Industrial Engineering and Management
MSc Thesis

Optimize the Automated Storage and Retrieval System (AS/RS) of Vink Kunststoffen to improve warehouse efficiency

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Acronyms

AS/RS Automated Storage and Retrieval System. vii, ix, xi, 1, 2, 4, 5, 8, 9, 13, 15, 17–24, 26–29, 31–34, 47, 54, 56, 58, 59, 63

CFAM Class formation allocation model. 27, 32, 33

DES discrete event simulation. 29, 32–34

FCFS First Come First Serve. 11, 34, 43

KPI Key Performance Indicator. ix, 4, 5, 8, 11, 22, 24, 32, 47, 51

LIFO Last In First Out. 33

LP linear programming. 28, 32, 33

MPSM Managerial Problem Solving Method. 2, 6

PSP Plate Stacking Problem. 26, 28, 29, 31–33, 56, 59

SKU Stock Keeping Unit. ix, xi, xii, 4, 6, 8–11, 15, 17, 20–29, 31, 32, 34–44, 47, 48, 50–59, 64, 67

SLAP Storage Location Assignment Problem. 26, 27, 31–33, 35, 56

Glossary

Automated Storage and Retrieval System A system that uses automated technology for the storage and retrieval of goods from a warehouse or storage facility.. 1, 22

class-based storage A storage policy that categorizes items into different classes based on factors such as demand, with each class assigned specific storage. 25, 32

dedicated storage A storage policy that reserves specific storage locations for particular items or SKUs.. 17, 25, 32

Hall One In this hall, the automated warehouse will be placed. This hall stores the largest plastic plates.. xii, 8, 11, 13, 57

Hall Three This hall consists of the saw department and packaging department. Orders are further processed in this hall.. 13

Hall Two This hall is the plastic plate warehouse, most items are stored here, and the good receipt department is located here.. 13

Managerial Problem-Solving Method A systematic approach managers employ to identify, analyze, and resolve organizational challenges through a structured process encompassing problem definition, data analysis, solution generation, decision-making, implementation, and ongoing evaluation.. 6

Plate Stacking Problem A logistics problem focused on efficiently stacking plates in a warehouse, considering travel and shuffling time factors.. 22

random storage A storage policy where items are placed in storage locations without specific order or arrangement.. 17, 25, 29, 32

replenishment strategy A plan or approach for restocking inventory in a warehouse or storage system.. 28

shared storage A storage policy where multiple items are assigned to the same storage locations, improving space utilization.. 17, 25, 32

storage density The amount of material that can be stored in a given space, often measured as the ratio of stored material volume to the total storage space.. 15, 17

warehouse occupation rate The percentage of space within a warehouse currently utilized.. xii, 9, 15, 21, 54, 55, 57, 58

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Preface

Dear reader,

You are about to read my master's thesis, "Optimizing the Automated Storage and Retrieval System (AS/RS) of Vink Kunststoffen to Improve Warehouse Efficiency." Completing this thesis also marks the completion of my student time in Enschede. Over the past seven years, I have learned invaluable lessons, developed myself, and experienced moments that I will always remember.

First, I would like to thank Vink Kunststoffen for giving me the opportunity and trust to do this project. I enjoyed my time at the company. I have gained new insights and enhanced my experience managing projects within a corporate environment. I am particularly grateful to my company supervisor, Hans Dooper, for his guidance and support throughout the project. Besides this, I had a lot of freedom during my research, which I appreciated. I always experienced our meetings as efficient and productive. Additionally, I want to thank all the employees at Vink, especially those in the logistics department, for their assistance with my research and for making me feel welcome. The friendly working atmosphere was much appreciated.

I also thank my first supervisor at the University of Twente, Breno Alves Beirigo. His interest in the project and continuous guidance were crucial to my research. I experienced our meetings as pleasant, encouraging, and effective. These meetings helped me improve the quality of my thesis, especially the academic part. I also want to thank my second supervisor, Alessio Trivella, for his interest in my work and for providing extensive feedback. His insights really improved the quality of my work, particularly in the final stages of my thesis.

Lastly, I would like to acknowledge my friends for the unforgettable times we shared during these seven years and my family's continuous support throughout my studies. I encountered some challenging moments, but knowing I could always count on your support made all the difference! I also want to thank everyone who contributed to my journey, even if I have not mentioned you by name here, your support and encouragement have been invaluable. I hope you enjoy reading this thesis!

Bram Lamers

Wehl, July 2024

Management Summary

Problem

This research was done at Vink Kunstoffen B.V. in Didam, a company that sells plastic semi-finished products. The company aims to increase its turnover by twenty million euros to maintain market leadership but is not succeeding in this for now. The company operates within space and staff limits because of its low storage density. To solve this problem, the company bought an AS/RS (Automated Storage and Retrieval System), a system where sheets can be stored without racks and on top of each other, which improves the storage density. However, when different SKUs are stored on each other, the system must shuffle blocking SKUs to retrieve an ordered SKU. For now, the company uses a limited item selection and zoning strategy for the system. The research problem of this research is, therefore,

"Which zoning strategy and item selection for Vink's AS/RS gives the best balance between an adequately filled system and acceptable travel times that do not exceed the system's operational capacity constraints?"

We analyzed the current performance of the warehouse, where an average manual order takes 6.11 minutes, and an average automated order takes 37.97 minutes. Manual picking is, therefore, faster, and we must focus on slow-moving SKUs for the AS/RS. Furthermore, the occupation grade of the warehouse is determined and is above 90%, confirming that the warehouse is at its limits.

Solution

The solution approach consists of a simulation model that simulates and optimizes the zoning of the automated system and analyzes performances. The simulation model consists of four stages: initialization, creating an initial placement, order processing and objective calculation, and simulated annealing. With the help of simulated annealing, zone values of SKUs and locations are changed, and the algorithm checks whether this results in better solutions and objectives.

Results

We analyzed 30 scenarios with the simulation model, which follow from six zoning strategies (random, AB, ABC, ABCD, ABCDE, current layout) and 5 item selections (349, 394, 408, 455, 476 SKUs). The outcomes of the experiments showed the following results.

- For the current item selection, the current layout works best
- When the number of SKUs increases, AB zoning outperforms all other zoning strategies.
- Item selection 1 and 2 (349, 394 SKUs) are within the system's operational capacity, the other item selections are not.
- Choosing item selection 2 for the system would increase the system's SKUs in the system by 12.89%.
- Choosing item selection 2 for the system would increase the number of sheets in the system by 12.70%
- Adding these items to the system could lower the warehouse occupation rate in the traditional warehouse by 2.44%.

Recommendations

Based on the results, the following recommendations are given:

- Choose item selection 2 with an AB zoning strategy to increase the system utilization.
- Adhere to the guideline of item selection 2.
- Search for options to optimize rack height and space occupation to improve efficiency in the traditional warehouse.
- Explore just-in-time ordering strategies for certain orders to prevent occupying large amounts of space for extended periods and ensure full pallets are shipped quickly.
- Continue with dividing Hall One in subsections.

Chapter 1

Introduction

This chapter will briefly describe the company and the problem context of this research. The problem will be described by using a problem cluster. Based on the problem cluster, we will elaborate on the core problem choice. To solve this problem, the research problem and research questions are formulated, which all need to be answered at the end of this thesis. Lastly, the research design will be described, including the steps taken, scope, deliverables, and first limitations of this research.

1.1 Company description

Vink Kunststoffen B.V. in Didam is a company that processes and sells plastic semi-finished products. In Europe, Vink has the most expansive stock program in plastic sheet material, rods, profiles, and piping systems. They supply plastic semi-finished products in a wide range of plastic types to almost all industrial sectors, with a clear emphasis on markets within the production of signs and displays, mechanical engineering, chemical industry, equipment construction, water treatment, and the construction sector. The vision of Vink is to maintain a sustainable market leader in the plastic industry. The company wants to achieve this with knowledge sharing, innovation, high quality, logistics services, and communication (VinkKunststoffen, 2023). Vink is very customer-based; they offer various products and aim for quick delivery (one day).

1.2 Problem description

To maintain market leadership, the company aims to increase its turnover from X to a Y million euros, a turnover improvement of Z%. The company has noticed that it operates within its space and staff limits. Therefore, it seeks ways to improve internal processes to create more output. An essential part of this is the warehouse. Plates in the warehouse are either directly delivered to customers or routed to the sawing department for further processing. Most picking is done manually with the help of a forklift; for storage and picking purposes, Vink automated parts of the order picking process in the form of an automated warehouse, also known as Automated Storage and Retrieval System(AS/RS). The primary motivation behind this addition is to achieve greater efficiency in space utilization. Also, more careful order picking, which leads to less damaged products and better labor conditions, played a role in buying the system. Furthermore, speed is an essential factor for the company because of the company's next-day delivery policy when ordered before 17:00. This thesis aims to make the warehouse more efficient by improving the working of the AS/RS and let it operate more to its full capacity. Appendix A1 until A4 shows pictures of the system.

1.3 Core problem

The problem identification of this thesis has been done following the principles of the Managerial Problem Solving Method (MPSM) by Heerkens and van Winden (2021). Problems can be separated into action problems and core problems. Action problems are problems that deviate from the desired norm. Core problems are problems that cause the action problems with no further causes. The previous section shows that creating the desired output for turnover growth is the action problem; the reality deviates from the norm here. To make all problems and causes visible, a problem cluster is created. Figure 1.1 shows the problem cluster of Vink's problems.

The action problem of not reaching the desired output has several underlying causes. Among these is the need for more standardization, a consequence of the company's diverse product categories due to its commitment to a customer-oriented approach. Additionally, this customer-oriented approach influences the warehouse. Vink has a high warehouse fill rate because it holds safety stocks for nearly all products to ensure the one-day delivery guarantee, further complicating the warehouse's storage. Also, throughput issues, such as staff shortages and limitations in sawing capacity, contribute to throughput issues and the action problem. The company's commitment to being customer-oriented is a strategic choice. Because customer satisfaction is the most important thing for the company, it is impossible to influence this core problem because we would also scupper Vink's prime values in that case. The labor market influences staff shortages, an external factor beyond the company's control. Therefore, the possible core problem of staff shortage is inherently challenging and beyond direct influence. While tackling the finite number of saws is possible, creating additional saw capacity would only marginally impact operations, offering less output improvement than addressing broader issues affecting all operations. The focus for the selected core problem is, therefore, on storing material. The low storage density is caused by the company's traditional warehouse methods, which lowers storage density, and the new AS/RS system is not operating at full capacity because zoning and the item selection are limited and not adjusted. the chosen core problem is the limited zoning and item selection of the AS/RS since the company just invested in this machine and wants a good return on investments. Tackling this problem would yield the quickest improvements, and the highest output improvement could be achieved by solving this problem. The core problem of traditional warehouse storage methods is more time-consuming and static. Therefore, we choose the limited zoning strategy and item selection the AS/RS as the core problem instead of the traditional warehouse storage methods.

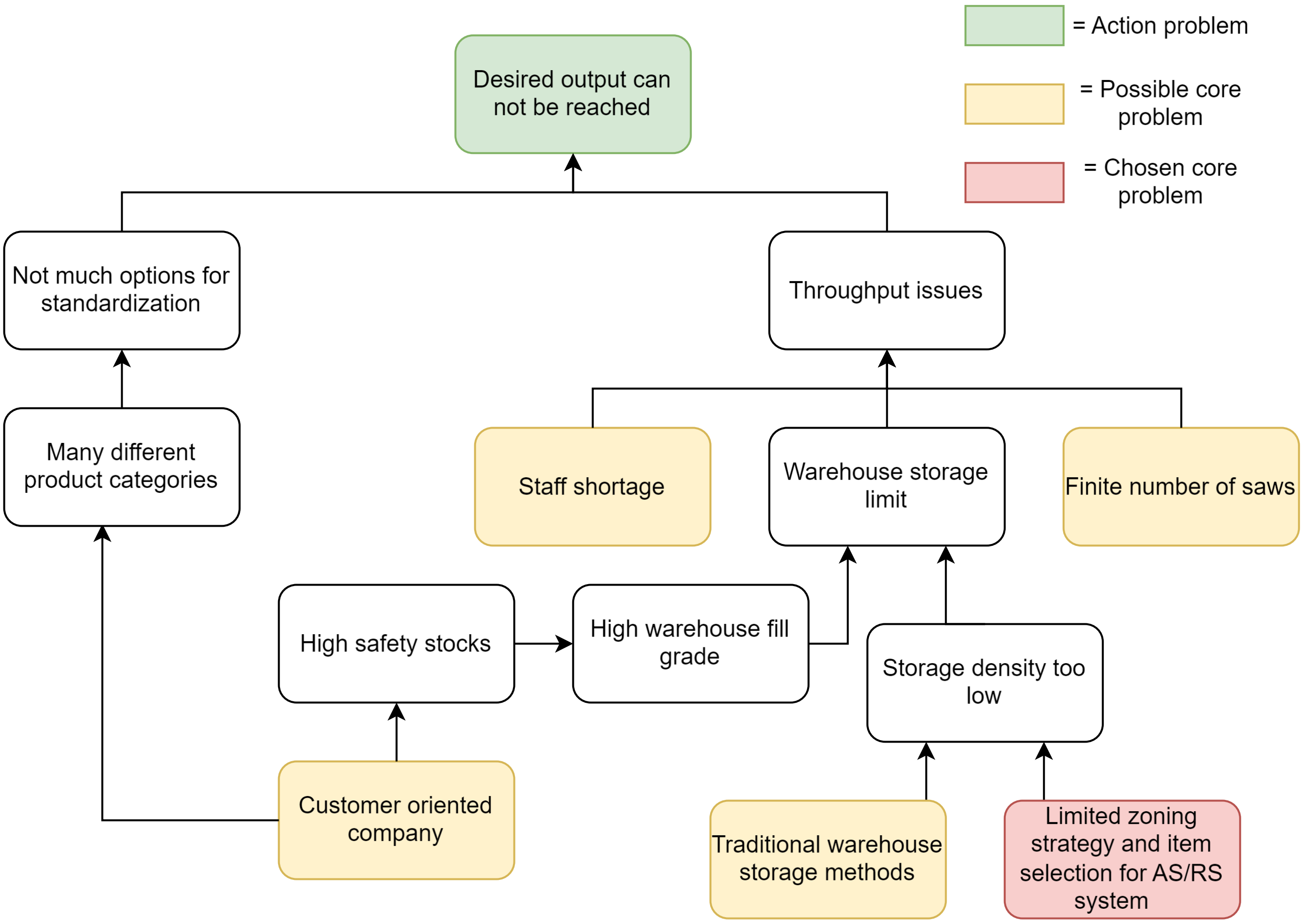

FIGURE 1.1: Vink's problem cluster with the action and core problems.

1.4 Research problem

As the management seeks to address the core challenges of storage density and warehouse limitations, partially solved by warehouse automation, a crucial need remains to improve the performance of the AS/RS. Hence, the research problem for this thesis is:

"Which zoning strategy and item selection for Vink's AS/RS gives the best balance between an adequately filled system and acceptable travel times that do not exceed the system's operational capacity constraints?"

1.5 Research questions

To solve the research problem, research questions must be answered. The research questions are further divided into sub-questions. Each research question represents a chapter from Chapter 2 to 6.

1. What is the current situation?
   (a) What is the current process of plate processing and order picking?
   (b) What is the demand pattern of SKUs?
   (c) What is the current warehouse layout and resources?
   (d) What is the current space utilization of the warehouse?
   (e) How does the AS/RS system work in detail?
   (f) Which SKUs are considered for the AS/RS?

   The first research question must give insight into the current situation of the company and the warehouse. The whole plate processing process will be examined to understand the processes and the warehouse. Also, the space utilization, replenishment strategy, and working of the automated system will be reviewed. Lastly, suitable products for the AS/RS will be classified.

2. Which modeling techniques are used in literature for similar problems?
   (a) On which level (strategic, tactical, operational) of warehouse decisions can we place this research?
   (b) Which storage and slotting strategies can be used?
   (c) Which Key Peformance Indicators (KPIs) are often used in warehousing?
   (d) What information is available on modeling similar automated warehouse systems and their associated challenges?
   (e) Which techniques can be used for optimization?

   The literature review will focus on strategies and principles to solve the problem. Warehouse design principles for regular and automated warehouses will be discussed. Furthermore, storage and slotting strategies for the AS/RS are mentioned in this chapter. Often used KPIs in warehousing will be discussed. More details on similar problems and various associated modeling techniques will also be provided. Lastly, optimization techniques for improving the solution will be explained.

3. How to model the working of the AS/RS system?
   (a) Which assumptions are needed to make the model as realistic but still executable?
   (b) Which input data is needed to model the AS/RS?
   (c) What parameters should be used?
   (d) What KPI should be considered as objective value?
   (e) What are the decision variables?
   (f) Which constraints need to be used?

   In Chapter 4, the solution tool will be set up. The section will explain the requirements and assumptions to make the model realistic but executable in the given time frame. For simplification, assumptions need to be made; therefore, this chapter will explain the assumptions and why these assumptions are made. Furthermore, the model's input data, parameters, objective value, decision variables, and constraints will be outlined in this chapter. As well as the working and operation of the solution tool.

4. How can the solution tool be used to analyze results?
   (a) Which parameters are needed for the optimization process?
   (b) Which scenarios gained the best results?
   (c) How does the system's performance react to different item selections?
   (d) Which capacity gain comes with the best solution?

   This chapter will analyze the performances of the solution tool in different circumstances based on the given KPI. Experiments under different scenarios will be conducted, and we will compare and elaborate on all outcomes. This chapter must show the best solution and the warehouse efficiency gained by it.

5. Which conclusions can be drawn from the results?
   (a) Which zoning strategy performs best?
   (b) What is the most suitable item selection?
   (c) To what extent does the solution contribute to solving the core and action problem?

Based on the results in the previous chapter, conclusions will be drawn about the best configurations for the AS/RS regarding item selection, location zoning, and item slotting. Based on these conclusions, recommendations for the company will be given. The results must provide more insight into the system's appropriate zoning strategy and item selection. More SKUs means more reshuffling operations and higher order completion time. On the other hand, more SKUs in the system creates more space in the warehouse; therefore, the trade-off between extra storage space and order-picking speed must be considered in evaluating the different scenarios and outcomes.

1.6 Research design and planning

1.6.1 Research design

This thesis will follow the principles of the Managerial Problem-Solving Method (MPSM) created by Heerkens and van Winden (2021). The MPSM consists of the following phases:

1. Defining the problem
2. Formulating the approach
3. Analysing the problem
4. Formulating (alternative) solutions
5. Choosing a solution
6. Implementing the solution
7. Evaluating the solution

The thesis will follow all seven phases through the different chapters. Defining the problem is done in Chapter 1 and formulating the approach. In Chapter 2, the problem situation will be analyzed further in the context analysis. The context analysis will examine the problem situation in more depth. By delving deeper into the complexity of the problem, we aim to gain a comprehensive understanding of all its aspects. This deeper understanding will enable a better modeling process and a more effective solution tool. In Chapter 3 (partial), solutions will be provided in the literature review. After that, the problem solution tool will be formulated in Chapter 4. In Chapter 5, the solution tool will be used, and the results of different scenarios will be provided. Finally, the solution is evaluated, and conclusions are drawn in Chapter 6. Figure 1.2 shows how the research questions and chapters are related to each other with their input and output.

