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Improving the Occupancy Rate in the Distribution Center by Developing a Material Handling System Optimization Approach

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Preface

Dear reader,

This master's thesis, 'Material Handling System optimization approach for improving the occupancy rate in the DC', is the result of my research to finalize the Master Industrial Engineering and Management at the University of Twente. This research has been conducted at Riedel, located in Ede.

At Riedel, I learned a lot about how to bring the theory, learned at the University of Twente, into practice. I have developed my personal growth in various ways. The completion of this thesis would not have been possible without the opportunities given by Riedel. I would like to thank all of my colleagues at Riedel who contributed to this thesis. Their experiences and knowledge helped me in delivering this thesis. A special thanks to my supervisor at Riedel, Wouter van der Berg, who guided me through the process. His expertise and insights inspired me to strive for the best outcome. Our in-depth discussions on the topic during our meetings made me think of better solutions. I would also like to thank them for the opportunity to visit Tetra Pak in Germany. It was a really interesting day where I learned about the process of making packaging and the sustainability aspects of it.

I would also like to express my gratitude to my first supervisor, Patricia Rogetzer. She also supervised me during my bachelor's thesis, which was such a pleasant cooperation. Therefore, I contacted her again and I was glad that she wanted to supervise me again. I would like to thank her for her time and effort. Besides that, thanks to Breno Alves Beirigo for providing me with additional feedback and insights into the topic.

This thesis is the final chapter of my student life. I am really happy for the years of fun I had in Enschede. I would like to thank my friends and family for supporting me through these years and always believing in me. Thank you to De Beverburcht for being my home these years and for all the great activities we did together. Thank you to my teammates at Arriba for the basketball nights and games. I would also like to thank the girls I met during the Kick-In for the amazing years where we built an incredible friendship. Finally, thank you to Emiel who has given me unlimited support. I am grateful for our talks and his motivation while writing this thesis.

I hope you enjoy reading my master's thesis!

Carmen Cijffers
Ede, August 2024

Management summary

This research was conducted at the distribution center (DC) of Riedel, the market leader in fruit juices such as Appelsientje, CoolBest, and Taski. Currently, Riedel experiences a decreasing service level from spring until the summer. In 2023 the service level dropped below 90%, whereas the target service level is set to 99%. Pentecost and Ascension Day cause a production delay because the factory is shut down during these holidays, but Riedel cannot make use of preventive storage in the DC. This is because of the restricted floor space of the DC, a high variety of products, the usage of drive-in pallet racking systems, and the missing knowledge on the optimal occupancy rate. This research tackles the core problem of 'The optimal occupancy rate for future product portfolios is unknown'.

The goal of this research is to increase the floor space utilization in the DC by improving the occupancy rate. Since the demand is uncertain, possible future product portfolios should be taken into account to ensure that the solution has long-term advantages. The occupancy rate and capacity requirements are majorly dependent on the type of pallet racking used. Therefore, this research develops an improvement heuristic to find an improved configuration of pallet racking systems by answering the following main research question.

How should the occupancy rate of the DC be optimized to reach the target service level for possible future product portfolios?

Currently, Riedel uses the single-deep pallet racking system and five drive-in pallet racking systems with different heights and lengths. The pallet racking systems result in a total pallet capacity of 14,121 block pallets and 18,069 Euro pallets, and a target maximum occupancy rate of 72.8%. The current product portfolio has an increasing variety of Stock Keeping Units (SKUs) since currently it consists of 287 SKUs, whereas 4.5 years ago these were 132 SKUs.

The literature review discovered that the drive-in pallet racking system is mainly used for the storage of SKUs with larger volumes rather than a high SKU variety because one pallet racking can only store one batch. Therefore, the drive-in pallet racking system does not match the product portfolio of Riedel. It increases the loss of space because of the creation of empty but unusable storage locations (honeycombing effect). To improve the occupancy rate, this research develops an improvement heuristic that searches for a configuration of pallet rackings with the best trade-off between Key Performance Indicators (KPIs) according to the problem owner.

The developed improvement heuristic uses past data from January 2024 until April 2024 on the inventory levels of the end products and the current configuration of pallet rackings in the DC. As an initial solution, the improvement heuristic uses the current configuration of pallet rackings because the closer the final configuration is to the current situation, the less expensive it is to implement it. The improvement heuristic uses the Simulated Annealing (SA) method and iteratively performs neighborhood operators.

To cope with the uncertainty of future demand, the following scenarios of future product portfolios are created.

- Scenario 1: Increased volume, same initial inventory;
- Scenario 2: Increased volume, increased initial inventory;
- Scenario 3: Adding low-volume SKUs;
- Scenario 4: Splitting SKU volumes.

Table 1 shows the difference between the initial and best configuration of the base and future product portfolio scenarios. The best configuration of all scenarios results in an improvement in the objective function value and increases the flexibility of pallet storage. Table 2 shows the differences of the output KPIs between the initial and best configuration of the base and future scenarios. It shows why the improvement heuristic selected the best configurations. In each scenario, the best configuration reduces the honeycombing effect resulting in an increase of available pallet locations. Therefore, more pallets fit into the DC allowing a higher pallet inventory in all scenarios. This suggests that implementing the proposed configuration provides room for expanding the product portfolio in the future.

Table 1: Initial configuration and differences to best configurations, base and future scenarios

	Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
Initial	4	283	24	24	59	0	0
Base scenario	+18	-50	+7	+34	-1	+7	0
Scenario 1	+18	-50	+40	+10	-3	+4	0
Scenario 2	+19	-50	+22	+29	-1	+8	0
Scenario 3	+12	-48	+31	+39	0	+5	0
Scenario 4	+5	-50	+41	+23	+1	+5	0

Table 2: Differences output KPIs between initial and best configuration, base and future scenarios

	Capacity (block/Euro)	**Mean inventory**	**Mean available locations**	**Mean honeycombing locations**
Base scenario	-216 / -284	+24	+809	-1,000
Scenario 1	+29 / -15	+152	+982	-910
Scenario 2	+141 / +147	+170	+1,097	-917
Scenario 3	-181 / -219	+302	+1,496	-1,245
Scenario 4	-282 / -388	+82	+841	-1,113

The insights gained from this research provide Riedel with the following recommendations.

1. Optimize the layout of the DC to incorporate the proposed pallet racking configuration depending on the envisaged future product portfolio;
2. Make a decision on expanding the DC by performing an analysis on the floor space requirements;
3. Upgrade the Warehouse Management System (WMS) to implement the new structure of pallet rackings;

4. Extend the data storage to allow better decision-making.

Based on the analysis of the results, the following conclusions can be made.

1. Without bypassing the allocation suggestions of the WMS, the current configuration of pallet rackings does not provide all inbound pallets with a pallet location in the base scenario. The improved configuration of Table 3 is proposed to decrease the probability of a stock out to reach the target service level in the future.

Table 3: Base scenario, best configuration

Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
22	233	31	58	58	7	0

2. With the current configuration of pallet rackings, splitting the volume of 5% of the SKUs performs best, then increasing the volume (and initial inventory) by 5%, and finally adding 5% of the SKUs to the product portfolio. When increasing the total volume, the current configuration is better utilized by a larger volume than by a higher SKU variety. Thus, the current configuration of pallet rackings cannot cope with the increasing variety of SKUs.

3. The proposed configurations of pallet rackings of the future product portfolio scenarios align closely with the proposed configuration of the base scenario. This suggests that the proposed configuration for the base scenario is robust and adaptable to potential changes in the product portfolio. However, if the total volume increases, either by increasing the volume (and initial inventory) or adding low-volume SKUs, Riedel requires additional floor space to cope with it.

4. The results indicate a need for more low-capacity drive-in pallet rackings to decrease the honeycombing effect and increase the mean inventory. Within the current floor space, this results in a decrease in the total pallet capacity, but increases the flexibility and ensures high occupancy rates. Table 4 shows the improvement in the mean occupancy rate in each scenario. This research improved the mean occupancy rate on average by 1.2%, which ensures flexible storage prepared for the future.

Table 4: Improvement mean occupancy rate per scenario (in %)

Base	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
+1.3	+0.9	+0.5	+1.2	+2.0

Contents

Reader's guide

This thesis performed at Riedel is structured in eight chapters, which are shortly discussed below.

Chapter 1: Introduction
The first chapter describes the company, introduces the problem, and identifies the core problem using a problem cluster. This leads to a problem-solving approach consisting of research questions and a scope, limitations, and deliverables.

Chapter 2: Current situation in the DC
The second chapter elaborates on the current situation in the DC of Riedel by describing the current process and layout of pallet rackings. Furthermore, it determines the main KPIs and identifies the product portfolio in March 2024.

Chapter 3: Literature review
The goal of the literature review is to obtain academic literature on the main topics of this research. It describes types of pallet racking systems including their characteristics and elaborates on the topic of occupancy rate. Finally, the chapter discussed the storage capacity requirements and the methods to solve the warehouse capacity and design problem.

Chapter 4: Solution design
The solution design creates a detailed plan to deliver a good pallet racking configuration. First, it discusses the assumptions and develops a mathematical model consisting of the objective function and constraints. Then, it elaborates on the solution method. It explains the required input data, initial solution, Simulated Annealing (SA) method, neighborhood operators, and how to generate the objective value. Finally, the performance of the inventory algorithm is compared to the real world.

Chapter 5: Simulations base scenario
This chapter elaborates on the design and results of the improvement heuristic on the base scenario. The objective function is weighted, SA parameters tuned, results analyzed, and robustness evaluated using a sensitivity analysis.

Chapter 6: Scenarios of future product portfolio
To cope with the uncertainty in demand, this chapter creates future product portfolio scenarios and compares the results with the base scenario and each other.

Chapter 7: Conclusions and recommendations
The final chapter concludes the research and lists the recommendations derived from the results of the research. Then, it discusses the practical and scientific contribution. Finally, the limitations and consequential further research are listed.

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List of Abbreviations

Abbreviation	Meaning
AS/RS	Automated storage and retrieval system
AVS/RS	Autonomous vehicle storage and retrieval system
DC	Distribution Center
ERP	Enterprise Resource Planning
FIFO	First In First Out
KPI	Key Performance Indicator
LIFO	Last In First Out
MHS	Material Handling System
SA	Simulated Annealing
SBS/RS	Shuttle-based storage and retrieval system
SKU	Stock Keeping Unit
WMS	Warehouse Management System

1 Introduction

This report documents the research performed at Riedel for the completion of the master's studies in Industrial Engineering and Management at the University of Twente. This chapter introduces the topic and problem investigated in this research at Riedel. It starts with Section 1.1 which describes the company and introduces the department. Section 1.2 elaborates on the origin of the problem, selects the core problem to tackle, and explains the objective of this research. Section 1.3 formulates the main research question and describes the sub-research questions for each step in the problem-solving approach. Section 1.4 shapes the research design and explains the research scope and limitations. Section 1.5 lists the deliverables to be provided in this research. Section 1.6 depicts the structure of this report by dividing the sub-research questions across the chapters.

1.1 Company description

This research is conducted at the distribution center (DC) of Riedel. In 1879 J.P. Riedel started producing metal-free mineral waters and over the years Riedel produced more types of products. Years later they were taken over and through many mergers, they became part of Friesland Campina [58]. In 2017, Riedel became independent again because the juice market was under a lot of pressure due to negative health perceptions. Now six years later, they have become the market leader in the Netherlands within the category of fruity drinks. They produce fruit juices such as Appelsientje, CoolBest, Taski, DubbelFrisss, and so on. Their whole process takes place at their location in Ede, where the ingredients are supplied and processed into juices. These juices are packed in boxes, placed on pallets, and stored in the DC. From there, the pallets go by truck to their customers.

Within Riedel, the research is conducted at the DC, also called a warehouse, which consists of an ambient and cooled part. This research focuses on the ambient part of the DC. The DC is stocked with pallets containing the finished products to be distributed to retailers and wholesalers. The finished products come directly from the packaging department on pallets via a belt to the DC. The pallets arrive in bulk since they are produced in standard large sizes. They are stored in the DC until employees on forklift trucks move them when they are needed for shipments. Thus, the DC provides a buffer or safety stock to prepare for unexpected demand and to deal with seasonality.

1.2 Problem identification

During the holiday weekends of Pentecost and Ascension Day, the production at Riedel is shut down resulting in less stock after these weekends. Since there is more demand and less production during the summer, the service level decreases from Pentecost and Ascension Day until the end of the summer. The total pallet capacity in the DC is too low and the optimal occupancy rate is unknown. The occupancy rate is the ratio of the number of occupied pallet locations and the total pallet capacity. The occupancy rate can be calculated on a daily basis. The DC has a drive-in pallet racking system with a lower occupancy rate than other pallet racking systems because only one product batch with one expiration date can be stored in such a racking. It is not clear how to prevent the service level from decreasing. Thus, this section searches for the core problem to tackle in this research using a problem cluster and explains the research objective.

1.2.1 Problem cluster and action problem

This subsection identifies the relationships between the occurring problems. According to Heerkens and van Winden [33], a problem cluster is a helpful tool for understanding and communicating these relationships. Figure 1 depicts the problem cluster of the DC at Riedel. The blocks refer to the occurring problems and the arrows present the relationships from cause to effect. The target service level of Riedel is 99%, which means that 99% of the customers' orders should be satisfied on time. This is an important measure of performance to evaluate the efficiency of the organization. Riedel is coping with the following action problem, represented by the red box in the problem cluster.

"The service level of Riedel decreases from Pentecost and Ascension Day until the summer period"

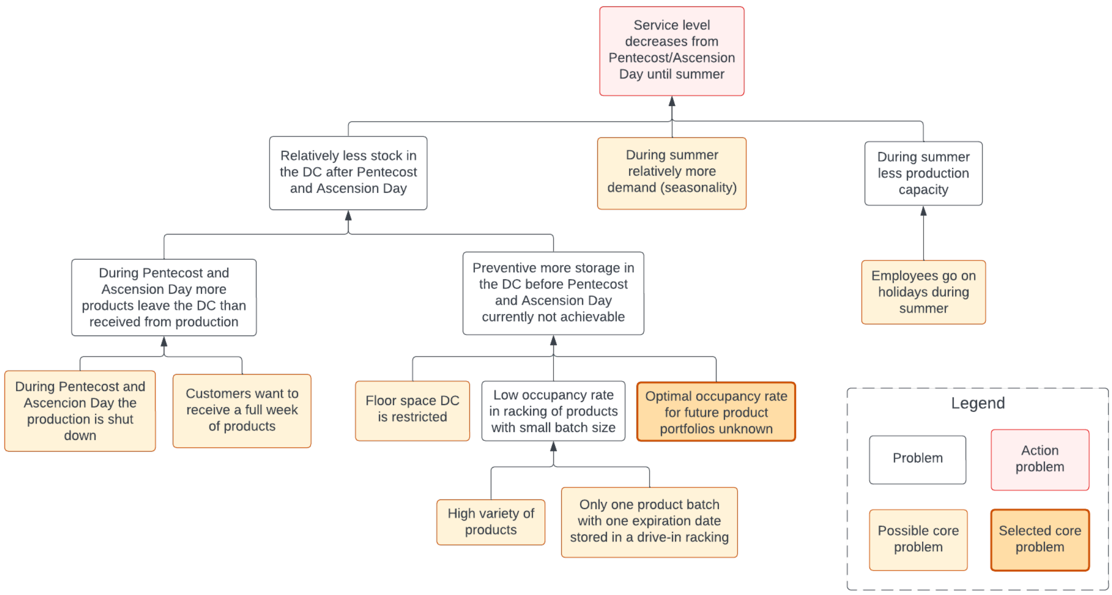

Figure 1: Problem cluster Riedel

Figure 2 depicts the service level per week over 2022 and 2023. The service level is the ratio between the number of delivered products on time and the total number of ordered products. The dashed line in the figure shows the target service level of 99%. In both years, the service level decreases significantly around week 21, which is around Pentecost and Ascension Day, and even drops beneath 90% in week 26. Thus, there is a gap between the observed reality and the norm as determined by the problem owner. In 2022, the service level slowly increased after week 26 to reach the target only at the end of the year. In contrast, the service level over 2023 increased faster because Riedel took desperate measures by cutting back on some products, such as products with a low volume or small return on investment. Therefore, the target was already reached around October, thus still only after the summer period. This problem is even worse if Kingsday and the 5th of May are also during the week since then Riedel has to cope with more days that the production is shut down.

Figure 2: Service level 2022 and 2023

The decreasing service level is caused by three underlying difficulties, as the problem cluster shows.

- After Pentecost and Ascension Day, there is relatively less stock in the DC which is explained further in the next paragraph.
- During the summer period, there is relatively more demand compared to the rest of the year due to seasonality. Figure 3 displays the average daily demand over the months of 2023, which shows the excessive demand during June and July. This is because of the higher outside temperatures during the summer period. People tend to drink more water and juices when the temperature outside is higher.
- During the summer period, there is less production capacity since employees in the production factory of Riedel go on holiday. Therefore, there is not enough capacity to cope with the seasonality.

