are returned, or liquidated (if not eligible for return). This is sensible since regular sale (keep in stock) does not generate revenue. $P_g^s = 100k$: SKUs are retained, sensible since regular customer sale generates such high revenues. Control decisions not affected by value of D_g^e, F_g^c, F_g^f.
2	N_g	€0	€100k	SKUs are only kept in stock if $N_g = 0$ and $D_g^e = 100$. SKUs are cleared if: either $D_g^e = 1095$, or $D_g^e = 100$ and $N_g = 100k$. In these cases, costs associated with keep in stock (holding, working capital, opportunity costs of keeping in stock) exceed the costs of clearing (transport costs, opportunity costs of clearing). It underlines that control decisions are not purely affected by the value of N_g, but are dependent on the eligibility of return and D_g^e.
3	C_g^s	€0	€100k	If $C_g^s = 100k$, SKUs are cleared (returned or liquidated). If $C_g^s = 0$, SKUs are kept in stock if $D_g^e = 100$ and cleared if $D_g^e = 1095$.
4	P_g^r	€0	€100k	If $P_g^r = 100k$ and the SKU is eligible for return, it is returned. This is sensible due to the high revenues. In the other scenarios, return is either not attractive due to $P_g^r = 0$, or not possible. If SKU not eligible and $D_g^e = 0$ it is kept in stock, if $D_g^e = 1095$ it is liquidated.
5	C_g^r	€0	€100k	All SKUs with $D_g^e = 100$ are kept in stock (independent of C_g^r). Only SKUs that are eligible for return with $D_g^e = 1095$ and $C_g^r = 0$ are actually returned. This is sensible since return costs of €100k would make a return not profitable. Since return costs are normally already low (€0.10-1.21), zero return costs are not likely to largely affect optimal control decisions.
6	P_g^l	€0	€100k	If $P_g^l = 100k$, SKUs are liquidated. This is sensible due to the high revenue compared to keep in stock and return. For $P_g^l = 0$ and $D_g^e = 1095$, eligible SKUs are returned, non-eligible SKUs are liquidated. Liquidation with zero revenue appears more attractive because it eliminates the high costs associated with keeping the SKU in stock, driven by the high value of D_g^e. SKUs with $P_g^l = 0$ and $D_g^e = 100$ are kept in stock.
7	D_g^e	85	100k	All SKUs with $D_g^e = 85$ are kept in stock. For $D_g^e = 100k$ all items are cleared. Immediate clearance is financially more attractive (saving holding and working capital costs over 100k days, and saving opportunity costs of keeping in stock). This is sensible, and also shows that D_g^e directly affects the control decisions.
8	C^w	0%	100%	SKUs with $D_g^e = 1095$ are all cleared, independent of the value for C^w. SKUs with $D_g^e = 100$ are kept in stock if $C^w = 0\%$, and cleared if $C^w = 100\%$. Thus, C^w affects control decisions but not independently of D_g^e.
9	M	€0	€100k	This experiment generates the exact same control decisions as C^w. This is sensible as a high value for M increases the opportunity costs of keeping an item in stock, making this less attractive (similar to C^w). Again, M affects control decisions, but not independently of D_g^e.
10	L	0	100k	All SKUs with $D_g^e = 100$ are kept in stock. For $D_g^e = 1095$ SKUs are returned if eligible, otherwise liquidated. With these selected parameter values, the control decisions are independent of L (control decisions equal the base scenario).
11	D	0	100k	All SKUs with $D_g^e = 1095$ are returned if eligible, otherwise liquidated. For $D_g^e = 100$, items are kept in stock if $D = 100k$ and cleared if $D = 0$ (returned if eligible, otherwise liquidated). The lower the value for D, the higher the opportunity cost of keeping in stock, the more attractive clearing becomes.

5.2.4. Conclusion

The BP model in Python is verified and behaves as expected. For each SKU, exactly one control decision is taken, affecting the entire excess stock level of that SKU. Additionally, SKUs are only returned if they are eligible for return. The costs of control decisions are correctly accounted for in the objective function. The value for expected days in stock (D_g^e) appears to significantly affect the optimal control decision. On the contrary, whether a SKU is currently or future financed does not seem to largely influence the control decision. However, this could be driven by the selected values for D_g^e. Possibly, F_g^f and F_g^c do affect the optimal solution if D_g^e takes less extreme values.

Some preliminary insights into excess stock management policies are created (in the situation that warehouse capacity is limited). A policy in which all excess SKUs are kept in stock, generates the highest costs (least attractive). In general, SKUs that are eligible for return should not be liquidated (with one exception). Liquidating all SKUs that are not eligible for return, or not allowing liquidation for SKUs eligible for return, both result in near-optimal results. As such, the set of SKUs eligible for return likely significantly impacts control decisions. These hypotheses and conclusions are preliminary. Further analysis is required and will be performed in the results sections, sensitivity and scenario analyses.

5.3. Optimization of Excess Inventory Management

The model has been optimized for the excess inventory within the [Product Category] of [Company XYZ] on 27 November 2024. The results are therefore not representative of the full stock, but specific to the subset that is considered to be excessive: SKUs with projected stock days greater than 12 weeks, with excess stock levels equaling the number of items that is expected to be sold after 12 weeks. As discussed in section 4.2, this corresponds to the definition of excess stock used by [Company XYZ].

The results will focus on the optimal control decisions and resulting costs of managing excess inventory. The optimal control decisions are described by the number of SKUs that is affected, rather than the number of items. As the optimization is performed at the level of the SKU, this allows for easier interpretation of model behavior. Nevertheless, the affected number of items gives insight into the scale and consequences for excess stock management. Therefore these are included for reference in Table D.1 in Appendix D.

Optimal Control Decisions
Table 5.2 shows the optimized control decisions for the excess SKUs, in the situation of limited and unlimited warehouse capacity ($\alpha = 1$ and $\alpha = 0$). During high season with limited warehouse capacity, 81% of the excess SKUs should be cleared (returned or liquidated). During low season with unlimited capacity, only 69% of stock is cleared. From the 86% of the excess SKUs eligible for return, 0 percentage point is liquidated (for both limited and unlimited capacity). For those excess SKUs eligible for return, returning is actually optimal for 79% ($\alpha = 1$) or 69% ($\alpha = 0$), the rest is kept in stock. It is concluded that return is always preferred over liquidation, driven by the typically higher return price compared to liquidation price ([80-100%][17] of the NNPP vs. [5-20%][17] of the selling price).

Table 5.2: Optimized control decisions for managing excess stock: number of affected excess SKUs

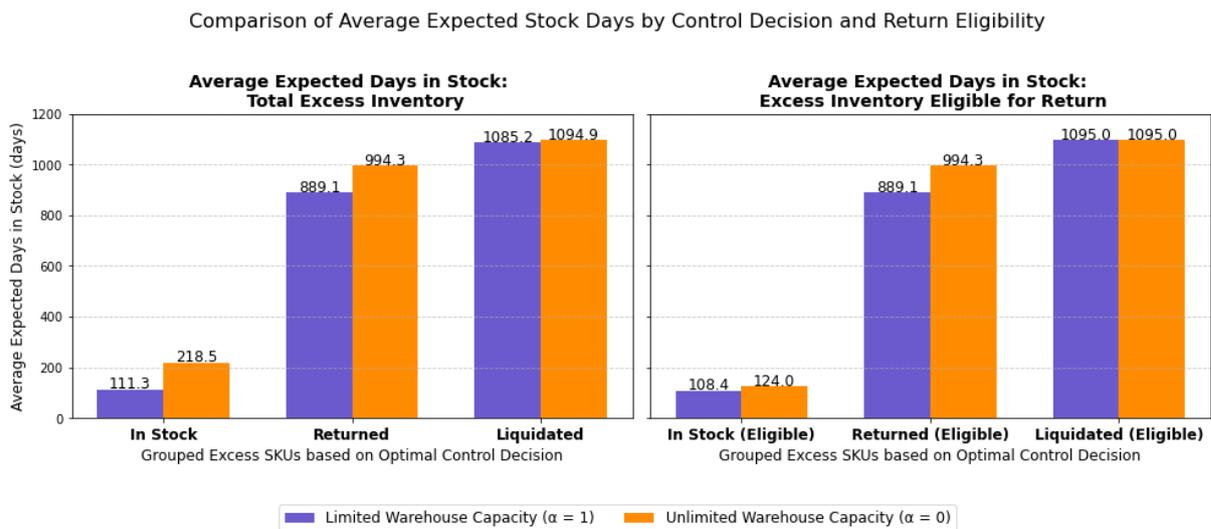|	Optimized Control Decisions				Eligible for Return			
	Total	In Stock	Return	Liquidate	Total	In Stock	Return	Liquidate
Limited Warehouse Capacity ($\alpha = 1$)								
Number of SKUs	19.1k	3.6k	12.8k	2.6k	16.3k	3.5k	12.8k	0.0k
% of Total	100%	19.1%	67.3%	13.6%	85.5%	18.3%	67.3%	0.0%
Unlimited Warehouse Capacity ($\alpha = 0$)								
Number of SKUs	19.1k	5.9k	11.2k	2.0k	16.3k	5.1k	11.2k	0.0k
% of Total	100%	30.6%	58.8%	10.6%	85.5%	26.7%	58.8%	0.0%

When considering the number of items affected by optimization (Table D.1) instead of SKUs, this shows an increased keep in stock rate. Under limited capacity, 23% of the excess items are kept in stock (vs.

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[17] For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

19% of the SKUs). Under unlimited capacity, this discrepancy increases further: 41% of the excess items is kept in stock, compared to 31% of the SKUs. This implies that SKUs that are kept in stock typically have a higher excess stock level compared to those that are cleared. Additionally, the transition from limited to unlimited capacity leads to the retention of SKUs with higher excess stock quantities. Further research would be required to determine whether these patterns are coincidental or systematic.

Figure 5.1 shows the SKUs grouped by their optimal control decision (kept in stock, returned, liquidated) under the two capacity scenarios, comparing the average expected days in stock per group (average D_g^e across all SKUs in the group). These bar charts illustrate that fast-selling SKUs are kept in stock, whilst slower-moving SKUs tend to be cleared (return or liquidate). In case of limited warehouse capacity, fewer items are kept in stock, prioritizing faster-moving SKUs, resulting in a lower average value of expected days in stock across all groups (compared to unlimited capacity). Note that the high average values for the return and liquidate categories are likely affected by the large number of SKUs without sales forecast (D_g^e assumed to be 1,095).

Based on the results in Table 5.2 it is calculated that 21% ($\alpha = 1$) or 31% ($\alpha = 0$) of the SKUs eligible for return is kept in stock. Figure 5.1 shows that SKUs eligible for return, that are kept in stock, have low average expected days in stock of 108.4 or 124.0. This suggests that retention is only preferred over return for fast-selling SKUs. Note that the averages for the 'Returned' and 'Returned (Eligible)' category are similar as these groups consist of the same subset of SKUs (all returned SKUs are eligible for return). Additionally, the diagram suggests that, on average, liquidation is attractive for the slowest-moving SKUs. Under unlimited warehouse capacity, the average value of 1094.9 days SKUs implies that liquidation is optimal almost solely for SKUs without sales forecast.

Figure 5.1: Average expected days in stock across excess SKUs grouped by optimal control decision and eligibility of return

Excess Stock Costs
The optimized costs of managing the excess stock of 27 November 2024 are illustrated in Table 5.3. It shows that through optimization, negative costs are generated, suggesting that optimal excess stock management would generate additional profit for [Company XYZ]. This is driven by the negative value for opportunity costs of clearing, indicating that more revenue is generated by instantly clearing a SKU, instead of selling it to a regular customer (corrected for the time value of money).

For limited warehouse capacity, the costs of managing excess stock amount to - €165.5k (profit increase of €165.5k). In case of unlimited warehouse capacity, the costs become more negative: - €214.7k. This is mostly driven by the exclusion of opportunity costs of keeping in stock, and the decrease in opportunity costs of clearing.

When warehouse capacity is limited, in-stock costs (including the opportunity costs of keeping in stock) lead to the clearing of some SKUs, even if the selling price exceeds the return or liquidation price. This

creates opportunity costs of clearing. Should warehouse capacity become unlimited, the in-stock costs decrease due to the elimination of opportunity costs of keeping in stock. This raises the financial benefit required for return/liquidate to justify clearing the SKU compared to a regular sale. As a result, SKUs for which clearing was not as attractive, for example SKUs with a selling price exceeding the return price, are increasingly kept in stock. This generates lower opportunity costs of clearing. As such, the profit of excess stock management is higher under unlimited compared to limited warehouse capacity.

Table 5.3: Optimized costs for managing excess stock

	Total Costs	Costs			Opportunity Costs	
	Total	Holding	Working Capital	Return	Clearing	In Stock
Limited Warehouse Capacity ($\alpha = 1$)	- € 165.5k	€ 7.7k	€ 2.8k	€ 10.8k	- € 218.3k	€ 31.4k
Unlimited Warehouse Capacity ($\alpha = 0$)	- € 214.7k	€ 18.2k	€ 9.8k	€ 8.3k	- € 251.0k	€ 0.0k

Model Benefit

The financial benefit of the model is defined as the difference between the optimized and actual costs of excess stock. To this end, the optimized value of the objective function is compared to the objective function value resembling the current situation of [Company XYZ]. As the company's current return and liquidation process for excess stock is unstructured, accurately determining the current situation is challenging. To this end, both the expected and maximum benefit of the model are estimated.

Table 4.3 highlights an increase in returns in 2024 compared to 2023. To ensure a conservative estimate of the model benefit, 2024 is assumed represent the current situation of the company. Since the optimization is performed with data of 27 November 2024, and no additional returns or liquidations are scheduled for the remainder of the year, it is assumed that this data represents the total returns and liquidations for 2024.

Given limited warehouse capacity, the maximum benefit of the model is €946.8k (€21.44 per item), and the expected model benefit €435.2k (€9.86 per item). Given unlimited warehouse capacity, the maximum model benefit is €378.5k (€8.57 per item), and the expected model benefit €205.4k (€4.65 per item). Note that these values are valid under the assumption of the time-independent parameter values (subsection 4.4.1) and the real-time stock data of 27 November 2024 (subsection 4.4.2). Changes in these parameter values requires recalculation of the model benefit.

The maximum benefit is estimated under the assumption that [Company XYZ] would retain all excess inventory of 27 November 2024 ('do nothing': no returns or liquidations). The costs from retaining all excess inventory in stock are calculated using the optimization model, fixing the control decisions to 'keep in stock'. This yields total excess stock costs of €781.3k under limited warehouse capacity, and €163.8k under unlimited warehouse capacity. The maximum benefit of the model equals the difference between these costs, and the optimized costs resulting from the model (shown in Table 5.3).

To calculate the expected model benefit, the actual return, liquidation and retention rates of 2024 are used. As mentioned in subsection 4.2.2, the company had a 53.2% return rate, 45.2% in-stock rate and 1.6% liquidation rate. The model was used to calculate the costs associated with each control decision, if this control decision would be executed for the full excess stock. Table 5.4 describes how these costs, return, liquidation and retention rates are subsequently used to calculate the current costs of excess stock within the [Product Category] of [Company XYZ]. Lastly, these costs are compared with the optimal costs in Table 5.3 to calculate the expected model benefit.

In subsection 5.3.1 and 5.3.2, more detailed analysis is performed on the model results and behavior specified for limited and unlimited warehouse capacity. This will improve the understanding of effective excess stock management during high and low season.

**Table 5.4:** Calculation of current costs of managing excess inventory

Formula	Value
Direct Costs	
Inventory Holding Cost = In-Stock Rate · Holding Costs (if all kept in stock)	€ 49.1k
Working Capital Costs = In-Stock Rate · Working Capital Costs (if all kept in-stock)	€ 24.9k
Return Costs = Return Rate ÷ Eligible for Return % · Return Costs (if all eligible returned)	€ 9.1k
Opportunity Costs	
Opp. Cost for Clearing (Liquidation) = Liquidation Rate · Opp. Cost for Clearing (if all stock liquidated)	€ 9.0k
Opp. Cost for Clearing (Return) = Return Rate ÷ Eligible for Return % · Opp. Cost for Clearing (if all eligible returned)	- € 101.4k
Opp. Cost for Keeping in Stock = In-Stock Rate · Opp. Cost for Keeping in Stock (if all kept in-stock)	€ 279.0k
Total Costs for Excess Stock	
Limited Warehouse Capacity ($\alpha = 1$) = Sum of all cost components	**€ 269.7k**
Unlimited Warehouse Capacity ($\alpha = 0$) = Sum of all cost components excluding opp. costs of keeping in stock	**- € 9.3k**

5.3.1. Limited Warehouse Capacity

This section analyzes the results for the optimization of excess stock within the [Product Category] under the assumption of limited warehouse capacity ($\alpha = 1$), representing the high season.

Figure 5.2 below shows the optimal control decisions for four subsets of SKUs: eligible for return (yes/no), and financing (current/future). These subsets are mutually exclusive and collectively exhaustive, encompassing the entire set of excess SKUs. This shows that under the assumption of limited warehouse capacity:

- Given the typically significantly higher return price vs. liquidation price, SKUs eligible for return should not be liquidated. This is independent of their financing status.

- Nearly all currently financed SKUs should be cleared: 92% of SKUs eligible for return, and 97% of SKUs not eligible for return.

- For future financed SKUs, significantly more SKUs are kept in stock: over 50%.
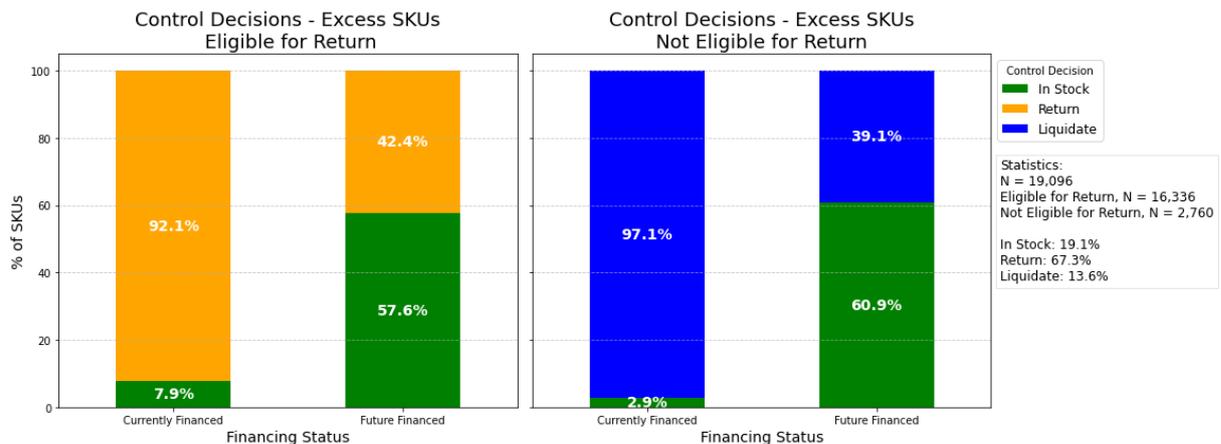
Figure 5.2: Distribution of optimal control decisions, under limited warehouse capacity

To gain insight into the effect of real-time stock parameters on the optimal decisions, various scatter plots have been created. These illustrate the optimal control decisions of excess SKUs, depicted as individual data points in a figure with real-time stock parameters plotted along the x- and y-axes (e.g., gross margin, expected days in stock). Comparing these plots revealed a clear relationship between control decisions, the expected days in stock, and financial upside of a control decision (vs. regular sale).

