Dynamic Operational Policies and Performance Evaluation in Hybrid Warehouse Optimization

A Case Study on Iterative Optimization in a Multi-Purpose Hybrid Warehouse

Master's thesis in Management and Economics of Innovation

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Gothenburg, Sweden 2025
www.chalmers.se

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Cover:

An aisle of a general conventional warehouse

Gothenburg, Sweden 2025

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Abstract

Since warehousing contributes to more than 25% of the supply chain's total cost and largely impacts its efficiency, the importance of optimized and efficient warehouse operations are evident. Growing demand, without increasing operational costs, requires dynamically integrated optimizations operations which can be used iteratively to counter fluctuations in order frequencies. While these challenges are investigated in existing literature, there remains a gap on how to perform this in a multiple purpose warehouse that is using a conventional warehouse complemented by automated storage solutions. Additionally, existing cases mostly discuss one-time solutions, while this thesis aims to address how to successfully iterate the optimization process.

This master's thesis combines quantitative data analysis with qualitative interviews and document analyses to illustrate the current challenges and objectives companies face in their warehouses. Different operational policies and performance evaluations methods and metrics are discussed to decrease the risk of re-shuffling warehouses without increasing their effectiveness. Similarly, different levels of decision making were involved in exploring divergences in challenges and objectives.

The study's findings suggest a class-based approach separating the conventional and automated parts of the warehouse as well as the different product purposes. The automated systems are found to be most effective, an approach utilizing volume and order appearance frequency is therefore used to assign the right products to the automated system. Additionally, by combining slotting, routing and picking policies the rest of the conventional warehouse's locations are classified. Order appearance frequency was then used to assign the products to the different classes, ensuring minimal travel time and increased efficiency. The performance evaluation metrics and methods provide a foundation for decision makers to know when to iterate the warehouse optimization. By integrating data instead of using an ad hoc strategy it is calculated that the warehouse could save up to 39% on their order picking.

Keywords: dynamic warehouse optimization, operational warehouse policies, performance evaluation methods and metrics, warehouse slotting policy, semi-automated warehouses.

Acknowledgements

The master's thesis was conducted during the spring of 2025 at the Department of Technology Management and Economics, under the division of Entrepreneurship and Strategy at Chalmers University of Technology. The project was carried out in collaboration with a case company within the fire hazard and safety industry.

Firstly, we would like to express our gratitude towards Kaj Sunesson at Chalmers University of Technology. By having the role as both our academic supervisor and examiner you have guided us through both practical and theoretical problems and challenges throughout the project. Your knowledge and supervision have been very appreciated when structuring and planning this thesis, as well as how to execute and finish it. Your feedback has ensured a greatly enhanced quality of our report.

Secondly, we want to thank our case company for giving us the opportunity to put our theoretical knowledge into practice. We extend our sincere thanks to our supervisor who not only provided expertise and knowledge but also support and direction which successfully shaped and concretized the project from start to end. The time and resources provided ensured the completion of this thesis.

Thirdly, we wish to thank all interviewees who shared their invaluable knowledge and experience with us throughout the project's continuation. Your commitment made it possible for us to illustrate the scope and scale of the challenges, making your participation crucial for completing this project.

Lastly, we wish to thank our thesis opponents, Wictor Arthur and Arvid Stenberg, for critical and constructive feedback. Your outside perspective and thorough suggestions provided us with knowledge that strengthened the final quality of the thesis. We are grateful for the time and resources you invested in reviewing our report.

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Terms and Definitions

This section includes abbreviations of academia and industry specific abbreviations as well as terminology connected to the research area at hand. Moreover, company specific words and concepts will be explained to facilitate the comprehension of the report. Lastly, the text written in italics shows the Swedish word that has been translated.

Abbreviations

KPI: Key performance indicator

RQ1.1: Research question 1.1

RQ1.2: Research question 1.2

RQ2: Research question 2

SKU: Stock keeping unit

ERP-system: Enterprise resource planning system

WMS: Warehouse Management System

EUR-pallet: A type of pallet with the dimensions …

SLAP: Storage location assignment problem

AS/RS: Automated storage and retrieval system

Glossary

AS/RS: A collection term to describe automated storage and retrieval solutions. An automatic rack within the warehouse that makes it possible to store a lot of smaller SKUs in a small area by leveraging height. Several different versions exist, the case company's AS/RS works like a Ferris wheel where storage shelves, filled with SKUs, rotate on a fixed axle.

Delivery Specialist: The workers in the warehouse performing picking, packing, and reshuffling amongst other similar tasks.

1. Introduction

The introduction aims to describe the research study's topic and introduce the purpose of the research. After that, three research questions are proposed to fulfill the purpose of the project.

1.1 Background

As an integral part of the supply chain, warehouses can accommodate variability caused by change in demand or supply from external factors (Gu et al., 2007). Throughout the last decades warehouse management has become increasingly crucial, constituting about 25% of a company's total logistics cost (Baker and Canessa, 2009). Growing demand for shorter lead times has resulted in increased investments in warehouses and increased complexity between its operations (Gu et al., 2010).

To reduce complexity, the concept of warehouse optimization can be broken down into smaller parts. Karásek (2013) breaks warehouse design down in three different parts: technical structure, warehouse management and operational policies. Similarly, these parts can be broken down into even smaller pieces which can highlight deficiencies and potential for optimization. In this way the warehouse managers can detect challenges in physical areas, assets like layout or system, or in work policies like picking and routing (Gu et al., 2007). Naturally some of these aspects are more difficult to change and have larger financial impact than others (Rouwenhorst et al., 2000). Focusing on aspects that are easier to change but still can contribute to large improvements (e.g. operational policies) is therefore particularly interesting.

The importance of warehouse optimization has resulted in multiple analytical studies; however, most studies are delineated to optimize a specific problem (Gu et al., 2010). For instance, existing literature on warehouse optimization predominantly focuses on single-purpose warehouse environments, such as distribution or manufacturing settings, and often assumes homogeneous automation levels — either fully automated or fully manual operations (Freitas et al., 2019). This simplification neglects the integration challenges of hybrid automation systems and the co-existence of multiple product purposes within a single warehouse — a situation frequently encountered in practice.

Lastly, warehouse optimization processes are destined to become inefficient due to changing conditions (Gu et al., 2010; Karásek, 2013). The warehouse optimization process therefore must be made dynamic and iterative for future re-optimization, which is often neglected in the current literature. Warehouse re-optimization furthermore implies the importance of performance evaluation to determine when to reoptimize. Gialos and Zeimpekis (2024) highlight the need for integrated performance evaluation in the operational policies of warehouse optimization. The performance evaluation should not only consider which metrics are relevant, but also which methods are useful to attain those metrics.

1.2. Purpose

This paper aims to contribute to the research frontier by developing a ***dynamic process*** *to facilitate* ***decision-making*** *in the* ***operational policies*** *of* ***warehouse optimization****, given* ***a warehouse combining conventional and automated storage*** *and* ***multiple product purposes.*** *This includes investigating which method and variables that relevantly* ***evaluate*** *the operational policies'* ***performance****.*

By integrating performance evaluation into warehouse optimization, the study aims to bridge the existing theoretical gap between performance evaluation and operational policies. By investigating warehouse optimization when conventional and automated systems are combined, as well when warehouses serve multiple product purposes, this study aims to broaden the existing knowledge of how warehouse optimization can be adapted to complex real world scenarios.

1.3 Research Questions

There is a gap within the existing theory on warehouse optimization for an dynamic operational policies decision making process that considers multiple product purposes and a combination of automated and conventional storage systems. Additionally, in many warehouses the alignment between performance evaluation and decision-making is skewed and not integrated. Given this and the project's purpose three research questions have been formulated to structure the research.

RQ1.1. What performance evaluation methods and metrics are most effective for assessing the impact of a warehouse optimization?

RQ1.2. How can a method for operational warehouse policy optimization be constructed that considers a combination of conventional and automated storage, and multiple product purposes?

RQ2. How can an integrated decision-making process be designed for optimizing the operational policies of a warehouse, considering changing conditions?

2. Theoretical Framework

The theoretical framework aims to break down the concept of warehouse optimization and find academic gaps in the existing literature. The chapter begins broadly, describing concepts from warehouse optimization, and then gets successively narrowed down to the research frontier.

2.1 Warehouse Optimization

A warehouse can broadly be defined as material handling stations dedicated to receiving, storing and shipping goods (Dotoli et al., 2015). Generally, warehouses can then be divided in three categories, distribution warehouses, production warehouses and contract warehouses.

Warehouse optimization aims to achieve optimal warehouse operations (Karásek, 2013). Optimal warehouse operations are achieved when each customer is completely satisfied with the order, the due time and all warehouse processes are done in the shortest possible time, with minimal cost and optimal utilization of resources under dynamic changing conditions. The general process in a warehouse is defined as receiving, storing, put-away, picking/retrieving and shipping goods (Karásek, 2013).

2.2 Review of Theoretical Frameworks for Warehouse Optimization

Warehouse design and warehouse optimization are complex issues (Karasek, 2013. Gu et al., 2010, Rouwenhorst et al., 2000). Many issues to investigate imply the need to break down the subject. There are several different ways to break down the subject into different components, therefore also different frameworks to conduct warehouse optimization.

2.2.1 Views on Warehouse Optimization

Karásek (2013) divides the warehouse optimization problem in three different subgroups. Firstly, optimization of the technical structure of a warehouse. The technical structure involves the layout design of the warehouse, the choice and dimensions of equipment and the design of physical interfaces with neighboring systems. Secondly, optimization of the operational policies, which include the inventory management policy, picking policy, routing policy and slotting policy. Lastly, optimization of the management system. The warehouse management system is used for the coordination and control of all the typical warehouse operations.

Gu et al. (2010) similarly describes how warehouse design can be divided into five key areas. Firstly, the overall structure which defines material flow, department specifications, and inter-departmental relationships. Secondly the sizing and dimensioning of the warehouse, which defines overall warehouse size and space allocation. Thirdly, the department layout focuses on the configuration of individual departments within the warehouse. For example, aisle orientation or automated storage and retrieval systems. Fourthly, the equipment selection, for example level of automation, selection of storage and handling equipment. Lastly the operational policies act as a framework for the day-to-day work in the warehouse. Once selected, these operational policies have an important impact on the overall system and are likely not to change often. Gu et al. (2010) mainly mentions storage and order picking policy as important examples of operational policies.

Rouwenhorst et al., (2000) initially proposes three key warehouse characteristics: The processes, the resources and the organization. The processes are defined as receiving, storage, order picking and shipping. Resources include storage units, systems, equipment and personnel. Organization describes how, for example policies are organized for order picking or storing and how tasks are assigned. Rouwenhorst et al., (2000) then proposes a warehouse design framework based on the characteristics. The framework divides the design process into three different levels: the strategic level, tactical level and the operational level. The strategic level is concerned with long-term decisions with significant financial impact. For example, process flow design, degree of automation and choice of equipment. The tactical level is concerned with medium term decisions. Tactical decisions typically concern the dimensions of resources. For example, storage system sizes, number of employees, the determination of a layout and several organizational issues. Lastly the operational level describes how day-to-day decisions will be handled within the constraints set by the higher level (Rouwenhorst et al., 2000). The main decisions at this level concern assignment and control of people and equipment. For example, the allocation of stock keeping units (SKUs) and the allocation of tasks.

2.2.2 Operational Policies

The operational policies are vital for a successful optimization (Gu et al., 2010; Karásek, 2013; Rouwenhorst et al., 2000). The first main part of the warehouse operational policies is inventory management, which involves external processes like purchasing and distribution of goods, but also how the warehouse is operated internally, which goods that should be brought in and how much of those goods are handled. (Karásek, 2013).

When goods arrive at the warehouse it needs to be stored away. How and where goods are stored are important later when retrieving the goods by order picking (De Koster et al., 2007). The storage assignment method or slotting policy is the second main part of the warehouse operational policies and involves a set of rules used of which products to assign to which location. De Koster et al. (2007) synthesis five main methods of storage assignment: random storage, closest open location storage, dedicated storage, full turnover storage and class-based storage. With a random policy every incoming product is assigned a random location of all the open locations with an equal probability. The random assignment results in a high space utilization but longer order picking times. The closest open location policy describes that each incoming product is assigned to the closest available open space (De Koster et al., 2007). This method arguably performs the same as the random storage but with a higher concentration of products in the front of the warehouse and a lower concentration at the back.

A dedicated storage policy on the other hand involves that each product has an assigned slot (De Koster et al., 2007). A dedicated policy might decrease space utilization but allows workers to become familiar with product locations, and therefore easier retrieval. Bahrami et al. (2019) mentions four main ways to prioritize products in a dedicated storage policy. Products can for example be ranked based on turnover, the ratio between retrieval operations and space requirement, duration of stay or correlation.

A full turnover storage policy describes that products are distributed over the storage area according to their turnover (De Koster et al., 2007). The products with the highest sale rates are located at the most convenient places. Whilst full turnover storage allows for efficient picking it is sensitive to varying demand rates and changing product assortment. Changes are problematic in full turnover storage as each change involves a large amount of reshuffling.

A class-based storage involves grouping products according to different characteristics (De Koster et al., 2007). For example, popularity. Each class is then assigned an area in the warehouse where allocation is random within the area. Karásek (2013) extends on the class-based storage by mentioning that it can be stored either by factors like picking frequency or using family grouping where similar products are clustered close to increase efficiency.

There are different views on which slotting policy is more favorable. In theory a dedicated storage policy is most promising in reducing travel time (Bahrami et al., 2019). Some others do however consider the dedicated storage policy practically impossible due to the extensive need of accurate data, continuous supervision and limited capability to cope with ceaseless changes. Aase et al. (2004) found that a class-based storage policy with three classes contributes to an improvement in overall picking efficiency 90% as great as dedicated storage over a random storage. Overall, class-based storage showed a 12-26% saving in picking time compared to a random storage, depending on number of classes and picking list length.

Furthermore, class partition affects the performance of a class-based storage. With two classes Aase et al (2004) found that a 30-70 or 40-60 percentage partition yields the best results. A 30-70 partition describes that the primary class consists of the 30% most important SKUs, and the secondary class consists of the remaining 70% of SKUs. Additionally, different storage implications and routing policies impacted the effectiveness of a class-based storage system. Lastly, SKU demand distribution also affects the performance of class-based policy. A demand distribution where a smaller percentage of the products account for a larger percentage of the total demand implies that a class-based storage can contribute to a larger improvement.

Moreover, there is debate over the optimal number of classes. Aase et al (2004) investigates a class-based storage with two to four classes. Four classes contributed to the largest relative improvements compared to a dedicated storage policy. Bahrami et al. (2019) however highlights that recent research has found a traversal relationship between the number of classes and the average picking time. The optimal number of classes was found to be between three to eight.

The picking policy is the third main part of operational warehouse policies and manages how orders are picked within the warehouse (Gu et al., 2010). Three different policies are brought up: wave picking, batch picking, and zone picking. Wave picking entails picking a fraction of the daily orders within the corresponding fraction of the day, while batch picking involves picking multiple orders in one trip. Zone picking means dividing the warehouse into different zones where different workers operate in different zones. Gu et al. (2010) states that the effectiveness of each picking policy is dependent on the specific case it is applied to. Conversely, Karásek (2013) highlights how the batching policy is superior concerning efficiency, while the zoning policy more effectively handles congestion in smaller warehouses. The main drawback for the zoning policy is the consolidation of the order after it has been picked by multiple warehouse operators.

Rouwenhorst et al. (2000) elaborate further on the operational policies involving the personnel and equipment. Regarding personnel, the authors suggest task allocation based on priorities and location, similar to the aforementioned zoning policy. Where picking is dependent on equipment, for example with multiple story racks or handling of heavy products the dwell point policy is crucial for efficient operation. The dwell point policy concerns where to place the idle order picking equipment to minimize travel distance and consequently order picking time (Rouwenhorst et al., 2000). Additionally, Gialos and Zeimpekis (2024) differentiate the concepts of low-level and high-level picking systems, emphasizing the challenge of slotting SKUs three dimensionally. In manual storage operations where equipment like forklifts is used it is therefore important to decide not only where to place the SKU in walking distance from the consolidation space, but also regarding the vertical distance. Gialos and Zeimpekis (2024) advise that heavy SKUs should be placed on the low-level, while high frequency SKUs belong on the medium level. The importance of considering the ergonomics for the warehouse operators is also stressed by the authors.

The fourth main part of the warehouse operational policies is routing policy (Karásek (2013). There are a few different policy options on how to pick the optimal travel path by choosing a routing policy. The policies brought up are S-shape, return policy, mid-point policy, largest gap policy and optimal routing. The policies show different ways a delivery specialist can travel between different slots in the warehouse to pick a complete order. The different policies are efficient in different ways depending on the technical structure of the warehouse, and some are dependent on big data sets, while others utilize the routine and experience of the delivery specialists (Karásek, 2013). In a multilevel warehouse the routing must be considered three dimensionally and it is of importance to have forklifts or similar tools placed within a given route to avoid deviance from the route and increased travel distance (Karásek, 2013).

Lastly, Bahrami et al. (2019) highlights that there is a significant statistical correlation between storage policy, picking policy and routing policy. A model integration of all parts of warehouse operational policies is therefore beneficial. Gu et al. (2010) extends this by emphasizing the positive synergies that may emerge by considering all parts. An effective slotting policy entails an effective routing policy and vice versa.

2.2.3 Conventional Compared to Automated Warehouse Optimization

Automated storage and retrieval systems (AS/RS) are commonly added to a warehouse's technical structure to increase efficiency (Karasék, 2009). The usage of AS/RS has several advantages compared to non-automated systems (Roodbergen and Iris, 2009). For example, savings in labor costs and floorspace or reduced error rates. However, automated systems are often costly and give less flexibility.

Gao et al. (2017) argues that many automated warehouses still utilize a manual or random slotting policy. Likewise, as in a conventional warehouse these methods do not guarantee high utilization, especially when more types of goods are present, and the number of goods is high. By optimizing slotting policy in automated storages travel time can be minimized by reducing travel time for cranes/shuttles, throughput can be increased by reducing congestion, storage density can be increased by placing items more efficiently and energy consumption can be decreased by optimizing movement patterns.

Roodbergen and Iris, (2009) presents several challenges to address in automated storage optimization. Likewise, as in a conventional storage setup slotting policy, picking policy and routing policy needs to be considered. The policies to handle these problems are mostly similar to those in a conventional warehouse setup. Overall items that need to be accessed frequently need to be placed close to the input/output point to increase efficiency. Slotting policy can therefore be dedicated, random, full turnover based, or class based. Regarding picking and routing several heuristics can be used. However, aspects such as elevator or crane travel time have to be considered as well as warehouse worker travel time.

2.2.4 Performance Evaluation

The concept of performance evaluation is an important subject in warehouse optimization since it measures the effectiveness of a warehouse design and thereby whether a warehouse design optimization is successful or not (Gu et al., 2010). Gialos and Zeimpekis (2024) highlight the importance of utilizing effective methods and variables to evaluate and benchmark the operational policies. While the methods mainly concern how to optimize the operational policies, the variables act as KPIs.

The methods used are mostly mathematical and analytical models relying on algorithms (Gu et al., 2010; Karásek, 2013), but other methods include simulation, field and lab tests, and surveys and interviews (Gialos and Zeimpekis, 2024). Each of the methods has its advantages and disadvantages for specific occasions and KPIs like price, scope and validity must be evaluated before deciding method. Gialos and Zeimpekis (2024) highlight that combining different methods can better illustrate the warehouse and facilitate decision-making.

The variables are in this case the KPIs which the methods aim to improve. The most common one regarding operational policies and picking optimization is order picking time (Gialos and Zeimpekis, 2024), but other KPIs like cost efficiency, throughput time, space utilization, speed to fulfill order, order accuracy can also be useful in benchmarking the methods performance (Gu et al., 2010; Rouwenhorst et al., 2000). Tompkins et al. (2003) displays how the order picking time can be divided, illustrating how time is the most important metric, but that many other metrics also impact the overall efficiency. The distribution of time can be seen in *figure 2.1*.