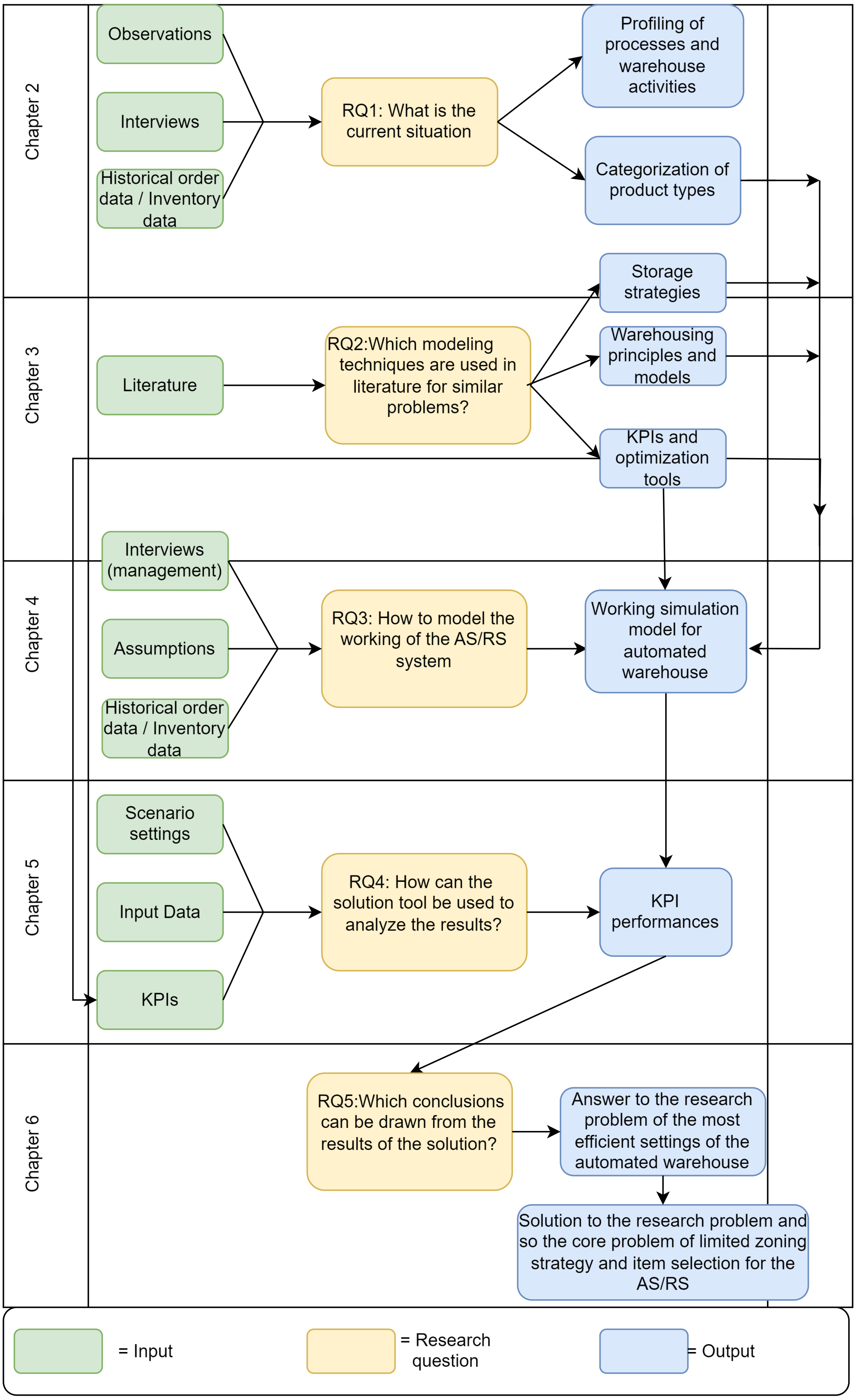

FIGURE 1.2: Research design with research questions, inputs, and outputs.

1.6.2 Scope

This thesis will focus on the AS/RS in Hall One. Therefore, only the SKUs fitting the location sizes in this system will be investigated. Table 1.1 shows the SKU sizes considered in this research. The research problem is focused on the system's SKU selection, zoning, and slotting, but it will not be possible to investigate all warehousing operations due to time constraints. While the SKUs considered in this research vary in size as specified in Table 1.1, they also differ in other attributes such as thickness, color, and material. Furthermore, SKUs can only be placed in locations with the same sizes when added to the automated system because otherwise, sheets bow and get damaged.

TABLE 1.1: Sizes of the SKUs considered in the research

Length (mm)	Width (mm)
4,050	2,050
4,050	1,500
4,050	1,050
3,050	2,050
3,050	1,550
2,050	1,550
2,050	1,050

1.6.3 Deliverables

This thesis will have the following deliverables:

- A simulation model simulating and improving the working of the AS/RS with desired KPI outputs for testing the baseline scenario and new scenarios.
- in-and-output Excel files that can be easily used to set up and analyze outcomes.
- Recommendations on the storage, slotting, and item selection of the AS/RS.
- Literature review
- Report

1.6.4 Limitations

This thesis will have the following limitations:

- Not all warehouse configurations will be tested in real life.
- The solution tool would be based on assumptions.
- The layout of the system is considered fixed in this research.

Chapter 2

Context analysis

In this chapter, we delve into the production process at Vink Kunststoffen. After this, an overview and analysis of the current order-picking process and demand pattern is given. Also, the current warehouse, its warehouse occupation rate, and the resources available are discussed. Additionally, we explain the layout and characteristics of the automated warehouse. Lastly, we describe the current item selection for the system. Through this context analysis, we aim to gain insights into the challenges and opportunities of the warehouse and provide a better understanding of the problem. Gaining context for modeling and solving the warehouse optimization problem effectively.

2.1 Processes

2.1.1 Production process

The production process at Vink Kunststoffen is split up into different activities that are interconnected with each other. Figure 2.1 visualizes all activities in a flowchart.

Order preparation department: The production process starts with orders that come in. The order preparation department conducts a thorough review of these orders. Upon verification, they provide the order pickers with pick lists, including accompanying sewing instructions if needed.

Order picking plate: There are two order picking crews, plate order pickers and order pickers for the sawing department. Plate order pickers receive order lists from the order preparation department. Following the specified order sequence, plates are picked up. While some orders may be consolidated on a single pallet, multiple heavier plates often lead to the distribution of orders on various pallets. The order pickers transport the pallet with the order receipt to the packaging department and proceed with the following order. Besides this, the order pickers also operate the AS/RS when SKUs must be retrieved from here.

Order picking sawing: The way of working for the order pickers for the sawing department is almost the same as the regular order plate picking. Instead of standard orders, the pallets with orders are not delivered to the packaging but to the sawing department.

Goods receipt department: The goods receipt department ensures that the warehouse is always adequately supplied. The goods receipt department unloads the lorry and scans all the incoming material to update the inventory system. After this, the pallets with plates are put in the warehouse at a given location, or a new location is made when the product type has no location yet.

Sawing department: The sawing department cuts standard format plates to customer-specified sizes. Sawing instructions have been received from the order preparation department. Since sawing machines operate solely in a horizontal direction, plates require rotation during cutting. In addition to plates delivered by sawing order pickers, the material from previous sawing is used. The order preparation department oversees the decision-making process, determining whether the order can be completed from previous rest material or if a new plate from the warehouse needs to be retrieved.

Packaging department: In the packaging department, plates are packed in cardboard and sealed. After this, the products are ready for transport. There are four stations, three where pallets are packaged and one where smaller orders are packed.

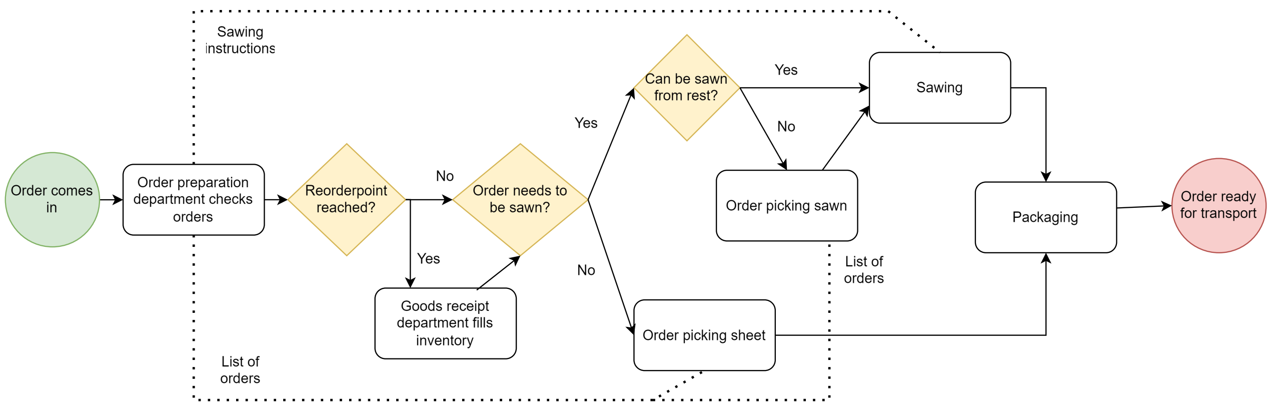

FIGURE 2.1: Flowchart of the production process of Vink Kunststoffen

2.1.2 Current order picking process

In the context of the earlier production process, it is important to highlight two distinct types of order pickers: those dedicated to non-sawing orders (mainly two in number) and a singular order picker specifically allocated for sawing orders. The execution of order picking involves the utilization of a forklift, where the order pickers select the appropriate-sized pallets and navigate to the specified location of the ordered SKUs. Subsequently, the selected SKUs are transported to the packaging station, marking the initiation of a repetitive cycle.

The primary challenges encountered in the order-picking process revolve around emergency orders and the storage constraints within Hall One. Emergency orders, particularly those received towards the end of the day, pose a challenge due to their potential cause of overtime, despite the efficiency of manual order picking. This process can be time-consuming and significantly damage the overall efficiency of the order-picking process.

The order prioritization in picking follows a First Come First Serve (FCFS) policy. The warehouse processes an average of 235.67 sheet orders and 1,693 sheets daily, 29.46 orders, and 211.63 sheets per hour. The average order completion time for manual picking stands at 6.11 minutes. Table 2.1 shows detailed key performance indicators (KPIs) related to throughput and picking speed for manual and automated picking. Following the analysis of orders, it can be seen that manual picking is, on average, quicker than automated picking.

TABLE 2.1: Current warehouse performances based on KPIs throughput and order completion time

KPI	**Manual picking**	**Automated picking**
Average sheet orders a day	235.67 orders/day	14.19 order/day
Average number of sheets picked a day	1,693 sheets/day	36.46 sheets/day
Average order throughput warehouse	29.46 orders/hour	1.58 orders/hour
Average sheet throughput warehouse	211.63 sheets/hour	4.05 sheets/hour
Average order completion time (idle time included)	6.11 minutes	37.97 minutes

2.2 Demand pattern

The demand pattern of SKUs is profiled to understand the flow of orders. The seasonality is reviewed on a monthly and weekly basis. Furthermore, the average number of orders per hour is given. The monthly seasonality in figure 2.2 shows a small peak in March and May. The months of April and August show some small dip. These dips can be explained by looking at the weekly seasonality in figure 2.3. The weeks 17 and 21 are weeks with a holiday day in it. Clients are less likely to order around these holidays. The most pointed out dip in demand is the one in the weeks 29 until 33. Also, this dip is explainable since these weeks are construction holidays (bouwvak in Dutch). During these weeks, most construction companies are closed. Since Vink delivers to construction companies or companies related to the construction sector, this week's demand is less than normal. Besides these small peaks and dips, the overall demand for SKUs is steady.

The order pattern on a day can be seen in Figure 2.4. Most orders are printed around 7 a.m. at the beginning of the day. Furthermore, there are some small peaks just before and after the lunch break. Besides these peaks, the figure shows that the demand pattern during the day is also relatively stable, and there is no extreme number of emergency orders at the end of the day.

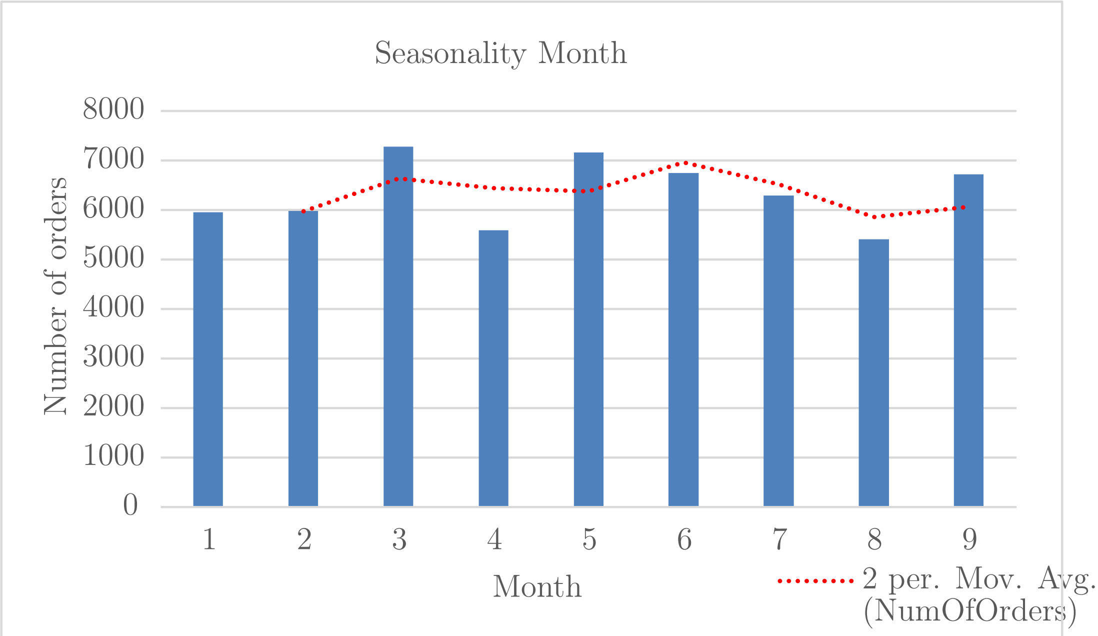

FIGURE 2.2: Seasonality measured over the months January until September with moving average trend line

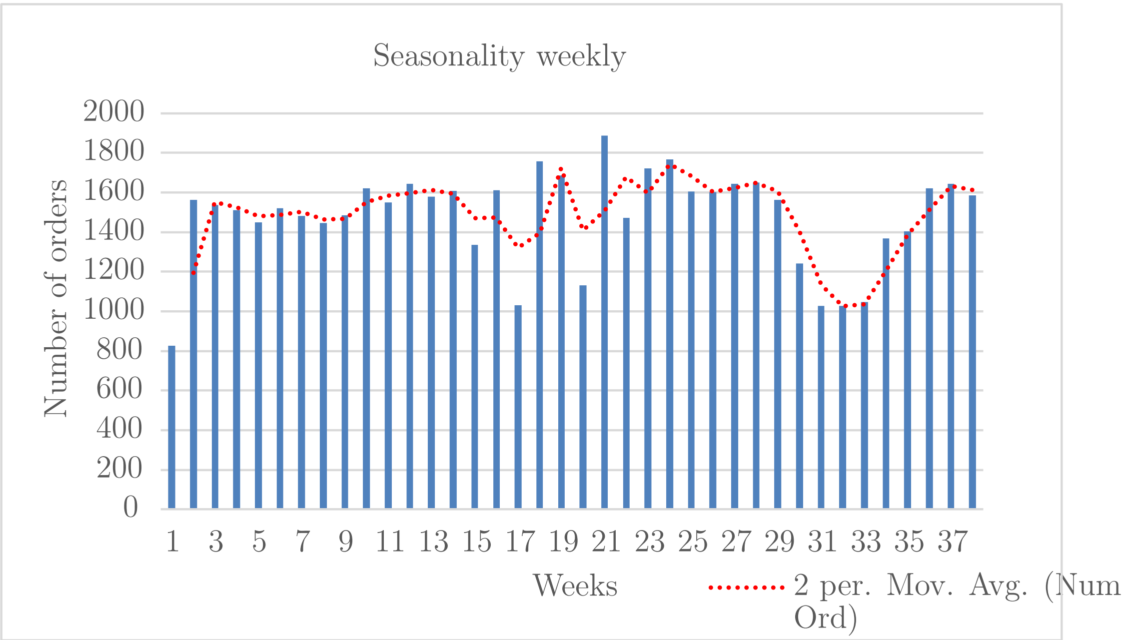

FIGURE 2.3: Seasonality measured over Weeks 1 till 37 with moving average trend line

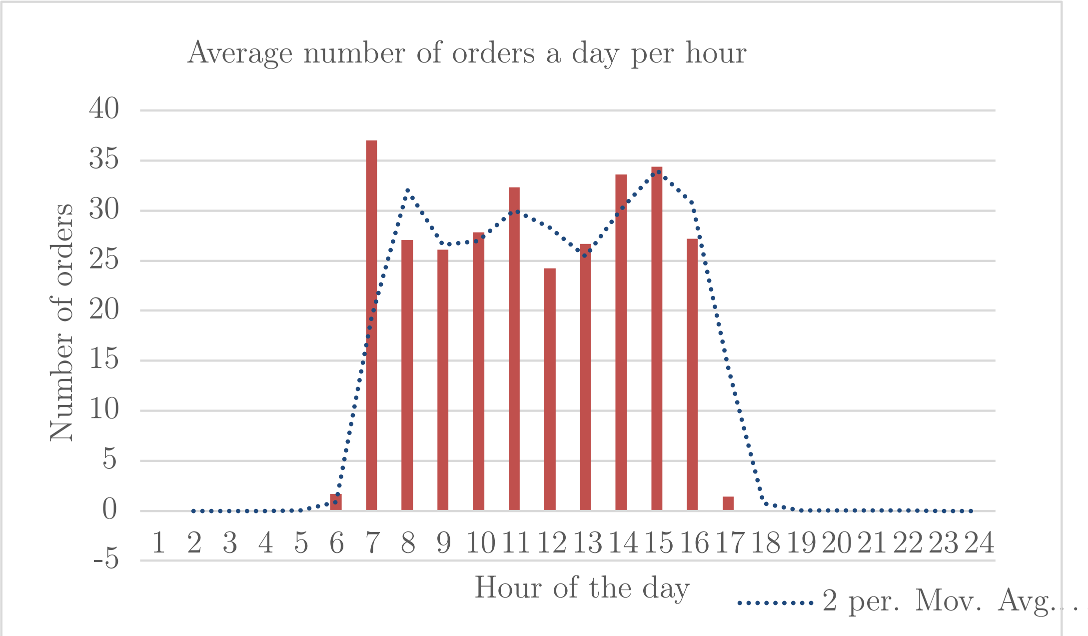

Figure 2.4: Average number of orders per hour with moving average trend line

2.3 Warehouse layout

The company installed the warehouse's three bought AS/RS systems. The AS/RS system in Hall One is the biggest and only one considered in this research. This section will show the warehouse layout with all three installed AS/RS systems.

The company's warehouse operations for order picking and sawing occur in halls One, Two, and Three. In Hall One, the AS/RS is placed. The AS/RS is installed to save room and create order in Hall One. Hall Two is the biggest warehouse where all other sheet material is held in inventory in a traditional warehouse. Sheets are picked here by hand. Hall Two consists of twelve aisles with around twenty sections with an average height of six pallet locations. Furthermore, the goods receiving area is located at the beginning of Hall Two. Hall Three is reserved for the sawing and packaging department. The packaging department is at the front of Hall Three, whereas the saws are in the back. Hall Three also functions as a warehouse for sawing rest material to prevent waste. Figure 2.5 shows the warehouse layout. The automated systems are called Machine One, Two, and Three. Machine one will be used to store sheet material. Machines Two and three will be used to store the (rest) material for the sawing department and are, therefore, out of the scope of this research.