For SKUs eligible for return, the optimal control decisions show a clear relationship with the expected days in stock and benefit of return vs. regular sale[18]. This is shown in Figure 5.3. Closer inspection in Figure D.1 in Appendix D reveals a down-sloped 'threshold' in the scatter plot, denoting the split between

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[18]Defined as: benefit of return vs. regular sale = return price - transport costs - selling price.

optimal control decision 'keep in stock' and 'return'. As the expected days in stock increase, the costs associated with keep in stock rise as well (holding, working capital and opportunity costs of keeping in stock), resulting in a higher chance of being returned. Even with a slight negative benefit of return, indicating that the selling price is higher than the profit generated from a return, returning is still attractive. This suggests that the revenue loss from returning is smaller than the savings of in-stock costs (holding and working capital costs, opportunity costs of keeping in stock). The orange vertical line shows that all SKUs without sales forecast should be returned, under the assumption that these will remain in stock for 3 years on average.

Whereas Figure 5.2 seems to suggest that the financing status significantly affects the optimal control decisions (implied by the significant change in keep in-stock, return, and liquidation rates), this is contradicted by Figure 5.3. The threshold, dividing the 'return' and 'keep in stock' control decision, is similar for both currently and future financed SKUs. For future financed SKUs, working capital costs are incurred at a later point in time, making 'keep in stock' more attractive. This is reflected in a 'threshold' that is shifted upwards (see Figure D.1). As working capital costs tend to be small, only 0.014% of the NNPP per day (which is €19.59 on average[19]), the threshold has only shifted slightly. This suggests that the financing status does not largely affect the optimal control decision. The keep in stock rate for future financed SKUs (Figure 5.2) is not significantly higher due to the working capital costs, but due to the distribution of the SKUs. Comparing the current and future financed SKUs in Figure 5.3 shows that the share of SKUs with a negative benefit of return vs. regular sale, is significantly higher for future financed SKUs. As future financed SKUs have been in stock for a shorter period of time, they have been discounted less frequently, resulting in higher selling prices. This results in a lower average benefit of return vs. regular sale, making return less attractive, thus leading to a higher retention rate.

Note: Benefit of return vs. regular sale = return price - transport costs - selling price
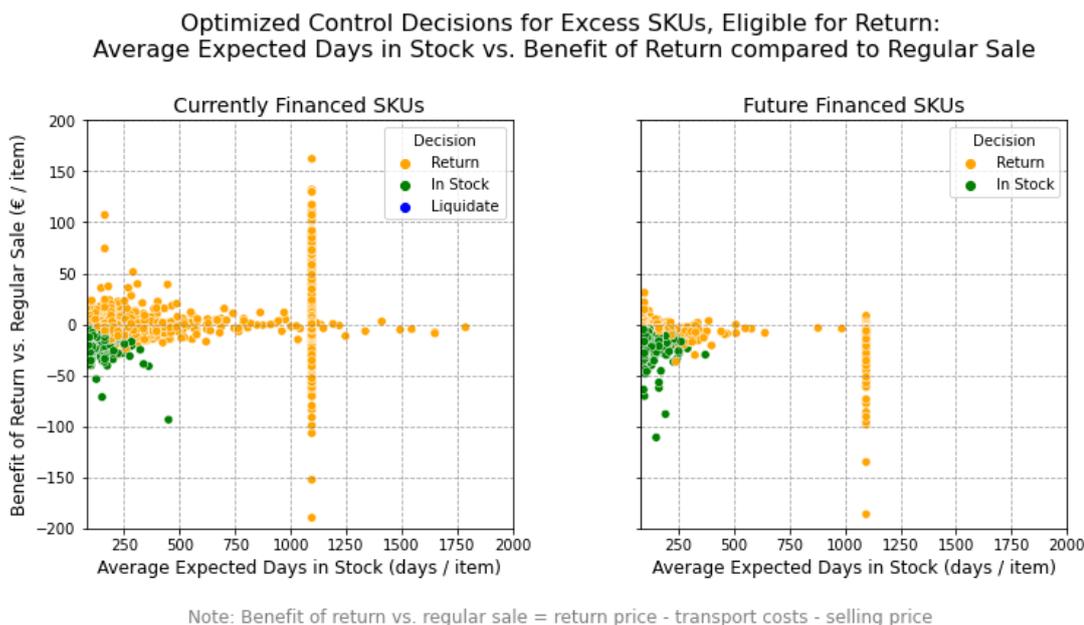
Figure 5.3: Optimized control decisions SKUs eligible for return: expected days in stock vs. benefit of return compared to regular sale, under limited warehouse capacity

Figure D.1 shows that the identified threshold for SKUs eligible for return is not a straight line: not all optimal control decisions can be defined by this threshold. Figure 5.4 demonstrates the same plot, but additionally includes the NNPP per item. The figure shows that SKUs, which optimal control decision cannot be characterized by the identified threshold, have an above-average NNPP. For currently financed SKUs this is an NNPP above 50 €/item, for future financed SKUs this is 30 €/item. These SKUs have greater working capital costs, making return attractive despite a larger financial downside of return. Additionally, SKUs with a higher NNPP typically have higher selling prices, resulting in larger value depreciation over time (in absolute terms), yielding lower opportunity costs of clearing and making return more attractive.

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[19]Weighted Average NNPP, based on the excess stock of the [Product Category] on 27 November 2024.

As the working capital costs tend to be relatively low (Table 5.3), opportunity costs of keeping in stock are expected to be the main driver.

Optimized Control Decisions for Excess SKUs, Eligible for Return:
Expected Days in Stock vs. Benefit of Return compared to Regular Sale

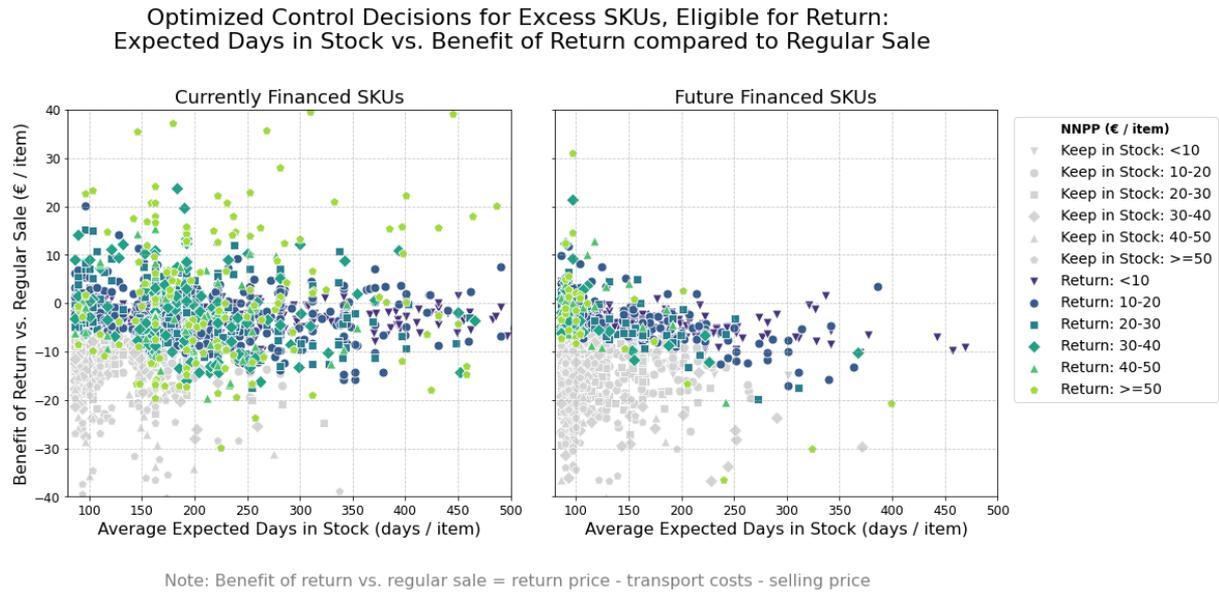Note: Benefit of return vs. regular sale = return price - transport costs - selling price

Figure 5.4: Optimized control decisions for SKUs eligible for return: expected days in stock vs. benefit of return compared to regular sale, and NNPP. Assumption: limited warehouse capacity.

For SKUs not eligible for return (Figure 5.5), the control decisions show a clear relationship with the expected days in stock, and the liquidation vs. selling price[20]. Note that the difference between the liquidation and selling price is always negative as the liquidation price equals [5-20%][21] of the selling price. A similar down-sloped 'threshold' as in Figure 5.3 can be identified: as the financial downside of liquidation becomes larger (more negative), the optimal decision shifts from liquidation to keep in stock. As the expected days in stock increases, liquidation becomes more attractive due to the in-stock cost savings. Again, all SKUs without sales forecast should be cleared, thus liquidated in this case.

Based on Figure 5.5 it is concluded that, similar to SKUs eligible for return, the financing status itself does not significantly affect the optimal control decisions. The higher keep in stock rates for future financed SKUs are driven by the typically lower benefit of return vs. regular sale - likely a consequence of the discounting procedure used by [Company XYZ]. The relationship between the optimal control decision, expected days in stock, and liquidation price vs. selling price, is relatively independent of the financing status.

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[20]Defined as: liquidation price vs. selling price = liquidation price - selling price.
[21]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

Figure 5.5: Optimized control decisions SKUs not eligible for return: expected days stock vs. liquidation price compared to selling price, under limited warehouse capacity

5.3.2. Unlimited Warehouse Capacity

This section analyzes the results for the optimization of excess stock within the [Product Category] under the assumption of limited warehouse capacity ($\alpha = 0$), representing the low season.

Figure 5.6 shows the optimal control decisions for four subsets of SKUs under unlimited capacity ($\alpha = 0$), representing the low season. Comparing this to the situation of limited capacity (Figure 5.2) shows that the optimal control decisions shift from clearing (liquidation, return) to keeping in stock. This observation holds for all four subsets of SKUs (eligibility of return and financing status) but is most apparent for future financed SKUs. Out of the future financed SKUs eligible for return, 72.6% should be kept in stock (vs. 57.6% under limited warehouse capacity). Out of the future financed SKUs not eligible for return, even 92.8% should be kept in stock (vs. 60.9% under limited warehouse capacity).

Figure 5.6: Distribution of optimized control decisions, under unlimited warehouse capacity

Under the assumption of unlimited warehouse capacity, the control decisions of SKUs eligible for return show a similar relationship as for limited capacity. As illustrated in Figure 5.7, the decision between 're-turn' and 'keep in stock' can again be characterized by a threshold based on the values for expected days in stock, and benefit of return vs. regular sale. Closer inspection in Figure D.2 showed that the thresh-

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old has shifted upwards with a flatter slope compared to the situation of limited capacity in Figure 5.3. Under unlimited warehouse capacity, opportunity costs of keeping in stock are omitted, not penalizing slow-moving items for taking up storage capacity. The costs associated with keep in stock are lower, requiring a higher benefit of return vs. regular sale to justify the return (denoted by the upward shift of the threshold). The flatter slope of the threshold suggests a reduced sensitivity to expected days in stock if warehouse capacity is unlimited. This is sensible as the expected days in stock significantly impact the opportunity costs of keeping in stock. These are omitted due to unlimited capacity, thereby reducing the sensitivity. As a result, optimal control decisions depend more directly on the benefit of return compared to regular sale. Similar to prior findings, all SKUs eligible for return without sales forecast should be returned. The control decision for SKUs eligible for return without sales forecast is thus independent of warehouse capacity and financing status. However, these control decisions are likely dependent on the assumed value of expected days in stock. This will be further tested in the sensitivity analysis.
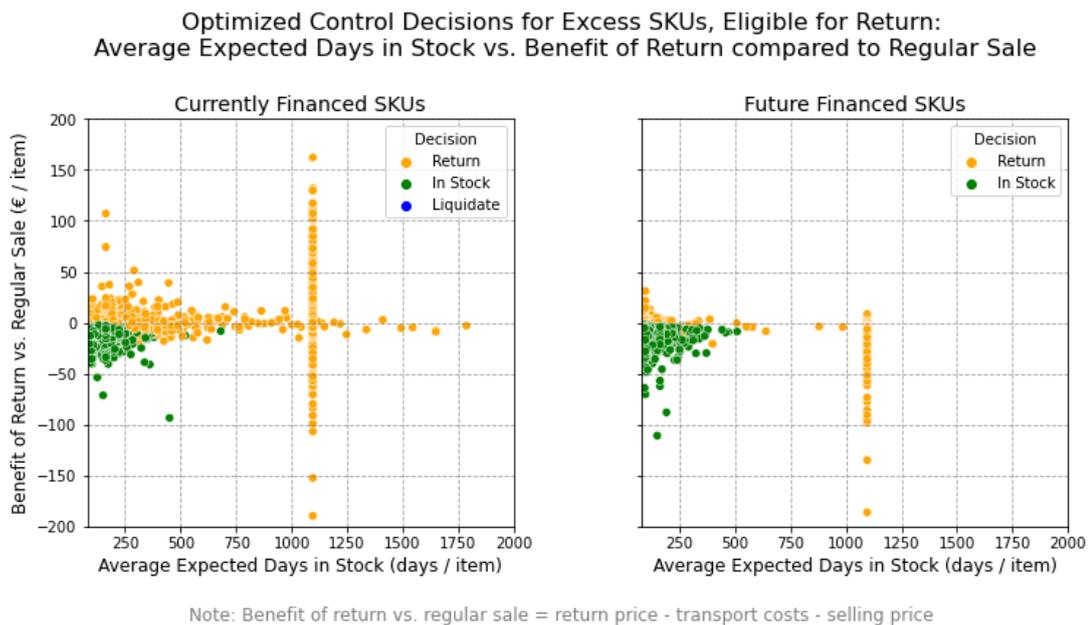
Figure 5.7: Optimized control decisions SKUs eligible for return: expected days in stock vs. benefit of return compared to regular sale, under unlimited warehouse capacity

Whereas under limited warehouse capacity, all SKUs not eligible for return and without sales forecast should be liquidated, this does not hold under the assumption of unlimited capacity. This becomes apparent from Figure 5.8, where no clear relationship between the control decision, expected days in stock, and liquidation vs. selling price can be identified. This suggests that additional real-time stock parameters affect the optimal control decision for this subset of SKUs under unlimited warehouse capacity. Figure 5.9 plots the optimal control decisions for SKUs not eligible for return without a sales forecast (assumed to be in stock for 3 years on average). This shows that control decisions of SKUs not eligible for return, without sales forecast and under unlimited capacity, are affected by both the liquidation price vs. selling price, and the daily holding costs. Again, some kind of threshold can be identified, splitting the control decisions 'liquidate' and 'keep in stock'. As the daily holding costs increase, the threshold value for liquidation price vs. selling price that is required to justify liquidation, decreases. Due to the lack of data for future financed SKUs, this observation only holds for currently financed SKUs not eligible for return without sales forecast, under unlimited warehouse capacity.

Figure 5.8: Optimized control decisions SKUs not eligible for return: expected days in stock vs. liquidation price compared to selling price, under unlimited warehouse capacity
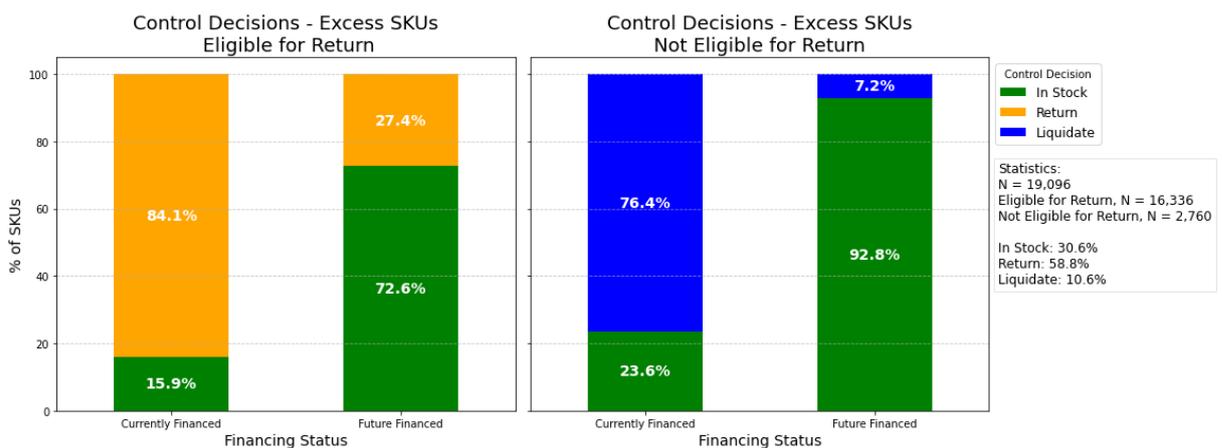

Figure 5.9: Optimized control decisions for SKUs without sales forecast and not eligible for return: daily holding costs vs. liquidation price compared to selling price. Assumption: unlimited warehouse capacity.

5.3.3. Conclusion

Optimizing the excess stock of the [Product Category] of [Company XYZ] on 27 November 2024 shows the critical role of warehouse capacity in determining reactive control strategies. Limited warehouse capacity, reflective of the high-season dynamics in November, yields a 67% return rate, 19% keep in-stock rate, and 14% liquidation rate. The excess stock costs amount to - €166k, implying that profit is generated from optimally managing this excess inventory. Comparing this to the estimated current excess stock costs of [Company XYZ] yields an expected model benefit of €435k, highlighting the financial benefit of clearing decisions under limited capacity due to significant opportunity costs associated with prolonged storage.

On the contrary, when warehouse capacity is unlimited and opportunity costs of keeping stock are excluded, the share of retained excess SKUs increases to 31%, returns and liquidations decrease to 59% and 11%. The total excess stock costs are - €215k, representing an expected cost improvement of €205k compared to the current situation (model benefit).

In both scenarios, it was found that SKUs eligible for return should not be liquidated, independent of warehouse capacity. Returns, and thus eligibility of return, also drive the expected financial benefit derived from the optimization model. This underscores the influence of return eligibility on control decisions for excess SKUs. Other key drivers of control decisions include the expected days in stock, benefit of return vs. regular sale, and liquidation price vs. selling price. These relationships are relatively independent of the financing status and NNPP of a SKU. Both the working capital and daily holding costs typically contribute minimally to the total excess stock costs. Nevertheless, daily holding costs influence decisions for a specific subset of excess stock: SKUs without sales forecast, not eligible for return, if warehouse capacity is unlimited.

Finally, a significant share of excess stock has no sales forecast for the coming 26 weeks, resulting in an assumed average of three years for expected days in stock. The assumption is likely to have affected the optimal control decisions for this 'no sales' inventory. This will be further tested in the sensitivity analysis (subsection 5.4.4).