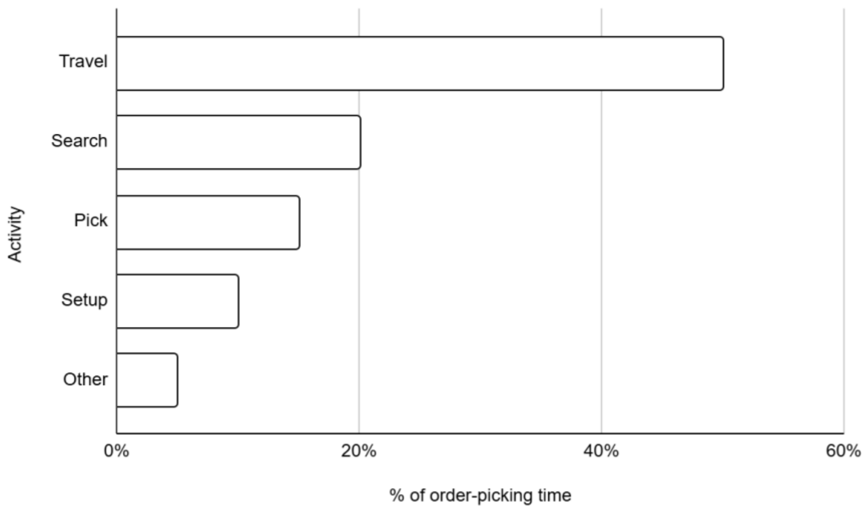

Figure 2.1. The division of picking an order

2.3 Decision making process

Snartland (2023) brings up three decision levels: strategic, tactical and operational. The strategic decisions are those causing the most comprehensive, long-term impact and are usually made by higher executives within the company. Tactical decisions are instead made by mid managers and concerns medium term like ordering quantities throughout a period. Lastly, the operational level concerns the delivery specialists working in the warehouse who are making daily decisions like allocations of products and picking of orders (Snartland, 2023). Each level is crucial for optimizing the warehouse and their focus can be seen in *table 2.1.*

Decision level	**Questions aimed to be answered**
Operational	How to execute?

Tactical	Where and how?
Strategic	Why and when?

Table 2.1. Questions aimed to be answered by each decision level

Aligning with the different levels of decision making, Chen et al. (2010) emphasize the importance of choosing to focus on the right policies to create positive synergies. Managers in the tactical and strategic level need to predetermine which policies that are of relevance and treat them together rather than isolated. Chen et al. (2010) explains that this is due to the close interrelation between the different policies such as slotting, routing and picking. If they are treated separately positive and negative effects can be neglected. It is therefore argued that all these policies should be integrated into one decision making problem, contrary to existing literature that treat them all separately despite their close linkage.

2.4 Project Specific Theoretical Framework

The frameworks presented above (Gu et al., 2010; Karásek, 2013; Rouwenhorst et al., 2000), have several similarities but also complement each other in other ways, this allows for them to be synthesized to create a framework that is mutually exclusive and collectively exhaustive. In *figure 2.2* the three frameworks described above are synthesized to create a general framework used in this research. Firstly, the technological structure is delineated. This is based on Karásek's (2013) description but complemented by the first four key areas described by Gu et al. (2010). Most decisions associated with the designing of the technical structure falls under the strategic level of Rouwenhorst et al., (2000) due to the high cost and effort to change any of these variables.

The operational policies is the second delineation. The operational policies involve setting policies for the day-to-day operations for a warehouse (Gu et al., 2010; Karásek, 2013). The operational policies are in-turn broken down into inventory management, picking policy, routing policy and slotting policy. Defining the operational policies mainly concerns the tactical level, since the effort to formulate and change these policies implies that it cannot be done too often. However, the operational policies also outline how work is carried out on the operational level.

The warehouse management is also delineated and describes the system used to control, coordinate and manage the warehouse (Karásek, 2013). The warehouse management system is concerned with for example monitoring orders, locations and employees. Overall, the warehouse management system enables effective operations and supports day-to-day activity. Changes in the management system can however be complex.

In addition, the performance evaluation criterion from Gu et al. (2010), and Gialos and Zeimpekis (2024) are integrated into the framework to evaluate the different variables and methods within each of the other three subsections. Performing evaluation is not only important in the operational work, but also in warehouse design, since a good performance evaluation model enables the correct decision regarding the best warehouse design (Gu et al. 2010).

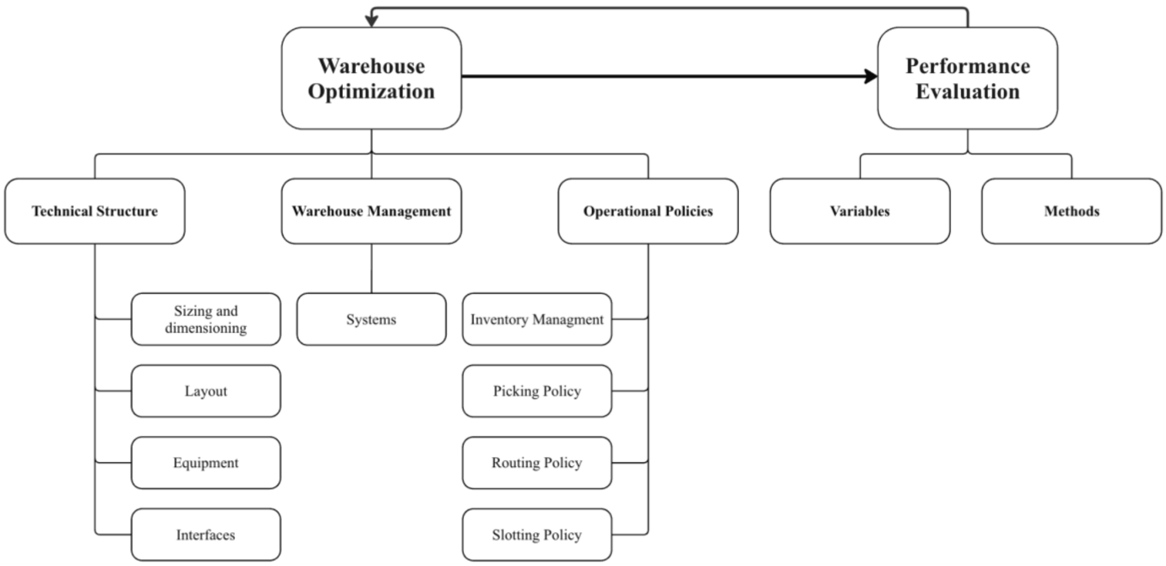

Figure 2.2. Theoretical framework identifying different parts of the research frontier

2.5 Relevant Gaps in Existing Literature

Existing academic research has primarily focused on analytical models for specific problems rather than integrated design approaches (Gu et al., 2010). There is therefore a need for development of integrated analytical and simulation models for better decision-making. There is also limited exploration of dynamic and uncertain operating environments (Gu et al., 2010). Overall, there are insufficient tools for aiding real-time decision-making during warehouse design.

Rouwenhorst et al. (2000) also highlights a significant focus on isolated problems (e.g., routing, batch picking) rather than integrated, holistic approaches in the current research. The focus also tends to be on automated systems rather than conventional warehouses. Overall, there is a need for more design related methodologies that consider interdependencies between design, operations, and performance. Lastly, (Rouwenhorst, et al., 2000) explains that there is also a need for more case-based studies to align research with real-world challenges.

Kofler et al., (2014) also highlights that operational policies regularly have to be remodeled due to change in company characteristics like growth or new product launches. The need to reoptimize also implies the need to research more dynamic processes and to evaluate the performance. Gialos and Zeimpekis (2024) elaborate on this and emphasize how the lack of considering multiple indicators, in addition to time, makes the methods more static and non-optimal. Order picking time is the chosen evaluation variable in 56% of the cases, while KPIs like number of warehouse operators, ergonomics and costs are evaluated in less than 7% of the cases (Gialos and Zeimpekis, 2024).

Lastly Bahrami et al. (2019) highlights a lack of balance in the research area of warehouse optimization between assumption restricted modeling approaches and those based on the complex reality of warehouses. These views can be connected to the lack of studies on hybrid warehouses that combine automated and conventional storage systems (Freitas et al., 2019). Freitas et al. (2019) also highlights the lack of studies on multi-activity warehouses with diverse activities. For example, warehouses that combine supply to production lines and supply to after-sales.

Combined knowledge from the existing literature has led to the identification of the following research needs within the area warehouse optimization:

- Need to investigate integrated warehouse optimization processes combining design, operations and performance evaluation.
- Need to study integrated operational policies, rather than separately to leverage synergies.
- Need of research on how warehouse optimization processes can be dynamic and handle changing conditions.
- Further need for case studies aligning research with real world problems.
- Further need for studies on the complex reality of warehouses rather than assumption-based modelling approaches.
- Further need for studies on hybrid and multiple-activity warehouses.

3. Method

The following section describes how the project will be conducted and why certain methods are selected. The section begins by outlining the overall project design, then describing the overall research design and lastly handling how and why different methods are used.

3.1 Case Study

Case study research is concerned with the complexity and nature of a particular case in question (Bell et al., 2022). A case study also implies that the system or situation being studied has a definite scope. In this case the definite scope is a single location, as a single warehouse is being investigated. The warehouse is meant to be used as a representative or typical case that seeks to exemplify how the research can be used in similar situations (Bell et al., 2022). The case was selected through purposive sampling. Purposive sampling is when researchers intentionally select a case subject based on specific characteristics relevant to the study (Bell et al., 2022). Purposive sampling is beneficial in this case since it allows for the selection of a particularly interesting subject for the study.

A case study is favorable in this research project due to several different reasons. Firstly, there is an expressed need for case studies within the area of warehouse optimization, to align research with real world problems (Rouwenhorst et al., 2000). Secondly a case study facilitates the exploration of complex real-world business issues in depth (Bell et al., 2022). Through the study of a case, deep and detailed insights can therefore be acquired from a real-world context, which is especially relevant when the focus is to generate real world applications rather than theoretical models. A case study is therefore favorable to investigate RQ2 as RQ2 is concerned with generating a real-world applicable decision-making process for warehouse optimization. Thirdly, a case study is favorable to use in qualitative research since it facilitates the use of several qualitative methods (e.g. interviews and observations) and therefore credibility. Additionally, case studies facilitate theory which to some degree can be generalized to other situations and therefore create transferability.

Bell et al. (2022) emphasize how a combination of qualitative and quantitative research are common in case studies to create an in depth understanding. This is applicable to this research paper's case which will be researched using both qualitative and quantitative measures. Additionally, it has been chosen to keep the case company anonymous. This is done to ensure a more authentic and honest study where the participants dare to highlight challenges and problems, thus increasing the reliability of collected data (Godfrey-Faussett, 2022).

3.1.1 Introduction to Case

The case company is a global provider of fire, flame and gas safety solutions to marine, energy, rolling stock and building sectors. Although the company has several locations this study will be limited to one. The case company is currently in a high growth phase. This has implied increased strain on the warehouse operations. The case company therefore has a need to either expand the warehouse operations through additional hires or ensuring more efficient operations. The decision to conduct a warehouse efficiency optimization was supported by the management team's hypothesis that the warehouse could be organized more efficiently. Additionally recent acquisition of barcode readers and their use in the warehouse has ensured a strong availability of data and therefore increased the feasibility of a warehouse efficiency optimization project. The high growth has also implied limited time to handle the warehouse optimization internally, which is why this degree project will be carried out.

Lastly, due to rigidity and high costs the company seeks a process which optimizes the operational policies rather than improving on the technical structure and warehouse management. However, the company does not seek a one-time solution, but rather a dynamic process that can be iterated in the future based on performance evaluation. The warehouse setup of the company is also suitable to answer RQ1.2 since the company deploys a mix of conventional storage shelves and AS/RS and has several product purposes as the warehouse both distributes finished products to customers, supply production and handle aftermarket sales. *Figure 3.1* displays our project specific theoretical framework, and which parts are relevant for the case.

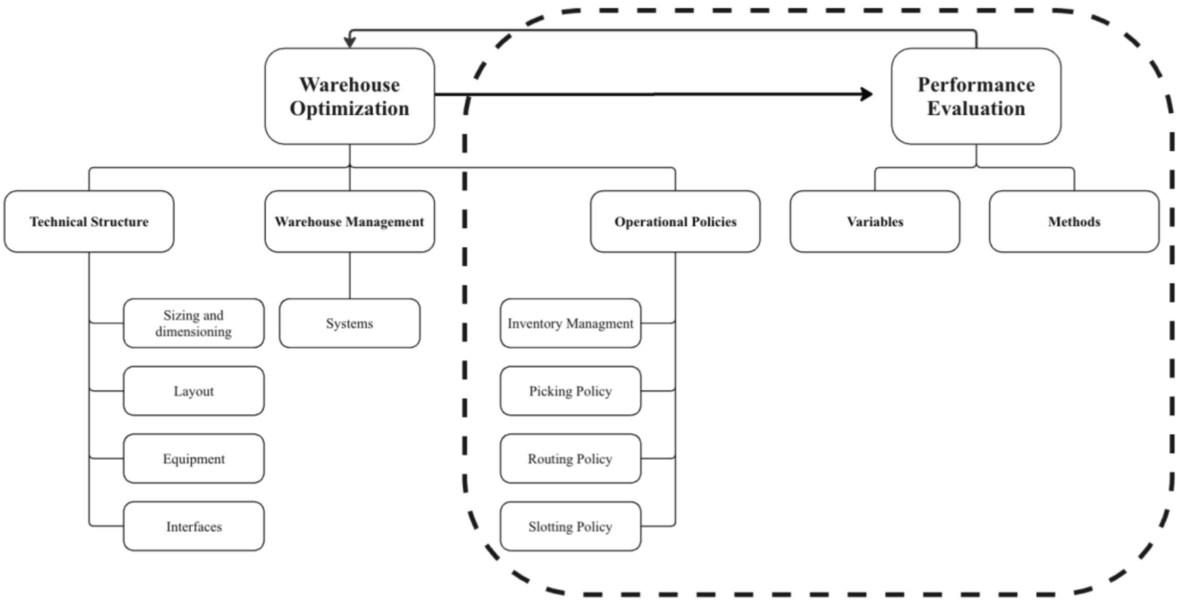

Figure 3.1. Theoretical framework highlighting relevant parts for this project

3.1.2 Case Study in Relation to Research Questions

The specific case study performed at the case company is as established before purposely chosen to contribute answers and insights to the two formulated research questions.

RQ1.1. What performance evaluation methods and metrics are most effective for assessing the impact of a warehouse optimization?

The literature highlights the need for research on the integration of performance evaluation with warehouse management. Moreover, the literature calls for research either evaluating other KPIs than just order picking time or evaluating multiple indicators in relation to each other. Similarly, the most prevalently used performance evaluation method is heavily reliant on advanced analytical models. Due to their recent introduction of digital tools, the case company lacks the capability to use these models and instead must opt for another method. Similarly, while picking time is still an important KPI, the need for assessing other performance metrics has been implied by the company. This enables the researchers to assess which methods and metrics are most effective for optimizing their operational warehouse policies. Furthermore, the case company has raised concern that the warehouse might need to be re-optimized in the future; there is therefore a need to investigate how performance metrics can be used to diagnose the warehouse optimization need and show the result.

RQ1.2. How can a method for operational warehouse optimization be constructed that considers a combination of conventional and automated storage, and multiple product purposes?

Similarly, the existing literature fails to acknowledge multiple purposes and hybrid warehouse solutions. Therefore, the objective is to use the metrics and methods found in RQ1.1 to construct a method that can optimize these types of warehouses. The case company suits this objective well since they utilize conventional and automated storage within their warehouse. The case company highlights the inefficiencies between their storages, which makes it highly relevant as a foundation for answering this RQ. Similarly, the case company's warehouse has multiple purposes. Firstly, the delivery specialists pick sales orders which are directly shipped to their customers, either as new sales or as aftermarket spare parts. Secondly, they pick raw material orders which are sent to the company's production department. It is therefore a combination of a distribution and production warehouse.

RQ2. How can an integrated decision-making process be designed for optimizing the operational policies of a warehouse, considering changing conditions?

The case company is currently going through rapid growth and to manage the higher demand on their warehouses they have decided to start using digital tools to make their warehouse operations more efficient and accurate. Similarly to the identified gaps in the research frontier, the case company has lacked an effective and dynamic decision-making process deciding how and when to iterate their warehouse optimization due to the changing conditions. The digital tools were implemented in March 2024, which gives the researchers a unique possibility to investigate and design the decision-making processes. In addition, the case company is using a hybrid warehouse which is specifically mentioned in RQ2 due to the gap in existing literature.

3.2 Research Strategy

The research strategy is based on a deductive approach. A deductive approach begins with theory or hypothesis and then tests this through observation, data collection, and analysis, working from general to specific (Bell et al., 2022). The deductive approach is suitable in answering the research questions since it facilitates the testing of different theories related to the subject, and then evaluating their effectiveness using quantifiable metrics and systematic evaluation methods.

Moreover, the research strategy requires a mix of quantitative and qualitative elements to answer the research questions. Quantitative research is based on the collection of numerical data and qualitative research is based on data compromising of written or spoken words and images (Bell et al., 2022). The societal view on the study is that it is continuously changing due to human interaction and changes in demand. The study therefore follows a constructivist view (Bell et al., 2022). In accordance with Bell et al. (2022) it is therefore important to include qualitative research to make the study more dynamic.

3.2.1 Research Quality

Qualitative research is sometimes targeted with criticism regarding lack of objectivity and being too influenced by the researcher (Bell et al., 2022). Quantitative research on the other hand needs to consider questions such as sample stability and context accuracy. To address these critics and to enable research quality, different quality criteria has been developed. Bell et al. (2022) mentions the quality criteria of *reliability, replicability and validity.* These are however mainly applicable in quantitative research due to the criteria gearing towards numbers. To address these concerns the quality criteria of *credibility, transferability, dependability* and *confirmability* have been developed as an overall assessment of the research *trustworthiness* can be achieved. Since these incorporate the criteria of reliability, replicability and validity, trustworthiness will be used to secure the research quality of this project.

Credibility describes how internal validity will be achieved, which describes how believable the findings are (Bell et al., 2022). Many different perceptions of the social world imply many different views that have to be incorporated. The ability to interpret findings and include them correctly is important to ensure credibility. To ensure credibility in this project interviewees will have the opportunity to read the research before publishing to ensure correct interpretation. Theory included will also be analyzed by both authors to ensure the common understanding. Lastly, to ensure internal validity in quantitative data a strong cause-to-effect relationship between variables need to be identified. Furthermore, an adequate large sample size will have to be used as well as tools to analyze statistical reliability.

Transferability describes how well the findings apply to other contexts, or external validity (Bell et al., 2022). To ensure transferability in the research a rich description of details of culture will be made. This will provide others with a database to determine if the research is transferable to other contexts.

Dependability describes the stability and consistency of research findings over time and under similar conditions, and therefore parallels reliability (Bell et al., 2022). To account for this criterion the paper aims to be as well-structured and transparent as possible. Methodological changes and how results are obtained will be well documented to facilitate the readers evaluation of the paper.

Confirmability concerns the objectivity of the research, therefore describing if the investigator has allowed their values to intrude on the project to a high degree (Bell et al., 2022). To ensure confirmability a detailed record of decisions, methods, and processes followed during the research will be maintained. The concept of triangularity will be applied when possible, using multiple data sources, researchers, or methods to cross-check findings. Lastly external audits are present, both in the form of a peer review at the end of the project and continuous checks by the project examiner.

3.3 Research Process

The project will be carried out in five different phases to investigate the research questions in a structured way. The complete research process is illustrated in *Figure 3.2.* The different phases consist of actions taken to answer the research question.

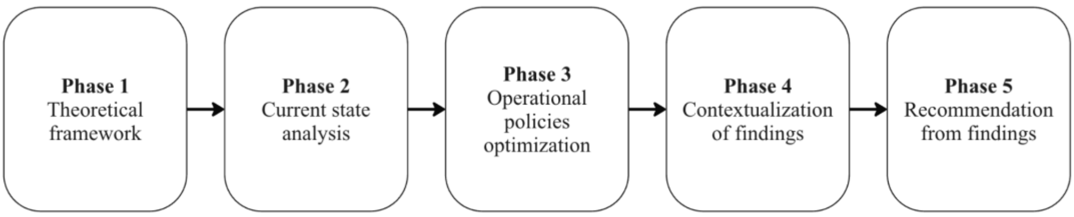

Figure 3.2. The research process

In the first phase, relevant literature about warehouse optimization will be reviewed and synthesized to create a theoretical framework. The theoretical framework will provide an essential foundation for answering the research questions through defining concepts and integrating prior research. The theoretical framework will therefore provide the overall structure that answers the research questions.