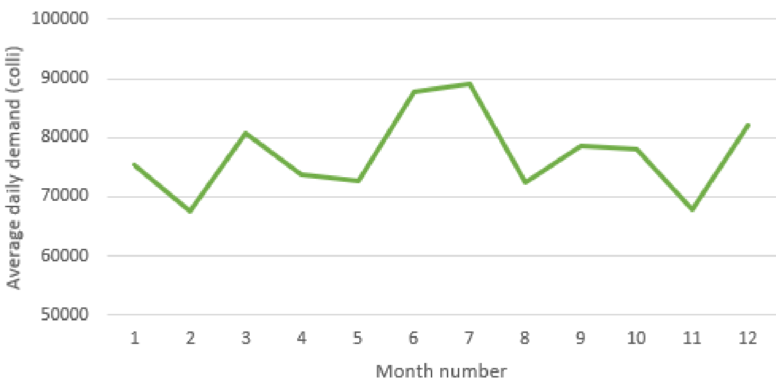

Figure 3: Average daily demand over 2023

As mentioned, there is relatively less stock in the DC after Pentecost and Ascension Day. This is caused by the following two dependent complications, as the problem cluster shows.

- During Pentecost and Ascension Day, more pallets with products leave the DC than received from production. This means that there is a delay in production because the factory is shut down during Pentecost and Ascension Day. Combined with this, the customers of Riedel still want to receive a full week of products to be able to supply their customers.
- Preventive storage of more pallets in the DC before Pentecost and Ascension Day is currently not achievable. This is because the number of pallets stored in the DC is already at the agreed maximum. However, the optimal occupancy rate is actually not known but based on experience. This means that the agreed maximum could be increased to ensure that it corresponds to the optimal occupancy rate. Preventive storage is not achievable because of a restricted floor space in the DC and a low occupancy rate. The latter arises from a high variety of products combined with the drive-in pallet racking system in the DC. Pallets stored in a drive-in pallet racking can only be reached from one side of the racking. Thus, a forklift employee can only reach the pallet at the back when first taking out all the pallets in front of it. Therefore, to ensure a First In First Out (FIFO) policy Riedel has the agreement that a pallet racking can only hold one product batch with the same expiration date. This also holds for batches with a small amount of pallets. Those batches cause the occupancy rate to decrease significantly since they leave many pallet places empty.

1.2.2 Core problem and motivation

The possible core problems from Figure 1, represented by the orange boxes, are the problems that do not have a direct cause themselves [33]. The problem cluster defines the following eight problems as possible core problems.

1. *During Pentecost and Ascension Day the production is shut down.* Pentecost and Ascension Day are both official holidays. Riedel decided that everybody in the organization has a free day during these holidays, meaning that the whole factory is shut down;
2. *Customers want to receive a full week of products.* Despite official holidays, the customers of Riedel want to receive the normal amount of products during these weeks even though there are fewer days to produce and deliver. Riedel is not going to change this since the more products it sells, the more revenue it earns;
3. *The floor space of the DC is restricted.* The DC has limited space to store the pallets. This causes issues in optimizing the total pallet capacity. Riedel does not have expanding opportunities since they are located in an urban area;
4. *High variety of products.* To increase customer satisfaction and loyalty, Riedel keeps developing more different types of products. Some years back, they had about one-third of the variety of products as they have now. This increase enhances competitiveness by creating more market share. Moreover, new regulations drive product research and development. The high variety of products combined with the drive-in pallet racking system in the DC causes a low occupancy rate resulting in fewer products fitting in the DC;

5. *Only one product batch with one expiration date can be stored in a drive-in racking.* Therefore, a pallet racking containing a product batch with a small size decreases the overall occupancy rate. If this batch is also a slow mover, the remaining empty pallet positions in the pallet racking could be unused for a long period. Hence, drive-in pallet racking systems seem inefficient. Contrarily, large product batches significantly increase space utilization due to the high-density characteristic. The drive-in racking system used to be a good option for the DC when they still had a relatively low variety of products. However, replacing all of them is expensive. The occupancy rate might increase by replacing part of them to become suitable for smaller batches;
6. *The optimal occupancy rate for future product portfolios is unknown.* Due to the usage of the drive-in pallet racking system, the occupancy rate should be determined under exceptional circumstances. The effect of the product portfolio on the optimal occupancy rate is unknown. The occupancy rate influences the service level majorly;
7. *During summer relatively more demand (seasonality).* Summer is the peak season for Riedel, as Figure 3 shows. With the higher outside temperatures the demand from their customers increases due to people drinking more juices;
8. *Employees go on holidays during the summer.* Riedel has to let employees take holidays and cannot forbid them to take them during the summer.

By eliminating the core problems that cannot be influenced, the following core problem is selected, presented by the dark orange box in the problem cluster.

"The optimal occupancy rate for future product portfolios is unknown"

1.2.3 Research objective

The goal of this research is to optimize the percentage of utilized pallet positions in the DC, which depends on the total pallet capacity and the optimal occupancy rate. To optimize this, the research should define the total pallet capacity and the target occupancy rate, but more importantly, determine the optimal occupancy rate. To understand the influence of the occupancy rate on the service level, the research defines scenarios. These scenarios contribute to examining measures to perform to reach the target level in the future with a changing product portfolio.

1.3 Problem-solving approach and research questions

To achieve the research objective of the previous subsection, the main research question is formulated as follows.

How should the occupancy rate of the DC be optimized to reach the target service level for possible future product portfolios?

The problem-solving approach used in this research contains six phases. Each phase of the problem-solving approach contains sub-research questions. Below, the sub-research questions per phase are stated and their relevance is explained.

Phase 1: Problem identification
This phase identifies action and core problems based on a problem cluster. This is achieved by conducting interviews. Moreover, this phase outlines the current situation by directly observing the process in the DC.

1. What does the current process from inbound to outbound in the DC look like?

1.1 What is the current layout of the DC?

1.2 What is the total pallet capacity and the (target) occupancy rate in the DC?
This sub-research question lays the foundation for effective research since it identifies the parts of the process where the core problem arises. Understanding the current process and layout of the DC contributes to finding the most suitable solution. To optimize the occupancy rate, the current total pallet capacity and target occupancy rate in the DC should be known. The answer to this question is derived by observing the process and conducting interviews with the manager of the DC and the operational production planner.

2. What is the current product portfolio of Riedel and the characteristics of their products?
This sub-research question analyses and classifies the products within the portfolio of Riedel. Recognizing different types of products that are stored in the DC contributes to establishing a better understanding of the situation. Different types of products have varying space and time requirements. Besides that, it is important to find out how many different types of products Riedel actually has because it can influence the solution to the problem. This is investigated by analyzing existing data.

Phase 2: Solution approach
This phase lays a foundation to develop the solution design by finding methods to solve the problem that are available in literature. Moreover, it identifies current ways of storing products in a DC that might contribute to the solution.

3. What are the different types of pallet racking systems?
This sub-research question might discover pallet racking systems that can improve the occupancy rate under certain scenarios. If it turns out that the occupancy rate cannot be increased enough by optimizing it with the current pallet racking systems, it might be helpful to switch (part of) them with other pallet racking systems. This information is derived by performing a literature review.

4. What factors influence the occupancy rate in a DC?
The goal of this sub-research question is to determine the factors that influence the occupancy rate since this will clarify the consequences of incorporating the solution. Moreover, awareness of how the occupancy rate influences the service level is required to ensure that the target service level is reached in the future. This information is derived by performing a literature review.

Phase 3: Solution method
This phase lays the foundation of the method to find a solution to the main problem. It creates a detailed plan to optimize the occupancy rate by formulating the model to be used in developing the solution.

5. What method can be used to optimize the occupancy rate of the pallet racking systems within the DC?
The goal of this sub-research question is to develop an approach to optimize the occupancy rate of the pallet racking systems within the DC. The approach includes several components such as the input, output, and method to solve the main problem of this research. The used method is based on literature derived in phase 2.

Phase 4: Solution development
This phase develops the solution that answers the main research question. It determines the future product portfolio scenarios by looking at different directions in which the future could progress. This contributes to the validity of the solution. Moreover, this phase shows the results and analyses them by comparing the results of the future scenarios with the base scenario and each other. It should be in line with the research objective described in Subsection 1.2.3. Moreover, we conduct a sensitivity analysis on the method and explain how the concepts of reliability and validity affect the outcomes.

6. What are possible improvements to the design of the pallet rackings within the DC?
This sub-research question points out the possible improvements to the design of the pallet rackings within the DC. Improvements could be on expanding or converting the pallet rackings. To achieve this, it analyses the results of the base scenario. The answer to this sub-research question results in a list of possible improvements to the layout of the DC.

7. What are relevant scenarios on the future product portfolio to investigate?
This sub-research question identifies relevant scenarios on the future product portfolio such as an increased volume or additional low volume products. This ensures that the proposed solution will have long-term advantages and not only takes the past and present into account. To gain this knowledge, we analyze the data on the products of Riedel.

8. How do the improvements influence the occupancy rate in different scenarios?
This sub-research question contributes to the solution by investigating how the improvements influence the occupancy rate. Moreover, the scenarios identified in sub-research question 7 are used to find out what the influence is in the future. This discovers different ways to reach the target service level by optimizing the occupancy rate. To come up with this, we analyze the available data and interpret the results.

Phase 5: Evaluation
The last phase evaluates the proposed solution and improvements. It concludes which

approach should be implemented to reach the target service level in the future and gives recommendations on how to implement it. Finally, it examines whether the main research question is answered and the solution is in line with the research objective.

1.4 Research design

Table 5 shows a summary of the research design including the knowledge questions, research subjects, and methods of data gathering and processing. The following subsections explain the research scope and limitations.

1.4.1 Research scope

This research takes place in the DC of Riedel. Therefore, the process of procurement, producing, and packaging the juices before reaching the DC and the transportation after exiting the DC is out of scope. The DC consists of a cooled and ambient part of which the cooled part is out of scope. This is because the cooled part has a different type of pallet racking system and the duration of the products is much shorter because of a shorter time until the best-before date. The pallet rackings that are blocked or dedicated to storing partial pallets are out of scope. The blocked pallets are out of scope because they are dedicated to pallets that are in recovery so Riedel wants to minimize the pallets stored in these pallet rackings. The latter is out of scope and not taken into account in the pallet capacity for calculating the occupancy rate because these pallet rackings should have a lower occupancy rate than the rest of the pallet rackings. Every batch that comes into the DC from production has a partial pallet and should be stored in these pallet rackings. Therefore, Riedel should keep track of the number of empty pallet locations dedicated to partial pallets separately.

1.4.2 Limitations

This research has some limitations, thus weaknesses in the research design that are not controllable. First, the research has a time constraint of 20 weeks because it is performed as a Master's thesis. Second, the research has to cope with data and literature availability. Some required data and literature might not be available resulting in shortcomings in the findings. Third, the research is a case study at Riedel and focuses on the data and layout of the DC of Riedel. Therefore, it is hard to generalize the research to other sectors and companies. However, the research method and design used in this research can contribute to other studies. We assume that these limitations do not significantly harm the outcomes of the research.

Table 5: Research design

Knowledge question	**Research subjects**	**Method of data gathering**	**Method of data processing**
1. What does the current process from inbound to outbound in the DC look like? 1.1 What is the current layout of the DC? 1.2 What is the total pallet capacity and the (target) occupancy rate in the DC?	Manager of DC Operational planner	Process observation Interviews	Visual design Textual description Numerical analysis
2. What is the current product portfolio of Riedel and the characteristics of their products?	Product portfolio	Documents and records	Textual description Numerical analysis
3. What are the different types of pallet racking systems?	Types of pallet racking systems	Literature study	List of pallet racking systems
4. What factors influence the occupancy rate in a DC?	Factors and influences	Literature study	List of methods List of factors
5. What method can be used to optimize the occupancy rate of the pallet racking systems within the DC?	Methods from literature	Combine observations and literature	Solution design
6. What are possible improvements to the design of the pallet rackings within the DC?	Data from DC Methods from literature	Analysis of data Documents and records	List of improvement options
7. What are relevant scenarios on the future product portfolio to investigate?	Demand planner Product portfolio	Interviews Documents and records	List of scenarios Numerical and textual description
8. How do the improvements influence the occupancy rate in different scenarios?	Improvements Scenarios	Analysis of data	Results interpretation

1.5 Deliverables

The following deliverables are the results of this research.

- Method to optimize the occupancy rate. The main goal of this research is to optimize the occupancy rate of the DC to reach the target service level. This is based on data analysis and methods from literature.
- Influences of the optimization method on the occupancy rate for several scenarios. This aims to show the influence of the method to optimize the occupancy rate with different future product portfolios.
- List of improvement recommendations. This list might include converting pallet rackings to another type of pallet racking system.

1.6 Structure of the report

Table 6 depicts the structure of this report. The phases of the problem-solving approach are linked to the chapters of the report and the research questions.

Table 6: Structure of the report

Phase	**Chapter**	**Research question(s)**
1. Problem identification	1. Introduction 2. Current situation	1. What does the current process from inbound to outbound in the DC look like? 1.1 What is the current layout of the DC? 1.2 What is the total pallet capacity and the (target) occupancy rate in the DC? 2. What is the current product portfolio of Riedel and the characteristics of their products?
2. Solution approach	3. Literature review	3. What are the different types of pallet racking systems? 4. What factors influence the occupancy rate in a DC?
3. Solution method	4. Solution design	5. What method can be used to optimize the occupancy rate of the pallet racking systems within the DC?
4. Solution development	5. Simulations base scenario	6. What are possible improvements to the design of the pallet rackings within the DC?
	6. Scenarios of future demand	7. What are relevant scenarios on the future product portfolio to investigate? 8. How do the possible improvements influence the occupancy rate in different scenarios?
5. Evaluation	7. Conclusions and recommendations	-

2 Current situation in the DC

This chapter elaborates on the current situation in the DC by describing the current process of products through the DC and the product portfolio at Riedel. The goal of this chapter is to answer the following research questions.

1. What does the current process from inbound to outbound in the DC look like?

1.1 What is the current layout of the DC?

1.2 What is the total pallet capacity and the (target) occupancy rate in the DC?

2. What is the current product portfolio of Riedel and the characteristics of their products?

Section 2.1 describes the current process of a product's journey from inbound to outbound in the DC. Besides that, it depicts the current layout of the DC, explains the computer system used in the DC, and determines the current pallet capacity and occupancy rate of the DC. Section 2.2 determines and elaborates on the current product portfolio of Riedel. Finally, Section 2.3 concludes the findings of this chapter.

2.1 Current process DC

The different types of pallets with boxes of finished products coming from the production hall are moved to the DC on a belt. The pallets arriving in the DC are scanned automatically so that the information about the product batch is saved to the Enterprise Resource Planning (ERP) system. The ERP system sends the information about the product batch to the Warehouse Management System (WMS). One product batch is divided over multiple pallets. The number of pallets of a product batch varies from only a few pallets to hundreds of pallets. Next to the belt, a computer depicts a screen from the WMS including the batch information of the pallets currently on the belt. An algorithm behind the WMS determines where these pallets and the rest of their product batch should be stored. The WMS is further explained in subsection 2.1.2. The forklift truck employees in the DC move the pallets from the belt to the correct pallet racking, which is determined by the WMS. This part of the process is called the inbound process [69].

The planning department of Riedel together with its transportation partner schedules the transportation of pallets from the DC to their customers. One truck transports the order of one customer, so not every truck necessarily transports a full truckload. A few hours before a transportation truck arrives, the forklift truck employees place the pallets included in the order in temporary pallet rackings next to the doors. Once the truck arrives, the employees place the pallets in the truck and the driver delivers it to the customer. This part of the process is called the outbound process [69].

2.1.1 Current layout DC

A DC is a key element of a modern supply chain and therefore an efficient layout or design can reduce costs and time [4]. In this research, understanding the current layout of the DC is important to identify the current situation of the pallet capacity and occupancy rate. To map the current layout of the DC, this subsection first identifies which types of pallet racking systems Riedel has. Section 3.1 describes the types of pallet racking systems found in literature and thus also elaborates further on the pallet racking systems used at Riedel.

Figure 4 shows the current layout of the ambient part of the DC. The cooled part of the DC is out of scope, depicted in grey on the left side of the layout. Appendix A shows a larger version of this figure. Figure 5 depicts the legend of the current layout, which includes the different types of pallet racking systems in the DC.