5.4. Sensitivity Analysis

To understand how the optimal solution is affected by parameter values, sensitivity analysis is performed. Parameter values are varied between -100% to 100% compared to the base case values of subsection 4.4.1. The section performs sensitivity analyses with the discount rate of excess stock, daily working capital costs, opportunity cost of keep in stock (average days in stock, average lead time, average contribution margin, discount rate overall stock), assumed expected days in stock for SKUs without sales forecast, and the projected days in stock threshold for defining excess stock.

The model sensitivity to real-time stock parameters was already explored in the scatter plots that were created as part of the results analysis. This showed that the optimal solution is significantly affected by: expected days in stock, benefit of return vs. regular sale, and liquidation price vs. selling price. Therefore, no further sensitivity analyses with real-time stock parameters is performed.

5.4.1. Model Sensitivity to Discount Rate Excess Stock

By definition of the objective function (Equation 4.6), the daily discount rate of excess stock affects both the in-stock costs (inventory holding and working capital costs) and opportunity costs of clearing. In the base scenario, the daily discount rate of excess stock is 0.086% (coinciding with a yearly discount rate of 37%). An increased discount rate reduces in-stock costs and opportunity costs of clearing, increasing the financial attractiveness of all control decisions. Therefore, changing the discount rate results in a trade-off between the cost improvements of these control decisions costs.

The sensitivity analyses for the excess stock discount rate are shown in Figure 5.10 (limited capacity) and Figure 5.11 (unlimited capacity). These diagrams show that the excess stock discount rate significantly influences return and retention decisions. Under unlimited warehouse capacity also liquidation decisions are significantly affected. If the discount rate decreases, the retention rate increases. If the discount rate increases, the return (and liquidation) rates increase - by clearing the SKUs, value depreciation is avoided, yielding a larger relative benefit of clearance. This results in more negative opportunity costs of clearing and total costs. Under limited capacity, the total excess stock costs vary between €128k to - €315k, representing a change in costs of + €293k to - €150k compared to the base case. Under unlimited capacity, the total excess stock costs vary between €33k to - €345k, representing a cost change of + €247k to - €130k.

Under unlimited capacity, reflecting the low season, liquidation rates are more sensitive to changes in the discount rate. Absence of capacity limitations allows for more flexibility in selecting control strategies, increasing the model's sensitivity to financial incentives, such as the depreciation in excess stock value that is avoided by liquidation. Despite this, the total costs demonstrate a lower sensitivity for unlimited capacity.

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Model Sensitivity Analysis to Daily Discount Rate Excess Stock (α=1)
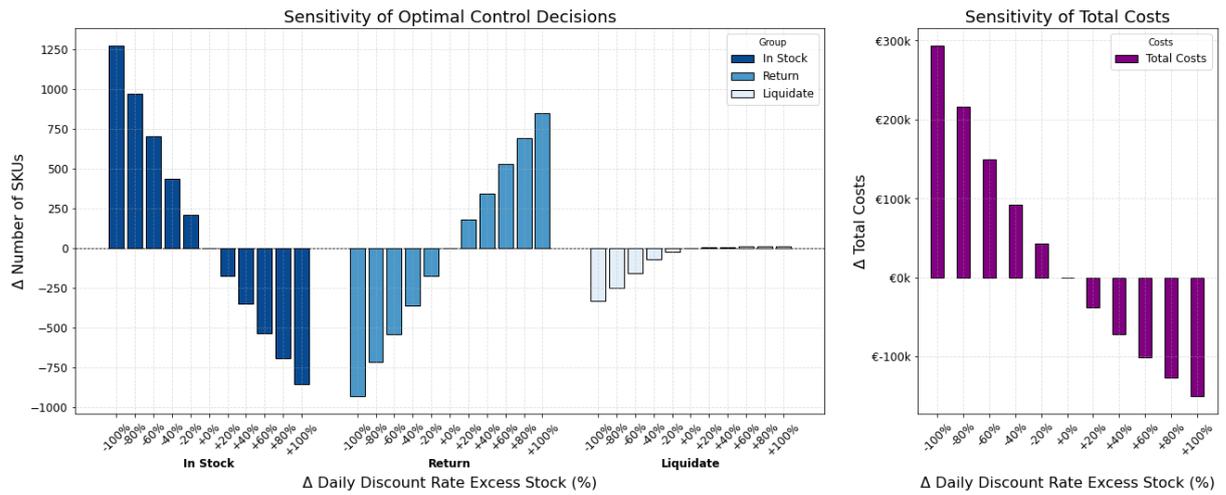
Figure 5.10: Model sensitivity to discount rate excess stock, under limited warehouse capacity

Model Sensitivity Analysis to Daily Discount Rate Excess Stock (α=0)
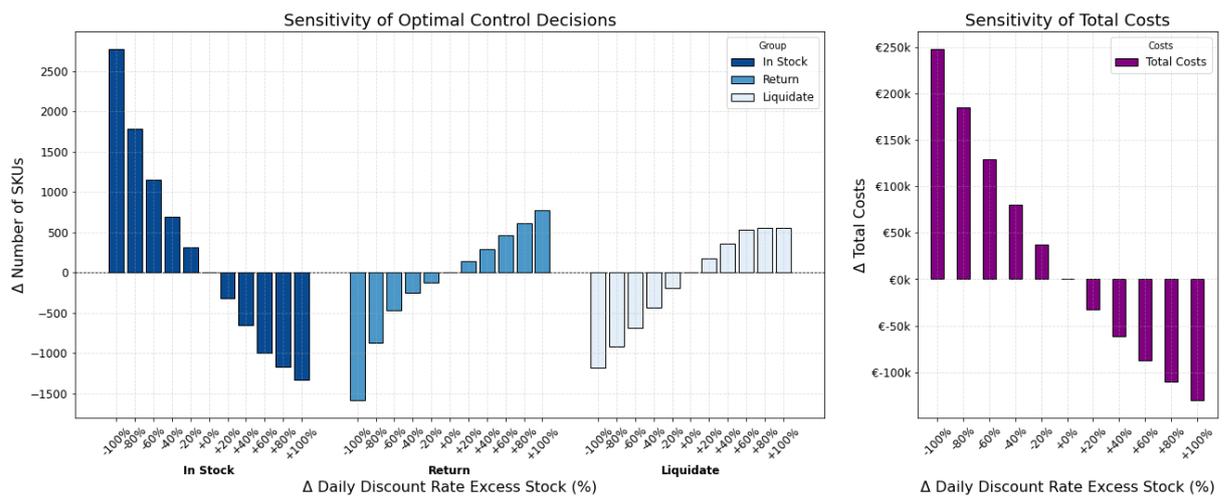
Figure 5.11: Model sensitivity to discount rate excess stock, under unlimited warehouse capacity

The results suggest that the discount rate of excess stock significantly affects the total excess stock costs. Control decisions are also affected, primarily through the effect on the opportunity cost of clearing (rather than through working capital and holding costs). Furthermore, the findings emphasize the importance of accurately calibrating discount rates, particularly during high-season periods where opportunity costs are high.

5.4.2. Model Sensitivity to Working Capital Costs

Analysis showed that the model is relatively unsensitive to changes in the daily working capital costs (as % of the NNPP). The sensitivity was larger for the situation with unlimited capacity. Therefore, these results are included in Figure 5.12 while the sensitivity analysis for limited capacity is included in Figure E.1 (Appendix E). With a base case value of 0.014% per day, the daily working capital costs are varied between 0% to 0.028%. Under unlimited warehouse capacity, at the extreme parameter values, only around 600 SKUs (out of 19,096) are affected. From these, it is mostly liquidation and retention decisions that are influenced - return decisions seem stable. Due to this insensitivity and generally low values of working capital costs (maximum of €11.9k), the total costs only change with - €11.2k to + €7.6k compared

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to the base case total costs of €214.7k. These findings suggest that, while working capital costs should be monitored, they do not significantly affect the financial performance of excess stock management.

Model Sensitivity Analysis to Daily Working Capital Costs (α=0)
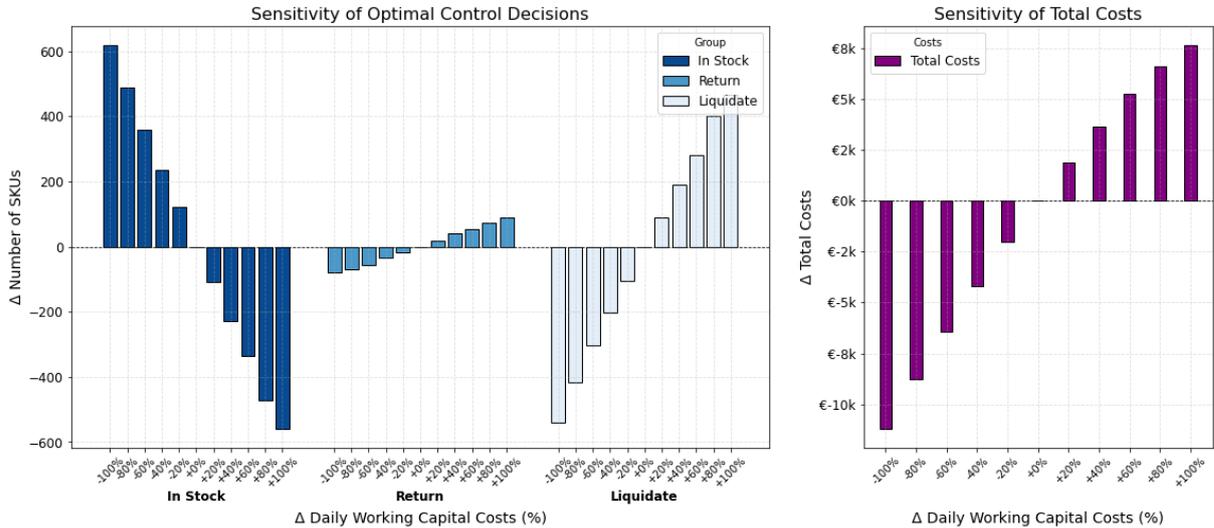
Figure 5.12: Model sensitivity to daily working capital costs, under unlimited warehouse capacity

5.4.3. Model Sensitivity to Opportunity Costs of Keeping in Stock

This subsection performs sensitivity analyses for all parameter values affecting the opportunity costs of keeping in stock: average days in stock per item (D), average lead time per item (L), average contribution margin per item (M), and discount rate overall stock (R^o). As shown in the mathematical model (section 4.3), the opportunity costs of keeping in stock SKU g with average expected stock days D_g^e and excess stock level S_g, are defined as follows:

$$S_g \cdot \alpha \left(\frac{D_g^e}{D + L} \cdot \frac{M}{(1 + R^o)^D} \right) \tag{5.1}$$

Since the opportunity costs of keeping in stock only play a role for limited warehouse capacity, the sensitivity analysis is performed with $\alpha = 1$. A decrease in the average days in stock, average lead time, and discount rate of overall stock, generate higher opportunity costs of keeping in stock. The average contribution margin has an opposite effect: the higher the margin, the higher the opportunity costs of keeping in stock. Increased opportunity costs imply that more financial benefit could be generated by storing other, faster-selling products. As such, excess stock retention is more expensive.

The analyses showed that the model is relatively unsensitive to changes in the overall discount rate and average lead time. To ensure comprehensibility of the report, these are included in the Appendix E in Figure E.2 and E.3. Even despite extreme changes in the overall discount rate R^o (-100% to +100%), maximum 28 SKUs are affected, changing total costs with just €512. As shown in Equation 5.1, the impact of the overall discount rate decreases as the average stock days increase, leading to small differences in opportunity costs across SKUs with high average stock days. The low sensitivity to average lead time (L) can be attributed to its initial value of only [7 days][22] compared to the average stock days (D) of [60 days][22]. Due to the dominance of D, opportunity costs of keeping in stock are minimally affected by changes in L (illustrated in Equation 5.1).

Figure 5.13 shows that changing the average days in stock has little to no effect on liquidation decisions. The return and keep in stock rate are significantly affected however - especially by a decrease in average stock days. In the extreme case that the average stock days for the products would be zero, the retention

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[22]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

rate reduces to 0% - keeping the item in stock would result in very high opportunity costs (if another item is stored, it would sell within a day). In the other extreme (+100% vs. base case), the retention rate increases to 24% (vs. 19% in the base case).

In practice, both extreme values of average stock days, are unlikely to occur. Average stock days between -60% to +60% of the base case value are more likely. For average stock days of -60% vs. base case, the costs increase with €25k, representing a 15% deterioration. For +60% average stock days, the costs change with - €13k, representing an 8% improvement. In both cases, total costs remain negative, implying that optimal excess stock management generates increased profits with €140k - €179k.

Model Sensitivity Analysis to Average Days in Stock (α=1)

Average Days in Stock for the Full Stock, including Non-Excess Inventory
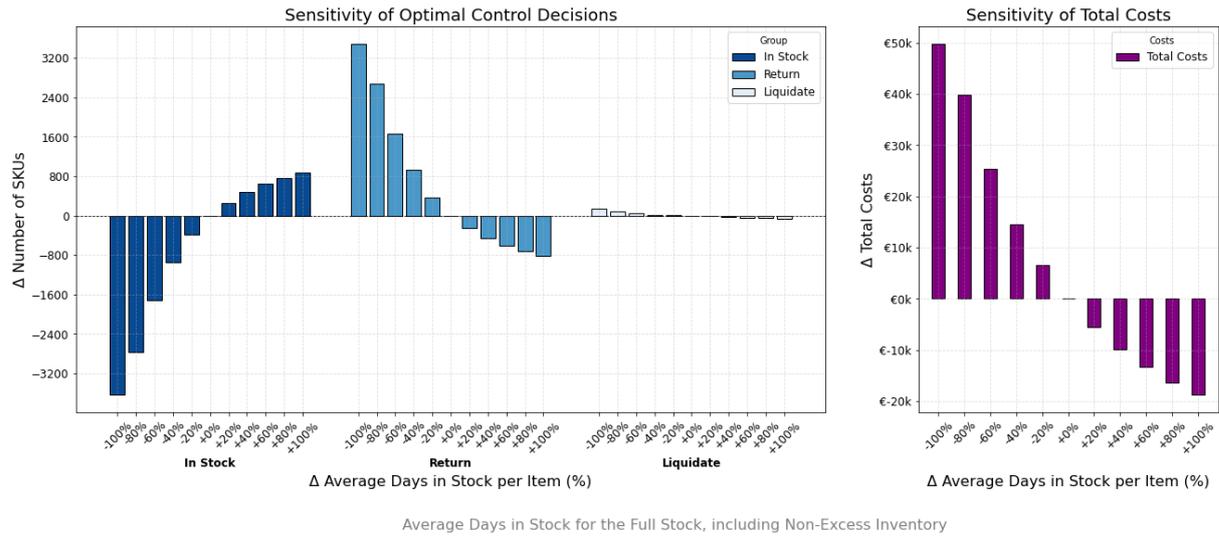
Figure 5.13: Model sensitivity to average days in stock per item, under limited warehouse capacity

Figure 5.14 shows that changes in the average contribution margin predominantly affects retention and return decisions. The costs are primarily affected by a decrease in the average contribution margin, resulting in cost improvements. With opportunity costs being directly proportional to the contribution margin, a lower margin reduces the costs associated with excess stock retention. Thereby, the cost differential between retention and clearance is narrowed, yielding lower total costs. An average contribution margin of 0% results in zero opportunity costs, generating the same results as the base case optimization under unlimited warehouse capacity.

Concluding, opportunity costs are most significantly affected by variations in average stock days and contribution margin, while changes in lead time and discount rate have a negligible impact. Across a realistic range of parameter values, the model consistently generates negative total excess stock costs, implying increased profits under optimal control decisions.

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Figure 5.14: Model sensitivity to average contribution margin per item under limited warehouse capacity

5.4.4. Model Sensitivity to Expected Days in Stock for SKUs without Sales Forecast

Out of the excess stock on November 27 2024, 65% of the SKUs have no sales forecast for the coming 26 weeks. In the base case, it was assumed that SKUs without forecast remain in stock for 3 years on average (1,095 days). A sensitivity analysis is performed, altering this value from 6 months to 5.5 years. The minimum value of 6 months corresponds to the end of the forecast period, the period in which no sales are expected.

For limited warehouse capacity (Figure 5.15), optimal control decisions are only significantly affected if SKUs without sales forecast would be in stock for six months. This is highly unlikely however since zero sales are projected for the coming six months. Should SKUs without sales forecast remain in stock for a year, the control decisions of 825 SKUs are affected, representing only 4% of the total.

Therefore, given limited capacity, the assumption of 1,095 expected days in stock for SKUs without sales forecast, is not likely to have significantly impacted the optimal control decisions. However, excess stock costs have likely been affected by this assumption. Reducing the assumption to one year increases total excess stock costs by €112k, while extending the assumption to five years reduces costs by €82k. This significant change could be driven by the fact that expected days in stock affect all cost components included in the objective function, except for return costs. Additionally, the changed parameter value applies to a significant share of the excess stock, changing the costs of all these items.

Given unlimited warehouse capacity (Figure 5.16), optimal control decisions are significantly more sensitive to the assumed expected days in stock (for SKUs without sales forecast). Increasing this parameter value affects both liquidation and retention decisions, as opposed to limited warehouse capacity where the model was only sensitive to a decrease in expected stock days for SKUs without sales forecast. Return decisions are less affected, especially since the minimum value for expected stock days (six months) is unlikely in practice. The sensitivity of excess stock costs is similar in both capacity scenarios.

It is concluded that the total excess stock costs are significantly influenced by the number of days that SKUs without sales forecast will remain in stock. The control decisions itself are sensitive to this value only under unlimited warehouse capacity. In this scenario, it is mainly the retention and liquidation decisions that are affected. To accurately decide whether to liquidate or retain excess stock without sales forecast, better estimates of stock days beyond the current 26-week forecast period are required.