The second phase involves a current state analysis of the case warehouse. Warehouse optimization is concerned with the improvement of an existing system, mapping the existing system is therefore important as a starting point. Furthermore, profound understanding of existing prerequisites and interaction with bordering systems are required to develop the integrated decision-making process described in RQ2. In *table 3.1* data required to investigate the research questions at the case company is listed. There is also a summary of how the data will be collected and to which RQ the data is relevant for.

Type of Data	**Explanation**	**Collection method**	**RQ relevance**
Warehouse layout	How is the warehouse currently organised?	Document study and observations	RQ1.1, RQ1.2 and RQ2
Equipment specification	What is currently used in the warehouse? (E.g forklifts and racks)	Interviews	RQ1.1, RQ1.2 and RQ2
Process specifications	What processes are there currently and how are they carried out? (E.g picking pattern, restocking)	Interviews and document study	RQ1.1, RQ1.2 and RQ2
Inventory management policy	How is inventory currently managed? (E.g stock keeping policy)	Interview and document study	RQ1.1, RQ1.2 and RQ2
Current product placements	Which products are there? Where and how are products currently stored?	Quantitative data extraction from the case company's ERP-system.	RQ1.1 and RQ1.2
Picking times	What time is required to pick the different specific products?	Quantitative data extraction from the case company's ERP-system.	RQ1.1 and RQ1.2
Picking frequencies	How often are products used?	Quantitative data extraction from the case company's IT-system.	RQ1.1 and RQ1.2

Picking type	Picking type for different product locations - Can the product be retrieved manually by a worker or is a forklift needed?	Interview, document study and oservations	RQ1.1, RQ1.2 and RQ2
Perceived bottlenecks and inefficiencies	What are the current perceived bottlenecks and inefficiencies?	Interviews	RQ2
Current evaluation methods and performance metrics.	How is evaluation currently made?	Interviews	RQ1.1
Current decision making processes	How are decisions currently made? Based on what and how often?	Interviews	RQ2

Table 3.1 Data needed and relevant data collection method

Data for RQ1.1 is collected with a focus on performance evaluation. The quantitative data is collected from the company's IT-system and will be used to develop a method to assess which performance metrics are most effective in evaluating a company's warehouse optimization. The metrics found in RQ1.1 will then be used in combination with other quantitative data and documents to answer RQ1.2. Documented data, like transaction data, current warehouse layout and how the case company currently handles orders, is gathered to structure an optimization approach, i.e. RQ1.2.

Data for RQ2 is collected to more broadly comprehend how they currently optimize their warehouse and how the decision-making process works. This is mainly qualitative, and the current state analysis aims to give foundation for an improved decision-making process.

The third phase concerns optimization of the operational warehouse policies, which entails identifying improvements to the current operational warehouse policies. For RQ2 this will be done mainly through interviews and discussions with the staff to detect deficiencies and bottlenecks which can be improved. This does not only concern the delivery specialists, but also other decision-makers. For RQ1.1 and RQ1.2 this phase includes consolidation and testing of quantitative data to improve their current method for optimizing operational policies. In

RQ1.2 the results from RQ1.1 are used to simulate different operational policies, and which one gives the optimal solution. The third phase thereby describes how operational warehouse policy optimization can be carried out and which evaluation methods and performance metrics are most suitable.

The fourth phase involves contextualizing the study. RQ2 describes that the goal with this research is an integrated decision-making process. Therefore, the results of the current state analysis and the improvements analysis will be synthesized to create an iterative, integrated decision-making process. Similarly, for RQ1.1, the two previous phases will be combined to understand which method and metrics are important to assess to improve on the existing system continuously. Lastly, for RQ1.2 the results from RQ1.1 in combination with the data from the previous two phases will be used to propose a warehouse optimization method. This method aims to be generally applicable to similar companies to the case company.

The last phase is to conclude the findings in a recommendation that can be generalized to firms like the case. The recommendation aims to be dynamic and facilitate the decision-making process by addressing how and when to reoptimize the warehouse regarding relevant performance evaluation methods and metrics.

3.4 Data Collection Methods

As stated above both qualitative and quantitative data collection will be carried out. Several different methods will be deployed to acquire sufficient data to answer the research questions.

3.4.1 Literature

To develop the research methodology and theoretical framework of this project, literature has been used. Literature used mainly includes academic articles and books. To construct the research methodology and to ensure research quality the book “Business research methods” by Bell et al., (2022) has been used. For the theoretical framework literature has been sourced and selected through Google Scholar and Chalmers library. Relevant search words for the scope have been used such as “warehouse optimization”, “warehouse slotting”, “slotting policy optimization”, “warehouse optimization management” and “warehouse operational policies”.

To construct a theoretical framework, it is important to critically evaluate literature to know what to include in the literature review (Bell et al., 2022). The literature is therefore also evaluated based on the *trustworthiness* criteria. The theoretical framework based on existing literature is used as the foundation for this project’s purpose.

3.4.2 Interviews

Interviews will be conducted throughout the research project to gain valuable insight from delivery specialists and decision makers within the case company. The interviews will be a combination of semi-structured interviews, with pre-prepared questions, and more loose discussions with different employees at the case company. The semi-structured interviews are advantages since they allow the interviewer to deviate from the planned questions to delve deeper or understand the reasoning from the interviewee, while simultaneously creating an agenda of what the interviewer wants answered (Bell et al., 2022). These types of interviews facilitate the early process since they narrow the scope and clearly illustrates the case. The looser interviews are instead advantageous in the latter part of the study since they allow two-way communication where both the interviewer and interviewee can ask questions and propose ideas. This combines theory and data analysis from the project with experience and routine from the employees, resulting in a more comprehensive optimization. The subject of discussion of the interviews as well as questions from the semi structured interviews can be found in *Appendix A.*

The choice of interviewees will be made using snowball sampling, where initial interviewees will be asked to refer to further participants with relevant experiences and characteristics (Bell et al., 2022). The snowball sampling method has been criticized for being biased and not representing the whole population and it is therefore important for the researchers to initiate contact with employees from various levels in the organization to create a more holistic view.

The data gathered from the interviews is presented in *table 3.1* above. The overall aim with the interviews is to complement the quantitative research performed and qualitatively research the current state of the warehouse operation policy and gain insights from delivery specialists. With whom and when the interviews were conducted are documented in *table 3.2*, and more information can be found *Appendix A.* All interviewees are important for answering all our RQ's and illustrating the operational work and decision-making process in different parts of the warehouse hierarchy.

Role	**Department**	**Date**
Manager Delivery	Warehouse	February 6th 2025 (Semi-structured)
VP Supply Chain	Finance	February 4th 2025 (Semi structured) March 13th 2025 (Loose structure)

Head of Supply Chain	Operational Management team	February 11th 2025 (Semi structured) March 18th (Loose structure)
Delivery Specialist	Warehouse	March 20th 2025 (Semi-structured) April 15th 2025 (Loose structure)

Table 3.2. Interviews conducted with employees at the company

3.4.3 Document Analysis

The warehouse layout, current process specifications and current inventory management policy are already mapped and documented by the case company. To leverage the data in this report a document analysis therefore must be carried out. Access has been granted to these documents. The document analysis helps map the current warehouse situation, which is important to answer RQ1.1 and RQ1.2 since it sets the prerequisites for the warehouse optimization process. However, care must also be taken to ensure that the document specifications also correspond to reality.

3.4.4 Quantitative Data

The data used in the process optimization has, as established before, been collected since March 2024 and thereby provides a large enough sampling population to objectively illustrate the current processes in the warehouse. To increase the accuracy further, the median, rather than mean, picking time will be used since it better represents the typical performance by being less affected by extreme values (Smoteks, 2024).

Access has been granted to data regarding the company's SKUs and their orders. This data and quantitative approach are used mostly to answer RQ1.1 and RQ1.2 since it illustrates their current warehouse policies, and which metrics are stored and used to evaluate its performance. However, the quantitative data collected can also be fundamental for the decision-making process by identifying shifts and trends in the changing environment, thus also being useful to complement the more qualitative research in RQ2.

Data regarding the warehouse and its SKUs has been extracted from the case company's ERP-system in the form of six different spreadsheets containing requested data from the researchers. The spreadsheets contents are described in depth in *table 3.3*.

Name	Description
Inventory on hand with current location	Contains all SKUs and where in the warehouse they are located. Additionally, the current available inventory of each SKU can be observed.
Warehouse location and profile	This spreadsheet describes how the different racks currently are being used, e.g if they are meant to be picked from or if they are used as buffer places.
Work line details Raw data	This spreadsheet contains every order since the introduction of the hand held units. Each order, include number of lines, order of lines, time to perform line, SKUs picked, quantity picked, and from which shelf the SKUs got picked.
Picking place with picking height	This data classifies if each location in the warehouse can be reached when picking from the floor or if a forklift has to be used.
Utlagringsdata W01 Weland AUTO1	This data highlights each order in the AS/RS called AUTO1 since May 2024. It includes SKUs and their location within the AS/RS. Since AUTO1 contains two lifts this also highlights in which lift the SKU is located.
Utlagringsdata W02 Weland AUTO2	This data highlights each order in the AS/RS named AUTO2 since May 2024. It includes SKUs and their location within the AS/RS.

Table 3.3. Received quantitative data

3.5 Ethical Considerations

When involving other people in the report through interviews and surveys it is crucial to consider ethics and potential implications. The ethics of business research can be broken down into four main principles: harm to participants, lack of informed consent, invasion of privacy, and deception (Diener and Crandall, 1978). To minimize the risk of harming research participants these ethical principles will be taken into consideration. Before the interviews the participants will be well informed about the research's purpose to decide whether to participate or not and to avoid complications the participants will remain anonymous. Moreover, it is important for the researchers to present their intentions clearly for the participants. Each participant should be handled with respect and their preferences should be accounted for to not invade their privacy. Lastly, to not deceive the participants the results of the study should not be used for any other purpose than what has been communicated to participants before.

3.6 Use of AI

Careful considerations have been made of the use of AI in this research. AI tools were utilized to gain an understanding of the subject and related fields, as well as to get an overview of which articles were important and how the field has developed over time. Additionally, AI has been used to summarize and bring forward important concepts from articles, thus showing their relevance to this project. **AI has not been** used to generate any written material nor any other related material used in this report. Lastly, AI has been used to facilitate programming in Python.

4. Empirical Data

The following chapter utilizes the previously constructed theoretical framework to outline the current warehouse design, decision making process and current benchmarking procedure. Outlining the current warehouse state and decision-making process is important in answering RQ2 and RQ1.2 since it determines the prerequisites for an improved operational warehouse process, thereby providing context for the improved decision-making process. Similarly, investigating the current benchmarking procedure is important to answer RQ1.1 since needs and organizational context determine how to build an effective evaluation method.

4.1 Technical Structure

As Karasek (2013) describes, the technical structure of a warehouse has a significant impact on the other warehouse optimization tasks. Understanding fixed prerequisites of the technical structure is therefore beneficial since it frames the decision-making process in what can be dynamically changed and what has to remain fixed.

Figure 4.1 illustrates the technical structure, i.e. layout, of the case warehouse. The figure is based on documentation from the case company and observations made by the authors but has been simplified for anonymity. Although simplified, it still preserves the key elements of the original data. The different letter symbolizes different racks. The placement of the racks is as established before fixed, but the SKUs' slots are changeable to optimize the operational work. The company has two stand-up trucks which are utilized to reach SKUs on the higher levels. The racks have two to eight different levels. How many levels can be reached whilst picking from the floor varies from zero to three. The different slots are named according to letter number letter code (e.g. A1A). Each slot (e.g. A1A) can hold up to three EUR-pallets, and several SKUs are often consolidated on one EUR-pallet. The slots can either be full height or half height. Other important remarks are that the A and S rack is currently used for finished goods and spare parts respectively. Additionally, AUTO1 and AUTO2 are AS/RSs, used for handling smaller SKUs. Lastly, it is important to highlight that the A rack is built differently than the other racks and does not fit EUR-pallets. Instead, it is built to fit larger cardboard boxes of finished goods.

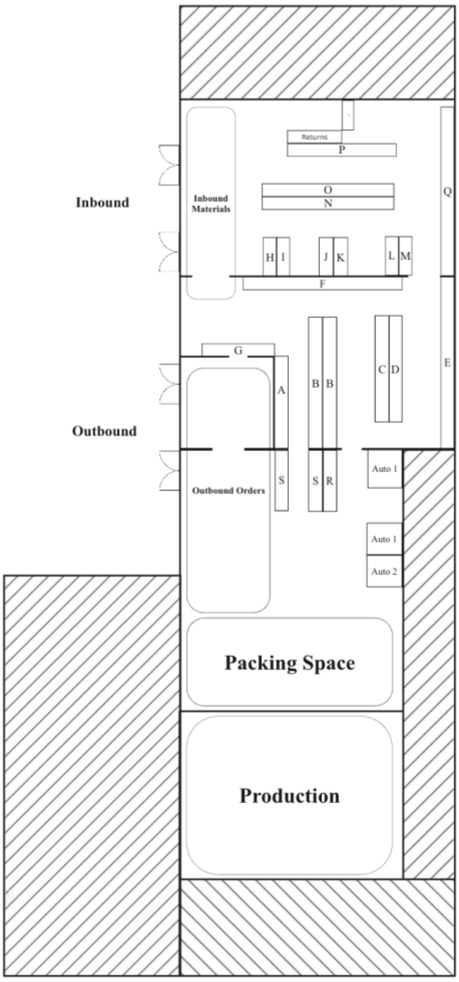

Figure 4.1. Map of the current warehouse layout, equipment and interaction with delineated systems

4.2 Current layout of the AS/RSs

The automated part of the warehouse consists of two towers, where one is concerned with spare parts (AUTO2) and the other to raw materials and sales orders (AUTO1). AUTO1 consists of two lifts, called H1 and H2, which are meant to work together to facilitate the picking of orders. The objective is that when the delivery specialists retrieve SKUs from one lift, the other lift should automatically bring forward the shelf with other SKUs to be picked in that order. The two lifts have a total of 112 shelves which can be customized to hold specific sizes and quantities of SKUs. *Figure 4.2* shows how these may look and are based on observational and documented studies made during the project.

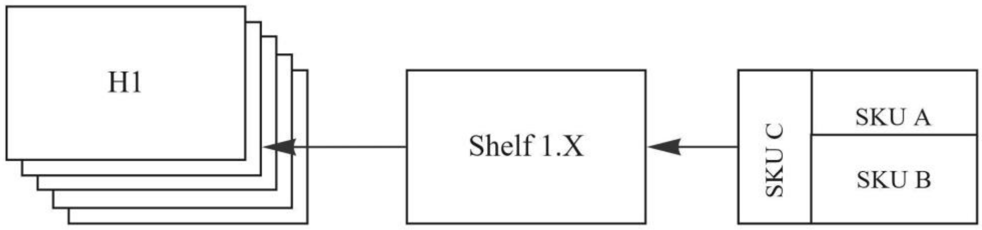

Figure 4.2. Example of AS/RS layout

For maximum efficiency the two lifts should be balanced, which means that the same number of lines should be picked. *Table 4.1* shows how many order lines that are picked from each of the lifts. Every unique SKU in an order has its own order line, e.g. an order with three different SKUs has three order lines. *Table 4.2* displays the total number of orders that make use of each lift or both. Lastly, the number of SKUs in each lift is shown in *table 4.3.* Together the tables highlight how AUTO1 has been operating since May 2024.

	Number of order lines	Percentage of order lines
H1	20864	24,4%
H2	64718	75,6%

Table 4.1 Number of lines per lift

	Number of orders	Percentage of orders
Both	5186	36,5%
Only H1	3434	24,2%
Only H2	5576	39,3%

Table 4.2 Number of orders per lift

	Number of SKUs	Percentage of SKUs in Auto1
Both	9	0,8%
Only H1	491	43,1%
Only H2	639	56,1%

Table 4.3 Number of SKUs per lift

The head of supply chain (Personal communication: March 18, 2025) explains that the goal earlier was to place SKUs that often occurred in the same order on the same shelf to create a prepared product assembly slot. However, this proved to demand a lot of time and resources to maintain and has not worked accordingly. Consequently, this has caused a lot of idle spaces within AS/RSs that are occupied by either low frequency goods or completely empty.

4.3 Warehouse Management System

The warehouse management system (WMS) is used for coordination and control of warehouse activities (Karasek, 2013). Understanding of how the WMS works is therefore important in understanding how flow of people, machines and goods is handled. Understanding the WMS helps answer RQ2 since the WMS needs to be integrated in a dynamic decision-making process. Lastly the WMS is used to gather data, the WMS therefore sets the prerequisites for which evaluation methods and metrics can be used, which is an important aspect to be handled in RQ1.1 and RQ1.2.

The vice president of Supply Chain (Personal communication: February 4, 2025) at the case company explains that the case company uses an ERP-system to keep track of their order data. The data used in this project is gathered from that system. Handheld units with barcode readers are used in the daily work and interact with the ERP-system. Power BI is used to forecast and plan future demand and number of work hours needed to complete predicted orders.

4.4 Current Operational Warehouse Policies

The optimization of operational policies of a warehouse consists of four main areas: Inventory management, slotting policy, picking policy and routing policy (Karasek, 2013). All these areas are important to consider in RQ1.1. RQ1.2 and RQ2 since they are parts of the warehouse processes. The case company's current warehouse process is illustrated in *figure 4.3* with the relevant areas of operational warehouse policy highlighted. The process is taken from the company's documentation but is simplified and connected to this study's theoretical framework to remain comprehensive and anonymous.

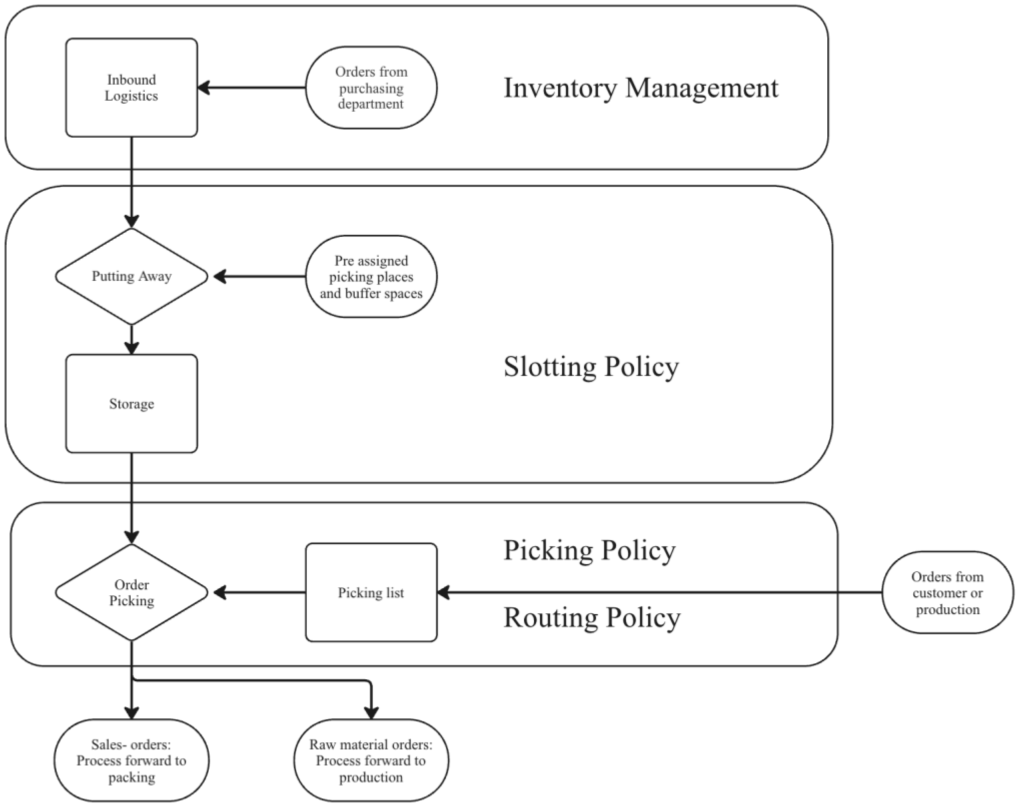

Figure 4.3. The Operational warehouse process

4.4.1 Inventory Management

The purchasing department is responsible for inventory management, i.e. replenishment of materials and stock keeping levels (Manager delivery, personal communication, February 6, 2025). Decisions are therefore mostly made outside the warehousing department's control in the case company, forcing the warehousing department to adapt. However, some policies are deployed that directly affect the warehousing situation. Firstly, a FIFO policy is employed. This implies that if a product has two dedicated places goods should be picked from where the product was first place. The FIFO policy can imply inefficiencies, as goods are not always retrieved from the most convenient place. Secondly besides dedicated product places there are also buffer slots. Buffer slots are used to store excessive volume of products when an extraordinary amount arrives.