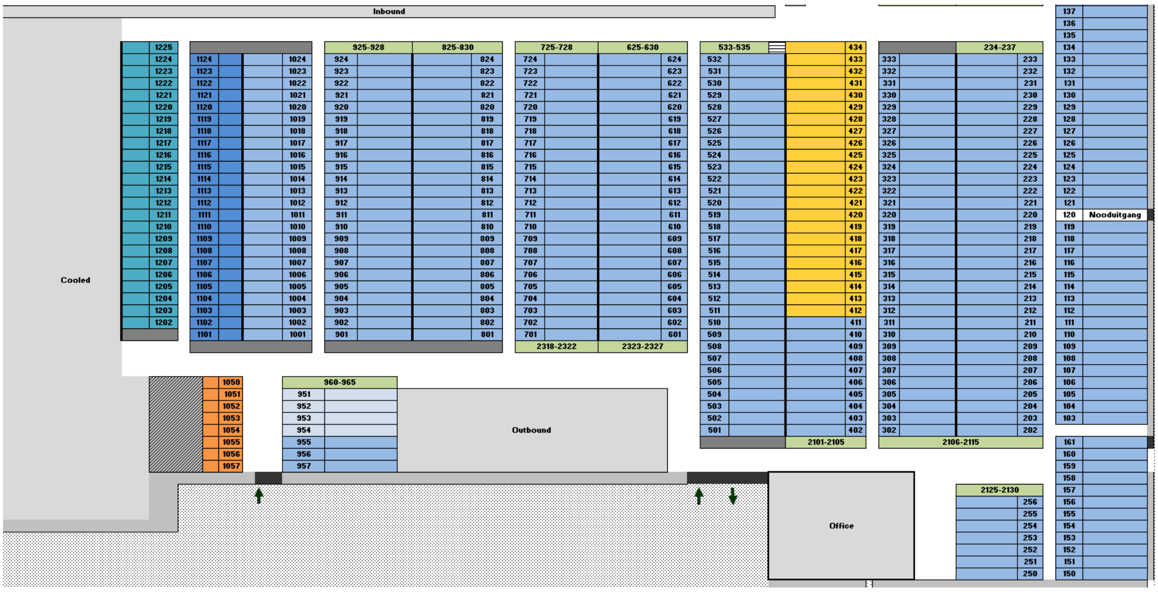

Figure 4: Current layout DC

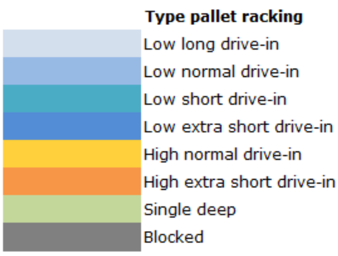

Figure 5: Legend current layout DC

The main type of pallet racking system at Riedel is the drive-in pallet racking system, depicted in yellow, orange, and four shades of blue in Figure 4. A drive-in pallet racking can hold multiple pallets behind and on top of each other on rail beams. These pallet racking systems have enough space for a forklift to move into them [74], but the pallets can only be stored and retrieved at one side of the racking. Thus, only the first pallets can be reached which limits accessibility to the other pallets. Therefore, a drive-in pallet racking requires a Last In First Out (LIFO) strategy [72]. However, Riedel applies a FIFO policy to its products to make sure that they do not exceed their best-before date. Thus, for each product type, the first products that are stocked are the first to be transported to the customer. Hence, a drive-in pallet racking can only hold one product batch at a time, thus storage is according to the type of product and production date. This means that in the case of Riedel the drive-in pallet racking system is most suitable for batches with large volumes.

The other type of pallet racking system Riedel has, is the single-deep pallet racking system, depicted in green in Figure 4. In this system, each pallet is individually reachable [46, 55]. In the DC of Riedel, the single-deep pallet rackings are standing next to the first or last drive-in pallet racking system of an aisle. These pallet racking systems are used for partial pallets and batches containing a few pallets. Subsection 2.1.2 explains this further. Some of the single-deep pallet rackings are blocked for certain operations, such as for damaged products or products that exceeded their expiration date [72]. These pallet rackings are depicted in grey in Figure 4.

The DC has six different drive-in pallet racking systems depending on the depth of the pallet racking and the height of the pallet locations. A long pallet racking has a depth of 800cm, whereas a normal pallet racking has a depth of 720cm, a short pallet racking has a depth of 400cm and an extra short pallet racking has a depth of 320cm. The difference in depth allows the WMS to place smaller batches in a shorter pallet racking so that more pallet locations are utilized. Section 2.1.2 further explains the WMS. A high pallet location has a height of 200cm, whereas a low pallet location has a height of 160cm. One drive-in pallet racking either has low or high pallet locations. However, one single deep pallet racking can have rows of low and high pallet locations mixed. For example, if the bottom row contains high pallet locations, the rows above can be low pallet locations. Figure 6 presents pictures of the different types of pallet racking systems in the DC of Riedel. From left to right these pictures depict a high drive-in, low drive-in, and single-deep pallet racking system.

Figure 6: Pictures high drive-in, low drive-in, and single deep pallet racking

Each pallet location can hold two types of pallets; block and Euro pallets. Euro pallets are slightly smaller (80x120cm) than block pallets (100x120cm). Hence, five Euro pallets can be stored in an equal space as four block pallets. Table 7 shows the number of Euro and block pallets that fit in the height and depth of the different types of drive-in pallet racking systems. Besides that, it shows the total number of Euro and block pallets that fit into the drive-in pallet racking systems. The single deep pallet racking systems do not have a fixed height and depth so they are excluded in this table. Using this information, we calculate the pallet capacity in Section 2.1.3.

Table 7: Height and depth of drive-in pallet racking systems for block and Euro pallets

<table>
<tr><th></th><th></th><th colspan="3">Number of block pallets</th><th colspan="3">Number of Euro pallets</th></tr>
<tr><th>Height pallet location</th><th>Depth pallet racking</th><th>Height</th><th>Depth</th><th>Total</th><th>Height</th><th>Depth</th><th>Total</th></tr>
<tr><td rowspan="4">Low</td><td>Long</td><td>6</td><td>8</td><td>48</td><td>6</td><td>10</td><td>60</td></tr>
<tr><td>Normal</td><td>6</td><td>7</td><td>42</td><td>6</td><td>9</td><td>54</td></tr>
<tr><td>Short</td><td>6</td><td>4</td><td>24</td><td>6</td><td>5</td><td>30</td></tr>
<tr><td>Extra short</td><td>6</td><td>3</td><td>18</td><td>6</td><td>4</td><td>24</td></tr>
<tr><td rowspan="2">High</td><td>Normal</td><td>4</td><td>7</td><td>28</td><td>4</td><td>9</td><td>36</td></tr>
<tr><td>Extra short</td><td>4</td><td>3</td><td>12</td><td>4</td><td>4</td><td>16</td></tr>
</table>

2.1.2 Warehouse management system

A WMS is used to control and manage warehouse systems which as a by-product provides data [67]. It can process data quickly and coordinate the movements within the warehouse. The main relevant advantages are real-time and remote stock visibility and traceability, accurate stock records, and minimized paperwork [56]. There is a variety of types of WMSs available which makes it hard to define such a system [72]. There is no one-size-fits-all WMS, but the type of WMS used depends on for example the size of the company and the product or service sold.

The WMS of Riedel decides on what type of pallet racking the forklift truck employees store the pallets with finished products. To make this decision, the algorithm of the WMS distinguishes between pallets based on the following characteristics [45].

- Full or partial pallet: a partial pallet is a pallet that does not have a full pallet quantity of the product [44]. To keep track of the exact location of the partial pallet, they are placed in dedicated single-deep pallet rackings. These pallets are used for picking or are combined to become a full pallet.
- Type of pallet: a pallet can be a block or Euro pallet. Some customers request to receive the finished products on Euro pallets. There are no pallet locations dedicated to a specific type of pallet. However, Euro pallets are smaller so less space is needed to store them compared to block pallets.
- Height of pallet: a pallet can be high or low depending on the type of product. Low pallets can be put in high pallet racking systems, but not vice versa [18].
- Size of pallet batch: a pallet can belong to pallet batches of varying sizes. If the batch size is small, the pallet is placed in a short pallet racking. If the batch size is even smaller, the pallet should be placed in an extra short pallet racking. If

the batch consists of just a few pallets, the pallet is placed in a single deep pallet racking. The definition of small depends on the height and type of the pallet, as Table 7 shows. If a batch does not fit the assigned drive-in pallet racking exactly, the number of remaining pallet(s) is seen as the batch size. For example, if a batch contains 44 low block pallets, the WMS can assign 42 pallets to a normal drive-in pallet racking and the other two pallets to a single deep pallet racking.

After the WMS decides on the type of pallet racking, it decides on the exact pallet location to store the pallet. This is based on the ABC classification of the product. This classification categorizes the products by volume and frequency of sales [56]. Category A contains fast-moving, category B medium-moving, and category C slow-moving products. The WMS uses class-based storage with regard to the ABC classification [30]. It divides the DC into sections dedicated to category A, B, and C products. Category A is closer to the inbound and outbound than category B and category B is closer to the inbound and outbound than category A.

Once a forklift truck employee moves a pallet from one pallet racking to another, the employee registers this in the WMS. This ensures an up-to-date WMS that always has real-time data on the location of each pallet in the DC. Each time the location of a pallet gets updated, the WMS sends this information to the ERP system.

2.1.3 Current pallet capacity and (target) occupancy rate

The current layout of the DC provides a total pallet capacity of 14,121 block pallets or 18,069 Euro pallets. The pallet capacity is equal to the total number of pallet locations available and is divided over the seven different types of pallet racking systems. Table 8 presents the number of pallet racking systems, block pallet locations, and Euro pallet locations for each pallet racking system type. The number of single-deep pallet rackings does not include the ones that are blocked or dedicated for storing partial pallets because they are out of scope, as described in Subsection 1.4.1.

Table 8: Number of pallet rackings and locations per pallet racking system type

Pallet racking system	Pallet rackings	Block pallet locations	Euro pallet locations
Low long drive-in	4	192	240
Low normal drive-in	283	11,886	15,282
Low short drive-in	24	576	720
Low extra short drive-in	24	432	576
High normal drive-in	23	644	828
High extra short drive-in	8	96	128
Single-deep	59	295	295
Total	**440**	**14,121**	**18,069**

The occupancy rate of a DC is the percentage of storage capacity utilized. Using the data over the past two years, we calculate the occupancy rate. The target occupancy rate is the desired maximum percentage of locations that are occupied in DC. The planners must ensure that the actual occupancy rate does not exceed this. The target occupancy rate is determined to be 74.4% block and 58.1% Euro pallets because experience shows that to stay productive a maximum of 10,500 pallet locations are allowed to be occupied [49]. Block pallets are the main type of pallets stored in the DC with a ratio of 9 to 1 because only a few customers request Euro pallets. Therefore, the target occupancy rate is set to 72.8% by using the following formula.

$$Occupancy\ rate = 0.1 * Euro\ occupancy\ rate + 0.9 * Block\ occupancy\ rate$$

Figure 7 depicts the pallet inventory and occupancy rate over the past two years. Besides that, it shows the pallet capacity and target maximum occupancy rate. An occupancy rate of 100% is equal to the total pallet capacity. Some data points are missing in the graph because on those days the inventory level was not measured. At the start of the graph in May 2022, the occupancy rate was relatively low because it was just after Pentecost and Ascension Day. After May the occupancy rate increased again until summer. During the summer of 2022, the occupancy rate decreased slightly and then increased again until Ascension Day. Riedel wanted to make sure that the inventory would be sufficient to cope with the demand during the holidays.

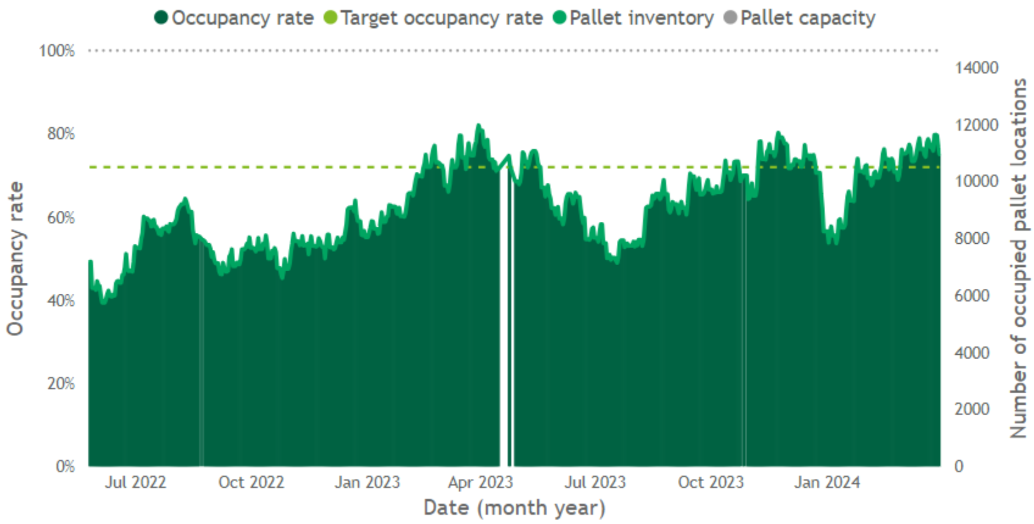

Figure 7: Pallet inventory, capacity and (target) occupancy rate

As Subsection 1.2.1 shows, the service level after Pentecost and Ascension Day decreased just as much in 2023 as in 2022. However, in 2023 it increased faster during summer than in 2022. This might be explained by the higher occupancy rate during summer in 2023 than in 2022. It was even so high that the occupancy rate exceeded the target in November and December of 2023. There was a huge drop in the occupancy rate after that because Christmas was on Monday and Tuesday so the factory was shut down and the same problem occurred as after Pentecost and Ascension Day. However, towards the end of the graph, the occupancy rate increased again to cope with the demand during Pentecost and Ascension Day.

2.2 Current product portfolio Riedel

The product portfolio of a company is the collection of the products that the company offers to its customers. A Stock Keeping Unit (SKU) represents the smallest physical unit of a product [39]. They are completely specific as to function, style, size, color, and location. Offering a wide variety of SKUs raises the complexity levels in internal processes of companies, such as within their inventory system [68]. Therefore, it is crucial in this research to identify the product portfolio. The inventory policy of the SKUs is influenced by their characteristics [68]. Hence, this subsection also identifies the characteristics of the SKUs within the product portfolio.

The information on the characteristics of the SKUs is based on the master data of Riedel. We use the master data because it is not changed over a longer period and the main warehouse functions and control mechanisms are based on it [72]. The characteristics included in this research consist of the product description, product code, pallet type, ABC classification, and pallet height. Figure 8 shows the first ten SKUs of the ambient product portfolio list sorted on the product code.

Product description	Product code	Pallet type	DC type	ABC classification	Pallet height
TK Tropisch Fruit GST 1,5L PK DS8	004285	Block	Ambient	A	Low
AS Zontomaat 1L PK DS8	004720	Block	Ambient	B	Low
AS Tomaat-Groentesap 1L PK DS8	004721	Block	Ambient	B	Low
AS Bio Appel/Mango 0,75L PK DS6	005001	Block	Ambient	C	Low
AS Bio Appelsientje 0,75L PK DS6	005003	Block	Ambient	C	Low
Extran Performance Lemon 0,5L PET TR6	005020	Euro	Ambient	B	High
Extran Performance Orange 0,275L Pet TR12	005042	Euro	Ambient	B	High
Extran Performance Orange 0,5L Pet TR6	005044	Euro	Ambient	B	High
Extran Performance Blueberry 0,5L Pet TR6	005045	Euro	Ambient	B	High
DF Appel-Perzik 0,5L Pet TR6	005046	Euro	Ambient	B	High

Figure 8: Product portfolio, first ten SKUs

The product portfolio is based on a list of the ambient SKUs having demand over the years 2023 and 2024. The complete list includes 380 SKUs, but the list also includes SKUs that are not in the product portfolio anymore. We consider the SKUs from the list that are currently in the product portfolio and meet the following criteria.

- Select the SKUs that had demand in every week of 2024 until the current week (week 10).
- Select the SKUs that are currently in stock.
- Select the SKUs that have demand after the current week.
- Delete the SKUs that do not have any demand in 2024.
- Delete the SKUs that are canceled according to the ERP system.

This resulted in a product portfolio of 287 ambient SKUs in March 2024. Based on previous research, in September 2019 there were 132 ambient SKUs [57]. Thus, the ambient product portfolio of Riedel consists of more than twice as many SKUs as 4.5 years ago. From this product portfolio, 59% of the products are stored on a block pallet, whereas 41% on a Euro pallet. This means that more products are stored on block pallets, but does not indicate which type is used more often because the products have a variety of demand. Additionally, 87% of the products are low pallets, whereas 13% are high pallets. This ratio does not indicate that 13% of the pallet locations should be high but, the ratio is somewhat in line with the percentage of high drive-in pallet locations, which is 5.4%.

2.3 Conclusion

This chapter answers research question *'What does the current process from inbound to outbound in the DC look like?'*, its sub-research questions, and research question *'What is the current product portfolio of Riedel and the characteristics of their products?'* by elaborating on the current situation in the DC.

The current layout of the DC results in the identification of five different drive-in pallet racking systems with different heights and lengths. Additionally, Riedel uses the single-deep pallet racking system. In the pallet racking systems, the pallets coming from production are stored until they are transported to the customers. The system managing and recording the activities within the DC distinguishes between pallets based on four characteristics. The layout of the DC provides a total pallet capacity of 14,121 block pallets or 18,069 Euro pallets divided over the six different types of pallet racking systems. This total pallet capacity together with the data on the pallet inventory over the past two years results in a graph indicating the occupancy rate over time. To stay productive, a maximum of 10,500 pallet locations are allowed to be occupied so the target occupancy rate is set to 72.8%. Finally, this chapter identifies the product portfolio based on the demand over 2023 and 2024. The product portfolio consists of twice as many SKUs as 4.5 years ago indicating a growing product portfolio with an increasing variety of SKUs.

3 Literature review

This chapter collects relevant research and existing knowledge about the operations in a DC. The first main topic of this chapter is the types of pallet racking systems since that is the major object in a DC that handles pallets. The second main topic of this chapter is the occupancy rate because it is crucial for this research to identify the factors that influence the occupancy rate so that the optimal maximum occupancy rate can be determined. Therefore, the goal of this chapter is to answer the following two research questions.