Model Sensitivity Analysis to Expected Days in Stock for Excess SKUs without Sales Forecast (α=1)
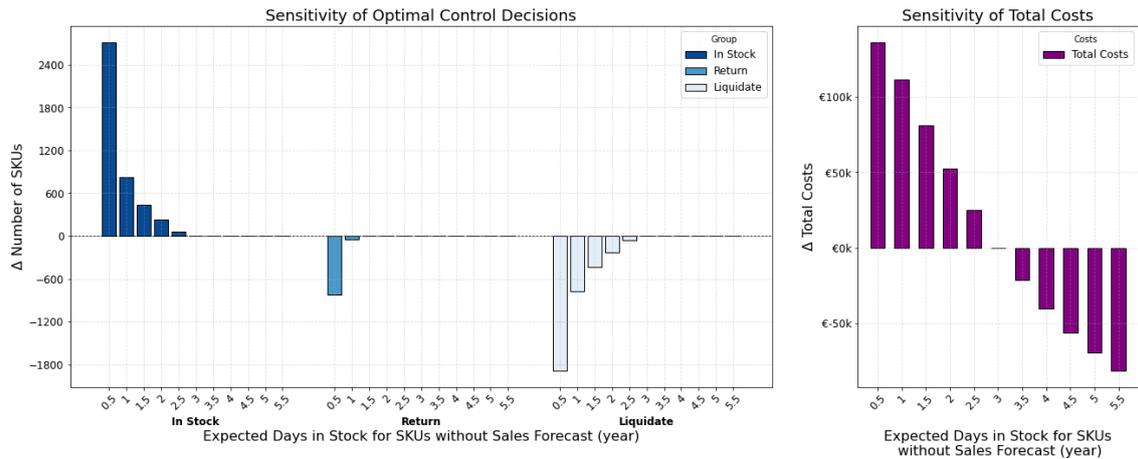
Figure 5.15: Model sensitivity to expected days in stock for SKUs without sales forecast, under limited warehouse capacity

Model Sensitivity Analysis to Expected Days in Stock for Excess SKUs without Sales Forecast (α=0)
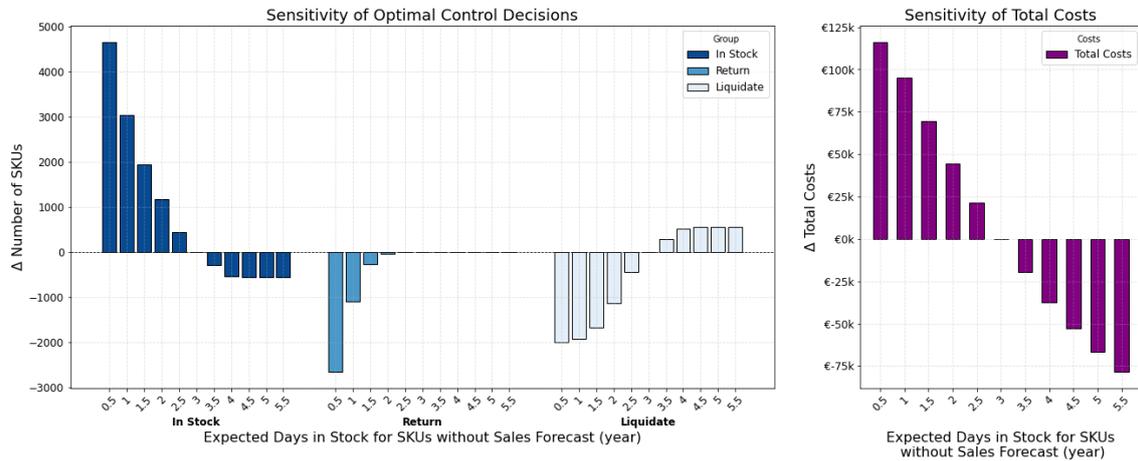
Figure 5.16: Model sensitivity to expected days in stock for SKUs without sales forecast, under unlimited warehouse capacity

5.4.5. Model Sensitivity to Excess Stock Definition

This section explores how changing the threshold for the excess stock definition, based on the projected stock days, would affect the optimal control decisions and expected model benefit (defined as the difference between the optimized and current excess stock costs). The current 12-week threshold for projected stock days is varied between 8 to 26 weeks, yielding a total of 15 different thresholds. Literature highlighted the importance of considering slow-moving inventory as potential dead stock. Since inventory with projected stock days up to 8 weeks is considered to be normal-moving within the [Product Category] (Table 4.1), this is considered to be the minimum threshold. The demand forecast is only available for the coming 26 weeks thereby serving as the maximum possible threshold. The model has been optimized using the 15 data sets, based on the different thresholds for identifying excess stock. For each optimization, the optimal control decisions are analyzed and expected model benefit is calculated.

Optimal Control Decisions Across Thresholds

The optimal control decisions across the various thresholds for defining excess stock are depicted in Figure 5.17. This shows that, as the threshold is lowered from 12 weeks, the set of excess SKUs increases. The expansion of the excess stock definition is mostly reflected in a growing number of SKUs that is retained. Only a small increase in the number of returns is observed, and the number of liquidated SKUs is stable. Increasing the excess stock threshold reduces the set of excess SKUs. Similarly, this

reduction is mainly reflected by the decrease in the number of SKUs that is retained. This observed model behavior is similar for both capacity scenarios.

When considering a 26-week threshold, the keep in stock rate is marginal. This can be explained by the fact that a large share of these excess SKUs does not have a sales forecast. These are assumed to remain in stock for 3 years. As shown in Figure 5.3, 5.5, 5.7, 5.8, nearly all of these SKUs should be cleared (dependent on the availability of storage capacity).
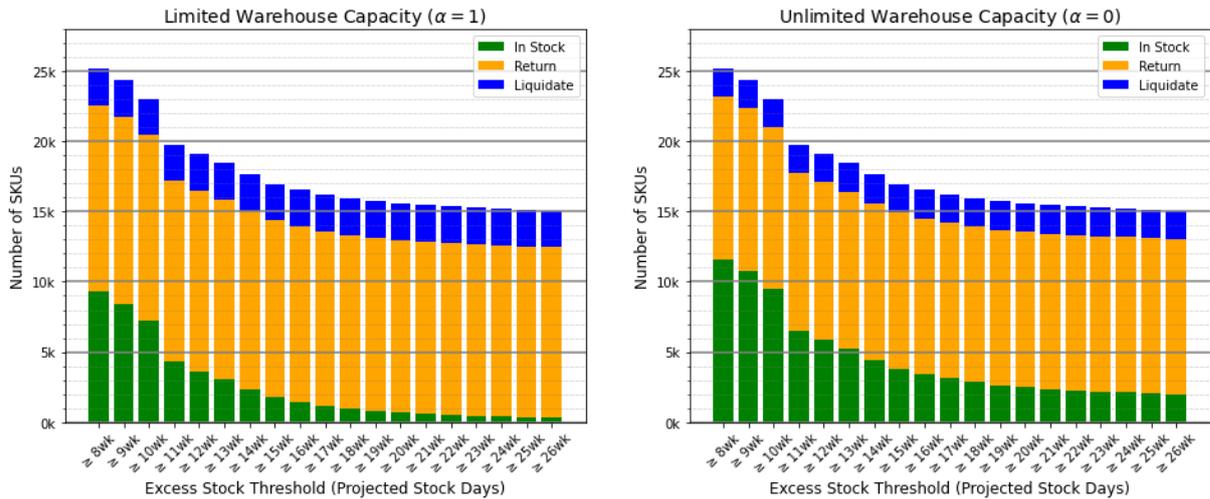
Figure 5.17: Optimal control decisions for excess stock management, across excess stock definitions

Recalculation of Expected Model Benefit
Currently, [Company XYZ] only returns and liquidates SKUs with projected stock days ≥ 12 weeks. As such, the actual return and liquidation percentages apply only to this subset of SKUs. To estimate the expected model benefit using a different threshold, the expected benefit of 12-weeks served as a base line: €435.2k for limited warehouse capacity, €205.4k for unlimited warehouse capacity. This 12-week benefit is adapted as follows:

For thresholds between 8-11 weeks, the 12-week benefit is increased with the benefit of including additional SKUs. For example, the 8-week model benefit is the sum of: the 12-week model benefit, and the difference between the optimal objective function for SKUs with projected stock days between 8-12 weeks and the objective function for keeping this subset in stock.

For thresholds between 13-26 weeks, the 12-week benefit is reduced to reflect the exclusion of SKUs with projected stock days between 12 weeks and the new threshold. For example, the 16-week model benefit is: the 12-week model benefit, minus the difference between the optimal objective function of excess stock with projected stock days of 12-16 weeks and the objective function for keeping this subset in stock.

Expected Model Benefit across Thresholds
Using the approach outlined above, the expected model benefit has been calculated across all excess stock thresholds. Additionally, the benefit per item is calculated as the total model benefit divided by the number of excess items. The results, under both limited and unlimited warehouse capacity, are illustrated in Figure 5.18. Table E.1 can be consulted for insight in the exact numbers.

Changing the threshold between 8-26 weeks has relatively little impact on the total model benefit. Relaxing the excess stock definition to 8 weeks would only increase the expected benefit with €10k ($\alpha = 1$) or €7k ($\alpha = 0$). Tightening the excess stock definition to 26 weeks is expected to decrease the model benefit only with €21k ($\alpha = 1$) or €10k ($\alpha = 0$). Compared to total costs, these changes are relatively small, driven by the fact the altering the threshold mostly affects the number of retained SKUs. As the financial benefit is largely driven by returned SKUs, the total expected model benefit is not significantly affected.

This also explains why the financial benefit under unlimited warehouse capacity is lower: more SKUs are kept in stock, yielding a smaller improvement in costs for excess stock management (compared to the current situation).

As the threshold is lowered to 8 weeks, a larger pool of SKUs is included in the optimization model (+32% compared to 12 weeks). From the additionally included SKUs, over 93% is kept in stock. As the retention rate increases, the model benefit per item decreases, suggesting a reduction in model efficiency.
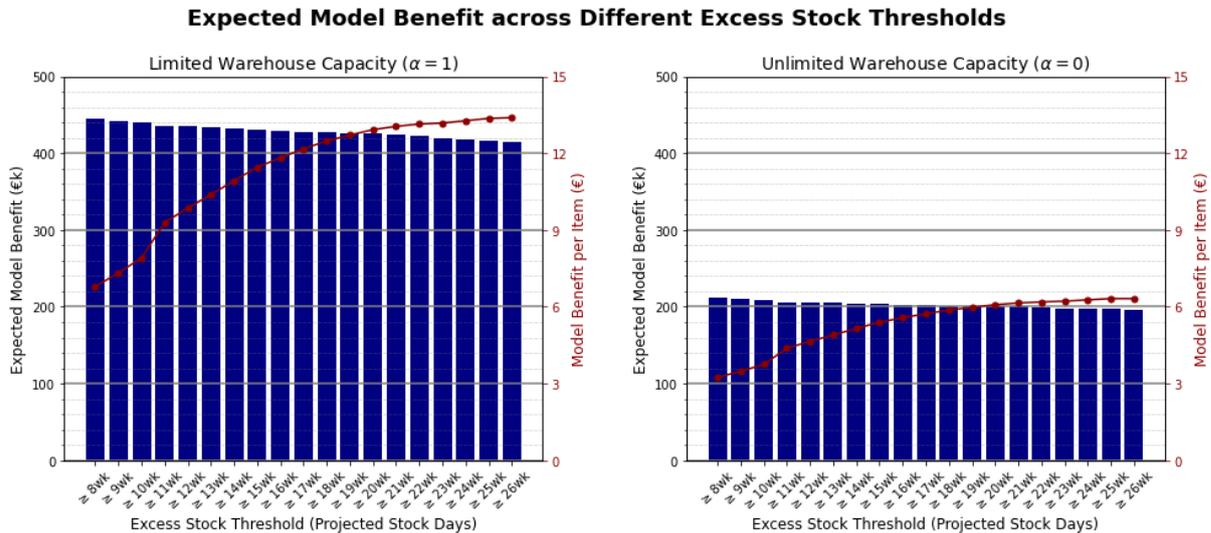
Figure 5.18: Expected model benefit across excess stock definitions, based on projected stock days (current threshold of 12 weeks)

Although the analysis showed that the expected model benefit is not significantly affected by the excess stock threshold value (ranging between 8-26 weeks), this conclusion has two important limitations.

First of all, the findings are dependent on the real-time stock data set. The distribution of the expected stock days is not uniform. A relatively small share of SKUs has projected stock days ranging between 11-26 weeks, contributing to the relatively small change in model benefit. Further experiments with different data sets would be required to generalize the findings of this sensitivity analysis.

Second, the expected model benefit is based only on costs included in the objective function (Equation 4.6): inventory holding costs, working capital costs, return costs, opportunity costs of clearing, and opportunity costs of keeping in stock (if limited storage capacity). Changing the excess stock threshold probably constitutes other costs that are currently not incorporated into the model. For example, by lowering the threshold, SKUs with relatively low projected stock days could be cleared. This affects the product assortment, availability and out-of-stock risk, possibly resulting in lower customer satisfaction and revenue losses (Tanaka & Sagawa, 2018). Further research would be required to assess what additional costs or benefits would be generated by changing the threshold. Combining these with the expected model benefit in Figure 5.18, would allow for selecting the most appropriate threshold for the excess stock definition.

5.4.6. Conclusion

The analysis demonstrates higher model sensitivity under unlimited warehouse capacity, compared to limited capacity (with the exception of daily discount rate of excess stock). Due to the reduced in-stock costs under unlimited capacity, excess stock policies demonstrate higher flexibility and thus sensitivity.

Discount rates for excess stock and opportunity costs of keeping in stock - specifically the contribution margin and average stock days - emerge as highly influential factors. Working capital costs minimally affect model outcomes, suggesting that these do not play a pivotal role in optimization. For SKUs without sales forecasts, assumptions about expected days in stock substantially influence costs, as well as liquidation and retention decisions under unlimited capacity. This highlights the importance of accurate forecasting.

Changing the excess stock definition has a relatively small impact on the expected model benefit. The model benefit would be maximized under an 8-week threshold for projected days in stock, yielding a 2-3% increase in model benefit. While the sensitivity analysis provides valuable insights, it is not sufficient for refining the excess stock definition. The model does not capture all costs and benefits associated with changing the excess stock thresholds (e.g., loss of customers, out-of-stock risks). Further research would be required to assess the financial implications paired with changing the threshold. These should be incorporated into the calculated values of expected model benefit, to assess whether changing the threshold is financially attractive.

In two cases, the model did not produce negative excess stock costs: daily excess stock discount rate of 0% or 0.017%. These low discount rates drive a shift to excess stock retention and significantly increase the opportunity costs of clearing. Nevertheless, the robust model performance across most realistic scenarios validates its applicability as a tool for excess stock management. Future research should focus on improved demand forecasting and calibration of the discount rate for excess stock.

5.5. Scenario Analysis

Scenario analysis is performed to see how certain inventory management policies would affect the optimal control decisions and financial performance of excess stock. In total, three different types of policies are assessed. First, subsection 5.5.1 assesses revenue opportunities by changing the liquidation policy from a general to specialized liquidator offering higher prices. Second, subsection 5.5.2 explores how the financial performance of excess stock would be affected if all excess SKUs with a total stock quantity of one (i.e., excess stock = 1 and non-excess stock = 0), are retained in inventory. Lastly, subsection 5.5.3 takes a different approach by assessing whether relatively simple decision rules for excess stock management could approximate the optimal solution obtained by the model.

The scenario analyses are performed using the excess stock data set of 27 November 2024. The experiments are performed for the situation with limited and unlimited warehouse capacity ($\alpha = 1$, $\alpha = 0$), representing the high and low season.

5.5.1. Scenario: Specialized Liquidation Policy

As mentioned in subsection 4.2.3, there is an opportunity for [Company XYZ] to liquidate products to a specialized party. Whereas the current general liquidator offers liquidation prices equaling [5-20%][23] of the selling price, the specialized liquidator offers prices of [10-30%][23] of the selling price (excl. VAT) for products that sell for [€12][23] or more. For simplicity, it is assumed that the VAT is 9% for all products.

Two different policies are explored:
Specialized Liquidation in which only items with a selling price above [€12][23] are liquidated at the specialized party.
Hybrid Liquidation in which items with selling prices below [€12][23] are liquidated to the general party, and items with selling price higher than [€12][23] to the specialized party.

Both policies are tested for limited and unlimited warehouse capacity ($\alpha = 1$, $\alpha = 0$). Table 5.5 shows the results of the optimization with the specialized liquidation policies, comparing these to the base case optimization (the results from section 5.3).

The effect of the two liquidation policies is relatively similar. During high season with limited warehouse capacity, optimal control decisions are barely influenced by a change in liquidation policy - only 2 SKUs are affected. During low season with unlimited warehouse capacity, the effect of a changed liquidation policy is more significant. For 274 SKUs, the optimal control decision shifts from keep in stock to liquidate. Considering the total of 19,096 SKUs, this effect remains small.

Under limited warehouse capacity, specialized liquidation generates a cost improvement (profit increase) of €4.1k or €5.1k (2.5% and 3.1%). Under unlimited warehouse capacity, specialized liquidation yields a lower cost improvement: €1.3k or €2.2k (0.6% and 1.1%). This yields an additional profit of €0.41 - €1.30 per item that is liquidated.

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[23]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

Limited warehouse capacity makes liquidation attractive at lower liquidation prices (compared to unlimited capacity) as it saves opportunity costs of keeping in stock, leading to a relatively high liquidation rate. Since SKUs are liquidated despite a relatively large downside of the liquidation price vs. selling price, an improvement in the liquidation price results in a larger cost improvement. Additionally, the number of SKUs liquidated is higher, yielding a larger absolute cost improvement of a new liquidation policy.

It is concluded that the financial benefit of specialized or hybrid liquidation is relatively little. Specialized and hybrid liquidation likely involves higher costs as liquidation in batches (together with other product categories) is not possible. Further research is required to assess whether the benefits outweigh the additional costs of designing, implementing and executing these liquidation policies.

Table 5.5: Expected benefit of specialized liquidation policies for excess stock

| | New Liquidation Policy | | | | Δ with Base Case | | | |
| | Number of SKUs | | | | Number of SKUs | | | |
	In stock	Return	Liquidate	Total Costs	In stock	Return	Liquidate	Total Costs
Limited Capacity								
Specialized Liquidation	3,649	12,847	2,600	-€ 169.7k	+1	+1	-2	-€ 4.1k
Hybrid Liquidation	3,646	12,846	2,604	-€ 170.6k	-2	0	+2	-€ 5.1k
Unlimited Capacity								
Specialized Liquidation	5,576	11,232	2,288	-€ 216.0k	-274	+1	+273	-€ 1.3k
Hybrid Liquidation	5,576	11,231	2,289	-€ 216.9k	-274	0	+274	-€ 2.2k

5.5.2. Scenario: Single-Item Retention Policy

[Company XYZ] is highly focused on growing market share. To reach this goal, the company has defined the strategy to offer a large selection of different products with short delivery times. Considering this, the company might execute a policy in which SKUs that are considered to be 'excessive', but have a total stock quantity of one item, are retained in stock. Such a policy would prohibit excess stock management from reducing product assortment and availability. In total, three different policies are tested under limited and unlimited warehouse capacity.

Single-Item Retention Policy 1: Keep in stock all excess SKUs with a total stock quantity of 1
Single-Item Retention Policy 2: Keep in stock all excess SKUs with a total stock quantity of 1, and expected days in stock < 365
Single-Item Retention Policy 3: Keep in stock all excess SKUs with a total stock quantity of 1, and expected days in stock < 182.5

Nearly half of the SKUs that is considered to be excessive, has only one item in the full stock (i.e., excess stock quantity = 1, non-excess stock quantity = 0). As such, policy 1, retaining all single-item excess SKUs, strongly affects excess stock management (illustrated in Table 5.6). Under limited warehouse capacity, 9.7k SKUs shift from clearing to keep in stock. This shift is mainly driven by a decreasing number of returns. As a result, the costs of managing excess stock increase with €408.8k to €243.3k. The constrained policy lowers the flexibility for excess stock management significantly - the model is not able to generate negative costs. Under unlimited warehouse capacity, both optimal control decisions and total costs are affected to a lesser extent.