In addition, the case company divides their products into two different abstract warehouses. W01, W02. Although everything is picked from the same physical warehouse, W01 concerns the products picked for sales orders and to production, while W02 concerns spare parts. Each of the warehouses contains both a conventional part and an AS/RS. By separating them from each other the case company can put different prices on the same products depending on which warehouse it is in. Spare parts are sold with higher margin (VP of supply chain, Personal communication: March 13, 2025). W02 is replenished by picking SKUs from W01 and transferring them to W02 both digitally and physically, there is therefore no need for different buffer slots for the same SKU.

4.4.2 Slotting Policy

The manager delivery (personal communication, February 6, 2025) describes that the case company currently employs a fixed position warehouse slotting policy. Each SKU is assigned one or more slots in the warehouse. It is desirable that the SKUs are assigned to one slot close to the floor where products can be conveniently retrieved, and one or more less convenient slots where excess storage is located. That is, however, not always the case. Additionally, if the SKU is small and picked frequently, it often also has a slot within one of the two AS/RSs. Although, one current drawback is that when one SKU has been placed in the AS/RSs once it usually stays there and keeps its place despite it not being optimal (Delivery specialist, personal communication: April 15, 2025). When new goods arrive, they are therefore often located in buffer slots and replenishment of picking slots is often done from buffer slots. Assigned slots are recorded in the ERP-system and slot names are marked in the warehouse. The current system therefore represents neither of the five different slotting policies described by De Koster et al. (2007) but is rather a combination of several methods.

Determining a product's fixed locations is currently ad hoc and experience based (Manager delivery, personal communication, February 6, 2025). Implying that a product's allocated slot is changed when a delivery specialist raises concern that it would be more efficient to change the slots. There are, however, some main guidelines in the slotting policy. Raw material is most commonly assigned to the AS/RSs or another particular shelf, due to their high pick frequency and small size.

4.4.3 Picking and Routing Policy

Orders are released to the warehouse operators throughout the day (Manager delivery, personal communication, February 6, 2025). Picking in the warehouse is done by order. However, the orders that require picking from both the conventional and automated storage are divided into two different orders, which later are combined when it is time to pack the order. To increase efficiency SKUs from the bottom levels are picked first and when that is done stand-up trucks are used to reach the higher levels of the warehouse.

The head of supply chain (personal communication, February 11, 2025) at the case company explains that there are two different types of orders. Firstly, orders within W01 or warehouse one. These are orders either going directly to customers via sales orders or raw material orders going to the internal production of the case company. Secondly, there are the orders within the W02. These are orders of spare parts which are picked directly for customers. W01 consists of 3367 different SKUs, while W02 consists of 591.

Orders within the W01 and the W02 are always picked separately as WMS-system classifies these as different works (Head of supply chain, personal communication, February 11, 2025). Additionally, all products in the automated area are also handled in separate works. This implies that there are four different picking types depending on purpose and part of the storage. The order types are illustrated in *figure 4.4*. The separate works imply that W01 SKUs located in the automated storage are never picked with W01 SKUs located in the conventional storage and so on.

		Order type	
		W01	W02
Picking typ	Conventional	W01-Conventinal	W02-Conventinal
	Auto	W01-Auto	W02-Auto

Figure 4.4. The different order types.

Handheld units are used to keep track of orders (Manager delivery, personal communication, February 6, 2025). The delivery specialist picks one order at the time. When a delivery specialist starts an order, a list of lines is received. Each line contains an SKU, where it is located and how many of the SKU that should be gathered. The delivery specialist then marks the line as completed when the product is gathered and moves on to the next product. The route between the different order lines shown in the handheld units follows a descending alphabetical order. After all lines in the order are complete the delivery specialist either drops off the order at the assigned location in the packing space or at the assigned location for production. The delivery specialist then starts a new order.

The handheld units are also used to gather data. Time between the finished lines can be extracted. This is the time it takes for a worker to go from one rack to another and pick the ordered quantity from that rack. For example, it measures the time to go from A1A to B1A and pick a quantity of X SKUs. In this way the time to walk between the racks and picking X quantity of the product is included each time, making the time dependent on three variables: distance, ease of picking, and quantity.

4.5 Performance Metrics and Evaluation methods

As a performance metric, the case company benchmarks towards 500 orders a day (Manager delivery, personal communication, February 6, 2025). Using 500 orders per day as a benchmark and planning method to forecast demand has this far worked fairly well, however there are some challenges too. One order could vary in size from just a few SKUs to more than 50. This greatly impacts the picking time of the orders and thereby also the continuous planning. Another challenge is delays due to lack of supply. The manager delivery (personal communication, February 6, 2025) mentions how many orders cannot be finished the day they are supposed to due to not having enough stock. Inconsistencies between stock on hand and assigned orders highlights to suboptimal communications between outbound- and inbound logistics planning.

The case company currently uses Power BI as a tool to evaluate their warehouse processes in relation to their performance metrics (Manager delivery, personal communication, February 6, 2025). This evaluation method makes it possible to use historic data to forecast future demand and in that way distribute the orders over time. This evaluation method has thus far been perceived as effective in measuring performance and has facilitated planning of resources, although it does not explicitly optimize the warehouse's operations. Furthermore, it is hypothesized that the order packing is a bottleneck (Manager delivery, personal communication, February 6, 2025). Using orders per day as a warehouse performance metric might therefore be misleading as it is affected by bottlenecks further down in the process.

4.6 Current Decision-Making Process

The decision-making process regarding the case company's operational policies can be viewed in multiple levels, from more strategic decisions regarding how to optimize warehouse's order picking time, to more ad hoc decisions in the warehouse deciding where to put specific SKUs. In regard to RQ2, it is important to navigate how these different levels of decision-making affect each other and the overall warehouse processes.

4.6.1 Strategic Decision-making and Planning

The warehouse's main objective is to be able to fulfill the order needs each day. By using tools like Power BI, the decision-making process is facilitated by giving the case company the ability to plan how to distribute orders effectively over time. As of now the planning process follows a cycle where day 0 is the current day and day 1 is the day after etc. (Manager delivery, personal communication, February 6, 2025). The goal is to complete all orders for day 0 without spilling over to the next day.

As mentioned before the case company is currently experiencing growth, leading to an increased number of orders. The strategic decision is to not increase the number of delivery specialists, but rather trying to optimize their operational policies. This shows how the three levels of decision-making currently act with the strategic level making a decision to optimize the warehouse, the tactical level has to decide how to do it, and the operational level lastly has to execute on the decision.

4.6.2 Operational Decision Making

Within the warehouse, delivery specialists are given big autonomy in decision-making regarding where to place SKUs. Most of the current movements are made due to the introduction of new SKUs and limited space on the racks rather than trying to make the warehouse more efficient (Manager delivery, personal communication, February 6, 2025). These changes are usually made ad hoc and based on the experience of the delivery specialists. This entails that SKUs sometimes are moved to slots based on existing space rather than an optimal spot (Delivery specialist, personal communication: March 20, 2025). There is a possibility for the delivery specialist to file suggestions for improvement to other levels of decision making, but it is utilized rather seldom and with little effect.

Since the delivery specialists make most of the decisions regarding where to optimally place each SKU one could consider them responsible for the tactical decisions as well since they both decide where to locate the SKUs and execute on that (Delivery specialist, personal communication: March 20, 2025). In addition, there is no communication from functions like purchasing expired or expiring products. Instead, the delivery specialists will receive a signal once they scan an expiring product and then find out. This results in expiring and expired products taking up good locations in the conventional and automatic part of the warehouse, thus wasting both time and space.

Lastly, the different levels of decision-making experience have some collaborative challenges. The VP of supply chain (Personal communication: March 13, 2025) raises the concern that the delivery specialists carry too much knowledge and information by themselves. This is due to most of the operational decisions concerning the warehouse are made by the delivery specialists without any information and data going to the other levels. Implementing the scanners was seen as a way to transfer the operational knowledge to the tactical and strategic level to facilitate more comprehensive decision making in the warehouse, but as of now it has not worked flawlessly

4.7 Current Order Flow of the Conventional Warehouse

Using the data collected two matrices have been constructed to illustrate how the warehouse and the orders within it currently works. *Figure 4.5* shows the median time it takes for a delivery specialist to move from a given rack to another rack and retrieve the line for that order. Similarly, *figure 4.6* shows the percentages of orders going from one shelf to another. Together the two figures display which racks are used most often and how quickly the delivery specialists can move between them. The data depicted also highlights which routes that take longer time than expected and which routes that may be underutilized. Additionally, the matrices show the incongruities in the retrieved data from the case companies ERP. As mentioned earlier, the orders from the AS/RS and conventional warehouse should be separated into different orders, but as evident from the matrices, this is not always the case. Similarly, the scanners should follow an alphabetical order, but there are exceptions in this data too. The figures are made using the quantitative dataset presented in the appendix.

Start	Auto	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Auto		167	77	96	93		68	57			12			215	115,5	95	118	91	91	26
A			71	71,5	74	149		43					125			133		54	84	
B				61	67,5	65	51	46,5	253	85	249		68	57	68	124,5	118,5	115,5	173	34,5
C			55		78	61	41	54		64	72	47	71,5		60	179	118	62		22
D			60	97		48	52	68		43	167		52,5	316,5	99,5	148	66,5	56	32	21
E			117	16			47	66		65,5	58		64	651	69	87	89	69	184,5	
F		137	58,5	86	188	163		40	139	86	90,5	255	75	170	74,5	91	97	49	116,5	39
G		64	46						118	73	115	310	83	284	87	74,5	109	66	148	64
H			138							60					109	48	112,5	328		
I											86,5		56	150	66	115	133	68	113,5	
J			37										108,5	111	56,5	76		54		
K														128	38	139,5	160,5	252	123	56,5
L			118											125,5	56	72	78	70		
M															98	74	124	787		
N		82	101		113											99	84	74	113	61
O																	67	70	200	
P			232		40			57										68	128	
Q			66,5														352		147,5	40
R		59	87		94															
S		73	71	77	79	141		241				84			126			251	19	

Figure 4.5. The median time between different racks

Start	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
A		13,87	2,50%	0,51%	0,32%	0,31%	0,18%	0,00%	0,00%		0,00%	0,00%			0,00%		0,02%	0,00%	
B		0,01%	8,08%	2,09%	0,74%	0,37%	0,05%		0,01%	0,01%	0,00%	0,01%	0,00%	0,06%	0,06%	0,03%	0,02%	0,00%	0,00%
C		0,02%	0,00%	5,08%	2,11%	0,59%	0,11%		0,00%	0,00%	0,00%	0,01%	0,00%	0,02%	0,01%	0,00%	0,03%		0,00%
D		0,01%	0,00%		6,49%	3,24%	0,08%	0,01%	0,00%	0,01%		0,01%	0,01%	0,04%	0,01%	0,01%	0,03%	0,00%	0,01%
E	0,00%	0,01%	0,00%	0,00%	0,00%	9,45%	5,09%	0,01%	0,10%	0,01%		0,02%	0,00%	0,09%	0,03%	0,01%	0,05%	0,00%	
F	0,00%	0,01%					20,59	0,03%	0,51%	0,09%	0,00%	0,07%	0,01%	0,28%	0,03%	0,04%	0,09%	0,02%	0,00%
G		0,00%						0,08%	0,01%	0,08%	0,08%	0,17%	0,34%	0,41%	0,36%	0,10%	0,65%	0,05%	0,00%
H									0,13%					0,00%	0,01%	0,00%	0,02%		
I		0,00%								0,01%		0,01%	0,15%	0,04%	0,05%	0,02%	0,11%	0,00%	
J										0,03%		0,02%	0,01%	0,05%	0,02%		0,01%		
K		0,00%									0,01%		0,00%	0,01%	0,01%	0,00%	0,00%	0,00%	0,00%
L												0,28%	0,00%	0,34%	0,05%	0,02%	0,04%		
M	0,00%	0,02%	0,00%	0,00%			0,00%						0,08%	0,06%	0,11%	0,01%	0,01%	0,01%	
N										0,00%				1,44%	0,64%	0,32%	0,75%	0,01%	0,00%
O		0,00%		0,00%			0,00%								0,75%	0,19%	0,23%	0,05%	
P		0,01%				0,00%										0,39%	0,27%	0,01%	
Q	0,00%	0,00%		0,00%						0,00%						0,00%	0,98%	0,17%	0,00%
R	0,00%	0,04%	0,01%	0,02%	0,00%	0,00%	0,01%											0,49%	
S										0,00%	0,00%			0,00%	0,00%		0,00%	0,00%	3,88%

Figure 4.6. The percentage of order lines going from one rack to another

5. Analysis

The analysis is divided into three parts, where the first part aims to explain how performance evaluation metrics and methods can be utilized to optimize the warehouse, therefore answering RQ1.1. The second part uses the findings from the first part to analyze how an operational warehouse optimization method can be created to account for multiple product purposes and balancing of automation and conventional storage; thereby answering RQ1.2. Lastly the third part analyses how the method can be made into a dynamic and iterative decision-making process, thereby answering RQ2.

5.1 Performance Evaluation

Given the findings from empirical research, the following chapter aims to analyze bottlenecks and where there is potential for optimization within the warehouse. The chapter is structured like the theoretical framework to emphasize each strategic operation and what measures have been taken to optimize it. Note the big emphasis on how and why actions are taken, since the objective is to develop a coherent and reusable method, rather than solving a problem once.

5.1.1 Performance Evaluation Metrics in Conventional Warehouses

As earlier studies have brought up, the main performance evaluation metric being used when optimizing a warehouse is time it takes to perform the order picking operation (Gialos and Zeimpekis, 2024). Reducing time and in that way, costs is also of great essence in this project and the case company aims to evaluate the performance evaluation method using time saved. However, overall warehouse efficiency is dependent on several factors which also can be divided into smaller parts. *Figure 5.1* displays these connections and how they relate.

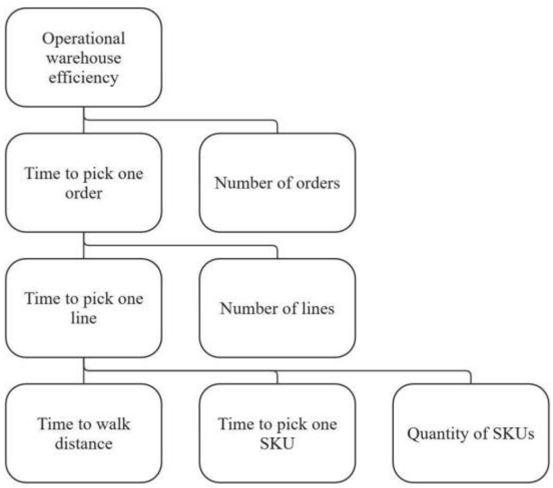

Figure 5.1. How the conventional warehouse optimization can be divided into smaller parts

As *figure 5.1* shows, the overall efficiency of the warehouse is dependent on how quick an order can be picked and the number of orders that must be picked within that time. Similarly, the time to pick one order is dependent on how fast each line can be picked and how many lines each order has. Additionally, time to pick one line is dependent on the distance the delivery specialist must travel plus the ease of picking that SKU multiplied with the quantity of SKUs to be picked. Moreover, in bigger warehouses the time to find an SKU also must be considered. This is most evident when multiple SKUs share one shelf. As one of the case company's biggest inefficiencies is picking errors (Delivery Specialist, personal communication: March 20, 2025), this must be addressed. The picking ambiguity could be minimized by giving the SKUs enough space and clear labeling throughout the warehouse.

The distribution between the activities of the order-picking can vary (Tompkins et al., 2003). *Figure 2.1* illustrates a typical distribution of picking an SKU but neglects the quantity of given SKU that must be picked. *Figure 5.1* combined with the typical distribution between activities as presented in the theory section allows the conclusion that the travel distance should be reduced to optimize the warehouse, but the bigger the quantity of one SKU to pick is, the smaller the percentage of the order picking travel time becomes. Therefore, to optimize the operational policies, focus should be on how many orders each SKU is a part of rather than the picked quantity of each SKU since this will yield the biggest impact on total order picking time.

As the number of lines and orders are dependent on demand they are difficult to explicitly influence from the warehouse, but as the manager delivery (Personal communication: February 6, 2025) mentioned, the case company are using benchmarking as a tool to plan number of orders per day and if the total order time is reduced by using a more effective operational policies, they could meet a higher demand per day. This will implicitly result in being able to meet demand and manage more orders per day. Importantly, the demand is currently bigger than the case company can supply, which means that by being able to complete more orders they can satisfy a bigger demand, thereby increasing their revenue.

By using benchmarking, significant factors affecting the warehouse are neglected. Additionally, as established before the number of lines per order has a great variance. A more precise metric to use would therefore be time per line, which in turn is dependent on factors illustrated above. Starting narrowly on smaller challenges will allow continuous improvements without causing too big risks. Smaller changes in performance metrics are also more likely to be accepted by the workers than a sudden big change in their current benchmarking (Kirk, 2022). As the case company's goal is to increase the warehouse efficiency without having to employ more workers, it is crucial to keep the existing worker satisfied and not make it seem like they are being exploited and overworked.

The chosen metric will be applied to all levels of the operational policies and will be used to evaluate the effectiveness of each suggested method. The operational policies are divided similarly to the theoretical framework, where different methods to optimize it will be evaluated. Time to pick one line is as illustrated by *figure 5.1* dependent on three factors and each one of those correspond to a different part of the operational policies. *Table 5.1* shows how each operational policy relates to each performance metric.

Operational Policy	**Performance Metric**
Inventory Management	Space utilization
Picking Policy	Distance to walk Time to pick each SKU Quantity of SKUs
Slotting Policy	Distance to walk Time to pick each SKU Space utilization
Routing Policy	Distance to walk

Table 5.1 Relations between operational policies and performance metrics

The synergies within the warehouse are important to highlight and the performance metric of space utilization is useful to notice them. For example, this far the total order picking time has been used as an evaluation metric, but that neglects the time it would take to replenish the SKUs in the warehouse. If order picking time is the only metric used, the importance of buffer places would be disregarded. Initially, this would not be noticed in the order picking time, but once the SKUs need to be replenished the inflexibility and inefficiencies of the solution would be seen.

5.1.2 Performance Evaluation Metrics in Automated Warehouses

The performance metrics for the automated parts of the warehouse is relatively similar to those of the conventional warehouse. However, instead of walking distance the focus should be on shortening the lift travel distance to save time. Since the case company has two lifts in their AS/RS meant to work together, the picking time is not only dependent on how fast one lift can bring an SKU, but also how fast the other lift can bring the other SKUs in that order. The goal should therefore be that when the SKUs are picked from one of the lifts, the other one should retrieve the next SKU, resulting in reduced waiting time.

The case company highlights how the unbalanced lifts reduce the effectiveness of the automated storage. About 70% of orders from the automated storage is handled by one lift, resulting in unnecessary stall time on the other lift. Additionally, only about 70 orders are completed using the AS/RS daily, compared to the 500 daily orders they should be capable of picking. Therefore, it is not only important to pick a shelf with short lift travel time, but also in which lift the SKU should be placed. Connecting with Gu et al. (2010) and Rouwenhorst et al. (2000) this therefore becomes a multivariable case where the main goal is to reduce picking time, but metrics like travel distance, SKU allocation and limiting space also play a big part in how to optimize the automated storage. This directly translates to the metric of space utilization which further complicates the case. When filling the AS/RSs one could either try to fit as many SKUs as possible or fewer, but the most frequently picked ones. Giving the SKUs too little space in the AS/RSs would entail higher rates of replenishment, thus reducing the overall efficiency of that solution. Conversely, having too few SKUs in the AS/RSs would mean that most of the order is picked in the conventional warehouse, thus not utilizing the AS/RSs effectively. It is therefore of importance to consider these tradeoffs in metrics and evaluate the total change and not each metric separately.

5.1.3 Creating method from metrics

To analyze the current slotting policy a framework was constructed using aforementioned performance evaluation metrics. The framework divides the current product into four different categories depending on importance and slot quality. The framework is illustrated in *figure 5.2.* SKUs that currently are important and have a good placement in the warehouse are categorized as prime pricks, implying that those products already have an adequate placement. Likewise unimportant products with lesser places are dust collectors, implying that these products are rather irrelevant and that less optimal places are adequate. More important products with bad places are defined as lost essentials. Irrelevant products with good locations are defined as premium waste. The framework illustrates that lost essentials need better places whilst premium waste SKUs can be moved to worse places.