3. What are the different types of pallet racking systems?

4. What factors influence the occupancy rate in a DC?

Section 3.1 elaborates on the different types of pallet racking systems and explains ways of automatically storing and retrieving the pallets from the pallet rackings. Section 3.2 defines the occupancy rate, explains how to determine the occupancy rate, discusses the influences on the occupancy rate, and elaborates on storage capacity and requirements in a DC. Then, Section 3.3 discussed methods to solve the warehouse capacity and design problem. Finally, Section 3.4 concludes the findings of this chapter.

3.1 Types of pallet racking systems

The DC of Riedel stores pallets containing the finished products in pallet racking systems. These systems are the most common type of pallet storage [72]. This section determines the different types of pallet racking systems found in the literature. Moreover, it explains three types of automatic storage and retrieval systems.

3.1.1 Single- and double-deep pallet racking system

Pallet racking systems are single-, double-, or multi-deep depending on the depth of the pallet racking system in terms of the number of pallets that can be stored behind each other. Figure 9 shows the difference between a single- and double-deep pallet racking. A single-deep pallet racking, also known as selective pallet racking, stores pallets one deep, so each pallet is independently accessible [6]. Thus, an SKU can be retrieved from any pallet location at each level of the pallet racking. This allows space sharing among SKUs within one pallet racking and therefore requires fewer total storage locations than other pallet racking systems [17]. However, it provides the lowest density storage since it requires relatively more aisle space to access the pallets compared to other pallet racking systems [6, 17]. This type of pallet racking system is often used in the retail and manufacturing industry because of the wide variety of products and the system supports smooth production flows.

A double-deep pallet racking consists of two single-deep racking systems placed behind each other, so the pallets are stored two deep [6]. Each two deep lane is independently accessible, but one lane should be filled with a single SKU. However, a double-deep pallet racking generally saves 50% aisle space in comparison with a single-deep pallet racking [42]. This pallet racking system is often used in wholesale where product batches are larger than in the retail and manufacturing industry.

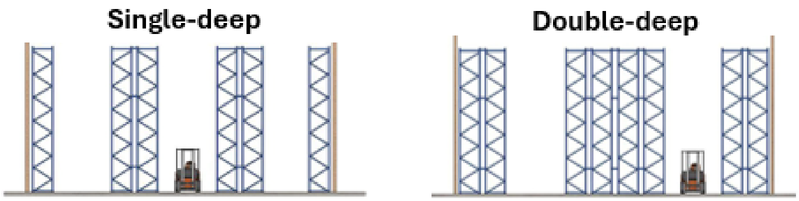

Figure 9: Single- or double-deep pallet racking [70]

3.1.2 Multi-deep pallet racking systems

If a pallet racking system consists of more than two lanes it is called a multi-deep or compact pallet racking system. These pallet racking systems are increasingly popular because they provide a solution to the space and storage density problems [55]. This is because a multi-deep pallet racking system only requires a single access aisle for the forklift trucks to reach multiple rows of pallet locations [59, 74]. Thus, part of the space that a single- or double-deep pallet racking uses for aisles is saved. However, a disadvantage is that only the foremost pallet of a lane can directly be accessed [9]. Therefore, in practice often every storage lane in a pallet racking system stores one SKU [83]. Multi-deep pallet racking systems are often used in cases where high utilization of space is required, such as in refrigeration and freezing cold controlled spaces [55, 72]. Moreover, they are often used in the beverage industry to store large quantities of similar products. Eventually, this means that the selection between a single-, double-, or multi-deep pallet racking system is a trade-off between storing a higher number of SKUs or a higher volume per SKU. There are numerous types of multi-deep pallet racking systems of which the following are explained below: drive-in, drive-through, push-back, gravity flow, and mobile pallet racking systems.

Drive-in and drive-through pallet racking systems
A drive-in or drive-through pallet racking system allows a forklift truck to drive within the racking frame to access the pallets [6]. As explained before, each level of each lane must be devoted to a single SKU to avoid reshuffling. Reshuffling is removing pallets that block the exit for another pallet that needs to be retrieved [55]. Figure 10 shows the difference between a drive-in and a drive-through pallet racking. In a drive-in pallet racking system the forklift trucks can only enter the lanes at the front [55]. Thus, the pallets are stored at and retrieved from the same side [72]. This means that a drive-in pallet racking system requires a LIFO strategy to avoid reshuffles. Hence, this type of pallet racking is mainly used for the storage of SKUs with large volumes where accessibility to a particular pallet has a low priority [26]. In a drive-through pallet racking system the forklift trucks can enter the lanes at the front and back. Thus, the pallets are stored and retrieved on opposite sides. This results in a FIFO strategy, but the pallets cannot be transferred within the aisles [72]. The disadvantage of a drive-through pallet racking system in comparison to a drive-in pallet racking system is the use of an extra aisle.

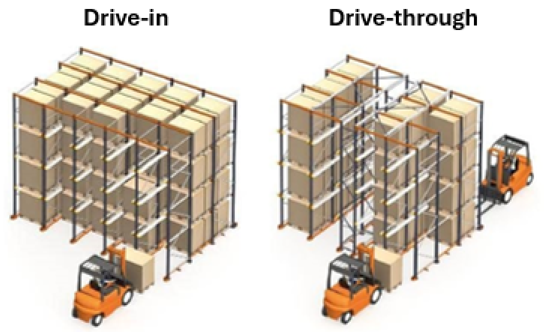

Figure 10: Drive-in versus drive-through pallet racking [47]

Push-back pallet racking system
In a push-back pallet racking system, the pallets are stored on a cart that is able to roll. Thus, one pallet can push back the pallets already stored in the pallet racking. If the front pallet is removed, the pallet behind it rolls forward. A push-back system is an extension of a double-deep system to three to five pallet positions with at the same time the possibility to access the inner pallets [6]. Thus, each lane at any level is independently accessible, but the pallets within one lane are not.

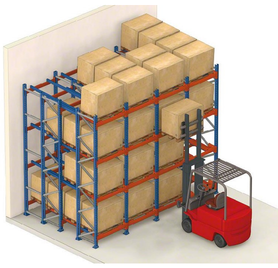

Figure 11: Push-back pallet racking [79]

Gravity flow pallet racking system
In a gravity flow pallet racking system, the metal shelves are equipped with rollers or wheels that move the items by using gravity force [31]. The pallets are stored on one side but retrieved on the other side since they roll there themselves. Therefore, gravity flow systems support the FIFO discipline so they are suitable for dated goods that have a best-before date [17]. This also means that it requires a front and back aisle, just like a drive-through pallet racking system. But implementing this system compared to a drive-through pallet racking system potentially reduces travel by forklift trucks, because the pallets move themselves to the other side of the pallet racking [17, 65]. The storage depth is usually limited to about eight pallets because of weight considerations [6]. Nevertheless, the use of gravity conveyors in the design is associated with danger [65].

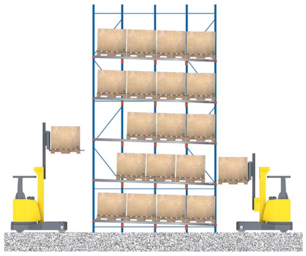

Figure 12: Gravity flow pallet racking [71]

Mobile pallet racking system

In a mobile pallet racking system, an engine moves aside neighboring rackings to open the aisle of the SKU that has to be retrieved [9]. This increases the space utilization by providing only a few open aisles. Besides that, an SKU can be retrieved from any pallet location at each level of the pallet racking, just like in a single-deep pallet racking system. However, it may be that many adjacent pallet racking systems have to be moved so that an aisle is created which takes a significant amount of time [77].

Figure 13: Mobile pallet racking system [38]

3.1.3 Automatic storage and retrieval systems

There are two ways to operate pallet racking systems, manually with forklift trucks or using an automated alternative [55]. To increase the throughput of warehouse operations, companies often use an automated storage and retrieval system (AS/RS), autonomous vehicle storage and retrieval system (AVS/RS), or shuttle-based storage and retrieval system (SBS/RS) [65]. These three types of automated storage and retrieval systems are explained below.

Automated storage and retrieval system

An AS/RS usually consists of racks served with cranes running through aisles between the racks, so it can handle pallets without an operator [61]. Thus, forklift truck employees are not needed anymore. Implementation of such a system represents a major corporate investment but provides a fast, accurate, and efficient handling of materials [23]. Therefore, effective use will reduce direct and indirect labor, energy, maintenance, and building costs [66].

Autonomous vehicle storage and retrieval system

An AVS/RS is an applicable alternative to AS/RS. AS/RS cannot easily adapt to rapid changes in warehouse operations, but AVS/RS are more flexible because vehicles can access any aisle [34]. In an AVS/RS, autonomous vehicles can move independently to handle pallets between the inbound, pallet racking systems, and the outbound [75]. Besides the vehicles, this system needs a lift for vertical movements [82]. Each aisle has a single lift, so it mostly becomes the bottleneck [16].

Shuttle-based storage and retrieval system
A more affordable storage and retrieval system is the SBS/RS. This system makes use of shuttles, which are flat, electric-driven platforms [8]. The shuttle automatically moves the pallets in and out of the multi-deep pallet racking systems [42, 80]. Outside of the pallet racking systems, forklift trucks take care of the movements of pallets. The number of shuttles is typically smaller than the number of pallet racking systems since they are expensive. Thus, the forklift trucks need to transfer the shuttles between lanes [80]. An SBS/RS can achieve a high throughput that a double-deep pallet racking can achieve but a multi-deep normally cannot [52]. Therefore, these systems are widely used in warehouses that require dense storage with high efficiency [80]. This efficiency is reached because each lane can store a unique SKU, but the LIFO strategy is still needed [52].

3.2 Occupancy rate

The previous section determines the types of pallet racking systems in a DC. Now, the missing knowledge is the number of pallets that can be stored in these pallet racking systems. Therefore, this section defines the occupancy rate and determines the factors that influence the occupancy rate of certain types of pallet racking systems. The occupancy rate is represented by the average volume of products stored throughout the year [76]. In this research, the occupancy rate is defined as follows [6, 72, 73].

$$Occupancy\ rate = \frac{Number\ of\ occupied\ pallet\ locations}{Total\ pallet\ capacity}$$

Much research has been conducted on optimizing space within warehouses or DCs. However, the occupancy rate is a less studied topic. Researchers use many different terms to define the occupancy rate, such as storage efficiency and space utilization. However, most studies about optimizing warehouses focus on the design or operations in the warehouse, such as Karásek [39]. The author determines the optimal technical and operational structure and explains the typical operations in warehousing. Moreover, Revillot-Narváez et al. determine a tool for improving the performance of storage and retrieval systems [55]. Additionally, Hudock focuses on the distribution of space in the warehouse [36]. Nevertheless, some researchers also focus on the occupancy rate, storage efficiency, or space utilization in the way presented in this research, such as Kimball [40], Frazelle [21, 22], and Richards [56].

3.2.1 Relationship productivity and occupancy rate

One of the main reasons to optimize a warehouse is to ensure productivity [39]. The formal definition of productivity is the ratio of the output of an entity to the resources consumed to achieve that output, whereas space productivity is defined as the ratio of the amount of inventory storage capacity to the square footage in the warehouse

[22]. The higher the storage capacity, the higher the space productivity. However, the maximum storage capacity depends on the available space in the warehouse. Productivity and utilization are not equal to each other. One of the main differences between them is that we always want to maximize productivity, but utilization has appropriate control limits [22]. Figure 14 shows the relationship between productivity and occupancy. Here, with productivity, we mean the labor productivity. Thus, the ratio of orders shipped out of the warehouse divided by the number of person-hours spent in operating the warehouse [22].

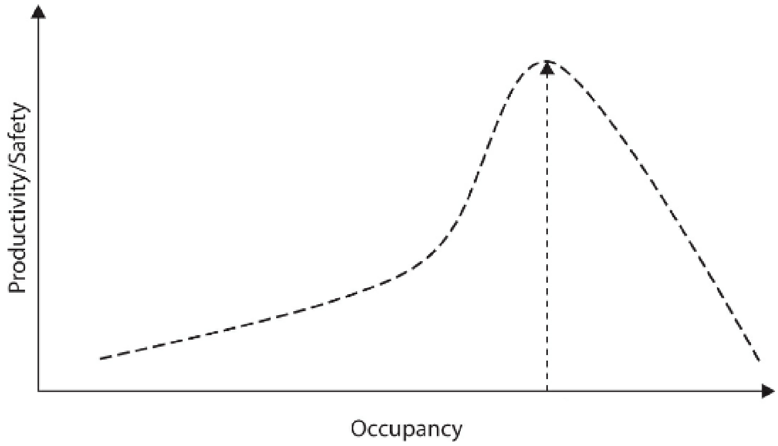

Figure 14: Productivity versus occupancy in warehouses [22]

According to ten Hompel and Schmidt, at an occupancy rate below 80%, a large part of the warehouse is not optimally occupied [72]. This results in unnecessary costs for unneeded storage or demand that cannot be met. Therefore, companies want to increase the occupancy rate to maximize the number of pallets stored in their DC and therefore increase productivity. However, if the occupancy rate exceeds a certain threshold, the productivity and safety of the operations in the warehouse decline dramatically. The arrow in Figure 14 shows this threshold, the maximum optimal occupancy rate to still be productive. Attempting to increase the space utilization beyond the threshold leads to the emergence of bottlenecks in the process of storing and retrieving pallets in the DC [56]. In other words, an occupancy rate beyond the threshold results in more person-hours per order shipped out of the warehouse because of bottlenecks within the warehouse process. Nonetheless, many managers are uncomfortable with a warehouse that is not full, but a warehouse that is full all the time is also not desirable [7].

Companies should determine the threshold to find a balance between storage utilization and productivity. However, there is not much research about how to determine this threshold. Kimball introduces 'effective utilization' as the storage level that can be maintained as a percent of total capacity without degrading productivity and throughput [40]. His case study proved that a high occupancy rate requires more personnel and forklift trucks. While determining the storage capacity of a DC, a company should take into account the storage utilization factor to allow for additional pallet locations. These pallet locations should be added on top of the pallet inventory to cope with fluctuations in inventory and honeycombing. Honeycombing is the loss of space because of the creation of empty but unusable storage locations [6]. The term 'honeycombing' is used because the pallets can resemble a honeycomb pattern, with irregular empty spaces in between items [64]. These empty spaces could be due to a difference in the batch size and the number of pallet locations in one lane.

3.2.2 Factors influencing the occupancy rate

To find a balance between storage utilization and productivity, this subsection determines the factors that influence the occupancy rate. The following factors are explained below: type of pallet racking system, product portfolio, and storage policy.

Each type of pallet racking system has a different storage utilization factor and thus a different maximum occupancy rate. This is because honeycombing is more common in some types of pallet storage systems than others. Section 3.2.1 refers to honeycombing as the loss of space because of the creation of empty but unusable storage locations. Storing one batch of pallets in multi-deep lanes increases honeycombing [14]. When only one SKU can be effectively stored in a lane, empty pallet locations are created, which cannot be utilized until the entire lane is emptied [73]. Thus, many lanes are only partially filled at some point through the storage process [53]. Therefore, every DC must have extra pallet locations to cope with honeycombing. The more honeycombing occurs, the fewer pallet locations are occupied, the lower the occupancy rate is. An SBS/RS, as explained in Section 3.1.3, can partially solve honeycombing in a multi-deep pallet racking system because it ensures that each lane can store a unique SKU. The deeper and higher the row, the higher the probability of not utilizing pallet locations. Thus, the more pallet locations per pallet racking lane, the lower the occupancy rate can be to still have a high labor productivity in the DC. For a single-deep pallet racking, Kimball recommends 90% utilization at peak inventory levels [40]. For double- and multi-deep storage, the effective utilization differs depending on the number of pallet locations in a storage lane. According to Kimball, these pallet racking systems have a storage utilization factor below 80% [40].

The type of pallet racking system alone is not sufficient to determine the threshold of the occupancy rate. A single-deep pallet racking system ensures high accessibility to the pallets, whereas a multi-deep pallet racking system can store high volumes of pallets. Therefore, the product portfolio of a company majorly influences the occupancy rate in a DC. At any time, a DC should have sufficient empty pallet racking systems to provide storage space for incoming SKUs [15]. When the SKU variety is high, more and smaller pallet rackings are needed, whereas when the SKUs have a high volume, less and larger pallet rackings are needed. Thus, the combination of the type of pallet racking system and the product portfolio should match.

The storage policy also influences the occupancy rate since some types of storage policies have a lower occupancy rate than others. Dedicated storage requires more pallet locations than class-based storage, and class-based storage requires more than randomized storage [28]. In a dedicated storage policy, each product has a particular location, whereas a random storage policy leaves the decision to the WMS [62]. In between these two policies is class-based storage, where zones are allocated to certain product groups. The space requirements increase with the number of classes or the number of SKUs dedicated to a specific area of the DC [28]. However, it has many advantages to store related products together, such as products from the same shipment or products that are often requested together [60]. This reduces travel and search time for the forklift truck employees. Therefore, the trade-off between the occupancy rate and storing products together should be made. As mentioned in Section 2.1.2, the DC of Riedel uses the ABC classification, so it concerns class-based storage.