On average, single-item excess stock is expected to be in stock for 1043 days, driven by the large share of SKUs without sales forecast (94%). Due to this distribution, policies 2 and 3 have a significantly smaller impact on the management of excess stock. Compared to the base case, the costs would only deteriorate with €1k to €6k, which is driven by the fact that only 63 to 268 SKUs are affected by these policies.

Only considering the additional costs from single-item excess stock retention provides an incomplete perspective. Additionally, the benefit from holding these SKUs should be incorporated, e.g., from increased customer loyalty or satisfaction. This lies outside the scope of the research however. Further research would be required to assess whether the increased costs of managing the excess stock outweigh the benefit that could be derived when retaining all excess SKUs that only have one item in stock.

Table 5.6: Expected benefit of polices for retention of single-item excess SKUs

	Retain Single Stock Excess SKUs				Δ with Base Case			
	Number of SKUs				Number of SKUs			
	In stock	Return	Liquidate	Total Costs	In stock	Return	Liquidate	Total Costs
Limited Capacity								
Single-Item Retention Policy 1	13,308	5,307	481	€ 243.3k	+9,660	-7,539	-2,121	+€ 408.8k
Single-Item Retention Policy 2	3,916	12,579	2,601	- € 159.5k	+268	-267	-1	+€ 6.0k
Single-Item Retention Policy 3	3,822	12,672	2,602	- € 164.2k	+174	-174	0	+€1.3k
Unlimited Capacity								
Single-Item Retention Policy 1	14,876	3,846	374	- € 49.8k	+9,026	-7,385	-1,641	+ € 164.9k
Single-Item Retention Policy 2	5,967	11,114	2,015	- € 211.1k	+117	-117	0	+ € 3.6k
Single-Item Retention Policy 3	5,913	11,168	2,015	- € 214.1k	+63	-63	0	+ € 0.6k

5.5.3. Scenario: Inventory Management using Decision Rules

Managing excess inventory through model optimization requires time and effort. The goal of this section is to explore whether simple excess inventory management decision rules could approximate the optimal solution, thereby enabling efficient low-cost excess inventory management.

In the results analysis, it was found that optimal control decisions are significantly influenced by the expected days in stock, benefit of return vs. regular sale, and selling price vs. liquidation price. Under unlimited warehouse capacity, also the daily holding costs affect the control decisions for SKUs not eligible for return, lacking a sales forecast. By defining threshold values for these metrics, sets of possible decision rules are established, specific to eligibility for return and availability of warehouse capacity. These decision rules are implemented in the optimization model as additional constraints. By comparing the results with the optimal solution, the effectiveness of policies can be tested.

Decision Rules for Limited Warehouse Capacity during High Season
As shown in Figure 5.3, SKUs eligible for return are either returned or kept in stock, not liquidated. As the decision is clearly characterized by the expected days in stock, and benefit of return vs. regular sale, these metrics are used to define decision rules. In total, 4 different threshold values for expected days in stock, and 10 different values for benefit of return, are used. The set of policy rules is established by selecting one threshold value for each metric, yielding a total of 40 different policy options.

Set of Possible Policies for SKUs Eligible for Return, under Limited Warehouse Capacity:

- Return SKU if:
    - *Expected Days in Stock* > {200, 250, 300, 350}, **or**
    - *Benefit of Return vs. Regular Sale* > {-2, -4, -6, -8, -10, -12, -14, -16, -18, -20}.
- Otherwise: Keep the SKU in stock

Testing each of these possible policies showed that the optimal solution is best approximated by a threshold of 200 for expected days in stock, and -6 for benefit of return vs. regular sale. Applying these decision rules yields total excess stock costs of managing excess stock of - €160k, representing a deterioration of €6k (3.2%) compared to the optimal solution.

For SKUs not eligible for return, the decision whether to keep in stock or liquidate is characterized by the expected days in stock, and liquidation price vs. selling price. Closer inspection of Figure 5.5 yielded a set of possible threshold values for each of these metrics, leading to the set of 12 possible policies below.

Set of Possible Policies for SKUs not Eligible for Return, under Limited Warehouse Capacity:

- Liquidate SKU if:
    - *Expected Days in Stock* > {400, 500, 600}, **or**
    - *Benefit of Liquidation vs. Regular Sale* > {-5, -10, -15, -20}.
- Otherwise: Keep the SKU in stock

Testing these policies yielded the best result for a threshold of 400 for expected days in stock, and -5 for liquidation price vs. selling price. The total costs of managing excess stock are - €165k, which is only a €0.4k or 0.2% deterioration compared to the optimal solution.

Decision Rules for Unlimited Warehouse Capacity during Low Season

Results analysis in subsection 5.3.2 showed that under unlimited warehouse capacity, optimal control decisions for SKUs eligible for return are also characterized by the expected days in stock, and benefit of return vs. regular sale. A threshold, based on these metrics, divides the decision to keep in stock or return. Detailed analysis of this threshold in Figure D.2 shows that, compared to limited warehouse capacity, the threshold has shifted upwards with a flatter slope. This results in a lower return rate, and thus higher keep in stock rate. This observation is incorporated into the possible set of policies by selecting higher threshold values for expected days in stock, and the benefit of return vs. regular sale (compared to limited warehouse capacity). In total, 15 different policies are tested.

Set of Possible Policies for SKUs Eligible for Return, under Unlimited Warehouse Capacity:

- Return SKU if:

    - *Expected Days in Stock* > {300, 350, 400}, **or**

    - *Benefit of Return vs. Regular Sale* > {-2, -4, -6, -8, -10}.

- Otherwise: Keep the SKU in stock

Testing these policies yielded the best result for a threshold of 350 for expected days in stock, and -2 for benefit of return vs. regular sale. The accompanying total costs of managing excess stock are - €209k. This represents a €5k or 2.5% deterioration compared to the optimal solution.

For SKUs not eligible for return, Figure 5.8 revealed that all SKUs that are expected to be sold within 900 days should be kept in stock. For these SKUs, the decision whether to liquidate or keep in-stock is dependent on the daily holding costs, as well as the expected days in stock and liquidation vs. selling price. A set of 19 possible policies is established, in which the decision rules are based on the expected days in stock, and either or both of the liquidation vs. selling price, and daily holding costs.

Set of Possible Policies for SKUs not Eligible for Return, under Unlimited Warehouse Capacity:

Subset 1

- Liquidate SKU if:

    - *Expected Days in Stock* > {900}, **and**

    - *Liquidation Price vs. Selling Price* > {-10, -15, -20, -25}.

- Otherwise: Keep the SKU in stock

Subset 2

- Liquidate SKU if:

    - *Expected Days in Stock* > {900}, **and**

    - *Daily Holding Costs (€/(item · day))* > {0.014, 0.017, 0.025}

- Otherwise: Keep the SKU in stock

Subset 3

- Liquidate SKU if:

    - *Expected Days in Stock* > {900}, **and**

    - *Liquidation Price vs. Selling Price* > {-10, -15, -20, -25} **or** *Daily Holding Costs (€/(item · day))* > {0.014, 0.017, 0.025}

- Otherwise: Keep the SKU in stock

The best result was obtained with the policy that incorporates all three metrics with threshold values: 900 for expected days in stock, -20 for liquidation vs. selling price, and 0.017 €/(item·day) for daily holding

costs. This policy yielded a total cost of managing excess stock of - €214k, representing a deterioration of only €0.5k (0.25%) compared to the optimal solution.

5.5.4. Conclusion

It is concluded that specialized liquidation policies have a marginal benefit for excess stock management of the [Product Category] at [Company XYZ]. The expected improvement in total cost is €1.3k-€5.1k, corresponding to an additional benefit of €0.41-€1.30 per liquidated item. This improvement might not outweigh the additional costs involved with specialized liquidation, prohibiting large scale in-bulk liquidation. Further research is required to quantify additional costs.

Retaining all excess SKUs with only one item in the entire stock, would lead to a cost increase of €165k or €409k (unlimited and limited capacity), reducing the expected model benefit to only €40k or €26k. Over 94% of the single-item excess stock SKUs has no sales forecast. To accurately determine which of these SKUs should be retained, a reliable estimate of the expected stock days is required. Alternatively, other criteria could be explored to evaluate the importance of keeping these items in stock. Retaining single-item SKUs increases product availability, possibly enhancing customer satisfaction and loyalty, potentially leading to (long-term) financial benefits. However, the financial benefit of retaining these single-item excess SKUs is questionable, given that 94% of these has no projected sales for the coming half-year. Further research should focus on quantifying the financial implications of single-item retention, beyond the holding, return, and opportunity costs that were considered in this research.

Using simple decision rules for excess stock management has proved to be a suitable and cost-efficient alternative to model optimization. Out of the tested policies, the set of decision rules below has proved to be most effective. Executing these would yield total costs for managing excess stock of - €160k for limited warehouse capacity, and - €208k under unlimited warehouse capacity. This is only a €6.4k (4%) or €5.5k (3%) deterioration compared to the results obtained with the optimization model.

Policy under Limited Warehouse Capacity:

- *For SKUs Eligible for Return:* Return if Expected Days in Stock > 200, or the Benefit of Return vs. Regular Sale[24] > -6. Keep in stock otherwise.
- *For SKUs Not Eligible for Return:* Liquidate if Expected Days in Stock > 400 or Liquidation Price vs. Selling Price > -5. Keep in stock otherwise.

Policy under Unlimited Warehouse Capacity:

- *For SKUs Eligible for Return:* Return if Expected Days in Stock > 350, or the Benefit of Return vs. Regular Sale[24] > -2. Keep in stock otherwise.
- *For SKUs Not Eligible for Return:* Liquidate if Expected Days in Stock > 900 and (Liquidation Price vs. Selling Price > -20 or Daily Holding Costs > 0.017 €/(item·day). Keep in stock otherwise.

The suitability of these policies for effective excess stock management only applies to excess stock with similar properties to the data set used in this research. Generalizing these policy rules would require further testing on different data sets.

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[24]Defined as: benefit of return vs. regular sale = return price - transport costs - selling price

6

Conclusion

The research is concluded by answering the research questions in section 6.1. Subsequently, key limitations of the research are discussed in section 6.2. Following this, recommendations for excess stock management of durable finished goods inventory within e-commerce platforms are provided in section 6.3. Additionally, interesting areas for future research are presented.

6.1. Research Findings and Conclusions

Below the findings of the research are concluded by answering the six sub research questions, and finally the main research question.

Sub Question 1: How can excess inventory be defined?
A review of the literature revealed that excess inventory classification should be based on the current stock level and product movement, in which excess and non-excess stock should be distinct using threshold values based on the specific business context. To ensure efficient pro-active excess stock management, slow-moving stock is considered as potential dead stock. Therefore, this research deployed the excess stock definition of [Company XYZ] in which also slow-moving stock is considered to be excessive. If the projected stock days of a stock keeping unit (SKU) exceed 12 weeks, the SKU is classified as excessive; the corresponding excess stock level is the number of items expected to still be in stock in 12 weeks.

Using this threshold, on average, around 25% of the inventory of the [Product Category] at [Company XYZ] qualifies as excessive. This corresponds to a 2024 yearly average of 90k excess items with an estimated total value of €1.2 million. On 27 November, the excess stock consisted of 19,096 excess SKUs, corresponding to 44,160 excess items. Among the excess stock, 65% of SKUs and 41% of the excess items are projected to have no sales within the coming half-year (corresponding to the end of the forecast period). This highlights the importance of effectively managing excess inventory to improve financial performance.

Changing the excess stock threshold of 12 weeks, impacts the set of excess SKUs that is optimized, and the resulting financial performance of excess stock. Threshold sensitivity analysis showed that altering the threshold marginally impacted financial performance - an 8-week threshold yielded the best result, improving costs by only €7k–€10k or 2–3%. Lowering the threshold reduces product availability and increases the out-of-stock risk. As these costs were outside the scope of the research, the financial superiority of any excess stock threshold remains inconclusive. Therefore, the 12-week threshold was retained for defining excess stock in this research.

Sub Question 2: What reactive strategies available in literature can be leveraged in the context of this work?
Literature review highlighted five reactive excess stock strategies as financially and operationally feasible: retention (keep in stock), return, liquidate, recycle, and discount. Including the specific context of the

[Product Category] at [Company XYZ], this research focused on three strategies: retention, return, and liquidation. Recycling was excluded due to the consistent financial superiority of liquidation. Discounting was omitted due to the unavailability of data on the price elasticities of demand at product level. Due to the scale of the optimization, 19,096 excess SKUs, assumptions about these elasticities would generate unreliable results.

Although recommendation systems and product bundling are widely adopted within e-commerce platforms, their role in excess stock management specifically is relatively novel. No quantitative insights into financial implications were available in literature or practice. Hence, these strategies were excluded.

Sub Question 3: How can a mathematical model be developed to improve control decisions for excess inventory?

A binary programming (BP) model was developed for optimizing reactive control strategies for a set of excess inventory, at a given moment in time. The model assumes reactive control strategies to be executed instantly, finding the optimal control decisions based on cost minimization. These costs consists of: holding and working capital costs associated with stock retention (over the expected holding period), transport costs for clearance decisions, opportunity costs of keeping in stock, and opportunity costs of clearing. The opportunity costs account for indirect costs resulting from a loss in revenue. If warehouse capacity is limited, retaining items lowers available storage space and reduces the revenue from the sale of other (faster-selling) items, yielding opportunity costs of keeping in stock. If an excess item is cleared (returned, recycled, liquidated) this leads to a revenue difference compared to a regular customer sale, resulting in opportunity costs of clearing. The model integrates warehouse capacity constraints, supplier agreements, and excess stock data such as the expected days in stock and selling price.

The BP model has been tailored to the use case of the [Product Category] of [Company XYZ], changing the optimization level from individual product item to SKU. Consequently, one control decision should be executed for all excess items of that SKU. Furthermore, recycling was excluded as control strategy. The excess stock of the [Product Category] on 27 November 2024 has been optimized for two capacity scenarios. In case of limited warehouse capacity, representing the high season, the optimal solution yields a 19% retention rate, 67% return rate, and 14% liquidation rate. These percentages apply to the excess stock only (calculated at the level of SKU). The total costs of excess stock amount to - €166k, implying that optimal management would lead to a profit increase. Comparing these to the estimated current excess stock costs of €269k (given limited capacity), implies that the model would result in a benefit of €435k. In case of unlimited warehouse capacity, the opportunity costs of keeping in stock are eliminated, yielding a 31% retention rate, 59% return rate and 11% liquidation rate. This results in a total cost of - €215k. Comparing this to the estimated current excess stock costs of - €10k (given unlimited capacity), implies that the model would result in a benefit of €205k.

The negative total costs for excess stock are driven the returns, generating opportunity costs of - €218k (limited capacity) or - €251k (unlimited capacity). This finding is specific for the use case of the [Product Category] at [Company XYZ], where excess stock is assumed to depreciate with 37% per year and typically has low gross margins (€0.95 per excess item on average). Also the selling prices are relatively low: 36% of excess SKUs actually has a return price exceeding the selling price. These drive negative opportunity costs of clearing, implying that returning these SKUs generates higher revenues compared to regular customer sales.

Sub Question 4: Considering the level of complexity and size of the mathematical model, what is a suitable solution method?

The BP model was implemented in Python, using the Gurobi solver. Using the data set from 27 November 2024, the model consisted of nearly 60,000 decision variables. Despite this scale, the model solved computationally efficient, requiring no additional simplifications or heuristics. This can be attributed to the fact that the decision variables across SKUs are independent, only the control decisions of a specific SKU affect each other (dependence among three decision variables). This resulted in an efficient model that achieved an optimization gap smaller than 1×10^{-325}. This efficiency highlights the operational practicality of the model for [Company XYZ] and similar e-commerce platforms.

Sub Question 5: How do various factors, such as right of return and expected stock days, affect excess inventory control decisions and financial performance?

Results and sensitivity analyses revealed that excess stock control decisions and financial performance are significantly impacted by: warehouse capacity constraints, return eligibility, expected days in stock, benefit of return compared to regular sale, and liquidation price vs. selling price.

The attractiveness of returning is supported by the high and relatively stable return rate across sensitivity analyses. The return rate ranged between 45-75%, with changes in the number of returns exceeding 10% occurring only in 8% of experiments. The pivotal role of return eligibility was also underlined by the consistent preference of return over liquidation. This is driven by the return price equaling [80-100%][25] of the purchase price, whereas the liquidation price is only [5-20%][25] of the selling price.

For SKUs eligible for return, the decision of whether to return or keep in stock can be characterized by the following two metrics: expected days in stock, and benefit of return vs. selling price (defined as return price minus transport cost for return minus selling price). For SKUs not eligible for return, the decision of whether to liquidate or keep in stock can be characterized by the expected days in stock, and liquidation price vs. selling price.

The daily holding and working capital costs typically have a small impact on costs, suggesting that the financing status of a SKU is relatively irrelevant. Consequently, the costs associated with excess stock retention are mainly influenced by the opportunity costs of keeping in stock which are especially sensitive to the average days in stock and the average contribution margin. Higher contribution margins or lower average days in stock significantly increase these opportunity costs, prioritizing clearance strategies for slower-moving items and leading to higher total excess stock costs. Adjusting these parameter values by -100% to +100% results in changes to the total excess stock costs, ranging from - €49k to + €50k. The significance of the opportunity costs of keeping in stock underscores the importance of considering storage capacity. Unconstrained capacity eliminates these costs, yielding an 12ppt increase in retention rate and cost reduction of €49k.

For clearance decisions, the opportunity costs of clearing are the main cost driver, explaining the model's sensitivity to the daily discount rate, while transport costs for clearing are marginal. Varying the discount rate between -100% to +100% compared to the base value of 37% per year, changes excess stock costs with + €293k to - €150k. In the extreme cases, the control decisions of up to 2.8k SKUs are affected (15% of total).

Lastly, the financial performance of excess stock demonstrates high sensitivity to the assumed stock days of 3 years for SKUs lacking a sales forecast (no projected sales for the coming half-year). Should these SKUs only remain in stock for a year, the optimal solution shifts to a higher retention rate, leading to increased excess stock costs with a maximum of + €112k. On the contrary, should these SKUs be in stock for 5.5 years, the total costs would change with a maximum of - €82k.

Sub Question 6: What are successful reactive control strategies for improving financial performance of excess inventory, and how can these be implemented?

Optimization shows that SKUs eligible for return should not be liquidated. Under limited capacity, the opportunity costs of keeping in stock play a pivotal role, leading to an optimal solution in which all SKUs without sales forecast are cleared. On a slightly more granular level, relatively simple decision rules have proved to be effective for excess stock management, providing a cost- and time-efficient alternative to exact optimization. These decision rules should be based on key determinants in the optimization: availability of warehouse capacity, expected days in stock, return eligibility, benefit of return vs. regular sale, and liquidation price vs. selling price.

Main Research Question: To what extent can reactive strategies improve the financial performance of managing excess inventories in an e-commerce platform?