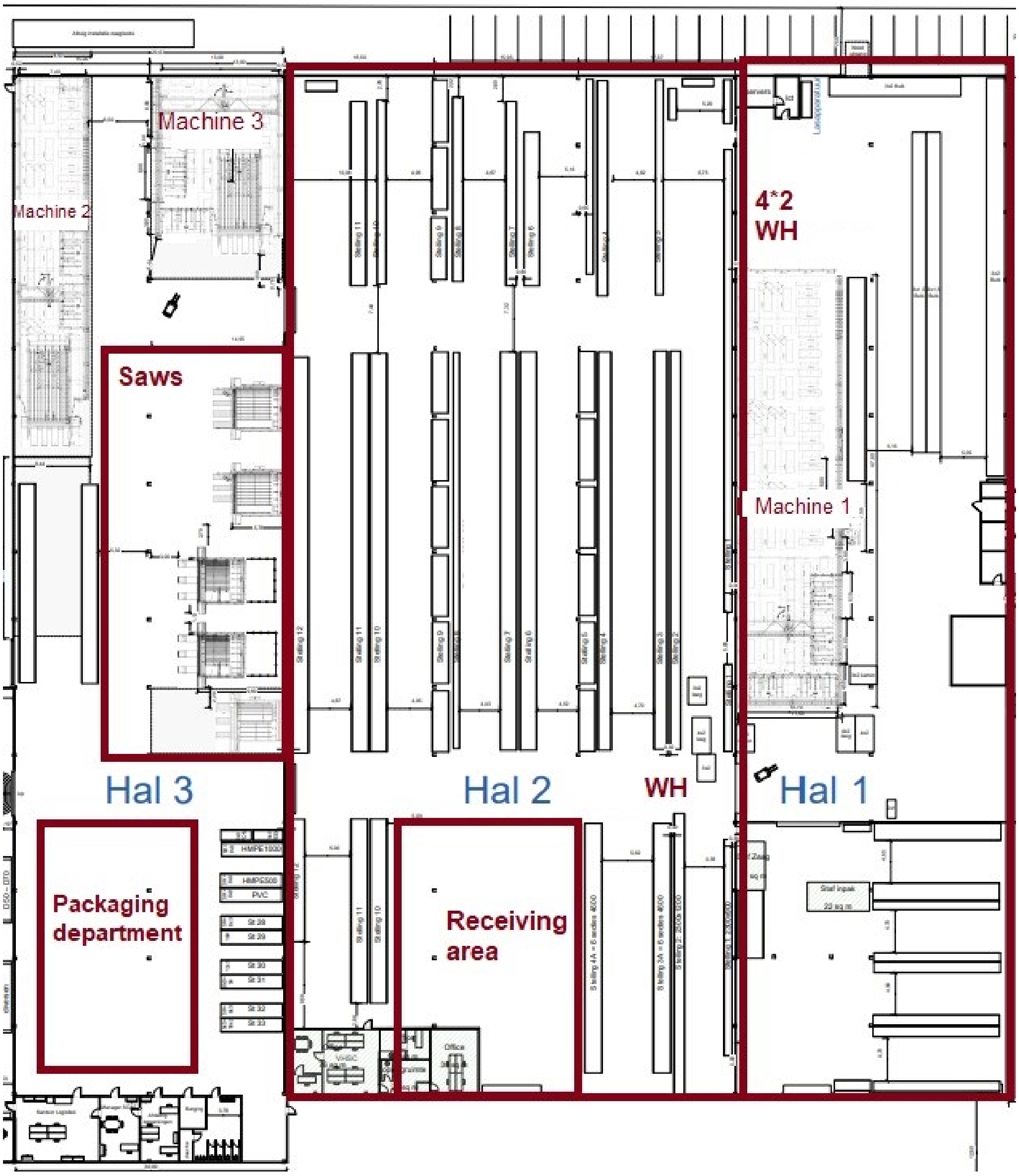

FIGURE 2.5: Layout of Vink's warehouse with the different departments

2.3.1 Warehouse occupation

According to Tompkins and Smith (1998), a warehouse occupation rate exceeding 90% damages warehouse efficiency. Beyond this threshold, the time required to locate positions increases, and the presence of slow-moving SKUs among fast-moving ones may pose challenges. Thus, maintaining a warehouse occupancy within the range of 85% to 90% is optimal, ensuring a balance between operational efficiency and extra space for unforeseen orders or events. Striking this balance is crucial as a low occupancy under-utilizes warehouse capital, leading to additional expenses. Table 2.2 presents the warehouse occupancy metrics for Vink's sheet material on the reference date of 31-10-2023.

TABLE 2.2: Warehouse occupancy of sheet material at Vink Kunststoffen as of 31-10-2023.

Occupation Characteristic	**Value**
Total Pallet Locations in Sheet Warehouse	1,846
Pallet Locations Occupied in Sheet Warehouse	1,735
Warehouse Occupancy Rate	93.99%
Number of Pallets in External Storage	215
Percentage of Pallets in External Storage	11.65%

Primarily, the current warehouse occupancy is notably high, caused by safety stocks, the storage density issue, a recent inventory takeover from a competitor, and the limited zoning and item selection of the AS/RS. Additionally, a portion of the inventory is held externally. Given the higher costs associated with external inventory and the resulting logistical challenges in responding quickly to orders, limiting external storage is preferable. However, this external storage is necessary for now.

2.3.2 Inventory and handling systems

The company uses different storage systems like pallet racks, regular storage racks (Figure 2.6 and 2.7), a shuttle, and pallet boxes for waste management. The AS/RS is recently added to this list of storage systems. The pallet racks have different sizes, depending on the SKU sizes. The company uses an ERP system and software for inventory management. This software examines trends in sales and improves product forecasting. The company has an s,Q inventory policy for most products. An s,Q inventory policy reorders with a fixed amount q when the inventory enters or drops below threshold value s. Most products have a minimum order quantity, and most arrive in full pallets, following the s,Q inventory policy size q (El-Aal et al., 2010). The company has some additional handling material in the picking process. This is done manually but with the help of a counterbalanced forklift. Also, a manual operating crane is available to lift heavy material. These cranes use air pressure and make a vacuum to attach the material to the crane, but this takes a lot of time. The crane in the AS/RS works with the same principle.

FIGURE 2.6: Pallet rack storage in the warehouse.

FIGURE 2.7: Regular storage rack in the warehouse.

2.3.3 The AS/RS

The AS/RS system in this thesis is designed to handle and store plastic sheets in warehouse logistics efficiently. At its core is a crane utilizing air pressure and vacuum technology to transport individual plastic sheets precisely. The crane leverages air pressure to create a vacuum, ensuring the plastic sheets are secure and delicately handled. This technology enables the system to lift and transport individual sheets with efficiency.

The system supports two primary storage modes. dedicated storage involves assigning specific locations to one SKU, promoting a structured arrangement. Shared storage/random storage allows multiple plastic sheets to be consolidated in a single stack and location, providing flexibility in storage configurations and increasing storage density. The location groups are based on the sizes mentioned in Table 1.1. Based on the number of preferred locations per size (via expert opinion), the company produced a layout with a space occupation of 83.93%, with the help of a 2D bin packer tool, which is also used in nesting at the sawing department. Figure 2.8 shows the current layout of the AS/RS and an additional layout that could result from running the model and has thus a more optimized zoning and slotting of SKUs, which should be the model's output.

The system imposes a maximum stack height of two meters; therefore, the maximum capacity of the current layout is 108.65 m of total stack height. This is a lot, but a trade-off exists between filling capacity and sheet retrieval time. Therefore, the current storage does not reach the capacity constraint (15.83m). More SKUs in the system means more orders and shuffling operations, which could lead to an overloaded system. The outcome of this research must be a robust solution that balances this trade-off. The system must be adequately filled without extremely worsening performance. The machine's preference for placing SKUs on the lowest stack possible during storage and shuffling is noteworthy. The system follows a sequential approach during the retrieval process, especially in shared/random storage. The crane searches for the location where the target sheet has the least blocking sheets, then systematically removes and relocates SKUs positioned above the target plastic sheet until the target sheet lies on top. When it lies on top, it is retrieved. After retrieval, the relocated SKUs remain undisturbed in their new positions until retrieval or repositioning is necessary again. This design choice, coupled with the maximum stack height limitation, enhances operational stability and minimizes movement within the storage system. The machine's storage and retrieval policy is fixed and can not be changed.

In conclusion, the AS/RS system with air pressure crane technology, featuring a maximum stack height of 2 meters, offers a solution for handling plastic sheets. It integrates technology, flexible storage modes, and a sequential retrieval process. The system's decisions during operation are described in Figure 2.9 as a flowchart. Also, Appendix A1 till Appendix A4 shows drawings and pictures of the system, and Table 2.3 shows the system's specifications.

FIGURE 2.8: Current AS/RS layout and possible layout generated by the model for reducing total travel time.

TABLE 2.3: Specifications of the AS/RS system

Characteristic	**Value**
System length	45.53m
System width	10.24m
Speed vertical (v_y)	0.6 m/s
Speed horizontal (v_x)	1.6 m/s
Pick up time	10.75 s
Drop time	10.75 s
Max stack height	2m
Max Capacity	108.650 m
Current capacity occupancy	15.826 m

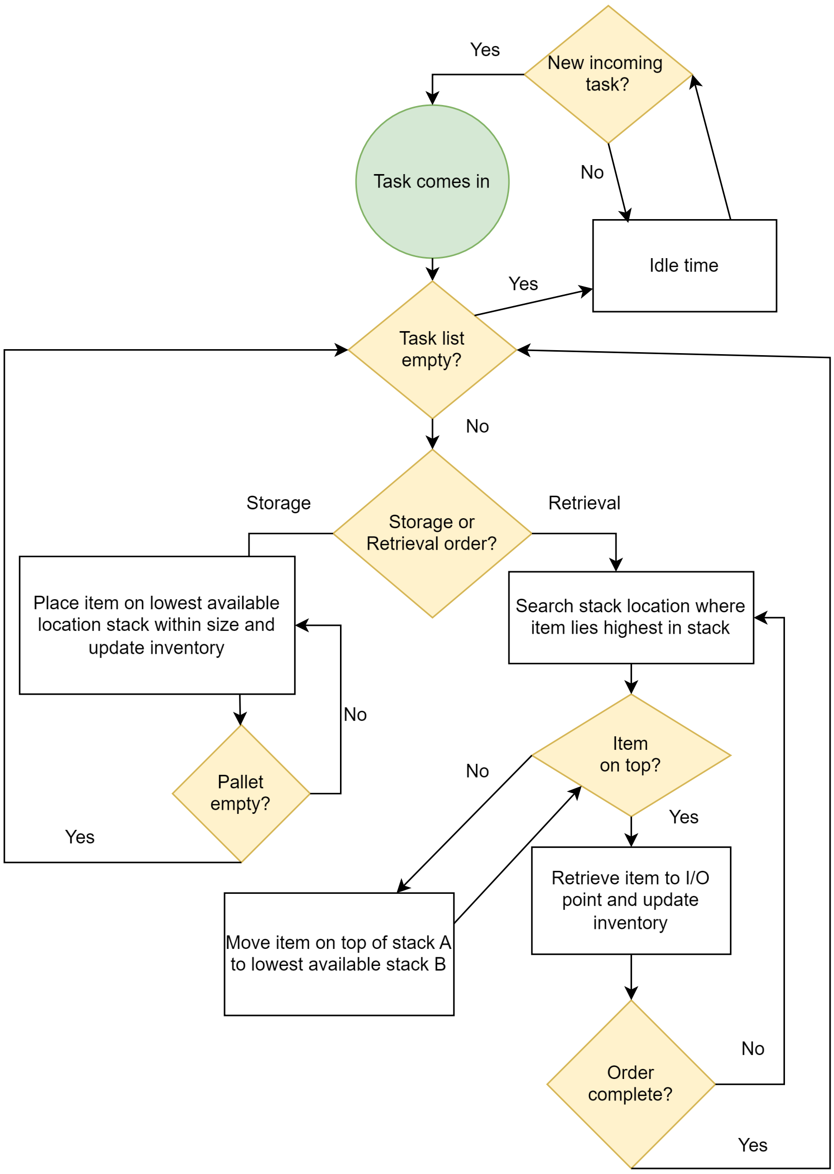

FIGURE 2.9: The working of the AS/RS system given in a flowchart

2.4 Item selection

The primary goal of the AS/RS is to enhance storage density and facilitate organized material storage. To pursue this objective, a selection of SKUs suitable for integration into the AS/RS is needed. Because of labor efficiency, the company's current selection strategy entails allocating all four-meter sheets, weighty and easily damaged products to the AS/RS. The remaining space is filled with slow movers, the so-called E-items. SKUs that are sold at a maximum of one time a month are considered E-items. Slow-moving SKUs are selected because of speed. The AS/RS has a comparatively lower picking capacity than manual picking. Furthermore, the system has a hard constraint that requires sheets to have a minimal thickness of 3mm to prevent errors. Slow movers are indicated by an ABCDE classification based on the number of picks. Class E-items are considered slow movers and, therefore, are based on one pick a month on average. Table 2.4 presents the comprehensive selection criteria employed, while Table 2.5 presents the results of the ABCDE analysis. The base scenario selection resulted in 349 SKUs, where 34.57% is selected based on the ABCDE classification, 21.14% based on weight, and 44.29% based on easily damaged material. Other scenarios of item selections could be created when criteria are relaxed.

TABLE 2.4: Selection criteria for AS/RS selection if at least one criteria are fulfilled SKU is placed in AS/RS

Selection criteria	**Criteria**
Damage sensitive	Material types: PPMA, Lexan
Thickness	$\geq$ 3mm (minimal thickness for the system)
Weight	$\geq$ 100 kg
Length size	$\geq$ 4000 mm
E-items	#picks per month on average $\leq$ 1

TABLE 2.5: ABCDE analysis of sold SKUs from 1-1-2023 till 13-10-2023

Class	**#SKUs**	**Tot. #Picks**	**%SKUs**	**%Picks**	**ABCDE #picks/month**
A	10	20,380	1.39%	20.17%	>150
B	481	83,719	66.71%	77.53%	[3-150]
C	52	1,188	7.21%	1.10%	[2-3]
D	57	759	7.91%	0.70%	[1-2]
E	121	542	16.78%	0.50%	[0-1]

2.5 Summary

This chapter sketched the situation in the warehouse. Furthermore, the order-processing activities are described as a flowchart, further explaining the order-picking process. The average throughput of order picking is 29.46 per hour for manual picking and 1.58 orders/hour for automated picking. On average, automated picking is 6.22 times slower than manual picking, looking at order completion times. Furthermore, the demand pattern is profiled to analyze if there is seasonality in the demand pattern. The demand pattern does not show notable seasonality during months, and no extreme order peaks during the day. The process description focuses on the order-picking process in the manual and automatic settings. Also, the handling material, storage systems, and inventory strategy are explained. Also, this section analyzed the current warehouse occupation rate, which is currently 93.99%. A rate between 80% and 90% is more convenient. Furthermore, the company has a lot of external storage. It is costly and time-consuming to move these SKUs. Lastly, the layout for the AS/RS and the current selection of SKUs suitable for the AS/RS is presented. However, this layout can change; the company does not desire changes because it leads to downtime of the machine and a new installation procedure. This context analysis pointed out Vink's challenges in the current warehouse operations situation.

1. The storage density could be improved by the AS/RS; the system is, on average, with a factor around 6.22 times slower than one manual order picker. So, putting fast-moving SKUs in the system is not convenient.

2. Some material is stored inefficiently and unordered, leading to a warehouse occupation rate of 93.99%.

3. The company has made a layout for the system based on space efficiency, resulting in a design with a space occupation of 83.93%. Besides this, the company must still have an improved zoning, slotting, and item selection strategy.

Chapter 3

Literature review

This chapter will form the theoretical framework of this thesis. It will answer the third research question: "Which modeling techniques are used in literature for similar problems?". First, warehouse layout principles and warehouse decisions will be discussed. This section will dive into the critical decisions on which level and the impacts the decisions in the AS/RS could have on the operational performance of the whole warehouse. In the second section, commonly used (automated) warehouse KPIs, who offer options for making later KPI-related decisions, will be given. The third section will point out different storage and slotting policies that could be operated in the automated system. The fourth section will dive deeper into ways to categorize and model the working of the automated system. For this, four domains of literature are examined: optimal zoning and slotting boundaries, general Automated Storage and Retrieval System literature, literature on the Plate Stacking Problem (PSP), which incorporates the shuffling of plates and 3D compact storage systems literature. After discussing these domains, this research's most critical points and categorization will be presented. Also, improvement heuristics are reviewed to optimize the initial solution. Finally, this section will summarize the information in this chapter in the summary section.

3.1 Warehouse layout level decisions

Warehouses are an essential component in the supply chain. Warehouses work as a buffer in material flow along the supply chain; they consolidate products from various suppliers for a combined delivery and add value by pricing, labeling, and product customization (Gu et al. 2007; Faber et al. 2018). The research agenda in warehousing includes optimization-based decision models for strategic, tactical, and operational warehouse problems. Key in this research field is the performance analysis of manual and AS/RS systems in combination with stochastic models, new warehouse design principles, and categorized material handling solutions (Koster et al., 2017). Rouwenhorst et al. (2000) distinguish the warehouse operations into four processes. The receiving process is the first process. Products arrive by truck or internal transport. The products may be checked and wait for further processing. In the storage process, SKUs are placed in storage locations. The storage area could be split into a fast and reserve pick. After that, orders can be picked in the order pick process, where after that, they are packed, checked, and shipped. The warehouse layout setting can be divided into three levels: strategic level, tactical level, and operational level (Carla et al. 2008; Rouwenhorst et al. 2000)

3.1.1 Strategic level

Strategic decisions have a long-term impact and involve big investments. The most important decisions on a strategic level in warehouse layout are the process flow design and the selection of warehousing systems (Rouwenhorst et al., 2000). The process flow represents how SKUs must be processed through the warehouse. The primary product flow consists of receiving, storage, order picking, and shipment. More activities could be added depending on the kind of warehouse operations. The selection of warehousing involves choosing warehouse systems such as storage and sorting systems. These selections are interrelated with the process flow design. The selection process creates two decision problems, one based on technical capabilities, which questions what is possible within the warehouse, and one based on economic considerations, which examines the benefits and costs (Rouwenhorst et al., 2000). The decision of the company to buy the AS/RS is an example of a strategic decision.

3.1.2 Tactical level

The tactical level decisions follow from the strategic level decisions. Tactical decisions typically are about the dimensions of resources and other organizational issues. Furthermore, it includes the dimensioning of picking, storage areas, and determining ABC zones, as well as the forward and reserve areas. These decisions aim at throughput, response times, and storage capacity (Rouwenhorst et al., 2000). This thesis tries to improve Vink's system by optimizing the zones for locations and SKUs and selecting appropriate items for the system. These decisions fall in the dimensioning packing and storage areas and determining the ABC zones. Therefore, this thesis focuses on warehouse decisions on a tactical level.

3.1.3 Operational level

On the operational level, the day-to-day activities of the warehouse play a role, such as order picking, routing, allocation of goods, and truck arrivals. The processes on an operational level have to be carried out within the constraints set by the strategic and tactical decisions made at the higher levels (Rouwenhorst et al., 2000). Therefore, a good fit between the three layers is essential to let the warehouse operate as desired. The operation of the system itself falls under operational decision-making since this is dependent on the decisions made at the tactical level.

3.1.4 Warehousing decisions

Warehouse design decisions are often interconnected, making it difficult to shape sharp boundaries. Warehouse decisions contain five choices. The overall structure, department layout, operation strategy selection, equipment selection, and sizing and dimensioning (Gu et al., 2010). The overall structure determines the material flow that products must follow through the warehouse, the specification of departments, and the flow relationships between these departments. The size and dimensioning of the warehouse focus on the space allocation of departments (Roodbergen et al., 2014). Department layout focuses on the detailed configuration of the warehouse, such as aisle design. The equipment selection decision focuses on the warehouse's automation level, size, and storage method. The system's choice is primarily driven by product characteristics and demand frequency (Roodbergen et al., 2014). Fast-moving SKUs are stored differently from slow-moving SKUs. The operation strategy selection decision determines how the warehouse operates, decisions like pick strategy and storage policies (Gu et al., 2010). The decisions that are influenced by this thesis are sizing and dimensioning, department layout (storage method), and operation strategy selection.

3.2 Warehousing KPIs

Warehouse problems have several different performance measures that can be optimized. The most commonly used are associated with space and distance, which includes the minimization of travel distances (Reyes et al., 2019). Warehouse performances can be expressed with generic performances, time-related performances, cost performances, information system performances, and warehouse measure (Faveto et al., 2021). Faveto et al. (2021) focus on suitable KPIs for AS/RSs. Most of these KPIs are related to occupation, the order-picking process, and time. KPIs commonly used to measure performance in automated warehouse systems based on the papers of Reyes et al. 2019; Faveto et al. 2021 are shown in Table 3.1. For the automated system in this thesis, the total travel time is the most important KPI.

TABLE 3.1: Suitable KPIs for measuring AS/RS performance (Reyes et al. 2019; Faveto et al. 2021)

KPI	Unit
Space occupation	%
Throughput	units/min
Resource utilization	%
Unprocessed orders	%
Picking time	min
Total travel time	min
Queue waiting time	min
Makespan	min

3.3 Storage policies

Storage policies influence the system's working because storage policies influence the travel time and number of shuffles in the case of shared storage for Vink's system. Also, the number of SKUs plays a role because a trade-off exists between the number of SKUs in the system and the retrieval time. More inventory in the system means more shuffling in a blocking situation. Standard storage policies used in an (automated) warehouse are (Dmytrów 2022; Bartholdi and Hackman 2019; Roodbergen and Vis 2009):

1. random storage
2. dedicated storage
3. shared storage
4. class-based storage

3.3.1 Random storage

With random storage, SKUs are placed at a random location when this one is free. The only information needed to implement this policy is whether the storage locations are available. The most common random policy consists of random location assignment, closest open location, farthest open location, and longest open location (Bahrami et al., 2019). A random storage policy can create a lot of flexibility when appropriately implemented, but it lacks options for optimizing order-picking.

3.3.2 Dedicated storage

Dedicated storage policies reserve specific storage locations for SKUs. These allocations are based on four key factors (Bahrami et al., 2019)

1. Compatibility: SKUs that can be stored together without risking contamination, damage, or other issues are compatible.
2. Complementary: Complementary products are those often ordered together. Placing them in favorable locations can improve efficiency.
3. Popularity: Popular SKUs with high demand should be stored closer to the input/output point. This reduces the total travel distance since these SKUs contribute significantly to this distance.
4. Size: Smaller SKUs are accessible and can be slotted near the input/output point.