3.2.3 Storage capacity and requirements

If a company needs more pallet locations in its DC but the maximum occupancy rate cannot be increased, the total pallet capacity should be increased. In addition to honeycombing, aisles also contribute to the overall wasted space because they are not directly used for storage [14]. Under shared storage, space utilization increases with additional storage locations and fewer aisles, but at a diminishing rate [6]. Eventually, aisles are needed to provide access to stored pallets so a designer should reduce aisles to their minimum [64]. A company should determine the required storage capacity taking into account their product portfolio, type of pallet racking system, storage utilization factor, and type of storage policy. The space required is often based on the desired production rate, which is determined by the operational planner [19]. The production rate is determined by the demand from the customers [19].

The total storage capacity could be based on the average inventory or peaks in business. To determine the average inventory level of an SKU, it is important to understand the characteristics and size of the demand, including seasonality and variety within the product portfolio [62]. When basing it on the peaks in business, the company should determine what portion of the peak to accommodate with the storage capacity. Frazelle determines two scenarios [22]. In the first scenario, the peak in storage demand is short-lived, so less than half a year. Moreover, the peak-to-average storage ratio is high, so the storage demand during the peak is at least five times as high as the average demand. The solution for such peaks is an outside warehouse or trailer storage to accommodate the peak. This causes temporarily more storage space. In the second scenario, the peak in storage demand is for an extended period, so more than half a year. Moreover, the peak-to-average storage ratio is low, so the demand during the peak is at most two times as high as the average storage demand. In this scenario, the storage capacity should be at or very near the peak requirements.

Determining the storage capacity and size of a warehouse can affect the overall operations of a company for many years [37]. A company cannot easily change the size or layout of a warehouse overnight. Thus, once the size of the warehouse is determined, it will act as a constraint that may last for a long period [25]. If the storage capacity is insufficient, the company can lease space from a public warehouse which is often less expensive than expanding their warehouse or DC [54].

3.3 Methods on warehouse capacity and design

This section positions the warehouse design problem of this research within the current literature and identifies methods to solve it. Section 3.3.1 positions this research within the literature and discusses studies of warehouse capacity and design. A warehousing problem can be solved exact or using a heuristic, depending on the complexity and size of the problem. These two approaches are discussed in Section 3.3.2 and Section 3.3.3.

3.3.1 Warehouse capacity and design studies

Rouwenhorst et al. [62] presents a framework of warehouse design and control problems. Figure 15 depicts the design process as a sequential approach with three levels: strategic, tactical, and operational. The green box presents the positioning and scope of this research within the framework. On the one hand, it is placed in the 'Selection types of technical systems' within the strategic level because it includes decisions concerning the selection of the types of storage systems. On the other hand, it is placed in the 'Dimensioning of the storage system' within the tactical level because it determines the sizes of the storage systems and thus the storage capacity.

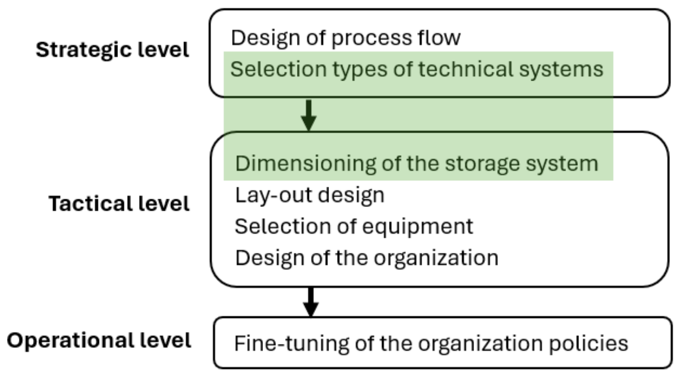

Figure 15: Framework warehouse design problems [62]

According to Gu et al. [29], there are two scenarios during determining the storage capacity: the warehouse has no direct control over the inventory levels and the warehouse can directly control the inventory policy. In this research, the demand is uncertain and thus stochastic, so the warehouse does not have direct control over the inventory levels. Therefore, the model should not take into account the inventory policy and costs. However, it should take into account managing the multiple product inventory over the time horizon by allocating the pallets containing the products to storage locations. Hausman et al. [32] refers to the allocation of pallets as 'storage assignment'. Multiple researchers have studied the storage assignment problem. However, only a few incorporate the specific characteristics of drive-in pallet racking systems, such as storing one batch in a pallet racking at a time. Besides managing the multiple product inventory, the main goal of the model is identifying the capacity of the storage system with multiple racking options with varying capacities. This combination of allocating items and finding a configuration of storage systems is uncommon.

Mital et al. [48] develop a model to design a warehouse deciding on the number of aisles, columns, and rows to minimize the cycle and travel time for handling the pallets. It includes the management of storing all inventory, but can only select one pallet racking size. Accorsi et al. [2] develop a model that identifies the optimal configuration of lane depths and storage modes, thus can select different racking sizes. Moreover, the model allocates incoming product batches to the optimal lane, depth, storage mode, and zone. However, the storage system studied is block stacking, which is less complex than drive-in pallet rackings when allocating pallets. Goetschalckx and Ratliff [27] also identify the optimal lane depth in block stacking storage systems to maximize space utilization. Gebennini et al. [24] does include pallet rackings when assigning items to the optimal type of lane. However, the model assigns an item to one lane type for the entire time horizon.

3.3.2 Exact approach

Warehousing problems can be solved using an exact method, such as linear programming and branch-and-bound. It optimally solves the problem and with complete accuracy. Geraldes et al. [25] concluded that for large instances the computational time increases considerably.

The most common exact approach found in literature is the I(L)P method. This method develops an I(L)P model and solves it using a solver. Accorsi et al. [2] validate their ILP model by using a case study. Additionally, Gebennini et al. [24] use a mathematical program solver in their case study. Another exact approach is dynamic programming where subsets of the problem are optimized. Goetschalckx and Ratliff [27] develop a dynamic programming algorithm by assuming that the number of lanes is at most equal to the number of stacks.

3.3.3 Heuristic approach

If a problem is NP-hard, finding a polynomial optimal algorithm is impossible [43]. To cope with NP-hard problems, researchers use heuristic algorithms instead of solving the problem exact. The disadvantage of these methods is that they cannot guarantee an optimal solution [43].

Besides using dynamic programming, Goetschalckx and Ratliff [27] also provide heuristics to solve the problem considering more instances. These solve the problem in a fast and efficient way. Additionally, Mital et al. [48] propose an algorithm to identify all Pareto-optimal configurations and find a trade-off between the objectives according to the problem owner. Their final selection decision is made based on the Pareto graph and other considerations. Since the future demand is uncertain, they set up scenarios to capture this.

According to Yener and Yazgan [81], studies on warehouse design often use the simulation technique in combination with other techniques, such as mathematical models and heuristic algorithms. For example, Pan et al. use a simulation model to implement the proposed heuristic algorithm, validate the performance, and compare the results generated by the simulation model [50]. It ensures that different input settings of the real-world problem are tested within the theoretical environment.

There are two types of heuristic algorithms: construction and improvement algorithms. A construction algorithm starts with an empty solution and adds elements until a solution is found, whereas an improvement algorithm starts with an initial solution and iteratively improves it. A construction algorithm allows getting solutions in a simple and fast way, while satisfying the existing set of constraints [63]. The goal of such an algorithm is mainly to find a solution fast, the quality of the solution cannot be guaranteed. Contrarily, an improvement algorithm seeks to find a near-optimal solution. A candidate solution can for example be constructed by inserting or deleting items from the previous solution [12]. The candidate solution is then evaluated based on the objective to be improved.

Local search algorithms converge to a local optimum, the best solution within a neighborhood where no improvement is possible anymore [13]. To exit the local optimum and reach the global optimum, an algorithm should climb uphill by moving to worse neighbors. Simulated Annealing (SA) is considered an extension of a hill-climbing algorithm that consists of transitions across solutions while improving an objective function [3]. The concept of SA was introduced in 1983 by Kirkpatrick et al. [41]. It is one of the most studied metaheuristics, which are known for compromising between the quality of the solution and the execution time [20]. A metaheuristic balances intensification and diversification to not get stuck in a local optimum. SA does this by starting with a high temperature that ensures a higher acceptance of worse neighbors. Then, the temperature is lowered as the search progresses and fewer worse neighbors are accepted [10]. To achieve this within SA, it is crucial to appropriately set the temperature parameter [20].

3.4 Conclusion

This chapter answers research question *'What are the different types of pallet racking systems?'* and research question *'What factors influence the occupancy rate in a DC?'* by collecting relevant research and existing knowledge about the operations in a DC.

The first section of this chapter determines that pallet racking systems can be single-, double-, or multi-deep depending on the number of pallets that can be stored behind each other. The selection between these three is a trade-off between storing a higher number of SKUs or a higher volume per SKU. A single- or double-deep pallet racking system is more suitable for a product portfolio with a larger variety of SKUs since each pallet is independently accessible. Contrarily, a multi-deep pallet racking system is more suitable for a product portfolio with higher volumes for each SKU since it has a higher storage density. There are different types of multi-deep pallet racking systems, each with different advantages and disadvantages. Examples are fewer aisles, the choice between a FIFO or LIFO strategy, pallet accessibility, and safety concerns. There are two ways of operating the pallet racking systems, manually with forklift trucks or using an automated alternative. The implementation of an automated system involves major investment costs but increases efficiency.

The second section of this chapter defines the occupancy rate, also named storage efficiency or space utilization. Compared to the optimization of space within the DC, the occupancy rate is a less studied topic. One of the main reasons to optimize a warehouse is to ensure productivity. However, productivity and utilization are not equal to each other since utilization has appropriate control limits. A low occupancy rate results in unnecessary costs, but an occupancy rate that exceeds a certain threshold results in productivity declining dramatically. Research shows that extra pallet locations should be added on top of the pallet inventory to cope with fluctuations in inventory and honeycombing. The main factors influencing the occupancy rate in a DC are the type of pallet racking system, product portfolio, and storage policy. Riedel uses a class-based storage policy. When the occupancy rate cannot be increased, a company needs to increase the storage capacity. The storage capacity could be based on the average inventory or peaks in business, which depends on the length of the peak in business and the peak-to-average ratio. If the storage capacity is insufficient, a company can lease space from a public warehouse.

The third section finishes by positioning the problem within the current literature and elaborating on methods used in literature to solve warehouse capacity and design problems. The problem is placed on both a strategic and tactical level within the framework of Rouwenhorst et al. [62]. The problem concerns managing the multiple product inventory over a time horizon by allocating the pallets containing the products to storage systems that are identified from multiple racking options with varying capacities. Depending on the complexity and size, a problem can be solved exact or using a heuristic. Exact methods, such as using a solver on the I(L)P model and dynamic programming, are used to find the optimal solution. These methods become complex when increasing the size of the instances. Then, heuristic approaches are suggested.

4 Solution design

This chapter creates a detailed plan of how to reach the goal of this research, optimizing the percentage of utilized pallet positions in the DC. The type of pallet rackings currently in the DC does not match the increasing SKU variety of the product portfolio, thus this chapter designs a solution approach to find a configuration of pallet rackings with the best trade-off according to the problem owner. It explains the components such as input, output, and method. This chapter answers the following research question.

5. What method can be used to optimize the occupancy rate of the pallet racking systems within the DC?

Section 4.1 determines the assumptions made. Section 4.2 presents the problem statement including the notations, decisions, objective function, and constraints of the mathematical model. Section 4.3 describes the improvement heuristic used as a method to find an efficient pallet racking design. It derives the input data, determines the initial solution, explains the specific method used, discusses the approach to finding candidate solutions and elaborates on how to generate the objective value by explaining the inventory management. Section 4.4 validates the heuristic by comparing the output of algorithm 3 with the performance in the real world. Finally, Section 4.5 concludes the findings of this chapter.

4.1 Assumptions

This research assumes the following.

- Products are retrieved on a FIFO basis.
- We assume that the historical inventory data is an indication of future storage demand. The scenarios in Chapter 6 show possible future settings that represent a simulation of how the real world could develop.
- The dates that are missing in the input inventory data are skipped. This is assumed to not have a significant impact on the overall performance.
- The pallet rackings holding partial pallets or pallets in repair, such as pallets with leaking boxes, are not considered because these pallet rackings are reserved for these pallets and do not hold regular inventory.
- The current configuration of pallet rackings serves as the initial solution. This assumes that it is a good starting point to optimize.
- The exact location of where the pallets are stored is not taken into account, only the type of pallet racking. In the real world, the WMS considers allocating fast-movers closer to the inbound and outbound than slow-movers.
- The real-world sequence of inbound and outbound pallets is not considered since the input data does not include the time stamp of the arrival and departure of pallets. Therefore, the inbound pallets arrive first so that the outbound pallets

departing on the same date are placed in the pallet rackings. After the outbound process, the pallets still on the belt are still allocated to pallet rackings if possible.

- The required storage capacity is solely based on the storage demand. However, other factors also influence the storage capacity, such as raw material supply, labor availability, and equipment accessibility.
- The number of high normal and high extra short drive-in pallet rackings are kept the same as the initial configuration.

4.2 Problem statement

This section develops a mathematical model to formulate the problem of this research. This research considers the problem of selecting the types of storage systems and determining their sizes for a DC. For this, we include managing the inventory of pallets to the storage systems. The objective of the model is to minimize the inbound pallets that cannot be placed in inventory while maximizing the available pallet locations of the storage systems, and minimizing the additional required floor space. The DC has multiple types of pallet racking systems, each with a different capacity and floor space. The inbound pallets are divided over batches that need to be stored over a given time horizon. Each pallet racking system can only store one batch at a time because Riedel retrieves the products on a FIFO basis. The model must decide on the following.

1. The number of pallet racking systems of each type, which is fixed over the time horizon.
2. In which pallet racking to allocate the inbound pallets on a daily basis.
3. From which pallet racking to retrieve the outbound pallets on a daily basis.

4.2.1 Notations and definitions

Tables 9, 10, 11, and 12 present the sets, parameters, auxiliary variables, and decision variables of the mathematical model of this research.

Table 9: Sets mathematical model

Set	**Explanation**
$t \in \{3, ..., T\}$	Date numbers
$i \in \{LowLong, LowNormal, LowShort, LowExtraShort, SingleDeep\}$	Types of pallet racking systems
$j \in \{1, ..., \sum_{i \in I} n_i\}$	Pallet racking systems in configuration
$s \in \{1, ..., S\}$	SKU numbers
$b \in \{1, ..., B\}$	Batch numbers

Table 10: Parameters mathematical model

Parameter	**Explanation**
d_{tb}	Demand inbound pallets on date t of batch b
o_{tb}	Supply outbound pallets on date t of batch b
c_i	Capacity of pallet racking type i
f_i	Floor space required for pallet racking type i
F	Current floor space required for initial configuration of pallet racking systems
I_{j3b}	Inventory level in pallet racking j at the beginning of the time horizon ($t = 3$) of batch b
M	Big M
Ci	Cost of not placing one inbound pallet in inventory over the time horizon
Ra	Reward of one available pallet location over the time horizon
Cp	Cost of one pallet depth of additional required floor space

Table 11: Auxiliary variables mathematical model

Auxiliary variable	**Explanation**
C_j	Capacity of pallet racking j
I_{jtb}	Inventory level in pallet racking j at the end of date t of batch b
P_{tb}	Inbound pallets that cannot be placed in inventory on date t of batch b
A_{jt}	Available pallet locations of pallet racking j on date t
R	Total required floor space for all pallet rackings

Table 12: Decision variables mathematical model

Decision variable	**Explanation**
x_{jtb}	Number of pallets allocated to pallet racking j on date t of batch b
y_{jtb}	Number of pallets retrieved from pallet racking j on date t of batch b
B_{jt}	Binary variable for whether pallet racking j is occupied at the end of date t
Q_{jtb}	Binary variable for whether batch b is placed in pallet racking j on date t
n_i	Number of pallet racking systems of type i

4.2.2 Mathematical model

The objective function and constraints of the mathematical model are given below. The model is based on the models of Accorsi et al. [2], Mital et al. [48], and Gebennini et al. [24]. It is extended with elements specific to this research, such as the characteristics of drive-in pallet rackings, the inbound pallets that cannot be placed, and tracking the available pallet locations. The objective function is multi-objective and minimizes the following three penalties simultaneously.

1. Penalty for the average daily inbound pallets that cannot be placed in inventory. This penalty ensures that as many inbound pallets are allocated to the pallet racking systems as possible to improve the service level.

2. Penalty for the average daily available pallet locations (average block and Euro). Since this has to be maximized, it is subtracted in the objective function. This penalty reflects on the capacity utilization of the configuration. More available pallet locations indicate that the configuration experiences less of the honeycombing effect (Section 3.2.1), whereas less available pallet locations indicate a low utilization of the capacity of the pallet racking systems. Accorsi et al. [2] also incorporate honeycombing into their objective function in terms of costs.
3. Penalty for the additional required floor space for the pallet racking systems. This penalty ensures that the pallet racking systems selected fit into the floor space of the DC, while utilizing as much floor space as possible.