Reactive strategies demonstrated to significantly improve the financial performance of excess stock for the [Product Category] at [Company XYZ]. The benefit was realized particularly by optimizing returns and

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[25]For confidentiality, this parameter value has been anonymized. This only applies to the text, the actual value is deployed in the optimization.

cost-efficient retention. The findings underscore the importance of balancing financial and operational factors for effective excess inventory management.

6.2. Discussion of Study Limitations

A key limitation of this research lies in the one-time optimization of excess stock for 27 November 2024. To generate more robust insights and conclusions, sensitivity analyses have been performed with time-independent model parameters. The conclusions and findings remain dependent on the parameters specific to the excess stock data set from 27 November, such as expected days in stock and selling prices.

The financial performance of excess stock could be overstated due to the assumption of defect-free inventory. In practice, defects lead to reduced return eligibility and liquidation opportunities. Also, the assumption of immediate revenue generation from clearance decisions, is likely to have overestimated the model benefit. Finally, although the assumed 3 years of expected stock days for SKUs may not largely affect control decisions, it significantly impacts the excess stock costs. Given that 65% of the SKUs lacked a sales forecast (within the half-year forecast period), this affects the reliability of the results.

Due to the lack of data on price elasticities of demand, discounting could not be included as control strategy. This poses a significant limitation as discounting is currently the standard strategy for excess stock management within [Company XYZ]. Although the research provided insight into the effect of the selling prices on excess inventory management, no direct recommendations can be made for the discounting strategy. However, given the fact that 36% of the excess SKUs had a selling price below the best return price, it is recommended to reconsider the discounting strategy.

Although the model relies on the most recent selling price, it does not consider the possibility that these prices could change over the holding period of excess stock. Due to [Company XYZ's] discounting strategy, this is a common practice, thereby posing an important limitation of the research. Due to the exclusion of these dynamic changes, the financial benefit of excess stock retention and subsequently the retention rate, could be overstated.

Finally, despite the inclusion of indirect costs from revenue losses, the cost minimization performed in this research provides an incomplete perspective. Since the model assumes that all SKUs included in the optimization are excessive, no costs or risks are associated with overly aggressive clearance. In practice, this could constitute a loss of customers and revenues, especially given the typically high competition within e-commerce.

6.3. Recommendations

The objective of this research is to help decision makers within e-commerce platforms to improve the financial performance of excessive, durable, finished goods inventory. Specifically, this research has the objective to enhance the financial performance of [Company XYZ] by improving the control strategies of excess inventory of the [Product Category].

6.3.1. Recommendations for Excess Stock Management at Company XYZ

As noted in the research, current procedures for excess stock management at [Company XYZ] are sub-optimal due to their unsystematic nature where control decisions are not based on thorough analysis of excess stock data, or financial implications. Implementing the proposed BP model can significantly improve the financial performance of excess stock within the [Product Category]. The expected financial benefit, for optimization on 27 November 2024, is €435k given the high season where capacity was limited. Should capacity be unlimited, the benefit is still substantial: €205k. The expected benefit per item was €21.44 (limited capacity) or €8.57 (unlimited capacity). When optimizing for a different data set of excess stock, with similar properties, these values can serve as a benchmark for expected model benefit.

Given the model sensitivity to the discount rate of excess stock, it is important to calibrate this parameter value before implementing the optimization model in practice. Considering that the sensitivity of control decisions is largest for unlimited capacity, which is a valid assumption for over 80% of the time, further highlights the importance.

Given the influence of warehouse capacity constraints, it is recommended to perform optimization prior to the start of the high season (November). By including opportunity cost of keeping in stock, excess stock retention is increasingly penalized, shifting to a higher clearance rate which is beneficial during times where storage capacity is actually a limiting factor to the number of sales. Additionally, as the financial benefit is significantly affected by the returns, it is recommended to optimize excess stock with an interval equal to the smallest maximum return period of suppliers.

Additionally, excess inventory management shows significant dependence on the expected days in stock, underlining the importance of accurate demand forecasts. Given that 65% of the excess SKUs had no sales forecast, suggests potential value of extending accurate demand predictions beyond the current 26-week forecast period. Additionally, it would enable better assessment of single-item retention policies. Out of single-stock excess SKUs, 94% lack a sales forecasts. As such, it is challenging to assess the commercial significance of this inventory. Extending demand forecasts would help in finding the optimal trade-off in retention costs and benefit (e.g., due to increased customer satisfaction or retention from larger product availability).

Given that improved performance is mainly driven by lower retention and increased returns, optimizing the trade-off between these decisions should receive priority. The algorithm developed for identifying the best return offers a good starting point. It considers crucial factors such as the right of return, return refund, transport costs, and accepted return period. This allows for a substantial improvement from the current situation, where the set of SKUs eligible for return is not insightful, and it is unclear which supplier offers the best return. Using real-time stock data within the digital environment of [Company XYZ], this algorithm can be easily applied in practice - also within the broader context of the company for other product groups.

The financial attractiveness of return compared to retention and liquidation, can be partially justified by the observation that for 36% of the excess SKUs return prices exceeded their selling prices. This suggests potential misalignment in the current pricing and discounting strategy of [Company XYZ], where some items may be discounted below their return value. To maximize financial performance, the company should use these insights to reevaluate its pricing strategy.

Although the model solves efficiently, relatively simple decision rules for excess stock management are considered a useful alternative that can be easily implemented. The following set of decision rules would generate excess stock costs of - €160k for limited warehouse capacity, and - €208k for unlimited warehouse capacity, representing only 3-4% deterioration compared to exact optimization. In high season (limited capacity), SKUs that are eligible should be returned if the expected days in stock exceed 200, or the benefit of return vs. regular sale exceeds - €6 per item. SKUs not eligible for return should be liquidated if the expected days in stock exceed 400, or the liquidation vs. selling price is greater than - €5 per item. In low season (unlimited capacity), eligible SKUs should be returned if the expected days in stock exceed 350, or if the benefit of return is greater than - €2. SKUs not eligible for return should be liquidated if the expected days in stock exceed 900, and either the liquidation vs. selling price is greater than - €20 or the daily holding costs are greater than €0.017 per item. If none of these criteria are met, the SKU should be retained in stock. These threshold values are only valid for excess stock with similar patterns as the data from 27 November 2024. It is recommended to repeat the optimization for different excess stock data sets of the [Product Category], to generalize these decision rules.

6.3.2. Recommendations for Excess Stock Management in E-commerce
The BP model can be used for optimizing reactive control strategies within the broader e-commerce context of durable finished goods inventory. For effective model use, it is crucial to have a clear definition of excess stock, accurate stock data, and reliable demand forecasts. In general, this research highlighted the importance of considering opportunity costs in excess stock management, particularly for relatively small and low-value products as these typically incur low holding and working capital costs. Furthermore, excess stock management strategies should be specified for seasonality (low vs. high season) if warehouse capacity is constrained.

The financial benefit of reactive excess stock control is highly dependent on the business specifics. Therefore, the stated financial benefits in this study should not be used as a direct benchmark. While the financial benefit may vary, the model provides value by creating insights into trade-offs between control

decisions and identifying key stock parameters for informed decision-making. As such, the findings of this research have the potential to enhance the financial performance of excess stock in the broader e-commerce environment.

6.3.3. Scientific Recommendations
This section discusses the scientific implications of the findings, as well as interesting areas for future research.

Implications of Findings
As noted in this research, the body of knowledge on reactive control for excess inventory is limited. Having developed a mathematical model for excess stock optimization that incorporates multiple reactive control strategies, including the retention decision, this research addresses the identified knowledge gap. The model does not consider product characteristics like perishability and defects, assumes a single sales market, and relatively high depreciation of excess stock value, making it specifically applicable to durable finished goods inventory. The effectiveness of the model relies upon an accurate definition of excess stock within the specific context.

Having identified key considerations for reactive excess inventory management, this research contributes to the current state of knowledge. The findings suggest that considering opportunity costs, resulting from revenue losses, is crucial in excess stock management. Merely considering direct costs from holding, working capital and transport provides an incomplete perspective. The costs of excess inventory are namely mainly affected by differences of revenues across control decisions (vs. regular customer sale), and the loss of revenue from other products if excess stock is retained (given constrained warehouse capacity). Since it was assumed that revenue from clearance is immediately generated, compared to stock retention where revenue is generated only after the expected days until sale, depreciation of excess stock value is also important to consider.

When deciding on the optimal control decision, the following stock metrics should be incorporated: expected stock days, warehouse capacity, eligibility of return, benefit of return vs. regular sale, and liquidation vs. selling price.

Further Research
First of all, it would be valuable to expand the research context by repeating the analyses for excess stock data with different characteristics. This could uncover new model sensitivities, leading to more robust excess inventory policies across different contexts or product groups.

The exclusion of discounting as control strategy poses a significant limitation of the research, thereby providing a relevant direction for future studies. As discounting is intertwined with the pricing strategy, these can not be optimized individually. Future studies should aim to include discounting as additional control strategy, possibly requiring multi-period optimization as discounting could be applied multiple times over the holding period. The accuracy of the results remains dependent on the availability of price elasticities of individual product items.

Moreover, future research could be aimed at quantifying the financial implications of excess stock retention and clearance beyond the holding, working capital, return, and opportunity costs. Incorporating a broader perspective, for example by considering out-of-stock costs and customer satisfaction, could further improve excess stock management. Robust financial analysis would be required for appropriate decision-making regarding the definition of excess stock (based on a threshold for projected stock days), and evaluation of single-item excess stock retention policies.

Considering the financial attractiveness of returns in excess stock management, it would also be interesting to explore the inclusion of eligibility of return as criterion in procurement processes. As return eligibility improves the financial performance of excess stock, this gives rise to a potential trade-off: to what extend would a higher purchase price be justified if the item is eligible for return? Improved alignment of procurement and excess stock management could enhance a business' overall financial performance.

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A
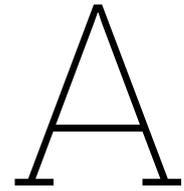
Data Analysis Expected Days in Stock for the Full Excess Inventory

Figure A.1 below shows the distribution of the expected stock days per SKU that is part of the excess inventory within the [Product Category] of [Company XYZ] on 27 November 2024. The histogram shows a substantial spike around 10^3 expected days in stock. This is driven by 12,403 SKUs without sales forecast which are assumed to be in stock for 3 years (1,095 days).

As a result, the median value for expected days in stock is 1,095. The minimum value corresponds of 85 days is driven by the excess stock definition where only SKUs with projected stock days greater than 84 days are considered to be excessive. The maximum value of 15,299 is likely caused by a weekly demand forecast approximating zero. As improvements in the sales forecast lie outside the scope of the research, this has not been further investigated.
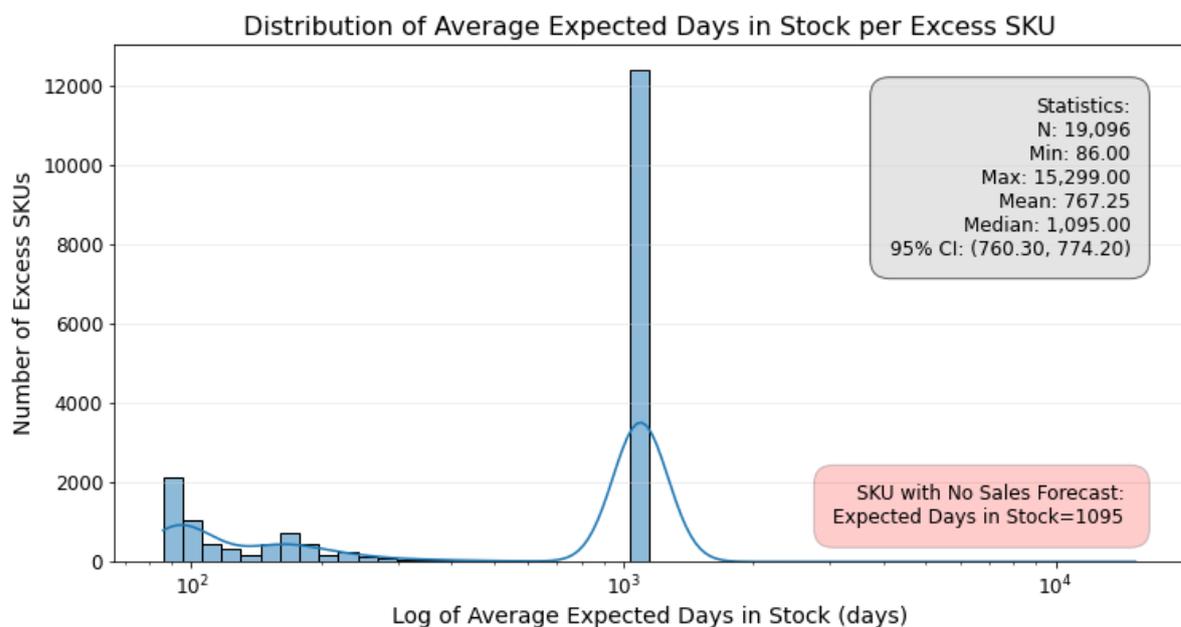
Figure A.1: Distribution of expected days in stock for excess inventory of the [Product Category], data from 27 November 2024

B

Python Model

For confidentiality, this parameter values M, D, L have been anonymized in the code below. This only applies to the text, the actual value is deployed in the optimization.

```python
#==============================================================================
# -*- coding: utf-8 -*-
"""
Spyder Editor

This is a temporary script file.
"""

#Thesis Noa Zijlmans

from gurobipy import *
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
from matplotlib.font_manager import FontProperties
import seaborn as sns
import math
import random
from scipy import stats

# ============================================================================
#Define the Model

model = Model('Excess Stock Optimization: Model 2')

# ============================================================================
#Define the Model Parameters

#Real-time Stock Parameters (SKU specific):

#Extract data from excel
#Read the data, assign column names, set the first column (SKU)  as index
column_names = ['G', 'S', 'PS', 'DE', 'DC', 'PP', 'FC', 'FF', 'CS', 'NP', 'Eligible_Return', '
                                          PR', 'CR', 'PL']
df = pd.read_csv('12wk.txt', header=None, delimiter='\t', names=column_names, usecols=range(
                                          len(column_names)))
df.set_index('G', inplace=True)


#Time-independent Parameters (not SKU specific):

CW = 0.00014 #daily working capital costs [% of NNPP/day]
alpha = 1 #scaling factor for availability warehouse capacity
M = 2.2 #average contribution margin [euro/item]
D = 60 #average days in stock [euro/item]
```

```python
45  L = 7 #average lead time [days]
46  RE = 0.00086 #daily discount rate excess stock [% per day]
47  RO = 0.00023 #daily discount rate overall stock [% per day]
48
49
50  # ==============================================================================
51  #Sets
52  G = df.index.tolist() #set of SKUs
53  Gr = [] #empty list for set of SKUs that can be returned
54  Gnr = [] #empty list for set of SKUs that can not be returned
55
56  #Assign SKUs to sets Gr and Gnr
57  for g in G:
58      if df.loc[g,'Eligible_Return']==1:
59          Gr.append(g)
60      else :
61          Gnr.append(g)
62
63
64  #Defining the set F: set of days that SKU g is financed by [Company XYZ]
65  #If SKU is currently financed by [Company XYZ], the set F spans from day 0, to the day of sale
66  #If SKU is future financed by [Company XYZ], the set F spans from the first day that the SKU
                                                  is financed by [Company XYZ] (payment period -
                                                  current stock days), to the day of sale
67  #If the SKU will never be financed by [Company XYZ], the set F consists only of the value zero
68
69  F = pd.DataFrame(index=G, columns=['F_start','F_end'])
70
71  for g in G:
72      if df.loc[g, 'FC'] == 1:
73          F.loc[g, 'F_start'] = int(0)
74          F.loc[g, 'F_end'] = int(df.loc[g, 'DE'] +1)
75
76      elif df.loc[g, 'FF'] == 1:
77          F.loc[g, 'F_start'] = int(df.loc[g, 'PP']) - int(df.loc[g, 'DC'])
78          F.loc[g, 'F_end'] = int(df.loc[g, 'DE'] +1)
79
80      elif df.loc[g, 'FC'] == 0 and df.loc[g, 'FF'] == 0:
81          F.loc[g, 'F_start'] = 0
82          F.loc[g, 'F_end'] = 0
83
84  F['F'] = F.apply(lambda row: list(range(int(row['F_start']), int(row['F_end']))), axis=1)
85
86
87  #Defining the set I: set of days that SKU g is expected to be in stock
88  I = pd.DataFrame(index=G, columns=['I_start','I_end'])
89  I['I_start'] = int(0)
90  for g in G:
91      I.loc[g, 'I_end'] = int(df.loc[g,'DE']+1)
92  I['I'] = I.apply(lambda row: list(range(int(row['I_start']), int(row['I_end']))), axis=1)
93
94  # ==============================================================================
95  #Decision Variables
96
97  #control decision w_g: keep SKU g in stock (1) or not (0) [binary]
98  w = {}
99  for g in G:
100     w[g] = model.addVar(lb=0, vtype=GRB.BINARY, name = 'w[' + str(g) + ']' )
101
102 #control decision x_g: return SKU g (1) or not (0) [binary]
103 x = {}
104 for g in G:
105     x[g] = model.addVar(lb=0, vtype=GRB.BINARY, name = 'x[' + str(g) + ']' )
106
107 #control decision y_g: SKU g(1) or not (0) [binary]
108 y = {}
109 for g in G:
110     y[g] = model.addVar(lb=0, vtype=GRB.BINARY, name = 'y[' + str(g) + ']' )
111
112 model.update()
113
```

```
114
115
116   # ============================================================================
117
118   #Objective Function
119   model.setObjective(
120       quicksum(
121           df.loc[g, 'S'] * ((
122           (
123               quicksum(df.loc[g, 'CS'] / (1 + RE) ** d for d in I.loc[g, 'I']) +
124               (df.loc[g, 'FC'] + df.loc[g, 'FF']) * CW * df.loc[g, 'NP'] * quicksum(1 / (1 + RE)
                                                        ** d for d in F.loc[g, 'F'])
125           ) * w[g] +
126           (df.loc[g, 'CR'] if pd.notna(df.loc[g, 'CR']) else 0) * x[g] +
127           (df.loc[g, 'PS'] if pd.notna(df.loc[g, 'PS']) else 0) * (x[g] + y[g]) / (1 + RE) ** df
                                                        .loc[g, 'DE'] -
128           ((df.loc[g, 'PR'] if pd.notna(df.loc[g, 'PR']) else 0) * x[g] +
129            (df.loc[g, 'PL'] if pd.notna(df.loc[g, 'PL']) else 0) * y[g])
130       ) + (alpha)*(df.loc[g, 'DE']/(AD+AL)*AM/(1+RO)**AD)*w[g]) for g in G)
131   )
132
133   model.modelSense = GRB.MINIMIZE
134   model.update()
135
136
137   # ============================================================================
138   #Constraints
139
140
141   #Constraint 1: Exactly 1 Control Decision per SKU
142   con1 = {}
143   for g in G:
144       con1[g] = model.addConstr( w[g] + x[g] + y[g] == 1)
145
146   #Constraint 2: Return Not Possible if SKU is not Eligible for Return
147   con2 = {}
148   for g in Gnr:
149       con2[g] = model.addConstr(x[g] == 0 )
150
151
152   # ============================================================================
153   #Solve the Model
154
155   model.setParam( 'OutputFlag', True) # silencing gurobi output or not
156   model.setParam ('MIPGap', 0);        # find the optimal solution
157   model.write("output.lp")             # print the model in .lp format file
158
159   model.optimize ()
```