The system is also capable of dedicated storage. here, one location (stack) is reserved for only one SKU.

3.3.3 Shared storage

Dedicated storage uses the warehouse not always efficiently. A warehouse may contain a lot of storage locations. If using dedicated storage, each location will have an assigned product. Still, each product has a different replenishment cycle, so many of these storage locations can become half-full, nearly empty, or even empty. (Bartholdi and Hackman, 2019) So, on average, the storage capacity is not fully utilized. To improve on this, a shared storage strategy can be used. The idea here is to assign a product to multiple storage locations. When cycling times are low, a shared storage policy could be easily accessible. (Bartholdi and Hackman, 2019). Shared storage is also used in the machine, but is called chaotic storage. This chaotic storage mode needs at least two locations and puts different SKU in one stack. To retrieve blocked SKUs, the first shuffle operations must occur to the other location(s) to free and retrieve the ordered SKU.

3.3.4 Class-based storage

Class-based storage divides the SKUs of a warehouse into different classes, most of the time according to an ABC popularity curve, which is based on demand per product. (Guo et al., 2015). The locations are divided into zones, and the pick locations closest to the I/O point are considered class one, the ones behind class two, and so on until class n. A standard class-based storage method is ABC class storage. Commonly used divisions for ABC classification are 80-20 for A and B class storage and 80-15-5 for ABC storage. For A and B classification, all SKUs responsible for 80% of the orders will be classified as A-SKUs, and the remaining 20% will be classified as B-SKUs. In ABC zoning, the B SKUs will be split up into 15% that remains B-item and 5% that becomes C-SKUs (Kučera and Suk, 2019). Also, the system can zone locations and SKUs in zones. every location can be assigned to a zone so that SKUs are only placed and shuffled within that zone in chaotic storage, or a separate zone is created for dedicated storage.

3.4 Modeling the system

This section overviews four key areas relevant to modeling the problem and system. The sections focus on different problems and systems in warehousing that show similarities to the system and problem being studied in this thesis. The areas examined are: optimization models for zoning and slotting, AS/RS literature, Plate Stacking Problem (PSP) literature, because of the shuffling element and 3D compact storage systems. These fields are examined because of their similarities and potential applicability to the unique challenges in optimizing Vink's storage system.

3.4.1 Optimization techniques for zoning and slotting

The optimization of zoning and slotting of locations and SKUs in warehousing has gained more attention in the literature, with various approaches proposed to increase efficiency and reduce travel time by effective zoning and slotting. The problem of zoning SKUs and locations is known as the Storage Location Assignment Problem (SLAP) in literature. While some studies have focused on general ABC classification methods, others have delved into more detailed optimization strategies for zoning of the locations and the slotting of SKUs. Yu and De Koster (2009) and Zhang et al. (2013) both formulated a mixed-integer non-linear programming model to determine the zone boundaries in a rack-based AS/RS. The model shows that zoning

can significantly impact reducing travel time. Yu and De Koster (2009) assumes that each unit load holds only one item type. Also, all storage locations and unit loads are the same size. Therefore, all storage locations can be used to store any unit load. This makes these models less suitable for our case since we must consider the different item sizes and locations.
For solving the SLAP Muppani and Adil (2008) created the Class formation allocation model (CFAM). This model optimizes the zoning of locations and allocation of SKUs to minimize the sum of storage space cost and order-picking costs. Roshan et al. (2018) builds further on this model in an automated setting and considers energy consumption. The model of Roshan et al. (2018) takes the same decision variables. The objective value of these models also incorporates storage costs. This is not considered in this thesis since we assume unlimited capacity. Roshan et al. (2018) also considers the cube-per-order index. This index places smaller, more frequently asked SKUs in more favorable locations. Because the SKUs in Vink's system needs to be a size that fits the location, we do not see much-added value in incorporating the cube-per-order index. Despite these limitations, the CFAM models remain valuable for optimizing location zoning and item allocation in automated settings. Furthermore, the shuffling aspect of Vink's system does not limit the applicability of parts of these models.

3.4.2 AS/RS systems

According to Roodbergen and Vis (2009), a regular AS/RS system is a storage system with fixed-path storage and retrieval machines moving on rails between stationary arrays of storage racks. The critical components of an AS/RS are racks, cranes, aisles, I/O-points, and pick positions. An AS/RS improves the productivity of transporting. This system has a high-rise storage capability and optimizes available floor space. Traditional warehouses, in comparison with automatic systems, have low utilization of space and higher labor costs due to the use of conventional forklift operation (Wang et al., 2009). According to Roodbergen and Vis (2009), the research in the field of AS/RS should move towards developing models, simulation models, and heuristics that include more dynamic and stochastic aspects. Also, the development of simulation models comparing different designs while considering combinations in comparison with automatic systems should be encouraged.
Cranes in these kinds of systems follow a Chebyshev travel metric. The travel distance from one location to another equals the maximum horizontal travel time and vertical travel distance. In formula the distance between point (x1,y1) and (x2,y2) equals $max(|x1 - x2|, |y1 - y2|)$ (Liu et al., 2020).

Singbal and Adil (2021) proves that turnover-based storage policies can help reduce the average travel time of an AS/RS by assigning fast-moving products to storage locations closer to the I/O point. Three class-based storage assignments based on product turnover are examined.
Kulturel et al. (1999) compares storage assignment policies in an AS/RS using computer simulation and incorporating a replenishment strategy. The AS/RS operates

under a continuous review replenishment strategy. The outcomes of this study state that the turnover-based policy outperforms the duration of stay-based policy, resulting in shorter machine travel times. Differences between storage policies become negligible when the system's number of product types increases. The study also explores the effects of order quantities and ABC classification, revealing that smaller replenishment order quantities reduce travel time but may lead to higher back-order levels. The study suggests that using the continuous review replenishment strategy for order quantities, selecting the turnover-based policy for storage assignment, and partitioning rack space into classes with proportions of 10/45/45 yield the shortest average machine travel time. The study focuses only on dedicated storage, which is one of its limitations.

3.4.3 Plate Stacking Problem

As mentioned in the previous sector, the literature about AS/RS is dominated by dedicated storage assignments where no shuffling of SKUs is considered. Therefore, the problem central in this thesis also contains properties of the PSP, sometimes called the slab stack shuffling problem. In this problem, SKUs may share storage locations and must be rearranged or shuffled within the storage structure. This problem mainly occurs in the steel industry. Stackable products such as plates can be stacked on each other, forming product columns or stacks. In general stacking problems, access to SKUs on lower levels is obstructed by SKUs above them in the stack; this is called a blocking situation (Kofler, 2014). A shuffle has to be performed to access SKUs from within a stack; a shuffle moves the blocking SKUs so that the blocked SKUs can be retrieved. Many slotting formulations aim to reduce both the number of shuffles and the travel time (or distance) during order picking(Kofler, 2014). Three heuristics for improvement are used in the paper of Kofler (2014). Namely, local search, tabu search, and simulated annealing. Besides this information, the available literature on the PSP problem is limited (Fernandes et al., 2010).

Fernandes et al. (2010) addresses the plate stack shuffling problem in steel processing, aiming to create an item placement that minimizes the shuffling of slabs in the yard for SKUs by linear programming (LP). The goal is to choose the optimal slab sequence for retrieval that meets the desired demand. Kim et al. (2011) focuses on simplified steel PSP with a predetermined outgoing order and unlimited capacity. The objective is to minimize the number of shifts in the delivery stage. The paper introduces mathematical models for optimal solutions in small problems and a randomized approach for large instances. Bruno et al. (2023) introduces a theoretical framework and a mathematical model for the PSP, considering slabs' deadlines and yard design strategies. They emphasize the trade-off between minimizing shuffles and reducing the number of expired slabs. Future research directions are extending computational experiments to larger instances and more tailored solution approaches (Bruno et al., 2023). All these models assume that all plates can be stacked upon each other.
Tang et al. (2012) created an LP model that focuses on the PSP. This paper emphasizes logistics costs, including travel time and shuffling time. In this model,

the warehouse contains N SKUs, including M target SKUs to be retrieved. The model aims to minimize the total logistics cost for shuffling operations. It considers the retrieval sequence of target plates and the distance between stacks. The model splits the total retrieval time into travel and shuffle time. The problem in this thesis contains properties of this problem. The PSP does not consider the zoning of locations.

3.4.4 3D compact storage systems

An upcoming type of warehousing is the one of 3D compact storage systems. These smaller storage systems are used to lower room investment and operational costs. These systems require less space than 2D systems since no aisles are needed (Zaerpour, 2008). The most commonly known 3D compact storage system is the AutoStore system. This system stores small SKUs in standardized bins organized in a three-dimensional grid. Robots on top of the grid retrieve requested bins and bring these to the workstations for order-picking or storage-replenishing tasks. Bins within the system are placed on top, so high-demand bins move to the top of the grid, whereas bins with lower demand drop more to the bottom (Yue, 2023). Also, in this system, reshuffling and digging out SKUs plays a role, and therefore, it shows similarities to the AS/RS of Vink. Yue (2023) made a discrete event simulation (DES) for the AutoStore system to minimize bin retrieval time. Input parameters in this model are the acceleration of robots, lift speed, loading time, unloading time, turning time, the number of robots, the number of I/O points, the number of robots, and the bin request rate. Also, Beckschäfer et al. (2017) made use of DES to analyze settings for maximizing output. The model analyzed the following input: the set of bins, sequence of orders, set of robots, set of I/O points, bin retrieval-and-replacement policies, travel time, lifting time, and the maximal time of planning horizon. Furthermore, Trost et al. (2022) analyzed the AutoStore system with shared chaotic random storage with the help of DES. The objectives of this research are cycle time and throughput. Trost et al. (2022) uses additional parameters in the model, such as stack height, number of stacks, and velocity in x and y direction. Table 3.2 shows these models' most important input parameters that can be used for our system.

TABLE 3.2: 3D compact storage systems model parameters usable for modeling the system

Parameter	Symbol	Unit
(Un)loading Time	t_l	s
set of I/O Points	P_I, P_O	-
Max Planning Horizon	T	Days or Hours
# Stacks	n_{Stacks}	-
Stack height	s_h	-
Velocity x-direction	v_x	m/s
Velocity y-direction	v_y	m/s
Set of orders	O	-

3.5 Improvement of solutions

Heuristics are problem-solving techniques used when finding an optimal solution is computationally expensive or infeasible due to the problem's complexity. Also, Vink's zoning and slotting problem is complex. Therefore, we need to use heuristics to find executable and feasible solutions.
After constructing a feasible initial solution from a heuristic-based approach, it is possible to improve solutions further with the help of improvement heuristics. improvement heuristics aims to explore quick, improved solutions. (Blum and Roli, 2001). One of the most commonly known improvement heuristics is simulated annealing, which has also been mentioned in some previously examined papers.

3.5.1 Simulated annealing

The idea behind simulated annealing is to allow changes in the current solution, which at first results in a worse objective value than the previous solution, in other words, a solution of worse quality. In this way, it escapes from local minima. The probability of accepting such a worse solution is decreased during the search. It starts with an initial solution, explores neighbor solutions, and accepts them sometimes, and the temperature decreases during the search to find an optimal solution(Blum and Roli, 2001). The Boltzmann distribution can calculate the probability of accepting worse solutions by $\exp\left(\frac{f(s')-f(s)}{T}\right)$, with $f(s')$ being the current found solution, $f(s)$ the current best solution and T the temperature (Blum and Roli, 2001). Neighborhood solutions can be created by swapping, moving, or reconstructing elements of the current or initial solution. The temperature for the next iteration can be calculated by multiplying the current temperature with the decrease factor a following the formula $Temp = \alpha \times Temp$. The steps taken by the simulated annealing algorithm are shown below in Algorithm 1 (Maan-Leeftink, 2022).

Algorithm 1 Simulated Annealing

$Temperature = StartTemperature$
$Solution = Initial(Greedy)Solution$
$CurrentBestSolution = Solution$
while *stoppingcriteria* not met **do**
  for $m = 1$ **to** $MarkovChainLength$ **do**
    $NeighborSolution = ConstructNeighborSolution(Solution)$
    if $NeighborSolution < Solution$ **then**
      if $NeighborSolution < CurrentBest$ **then**
        $CurrentBest = NeighborSolution$
      end if
      $Solution = NeighborSolution$
    else
      if $RandomNumber \leq \exp\left(\frac{CurrentSolution - NeighborSolution}{Temperature}\right)$ **then**
        $Solution = NeighborSolution$
      end if
    end if
  end for
  $Temperature = \alpha \times Temperature$
end while
return $CurrentBest$

Simulated annealing can escape local optima by allowing worse solution moves with decreasing probability controlled by a temperature parameter. This temperature balances exploration and exploitation. The decreasing temperature leads to conversion towards optimal solutions. In short, the simulated annealing probabilistic acceptance criterion, ease of implementation, and successful application across various domains make it a good choice for optimization tasks requiring global exploration and improved solutions (Blum and Roli, 2001). Therefore, it is a very suitable improvement heuristic for our model.

3.6 Research gap

Literature on zoning optimization and the SLAP shows that zoning can significantly reduce travel time. However, these papers assume that each unit load holds only one item type, and all storage locations and unit loads have the same size. Therefore, all storage locations can be used to store any unit load. This research considers the item and location sizes. Because of this, SKUs can not be placed in any location, which is a big difference from the zoning problems given in the literature.

Most existing automated warehousing literature focuses on rack-based AS/RS or 3D compact storage systems with robots. In contrast, our system incorporates AS/RS, PSP, and 3D storage aspects, where SKUs share storage locations and must be rearranged for retrieval. This is a unique combination not found in the literature. We chose to combine aspects of these three systems to model the system.

This approach is used because it reflects the operational reality of Vink's system. Most 3D compact storage systems, or systems comparable to that, are optimized by using DES. This thesis will use a simulation model with the help of simulated annealing for optimization. This is done because this thesis does single-objective optimization. Unlike other 3D storage systems, this thesis uses real data input to ensure an accurate and reality-based optimization. Also, this ensures that data is deterministic, which fits the LP modeling better. Another point where the research differs from the existing literature is that item slotting and location zoning are optimized. However, the research of Muppani and Adil (2008) and Roshan et al. (2018) proposes this; these models do not consider the shared storage of SKUs.

3.7 Summary

Warehouse decision-making can be divided into three levels: strategic, tactical, and operational. This thesis focuses on Vink's tactical decision-making level. It tries to improve the system by optimizing zoning and slotting for locations and SKUs. These actions also relate to warehouse decisions: sizing and dimensioning, department layout (storage method), and operation strategy selection. The most important warehousing KPI in this study will be (total) travel time, often used in automated warehouse system literature (Faveto et al., 2021). The system can use four types of storage: random storage, dedicated storage, shared storage and class-based storage. With the possibility of mixing the last three. The problem of optimizing zoning and slotting is also known in the literature as the SLAP. For modeling the system and problem, four key areas considered relevant and similar to the system and problem are reviewed. The areas examined are optimization models for zoning and slotting, AS/RS literature, PSP literature, and 3D compact storage systems; all papers reviewed for modeling can be found in Table 3.3. This review showed the zoning of locations and SKUs in the CFAM (Muppani and Adil, 2008) with the same decision variables as our problem. Furthermore, AS/RS literature showed the Chebyshev travel time the system operates with (Liu et al., 2020), and the possible benefit of class-based storage (Singbal and Adil, 2021; Kulturel et al., 1999). The PSP literature shows that the literature on systems with shuffling is limited. Some models are provided that try to minimize the number of shuffles or travel time. However, these problems do not incorporate zoning. The 3D storage system literature presents some relevant parameters for modeling, which are given in Table 3.2. Because of the complexity and the data input size, the aim is to solve the problem with the help of heuristics. One of the most common improvement heuristics is simulated annealing. Simulated annealing changes solutions and escapes local minima to explore a wider solution space and find better solutions. Lastly, this chapter elaborates on the difference between existing literature and this study. This research considers varying item and location sizes, integrates AS/RS, PSP, and 3D storage system aspects, and uses single objective optimization with real data for accurate, practical modeling, unlike most 3D storage system literature. Lastly, the research optimizes item slotting and location zoning in a shared storage context, where existing literature mainly focuses on dedicated storage.

Table 3.3: Examined papers for modeling Vink's system

Paper	System/problem	Solution Method	Data source	Objective	Storage type	Retrieval	Travel movement
Yu and De Koster (2009)	Zoning boundaries	MINLP	Real-world	Travel Time	Random, Class-based	Order sequence	-
Zhang et al. (2013)	Zoning boundaries	MINLP	Synthetic data	Travel Time	Random, Class-based	Order sequence	-
Muppani and Adil (2008)	SLAP	CFAM with Simulated annealing	Real-world	Combined KPI: storage-space cost order-picking cost	Class-based	Order sequence	-
Roshan et al. (2018)	SLAP	CFAM Multi-objective optimization	Real-world	(1) Energy consumption, (2) sustainability, (3) costs (AHP)	Class-based	Order sequence	-
Liu et al. (2020)	AS/RS rack based	M/G/1/N/N queue model	Synthetic data	Travel Time	Dedicated, Random	Order sequence	Chebyshev travel
Singbal and Adil (2021)	AS/RS rack based	Travel time model	Real-world	Travel Time	Dedicated Class-based, full turnover	Order sequence	Chebyshev travel
Kulturel et al. (1999)	AS/RS rack based	Simulation model	Synthetic data	Travel time, Costs (Weighted)	Dedicated, turnover-based, duration of stay	Order sequence	Chebyshev travel
Kofler (2014)	PSP	LP with tabu search, SA	Real-world	#Shuffles	Shared, Random	Retrieval sequence	Euclidean, Manhattan travel
Fernandes et al. (2010)	PSP	LP	Synthetic data	#Shuffles	Shared, Random	Retrieval sequence	-
Kim et al. (2011)	PSP	LP heuristics	Real-world	#Shuffles	Shared, Random	Retrieval sequence	-
Bruno et al. (2023)	PSP	BIP model	Real-world	#Shuffles	Shared, Random	Retrieval sequence	Not mentioned
Tang et al. (2012)	PSP	LP with greedy, tabu search	Real-world	Retrieval time	Shared, Random	Retrieval sequence	Manhattan travel
Yue (2023)	3D Storage system, SLAP	DES	Synthetic data	Retrieval Time	Shared, Random, Last In First Out (LIFO)	Incoming orders, closest item	Manhattan travel
Beckschäfer et al. (2017)	3D Storage system, SLAP	DES	Real-world	Throughput	Shared, Random, LIFO	Incoming orders, empty, add retrieval	Manhattan travel
Trost et al. (2022)	3D Storage system, SLAP	DES	Synthetic data	Throughput, Cycle Time	Shared, Random, LIFO	Incoming orders, closest item	Manhattan travel
This thesis closest item	SLAP	Simulation model with Simulated annealing	Real-world	Travel Time	Dedicated, Random shared storage LIFO on lowest stack	Order sequence, highest placed item	Chebyshev travel

Chapter 4

Solution tool

This chapter will answer the research question: "How to model the working of the AS/RS system?". This thesis will focus on the AS/RS on a tactical level to analyze the system's performance of different zoning layouts and optimize them further with the help of simulated annealing. The number of zones and zoning allocation of locations and SKUs are the tactical decisions of the model. Eventually, the item placement will be the machine's operational decision, depending on the zoning strategy. This section will describe the assumptions made, the problem definition, the possible movements, the working of the simulation model, and the model's validation. Based on the model for zoning of locations and SKUs of Muppani and Adil (2008) and parameters given in the DESs of Yue (2023); Beckschäfer et al. (2017); Trost et al. (2022), the simulation model for optimizing the zoning and slotting is made.

4.1 Assumptions

Assumptions and simplifications are necessary to model the working of the automated warehouse. Nevertheless, the model aims to provide an output as realistic as possible. This section will highlight all assumptions and simplifications regarding ordering and the system.

4.1.1 Ordering

1. ***Retrieval and storage orders are known beforehand:*** Retrieval and storage orders are based on historical data from 1-1-2023 until 13-10-2023 (202 working days). Furthermore, every order consists of one SKU that can have multiple quantities. Using historical data ensures that the outcomes reflect actual patterns and trends, enhancing the outcomes' reliability. Limiting each order to one SKU with multiple quantities simplifies the order process and does not influence the outcomes since orders are processed following FCFS principle.

2. ***Order prioritization:*** Orders are processed by date on a FCFS principle. Nevertheless, all storage orders are processed first to prevent potential stock-outs and ensure a smooth flow of operations.