Combining these three penalties yields the following objective function (the costs and reward are determined in Section 5.2).

$$min \quad \frac{\sum_{t,b} P_{tb}}{T} * Ci - \frac{\sum_{j,t} A_{jt}}{T} * Ra + \max\{0, R - F\} * Cp \tag{1}$$

Constraint 2 ensures that the inventory of each pallet racking j on each date t is managed by comparing the inventory level of each batch b in a pallet racking on the current date t to the inventory level of the prior date $(t-1)$ plus the inbound pallets minus the outbound pallets of the batch. This constraint is equal to the first constraint from Gebennini et al. [24].

$$I_{jtb} = I_{j(t-1)b} + x_{jtb} - y_{jtb} \quad \forall t > 3, \forall j, b \tag{2}$$

Constraint 3 gives the relationship between the capacity of pallet racking j to the capacity of the accompanying pallet racking type i. Constraint 4 makes sure that the inventory level of each pallet racking j and date t does not exceed its capacity. This refers to constraint 13 used by Mital et al. [48].

$$C_j \leq \begin{cases} c_1 & \text{if } 1 \leq j \leq N_1 \\ c_2 & \text{if } N_1 < j \leq N_2 \\ c_3 & \text{if } N_2 < j \leq N_3 \\ \vdots & \vdots \\ c_I & \text{if } N_{I-1} < j \leq N_I \end{cases} \quad \text{with } N_i = \sum_{k \in I} n_k \tag{3}$$

$$\sum_{b \in B} I_{jtb} \leq C_j \quad \forall j, t \tag{4}$$

Constraint 5 models the allocation of the inbound demand of batch b on date t, whereas 6 ensures that all inbound pallets are handled, either in inventory or left unplaced, for each date t and batch b. Constraint 7 models the allocation of the outbound pallets of batch b on date t.

$$\sum_{j \in J} x_{jtb} \leq d_{tb} \quad \forall t, b \tag{5}$$

$$\sum_{j \in J} x_{jtb} + P_{tb} \geq d_{tb} \quad \forall t, b \tag{6}$$

$$\sum_{j \in J} y_{jtb} \leq o_{tb} \quad \forall t, b \tag{7}$$

Constraints 8 and 9 create a binary variable to whether batch b is allocated to pallet racking j on date t. Accorsi et al. [2] use this method to assign an incoming batch to a storage mode of k-deep lanes.

$$Q_{jtb} \leq x_{jtb} \quad \forall j, t, b \tag{8}$$

$$x_{jtb} \leq Q_{jtb} * M \quad \forall j, t, b \tag{9}$$

Constraint 10 ensures that at most one batch b can be allocated to pallet racking j on date t, but only if there was not already a batch in inventory on the prior date $(t-1)$. However, only the drive-in pallet racking types are included $(i = 1, ..., 4)$. A similar constraint is the first constraint of Accorsi et al. [2] and the first constraint of Gebennini et al. [24] that avoids splitting a batch in different storage areas and facilitates the FIFO policy.

$$\sum_{b \in B} Q_{jtb} + I_{j(t-1)b} \leq 1 \quad \forall j \leq \sum_{i=1}^{4} n_i, \forall t > 3, \forall b \tag{10}$$

Constraint 11 and 12 create binary variable B_{jt} to whether pallet racking j on date t is occupied based on the inventory level using the big M approach. The binary variable becomes 1 if the pallet racking is occupied and 0 if it is not.

$$B_{jt} \leq \sum_{b \in B} I_{jtb} \quad \forall j, t \tag{11}$$

$$\sum_{b \in B} I_{jtb} \leq B_{jt} * M \quad \forall j, t \tag{12}$$

Constraint 13 makes sure that the total number of pallet racking systems occupied cannot exceed the number of pallet racking systems decided for the configuration.

$$\sum_{j \in J} B_{jt} \leq \sum_{i \in I} n_i \quad \forall t \tag{13}$$

Constraint 14 sets the available pallet locations of drive-in pallet racking j (excluding the single-deep pallet rackings) on date t to 0 if it is occupied and equal to its capacity if the pallet racking is not occupied. Thus, pallet locations are only available if the complete pallet racking is empty. This is a characteristic of the drive-in pallet racking system. Single-deep pallet rackings do not have this characteristic, so Constraint 15 sets the available pallet locations of single-deep pallet racking j on date t to the number of empty pallet locations.

$$A_{jt} \leq C_j * (1 - B_{jt}) \quad \forall j \leq \sum_{i=1}^{4} n_i, \forall t \tag{14}$$

$$A_{jt} \leq C_j - \sum_{b \in B} I_{jtb} \quad \forall j > \sum_{i=1}^{4} n_i, \forall t \tag{15}$$

Constraint 16 sets the total required floor space to the required floor space for each pallet racking type i multiplied by the number of each type.

$$R \geq \sum_{i \in I} f_i * n_i \tag{16}$$

Constraints 17 and 18 are the sign constraints of this model.

$$C_j, I_{jtb}, P_{tb}, A_{ti}, R, x_{jtb}, y_{jtb}, n_i \geq 0 \quad \forall j, t, b, i \tag{17}$$

$$B_{jt}, Q_{jtb} \in \{0, 1\} \quad \forall j, t, b \tag{18}$$

This problem combines the warehousing problems of allocating multiple items to pallet rackings over a time horizon and finding a configuration of storage systems with multiple racking options. There exist studies that also combine these two warehousing problems. However, none of the studies is completely applicable to the problem of this research. Moreover, the problem has no restriction to the number of each pallet racking type so the solution space is extremely large. Additionally, the mathematical model assumes one height and depth of the pallets, whereas there actually exist two heights and two depths of pallets. The method should also take this into account. Finally, the third penalty of the objective function is non-linear because it creates a piecewise linear function. Therefore, the problem is too complex to solve in polynomial time and is considered to be NP-hard. Thus, the solution method of this research is an improvement heuristic, which is described in Section 4.3.

4.3 Improvement heuristic

The problem owner does not require an optimal output but rather receives various options with good output values by changing the configuration of pallet rackings. Therefore, the goal of the heuristic to be developed is to present multiple outcomes and find a trade-off between the output values according to the needs of the company. The improvement heuristic of this research searches for an efficient configuration of the number of pallet rackings per type. Section 4.3.1 determines the required input data for the improvement heuristic. Section 4.3.2 determines the initial solution to start the improvement heuristic with. Section 4.3.3 elaborates on how the chosen heuristic type is adapted to this problem. To find candidate solutions, the heuristic uses the neighborhood operators explained in Section 4.3.4 and Section 4.3.5 explains how the objective value is generated.

4.3.1 Input data

As explained in Section 3.2.3, the storage capacity required in a warehouse is often based on the desired production rate which is determined by the demand from the customers [19]. At Riedel, the desired production rate is also dependent on a lot of other factors besides customer demand, such as the equipment capacity in the factory, the supply of raw materials, labor availability, processing time, and quality control standards. Therefore, in this case, the conversion from demand to storage capacity is hard to make. Thus, the heuristic developed in this research uses past data on the inventory of pallets in the DC. Section 3.2.3 explains two scenarios concerning the storage requirements of a DC depending on the duration of the peak in demand and the peak-to-average ratio. The input data is retrieved from the WMS and includes the months January 2024 until April 2024 since the peak in demand is from January until summer and the data is retrieved in April 2024. Therefore, the peak in storage demand is around half a year and the peak-to-average ratio is below two. Thus, the demand of the DC of Riedel is linked to the second scenario mentioned in Section 3.2.3, in which the storage capacity should be at or very near the peak requirements. This drives the heuristic to find a good configuration of the number of pallet rackings per type to cope with the yearly peak in demand.

The input data required for the heuristic contains the inventory levels of the end products for the period January until April 2024 and the current configuration of the number of pallet rackings per type. The inventory data should contain the articles that were stored in the DC including their information such as article number, type of pallet on which they are stored, height of the pallet, batch number, and pallet racking location. Only the ambient part of the DC is included in this data. Table 13 shows three example rows of the inventory input data. Each row shows the inventory of one pallet of an article. Pallets from the same batch are also split among the rows so that the location of each individual pallet is known. The heuristic to be developed can then also go over each pallet individually to place them in the pallet rackings. The *Date number* is a count that starts on January 1st 2024, so date number 3 is January 3rd 2024, and date number 32 is February 1st 2024. The *Article number* is an internal number that is linked to more information about the article such as the name and amount stored on a pallet. The *Type of pallet* refers to a block or Euro pallet and the *Height of pallet* is either a low or high pallet. The amount of an article stored on a pallet depends on the package size, type of the pallet, and height of the pallet. The *Batch ID* is also an internal number that refers to the batch. As explained in Section 2.1.2, the last pallet of a batch is called a partial pallet and holds fewer packages of juices. Finally, *Rack X Y* is the rack number, x-coordinate, and y-coordinate of the pallet location. This is further explained below.

Table 13: Examples inventory input data

Date number	**Article number**	**Type of pallet**	**Height of pallet**	**Batch ID**	**Rack X Y**
3	001234	Block	High	P0012345	02 34 1
3	054321	Euro	Low	P0023456	10 14 0
3	054321	Euro	Low	P0023456	10 14 0

After reviewing the inventory data, it appears that the link between the WMS and the database of Riedel malfunctioned on some days within the time frame. These dates are arbitrary and the cause has not been found yet. The inventory data on the following dates are missing: 05/04/2024, 06/04/2024, 07/04/2024, 09/04/2024, 11/04/2024, 13/04/2024, 16/04/2024, 20/04/2024, 21/04/2024, and 22/04/2024. Therefore, the input data does not include these dates, and the heuristic skips these dates as they do not exist. The heuristic loops through the date numbers and automatically does not include the dates of the missing data.

The input data on the current configuration of the number of pallet rackings per type, as determined in Section 2.1, should contain the information about the pallet rackings such as its number, coordinates, capacity, height, and type. Again, this data only includes the ambient part of the DC. Table 14 shows three example rows of the pallet rackings input data. Each row shows the characteristics of one single-deep pallet location or one drive-in pallet racking. The *Racking number* refers to the aisle in which the pallet location or racking is located. The *X-coordinate* indicates the row number within the aisle. For the single-deep pallet locations, the *Y-coordinate* refers to the height of the pallet location. For the drive-in pallet rackings, this is always zero and thus not relevant. The reason for this is that a drive-in pallet racking can only hold one batch within one pallet racking, whereas a single-deep pallet racking can hold different batches at each pallet location, as explained in Sections 2.1.1 and 3.2.2. The *Capacity euro pallets* and *Capacity block pallets* are the maximum number of pallets able to be stored in the pallet location or racking. The *Rack X Y* is a combination of the racking number, x-coordinate, and y-coordinate so it serves as the link between both input data tables. The *Height of racking* can either be low or high. The pallet locations within one single-deep pallet racking can be low and high mixed together, whereas one drive-in pallet racking only contains either low or high pallet locations. Finally, the *Type of racking* shows the type of pallet racking, which is either a drive-in or single-deep pallet racking.

Table 14: Examples pallet rackings input data

Racking number	**X-coor**	**Y-coor**	**Capacity euro pallets**	**Capacity block pallets**	**Rack X Y**	**Height of racking**	**Type of racking**
01	03	0	54	42	01 03 0	Low	Drive-in
02	34	1	1	1	02 34 1	High	Single-deep
04	12	0	36	28	04 12 0	High	Drive-in

4.3.2 Initial solution

The improvement heuristic starts with the current situation of pallet rackings which serves as the initial solution. This configuration is based on the input data explained in Section 4.3.1. This eliminates the need for a construction heuristic that creates a configuration from scratch. This research uses this method because the closer the final configuration is to the current situation, the less expensive it is to implement it. Through iterative evaluation and adaption, the improvement heuristic strives to improve the initial solution to ensure operational benefits.

Table 15 shows the initial configuration of pallet racking systems, also described in Section 2.1.3. The number of high normal and high extra short drive-in pallet rackings is fixed, because the inventory input data does not include the months March until December. However, within these months demand peaks of high pallets occur. For example, children's champagne is stacked high and has a demand peak in December because of Christmas. Therefore, the heuristic cannot research and substantiate the minimum required number of high drive-in pallet rackings. The SBS/RS and two half pallet racking systems are an extension to the current types of pallet racking systems in the DC.

Table 15: Initial configuration pallet racking systems

	Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
Number of pallet rackings (n_i)	4	283	24	24	59	0	0
Pallet capacity (block/Euro) (c_i)	48/60	42/54	24/30	18/24	5/5	35/45	30/36
Number pallet locations (block/Euro)	192/240	11,886/ 15,282	576/720	432/576	295/295	0/0	0/0
Required floor space pallet racking (f_i)	11	10	6.5	5.5	3	10	10

Table 15 shows that each type of pallet racking system has a different pallet capacity which is described in Section 2.1.1 as well. To get the number of pallet locations of each type of pallet racking system, the number of pallet rackings is multiplied by its pallet capacity ($n_i * c_i$). Table 15 also shows that each type of pallet racking system also has a required floor space (f_i) to build one pallet racking. The required floor space in terms of pallet depth of a pallet racking consists of the pallet racking itself and the aisle to reach the pallet racking. The following formula calculates the required floor space in terms of pallet depth.

$$f_i = \text{AisleSpace} + \frac{\text{DepthEuroPallet} + \text{DepthBlockPallet}}{2}$$

Based on the type of pallet racking system, the average of the block pallet and Euro pallet depth (see Section 2.1.1) is added to the aisle depth. The aisle depth is set to 2 pallets. Using the formula above, the required floor space of one low short drive-in pallet racking is calculated as follows: $f_3 = 2 + \frac{5+4}{2} = 6.5$

4.3.3 Simulated annealing method

Algorithm 1 shows the SA method used in this research. The data required for the method contains the inbound and outbound pallets, the configuration of the pallet racking systems, the start temperature, alpha, and the length of the Markov chain. It results in the best solution found. The algorithm starts with the initial solution and iteratively searches through different neighborhoods. The outer while loop decreases the temperature level according to a certain cooling scheme [3]. In each iteration, the algorithm accepts a neighborhood solution as the new solution if it is better than the current solution. If it is also better than the best solution so far, it is accepted as the new best solution. If the neighborhood solution is worse than the current solution it is still accepted with a certain probability. This probability depends on the current temperature. Since this temperature decreases throughout the iterations, it starts by encouraging the algorithm to investigate new neighborhoods (diversification) and ends with further examining promising neighborhoods (intensification).

Algorithm 1: Simulated annealing

```
Data: InboundPallets, OutboundPallets, Rackings, StartTemp, Alpha, MarkovChainLength
Result: BestSolution
Temp ← StartTemp;
Solution ← InitialSolution(Rackings);
SolutionValue ← InventoryTimeHorizon(Inbound, Outbound, Solution);
BestSolution ← Solution;
BestSolutionValue ← SolutionValue;
while Temp > StopTemp do
    for m ← 1 to MarkovChainLength do
        NeighborhoodSolution ← FindNeighborhoodSolution(Solution);
        NeighborhoodSolutionValue ← InventoryTimeHorizon(Inbound, Outbound,
         NeighborhoodSolution);
        if NeighborhoodSolutionValue < SolutionValue then
            if NeighborhoodSolutionValue < BestSolutionValue then
                BestSolution ← NeighborhoodSolution;
                BestSolutionValue ← NeighborhoodSolutionValue;
            Solution ← NeighborhoodSolution;
            SolutionValue ← NeighborhoodSolutionValue;
        else
            if RandomNumber ≤ exp((SolutionValue − NeighborhoodSolutionValue) / Temp) then
                Solution ← NeighborhoodSolution;
                SolutionValue ← NeighborhoodSolutionValue;
    Temp ← Temp * Alpha
```

4.3.4 Neighborhood operators

To find candidate solutions to evaluate, the SA method performs neighborhood operators. In each iteration, it finds a neighborhood solution, as Algorithm 2 shows. It uses the following neighborhood operators.

- Add one pallet racking
- Delete one pallet racking
- Exchange two pallet rackings

The add operator is used to explore configurations with an increasing pallet capacity to examine if it improves the objective function. The delete operator tests if decreasing the pallet capacity increases efficiency by identifying redundant pallet rackings. The exchange operator allows for fine-tuning the configuration by revealing unexpected benefits that might not be visible by adding or deleting a pallet racking alone. In each iteration, the SA method randomly selects one of the neighborhood operators. Random selection is used to promote diverse exploration of the SA method and to stay unbiased.

Algorithm 2: FindNeighborhoodSolution

Data: Solution

Result: NeighborhoodSolution

$RandomOperator \leftarrow Random(1, 3)$;
if $RandomOperator = 1$ **then**
  $NeighborhoodSolution \leftarrow AddRacking(Solution)$;
else if $RandomOperator = 2$ **then**
  $NeighborhoodSolution \leftarrow DeleteRacking(Solution)$;
else
  $NeighborhoodSolution \leftarrow ExchangeRacking(Solution)$;

The add operator selects a pallet racking to add to the current configuration as follows. It selects a single-deep pallet racking with 15% and a drive-in pallet racking with 85% chance, which is equal to the ratio of single-deep and drive-in pallet rackings in the initial solution. When a single-deep pallet racking is selected, it adds five single-deep pallet locations at a time, because one row of a single-deep pallet racking has a height of five pallet locations. When a drive-in pallet racking is selected, it randomly with equal probability selects the depth based on the height of the new pallet racking.