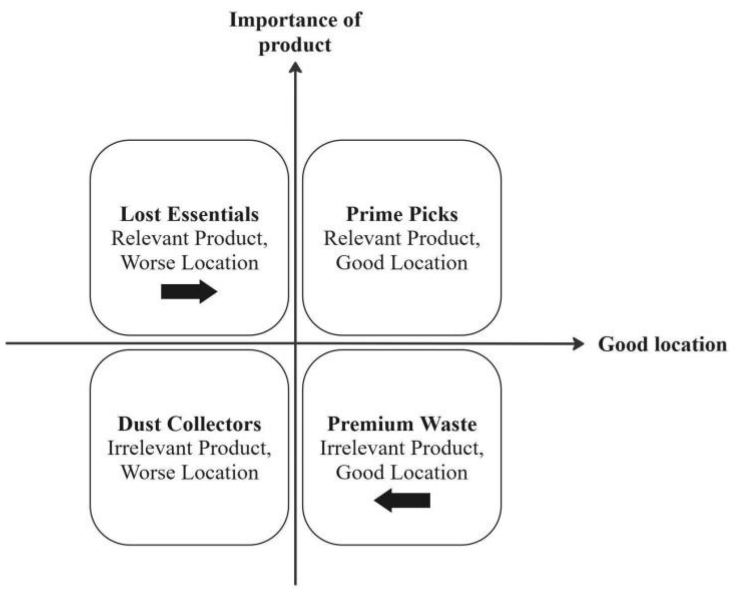

Figure 5.2. The slotting policy framework

The objective with this framework is to identify the lost essentials and premium waste. After doing that the SKUs can be sorted after order frequency to their new positions, reshuffling the lost essentials and premium wastes. This will result in frequently picked SKUs being placed on better locations, thus increasing warehouse efficiency.

The framework requires a defined breakpoint between the x-axis and the y-axis. i.e. a limit between more and less important products and better and worse locations. In this case the distribution between the number of orders per product shows heavy skewness. Implying that a lot of products are included in a few orders whilst a few products are included in very many orders. The important products should account for 90% of the total orders. In this case this implies that the top 15% of the most ordered products are defined as important. The limit implies that all products that have been ordered more than 77 times are defined as important. To define the breaking point between worse and better locations the racks' distance from the packing zone, i.e. the start and end point of each order, was used. Similarly, all shelves accessible without forklifts were rated as better than those where assistance is needed. The automated part of the storage is fastest and is ranked as the best place if the SKU can fit in its limited space.

This framework manages to evaluate and illustrate the performance of the two most important factors in the warehouse, the locations and the SKUs. As mentioned in the previous chapter, travel distance is the biggest contributor to overall picking time, and by placing the best SKUs at the best location that distance is reduced as much as possible. By using these performance evaluation metrics, products could more easily be placed in different classes to see which ones that should be moved to optimize the warehouse. By adjusting the evaluation metrics different classes can be created and evaluated to optimize the warehouse efficiency.

5.2 Warehouse optimization

As highlighted in the theory section there is a proven correlation between routing, picking and slotting (Bahrami et al. 2019). These aspects should therefore be handled together in an integrated approach to capture positive synergies.

5.2.1 Inventory Management

Inventory management is a crucial part of operational warehouse policies. However, inventory management is more important when considering performance metrics such as space utilization than picking efficiency. Conversely, large stock keeping quantities imply more space needed per product and therefore less products that can fit in prime locations. Inventory management is therefore highly related to slotting policy. However, as discussed above inventory management has a more indirect effect on the operational warehouse efficiency than routing, picking and slotting policy.

Additionally, whilst other parts of the operational warehouse policy are handled by the warehousing department, inventory management is largely handled by the purchasing department. The case company illustrated how these functions are often disconnected. The warehousing department therefore had limited power to change inventory management. This leads to inefficiencies and a need to adapt to inventory management policy rather than an ability to change inventory management policy. Knowing this, flexibility becomes increasingly significant when analyzing space utilization.

5.2.2 Picking Strategy

As established in the theory, picking by order allows for increased efficiency compared to picking one product at a time whilst maintaining good structure due to clear boundaries (Karásek, 2013). Additionally given multiple purposes, picking by order is beneficial for forward processing. Since picking errors are prevalent in the case company it is crucial to choose an as structured and clear as possible strategy. Picking by order is therefore suggested to minimize the number of errors in both the picking and packing process. Other methods, such as picking more than one order at a time or picking by product, could increase consolidation in the picking process and thereby efficiency. On the other hand, such policies would also imply that products need to be sorted by order after picking, thereby decreasing structure and creating new time-consuming tasks. Zoning policy may also be useful, but in a warehouse like the case company's where the start and end zones are fixed at the end of the warehouse rather than in the middle it is less effective. This is because all delivery specialists start from one point and move in the same direction, resulting in no reason to have them operate in different zones. Picking by batch and order is therefore concluded to be most suitable in this case.

Additionally, the empirical data shows that picking products from higher shelves is very inefficient and something that should be minimized. *Table 5.2* shows the median time to pick one order line with different retrieval methods. Retrieving goods from higher locations should only be done when replenishing goods. Due to a limited amount of floor space exception does however have to be made for SKUs that are picked very infrequently.

	Picking from reachable slots	Picking from slots where a forklift is needed
Time (s)	56	203

Table 5.2. Picking time per order line from lower and higher shelves

5.2.3 Slotting Policy

Slotting optimization influences both the performance metric of total picking time and space utilization as stated above. To improve warehouse efficiency an effective slotting policy is therefore of high importance. As mentioned in the theory section, both a class based and dedicated slotting policy has proved to outperform a random slotting policy in reducing picking time (Aase et al., 2004). A dedicated full-turnover slotting policy furthermore outperforms other methods in terms of picking efficiency (De Koster et al., 2007). However, this report also aims to explore methods that are iterative, dynamic and can easily be tailored for multiple product purposes and combining automated and conventional storage solutions. A dedicated full-turnover policy requires more data and change in demand can quickly make the policy ineffective. Moreover, potential re-optimizations can be costly due to a large number of shuffles (De Koster et al., 2007). The full turnover storage policy might therefore be too rigid to be beneficial when for an iterative and dynamic method.

Conversely, a class-based storage is easier to implement (De Koster et al., 2007). As mentioned above a class-based storage with three classes has shown to contribute to a relative improvement of 90% compared to a dedicated storage. Additionally, a more favorable product demand distribution can contribute to an even larger relative improvement. In this case 20% of products with most order lines account for 91% of the total order lines, thereby implying a more favorable demand distribution, which would benefit the relative efficiency of a class-based system. Moreover, due to SKU placement within classes being random, less reshuffling when changes occur are needed and space utilization can be more effective. Furthermore, as mentioned above, different product purposes and different storage constellations within the same warehouse complicates the slotting assignment problem. With a class-based policy classes can be used to handle different picking types. Thereby easily managing more complex situations. Overall, a class-based system is therefore beneficial in an iterative, complex and dynamic system due to flexibility whilst still contributing to relatively large improvements compared to a dedicated full turnover slotting policy.

Figure 5.3 illustrated how a class based slotting policy could be designed for the case company to account for multiple product purposes and a mix of automated and conventional storage.

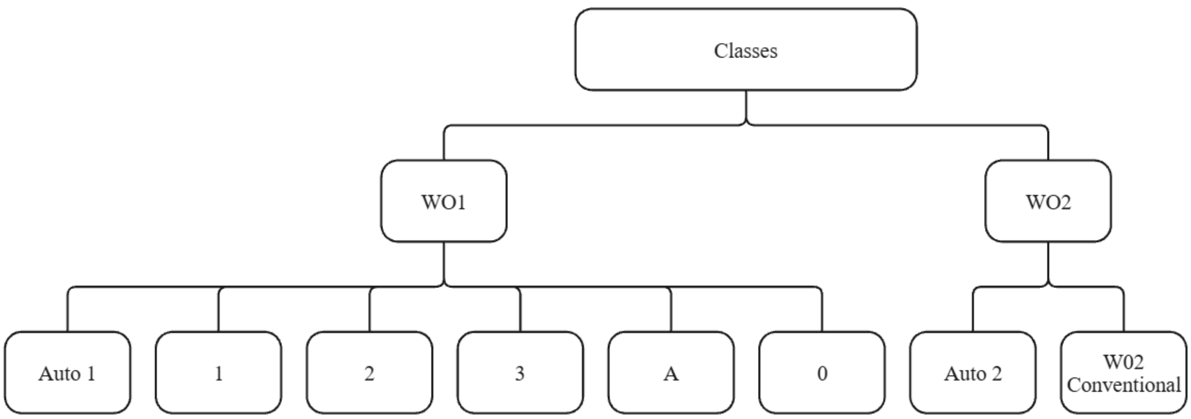

Figure 5.3. A potential class based slotting policy for the case company.

5.2.3.1 Multipurpose Consideration

Firstly, two different subgroups are created, one for W01-products and one for W02-products. The division of W01 and W02 products are made due to the picking policy. W01 and W02 products are never in the same order and therefore never picked together. How W01 and W02 products are placed in relation to each other is therefore irrelevant for picking efficiency. *Table 5.3* shows the number of SKUs in each subgroup and how many order lines these SKUs have accounted for. The period studied is 2024-03-06 to 2025-02-04. This time period is used since it includes all available data.

Classification	Number of SKUs	Number of Order lines
WO1	3367	179 099
WO2	610	17 646

Table 5.3. SKUs and order lines for each category

5.2.3.2 Assigning Products to the AS/RSs

Secondly, for optimal warehouse efficiency, the right SKUs need to be assigned to the AS/RSs. As mentioned above, space utilization is particularly important in the AS/RSs due to their high efficiency. Besides demand it is therefore suitable to integrate SKU to determine which SKUs are most suitable for the AS/RSs, for example by using a utility score (U). *Equation 5.1* states how the utility score for each SKU is calculated. The utility score weighs the number of orders the SKU has been included in (D), the approximate required volume of the SKUs (S) and how uncertain the volume of the SKU is (CV). α, β and γ are used as weights for the different parameters to balance the equation according to the parameters' determined importance. A utility score of zero is used for products where the calculated utility score is less than zero.

- $U_i = Utility\ Score\ for\ SKU\ i$
- $D_i = Order\ frequency\ for\ SKU\ i$
- $S_i = Required\ space\ for\ product\ i$
- $CV_i = Volume\ uncertainty\ for\ SKU\ i$
- $\alpha = Order\ coefficient$
- $\beta = Volume\ coefficient$
- $\gamma = Volume\ uncertainty\ coefficient$

$$U_i = \alpha * D_i - \beta * S_i - \gamma * CV_i \qquad (5.1)$$

In this case volume is the bottleneck for how many products can fit in the AS/RS (delivery specialist, personal communication: March 20, 2025). Complication however arises since the case company does not have data on SKU volumes. Estimates therefore must be made based on available data, primarily SKU weight and SKU category. To gain a rough volume estimate it is assumed that all SKUs have the same density (1 kg/dm^3). However, since that simplification creates uncertainty, the uncertainty needs to be accounted for. Through *equation 5.3* a delineation is calculated which states that there is a 95% probability that the volume of a SKU is below this value, assuming normal distribution within the SKU category. *Equation 5.2* calculates the volume uncertainty for a SKU category by dividing the standard deviation of SKU volumes within the category by the average volume within the category.

- $\sigma_{V1} = weight\ Standard\ deviation\ for\ SKU\ category\ 1$
- $\underline{x}_{V1} = weight\ average\ for\ SKU\ category\ 1$
- $V_i = volume\ for\ SKU\ i$

$$CV_1 = \frac{\sigma_{V1}}{\underline{x}_{V1}} \quad (5.2)$$

$$95\%\ est\ Volume\ for\ product\ i = V_i * (1 + 1.645 * CV_1) \quad (5.3)$$

To determine how many SKUs that fit in the AS/RSs the space requirement (S) for each SKUs calculated through *equation 5.4*. The VP Supply Chain (Personal communication: March 13, 2025) states that inbound orders for the case companies' most common SKUs are received every two to four weeks. Since the AS/RS needs to be refilled manually when goods arrive there is a trade-off between space utilization in the AS/RS and how often the SKUs need to be refilled. Refilling SKUs is time consuming and creates bottlenecks where the AS/RS cannot be used for order retrieval. Besides, the delivery specialist (personal communication: March 20, 2025) raises concern that it is more convenient when a full inbound order batch fits in the AS/RS, as replenishment is easier and no additional space must be used for excessive goods. It is therefore relevant to use a month's worth of demand for each SKU located in AS/RS as the desired stock keeping level.

- $Q_i = average\ order\ quantity\ for\ SKU\ i$

$$S_i = 95\%\ est\ Volume\ for\ product\ i * \left(\frac{Q_i * D_i}{12}\right) \quad (5.4)$$

There are 112 shelves in total in Auto 1. The space on each shelf is modular and can be adapted for SKU needs. The shelves are 24.4 decimeters wide, 8,2 decimeters deep and 2 decimeters high. The total available volume (S_{max}) in Auto 1 is therefore 44 818 dm^3. Auto 2 has the same specification except for 54 shelves instead of 112. Auto 2 therefore has a capacity of 21 609 dm^3.

To optimize the utility score (U) for the SKUs in Auto 1 linear optimization can be used. The goal of the model is to maximize the total utility score (Z) (*equation 5.5*), under the condition that the sum of all SKUs space requirements (S_i) does not surpass the maximum total space available (S_{max}) (*equation 5.6*). This is done by assigning either one or zero to SKUs if they should be selected or not. For the utility score function $\alpha = 0.5, \beta = 0.1$ and $\gamma = 10$ are used as weights. *Table 5.4* displays the result of the linear optimization in this case. The linear optimization is firstly carried out on both the W01 and W02 subgroups. W01 products are placed in Auto 1 and W02 products are placed in Auto 2.

- $n = number\ of\ SKUs$
- $x_i \in \{0,1\} = decision\ variable, where\ x_i = \begin{cases} 1\ if\ SKUi\ is\ selected \\ 0\ otherwise \end{cases}$
- $U_i = utility\ score\ of\ SKU\ i$
- $S_i = space\ requirement\ of\ SKU\ i$
- $S_{max} = maximum\ total\ space\ available$

Objective: $Maximize\ Z = \sum_{i=1}^{n} \quad U_i x_i$ *(5.5)*
Subject to: $\sum_{i=1}^{n} \quad s_i x_i \leq S_{max}$ *(5.6)*

$$x_i \in \{0,1\}\ for\ i = 1,2, \dots, n$$

	AS/RSs	Conventional
W01	548 SKUs	2819 SKUs
W02	199 SKUs	411 SKUs

Table 5.4. SKUs assigned to AR/RSs and the conventional storage for both subgroups

Appendix B shows an example of the data used above. *Appendix C* shows an example of the calculations and *Appendix D* summarizes the inputs and assumptions used for the linear model. *Appendix E* summarizes the dataset used and the complete dataset can be found in *Appendix H.*

5.2.3.3 Conventional W01-Classes

Within the W01-subgroup there are additionally some suitable exception classes. Firstly, some of the products that have assigned slots in the warehouse have not been picked during the studied period. Products that have not been picked during the studied period but are assigned a slot in the warehouse are grouped into Class 0. There are several reasons why these products still are kept in stock. Namely, that the case company is required to keep in stock due to different agreements (Head of supply chain, personal communication, February 11, 2025). Another reason might be that demand varies, situations where products are not picked in a long time and then needed more frequently (Delivery specialist, personal communication: April 15, 2025). A third reason is that there is a lack of a process for phasing out products and cleaning out old unused products (Delivery specialist, personal communication: April 15, 2025). Class 0 is therefore useful to raise awareness of products that have not been used for a long time so that the warehouse personnel could look over these products to see if they should be removed or not.

Secondly, for the case company the A-shelf is used to finish products that are built for customer orders. This shelf does not have pallet slots like the rest of the conventional shelves. Whilst the products on the A-shelf are picked less frequently it makes sense for these to be a separate class. Mainly due to the A-shelf being ill suited for other products due to small shelf slots that do not fit pallets.

The rest of the W01 products are divided into Class 1, Class 2 and Class 3. As stated above a small amount of the products typically make up a large part of the demand. *Figure 5.4* illustrates the relationship between the number of SKUs and percentage of the total order lines given different divisions between the classes in this case. In some cases, the right SKUs are placed in the right class like prime picks and dust collectors, while in other cases there are lost essentials that should be moved to a better class or premium wastes that should be moved to a worse class.

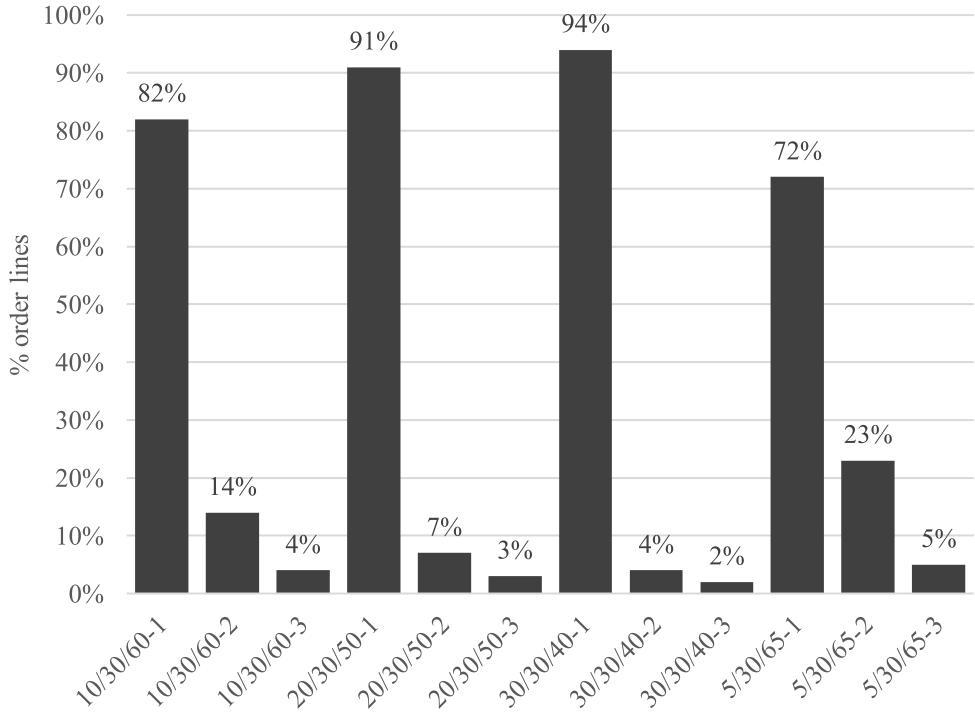

Figure 5.4. Different class distributions and their part of the total number of order lines.

As stated above a distribution where few SKUs account for a large part of the total demand implies larger expected improvements from a class-based system. (Aase et al. 2004). In this case the top 10% of SKUs account for 82% of the total order lines. The case company therefore has a SKU-demand distribution suitable for a class-based system. To keep a reasonable distribution between classes when considering demand the 10/30/60 distribution was chosen. This distribution furthermore implies reasonable demand limits between the classes. Class 1 consists of products picked more than 67 times during the studied period, Class 2 products picked more than seven times, and Class 3 products picked more than one time. *Table 5.5* summarizes the SKUs per class for W01.

W01-Class	Number of SKUs (#)
Class Auto 1	548
Class 1	104
Class 2	312
Class 3	622
Class A	108
Class 0	1673

Table 5.5. SKUs assigned to each class in W01

5.2.3.4 Conventional W02-Classes

The W02-subgroup includes less products than the W01-subgroup. Besides, the W02 products are in general picked less frequently than the W01-products. Therefore, W02 products are simply divided into an AS/AR-class and a W02-conventional class for simplicity. The conventional part of W02 is located, like before, on the S racks. No buffer slots are needed within W02 since they are replenished through W01.