4.1.2 System

3. ***Travel times:*** Travel times are calculated based on a Chebyshev travel time. Furthermore, the system's turning and acceleration are neglected, and the system travels with constant speeds v_y and v_x, dependent on its direction. Also, the drop-and-pick-up times are deterministic and the same for every sheet. Neglecting travel and drop-and-pick-up variation allows a more straightforward and manageable model.

4. ***Storage and retrieval policy:*** SKUs are stored and shuffled based on the lowest stack height within their zone (m) and retrieved based on the least number of blocking items. This is due to the limitations of the system and the system's programmed policies.

5. ***I/O point:*** Only I/O point one is considered and used, and the crane returns to the I/O point after every order. Because the system can further operate while emptying I/O points, we only assume I/O point one is the begin-and-end station of every order.

6. ***Setup activities and system errors:*** System errors or setup activities are not considered for the simplicity and feasibility of the simulation model.

7. ***Unlimited stack capacity:*** This assumption simplifies the storage by eliminating height constraints. This ensures that the focus remains on optimizing the zoning and slotting of the system. In practice, the actual height capacity is sufficiently high that it is not likely to impact operations, making this a reasonable simplification.

4.2 Problem description

As already mentioned in Chapter 3, this problem can be identified as a SLAP. These problems aim to determine the allocation of storage locations and assign items to these locations. This section shows all input data and variables that play a role in the simulation model. Because of the size of the input data of the problem and the conditions needed to keep track of every machine movement, we cannot solve the problem exactly and use the simulation model with simulated annealing as an optimization and solution tool. The main decision variables in the model are the decisions of to which zone assign the SKUs and locations.

Sets

This problem consists of a set of SKUs I that can be assigned to C zones. Also, the locations P can be assigned to C zones. Furthermore, the problem will be optimized based on N orders. The machine uses T movements to fulfill all orders. After every move of the machine, the system arrives in a new state $t+1$. Table 4.1 below gives an overview of the sets in the simulation model.

TABLE 4.1: Sets of the simulation model with data type and description

Set	Description
$I \in \mathbb{N}$	Set of SKUs $(1 \dots I)$
$P \in \mathbb{W}$	Set of locations $(0 \dots P)$
$C \in \mathbb{N}$	Set of (possible) zones $(1 \dots C)$
$N \in \mathbb{N}$	Set of orders $(1 \dots N)$
$T \in \mathbb{W}$	Time horizon $(0 \dots LastMachineMove)$

Parameters

The input parameters for the model are divided into three main groups: SKU data, system data, and order data. The SKU data is necessary for managing inventory and item placement. The first parameter discussed is the inventory stock ($Stock_{i,0}$), representing the initial stock level of item i at the beginning of the planning period ($t = 0$). This parameter is essential for tracking inventory levels and ensuring sufficient stock to fulfill orders. The height of every specific SKU is given by $ItemHeight_i$. This information is crucial for calculating the total stack height at locations, which influences the placement of items. The SKUs in the system have different sizes, and therefore, items are grouped by size ($ItemGroup_i$), which categorizes items based on dimensions (such as 4,000 x 2,000, 4,000 x 1,500, or 2,000 x 1,000).

The system data includes parameters that describe the physical layout and constraints of the warehouse. The travel time ($ChebyshevTravelTime_{p,k}$) between locations p and k is a crucial parameter. It is calculated using the Chebyshev distance formula, based on the coordinates of the locations ($X\text{-}coord_p$, $Y\text{-}coord_p$), the crane speeds (v_x and v_y) and the time the machine takes for vertical movement ($DropPickTime$). This time is added to the travel time to get the total operation time for moving items. Also, each location in the warehouse is classified by a location group $LocationGroup_p$, which options contain the same sizes as $ItemGroup_i$. These classifications help in matching SKU to location. The initial stack height ($StackHeight_{p,0}$) at each location p is formulated by summing up the height of all SKUs on that location at the beginning of the planning period (time $t = 0$). To track the initial placement of items in the warehouse, $Index_{i,p,0}$ is used, representing the place of item i in location p at the start of the planning period (time $t = 0$), where index 1 indicates the bottom of the stack, 2 the sheet above, etc. This index calculates the number of blocking items for selecting the location of retrieval and keeps track of the division of SKUs after a machine move.

The order data includes parameters that describe the specifics of each order. The order quantity ($OrderQuantity_{n,i}$) indicates the quantity of item i required by order n. This parameter ensures that the correct number of items is retrieved/stored to fulfill each order. The model knows two types of orders, which are retrieval ("Out") or storage ("In") orders. The type of an order is given by $OrderType_n$. This classification determines whether items are being added to or removed from the inventory and which operations need to be done by the system. Table 4.2 below gives an overview of all model parameters.

TABLE 4.2: Parameters of the simulation model with data type and description

Parameter	**Description**
SKU Data	
$Stock_{i,0} \in \mathbb{W}$	Initial stock of item i at time 0
$ItemHeight_i \in \mathbb{R}$	Height of SKU i
$ItemGroup_i$	Size group of item i (e.g., 4,000 x 2,000, 4000 x 1,500, 2,000 x 1,000)
System Data	
$ChebyshevTravelTime_{p,k} \in \mathbb{R}$	Travel time from location p to k
$v_x \in \mathbb{R}$	Velocity in the x-direction
$v_y \in \mathbb{R}$	Velocity in the y-direction
$DropPickTime \in \mathbb{R}$	Time for dropping/picking up sheet
$X\text{-}coord_p \in \mathbb{R}$	x-coordinate of location p
$Y\text{-}coord_p \in \mathbb{R}$	y-coordinate of location p
$StackHeight_{p,0} \in \mathbb{R}$	Initial height of location p at time 0
$LocationGroup_p$	Size group of location p (e.g., 4,000 x 2,000, 4000 x 1,500, 2,000 x 1,000)
$Index_{i,p,0} \in \mathbb{N}$	Index of item i in location p at time 0
Order Data	
$OrderQuantity_{n,i} \in \mathbb{N}$	Order quantity for order n for item i
$OrderType_n$	Order type for order n ("In", "Out")

Main decision variables

The decisions taken in the model are the zone allocation of SKU i and zone allocation of location p (Table 4.3). These two main decision variables are represented by $ZoneItem_i$ and $ZoneLocation_p$. These two variables decide on which locations the SKUs can be placed.

TABLE 4.3: Decision variables of the simulation model with data type and description

Main Decision variable	**Description**
$ZoneItem_i \in \mathbb{N}$	Zone of item i (1,2,..C)
$ZoneLocation_p \in \mathbb{N}$	Zone of item p (1,2,..C)

Other decision variables

Besides the two main decision variables that can be controlled, the system has some other variables that are not controlled in the simulation model and change value during the operation of the model. Because items are stored, retrieved, and shuffled from one location to another, the placement of items changes every time step t. The move a machine does at time t is represented by binary variable $Movement_{i,p,k,t}$, which is 1 if SKU i is moved from location p to location k at time t and is 0 otherwise. To keep track of the changed composition in the system, variable $Index_{i,p,t}$ is used to represent the position of a sheet at a location. Also, the stock of items and stack heights of locations differ over time, which is represented by $Stock_{i,t}$ and $StackHeight_{p,c,t}$. The other decision variables are shown in Table 4.4 below.

TABLE 4.4: Other decision variables of the simulation model with data type and description

Decision variable	**Description**
$Index_{i,p,t} \in \mathbb{N}$	Position of item i at location p at time t
$Stock_{i,t} \in \mathbb{W}$	Stock of item i at time t
$StackHeight_{p,c,t} \in \mathbb{R}$	Height of location p in zone c at time t
$Movement_{i,p,k,t} \in \mathbb{W}$	Binary variable indicating if SKU i is moved from location p to location k at time t
$LastMachineMove \in \mathbb{N}$	Number of moves the machine takes to process all orders

Objective function

The objective function that needs to be minimized is the total travel time. The model tries to minimize the total travel time by optimizing the zone allocations of locations and SKUs, which influence the placement of SKUs and the total travel time. The total travel time is calculated by summing up all order completion times, which consist of storage, retrieval, and shuffle operations. Since all operations consist of picking up/ dropping sheets and traveling, the total travel time can be calculated by summing up all required moves done by the machine to complete the order list. This means that it simply sums up the travel time of all operations. Below, the formulation of the objective function is presented.

$$\min(z) = \sum_{i\in\mathbb{I}} \sum_{p\in\mathbb{P}} \sum_{k\in\mathbb{P},k\neq p} \sum_{t\in\mathbb{T}} \text{Movement}_{i,p,k,t} \times \text{ChebyshevTravelTime}_{p,k}$$

Constraints

The simulation model has some constraints that must be followed to ensure that the model represents reality and operates effectively. The constraints of the model are mentioned and explained below.

1. ***Item and location fit:*** location size and zone must be the same for placement, therefore the number of possible locations for placing an item are the number of locations with the same zone and size.

2. ***Zoning:*** Every location must be assigned to a zone.

3. ***Storage and retrieval policy:*** SKUs are stored and shuffled based on the location with the minimal value of $StackHeight_{p,c,t}$ within their zone (m) and retrieved based on the least number of blocking items. As already stated in the assumption section, this is due to the limitations of the system and the system's programmed policies.

4. ***Stock*** Stock must be present at a location for retrieval

5. ***Order Fulfillment*** All orders must be fulfilled.

6. ***Shuffling:*** When items lies not on top of a location, first shuffle movements must be performed until the item lies on top and can be retrieved.

7. ***Dedicated storage:*** When dedicated storage is used, only one item can be allocated to that location.

4.2.1 Machine movements and travel time calculations

The simulation model makes three operations possible: retrieval, storage, and shuffle. This subsection will explain each movement separately in the form of small examples. The crane must go up and down twice for every operation to pick up/drop a plate. The time to do these two activities is given as $DropPickTime$ and is 21.5 seconds. $DropPickTime$ must be considered because it adds time to the total travel time, and more shuffles mean more vertical crane movements. For an operation, the crane always travels back and forth between the two locations, as mentioned in the assumptions section. Furthermore, the examples show how the algorithm works with the constraints considered.

Storage: Figure 4.1 visually represents a single storage operation. In a storage operation, the crane starts at the I/O point. It first goes down and up to pick up the SKU; this takes 1/2 $DropPickTime$ time. Then, it travels to the chosen location and drops off the sheet. Dropping of the sheet also takes 1/2 $DropPickTime$ time. After dropping the sheet, it returns to the I/O point empty, and the storage operation is finished.

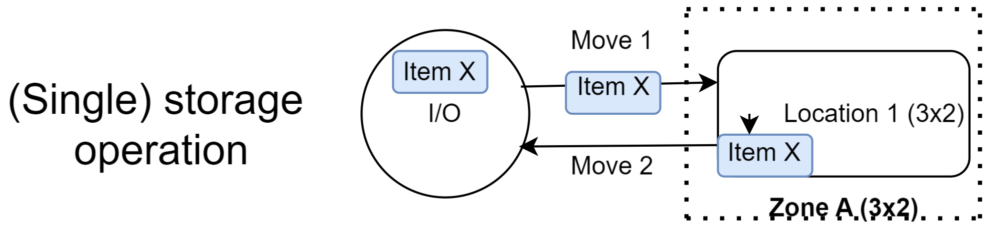

FIGURE 4.1: Visualization of a single storage operation

Retrieval: Retrieval follows quite the same pattern as storage; only here is the travel towards the location empty and back to the I/O point loaded. Figure 4.2 represents a single retrieval operation.

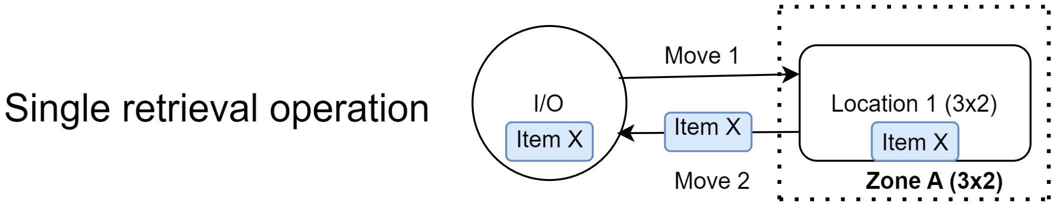

FIGURE 4.2: Visualization of a single retrieval operation

Shuffle: When SKUs need to be unblocked by shuffling, they must shuffle SKUs and lay blocking SKUs on other locations within the zone. Figure 4.3 represents a situation where SKU "X" is blocked by SKUs "Y" and "Z". In this situation, all SKUs have height 1, so the number of SKUs determines the stack height in this example. Possible locations to move "Z" and "Y" to are locations 2 and 3; the other locations do not match the size or zone and are, therefore, not valid for placement, according to the constraints set in the model. The first shuffle is to shuffle SKU "Z" from location 1 to location 2. Both locations have the same height, so the SKU is placed on the first lowest location, location 2. In the second shuffle operation, location 3 becomes the lowest valid location; therefore, SKU "Y" is shuffled to location 3 in the second shuffle. After this, SKU "X" can be retrieved and transported to the I/O point. Locations 4,5 and 6 do not match the size or zone criteria and are, therefore, impossible for placement of "X", "Y" and "Z".

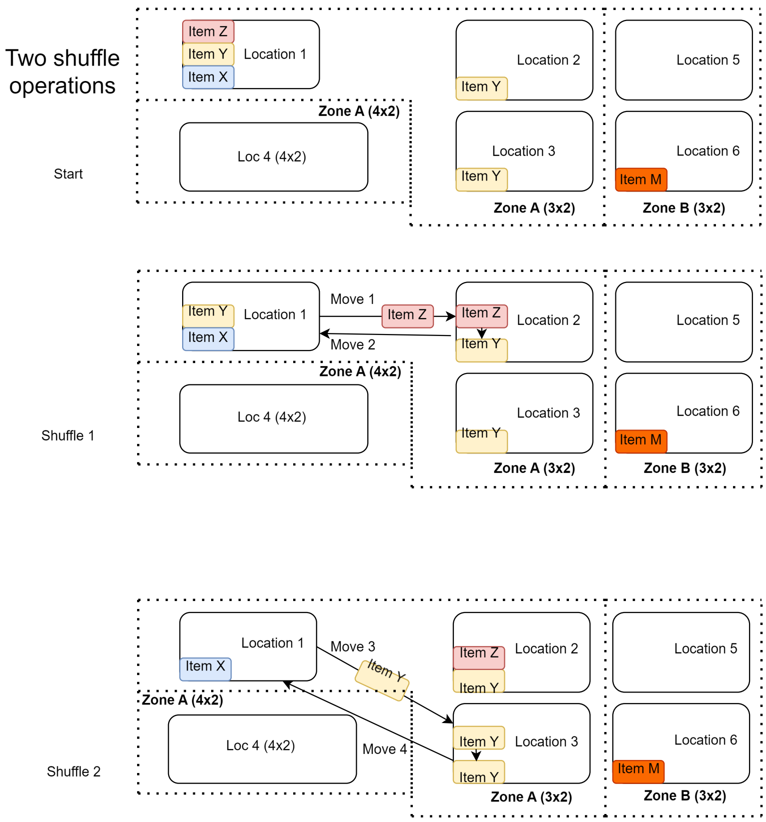

FIGURE 4.3: Visualization of two shuffle operations

Retrieval in combination with shuffle: When an order needs to be shuffled for retrieval, we can calculate the travel time by summing the time of a single retrieval from the location and the time of all shuffle operations needed to unblock SKU "X." Figure 4.4 represents this situation.

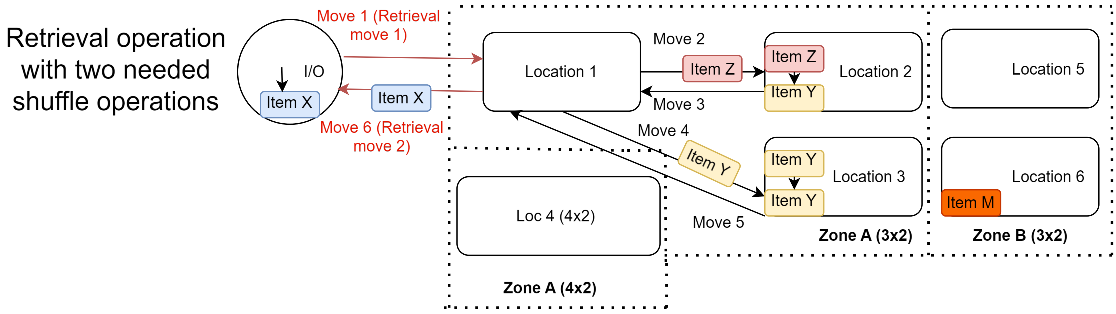

FIGURE 4.4: Visualization of retrieval operation with two shuffle operations needed

Travel time calculations: For every operation calculation, the machine must do 2 vertical movements for pick-up/drop sheets, each taking 1/2 $DropPickTime$. Furthermore, we assume it always travels back from where it departed. The total travel time between two locations $ChebyshevTravelTime_{p,k}$ could, therefore, for every operation, be expressed as:

$$2 \cdot \text{single travel time}(p,k) + \text{DropPickTime}.$$

With:

$$\text{single traveltime}(p,k) = \left(\frac{\max(|\text{X-coord}_p - \text{X-coord}_k|, |\text{Y-coord}_p - \text{Y-coord}_k|)}{\begin{cases} v_x, & \text{if } |\text{X-coord}_p - \text{X-coord}_k| > |\text{Y-coord}_p - \text{Y-coord}_k| \\ v_y, & \text{otherwise} \end{cases}}\right)$$

The single travel time between two locations is calculated based on the velocity of the crane. The crane travels quicker in the x-direction than in the y-direction ($V_x = 1.6$ m/s, $V_y = 0.6$ m/s). The crane travels following a Chebyshev travel (Liu et al., 2020), and because of that, it always travels the maximal distance between the x-coordinates or y-coordinates, $Max(|X1-X2|, |Y1-Y2|)$. This travel distance must then be divided by the velocity in the given direction. Therefore, when the maximal distance is in the x-direction, the distance must be divided by V_x; otherwise, it must be divided by V_y.

4.3 Model explanation

To better understand and overview the simulation model, this section will explain the solution approach and all algorithms used in the model with the help of flowcharts. The simulation model can be distinguished into four separate algorithms. One for loading in all data, one for creating an initial starting point, one for order processing and calculating the objective function, and finally, the simulated annealing algorithm to improve initial solutions.

4.3.1 Initialization

The first step in the simulation model is to initialize the system and load in all input data. Figure 4.5 shows an overview of the simulation model's initialization. All input data for the input of the SKUs is prepared in an Excel file. This Excel file contains all SKUs considered per experiment. This algorithm prepares the necessary information for SKU placement, order processing, and optimization. First, all selected SKUs is looped over to load in the IDs, stock levels, size groups, zone, and height per SKU. After that, the locations are defined by their size group, zones, and coordinates. Furthermore, the system's speed, drop, and pick-up time are initialized. Lastly, the order list is loaded, which consists of SKU IDs, order types, and quantities.

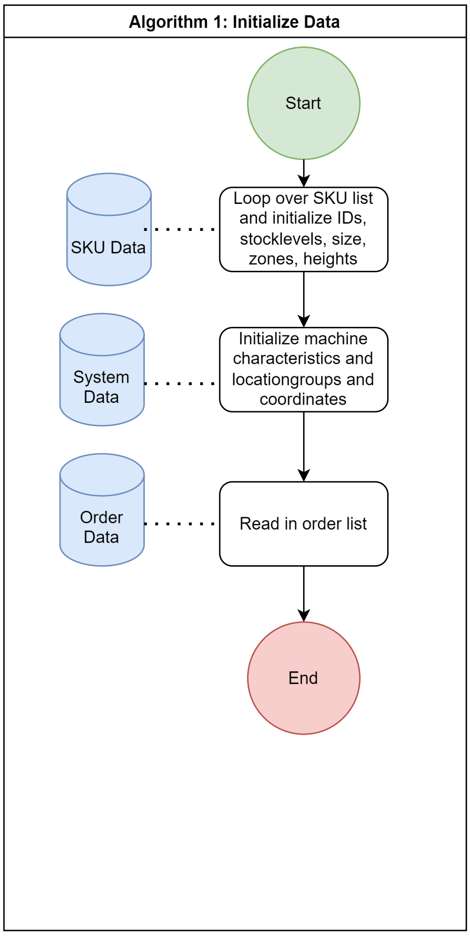

FIGURE 4.5: Flowchart of the initialization of the simulation model.