The delete operator selects a pallet racking to delete from the current configuration as follows. It selects a single-deep pallet racking with 15% and a drive-in pallet racking with an 85% chance, which is equal to the ratio of single-deep and drive-in pallet rackings in the initial solution. When it selects a single-deep pallet racking, it deletes five single-deep pallet locations randomly, because a single-deep pallet racking has a height of five pallet locations. When it selects a drive-in pallet racking, it randomly with equal probability deletes one of the types of pallet rackings in the current configuration. When deleting a pallet racking, the heuristic verifies whether there is inventory present in the pallet racking at the start date. If so, it moves the inventory to another pallet racking.

The exchange operator is a mixture of the add and delete operators together. It first deletes a pallet racking and then adds a different pallet racking. If there was inventory present in the deleted pallet racking at the start date, the heuristic again moves it, but after adding the other pallet racking. This ensures that the pallets can also be put in the new pallet racking. The exchange operator has an extension of exchanging a low normal drive-in pallet racking with two other types of pallet rackings. The first option is placing an SBS/RS in the pallet racking. The advantage is that it ensures that each row can hold a different batch of an SKU. However, the disadvantages are the loss of capacity and additional handling movements. The former arises because the shuttle takes up space equal to one row of pallet locations. Therefore, exchanging one low normal drive-in pallet racking with an SBS/RS ensures a decrease in capacity from 42 to 35 block pallets (depth of 7, height of 5). The second option is exchanging a low normal drive-in pallet racking with two shorter pallet rackings. This ensures that they can hold two different batches, but it requires an extra aisle resulting in a loss of capacity. Assuming that creating an aisle is equal to losing two meters, the SA method substracts two columns of block pallet locations from the capacity. Therefore, exchanging one low normal drive-in pallet racking with two smaller pallet rackings with a capacity of 15 block pallets decreases the capacity from 42 to 30 block pallets. To make sure that the SA method does not keep these two additional types of pallet rackings once exchanged, they are also included in the delete operator.

4.3.5 Generating the objective value

The heuristic developed in this research requires an objective function to decide whether to accept a neighbor solution. The objective function, developed in the mathematical model of Section 4.2.2, is defined as follows.

$$min \quad \frac{\sum_{t,b} P_{tb}}{T} * Ci - \frac{\sum_{j,t} A_{jt}}{T} * Ra + \max\{0, R - F\} * Cp$$

It makes a trade-off between three Key Performance Indicators (KPIs), carefully discussed and formulated based on the needs of the problem owner. The costs and reward of the objective function are determined in Section 5.2. At the start of the heuristic and during each iteration, the objective value is calculated. To determine the penalties and thus the output KPIs included in the objective function, the heuristic simulates the WMS of the DC. Before iteratively adding, deleting, and exchanging pallet rackings, the heuristic starts with the current configuration of pallet rackings from the pallet racking input data. For every iteration, the heuristic starts with the inventory present at the start date of the time horizon, retrieved from the inventory input data. The rest of the data on the inventory is converted to two tables. First, the inbound pallets table, which consists of the batches arriving in the DC from the inbound process on a certain date within the time horizon. Each row contains information about the batch, such as the batch ID, batch number, article number, number of inbound pallets, height of the pallets, and type of the pallets. Second, the outbound pallet table, which includes all outbound pallets leaving the DC to the outbound process. The input of Algorithm 3 consists of these two tables, along with the table of the current inventory and pallet rackings. It manages the inventory over the time horizon by placing and retrieving the pallets from the pallet rackings and calculating the output KPIs on a daily basis.

The algorithm iterates over the time horizon by looping through the range of dates. During each iteration, several operations are executed to manage the daily inventory. First, the inbound pallets arrive at the DC on a belt. An exception is made on the first date since the start inventory is already present. Figure 28 in Appendix B elaborates on the method of placing the inbound pallets in the pallet rackings. The decision on which pallet racking to store a batch in is based on the size of the batch and the availability of pallet rackings. The size of a batch is compared to the capacity of the pallet rackings. Iteratively, pallet rackings are filled with pallets of the batch. If there are no pallet locations available for the arriving batch, the information about the batch is saved so that it can still be stored in the DC when placing old inbound pallets in the pallet rackings.

Algorithm 3: InventoryTimeHorizon

Data: InboundPallets, OutboundPallets, Rackings
Result: SolutionValue

```
for i ← StartDate to EndDate do
    if i > StartDate then
        AddInboundToRackings(Inbound, Rackings);
    if i < EndDate then
        DeleteOutboundFromRackings(Outbound, Rackings);
    RelocatePallets(Rackings);
    AddOldInboundToRackings(InboundNotAdded, Rackings);
    DeleteOutboundDirectlyFromBelt(OutboundNotDeleted, Rackings);
    CalculateKPIsPerDay;
    SaveKPIsPerDay;
SolutionValue ← mean(KPIsPerDay);
```

Second, the outbound pallets leave the pallet rackings of the DC. An exception is made on the last input entry since the inventory of the next date is not known and thus the outbound pallets are not known. Figure 29 in Appendix B shows the method of retrieving the outbound pallets from the pallet rackings. The decision on which pallets to take from the batch is based on the inventory, capacity, and occupancy rate of the pallet rackings storing the pallets. Single-deep pallet rackings, pallet rackings with a low occupancy rate, and pallet rackings with a low capacity are considered first. The pallets are iteratively selected from the pallet rackings in the DC. If there are no pallets of the batch left in the DC, the information about the outbound pallets is saved so that the pallets can still be retrieved directly from the belt.

After the inbound and outbound process, the algorithm relocates pallets between pallet rackings to enhance the utilization of the pallet racking systems. The pallet rackings with a high capacity that hold one pallet are emptied, and those single pallets are moved to single-deep pallet rackings. This ensures a larger number of available pallet locations and more space to store incoming batches. In reality, the inbound and outbound processes occur simultaneously. However, the input data only specifies the arrival date without an exact time stamp. Therefore, after relocating the pallets, any inbound pallets still on the belt are stored in the pallet rackings after all if possible. Subsequently, any outbound pallets that are still on the belt leave the DC without being stored in the pallet rackings. Finally, the KPIs are calculated. At the end of the time horizon, the algorithm calculates the average of the KPIs over all days. The final output is a quantitative measure of the performance of the configuration of pallet rackings on which the improvement heuristic makes decisions.

4.4 Algorithm 3 versus real-world performance

To validate Algorithm 3, we compare the performance of the inventory management over the time horizon using the initial configuration of Section 4.3.2 with the performance in the real world. The initial configuration is used because that is the current configuration of the real world. Table 16 shows the performance of the real world versus the algorithm. In the real world, all inbound pallets fit in the pallet rackings of the DC. However, in the algorithm on average 20.76 pallets per day did not fit into the pallet rackings, which is 0.041% of the 503 inbound pallets on average per day. This results in on average 4.38 outbound pallets per day that were retrieved from the belt directly, which is 0.009% of the 474 outbound pallets on average per day. We assume that these differences are caused because in the real world if inbound pallets do not fit the employees put batches containing equal SKUs together in a pallet racking creating space for the inbound pallets. This is a manual intervention and the algorithm does not account for that.

Table 16: Output KPIs real-world versus algorithm 3

	Inbound pallets not placed per day	Outbound pallets directly from belt per day	Available pallet locations per day
Real-world	0	0	1,188
Algorithm 3	20.76	4.38	1,017
Difference	**20.76**	**4.38**	**171**

In the real world, on average the available pallet locations per day are 1,188, whereas in the algorithm, the average available pallet locations per day are 1,017. This is a difference of 171 pallet locations, which is 0,144% of the real-world available pallet locations and 0.011% of the total pallet locations of 16,095 (average of block and Euro). The difference indicates that the real-world WMS places pallets a bit more efficiently than the algorithm. However, the difference seems small and explainable, which indicates that it can be neglected. Thus, we can assume with high certainty that it will not be practically impactful. Therefore, we conclude that the algorithm aligns well with the real world.

Figure 7 in Section 2.1.3 shows that in the real world, the occupancy rate and thus the inventory of pallets increases between January and April 2024. Figure 16 shows the number of pallets in inventory and the number of inbound and outbound pallets per day. The figure indicates that the algorithm also shows an increasing inventory. The number of inbound and outbound pallets shows that the DC is closed during the weekend since then these values are zero. It can also be seen that April deviates from the rest of the data points because the input data of ten dates in April are missing, as mentioned in Section 4.3.1. Therefore, in April more dates have an inbound and outbound of zero compared to the other months. The algorithm determines the inbound and outbound pallets based on the difference in inventory between two consecutive days while skipping the dates on which the database malfunctioned, as explained in Section 4.3.1. Therefore, the number of inbound and outbound pallets on the dates subsequent to the missing dates is significantly higher than on other dates, which can be seen in Figure 16. If the data of a date is missing, the number of outbound pallets has a higher peak than expected the day before and the number of inbound pallets has a higher peak the day after. For example, the data of Tuesday the 16th of April is missing so the number of outbound pallets on the 15th of April is higher and the number of inbound pallets on the 17th of April is higher. This is because the inbound pallets are calculated by comparing the inventory to the date before and the outbound pallets are calculated by comparing the inventory to the date after.

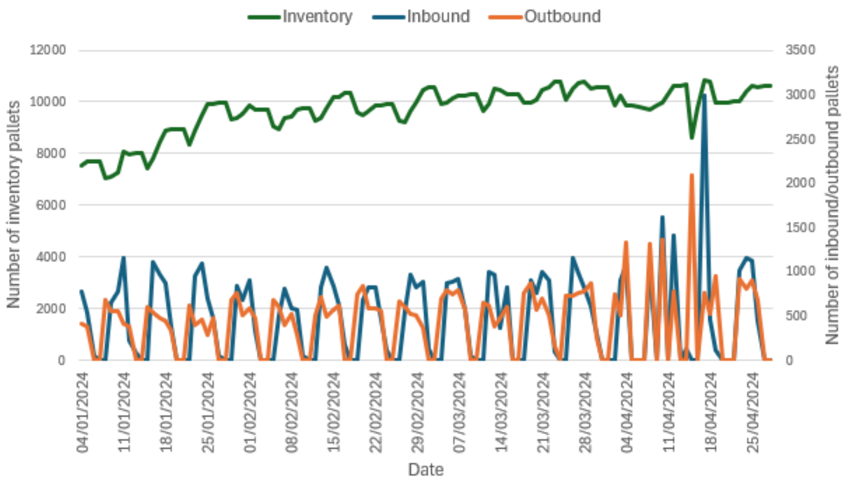

Figure 16: Algorithm 3 inventory, inbound and outbound

4.5 Conclusion

This chapter answers research question *'What method can be used to optimize the occupancy rate of the pallet racking systems within the DC?'* by describing an SA method to optimize the occupancy rate of the pallet racking systems within the DC.

The chapter determines a solution design by creating a detailed plan of how to find a good storage system design. To simplify the problem, the chapter starts by making certain assumptions. An important assumption is that we assume that the historical inventory data, although it skips the dates that are missing, is an indication of future storage demand. Moreover, we do not consider the real-world sequence of inbound and outbound pallets and the exact location of where the pallets are stored is not taken into account. After stating the assumptions, the problem statement is provided. It identifies the decisions to be made, the notations and definitions of the sets, parameters, auxiliary variables, and decision variables, and the mathematical model containing the objective function and constraints.

To solve the problem, an improvement heuristic is provided as the solution method. The required input data for the heuristic is elaborated on, consisting of the inventory levels of the end products and the current configuration of the number of pallet rackings. Then, the initial solution is determined, which is based on the current configuration of the pallet rackings. The number of high normal and high extra short drive-in pallet rackings are kept fixed, because of demand peaks of high pallets outside of the time horizon included in this research. The SBS/RS and two half pallet racking system types are added to serve as an extension to the current types of pallet racking systems.

To ensure that the improvement heuristic does not converge to a local optimum, this research uses SA since it balances intensification and diversification. The SA evaluates a neighbor based on the following objective function to be minimized.

$$min \quad \frac{\sum_{t,b} P_{tb}}{T} * Ci - \frac{\sum_{j,t} A_{jt}}{T} * Ra + \max\{0, R - F\} * Cp$$

The objective function is multi-objective and ensures that as many inbound pallets can be placed in inventory as possible, enough pallet locations are available for upcoming peaks, and the floor space is optimally utilized. These objectives are converted to penalties consisting of costs and rewards to balance the penalties. To generate the objective value, the heuristic simulates the WMS of the DC by managing the daily inventory in the pallet rackings over the time horizon. At the end of the time horizon, the heuristic calculates the output KPIs on which the heuristic can make decisions.

The chapter finishes by comparing the performance of the inventory management over the time horizon using the initial configuration with the performance of the real world to validate Algorithm 3. It observes some differences between the algorithm and the real world in terms of the number of inbound pallets not placed in the pallet rackings, the number of outbound pallets retrieved directly from the belt, and the available pallet locations. First, the difference between the inbound pallets not placed is 0.041% of the inbound pallets on average per day. Second, the difference between the outbound pallets directly retrieved from the belt is 0.009% of the outbound pallets on average per day. Third, the difference between the available pallet locations is 0.011% of the total average pallet locations. These differences seem small and explainable, which indicates that they can be neglected. Thus, we can assume with high certainty that it will not be practically impactful and we conclude that the algorithm aligns well with the real world. The algorithm is also validated by comparing the inventory over the time horizon of the algorithm with the real world. This shows that the increase in inventory is correct. Moreover, it was discovered that the missing dates in the inventory levels input data impact the number of inbound and outbound pallets at the end of the time horizon generating higher peaks.

5 Simulations base scenario

This chapter elaborates on the design and results of the simulations of the improvement heuristic. The goal of the improvement heuristic is to find a good design of the pallet racking systems in the DC to create more available space. This chapter focuses on the base scenario with past demand. First, it elaborates on the best solution to reveal the relationship between the objectives. Then, it analyses the output KPIs of all accepted solutions, their relationship with the pallet capacity, and each other. This chapter answers the following research question.

6. What are possible improvements to the design of the pallet rackings within the DC?

Section 5.1 explains the simulation design of the improvement heuristic. Then, Section 5.2 weights the costs and rewards of the objective function. Section 5.3 tunes the parameters of the SA method and Section 5.4 summarizes the parameters of the base scenario on which experiments are performed in Chapter 6. Section 5.5 discusses the results of the simulations on the base scenario by analyzing the best solution and the whole solution space. After that, Section 5.6 performs a sensitivity analysis to evaluate the robustness of the improvement heuristic. Finally, Section 5.7 concludes the findings of this chapter.

5.1 Simulation design

The design of the simulation involves the following steps to ensure the robustness of the results.

Step 1: Weighting the objective function (Section 5.2)
This step weighs the costs and reward of the penalties of the objective function. The goal is to balance the importance of each penalty to guide the heuristic toward a solution that meets the requirements. This is needed because the penalties of the objective function conflict with each other. Generally, when adding pallet rackings the penalty for required floor space increases, but the penalty for available pallet locations decreases.

Step 2: Parameter tuning SA (Section 5.3)
To ensure the accuracy of the results, this step tunes the parameters of the cooling scheme of the SA method to fit the problem. The cooling scheme consists of the start temperature, stop temperature, length of the Markov chains, and rule for decreasing the temperature [10]. In each scenario, the input is adjusted but the problem instance, such as the objective function, overall structure, and solution space, remains the same. Therefore, we assume that the parameters tuned for the base scenario are likely to perform well for the future scenarios.

Step 3: Analyse heuristic results (Section 5.5)
After the penalties of the objective function are weighted and the parameters of the SA are tuned, we run the heuristic for the base scenario. After the sensitivity analysis

of step 4, we also run the heuristic for the scenarios with future product portfolios to cope with the uncertainty in demand. Chapter 6 analyses the results of the scenarios and makes comparisons between the base scenario and future demand scenarios.

Step 4: Sensitivity analysis (Section 5.6)
This step identifies which objective function weight has the most impact on the output. This recognizes vulnerabilities and can lead to improvements in the design.

5.2 Weights objective function

The objective function consists of three penalties containing the following costs and rewards.

- Ci is the cost of not placing one inbound pallet in inventory over the time horizon.
- Ra is the reward of one available pallet location over the time horizon.
- Cp is the cost of one pallet depth of additional required floor space.

To have a benchmark for weighting the costs and rewards, we set the reward of one available pallet racking over the time horizon (Ra) to 1. The cost of one pallet depth of additional required floor space (Cp) is set to 8 to make sure that the cost of one additional pallet racking is always more than the reward of the available pallet locations of one pallet racking. Otherwise, the improvement heuristic keeps adding pallet rackings to gain the reward of the available pallet locations while accepting the penalty for additional required floor space.

When having one single-deep pallet racking less than in the current configuration, the heuristic does not reduce the required floor space. This is because no other type of pallet racking can be placed on the aisle next to the single-deep pallet racking since the forklift trucks use them to drive around. The gained pallet depth of deleting a single-deep pallet racking does not fit any of the other types of pallet racking systems and it is not possible to move consecutive single-deep pallet rackings to create space. Therefore, the improvement heuristic does not gain any reward when deleting a single-deep pallet racking.