5.2.3.5 Internal AS/RS balancing

The AS/RS in W01 comprises two lifts where the goal for overall efficiency is to have these as balanced as possible. Having completely dedicated places is argued before as inflexible, but by ranking the AS/RS class's SKUs they can be placed in a way that balances the lifts somewhat. No places are dedicated, but there should be a ranking that suggests how the SKUs should be split between the two lifts to make them as balanced as possible. After calculating which SKUs that should be in the AS/RS, they were ranked based on two criteria. First, their order frequency score, O_s, which was calculated using *equation 5.7*. Second, their co-occurrence score, C_s, which is calculated in *equation 5.8.*

$$O_s = \frac{(O_{sku} - O_{min})}{O_{max} - O_{min}} \quad (5.7)$$

$$C_s = \frac{(C_{sku} - C_{min})}{C_{max} - C_{min}} \quad (5.8)$$

By multiplying these normalized scores, a ranking of the SKUs within the AS/RS could be made. By placing every other SKU in lift 1 and lift 2, the lifts will become more balanced both individually due to their SKUs' order frequency score, but also collectively due to their co-occurrence score. Placing the highest scoring SKUs closest to the retrieval space will also minimize travel time for both picking and replenishing, thus increasing efficiency. For the AS/RS in W02 the ranking is less relevant since it only consists of one lift. Instead, the complete class-based approach is used here, resulting in both effectiveness and flexibility. Examples of the balancing calculations can be seen in *Appendix F*.

5.2.4 Routing Policy and Warehouse Areas

Lastly, areas in the warehouse must be assigned to each class. As mentioned in the theory, an integrated approach to warehouse policies is the most effective since it captures positive synergies between the different policies. The slotting locations of the classes have therefore been created in accordance with the optimal route expected to walk to pick one order. Following the performance metric in *table 5.1* the routing policy is mainly dependent on walking distance and the location for each class has therefore been created to reduce that distance as much as possible. Although this is more concretely applicable to the conventional warehouse, it can also be seen in the AS/RSs where the goal is for the lifts to travel as short as possible.

Size of the different areas is determined by the number of products in that class that requires picking places. The number of picking slots per class are presented in *table 5.6.* One picking slot in the conventional storage can fit one pallet, which in turn can fit one or more products. The AS/RSs and the A-shelf do not have pallet slots but rather have customizable shelves, implying that the number of picking slots can be customized. For the most important classes (Class Auto 1, Class Auto 2 and Class 1) each SKU is in general assigned their own picking slot. More picking slots per product is beneficial for easy retrieving and replenishment. High demand implies the need for more frequent replenishment and that more goods can be stored in the picking slots implies less frequent and easier replenishment. For Class 2 and 3 less picking spots are necessary. The least frequently used products in Class 2 are picked seven times during the period studied. The small demand implies that it is reasonable to place several of these products on one pallet to consolidate and make better use of the picking slots. Additional SKUs that cannot be placed in picking slots, primarily present in Class 3, Class 0 and W02 Conventional, are placed in slots higher up. Forklift is then needed for retrieval, but this is reasonable as these products are retrieved infrequently.

Areas	**Number of SKUs**	**Number of Picking Slots**
Auto 1	548	Customizable
Class 1	104	96
Class 2	312	155

Class 3	622	54
Class A	108	Customizable
Class 0	1673	0
Auto 2	199	Customizable
W02 Conventional	411	34

Table 5.6. Number of SKUs and number of picking slots assigned to each class

Another metric that can shorten the walking distance for order picking is the number of co-occurrences between SKUs and place SKUs that are frequently picked together closer. This highlights the aforementioned interrelation between slotting and routing where slotting an SKU at a specific location directly impacts the routing. Creating a routing policy for the different classes can easier illustrate the effectiveness of the slotting policy than observing it by itself. The routes for each class are highlighted in *figure 6.4*.

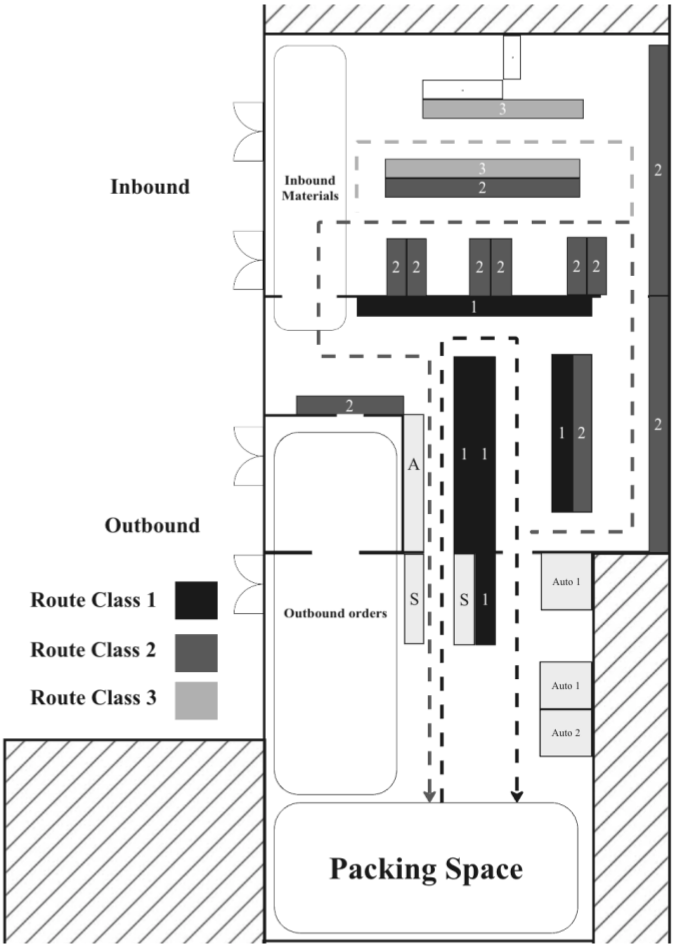

Figure 5.5. Routes and proposed classes

Contrary to the current routing policy which follows an alphabetical order, these proposed routes aim to create the shortest possible full route within each class. Routing typically follows alphabetical order, however, to create an optimal route the B rack is split. The route for Class 1 therefore follows the route B1-5, F, B6-10, C and R. Class 2 follows the same initial start as Class 1, but does not end at C. Instead, it continues with D-E-Q-M-N-L-K-J-I-H-G. Obviously, if the order only contains an SKU from D, the full route for Class 2 does not have to be completed. Class 3 includes rack O and P, and additional shelf spaces where a forklift is needed to retrieve the SKU. Lastly it is worth noting that the objective with zones is not for different delivery specialists to work in a different zone, but rather to optimize circular movement within the warehouse and minimizing congestion and linear deviations.

5.2.5 Replenishment and Buffer slots

Since one of the main concerns raised by the delivery specialists is that of either too small or too big purchasing quantities it is important to have effective buffer storage to create more flexibility within the warehouse. Buffer slots have been chosen to be located within the warehouse that will not directly negatively impact on the picking time, that is the shelves that need a forklift to reach. As mentioned before each class contains a different number of SKUs, where Class 1 has one SKU per picking slot and Class 2 about two SKUs per picking slot. Similarly, the AS/RSs have their modular shelves which can be customized for each specific SKU.

More space for the more frequently picked SKUs will result in a relatively stable replenishment process. Additionally, the vertical retrieval time for SKUs for replenishment is considerably longer than the two-dimensional movement between aisles. Connecting these two arguments highlights the advantages of using a random allocation for the buffer slots. While a dedicated buffer policy could be useful for clarity and visibility, the experience of the delivery specialists handling volatile purchase quantities will make the warehouse more flexible and reduce the risk of bottlenecks. Similarly, this will better manage change in demand for different SKUs where only the picking slots must change class, while the buffer slots can remain, thus saving time in only having to reshuffle each SKU once.

5.2.6 Quantitative Improvements for W01

To analyze what improvements to expect from the new class-based system a comparison is made with the current situation. *Figure 5.6* compares how many products that are placed in the different areas currently and how many would be placed in the areas given the proposed solution. *Figure 5.7* then compares how many order lines that are picked in each zone for the new solution and current situation.

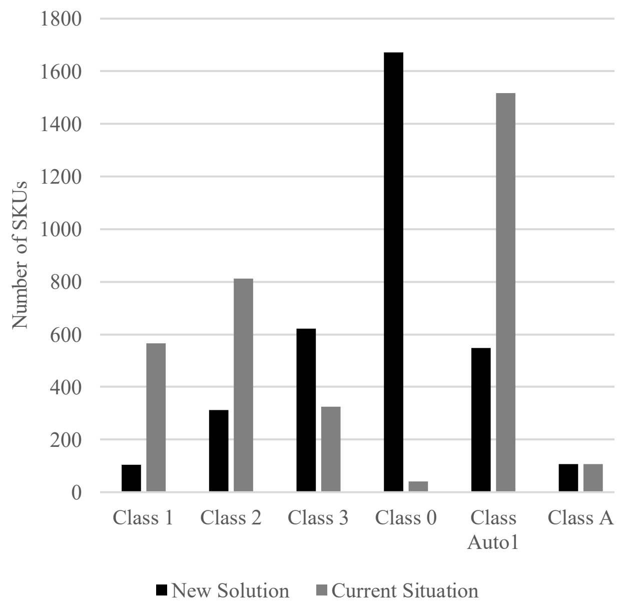

Figure 5.6. Number of SKUs in each W01-Area

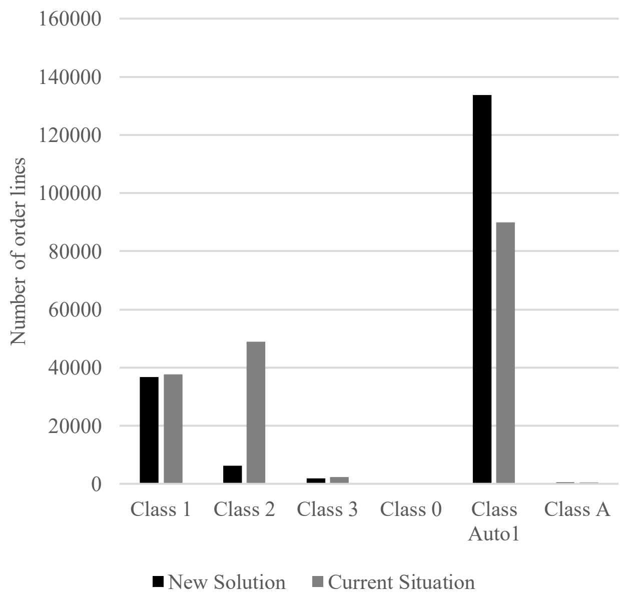

Figure 5.7. Number of order lines within each W01-Area

From the figures above it is apparent that the number of SKUs assigned to the important classes, Class Auto 1 and Class 1, has decreased whilst the number of SKUs assigned to the less important classes, Class 3 and Class 0, has increased. At first glance this might be interpreted as a deterioration. However, from *figure 5.7* it is evident that the number of order lines in Class 1 has remained the same and the number of order lines in Auto 1 has increased drastically. The change therefore implies that more important products are moved to Class 1 and Class Auto 1 whilst many unimportant products are moved to other classes. That a larger part of the order lines is handled in Class Auto 1 and Class 1 despite less assigned SKUs is a large improvement as it signals that the most accessible slots are better utilized. Similarly, more SKUs are assigned to Class 2, Class 3 and Class 0 whilst the number of order lines for those classes remains the same or has decreased. More unimportant SKUs are therefore consolidated and moved to less important slots, which implies that more good slots can be used for important products. Overall, the solution therefore implies better space utilization.

Moreover, significant time could be saved if picking of an order could be completed within only one area. *Figure 5.8* illustrates how many of the studied periods orders that have been completed within one area, compared to how many of the orders that would have been completed within one area if the new solution had been used. As *figure 5.8* shows there will be a significant decrease in how many of the orders that required picking in many classes. Similarly, the number of orders picked completely in Class Auto 1 or Class 1 would increase, which is an improvement. *Figure 5.9* illustrates how many order lines that are attributed to the orders that are picked completely within one class.

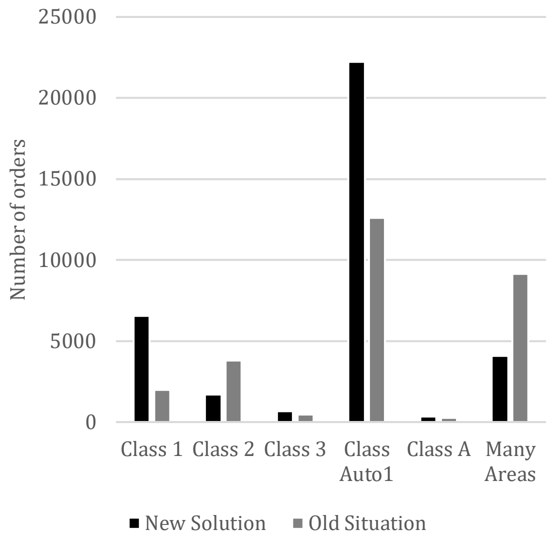

Figure 5.8. Complete orders within the different W01-areas.

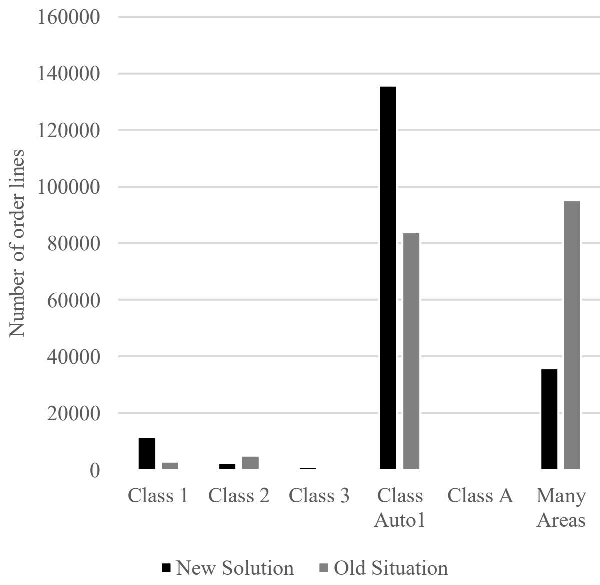

Figure 5.9. Number of order lines for complete orders within the different W01-areas.

Table 5.7 shows based on the historical data the average time to pick one order line in the different areas, when the order is only picked in that area. The time per order line for one area multiplied by the number of order lines in that area provides a simulated total time. The old situation would, according to this simulation imply 14.4 hours of picking time each day. The new solution would imply 8.8 hours of picking time each day. The new solution could therefore potentially imply a 39% saving in total picking time per day for W01. Aase et al. (2004) found that a class-based slotting policy can contribute to a 12-26% overall improvement in total picking time over a random slotting policy. The calculated 39% can compared to that be considered large. Examples of calculations performed can be found in *Appendix G*.

Area	Time to pick one order line
Class Auto 1	17.6s
Class 1	72.4s
Class 2	80.4s
Class 3	470.1s
Class A	130.1s
Many Areas	110.9s

Table 5.7. Time to pick one order line under the condition that the order is picked only in that class

5.2.7 Quantitative Improvements for W02

Figure 5.10 illustrates how many products are assigned to Class Auto 2 and Class W02-Conventional. The new solution proposes that less products should be assigned to the AS/RSs than currently is the case. *Figure 5.11* illustrates how many order lines each of the W02-classes account for.

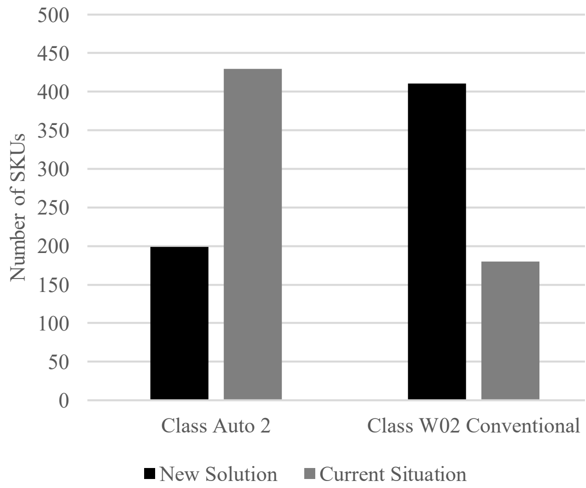

Figure 5.10. Products within the different W02-areas

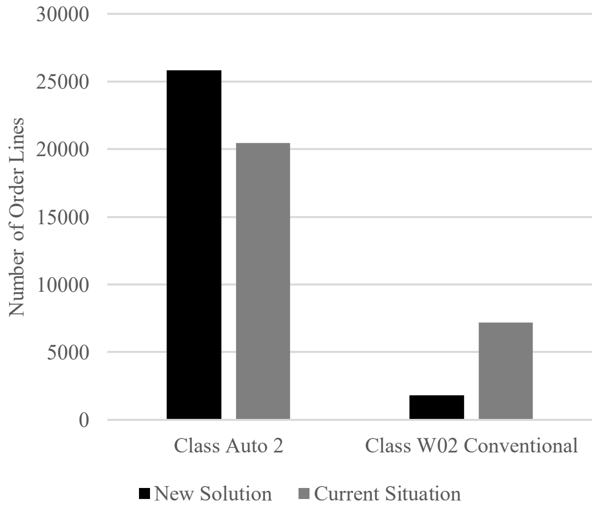

Figure 5.11. Number of order lines in the different W02-Areas

Once again despite less products in the AS/RS more order lines are handled within the AS/RS, which implies that more important products are assigned to the AS/RS and therefore better space utilization. Furthermore, with the new solution only about 1800 order lines are handled in the W02 conventional class, despite being made up of 411 SKUs. Overall, with the new solution 93% of the order lines for W02 are handled in the AS/RS. Compared with the current situation where 74% of order lines are handled in the AS/RS, the new solution thereby shows a significant improvement.

5.3 Decision-making Process

This chapter aims to apply the performance evaluation metrics and methods from the previous chapter as foundation for the decision-making process deciding when and how to reiterate the optimization of the warehouse. All levels within the hierarchy will be influenced by such a process and it is therefore of importance to combine the quantitative data from the previous chapter, with more qualitative data from interviews to provide a sustainable. long-term process. Aligning the previous theory to our specific case, the first part of the analysis mainly concerned the tactical level where ways of how the warehouse's operational policies can be optimized have been analyzed. The following part is instead focusing on the strategic decision level since its main focus will be on why and when the optimization of the warehouse should be reiterated.

Snartland (2023) emphasizes the importance of a well-informed decision maker in all levels, since the decision quality improves with improved information. The analysis' objective is therefore to provide enough information to facilitate a qualitative decision-making process.

5.3.1 Operational Level

The operational level mainly concerns the delivery specialists and short-term and quick decisions they make throughout their work (Snartland, 2023). In many cases the operational decision-making plays second fiddle to picking efficiency since the workers' main concern is to complete their given orders (Manager delivery, personal communication: February 6, 2025). In the case company's current operational policies this could cause problems due to SKUs being placed on non-optimal locations due to lack of time or space within the warehouse, resulting in worse performing picking, slotting and routing policies.

5.3.2 Tactical Level

The decision of allocating storage spaces for SKUs can be on both the tactical and operational level (Gu et al., 2007; Wang et al., 2020). The tactical allocation mainly concerns what type of policies are in use when deciding where and how to place the SKUs. As the empiri highlights, the delivery specialists are given a lot of autonomy and are in many cases responsible for both the operational and tactical decisions at the case company. This creates a divergence between the different levels of decision making since the delivery specialists in most cases prioritize short-term gain while allocating a spot for an SKU, while the strategic level focuses on the long-term.

The lack of a clear tactical level also implies problems for strategic decisions for the warehouse, since the level is not informed enough to make quality decisions. For example, the strategic level is not fully aware of the warehouse layout and how it is operated daily. Gu et al. (2007) mentions the SLAP (Storage location assignment problem) and how ill-informed strategic decision makers might neglect compatibility between storage space and SKUs and between different SKUs. Similarly, SLAP contains problems like storage capacity and efficiency and picker capacity, which usually are managed by the tactical level. The first part of the analysis raises this challenge in decision making and proposes a foundation based on the class-based storage allocation with dedicated spots based on co-occurrences within orders. With a comprehensive and cohesive method as a basis, many tactical challenges which arise with SLAP can be acknowledged and avoided when making decisions.

5.3.3 Strategic Level

The strategic level mainly concerns the long-term (Snartland, 2023). It is therefore of importance that the warehouse can be re-optimized due to changing conditions such as different demands and volumes. Metrics and methods from the first part of the analysis are therefore aimed to be used as a foundation for deciding when to iterate the optimization process. By having different classes of SKUs based on order inclusion frequency, it can be illustrated when two products from different classes should be reshuffled. If an SKU from Class 1 is picked less frequently than one from Class 2, they should change places. This performance metric and method facilitate the decision-making process of how the reiteration can be done. However, it still does not answer when it is most optimal to iterate. Below follows three different ways to decide **when** to re-optimize the warehouse.