4.3.2 Initial solution heuristic

After all data is loaded in the model, a starting point of the system must be created since we take the orders from 1-1-2023 until 13-10-2023. The starting inventory $Stock_{i,0}$ is set on the inventory levels on 1-1-2023. The purpose of this algorithm is to check all valid locations for placement regarding size and zones and then place sheets following the systems storage policy (lowest stack). After the placement of every sheet, the index and location height of the locations are updated. When no placement is possible, an error message is given, and the algorithm is stopped. The system loops over all SKUs and places them in the system as long as there is initial inventory. This would lead to a biased placement where the first SKU in the list is always at the bottom of the stack. After all SKUs are placed to prevent this biased placement, the stacks are randomly shuffled to create a more realistic starting point. Figure 4.6 visually represents the initial placement heuristic.

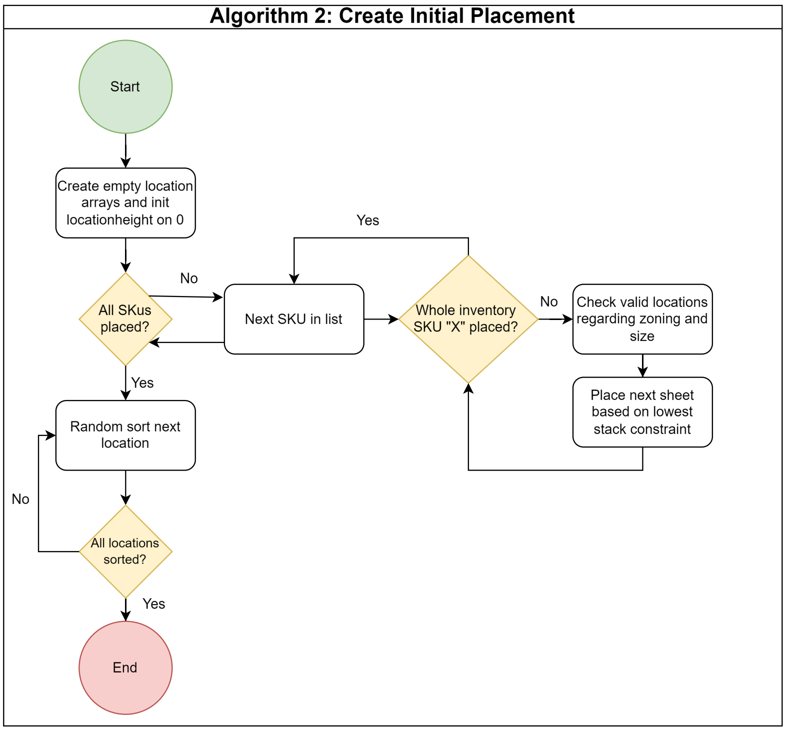

FIGURE 4.6: Flowchart of the construction of the starting point of the simulation model.

4.3.3 Order processing and objective calculation

The algorithm shown in Figure 4.7 processes the order list and calculates the objective for every order using a FCFS principle. First, every order is determined by whether it is an outgoing or incoming. In the case of an outgoing order, the retrieval procedure must start. The order quantity is taken, and the algorithm searches for the locations where the ordered SKU has the least number of blocking items. When this location is found, there is checked whether the ordered SKU lies on top, if that is the case it can be simply removed from the system and the travel time between I/O point and location can be calculated and added to the objective. When the item lies not on top, the algorithm moves SKUs to other valid locations (in the same way as placing SKUs) as long as the ordered SKU is not on top of the stack. When doing this, it keeps track of the total travel times added to the total objective at every move, the stack heights, and the SKU indexes. When the SKU is on top, it is removed from the location, and the travel time is calculated and added to the objective. This process repeats until the order quantity is fulfilled. After that, the next order is processed. When the order type is "In", the storage procedure must start. Then, the same principle as in the initial placement algorithm holds: valid locations are searched, and SKUs are placed based on the lowest stack height until the order quantity is reached. After every placement, travel time, stock, indexes, and stack heights are updated. Finally, when all orders are processed, the objective (sum of all travel time operations) and the end placement of SKUs are returned. The function $CalulateChebyshevTravelTime$ is used to calculate the order completion time. This function checks first which direction has the longest distance and then divides the longest distance by the appropriate velocity V_x or V_y as described in the travel time calculation.

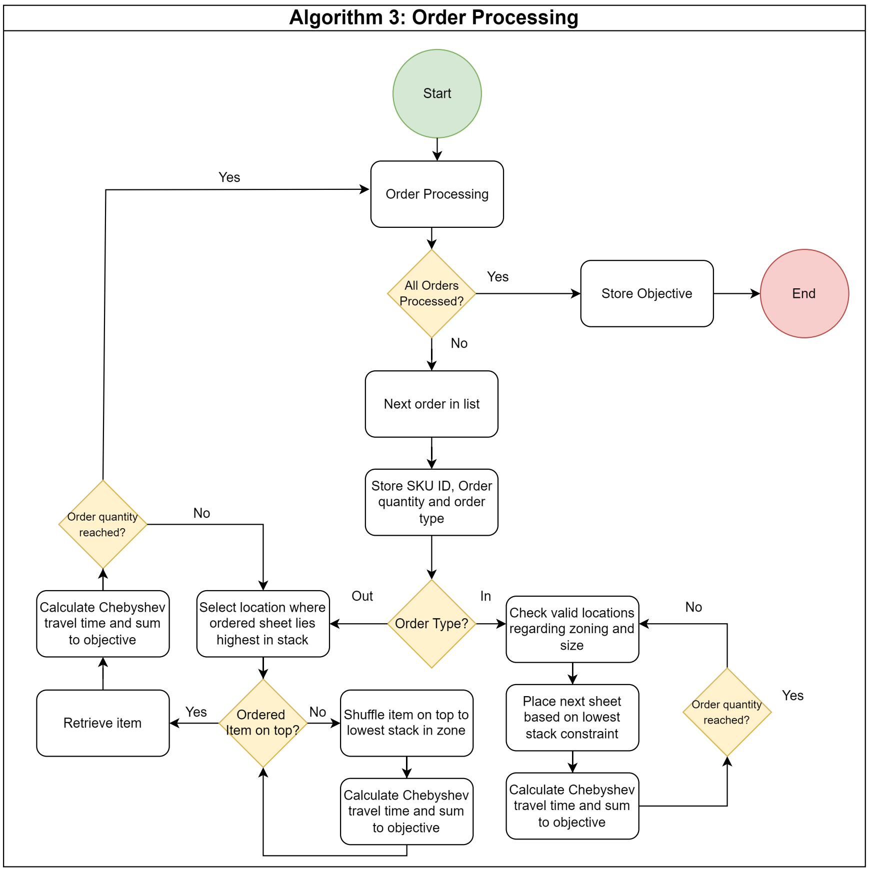

FIGURE 4.7: Flowchart of the order processing and objective calculation of the simulation model.

4.3.4 Improving algorithm

The simulated annealing algorithm aims to optimize the values of zones assigned to SKUs and locations by iteratively evaluating whether changes in these values improve the objective function by influencing machine movements. This algorithm draws inspiration from the simulated annealing method outlined in Chapter 3 and is shown in Figure 4.8. During each iteration, one SKU and location are reassigned to a different zone. After these zone assignments and changes, whether a feasible solution is still possible with these changes is checked. If this is not the case, the violating zone value(s) is/are restored. After this, Algorithm 1 (Figure 4.5) (with the new zone input), Algorithm 2 (Figure 4.6), and Algorithm 3 (Figure 4.7) are executed again to construct the new solution and calculate the new objective value.

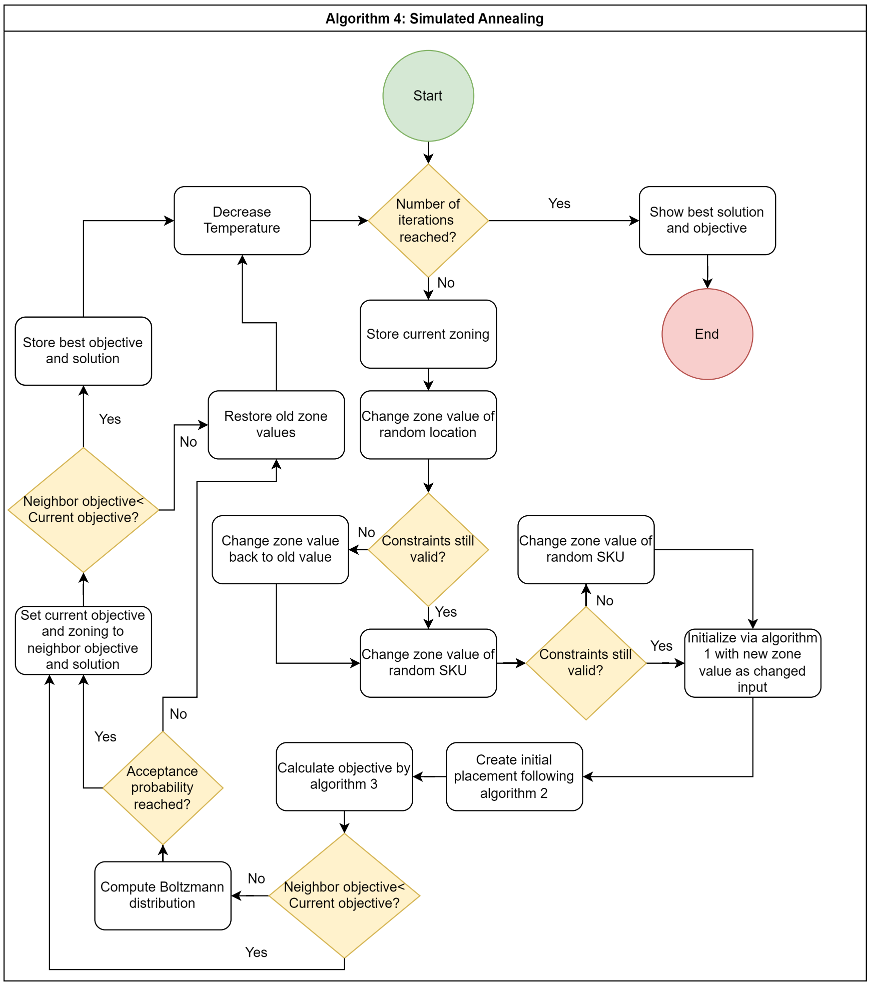

FIGURE 4.8: Flowchart of the improving algorithm of the simulation model.

4.4 Validation

For validation of the travel time and order completion time calculation, the orders of one day are simulated with the same movements in the model. Nine orders are reviewed, and following the paired t-test, a p-value of 0.358 is observed. This means the difference between the two data sets is not statistically significant for a confidence interval of 95%. Table 4.5 and Figure 4.9 show the validation results. A small difference between times is observed. The model is 2.10% quicker than real life. This could be explained by assumptions that are taken. First, the model considers only one I/O point, whereas, in real life, there are four. This can sometimes lead to different travel distances and times to the I/O point. Also, the turning and acceleration of the crane are not taken into account in the model; this could lead to shorter travel times in the model. The last reason for the differences in travel times is that the model's drop and pick-up times are deterministic, whereas, in real life, the crane, there could be a small difference in pick-up time.

TABLE 4.5: Validation model travel times with real travel times in seconds

Order	Type	Num. of movements	Model travel time (s)	Real travel time (s)	difference
1	Storage	8	786.3	859	-8.46%
2	Retrieval with shuffles	13	461.29	460	0.28%
3	Single retrieval	3	91	86	5.81%
4	Retrieval with shuffles	18	701.61	687	2.13%
5	Retrieval with shuffles	14	483.86	468	3.39%
6	Retrieval with shuffles	16	478.36	519	-7.83%
7	Retrieval with shuffles	5	140.94	143	1.44%
8	Retrieval with shuffles	10	262.39	267	1.73%
9	Retrieval with shuffles	14	528.81	530	0.22%
Total	-	101	3,934.56	4,019	-2.10%

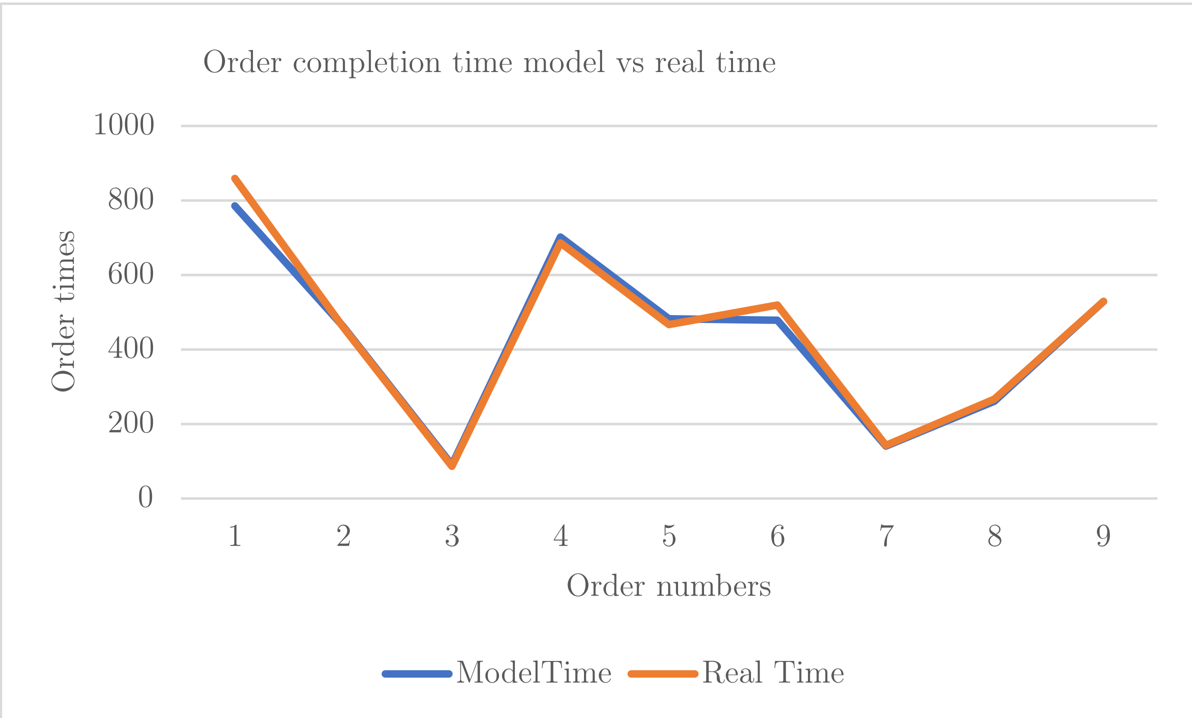

FIGURE 4.9: Model order completion times compared with real time

4.5 Summary

The research question of this chapter is "How to model the working of the AS/RS system?" This chapter explained all assumptions, input data, parameters, KPIs, decision variables, and constraints. After that, the working of the simulation model is presented. Lastly, we validated the model's input data and model itself by comparing it to real travel times. The core of the model revolves around three main operations: storage, retrieval, and shuffle operations; each operation is visualized by examples and described in detail (see Figures 4.1 till 4.4). The travel time calculations for these operations consider the crane's movement patterns, including travel distances, and the additional time required for dropping and picking SKUs. The most important decision variables in the model are the zone of locations and SKUs, which are represented by $ZoneItem_i$ and $ZoneLocation_p$

The model's initialization process is crucial, loading all necessary input data and preparing the system for initial placement, order processing, and optimization. It describes how SKUs are initially placed in the storage locations based on size and zone constraints. After initial placement following the provided item selection, a randomized shuffling over all locations is done to mimic the real-world conditions of chaotic storage; this randomization must be considered in the results section. The order process procedure is used to calculate the objective. After constructing an initial objective, zone values of $ZoneItem_i$ and $ZoneLocation_p$ are changed by the simulated annealing procedure, and the initial placement and objective calculation are done again to find a better solution and objective.

The validation section of the simulation model against real-world travel times confirms its accuracy, showing little differences within acceptable limits; according to the conducted paired t-test, no statistical difference between the two datasets with a 95% confidence interval is proven. However, the model is, on average, 2.10% quicker than the compared real-life travel times.

Chapter 5

Results

This chapter answers the research question: "How can the solution tool be used to analyze results?". First, the parameters needed to let the simulation model run properly and be valid are set. After that, we explain the settings for the scenarios, which consist of six different zoning strategies/heuristics and five item selections. This results in analyzing 30 conducted experiments. This analysis will consist of showing the best scenarios per item selection and a calculation to determine appropriate item selections for the system. Lastly, we will look at the improvements that could be made compared to the current situation and the yield in filled system capacity and storage room that comes with those improvements.

5.1 Parameter tuning

The initial placement has some randomness; we will take the average of multiple runs for the objective calculation to deal with this randomness. Subsection 5.1.1 determines the number of replications necessary to achieve this. Subsection 5.1.2 determines the parameters for the simulated annealing algorithm. For parameter tuning of the simulated annealing algorithm, we used a scenario with two zones, and we divided half of the SKUs in zone A and the other half of the SKUs/locations in zone B. In this way, the simulated annealing algorithm could improve the solution easily, and we can test the appropriate starting temperature, decreasing factor, and number of iterations. The different settings will be compared on time and solution improvement. Based on this comparison, the parameters of the simulated annealing algorithm are set.

5.1.1 Number of replications

The randomization process within Algorithm 2 means we must deal with randomness in the initial solution so that a change in the objective value cannot be considered coincidental. Because of this, the objective must be calculated by taking the average of multiple runs to validate that the change in the objective is due to changing zones. Therefore, we will use the sequential procedure (Mes, 2021). The idea behind this procedure is to make independent runs as long as the difference in the objective of the independent run is below the desired relative error, in this case, 0.05. Table 5.1 shows the number of replications necessary. We see that two replications are enough to validate that the difference in objective is not statistically significant. However, more replications ensure a higher validity; every replication increases the running time significantly. Because of this, we choose to do the necessary two runs and take the average objective of these runs in the simulated annealing for validation.

Table 5.1: Sequential procedure for ten independent runs

Exp Num	Objective	Mean	T-value	Error	Below relative error?
1	5,045,709.33	5,045,709.33	-	-	-
2	5,028,907.94	5,037,308.64	12.706	0.0212	Yes
3	5,152,355.19	5,075,657.49	4.303	0.0328	Yes
4	5,143,485.46	5,092,614.48	3.182	0.0201	Yes
5	5,069,406.93	5,087,972.97	2.776	0.0138	Yes
6	5,119,833.96	5,093,283.14	2.5701	0.0108	Yes
7	5,223,606.53	5,111,900.76	2.447	0.0124	Yes
8	5,088,506.62	5,108,976.50	2.365	0.0105	Yes
9	4,956,069.39	5,091,986.82	2.306	0.0119	Yes
10	5,008,335.54	5,083,621.69	2.262	0.0111	Yes

5.1.2 Simulated annealing parameters

Experiments with different simulated annealing parameters are done to optimize the parameters of the simulated annealing algorithm and find the best configuration for minimizing the objective function. The algorithm uses three primary parameters: the number of iterations, the starting temperature, and the decrease factor. More iterations generate more different options but increase the running time. A higher starting temperature focuses more on exploring different solutions than exploiting good ones. The decreasing factor determines how quickly the start temperature will drop and how quickly the simulated annealing goes into the exploitation phase. We will test the algorithm under different settings for the number of iterations, starting temperature, and decrease factor to find a balance between exploration-exploitation and running time. The specific values chosen for each parameter are as follows: The number of iterations: [5,000, 2,000 , 1,000], Starting Temperature: [1,000 , 500 , 200], and Decrease factor: [0.995, 0.99, 0.975]. These parameters differ greatly, so we must adequately analyze the best parameter settings. The outcomes of the experiments will be compared with running time and objective improvement. Based on these outcomes, balanced parameters ensure good improvements in reasonable running time are selected. Table 5.2 shows the five best experiments based on objective value, and appendix B1 shows all experiments for parameter setting.

Table 5.2: Top 5 best objectives from simulated annealing parameter setting experiment outcomes

Experiment	Iterations	StartTemp	Decrease Factor	Start Objective	Best Objective	Improvement	Running Time (hh:mm:ss)
8	2,000	200	0.995	4,376,267.99	4,057,717.35	7.28%	04:15:46
4	5,000	500	0.995	4,444,822.93	4,070,934.33	8.41%	12:12:30
25	5,000	200	0.975	4,380,937.50	4,072,425.38	7.04%	09:40:10
22	5,000	500	0.975	4,456,979.33	4,077,144.05	8.52%	09:42:31
5	2,000	500	0.995	4,391,135.76	4,084,014.09	6.99%	03:43:21

The results of our test settings have the following practical implications. We found that a certain number of iterations, specifically 2,000 and 5,000, is necessary for improving the solution significantly. Furthermore, the results indicate that a lower initial temperature is recommended, often with a high decrease factor. However, 5,000 iterations lead to greater improvements in percentages. The little extra objective improvement does not outweigh the enormous increase in running time. Therefore, considering the significant difference in running time, we set the number of iterations at 2,000. Moreover, since the starting temperature of 200 results in the best objective in combination with a high decrease factor, we set the initial temperature at 200 and the decrease factor at 0.995. These settings ensure the most functional use of the simulated annealing algorithm, with the following parameters: number of iterations: 2,000, initial temperature: 200, and decrease factor: 0.995.