The code below allows for the analysis of the results (optimized control decisions and related costs).

```
1    # ============================================================================
2    # Tracking control decisions per SKU and item
3
4    # Lists of SKUs per control decision
5    in_stock, returned, liquidated = [], [], []
6    # Lists of SKUs eligible for return per control decision
7    in_stock_eligible, returned_eligible, liquidated_eligible = [], [], []
8
9    # Lists of number of items (stock quantity) per control decision
10   items_in_stock, items_returned, items_liquidated = [], [], []
11   # Lists of number of items (stock quantity) eligible for return per control decision
12   items_in_stock_eligible, items_returned_eligible, items_liquidated_eligible = [], [], []
13
14   for g in G:
15       if w[g].x==1:
16           in_stock.append(g)
```

```
17              items_in_stock.append(df.loc[g,'S'])
18          if df.loc[g,'Eligible_Return']==1:
19              in_stock_eligible.append(g)
20              items_in_stock_eligible.append(df.loc[g,'S'])
21
22      if x[g].x==1:
23          returned.append(g)
24          items_returned.append(df.loc[g,'S'])
25          if df.loc[g,'Eligible_Return']==1:
26              returned_eligible.append(g)
27              items_returned_eligible.append(df.loc[g,'S'])
28
29      if y[g].x==1:
30          liquidated.append(g)
31          items_liquidated.append(df.loc[g,'S'])
32          if df.loc[g,'Eligible_Return']==1:
33              liquidated_eligible.append(g)
34              items_liquidated_eligible.append(df.loc[g,'S'])
35
36  #Number of SKUs per control decision
37  N_in_stock = len(in_stock)
38  N_in_stock_eligible = len(in_stock_eligible)
39  N_returned = len(returned)
40  N_returned_eligible = len(returned_eligible)
41  N_liquidated = len(liquidated)
42  N_liquidated_eligible = len(liquidated_eligible)
43
44  # Calculate the size of the sets G (total, eligible and not eligible for return)
45  total_G = len(G)
46  total_Gr = len(Gr)
47  total_Gnr = len(Gnr)
48
49  # Print number of SKUs per control decision and the keep in-stock, return and liquidation
                                                    rates
50  # Format results in matrix form
51  matrix = {
52      'Percentage of Total': [
53          N_in_stock / total_G * 100,
54          N_returned / total_G * 100,
55          N_liquidated / total_G * 100,
56          (N_in_stock + N_returned + N_liquidated) / total_G * 100
57      ],
58      '# SKUs': [
59          N_in_stock, N_returned, N_liquidated, N_in_stock + N_returned + N_liquidated
60      ],
61      '#SKUs Eligible for Return': [
62          N_in_stock_eligible, N_returned_eligible, N_liquidated_eligible, N_in_stock_eligible +
                                                  N_returned_eligible +
                                                  N_liquidated_eligible
63      ]
64  }
65
66  matrix_df = pd.DataFrame(matrix, index=['In Stock', 'Returned', 'Liquidated','Total'])
67
68  print(matrix_df)
69  print("\n")
70
71  #Number of items per control decision
72  N_items_in_stock = sum(items_in_stock)
73  N_items_in_stock_eligible = sum(items_in_stock_eligible)
74  N_items_returned = sum(items_returned)
75  N_items_returned_eligible = sum(items_returned_eligible)
76  N_items_liquidated = sum(items_liquidated)
77  N_items_liquidated_eligible = sum(items_liquidated_eligible)
78
79  # Calculate total number of items
80  total_items = N_items_in_stock + N_items_returned + N_items_liquidated
81  total_items_eligible = N_items_in_stock_eligible + N_items_returned_eligible +
                                                  N_items_liquidated_eligible
82  total_items_not_eligible = total_items - total_items_eligible
83
```

```
84   # Print number of items per control decision and the keep in-stock, return and liquidation
                                                   rates
85   # Format results in matrix form
86   matrix_2 = {
87       'Percentage of Total': [
88           N_items_in_stock / total_items * 100,
89           N_items_returned / total_items * 100,
90           N_items_liquidated / total_items * 100,
91           (N_items_in_stock + N_items_returned + N_items_liquidated) / total_items * 100
92       ],
93       '# items': [
94           N_items_in_stock, N_items_returned, N_items_liquidated, total_items
95       ],
96       '#items Eligible for Return': [
97           N_items_in_stock_eligible, N_items_returned_eligible, N_items_liquidated_eligible,
                                                   total_items_eligible
98       ]
99   }
100
101  matrix_df_2 = pd.DataFrame(matrix_2, index=['In Stock', 'Returned', 'Liquidated','Total'])
102
103  print(matrix_df_2)
104  print("\n")
105
106
107  # ============================================================================
108  # Grouping the SKUs based on control decision
109  # Calculating statistics per group of SKUs
110
111  def calculate_stats(group_list):
112      # Filter the DataFrame based on the group list
113      group_df = df.loc[group_list]
114
115      # Add calculated columns
116      group_df['Gross_Margin'] = group_df['PS'] - group_df['NP']
117      group_df['Liquidation_Downside'] = group_df['PL'] - group_df['PS']
118      group_df['Return_Upside'] = np.where(group_df['PR'].isna(), np.nan, group_df['PR'] -
                                                   group_df['PS'])
119
120      # Calculate statistics
121      avg_de = group_df['DE'].mean()
122      min_de = group_df['DE'].min()
123      max_de = group_df['DE'].max()
124
125      avg_dc = group_df['DC'].mean()
126      min_dc = group_df['DC'].min()
127      max_dc = group_df['DC'].max()
128
129      avg_gross_margin = group_df['Gross_Margin'].mean()
130      min_gross_margin = group_df['Gross_Margin'].min()
131      max_gross_margin = group_df['Gross_Margin'].max()
132
133      avg_nnpp = group_df['NP'].mean()
134      min_nnpp = group_df['NP'].min()
135      max_nnpp = group_df['NP'].max()
136
137      avg_cs = group_df['CS'].mean()
138      min_cs = group_df['CS'].min()
139      max_cs = group_df['CS'].max()
140
141      avg_ru = group_df['Return_Upside'].mean()
142      min_ru = group_df['Return_Upside'].min()
143      max_ru = group_df['Return_Upside'].max()
144
145      avg_ld = group_df['Liquidation_Downside'].mean()
146      min_ld = group_df['Liquidation_Downside'].min()
147      max_ld = group_df['Liquidation_Downside'].max()
148
149      # Return all calculated stats
150      return [
151          avg_de, min_de, max_de,
```

67

```python
152              avg_dc, min_dc, max_dc,
153              avg_gross_margin, min_gross_margin, max_gross_margin,
154              avg_nnpp, min_nnpp, max_nnpp,
155              avg_cs, min_cs, max_cs,
156              avg_ru, min_ru, max_ru,
157              avg_ld, min_ld, max_ld
158          ]
159
160  # Calculate averages for SKUs grouped by control decision
161  stats_in_stock = calculate_stats(in_stock)
162  stats_returned = calculate_stats(returned)
163  stats_liquidated = calculate_stats(liquidated)
164
165  # Calculate averages for SKUs eligible for return grouped by control decision
166  stats_in_stock_eligible = calculate_stats(in_stock_eligible)
167  stats_returned_eligible = calculate_stats(returned_eligible)
168  stats_liquidated_eligible = calculate_stats(liquidated_eligible)
169
170  # Format results as matrix
171  matrix = {
172      'Metric': [
173          'Average DE', 'Min DE', 'Max DE',
174          'Average DC', 'Min DC', 'Max DC',
175          'Average Gross Margin', 'Min Gross Margin', 'Max Gross Margin',
176          'Average NNPP', 'Min NNPP', 'Max NNPP',
177          'Average Daily Holding Costs', 'Min Daily Holding Costs', 'Max Daily Holding Costs',
178          'Average Return Upside', 'Min Return Upside', 'Max Return Upside',
179          'Average Liquidation Downside', 'Min Liquidation Downside', 'Max Liquidation Downside'
180      ],
181      'In Stock': stats_in_stock,
182      'Returned': stats_returned,
183      'Liquidated': stats_liquidated,
184      'In Stock (Eligible)': stats_in_stock_eligible,
185      'Returned (Eligible)': stats_returned_eligible,
186      'Liquidated (Eligible)': stats_liquidated_eligible
187  }
188
189  matrix_df = pd.DataFrame(matrix)
190
191  print('\nResults Matrix:\n')
192  print(matrix_df.to_string(index=False))
193  print('\n')
194
195
196
197  # ============================================================================
198  # Cost Calculations
199
200  # Calculate cost components of the objective function
201  # Check if manual total cost calculation coincides with value of objective function
202
203  # --------------------------------------------------
204  # Return revene, profit, and liquidation revenue
205  return_revenue = sum(
206      x[g].x * df.loc[g,'S']*(df.loc[g, 'PR'] if pd.notna(df.loc[g, 'PR']) else 0) for g in G)
207  return_profit = sum(
208      x[g].x * df.loc[g,'S']*((df.loc[g, 'PR'] if pd.notna(df.loc[g, 'PR']) else 0) - (df.loc[g,
                                                      'CR'] if pd.notna(df.loc[g, 'CR']) else 0)
                                                  ) for g in G)
209  liquidation_revenue = sum(
210      y[g].x * df.loc[g,'S'] * df.loc[g, 'PL'] for g in G)
211
212  print(f"Total return revenue: {return_revenue} euro")
213  print(f"Total return profit: {return_profit} euro")
214  print(f"Total liquidation profit: {liquidation_revenue} euro")
215  print("\n")
216
217  # --------------------------------------------------
218  # Calculated holding cost after optimization
219  optimized_holding_cost = sum(
220      w[g].x * df.loc[g, 'S'] * sum(df.loc[g, 'CS'] / (1 + RE) ** d for d in I.loc[g, 'I'])
```

```python
        for g in G
)

# Calculated working capital cost after optimization
optimized_working_capital_cost = sum(
    w[g].x * df.loc[g, 'S'] * CW * df.loc[g, 'NP'] * sum(1 / (1 + RE) ** d for d in F.loc[g, '
                                                F'])
    for g in G
)

# Calculated return cost after optimization
optimized_return_cost = sum(

    x[g].x * df.loc[g, 'S'] * (df.loc[g, 'CR'] if pd.notna(df.loc[g, 'CR']) else 0)
    for g in G
)

# Calculated opportunity cost for clearing after optimization
optimized_opp_cost_clearing = sum(
    df.loc[g, 'S'] * ((df.loc[g, 'PS'] if pd.notna(df.loc[g, 'PS']) else 0) * (x[g].x + y[g].x
                                            ) / (1 + RE) ** df.loc[g, 'DE'] -
    ((df.loc[g, 'PR'] if pd.notna(df.loc[g, 'PR']) else 0) * x[g].x + (df.loc[g, 'PL'] if pd.
                                            notna(df.loc[g, 'PL']) else 0) * y[g].x))
    for g in G
)

# Calculated opportunity cost of keeping stock after optimization
optimized_opp_cost_holding = sum(
    w[g].x * alpha * df.loc[g, 'S'] * (df.loc[g, 'DE'] / (AD + AL) * AM / (1 + RO) ** AD)
    for g in G
)

# Print these components after optimization
print("Optimized holding cost:", optimized_holding_cost)
print("Optimized working capital cost:", optimized_working_capital_cost)
print("Optimized return cost:", optimized_return_cost)
print("Optimized opportunity cost for clearing:", optimized_opp_cost_clearing)
print("Optimized opportunity cost for keeping stock:", optimized_opp_cost_holding)

# Define function to get the value from terms
# Using this to calculate the manual total cost with the helper function
def get_term_value(term):
    return term.getValue() if hasattr(term, "getValue") else float(term)

manual_total_cost = (
    get_term_value(optimized_holding_cost) +
    get_term_value(optimized_working_capital_cost) +
    get_term_value(optimized_return_cost) +
    get_term_value(optimized_opp_cost_clearing) +
    get_term_value(optimized_opp_cost_holding)
)

# Retrieve the objective value from Gurobi
objective_value = model.ObjVal

# Print and compare both values
print("\n")
print("Manual total cost after optimization:", manual_total_cost)
print("Objective function value:", objective_value)

print("\n")

# Check for discrepancy
if abs(manual_total_cost - objective_value) > 1e-6:  # Tolerance for floating-point precision
    print("Discrepancy detected! Double-check the components.")
else:
    print("Manual total cost matches the objective function value.")

# =============================================================================
```

C
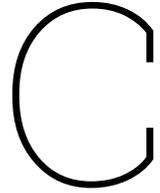
Verification Experiments

C.1. Verification Experiments based on Decision Variables

Table C.1 shows the experiments that have been performed as part of the model verification described in section 5.2.

Per experiment, one of the decision variables (w_g, x_g, y_g) is fixed at 0 or 1, for all SKUs within one specific set ($\mathcal{G}$, $\mathcal{G}_r$ or $\mathcal{G}_{nr}$). This test is repeated for all sets and decision variables, resulting in a total of 18 experiments (3 sets, 3 decision variables, 2 values per decision variable), and one base scenario where no additional constraints are added.

Each run resulted in an effective optimality gap of 0% and the manual cost calculation coinciding with the value of the objective function. Across runs, the total number of SKUs, and number (not) eligible for return, correspond to $\mid \mathcal{G} \mid$, $\mid \mathcal{G}_r \mid$ and $\mid \mathcal{G}_{nr} \mid$. This suggests correct formulation of the sets. Additionally, it has been verified that costs are only incurred if the related control decision is executed (e.g., return costs are zero if no returns are made).

In the base scenario, the value of the objective function is - €165.5k, driven by the negative opportunity costs of clearing: more revenue is generated by clearing than retaining stock. Each experiment constrains one of the decision variables, reducing the solution space, thereby yielding a less optimal values of the objective function compared to the base case. The deterioration, thus cost increase, is largest for experiments that prohibit returns for SKUs eligible for return ($g \in \mathcal{G}_r$), even yielding a positive objective function value. This relates to run 2, 4, 7, 9, 14 and 16 where SKUs are forced to be kept in stock or liquidated, or not allowed to be returned: $w_g = 1$, $y_g = 1$, or $x_g = 0$ $\forall g \in \mathcal{G}$ or $\forall g \in \mathcal{G}_r$. The least optimal objective function value (€781.3k) occurs when all SKUs are forced to be kept in stock - increasing the total costs with €946.8k compared to the base case optimization.

The value of the objective function is minimally affected in experiment 5, 15 and 18. In experiment 5 and 18, all SKUs not eligible for return are forced to be liquidated. This affects the optimal control decision for 159 SKUs (0.8% of total), leading to a small deterioration in the value of the objective function (+ €5.7k). In run 15, all SKUs that are eligible for return are not allowed to be liquidated. This affects the optimal control decision for only one SKU, leading to a negligible total cost increase of €0.05. Due to the rounding of values, this difference is not directly visible in Table C.1.

Experiment 11 yields the same objective function value as the base case: $x_g = 0$ $\forall g \in \mathcal{G}_{nr}$. This is sensible, the condition was already ensured by constraint 4.8: SKUs not eligible for return cannot be returned.

In experiment 8 and 12, SKUs that are not eligible for return, are forced to be returned. Since this contradicts constraint 4.8, these experiments result in an error: the model can not be solved.

Table C.1: Verification experiments with decision variables, based on excess stock data from 27 November 2024

Experiment	Description	Number of SKUs			Total Costs	Direct Costs			Opportunity Costs	
		In Stock	Return	Liquidate	Total	Holding	Working Capital	Return	Clearing	Keep In Stock
0	Base Constraints	3.6k	12.8k	2.6k	-€165.5k	€7.7k	€2.8k	€10.8k	-€218.3k	€31.3k
1	w[g]==0 for all g in G	0k	16.3k	2.8k	-€115.5k	€0.0k	€0.0k	€14.7k	-€130.2k	€0.0k
2	w[g]==1 for all g in G	19.1k	0k	0k	€781.3k	€108.7k	€55.1k	€0.0k	€0.0k	€617.4k
3	w[g]==0 for all g in Gr	0.2k	16.3k	2.6k	-€121.2k	€0.5k	€0.2k	€14.7k	-€138.7k	€2.0k
4	w[g]==1 for all g in Gr	16.5k	0k	2.6k	€687.2k	€91.7k	€45.5k	€0.0k	€24.3k	€525.7k
5	w[g]==0 for all g in Gnr	3.5k	12.8k	2.8k	-€159.8k	€7.2k	€2.6k	€10.8k	-€209.80k	€29.4k
6	w[g]==1 for all g in Gnr	6.2k	12.8k	0k	-€71.5k	€24.8k	€12.5k	€10.8k	-€242.6k	€123.1k
7	x[g]==0 for all g in G	6.4k	0k	12.7k	€251.3k	€19.5k	€11.0k	€0.0k	€140.1k	€80.8k
8	x[g]==1 for all g in G	*Error*								
9	x[g]==0 for all g in Gr	6.4k	0k	12.7k	€251.3k	€19.5k	€11.0k	€0.0k	€140.1k	€80.8k
10	x[g]==1 for all g in Gr	0.2k	16.3k	2.6k	-€121.2k	€0.5k	€0.2k	€14.7k	-€138.7k	€2.0k
11	x[g]==0 for all g in Gnr	3.6k	12.8k	2.6k	-€165.5k	€7.7k	€2.8k	€10.8k	-€218.3k	€31.4k
12	x[g]==1 for all g in Gnr	*Error*								
13	y[g]==0 for all g in G	6.2k	12.8k	0k	-€71.5k	€24.8k	€12.5k	€10.8k	-€242.6k	€123.1k
14	y[g]==1 for all g in G	0k	0k	19.1k	€560.0k	€0.0k	€0.0k	€0.0k	€560.0k	€0.0k
15	y[g]==0 for all g in Gr	3.6k	12.8k	2.6k	-€165.5k	€7.7k	€2.8k	€10.8k	-€218.3k	€31.4k
16	y[g]==1 for all g in Gr	0.2k	0k	18.9k	€554.2k	€0.5k	€0.2k	€0.0k	€551.5k	€2.0k
17	y[g]==0 for all g in Gnr	6.2k	12.8k	0k	-€71.5k	€24.8k	€12.5k	€10.8k	-€242.6k	€123.1k
18	y[g]==1 for all g in Gnr	3.5k	12.8k	2.8k	-€159.8k	€7.2k	€2.6k	€10.8k	-€209.8k	€29.4k

C.2. Verification based on Parameter Values

As part of the model verification based on parameter values in section 5.2, a set of eight SKUs has been artificially created. These SKUs with their parameter values are shown in Table C.2. Parameters independent of g are not included in the table below. For these parameters, the base values are used (mentioned in 4.4.1).