5.3.3.1 Continuous reshuffling

Snartland (2023) highlights the idea of using dynamic storage location assignment, which entails strategically moving SKUs from one part of the storage to another depending on volume and demand. This is normally used in warehouses with large seasonal variance or items with short shelf life but could be applicable to the case company's more robust demand. The demand for the case company is less volatile than aforementioned ones, but by still being dynamic the delivery specialists could make continuous reshuffling in the warehouse based on forecasts. The process of reshuffling goods can be time- and resource consuming, which means that for it to be implemented successfully the time saved by being dynamic must be bigger than the time to continuously reshuffling the SKUs (Snartland, 2023). On the other hand, continuous refueling could be done without warehouse down time. By integrating reshuffling as a part of the delivery specialist daily tasks, reshuffling could be carried out during less busy times during the day. One major advantage with continuously reshuffling the warehouse is the seamless allocation of new products. The VP of supply chain (Personal communication: March 13, 2025) explains that older products are usually phased out to new ones during a long period and sometime during that period the new product starts being picked more frequently than the old one. By using continuous changes this point can be seen, and the products can be reshuffled to keep the warehouse optimized.

5.3.3.2 Periodical reshuffling

Another approach is to reshuffle the SKUs after a given amount of time has passed. This could be done monthly, quarterly or annually depending on the company's fluctuation in demand. Instead of performing the operations simultaneously as picking orders specific times slots or personnel will be dedicated to the reshuffling of SKUs. On the one hand this will make the reshuffling go faster since no other operations will be interfering, but on the other hand it would entail warehouse downtime when the reshuffling is performed. Choosing between periodical and continuous reshuffling therefore causes a trade-off. Similarly, if periodical reshuffling is chosen the decision maker has to decide how long the period is. If the demand is seasonal, it would be most beneficial to have the periods aligned with those seasons. If the demand is random, the reshuffling should be more prevalent the more volatile the demand is (Zhaoyang et al., 2025). Additionally, choosing too long periods could imply long periods of suboptimal solutions.

5.3.3.3 Reshuffling based on triggers

The last approach involves using trigger metrics as a foundation to decide when to re-optimize the warehouse. By using a class-based storage allocation policy products are simply put in different classes depending on their quantity of order inclusions. As described earlier in the analysis, the top 10% of all products account for roughly 82% of the order lines, while Class 2 and Class 3 account for the next 30% and 60% of the products respectively. By having a hierarchy between the different SKUs based on order inclusions the warehouse becomes more observable, and it will be easier to realize when an SKU is in a non-optimal location.

The trigger used for reshuffling could either be used on total SKUs in the wrong class or based on percentages. For example, it might be time to reshuffle when 10 SKUs that, according to the SKU hierarchy, should be in Class 1 instead are in Class 2; or when 2% of all SKUs are placed in the wrong Class. The smaller the chosen trigger value is, the more often reshuffling must take place. The reshuffling can then be chosen to be done simultaneously as other operations within the warehouse or during downtime, thus offering choices like the two aforementioned reshuffling approaches.

Additionally, the trigger does not only have to be dependent on individual SKUs, but rather the co-occurrences between classes. As mentioned in the earlier part of the analysis, the number of orders completed within just one class can be used as a measurement as well. This trigger is instead focusing on the complete class and its optimization rather than finding the perfect location for one SKU. By using co-occurrences as a trigger, positive synergies could be created throughout the warehouse since the classes become more complete and walking distance is reduced.

5.3.3.4 Compilation of re-optimization approaches

In *table 5.8* below follows a compilation of the different approaches as well as their benefits and disadvantages.

Approach	Advantages	Drawbacks
Continuous reshuffling	Easy decisions for warehouse workers to just reshuffle SKUs based on SKU hierarchy. Right SKU is always located in the right class. No downtime and waiting for optimization. More trust on warehouse workers	Takes focus from other daily tasks. The same SKU may have to be reshuffled multiple times due to changing demand. Longer search times for delivery specialists due to

	entails fewer levels of decisions affecting the warehouse.	constantly reshuffled SKU locations.
Periodical reshuffling	Dedicated time to reshuffle SKUs after a period. Period length can be chosen based on industry characteristics. Does not interfere with daily picking operations.	More inclined to demand warehouse downtime. Passivity, the approach does not signal if the period length is chosen wrongly. Dynamic decision making for re-optimizing the warehouse is neglected.
Reshuffling based on triggers	Integrated approach putting focus on the class based allocation storage policy. Reshuffling is based on internal signals. Decision makers may choose a satisfying threshold which can be accepted in the warehouse, thus having more control over deficiencies. Triggers can be customized for specific companies and industries.	Large amounts of data is needed to choose viable triggers. Warehouse downtime might be needed if high thresholds are chosen. Difficult to choose the right trigger.

Table 5.8. Advantages and drawbacks of different reshuffling methods

5.3.3.5 Reshuffling method for specific case

Given the advantages and drawbacks with each reshuffling method this study has chosen to utilize the trigger option since it provides a dynamic and data integrated solution. Additionally, it suits the case company best since it does not rely on seasonality. To decide upon the trigger a simulation was made where six months' worth of product data was analyzed at a time. Firstly, by summarizing how many orders a product was included in from April to October the products were divided into the different classes. Secondly, a similar process was made for May to November, June to December, July to January and August to February. How many products that changed class each month was then calculated. The percentages of products that changed class each month can be seen in *table 5.9.*

Half year roll	Apr-Oct to May-Nov	May-Nov to Jun-Dec	Jun-Dec to Jul-Jan	Jul-Jan to Aug-Feb
Change (%)	4,30	4,72	4,57	5,27

Table 5.9. Percentage of SKUs changing class a month

Given the data shown in *table 5.8*, 5% is a suitable trigger threshold, since it is a bit larger than the average monthly change. Additionally, a 5% threshold will make sure that the warehouse always operates on 95% efficiency, while still remaining flexible. However, to minimize excessive reshuffling, the SKU must be recorded in the “wrong” class for two consecutive months before it gets reshuffled. Given this, the trigger for reshuffling should be when 5% of the SKUs have been in the wrong class two consecutive months. This solution should grant flexibility without hampering efficiency.

6. Discussion

This chapter aims to take the findings from the case company and make them generalizable for companies with similar structures. To make the chapter more comprehensible it is structured around each RQ combining findings coming from the empirical data and analysis.

6.1 Evaluations Methods and Performance Metrics

RQ1.1. What performance evaluation methods and metrics are most effective for assessing the impact of a warehouse optimization?

As the literature states, total picking time is the most important KPI regarding warehouse efficiency. However, as brought up in the analysis, total picking time is dependent on several important metrics to consider. The total picking time in both the automated and conventional storages are dependent on distance, number of lines and quantities of SKUs to be picked. This showcases that the two most important things whose performance must be evaluated is location and SKU. A way to evaluate each rack and shelf is by its distance from the packing space which often is an order's start and end point. If the rack is closer, it is better since the delivery specialist must move a shorter distance to retrieve that SKU. If the shelf can be reached without a forklift it is better since picking by hand is way faster. In this way every location of the warehouse can be evaluated. However, orders are seldom only picked from one rack, and sometimes circular routes can be more efficient than linear ones. Therefore, one must also consider the potential routes that have to be taken to pick one complete order.

While the location is evaluated by distances, the SKUs are evaluated based on the number of orders they have been picked in. This metric is chosen since each time an SKU must be retrieved, the delivery specialists must walk that distance. Having the most frequently picked SKUs closer to the packing area would therefore result in shorter walking distances and shorter picking times. To further improve this, frequently co-occurring SKUs should be slotted close to each other to minimize walking distance. Similarly, co-occurrences can be used in the AS/RSs to balance the lifts and thus reduce waiting time. The methods and metrics are summarized in *table 6.1.*

Dimension	**Performance metric**	**Evaluation method**
Location (Racks)	Distance (m)	The rack's performance is evaluated towards how close they are to the packing space which usually is the start and end for

		an order.
Location (Shelves)	Ease of picking (m from floor)	If the shelves can be reached without tools it is evaluated to perform better
SKU	Order frequency (#Orders)	SKUs appearing in more orders are considered more important
SKU	Co-occurrences (#Common orders between to SKUs)	SKUs frequently occurring in the same order are evaluated to perform better if placed close together

Table 6.1. How the performance of locations and SKUs are evaluated

However, as the case displays, order picking time is not always the best metric for evaluating the warehouse's performance. It is effective in warehouses where orders are standardized and have roughly the same number of lines, but in companies like the case company where the amount of order lines can vary drastically it is less effective as a performance evaluation method. This is because the number of lines is directly linked to walking distance, which is the most time-consuming part of picking an order. Therefore, the number of lines could be considered as a more reliable performance evaluation method.

Another important metric to consider is that of space utilization and maximizing it. Firstly, it is important to decide how many and which slots in the warehouse should be picking or buffer slots. Having more picking slots would increase the efficiency of picking orders, but fewer buffer slots would entail a more cumbersome replenishment process. Additionally, fewer buffer slots would create inflexibility when the order quantities fluctuate. Therefore, building on earlier arguments, the slots that can be reached without tools should be considered picking slots, and those that require forklifts should be buffer places.

However, there is a tradeoff while deciding how the SKUs should be divided between its picking and buffer slots. If too much of the SKU is placed in the picking slots it will reduce the space utilization since not all products can fit in the picking slots. On the contrary, if a too small quantity is placed in the picking slot it would lead to it having to be replenished more often and thereby causing inefficiencies. This is especially evident in the AS/RS where space is very limited. To counter this, forecasts on historical data can be used as a method to decide the division between the two slots and maximize utilization without causing inefficiencies.

This report proposes a class-based system where the different classes would have a different amount of picking slots. In this case Class 1 would have roughly one slot per SKU, while Class 2 would have about two SKUs per slot. This would create a good space utilization where the frequently picked products would have larger picking slots, thus resulting in a relatively even replenishment process for the warehouse workers. By doing this, the buffer places can be assorted randomly throughout the warehouse, resulting in more flexibility.

Deciding which metrics to use should be based on what the overall objective of the optimization is. If the objective is to increase efficiency in the warehouse without employing new delivery specialists the most crucial metric would be that of reducing picking time. Similarly, if the goal is to keep operations working without expanding the size of the warehouse, total space utilization is favorable to use. As the theory suggests, using multiple performance evaluation metrics can form a better optimization solution while managing complex warehouses. While reduced picking time is the main goal, one cannot completely neglect the importance of space utilization. By itself picking time could be optimized relatively easily, but without considering space utilization other operations like replenishment of the products would take longer time, which could result in an overall less effective warehouse. This highlights that although one metric is more favorable to optimize, the others must be considered too since there are a lot of different synergies in the warehouse.

6.2 Warehouse optimization method

RQ1.2. How can a method for operational warehouse optimization be constructed that considers a combination of conventional and automated storage, and multiple product purposes?

The first point worth discussing is the tradeoff between the optimal solution and flexibility in warehouse optimization. Whilst a full turnover slotting policy is considered most efficient with regards to picking time, implementation is hard. Flexibility is limited, changing conditions can easily render the policy inefficient and re-optimization involves a lot of reshuffling. Therefore, whilst a full turnover slotting policy has the potential to save resources on a day-to-day basis, maintaining the policy could demand extensive additional resources in the long run. Multiple product purposes and a mix of conventional and automated storage furthermore imply many considerations that could further complicate a full turnover slotting policy and make maintenance of the policy harder. A class-based policy on the other hand implies more flexibility, thereby making the model generalizable for different company conditions. Furthermore, less reshuffling must be made when conditions change. This also implies more flexibility in the decision-making process where shorter re-optimization intervals or even continuous re-optimization is possible. Therefore, even when the goal is to increase warehouse efficiency, a class based slotting policy is more suitable for a dynamic, iterative warehouse optimization method.

When implementing a class-based policy, the number of classes are crucial for overall efficiency. As the theory highlights, having too many classes could negatively impact the optimization of the warehouse. Therefore, whilst this report argues that the multiple product purposes and the combination of automation and conventional storage could be handled with a class-based system the number of classes should still be carefully considered. Additionally, having an integrated approach is crucial. When considering slotting policy, routing and picking policy must also be considered to leverage positive synergies. In this case the picking policy dedicates that some products are never picked together, it is therefore suitable to handle these separately, which results in more classes. Additionally, the mechanics of the AS/RS are different from those of the conventional storage. The AS/RSs therefore also needs to be handled with a different logic, which implies even more classes. Subsequently, multiple product purposes and use of conventional and automated storage implies a larger number of classes. The number of classes should be high enough to handle the different requirements of the warehouse, but still not be overdone and surpass how many classes that logically makes sense.

Care also must be taken to make sure that classes are of reasonable size. As previous literature highlights the extreme case of a class based slotting policy is a dedicated slotting policy, which happens when the number of classes begins to equal the number of products. This implies that the benefits of a class based slotting policy, such as flexibility decreases. Conversely, too few classes would imply that the slotting policy instead becomes more random, thereby making products harder to find and increasing the risk that important products are placed in suboptimal places.

Furthermore, when assigning classes care must be taken on which metric is used and how classes are divided. Overall products that are often picked together should be placed together and products that are picked frequently should be placed close to the start and drop of point. In this study products are mostly assigned slots based on picking frequencies rather than SKU order correlation. However, neglecting how often different products occur in the same order could lead to a suboptimal solution. On the contrary, using SKU order correlation quickly becomes very complicated. Ensuring an optimal solution using product correlations is therefore hard and could infringe on the solutions flexibility. Additionally, two products with high picking frequency are more likely picked together a larger number of times. Arranging products by picking frequency should therefore have some effect on products often picked together being close together.

One risk with implementing a class based or dedicated slotting policy is congestion. As a larger part of the orders are picked in a smaller part of the warehouse there is an increased risk of too much activity in a small space. For the case company this is mainly a risk in the AS/RSs. However, the AS/RSs currently handles about 70 orders per day. One person should alone be able to handle up to 500 orders per day with the AS/RSs according to specification. As only one person is needed, congestion is not a problem. However, for similar companies, congestion might be a larger problem and something to consider when implementing a similar solution.

This study also highlights that there is a deviation between the optimal solution according to theory and the optimal solution in practice. Firstly, several assumptions had to be made to determine which products to place in the AS/RS. The first assumption was due to a lack of product volume data. As weight was the only available data, it was assumed that all products had the same density, and that the volume of products within each product category followed standard distribution. These assumptions do not reflect reality completely, however they can to some degree be used to gain an indication of reality. There is to some degree a correlation between volume and weight for products. For example, very heavy products are more likely bigger and more difficult to handle and thereby less suitable for the AS/RSs. On the contrary, very light products are probably easier to handle and therefore more suitable for the AS/RS. Overall, the need for assumptions does however infringe on the accuracy of the output of the model.

Subsequently, the calculated optimal solution for the AS/RSs is a conservative approximation. Methods were used to calculate an upper limit rather than an exact value for volumes. Furthermore, the volume uncertainty was accounted for in the utility score, thereby making products with uncertain volume less suitable for the AS/RSs. However, this method is not completely optimal. As the AS/RSs are the most valuable spaces it is important with effective space utilization. A conservative estimate is therefore not optimal as more products could probably fit in the AS/RSs than calculated. It is therefore proposed that some flexibility should be included in the model. By leveraging experience-based expertise in the day-to-day operations delivery specialists could be tasked with placing additional suitable products from Class 1 or W02 in the AS/RSs if space is available. However, it is also important that the delivery specialists are then provided with the right information for those decisions.

6.3 Decision-making

RQ2. How can an integrated decision-making process be designed for optimizing the operational policies of a warehouse, considering changing conditions?

6.3.1 Which decisions are relevant?

As shown by earlier parts of the report, the decision-making process within the case company concerns multiple levels, factors and constraints. Firstly, it is important to highlight which decisions that can be made without costing too much time and resources. This report illustrates this by separating the operational policies from fixed parts of the warehouse like the technical structure and WMS. These parts can also be changed, but the high cost and time needed makes it difficult to make the process dynamic and adaptable to changing conditions.

Instead, the focus should be on which decisions yield the biggest impact and flexibility in relation to the cost and time it takes to implement that decision. The case showcases how different parts of the operational policies are relatively easy to change and RQ1.2 explains how this is done more in depth. However, when implementing such methods and KPIs as used in answering RQ1.2 there is still a big emphasis on decision making. For example, the proposed class-based storage allocation policy involves multiple decisions that can yield different results depending on which metrics are chosen. Aligning with Snartland (2023) some important decisions that must be made to implement this strategy is: How to classify the SKUs? Which class should each SKU belong to? Which part of the warehouse should that class be in? The more information and knowledge of the warehouse the decision maker has, the higher quality decisions will be made, emphasizing the benefits of being well informed.

Adding from the case company where a hybrid storage is used, it is important to have information about SKUs before deciding a slotting policy. For example, the AS/RSs has limited space and therefore cannot fit enough quantities of all SKUs to be effective. It is therefore of great interest to not only have knowledge about the warehouse, but also its specific SKUs.

6.3.2 Who is responsible for which decisions?

After finding which decisions to be made it is important to decide who should be responsible for which decisions. As mentioned in the analysis, decisions are made in three different levels aiming to facilitate different stages of the warehouse optimization. For this to work optimally there must be an effective flow of information between the levels. This will allow the different levels to share information which, as established before, is crucial for effective decision making. The decisions on the operational level are greatly impacted by those from the strategic level, but it is just as important for the strategic level to receive information from the operational.

The case highlights how the operational workers place similarly looking products further apart to reduce the possibility of picking the wrong SKU for an order. If that is not communicated the tactical level of decision making possibly would put those products close to increase picking time, but due to an increased amount of wrongly picked orders no time would be saved. Similarly, the case highlights a reluctance to change from the delivery specialists in the warehouse. A steadier and more effective flow of information would on the one hand help top level decision makers understand why there might be a reluctance, on the other hand it allows the delivery specialists to understand why changes are made.

The case displays how inefficient communication between decision makers of different functions and levels negatively impacts the optimization of the warehouse. The decision brought up earlier about placing similar SKUs far apart is made because there are no labels on the boxes showing which product is inside. More effective communications with the more strategic decision level could facilitate collaboration between functions like the warehouse and purchasing, which could result in labels on the boxes and a more effective warehouse.

When making decisions, no matter which level, it is also important to avoid myopia. As stated before, being well informed is crucial, but there is also a need to understand that one person cannot see and comprehend all information before making a decision. This can be avoided by involving outside parties in some parts of the decision-making process. For example, through data analysis the authors of this report discovered bottlenecks not mentioned by workers. The case company has utilized this before by employing six sigma green and black belts, although with dissatisfying results. Once again, more effective communication flow between internal and external operators could yield more positive results.

6.3.3 When should decisions be taken and changed?

Lastly, as the decision-making process aims to be integrated and dynamic, big emphasis is put on when different decisions should be made. When to iterate the optimization is dependent on the specific company and the industry it is operating in. The analysis suggests three different measures that can work as a foundation for deciding when to re-optimize. The case company is, as established before, experiencing growth in demand, but the industry as a whole is relatively stable. In the case of stable demand periodical reshuffling is not as efficient since their business is not affected by seasonality. For companies that know that different products are demanded at different seasons, periodical reshuffling is more effective as a basis for decision making.

The case company has, as the empiric evidence shows, relatively long product life cycles. When a substituting product is introduced, it takes a while for it to substitute the older product in picking frequency. Long product life cycles and relatively stable demand makes it unnecessary to use continuous reshuffling since it requires a lot of time and resources to make it effective. This decision-making method is more efficient with shorter product life cycles since newly introduced products require slots within the warehouse, causing a continuous reshuffling with increased demand for newly introduced products.

As the case company is experiencing growth re-optimizations of the warehouse are inevitable, but the overall stability of the warehouse's operational policies makes it more suitable for using triggers for reshuffling. As stated in the analysis the triggers can be customized to satisfy the company's objective and benchmarks. They can be narrowly dependent on the number/percentage of SKUs or more widely and depend on total orders within classes. This once again affects different levels of decision making since the strategic level must decide to use triggers, the tactical level of decisions must decide on which triggers to use, and the operational level must collect data and act on given triggers.