5.2 Initial states settings

The division of SKUs over the zones in the initial states is done based on their total contribution to all orders. All initial states for SKU and location zoning per scenario can be found in Table C1 and Figure C1. The percentage intervals in Table C1 represents the cumulative percentage attached to which zone in which scenario. Figure C1 shows the initial location assignment per scenario. Six scenarios over five item selections will be tested, resulting in 30 experiments. The zoning strategies and item selections are shown below.

Zoning heuristics

- Random
- AB Zoning
- ABC Zoning
- ABCD Zoning
- ABCDE Zoning
- Current Layout (Some AB in combination with fixed locations)

Item selections

- Instance 1, base scenario (349 SKUs)

- Instance 2, base scenario + adding fitting D-items (394 SKUs)
- Instance 3, base scenario + adding fitting $\geq$ 90 kg SKUs (408 SKUs)
- Instance 4, combining instance 2 and 3. (455 SKUs)
- Instance 5, base scenario + adding fitting $\geq$ 80 kg and fitting C-items (476 SKUs)

5.3 Experimental results

This section will present the outcomes of all 30 experiments. The experiments evaluated the performance and efficiency of proposed zoning layouts and the system's behavior under different item selections. Each experiment starts with a predefined layout and selection and is improved by the simulated annealing algorithm.

5.3.1 Zoning strategies

The experimental results are analyzed based on the KPI total travel time. By comparing these KPIs across different configurations, we aim to identify the most effective strategies for minimizing the total travel time and achieving an efficient layout, item selection, and performance. The detailed outcomes of these experiments are given in the format HH:MM:SS in Table 5.3 and in seconds in Figure 5.1.

TABLE 5.3: Experiment initial and improved outcomes

Item selection	**Instance 1**		**Instance 2**		**Instance 3**		**Instance 4**		**Instance 5**	
Layout	**Initial Objective** (HH:MM:SS)	**Improved Objective** (HH:MM:SS)	**Initial Objective** (HH:MM:SS)	**Improved Objective** (HH:MM:SS)	**Initial Objective** (HH:MM:SS)	**Improved Objective** (HH:MM:SS)	**Initial Objective** (HH:MM:SS)	**Improved Objective** (HH:MM:SS)	**Initial Objective** (HH:MM:SS)	**Improved Objective** (HH:MM:SS)
Random	1,402:23:13	1,323:37:27	1,765:57:23	1,733:04:38	2,689:17:29	2,565:21:22	3,815:19:06	3,605:25:52	4,169:40:10	3,953:29:26
AB	1,121:22:06	1,040:37:44	1,412:25:38	1,325:53:38	2,274:51:40	2,132:43:52	3,222:02:11	3,017:14:25	3,540:48:39	3,286:56:27
ABC	1,195:47:26	1,159:48:15	1,629:17:49	1,552:18:01	2,556:36:37	2,487:55:22	3,911:06:20	3,627:27:26	4,144:06:59	3,829:44:01
ABCD	1,266:53:60	1,214:36:01	1,723:06:06	1,692:09:59	2,594:10:54	2,756:02:40	3,831:03:19	3,621:39:15	4,284:49:22	3,979:50:18
ABCDE	1,340:12:12	1,250:11:55	1,878:58:41	1,785:00:34	2,823:50:57	2,920:04:51	4,271:01:32	4,047:30:47	4,780:17:22	4,513:47:29
Current layout	1,000:31:09	967:43:19	1,434:14:19	1,365:48:42	2,321:11:08	2,216:44:30	3,621:58:05	3,376:16:11	3,981:31:48	3,866:24:02

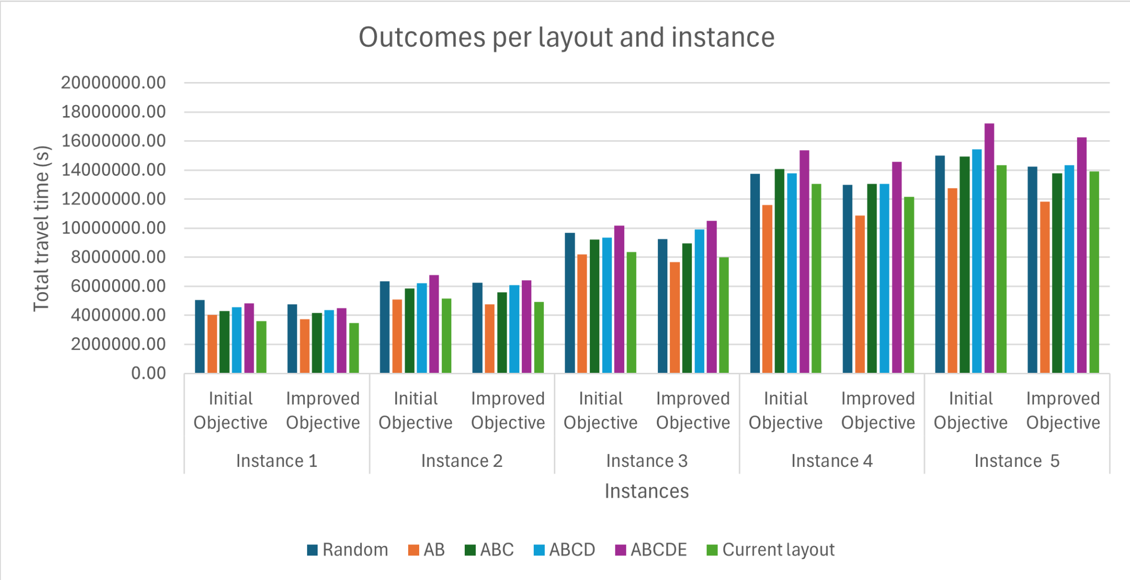

FIGURE 5.1: Experimental outcomes

The results show that the current layout works best for the current situation, so the company does well regarding layout and SKU placements. However, the current layout is improved a bit by simulated annealing (Appendix D1). Further filling the system requires a different layout and division of SKUs. The AB-zoning becomes the best strategy when more SKUs are added to the system. It results in the best travel times for all item selections after instance 1. Also, we can conclude from the results that more zones do not achieve lower travel times. Instead, it worsens the system's performance, for example, in an ABCDE zoning. This is probably because more zoning creates a less flexible system and causes more unequal divided stacks, which results in even more than fewer shuffles. Therefore, fewer zones work better, especially with greater item selections. Figure 5.2 shows the range of objectives over the different instances. This box plot shows that, on average, the AB-zoning strategy works best over all scenarios, followed by the AB-based layout. The ABCDE zoning strategy performs the worst, and the random, ABC, and ABCD zoning strategies fall in between and do not differ very much.

Furthermore, Appendix D1 shows that all initial solutions are improved by some small changes in zoning layout, except for instance 2, where no locations are changed from zone. This indicates that the initial layouts already provided a good zoning strategy, and the simulated annealing algorithm found no big improvement opportunities. Also, it shows that changing location zoning could greatly influence the total travel time. Emphasizing the importance of improving the layout. The simulated annealing algorithm also changed the zoning of SKUs. Appendix D1 shows the division of SKUs at the initial and improved solution for the best scenario per item selection. The difference in division between the current layout and AB zoning is notable. This is explainable by the fact that in the current layout, the 3,000 x 1,500, 4,000 x 1,500, and 2,000 x 1,000 locations did not have AB zoning, and all these items are considered zone A now. But still, if we look at the number of SKUs placed in zone B, this is relatively low. For AB zoning, we see that the division of zones follows an approximately 40%-60% division between A and B for all item selections. The simulated annealing will likely switch more items from A to B than the other way around.

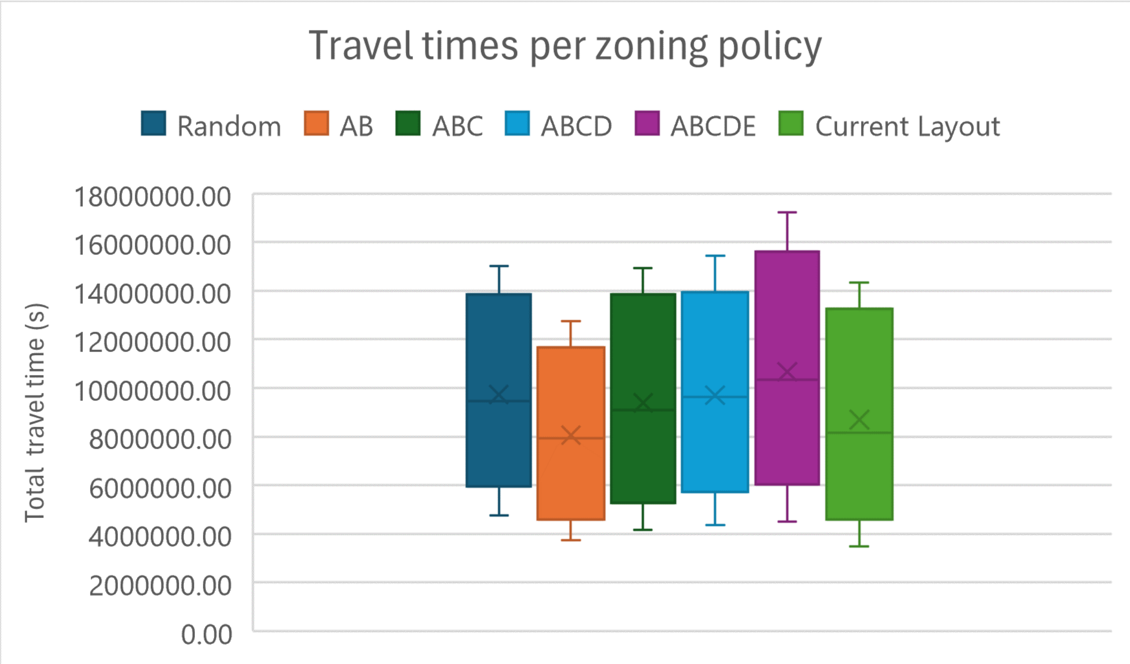

FIGURE 5.2: Boxplot of all objectives per zoning policy

5.3.2 Number of SKUs in system

Besides the slotting strategies and travel time, the results show a relationship between item selections and total travel time. We obtain the following average daily processing times when calculating the average daily processing hours for the best scenarios and objectives per instance (Table 5.4). The results show that the item selection matters. In instance 3, the base selection is increased with heavier SKUs. The demand for these SKUs is higher than the ones added in instance 2, based on low demand SKUs. Because of that, the machine has to handle way more orders, which leads to a higher total travel time. Therefore, although these item selections seem quite similar, they have very different outcomes. The system operates 9 hours a day, this means that for the time horizon of experiments the system has a capacity of approximately 1,818 hours for the chosen 202 days. This means all scenarios with a total travel time higher than this threshold are unsuitable. Table 5.4 shows that instances 3, 4, and 5 will take too much time to finish all orders in a working day of 9 hours. However, instance 1 has, on average, a few hours of idle time. Instance 2 results in a more adequately filled system with an acceptable total travel time and average daily operation time. The other instances exceed the hours in a working day and are therefore unsuitable.

Table 5.4: Average daily operating hours best objectives per item selection

Item selection	Objective in seconds	AVG day operating time (based on 202 days)
Instance 1 (349)	3,483,798.55	4.79 hours
Instance 2 (394)	4,773,228	6.56 hours
Instance 3 (408)	7,675,432	10.55 hours
Instance 4 (455)	10,862,064.72	14.94 hours
Instance 5 (476)	11,832,986.99	16.27 hours

5.4 Storage capacity

By increasing the number SKUs stored in the AS/RS, we create free storage space in the traditional warehouse. The results show that the base selection of 349 SKUs can be increased to the second selection of 394 SKUs. Table 5.5 shows the AS/RS extra storage of SKUs and the number of sheets comparing instances 1 and 2. When we compare these numbers to the calculation of the warehouse occupation rate in Chapter 2 (Table 2.2), we can conclude that the number of occupied pallet locations will be less when item selection 2 would be chosen. Based on the data presented in Table 5.5, the new number of occupied pallet locations would be 1,690, which will have resulted in a traditional warehouse warehouse occupation rate of 91.55% on the given reference date. This would result in an improvement of 2.44%.

Table 5.5: Fill grade of AS/RS comparing instance 1 and 2.

Item selection	Number of SKUs	Number of sheets (31-10-2023)	SKUs Gain in % based on base scenario	Number of sheets Gain in % based on base scenario
Instance 1	349	3,796	0,00%	0,00%
Instance 2	394	4,278	12.89%	12.70%
Difference	45	482	12.89%	12.70%

5.5 Summary

The research question of this chapter was "How can the solution tool be used to analyze results?" This chapter explained the parameters needed to improve the heuristic, the scenarios used, and the system's performance in different item selections.

Firstly, this chapter explored the parameters required for the simulated annealing algorithm. This involved determining the number of replications needed to achieve validated results and optimizing the number of iterations, starting temperature, and decrease factor for the simulated annealing part of the model. By comparing objective value outcomes of different experiments, it was determined that 2,000 iterations, a starting temperature of 200, and a decrease factor of 0.995 provided the best balance between exploration and exploitation while minimizing the objective function.

Secondly, the chapter examined the initial state settings, which involved dividing SKUs across zones based on their contribution to all orders. A starting point for every scenario and setting of scenarios is needed. Various zoning layouts and strategies were tested across different item selections, resulting in 30 evaluated and compared experiments. The baseline scenario consists of item selection 1 (349 SKUs), with the zoning strategy current layout (AB zoning for 4,000 x 2,000 and 3,000 x 2000 locations and some dedicated storage assignments for "fast movers").

Lastly, the experimental results were presented, which included the outcomes of all 30 experiments. The results indicate that the current layout works best in the base scenario, where the AB-zoning strategy performed best when the number of SKUs increased. This shows that more zones do not always lower travel times but can also create an increase. Looking at all experiments, the AB zoning performs best on average, followed by the current layout. The ABC, random (no zoning), and ABCD zoning have similar performances. The ABCDE zoning performs the worst; too many zones create a less flexible system and unequal (high) stacks that need a lot of shuffle movements. In the AB zoning strategy SKUs tend to have an 40%-60% division between A and B. Lastly, we analyzed the different item selections. We aimed to find appropriate item selections by fitting into the system's capacity. We see that only instances 1 and 2 do not exceed the system's capacity and are, therefore, suitable for use. Using item selection 2 would lead to a 12.89% increment of the number of SKUs in the system. This will also improve the warehouse occupation rate in the traditional warehouse with 2.44%, based on the taken reference day (31-10-2023).

Chapter 6

Conclusion and recommendations

This chapter will conclude all results outcomes and answer the last research questions: "Which zoning strategy performs best?" "What is the most suitable item selection?" and To what extent did the solution contribute to solving the core and action problems? This will answer the question: "Which conclusions can be drawn from the results?" By answering these questions also, the research problem of *"Which zoning strategy and item selection for Vink's AS/RS gives the best balance between an adequately filled system and acceptable travel times that do not exceed the system's operational capacity constraints?"* is solved.

6.1 Conclusions

This research aimed at making an improved zoning strategy and item selection for the AS/RS of Vink so that it is adequately filled and completes orders at acceptable times.

In the context analysis, we analyzed the warehouse operations at Vink, including the order-picking process, demand pattern, and storage systems. The warehouse has a high occupation rate of 93.99%, and the company has a lot of external storage, which is costly and time-consuming to move. The item selection, SKU slotting, and zoning strategy of the AS/RS could be improved. Furthermore, the system's fixed storage policy of placing sheets on the lowest stack within the zone and retrieval policy of retrieving the sheet that is most on top is notable.

The literature review discusses warehouse decisions on different levels and shows that this thesis involves warehouse decisions on a tactical level. Four storage policies are described: Random Storage, Dedicated Storage, Shared Storage, and Class-based Storage. The literature review also dived into modeling techniques for similar problems like AS/RS modeling, PSP situations, and 3D compact storage systems. The problem is categorized as a SLAP problem, and the research gap is the unique combination of different elements and the shuffle operations.

For modeling the system, the model makes use of similar variables and parameters from the models of Muppani and Adil (2008),Yue (2023),Beckschäfer et al. (2017)

and Trost et al. (2022). The simulation model consists of four main procedures: the initialization process involves loading input data from Excel files so that all needed information is present. After this, the system's initial placement and start situation is created, and then, the order processing is done to create a start initial objective. Finally, the simulated annealing procedure switches zones and searches for improved solutions and objectives. The comparison between model times and real-life travel times confirms the model's accuracy against real-world travel times.

The results chapter explores the parameters required for the simulated annealing algorithm, including the number of replications, iterations, starting temperature, and decrease factor. After that, the results of 30 experiments are presented under different scenarios and item selections; the results show that the current layout works best in the current base scenario. AB-zoning gives the best performance when increasing the number of SKUs. The analysis also provides insights into an appropriate item selection for further filling the system. The current base item selection and instance 2 are the only selections that do not exceed the system's capacity. Therefore, item-selection 2 seems the most convenient item selection, which increases the number of automated stored SKUs by 12.89% . This would improve the warehouse occupation rate with 2.44% on the given reference day and helps improving the company's storage and warehouse efficiency and reach its goals.

6.2 Recommendations

Based on the conclusions drawn from this research, the following recommendations are given to Vink Kunstoffen to improve warehouse efficiency. To optimize the storage capacity of the automated system and prevent system overfilling, it is suggested that item selection 2 be used with an AB-zoning strategy. In addition, we believe further actions could be taken to improve warehouse efficiency. This may involve optimizing rack height and space occupation in the traditional warehouse. Furthermore, we recommend adhering to the guidelines of item selection 2 and not adding more items into the system because setup activities take time, which is not considered in the simulation. Furthermore, we suggest continuing to divide Hall One SKUs into subsections. Finally, we recommend exploring just-in-time ordering strategies for certain orders. This approach can help prevent occupying large amounts of space for extended periods, as full pallets are shipped out quickly.

6.3 Limitations

Despite the efforts to optimize the automated system as well as possible, this study has limitations. The following limitations should be considered when interpreting the results. The first limitation is that item selections were made by relaxing earlier set criteria, which resulted in a relatively small difference between instances 4 and 5. Another limitation of this research is that the objective function is calculated by taking the average of only two independent runs to deal with randomness in initial solutions. Although this action was taken, there still may be a small change of influence by randomness due to the random sort in initial placement. The number of two replications follows from the large size of instances, input data, and the need to track all operations in modeling. Because of this, we were forced to keep the number of replications for objective calculation as low as possible to keep the acceptable running times of the simulation model. Furthermore, the validation of travel times was time-consuming because the movements were hard-coded in the validation model. Therefore, the validation of travel times is only done for one day of orders. Comparing more orders would lead to an even more accurate comparison. Due to time constraints and feasibility, the model is also based on assumptions and simplifications. However, the model still represents reality by validating the travel times and a randomized initial placement that represents a realistic starting point. Also, the model assumes that all selected SKUs-orders are processed by the system, which could result in a higher number of sheets in the system than in reality, which, in turn, influences the performance. It is also important to note that the research is based on data from a limited period from January 1, 2023, to October 13, 2023, and while these data are still comparable to today's operations, they may change in the future. Additionally, exploring more item selections could enable a more comprehensive investigation of the relationship between the types and number of SKUs, sheets, and total travel time. Finally, the model is deterministic and only focuses on the system's environment, meaning it does not consider setup activities and variability in travel times or machine errors.

6.4 Contribution to practice

This study's practical contribution lies in the field of warehouse operations. It provides valuable insights and recommendations that can be directly applied within the company.

Firstly, the study confirms that Vink's AS/RS current layout, with a few minor adjustments, works effectively for storage and retrieval operations in the current situation. Secondly, the study reveals that adopting an AB-class zoning layout is beneficial as the number of SKUs stored in the automated warehouse increases. This type of zoning allows for more efficient storage and retrieval of SKUs, probably due to more equal stack heights, improving productivity, flexibility, and reduced travel times. Thirdly, the study provides a guideline on the maximum number of SKUs stored in the system. The findings suggest that item selection 2 with 394 SKUs is a good guideline for SKU selection. This selection fills the system adequately while still having acceptable order completion times. This selection can also be used when item selections change. In this case, selecting a similar item based on size and demand would be beneficial. Finally, this research shows that the AS/RS storage could be improved and can make the warehouse more efficient. However, the shown improvements by this study warehouse occupation rate could be further improved after the implementation of the solution. Therefore, recommendations for additional actions to improve warehouse efficiency are also given.