Table C.2: Set of SKUs used for verification based on parameter values

g	S_g [#]	P_g^s [€]	D_g^e [days]	D_g^c [days]	P_g [days]	F_g^c [-]	F_g^f [-]	C_g^s [€]	N_g [€]	$g \in \mathcal{G}_r$? [-]	P_g^r [€]	C_g^r [€]	P_g^l [€]
10	1	20	1095	200	60	1	0	0.015	10	1	11	0.2	2
20	1	20	1095	200	60	1	0	0.015	10	0	-	-	2
30	1	20	100	200	60	1	0	0.015	10	1	11	0.2	2
40	1	20	100	200	60	1	0	0.015	10	0	-	-	2
50	1	20	1095	20	60	0	1	0.015	10	1	11	0.2	2
60	1	20	1095	20	60	0	1	0.015	10	0	-	-	2
70	1	20	100	20	60	0	1	0.015	10	1	11	0.2	2
80	1	20	100	20	60	0	1	0.015	10	0	-	-	2

D

Detailed Optimization Results

Table D.1 shows the results of the excess stock optimization within the [Product Category], using the data set of 27 November 2024. Since the optimal control decision for SKU g applies to its entire excess stock level S_g, this table shows how excess items are affected by the optimization.

The results show that the keep in stock rate, calculated by the number of items, actually exceeds the keep in stock rate by SKUs. This suggests that the retained SKUs typically have an above-average stock level. Similarly, the % of items eligible for return exceeds the % of SKUs eligible for return. This suggests that SKUs eligible for return have above-average excess stock levels (compared to other excess SKUs).

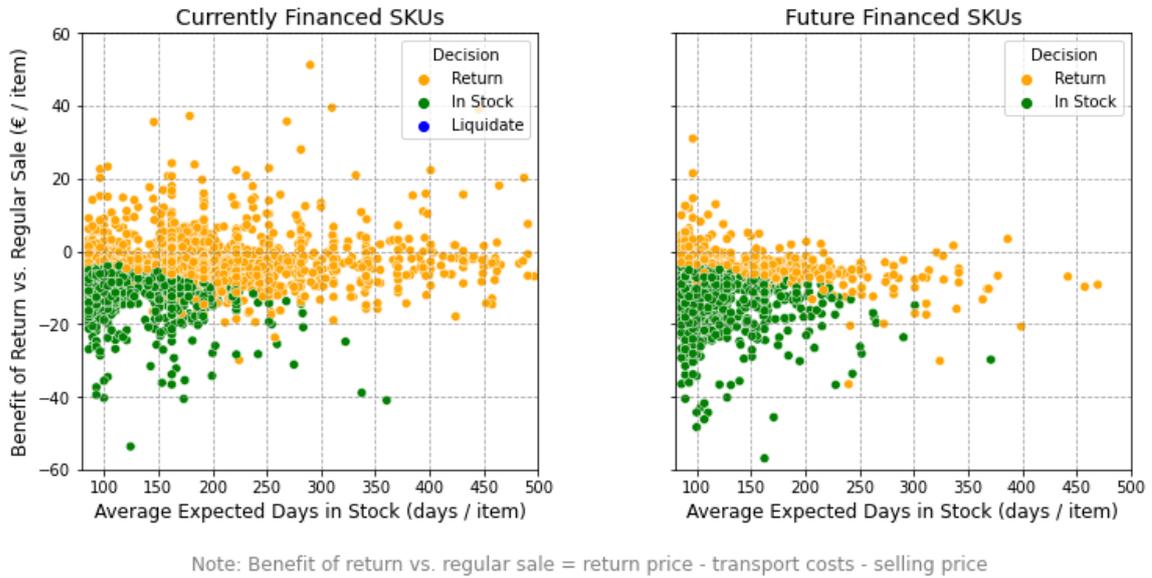**Table D.1:** Optimized control decisions for managing excess stock: number of affected excess items

	Optimized Control Decisions				**Eligible for Return**			
	Total	In Stock	Return	Liquidate	Total	In Stock	Return	Liquidate
Limited Warehouse Capacity ($\alpha = 1$)								
Number of Items	44.2k	10.2k	30.0k	3.9k	39.8k	9.7k	30.0k	0.0k
% of Total	100%	23.1%	67.9%	8.8%	90.0%	24.4%	75.4%	0.0%
Unlimited Warehouse Capacity ($\alpha = 0$)								
Number of Items	44.2k	18.0k	23.4k	2.8k	39.8k	16.4k	23.4k	0.0k
% of Total	100%	40.7%	52.9%	6.4%	90.0%	41.2%	58.8%	0.0%

Figure D.1 is a detailed version of Figure 5.3 in the main text. It illustrates the optimized control decisions of SKUs eligible for return, respective to the expected days in stock and benefit of return vs. regular sale[26] (under limited warehouse capacity). The x-axis has been scaled, so that the identified 'threshold', dividing the return and in-stock decisions, can be analyzed in more detail. Is shows that the threshold is not a perfectly straight line.

Comparing Figure D.1 and Figure D.2 shows that transitioning from limited to unlimited warehouse capacity, results in a threshold that has shifted upwards and has a flatter slope. In other words, under unlimited warehouse capacity (low season), optimal excess inventory management shifts towards higher keep in stock rates.
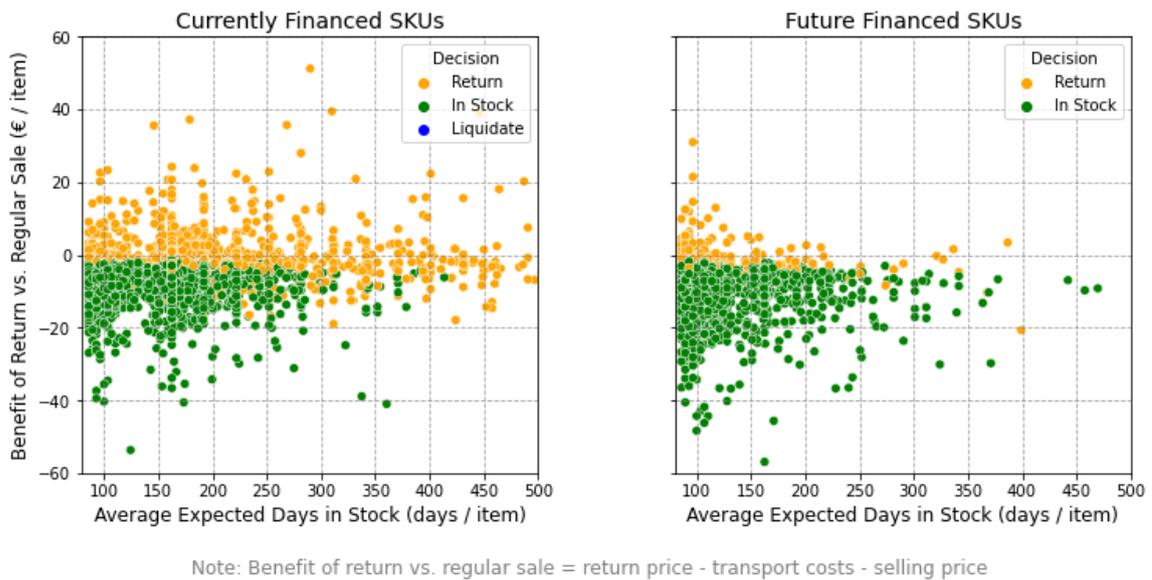
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[26]Defined as: benefit of return vs. regular sale = return price minus transport costs (return) minus selling price.

Figure D.1: Detailed plot of optimized control decisions SKUs eligible for return: expected days in stock vs. benefit of return compared to regular sale. Assumption: limited warehouse capacity.


Figure D.2: Detailed plot of optimized control decisions SKUs eligible for return: expected days in stock vs. benefit of return compared to regular sale. Assumption: unlimited warehouse capacity.

Detailed Results of Sensitivity Analyses

This appendix includes the results of the sensitivity analysis that revealed relatively low model sensitivity. First, Figure E.1 shows the results of the analysis with the daily working capital costs under limited warehouse capacity. This shows that costs are barely affected, changing only with + €2.7k to - €3.5, representing only a 2% change. This suggest that the daily working capital costs are not a key cost component in the optimization. Assumptions around the parameter value are unlikely to have significantly impacted the model results.
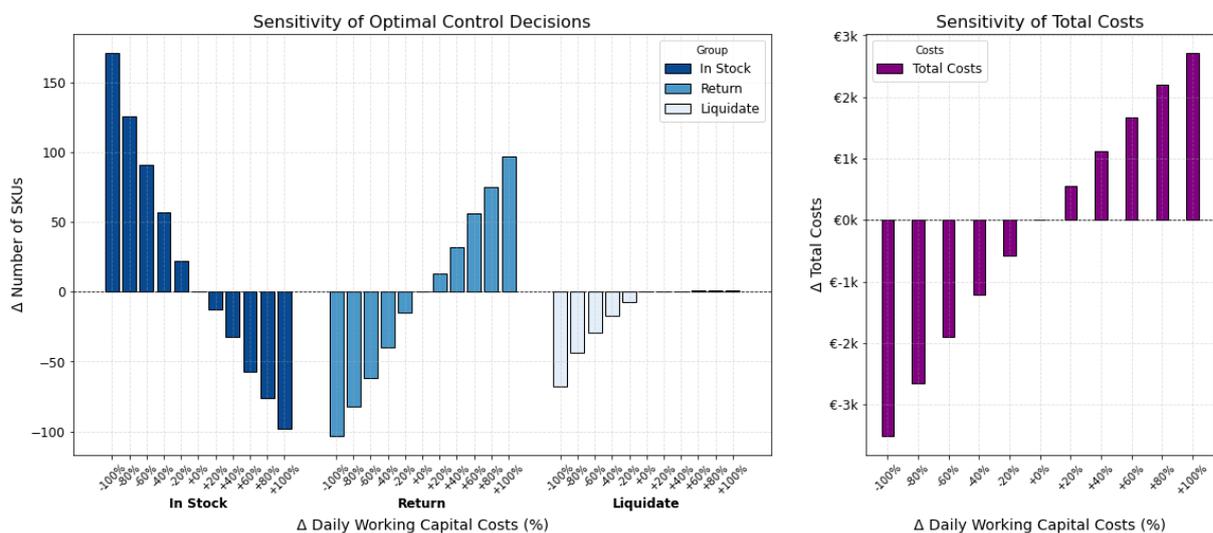
Figure E.1: Model sensitivity to daily working capital costs, under limited warehouse capacity

Subsequently, Figure E.2 and Figure E.3 include sensitivity analyses with the daily discount rate of overall stock and the average lead time per item, both affecting the opportunity costs of keeping in stock. These figures demonstrate even lower model sensitivity in both control decisions and total costs. As such, it is concluded that the model sensitivity to opportunity cost of keeping in stock mostly originates from the average days in stock, and average contribution margin.

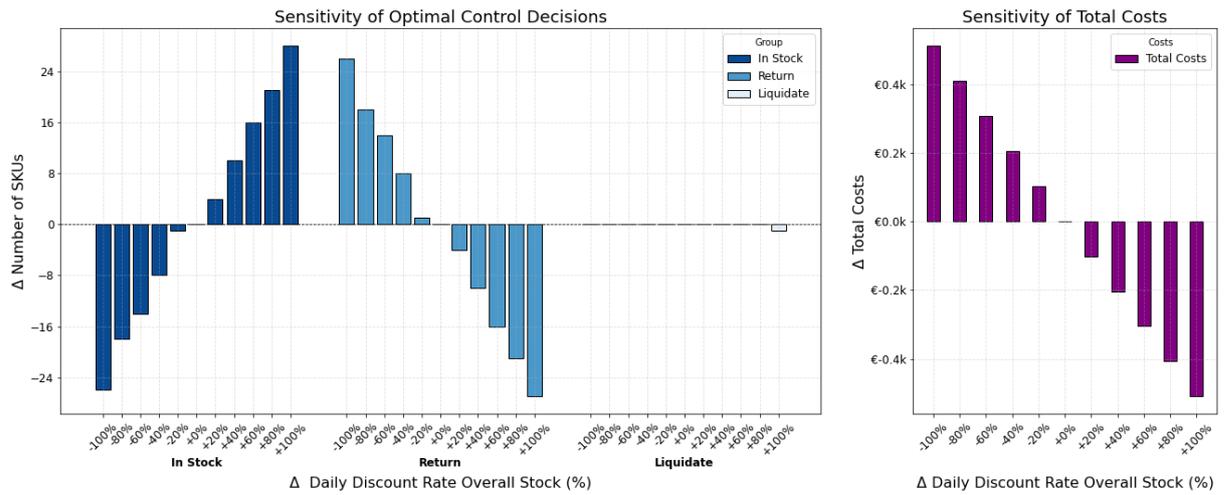## Model Sensitivity Analysis to Daily Discount Rate Overall Stock (α=1)

Figure E.2: Model sensitivity to discount rate overall stock, under limited warehouse capacity

Model Sensitivity Analysis to Average Lead Time per Item (α=1)
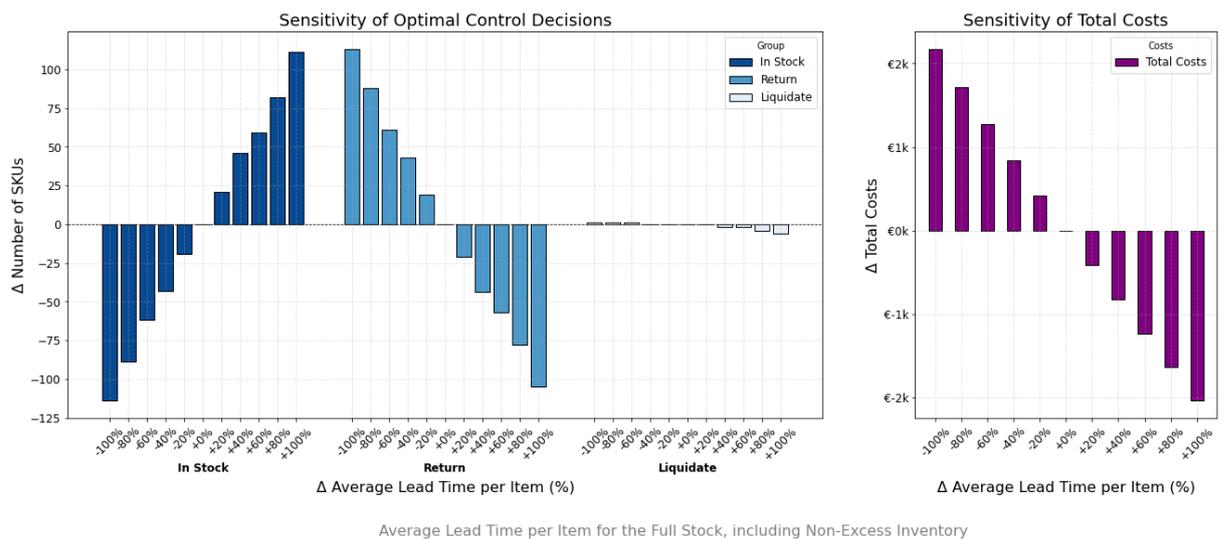

Figure E.3: Model sensitivity to average lead time per item, under limited warehouse capacity

Lastly, Table E.1 provides a detailed overview of the model benefit that is generated when using various excess stock definitions. The table can be used in addition to Figure 5.18 in the main text for more exact and precise insights.

Table E.1: Range of model benefits across excess stock thresholds, for limited and unlimited warehouse capacity

| | Total Model Benefit | | | | Model Benefit per Item | | | |
| | $\alpha = 1$ | | $\alpha = 0$ | | $\alpha = 1$ | | $\alpha = 0$ | |
Projected Stock Days	**Expected**	**Max**	**Expected**	**Max**	**Expected**	**Max**	**Expected**	**Max**
$\geq$ 8wk	€ 445.20k	€ 966.60k	€ 212.20k	€ 390.90k	€ 6.79	€ 14.74	€ 3.24	€ 5.96
$\geq$ 9wk	€ 442.40k	€ 963.90k	€ 210.10k	€ 388.80k	€ 7.32	€ 15.94	€ 3.48	€ 6.43
$\geq$ 10wk	€ 440.00k	€ 960.70k	€ 208.50k	€ 386.40k	€ 7.91	€ 17.28	€ 3.75	€ 6.95
$\geq$ 11wk	€ 436.10k	€ 949.20k	€ 205.90k	€ 380.10k	€ 9.29	€ 20.21	€ 4.38	€ 8.09
$\geq$ 12wk	€ 435.20k	€ 946.80k	€ 205.40k	€ 378.50k	€ 9.86	€ 21.44	€ 4.65	€ 8.57
$\geq$ 13wk	€ 434.10k	€ 945.30k	€ 204.80k	€ 377.50k	€ 10.38	€ 22.61	€ 4.90	€ 9.03
$\geq$ 14wk	€ 432.60k	€ 944.70k	€ 203.90k	€ 376.90k	€ 10.93	€ 23.87	€ 5.15	€ 9.52
$\geq$ 15wk	€ 431.10k	€ 944.70k	€ 203.30k	€ 376.50k	€ 11.45	€ 25.09	€ 5.40	€ 10.00
$\geq$ 16wk	€ 429.60k	€ 944.90k	€ 202.50k	€ 376.30k	€ 11.82	€ 26.00	€ 5.57	€ 10.35
$\geq$ 17wk	€ 428.00k	€ 944.00k	€ 201.60k	€ 375.60k	€ 12.17	€ 26.85	€ 5.73	€ 10.68
$\geq$ 18wk	€ 426.80k	€ 943.40k	€ 200.90k	€ 375.00k	€ 12.48	€ 27.58	€ 5.87	€ 10.96
$\geq$ 19wk	€ 426.20k	€ 943.70k	€ 200.60k	€ 374.90k	€ 12.71	€ 28.15	€ 5.98	€ 11.18
$\geq$ 20wk	€ 426.10k	€ 944.10k	€ 200.60k	€ 374.70k	€ 12.92	€ 28.62	€ 6.08	€ 11.36
$\geq$ 21wk	€ 424.80k	€ 944.80k	€ 200.10k	€ 374.90k	€ 13.05	€ 29.03	€ 6.15	€ 11.52
$\geq$ 22wk	€ 422.70k	€ 945.40k	€ 199.20k	€ 374.90k	€ 13.14	€ 29.39	€ 6.19	€ 11.66
$\geq$ 23wk	€ 419.30k	€ 946.10k	€ 198.00k	€ 375.00k	€ 13.18	€ 29.73	€ 6.22	€ 11.78
$\geq$ 24wk	€ 418.30k	€ 946.70k	€ 197.70k	€ 375.10k	€ 13.27	€ 30.03	€ 6.27	€ 11.90
$\geq$ 25wk	€ 416.90k	€ 946.80k	€ 197.10k	€ 374.90k	€ 13.36	€ 30.34	€ 6.32	€ 12.01
$\geq$ 26wk	€ 414.40k	€ 947.50k	€ 195.70k	€ 375.10k	€ 13.39	€ 30.62	€ 6.32	€ 12.12