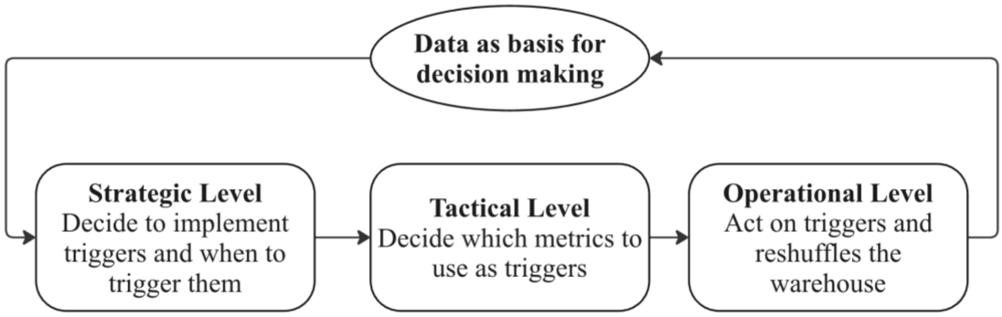

Figure 6.1. The cyclical nature of decision making based on all three levels

Figure 6.1 emphasizes how all three levels of decision making co-exist and how effective communications can cause a better flow of information and thereby higher quality decisions. The loop between the different levels also ensures lower risks of reluctance to change from different levels since everything is dependent on objective data rather than perceptions. For the data to flow as *figure 6.1* suggests, the case company must leverage their newly acquired equipment and capabilities to ensure quick communication between levels.

6.3.4 How does our recommendation impact decision making?

This project recommends using triggers to decide when to re-optimize the warehouse. Importantly, the recommendation will provide a basis for a process which integrates collected data into different levels of decision making.

The triggers chosen for the case company are based on the total class change that the company faces each month. Additionally, the choice that an SKU needs to be placed in a different class for two consecutive months is done to reduce the amount of excessive reshuffling. For other companies implementing a class-based approach other triggers could be more effective. For example, if most of the reshuffling happens between Class 1 and Class 2 it would be more advantageous to have a trigger based on percent of wrongfully placed SKUs in Class 1. The case company has an even spread of change between its classes and it is therefore optimal to use the total change as a trigger. Similarly, which percentage threshold that is chosen is dependent on the tradeoff between efficiency and flexibility. On the one hand if a company has millions of SKUs and a low trigger percentage it would mean that they would have to reshuffle fewer SKUs often. On the other hand, if they have millions of SKUs and a high trigger percentage it would mean that they would have to reshuffle very many SKUs, but more seldom. The smaller the trigger is the more closely it resembles the continuous shuffling. For a company with just a few hundred SKUs a too big trigger percentage could result in inefficiencies because it operates sub-optimally. Strategic decision-makers therefore have to decide if they want their reshuffling to be smaller and often, or bigger and seldom. To make a quality decision about this, they have to be informed bottom-up by the levels of decision-making to know which decision will yield the optimal solution.

The utilization of triggers also ensures that the suggested optimization method can be iterated, thus making it more dynamic. Implementing triggers will affect levels of decision making differently. Firstly, the operational level will experience a more standardized environment where it is easier to place SKUs in more suitable locations without wasting too much time. The case company has delivery specialists with much experience and relevant capabilities, and by implementing triggers and a class-based policy the case company can leverage this without becoming too dependent on them. The class-based policy allows the operational level to make slotting decisions but simultaneously allows the tactical level to decide which SKUs to place in which class. Additionally, better collected data allows the strategic level to better evaluate the performance of the warehouse. This ensures that the decision is better divided between the different levels, which limits the concern of being too dependent on a specific set of people.

Secondly, the logic from the recommendation will illustrate the warehouse better for the tactical and strategic level, who seldom visits the actual warehouse. The class-based approach is based on correlations between SKUs and locations and between different SKUs and by illustrating this data it is easier to quantify metrics and decide triggers for re-optimization. By being better informed of the warehouse, these levels may more easily interpret the data received by the operational level thus developing the organizational capabilities of data management and actions.

6.4 Generalizability and Contextualization

This whole project has been conducted on one case company where its limitations and barriers have been key to reaching this final recommendation. In reality one warehouse differs a lot from others. Metrics that are beneficial for the case company might not be as effective for a company with different prerequisites. Similarly, how the classes are divided is based on the existing exception at the case company. In spite of this, this report's aim has been to use the case to create a more general recommendation. That is why different metrics and methods have been discussed, and different optimization methods have been investigated. The discussion aims to show which different variables can be useful depending on how the warehouse or company currently operates. For example, different types of reshuffling methods are brought up and discussed, although only one of them is used for the case company. Using this report, companies can get a structured procedure on how they can optimize their warehouse dynamically, where the variables might be different from the case company's.

One limitation for other companies that follow this blueprint is that it demands a lot of documented data. Therefore, this recommendation might not be optimal for all hybrid warehouses with multi-purpose products, but more towards those that have a lot of accurate data. Furthermore, as the recommendation requires a lot of accurate data it is important to consider data collection in the day-to-day work in the warehouse. To ensure accurate data it is important that the warehouse has a standardized procedure. For example, in this case it is important that the barcode readers are used in the same way every time. To ensure that the actual times are accurate the warehouse workers should always scan the product when it is retrieved and not all products at once after all products are retrieved.

Lastly, barriers can be present when implementing a new warehouse optimization process. As noted in this case organizational resilience can be a problem. To ensure minimal organizational resilience decision makers on all levels must be coordinated. Moreover, the solution recommended in this case also involves a lot of initial work, such as reshuffling almost 4000 products, which means that the initial cost to implement can be high. Firms wanting to implement a new warehouse optimization process therefore must have a long-term view as the payoff is gradual and not instant. A long-term view is also important as the firms need to maintain and continuously work with the warehouse optimization process to ensure continuous optimization when conditions change.

7. Conclusion and Recommendation

Given the discussion, a conclusion can be formulated in the form of a recommendation towards companies that operate in a changing environment with warehouses that mix different product purposes, and combine conventional and automated storage systems. Firstly, before optimizing the warehouse it is important to decide upon a few factors. Given this report's reasoning, decision makers should consider which decisions yield the biggest positive impact in relation to cost and time. This is not only important when optimizing the first time, but also when it is time to iterate it.

This paper found that performance evaluation metrics should not be used in their lonesome but together to better illustrate the warehouse and its challenges. For measuring operational warehouse efficiency this paper recommended the combination of total picking time and space utilization. As the main goal is to optimize the warehouse, total picking time is an obvious metric but combining it with space utilization creates a more flexible solution since it considers other synergies within the warehouse like replenishment. The two metrics highlight the tradeoffs between operations and which decisions that yield a net positive solution in the warehouse.

Secondly, for warehouses that operate in a dynamic environment with multiple product purposes and a mix of automated and conventional storage a class based slotting policy is recommended. Whilst not the theoretically quickest, a class-based policy provides flexibility, which is crucial in a dynamic and iterative policy. Additionally, all parts of the warehouse operational policies must be considered in unison to leverage positive synergies. For companies similar to the case company a picking by order policy is recommended whilst routing must be made case specific based on technical structure. Overall, this report found that more effective operational policies can improve total picking time by up to 39%.

Thirdly, to facilitate decision making it is important for the warehouse and the company to create good flows of information. This concerns both vertical flow between levels of decision making and horizontal flow between different functions. Better information will reduce ambiguity and increase efficiency since less decisions will be made ad hoc and instead be integrated with data. However, the delivery specialists within the warehouse should retain their autonomy and be able to make operational decisions based on experience. This is because the warehouses often are irregular and all SKUs, depending on volume or quantities, cannot always fit in the most suited dedicated spot. Furthermore, by using hand scanners data can easily be collected and brought to the strategic and tactical decision makers. This report suggests that the data then can be used to formulate triggers that decide when to reoptimize the warehouse again depending on what satisfying threshold the decision makers set. In this way, both the operational and strategic decisions will be substantiated by integrated data. By implementing triggers for when to reoptimize, the company can choose their own threshold of how effective the warehouse must be in trade off to how often it has to be re-optimized.

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Appendix A - Interviews

For transparency reasons and to ensure that the research is trustable the following appendix presents the interview questions for the semi structured interviews as well as the subject of discussion for all of the interviews. See *table A.1* for subjects of discussion for the different interviews.

Interviewee	**Date**	**Subject of Discussion**
Manager Delivery	February 6th 2025	Introduction to the technical structure of the warehouse, explanation of the operational policies and explanation of the current performance evaluation process.
VP Supply Chain	February 4th 2025	Introduction to the technical structure of the warehouse and explanation of the operational policies.
VP Supply Chain	March 13th 2025	Discussion about replenishment, the decision making process on the strategic level and how the different product purposes are handled.
Head of Supply Chain	February 11th 2025	Introduction to the technical structure of the warehouse, explanation of the operational policies, explanation of the WMS and explanation of the AS/RSs.
Head of Supply Chain	March 18th 2025	Discussion regarding a potential class based slotting policy. Further discussion of the WMS. Explanation of how the different product purposes are currently handled and further explanation of the AS/RSs.
Delivery Specialist	March 20th 2025	The decision making process from the operational levels point of view.
Delivery Specialist	April 15th 2025	Discussion regarding a potential class based slotting policy. Opportunities, important aspects and potential drawbacks for an operational and tactical level.

Table A.1 Interviews and subjects of discussion.

Main Interview Questions for the Semi Structured Interviews:

Below the interview questions are presented for the semi structured interviews.

March 20th 2025:

1. Can you briefly describe the role of a Delivery Specialist?
2. In general terms, how has warehouse work changed during your time here?
3. Which past changes do you think have had the most positive impact?
4. Have any of the past changes made had a negative impact?
5. What common issues do you see in warehouse management, and how do you usually solve them
6. How do you think warehouse efficiency could best be improved?
7. What aspect of your job do you find to be the most time-consuming?
8. What do you consider the most important factor for a warehouse to function optimally?
9. How is the decision-making process when relocating an item? Do you make all decisions based on experience, or do you follow a specific guideline?

February 4th, February 6th and February 11th 2025:

1. Are there maps of the warehouse? For example, to show the layout, where everything is located, and what equipment is used.
2. How do you currently manage inventory levels?
    a. What inventory levels exist for the different products?
    b. How are the inventory levels determined?
    c. How and when are the inventory levels re-evaluated?
3. Are there process maps or process descriptions for the various warehouse operations?
4. What does the flow look like from incoming materials to outgoing finished products?
5. How does the picking process work?
    a. How do delivery specialists know what to pick?
    b. Do you pick multiple products at once (batches) or individual products?
    c. What do you do if a product is stored higher up?
    d. How is it currently decided where products should be located?
    e. How is it decided that products should be relocated or change positions?
6. Are the products standardized, or are many of them custom-built for specific orders?
    a. What types of products are manufactured in Gothenburg?
    b. How many components from the warehouse are included in each product?
7. How many people work at the same time?
    a. Do the warehouse workers only work in the warehouse, or do they have other responsibilities as well?
    b. Does everyone have a forklift license to access products stored higher up?
8. Is congestion an issue in the warehouse?

9. Is it documented where all products are currently located, which products should be in stock, and how they are stored?
10. What bottlenecks do you currently see?
    a. Do you think the bottlenecks can be changed?
11. What do you see as the biggest problem for the warehouse right now?
    a. Do you see any way to address those problems?

Appendix B – Sample of SKU Data and Calculations

Table B.1 shows examples of the data used to assign products to Auto 1. The SKUs shown are the case firms top 10 products in regard to order frequency. The SKUs have been anonymized due to case company requests. *Table B.2* shows a sample of the different product categories along with relevant measures. Examples of how the calculations are made are shown in *Appendix C*.

SKU	**Category**	**Order Frequency** (D_i)	**Average order quantity** (Q_i)	**Weight** (Kg)	**Space requirement** (S_i) (dm^3)	**Volume Uncertainty** (CV_i)	**95% est volume** (dm^3)	**Utility score** (U_i)	**Selected** (X_i)
SKU1	Mechanical parts	6072	4.27	0.06	1288	5.43	0.60	2853	1
SKU2	Detectors	4539	36.68	0.13	7029	1.76	0.51	1549	0
SKU3	Bases	4481	43.33	0.07	4477	1.80	0.28	1775	0
SKU4	Mechanical parts	3358	2.14	0.06	357	5.43	0.60	1589	1
SKU5	PCB	3294	1.19	0.09	169	2.89	0.52	1601	1
SKU6	Bases	3285	55.44	0.07	4200	1.80	0.28	1204	0
SKU7	PCB	3217	2.08	0.16	513	2.89	0.92	1528	1
SKU8	PCB	3171	1.46	0.08	178	2.89	0.46	1539	1
SKU9	PCB	3131	3.77	0.1	567	2.89	0.58	1480	1
SKU10	Mechanical parts	3093	1.53	0.04	157	5.43	0.4	1476	1

Table B.1. Example of data used to assign W01 products to Class Auto 1.

Example of product category	Number of SKUs	Average weight (Kg)	Weight Standard Deviation	Volume Uncertainty (CV_i)
Gas Detectors	607	2.17	1.72	0.79
PCB	208	0.25	0.72	2.89
Flame Detectors	56	3.63	2.71	0.75

Table B.2. Example of product categories and relevant measures.

Appendix C – Example Calculation

The calculations below exemplify how relevant calculations are made. SKU5, part of the PCB product category, is used as an example.

Volume uncertainty: $CV_{PCB} = \frac{0.72}{0.25} = 2.89$ (5.2)

95% est Volume for SKU5: $0.09 * (1 + 1.645 * 2.89) = 0.52\ dm^3$ (5.3)

Space requirement for SKU5: (S_{SKU5}): $0.52 * (\frac{1.19*3294}{12}) = 169\ dm^3$ (5.4)

Utility score for SKU5 (U_{SKU5}): $0.5 * 3294 - 0.1 * 169 - 10 * 2.89 = 1601$ (5.1)

Appendix D – Optimization Model Summary

Table D.1 summarizes the input used in the linear optimization model.

	W01	W02
Number of SKUs	3367	610
Total Available Capacity (dm^3)	44 818	21 609
Total Utility Score	64 808	6 752
Total Required Capacity (dm^3)	118 652	73 758
α	0.5	0.5
β	0.1	0.1
γ	10	10

Table D.1 Summary of inputs for linear optimization.

Assumptions

- We assume that the weights of products within a category is normally distributed
- We assume that a months' worth of demand for stock keeping level
- To simplify we assume that all products have the same density. The density is assumed to be 1 kg/dm^3.

Appendix E – Descriptive Statistics

Table E.1 summarizes the used dataset by disclosing relevant measures. The period used for the dataset is 2024-03-06 to 2025-02-04.

	W01	W02
Number of SKUs	3367	610
Unique orders	29 681	14 461
Mean order frequency	55.59	48.37
Median order frequency	1	8
Standard deviation order frequency	282.98	102.52
Mean weight	1.39	0.58
Median weight	0.05	0.12
Standard deviation weight	9.06	1.24
Mean 95% est volume	5.25	2.59
Median 95% est volume	0.28	0.57
Standard deviation 95% est volume	32.32	6.07
Mean utility score	1.06	0.51
Median utility score	0	0
Standard deviation utility score	132.16	58.36

Table E.1. Summary of quantitative data.

Appendix F - Balancing of AS/RS

Table F.1 shows an example of how the AS/RS is balanced using this reports method. Firstly, A co-occurrence and order frequency score is calculated using equation 5.7 and 5.8. These equations normalize the total scores of the products between 0-1. The scores are then multiplied leaving a total score for each SKU. The SKUs are lastly alternated between each lift to ensure an optimal balance.

SKU	**Co-occurrence score**	**Order frequency score**	**Total score**	**Lift**
SKU11	0.186	0.562	0.104	H1
SKU12	0.181	0.575	0.104	H2
SKU13	0.184	0.550	0.101	H1
SKU14	0.199	0.492	0.098	H2
SKU15	0.097	1.000	0.097	H1
SKU16	0.204	0.424	0.087	H2
SKU17	0.162	0.496	0.080	H1
SKU18	0.155	0.490	0.076	H2
SKU19	0.136	0.543	0.074	H1
SKU20	0.203	0.326	0.066	H2

Table F.1. Example of balancing the AS/RS

Appendix G - Quantitative Improvements Calculations

Firstly, complete orders within each category are calculated. *Table G.1* shows an example of the different orders and order lines. For example, order WO00101115 is only picked in Class Auto 1 both with the current situation and the new solution.

Order	Item number	Location	Warehouse	New class	Old class	Actual time (s)	Classes (current situation)	Classes (New solution)
WO00101115	SKU21	AUTO1	W01	Class Auto 1	Class Auto 1	0	Only Class Auto 1	Only Class Auto 1
WO00101114	SKU22	AUTO2	W02	Class W02 Conventional	Class Auto 2	0	Only Class Auto 2	Only Class W02 Conventional
WO00101114	SKU23	AUTO2	W02	Class Auto 2	Class Auto 2	0	Only Class Auto 2	Only Class Auto 2
WO00101113	SKU24	S1B	W02	Class Auto 2	Class W02 Conventional	176	Class W02 Conventional	Only Class Auto 2
WO00101113	SKU25	S5A	W02	Class Auto 2	Class W02 Conventional	23	Class W02 Conventional	Only Class Auto 2
WO00101113	SKU26	S5B	W02	Class Auto 2	Class W02 Conventional	11	Class W02 Conventional	Only Class Auto 2
WO00101112	SKU27	AUTO2	W02	Class Auto 2	Class Auto 2	0	Only Class Auto 2	Only Class Auto 2
WO00101111	SKU28	C1A	W01	Class Auto 1	Class 1	155	Only Class 1	Only Class Auto 1
WO00101069	SKU29	R3A	W01	Class 3	Class 1	729	Only Class 1	Only Class 3
WO00101068	SKU30	AUTO2	W02	Class W02 Conventional	Class Auto 2	0	Only Class Auto 2	Only Class W02 Conventional
WO00101068	SKU31	AUTO2	W02	Class W02 Conventional	Class Auto 2	0	Only Class Auto 2	Only Class W02 Conventional

Table G.1. Example of orders and order lines.

The actual time is the time in seconds from when the previous order line is marked as complete to the time that the current order line is marked as complete. For example, order WO00101113 is only picked in Class W02 conventional and has an average time per order line of $\frac{(176+23+11)}{3} = 70$ seconds.

Each order is categorized if it is picked in many or just one class. How many orders that are completed in only one class or in many classes are then summarized. Orders that would be picked in both an automated and conventional class according to the new solution are split into two orders since conventional and auto orders are never picked together according to the picking policy. How many complete orders that are picked in the different W01-classes according to the current situation and new solution is shown in *table 5.8.* Since W02 only consists of two classes and those classes are one conventional and one automated class W02 orders are always picked in just one of the two classes. Different metrics are therefore used to evaluate the improvement of this class.

In order to calculate the total time saved for W01 the number of order lines completed in each of the classes (shown in *table 5.9*) is multiplied by the average time to complete one order line in the different cases (shown in *table 5.7*). This is done for both the current situation and new solutions. The result is displayed in *table G.2 and Table G.3.*

W01-Class	**Average of Actual time (s)**	**Order lines - new solution**	**Total time - new solution (s)**	**Order lines - current situation**	**Total time - current situation (s)**
Class 1	72.4	11665	844 942	2985	216 215
Class 2	80.4	2313	186 108	5084	409 067
Class 3	470.1	998	469 978	490	230 751
Class Auto 1	17.6	135 743	2 392 914	83 787	1 477 020
Class A	130.1	480	62 458	372	48 405
Many Classes	110.9	35 894	3 983 096	95 217	10 566 068

Table G.2. Numbers used to calculate total time for W01.

W01	**Total picking time (day)**
Current situation	14,39h
New Solution	8,82h

Table G.3. Total picking time for W01 with the new solution and current situation.

Appendix H – Dataset Access

The QR-code (*figure H.1)* and link below grants access to the dataset. Due to requests from the case company products, product categories and work IDs have been anonymized. The full dataset used in this report is from the period 2024-03-06 to 2025-02-04, however only a month's worth of data has been approved for publication. The available dataset below is from the period 2024-04-01 to 2024-04-30.

Dataset Access

Figure H.1. QR-code for access to the dataset.

Appendix I - Division of Labor

Table I.1 shows the division of work between the two authors. As a lot of the work was conducted in unison and edited by both authors several parts of the work is accredited to both authors.

Author	**Tasks**
Felix Rydin	Introduction, theoretical framework, method, section 4.1 to 4.4 in the empirical data, section 5.2 in the analysis, section 6.2 in the discussion, conclusion and recommendation, appendix, interviews and data analysis.
Edvin Wallén	Introduction, theoretical framework, method, section 4.5 to 4.7 in the empirical data, section 5.1 and 5.3 in the analysis, section 6.1 and 6.3 in the discussion, conclusion and recommendation, interviews and data analysis.

Table I.1. The division of work between the two authors.

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