6.5 Contribution to literature

This study contributes to the literature in several ways. It combines the concepts of AS/RS PSP, and 3D storage systems literature, providing a comprehensive framework for modeling the system. The model description shows all needed sets, parameters, (decision) variables, and constraints to model the working of an automated warehouse system like the one in this thesis. The study goes beyond the existing literature on SKU and location zoning optimization by examining it in a different environment and with the help of simulated annealing. Furthermore, the study considers the shuffle environment of the system, which is often neglected in the literature, and shows how it impacts the system's overall performance. Furthermore, we present the workings of the simulation model and a way of optimizing zoning in these systems and analyzing performances over different scenarios. Additionally, the study demonstrates the effectiveness of the proposed model in a real-life environment, Vink's AS/RS. In this way, it shows how theoretical concepts work in practice. The study also reveals a relationship between the number of SKUs and travel time in a PSP environment, via sensitivity analysis over the different item selections.

6.5.1 Further research directions

Future research directions for this study include optimizing the layout from scratch instead of improving a layout with zoning and item slotting. From-scratch optimization could be done by determining how many locations are needed per size based on an item selection. Based on that, a location could be placed in the empty layout and optimized to optimize the number of locations and placement. Additionally, the Vink system or similar systems should be integrated with other warehouse operations, such as set-up activities, transportation management systems, or warehouse management systems. This could be explored to better analyze an overall warehouse performance. Furthermore, this study focuses on deterministic optimization, which could be expanded to include more stochastic elements. This would involve analyzing and optimizing the system's performance in a more dynamic and uncertain environment, such as human interaction, dynamic demand patterns, and system errors. Finally, more research could be done to investigate suited SKUs for automated systems, considering other or more extensive factors such as demand, weight, size, sensitivity to damage, and labor-intensive processing. This could provide valuable insights into effective criteria and assignment for SKU placement in similar systems.

Appendix A: Drawings and pictures of AS/RS

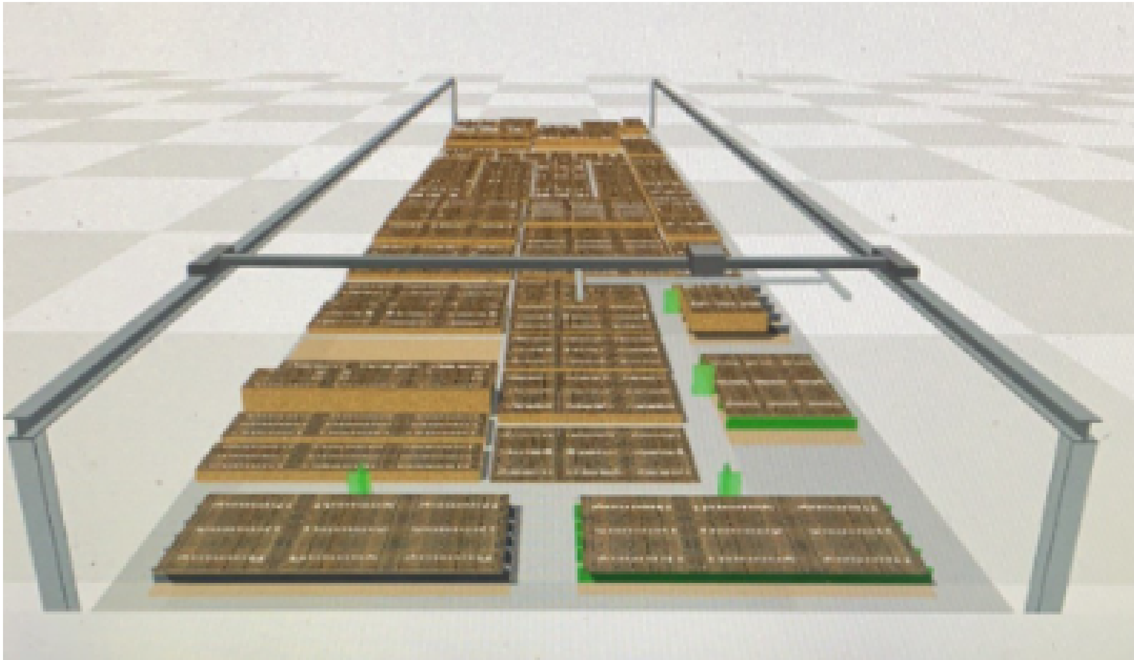

Figure A1: Front side of system with I/O points

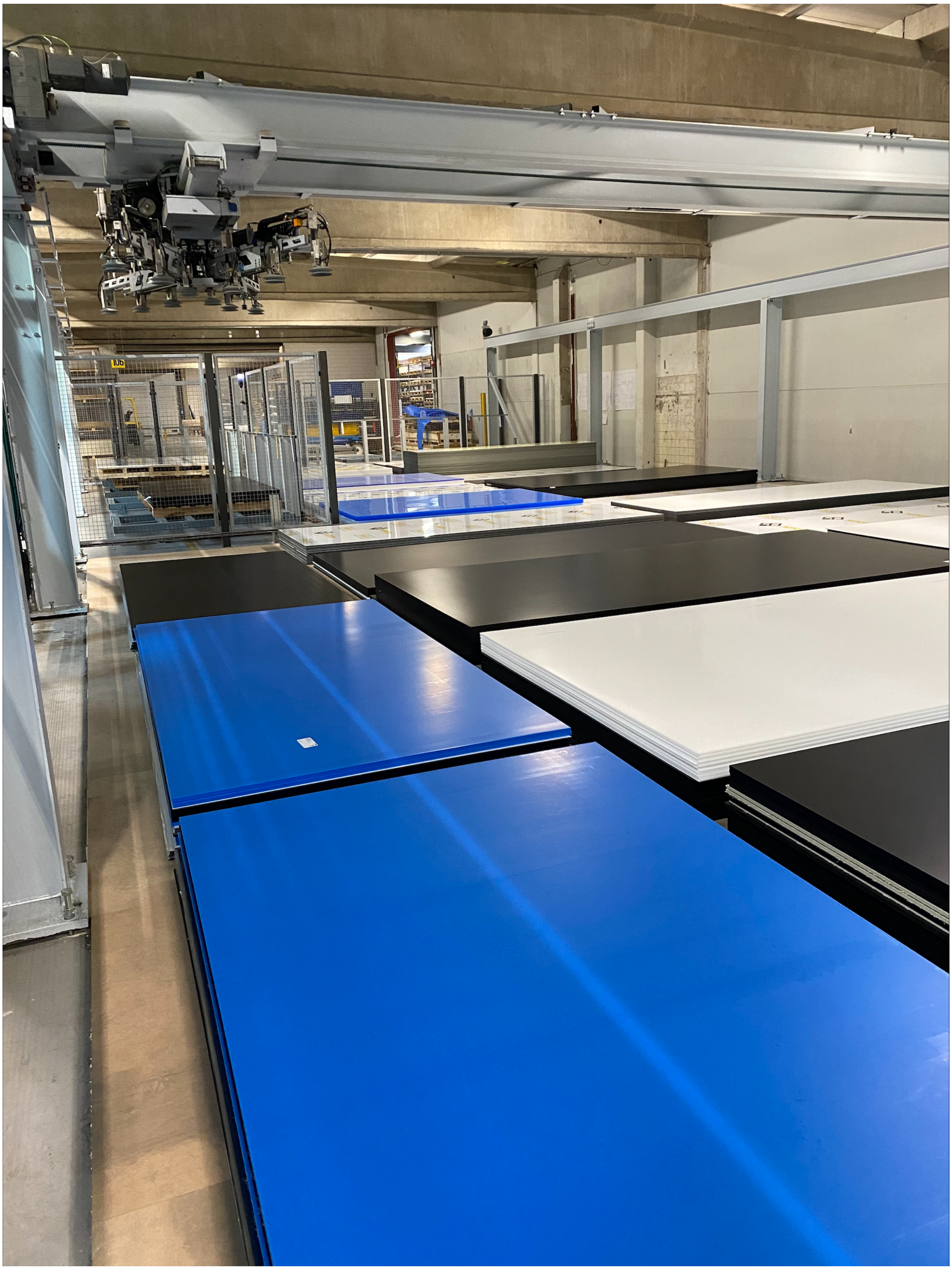

Figure A2: System with crane and stacks

Figure A3: I/O point 1

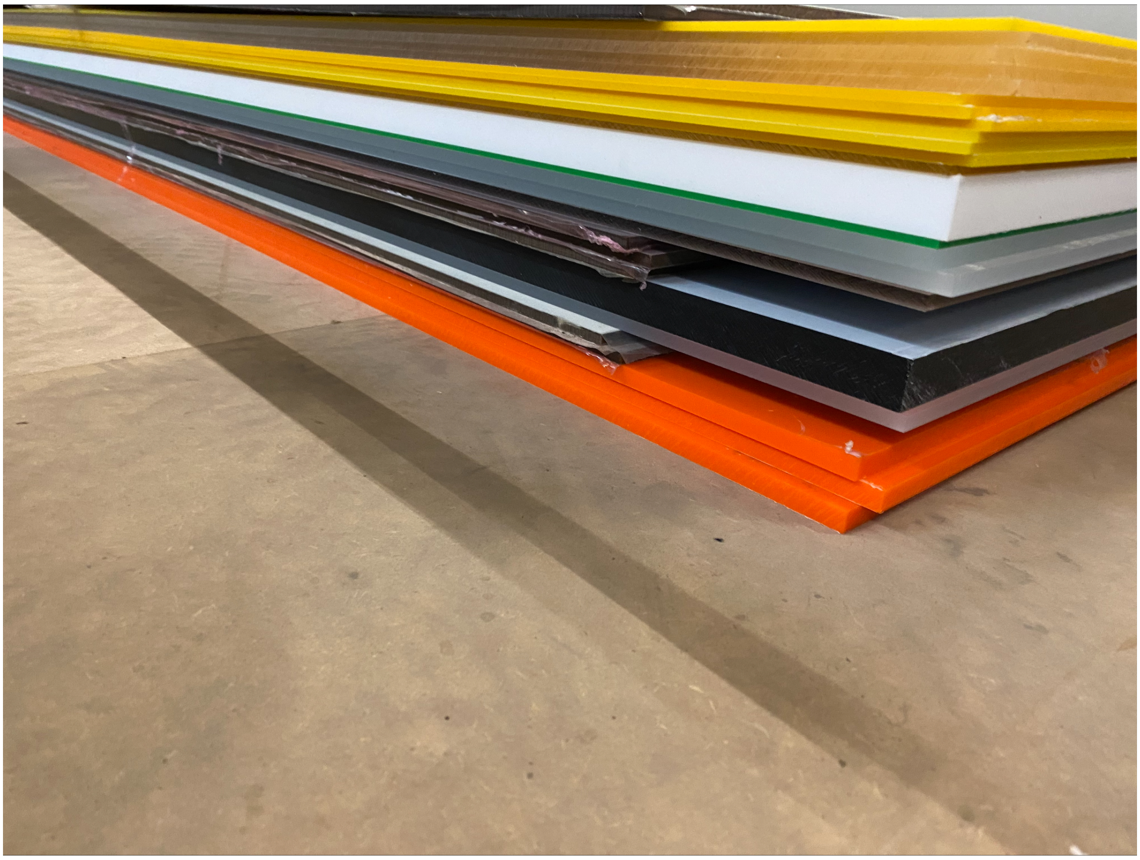

FIGURE A4: Example of a shared random storage stack in the AS/RS

Appendix B: Simulated annealing parameter setting experiments

Table B1: Simulated annealing parameter settings experiment outcomes

Experiment	Iterations	StartTemp	Decrease Factor	Start Objective	Best Objective	Improvement	Running Time (hh:mm:ss)
1	5,000	1,000	0.995	4,286,705.46	4,094,720.52	191,984.95	09:04:15
2	2,000	1,000	0.995	4,416,778.01	4,110,718.02	306,060.01	03:33:49
3	1,000	1,000	0.995	4,333,534.62	4,134,717.15	198,817.47	01:49:46
4	5,000	500	0.995	4,444,822.93	4,070,934.33	373,888.60	12:12:30
5	2,000	500	0.995	4,391,135.76	4,084,014.09	307,121.67	03:43:21
6	1,000	500	0.995	4,196,078.40	4,136,435.58	59,642.82	01:47:23
7	5,000	200	0.995	4,174,392.84	4,098,961.22	75,431.62	09:06:24
8	2,000	200	0.995	4,376,267.99	4,057,717.35	318,550.63	04:15:46
9	1,000	200	0.995	4,387,356.76	4,132,691.60	254,665.16	01:43:59
10	5,000	1,000	0.99	4,303,100.65	4,100,810.66	202,290.00	11:59:02
11	2,000	1,000	0.99	4,466,442.53	4,119,637.85	346,804.68	03:51:15
12	1,000	1,000	0.99	4,417,475.78	4,153,522.64	263,953.14	01:46:46
13	5,000	500	0.99	4,273,815.95	4,099,403.41	174,412.54	08:53:32
14	2,000	500	0.99	4,466,104.91	4,119,007.09	347,097.82	03:34:47
15	1,000	500	0.99	4,180,574.38	4,132,310.62	48,263.76	01:46:54
16	5,000	200	0.99	4,277,079.45	4,095,272.14	181,807.32	08:49:39
17	2,000	200	0.99	4,249,872.07	4,097,382.16	152,489.91	04:11:08
18	1,000	200	0.99	4,275,377.61	4,133,983.39	141,394.22	01:49:52
19	5,000	1,000	0.975	4,323,046.76	4,106,620.73	216,426.03	10:12:26
20	2,000	1,000	0.975	4,404,542.41	4,111,961.27	292,581.14	03:42:07
21	1,000	1,000	0.975	4,356,267.99	4,114,119.33	242,148.66	01:48:35
22	5,000	500	0.975	4,456,979.33	4,077,144.05	379,835.28	09:42:31
23	2,000	500	0.975	4,464,265.56	4,089,532.37	374,733.19	03:38:39
24	1,000	500	0.975	4,473,403.78	4,143,204.14	330,199.64	01:49:30
25	5,000	200	0.975	4,380,937.50	4,072,425.38	308,512.12	09:40:10
26	2,000	200	0.975	4,330,672.64	4,105,454.93	225,217.71	03:29:59
27	1,000	200	0.975	4,495,947.44	4,090,406.47	405,540.97	01:47:45

Appendix C: Initial state settings

Table C1: SKU division over zones per scenario, based on cumulative contribution to total orders.

Zone/Scenario	Random	AB	ABC	ABCD	ABCDE	Current Layout
A	[0%, 100.00%]	[0%, 75.00%]	[0%, 75.00%]	[0%, 75.00%]	[0%, 75.00%]	x
B	0.00%	[75.00%, 100.00%]	[75.00%, 90.00%]	[75.00%, 90.00%]	[75.00%, 90.00%]	x
C	0.00%	0.00%	[90.00%, 100.00%]	[90.00%, 97.00%]	[90.00%, 97.00%]	x
D	0.00%	0.00%	0.00%	[97.00%, 100.00%]	[97.00%, 99.00%]	x
E	0.00%	0.00%	0.00%	0.00%	[99.00%, 100.00%]	x

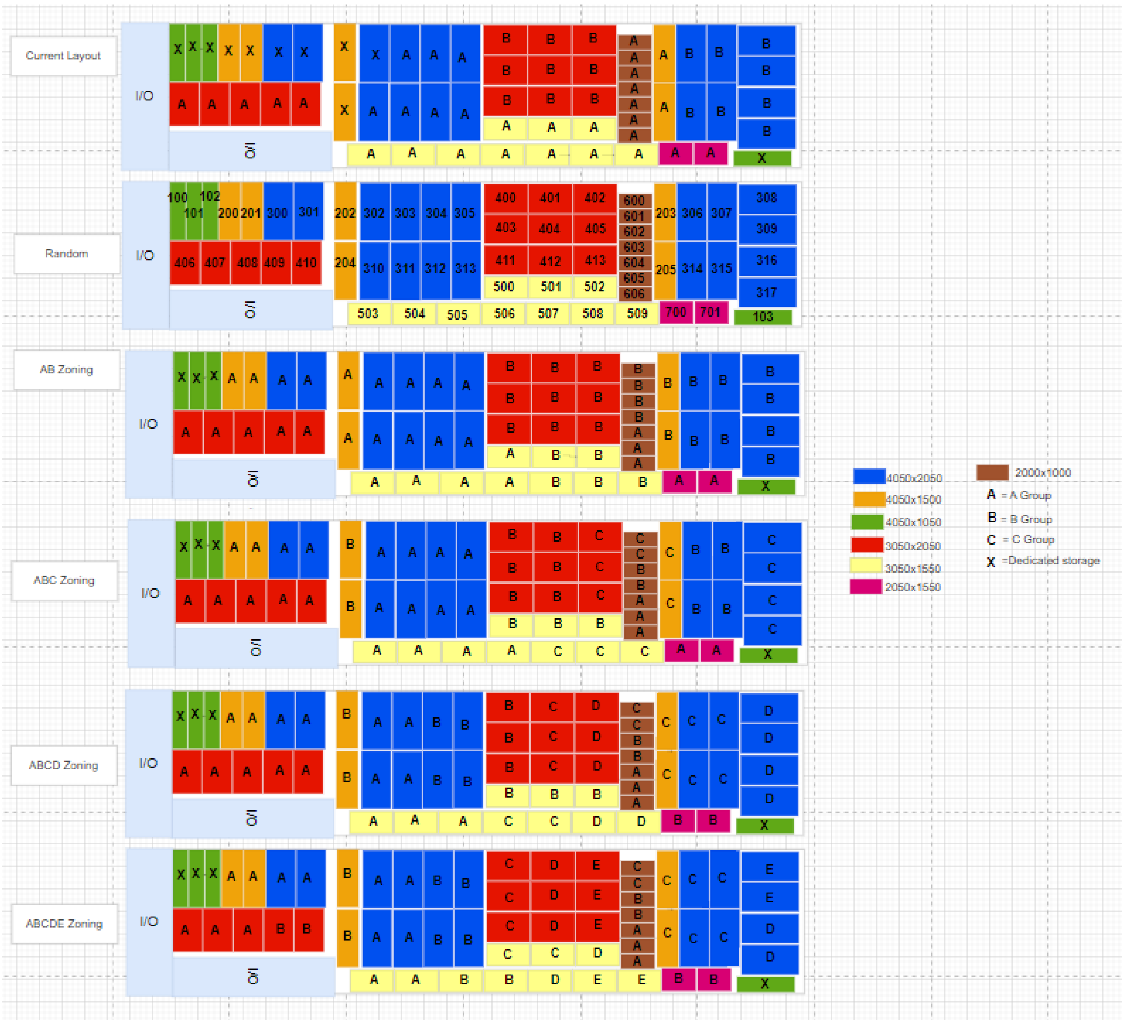

FIGURE C1: Layouts per scenario

Appendix D: Best scenario per item selection

FIGURE D1: Zoning of locations for best scenario per instance after simulated annealing

Table D1: Initial zoning and after simulated annealing zoning of SKUs for best scenarios per instance.

Instance	**Initial situation**			**After simulated annealing**		
	Zone	**#SKUs**	**%**	**Zone**	**#SKUs**	**%**
Instance 1	Dedicated	10	2.87%	Dedicated	10	2.87%
	A	253	72.49%	A	261	74.79%
	B	86	24.64%	B	78	22.35%
	Total	349	100.00%	Total	349	100.00%
Instance 2	Dedicated	4	1.02%	Dedicated	4	1.02%
	A	166	42.13%	A	160	40.61%
	B	224	56.85%	B	230	58.38%
	Total	394	100.00%	Total	394	100.00%
Instance 3	Dedicated	4	0.98%	Dedicated	4	0.98%
	A	179	43.87%	A	178	43.63%
	B	225	55.15%	B	226	55.39%
	Total	408	100.00%	Total	408	100.00%
Instance 4	Dedicated	4	0.88%	Dedicated	4	0.88%
	A	193	42.42%	A	189	41.54%
	B	258	56.70%	B	262	57.58%
	Total	455	100.00%	Total	455	100.00%
Instance 5	Dedicated	4	0.84%	Dedicated	4	0.84%
	A	199	41.81%	A	195	40.97%
	B	273	57.35%	B	277	58.19%
	Total	476	100.00%	Total	476	100.00%

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