Riedel wants to improve the configuration of pallet rackings without many changes. Thus, to guide the improvement heuristic to a solution with few changes compared to the initial configuration, the reduction of the required floor space is bounded. After deleting more pallet rackings of a certain type than the bound, the heuristic does not further reduce the required floor space. Above 4 low long, 50 low normal, 5 low short, and 5 low extra short drive-in pallet rackings the heuristic does not reduce the required floor space when deleting another pallet racking of that type.

The last cost to balance is the cost of not placing one inbound pallet in inventory over the time horizon (Ci). In agreement with the problem owner and the wishes of the company, this cost is set to 15 since it ensures that all inbound pallets will fit.

5.3 Parameter tuning

This section tunes the parameters of the SA method on the base scenario. As explained in Section 3.3.3, tuning the parameters balances intensification and diversification. We start by determining the start temperature based on the acceptance ratio. At the end of each Markov chain, the number of worse neighbors proposed and accepted are tracked and the acceptance ratio is calculated as follows.

$$\text{Acceptance ratio} = \frac{\text{Number of worse neighbors accepted}}{\text{Number of worse neighbors proposed}}$$

The cooling scheme is determined by the base scenario with a start temperature of 1,000, a stop temperature of 50, a length of Markov chains of 100, and a decrementing rule of $T_{k+1} = \alpha * T_k$ with T the temperature, k the k-th Markov chain, and an α of 0.9. Typically, the value for alpha lies between 0.8 and 0.99 [13]. Figure 17 shows the acceptance ratio for the temperature levels of each Markov chain during the simulation. Before decreasing, the temperature level first increases to reach an acceptance ratio of 1. After that, the acceptance ratio still has some high peaks. This indicates that the neighbors at the start have a high variety, resulting in the improvement heuristic accepting fewer neighbors. Thus, the current decrementing rule is not appropriate for this problem. Gonzales et al. [78] compare several different cooling schemes and decrementing rules. The decrementing rule selected in this research is based on a hybrid rule mentioned in their paper called the constant exponential rule. In the initial steps, the temperature level is fixed to ensure that the improvement heuristic finds a better initial point. The rule is adjusted to the following rule with I the length in iterations of the constant part of the rule.

$$T_k = \begin{cases} T_0 & k < I \\ \alpha * T_k & k \geq I \end{cases}$$

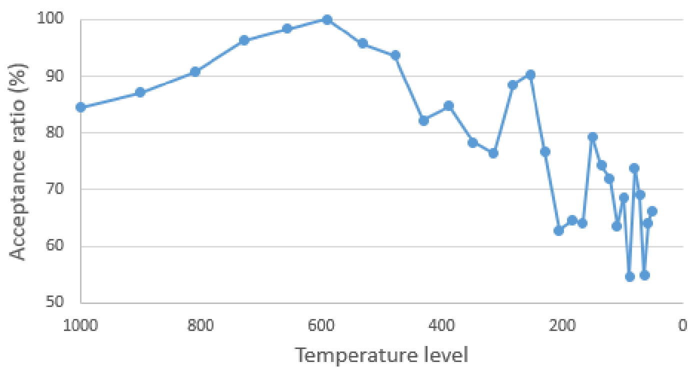

Figure 17: Acceptance ratio versus temperature level

To find the start temperature (T_0) and initialization length (I), we perform multiple experiments with a fixed Markov chain length of 50. Figure 18 displays the acceptance ratio over the initialization length of 400 iterations of the experiments with a start temperature of 200, 300, 400, and 500. According to Busetti [10], a suitable start temperature has an acceptance ratio 80%, which is the chance that a worse neighbor is accepted. During the initialization length we strive for a stable acceptance ratio around 80%. Thus, start temperature 200 is rejected since the experiment starts at an acceptance ratio of 50%. Start temperature 500 is rejected since the acceptance ratio starts too low and has an increasing trend. The start temperatures 300 and 400 have an acceptance ratio closer to 0.8. However, the acceptance ratio of the experiment with start temperature 300 increases rapidly after 100 iterations, and the acceptance ratio of the experiment with start temperature 500 increases to 1 already at iteration 200. Therefore, we perform another experiment with start temperature 350.

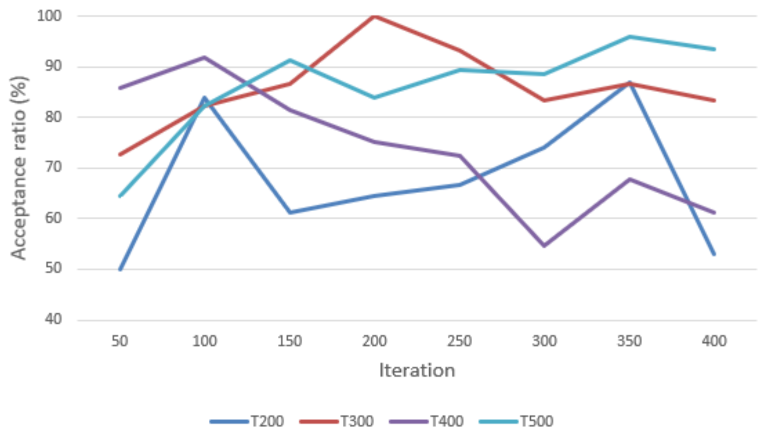

Figure 18: Experiments initialization length temperatures 200, 300, 400, and 500

Figure 19 shows the acceptance ratio over the initialization length of 400 iterations of the experiments with a start temperature of 300, 350, and 400. The acceptance ratio of the experiment with a start temperature of 350 starts at around 0.8 and fluctuates between 0.7 and 0.9 until 300 iterations. Therefore, we select start temperature 350 and an initialization length of 300 iterations.

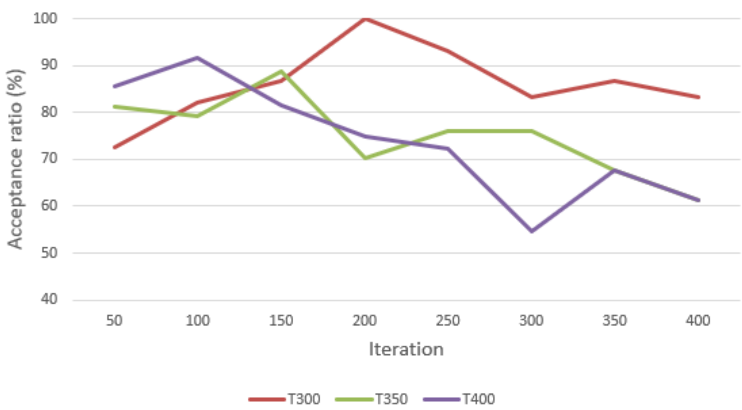

Figure 19: Experiments initialization length temperatures 300, 350, and 400

Experiments are performed on the alpha, stop temperature, and Markov chain length. Large values for alpha result in an increasing computational time, which is not necessary for this problem since the initial solution is close to the optimal. Thus, we consider an alpha of 0.8, 0.85, and 0.9. In each Markov chain, a sufficient number of acceptable transitions must be performed [13]. Therefore, for the Markov chain length we consider 25, 50, 75, and 100. The SA is terminated once the stop temperature is reached. For the stop temperature, we consider 5, 10, 20, and 50.

Figure 20 presents the best objective value and run time in hours of the 48 experiments on the parameters of the SA. The selection of the cooling scheme parameters is based on the trade-off between the run time and the best objective value found. Slower convergence leads to excessive run time but maximizes the likelihood of reaching the optimal objective value. The selected parameters ensure that the improvement heuristic finds a high-quality solution within an acceptable amount of time.

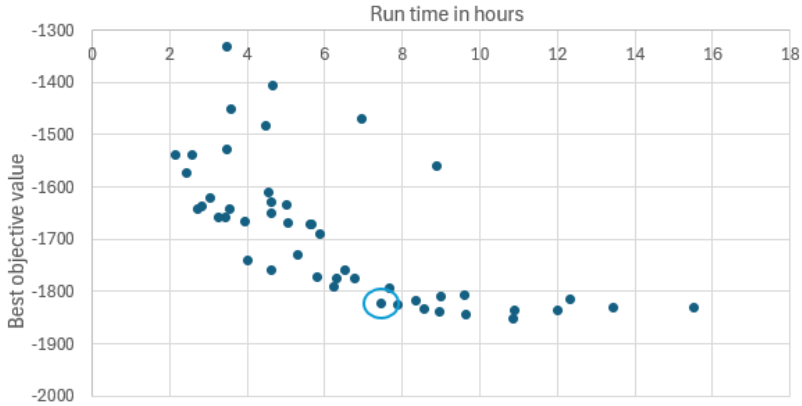

Figure 20: Experiments cooling scheme

From the 48 experiments, we select the light-blue circled experiment with a run time of 7.44 hours and a best objective value of -1,822. This experiment lies on the tipping point of the curve towards a flatter decline. Therefore, when selecting an experiment more to the right of the graph results in a relatively high run time compared to the small improvement in the objective function value. This experiment results in the following cooling scheme: initialization length 300, start temperature 350, alpha 0.8, stop temperature 10, and Markov chain length 100.

5.4 Experimental setup

Table 17 summarizes the parameters of the base scenario including the simulation setup, initial configuration, product portfolio parameters, inventory demand parameters, weights of the objective function, and simulated annealing parameters. The base scenario is based on the historical inventory input data. However, the future inventory demand and product portfolio are uncertain. To cope with this uncertainty, Chapter 6 explores scenarios that experiment on the following parameters.

1. Initial pallet inventory ($\sum_{j,b} I_{j3b}$)
2. Number of SKUs (S)
3. Number of batches (B)
4. Daily demand inbound pallets ($\sum_{t,b} \frac{d_{tb}}{T}$)
5. Daily supply outbound pallets ($\sum_{t,b} \frac{o_{tb}}{T}$)

To compare the scenarios of future product portfolios with the base scenario, all other parameters of Table 17 are fixed in the scenarios. Section 6.5.1 elaborates on the above mentioned parameters.

Table 17: Base scenario setting summary

Parameters	**Value**
Simulation	
Simulation horizon	107 days
Start date number	3
End date number	110
Time step interval	Daily
Number of iterations	1800
Initial configuration (Table 15)	
Number low long (n_1)	4
Number low normal (n_2)	283
Number low short (n_3)	24
Number low extra short (n_4)	24
Number single-deep (n_5)	59
Number SBS/RS	0
Number two half	0
Initial required floor space (F)	3,339
Characteristics pallet rackings	
Capacity per pallet racking type (c_i)	See Table 15
Required floor space per pallet racking type (f_i)	See Table 15
Product portfolio	
Number of SKUs (S)	240
Number of batches (B)	1,001
Inventory demand	
Total initial pallet inventory ($\sum_{j,b} I_{j3b}$)	7,152
Average daily demand inbound pallets ($\sum_{t,b} \frac{d_{tb}}{T}$)	503
Average daily supply outbound pallets ($\sum_{t,b} \frac{o_{tb}}{T}$)	474
Weights objective function	
Cost inbound pallets (Ci)	15
Reward available pallet locations (Ra)	1
Cost additional required floor space (Cp)	8
Simulated annealing	
Initialization length (I)	300
Start temperature (T_0)	350
Alpha (α)	0.8
Markov chain length (K)	100
Stop temperature (T_{100})	10

5.5 Results base scenario

This section analyses the results of the base scenario, that is based on the historical inventory input data. Section 5.5.1 elaborates on the best solution found by the improvement heuristic. However, the problem owner does not require an optimal output but rather receives various options with good output values to make trade-offs. Therefore, Section 5.5.2 analyses the output KPIs of all accepted solutions, their relationship with the pallet capacity, and each other.

5.5.1 Best solution base scenario

The best solution derived from the improvement heuristic reveals relationships between the different objectives. It contributes to discovering the relationships between the solutions of Section 5.5.2. Table 18 shows the initial (current configuration in the DC) and best configurations and their difference in number of pallet rackings.

Table 18: Base scenario, initial and best configuration

	Low long	Low normal	Low short	Low extra short	Single-deep	SBS/RS	Two half
Initial	4	283	24	24	59	0	0
Best	22	233	31	58	58	7	0
Difference	+18	-50	+7	+34	-1	+7	0

The best configuration results in the penalties and objective value displayed in Table 19 with the output KPIs of Table 20 and mean occupancy rates per pallet type of Table 21. The best configuration shows that exchanging low normal pallet rackings with other types utilizes all pallet locations more efficiently and increases the mean total occupancy rate by 1.3%. This results in an increased mean occupancy rate of the low normal pallet rackings, because it provides options to allocate small batches in pallet rackings with a low capacity. The improvement heuristic removed 50 low normal pallet rackings, which is exactly the reward bound as Section 5.2 explains.

Table 19: Base scenario, penalties objective function

	Penalty inbound not possible to place	Penalty available rackings	Penalty required floor space	Objective value
Initial	311	-1,016	0	-705
Best	0	-1,826	4	-1,822
Difference	-311	-810	+4	-1,117

Table 20: Base scenario, output KPIs

	Capacity (block/Euro)	Mean inventory	Mean available locations	Mean honeycombing locations
Initial	14,121 / 18,069	9,665	1,017	4,074
Best	13,905 / 17,785	9,689	1,826	3,074
Difference	-216 / -284	+24	+809	-1,000

Table 21: Base scenario, total occupancy rate and mean per pallet racking type (in %)

	Mean total	Low long	Low normal	Low short	Low extra short	Single-deep	SBS/RS	Two half
Initial	66.9	80.9	66.8	63.0	58.1	78.1	-	-
Best	68.2	77.1	69.3	69.5	61.5	63.9	62.8	-
Difference	+1.3	-3.8	+2.5	+6.5	+3.4	-14.2	-	-

The heuristic exchanges the 50 low normal pallet rackings with the other types. To cope with the large batches that do not fit into the low normal pallet rackings anymore, the improvement heuristic adds 18 low long pallet rackings to the configuration. This decreases the occupancy rate of low long pallet rackings since smaller batches will occupy them compared to the current situation. Moreover, it adds 7 low short, 34 low extra short, and 7 SBS/RS to cope with the smaller batches. This causes the occupancy rate of single-deep pallet rackings to decrease due to the increased flexibility of the low-capacity pallet rackings in the best configuration. However, the heuristic only removes one single-deep pallet racking, because no reward is given when removing them. The heuristic does not exchange low normal pallet rackings for two half pallet rackings since this costs the same as adding a SBS/RS but has less capacity and flexibility.

Despite the lower total capacity of the best configuration compared to the initial configuration, the flexibility increases because small batches are allocated more efficiently. If all low short pallet rackings are occupied, the heuristic allocates small batches to the low normal pallet rackings. Thus, a configuration with too few low-capacity pallet rackings results in a decrease in the occupancy rate of the low normal pallet rackings.

Table 22 determines the expected number and percentage of batches allocated to each pallet racking type by distributing the batches among the pallet rackings. Based on the current situation, if a batch is larger than the capacity of the low long pallet racking, we expect one part to be placed in low normal pallet rackings and the remainder in a smaller pallet racking. Therefore, 118 of the 769 batches expected to be placed in a low normal pallet racking is in between the bounds of its capacity. The other 651 batches are caused by large batches of which 335 remainders are placed in a smaller pallet racking.

Table 22: Expected number/percentage of allocated batches per type of pallet racking

	Number of pallets (block)	**Number of pallets (Euro)**	**Expected number/ percentage of allocated batches**	**Number/ percentage of pallet rackings**
Single-deep	[1, 5]	[1, 5]	66 / 4%	59 / 15%
Low extra short	[6, 18]	[6, 24]	207 / 14%	24 / 6%
Low short	[19, 24]	[25, 30]	138 / 9%	24 / 6%
Two half	[25, 30]	[31, 36]	119 / 8%	0
SBS/RS	[31, 35]	[37, 45]	94 / 6%	0
Low normal	[36, 42]	[46, 54]	769 / 52%	283 / 72%
Long long	[43, 48]	[55, 60]	85 / 6%	4 / 1%

The percentage of allocated batches per pallet racking type compared to the percentage of pallet rackings per type indicates that batches suitable for smaller pallet rackings are currently allocated to the low normal pallet rackings. Thus, adding low short and low extra short pallet racking systems increases their occupancy rates because larger batches are allocated to them compared to the current situation. Besides that, Table 22 indicates that exchanging low normal pallet rackings with two half and SBS/RS pallet rackings can increase the occupancy rate while still managing the inbound pallets. However, as explained above, two half pallet rackings are not efficient so the heuristic does not add them. Moreover, Table 22 shows that the current number of low long pallet rackings is also inadequate for the expected number of allocated batches. Therefore, batches that are expected to be allocated to these pallet rackings are distributed over pallet rackings with a lower capacity due to an inadequate number of low long pallet rackings.

The increase in available pallet locations and decrease in honeycombing pallet locations also indicate the increased flexibility of the best configuration. As explained in Section 3.2.1, honeycombing is the loss of space because of empty unusable locations. Exchanging low normal pallet rackings with low-capacity rackings decreases honeycombing because the same batch size creates less empty unusable pallet locations. For instance, allocating a batch of 20 pallets to a low normal pallet racking creates 22 honeycombing locations, whereas allocating it to a low short pallet racking creates 4.

Overall, the best configuration decreases the total capacity but simultaneously increases flexibility. Exchanging low normal pallet rackings with low long, low short, low extra short, and SBS/RS increases the mean total occupancy rate by 1.3% while decreasing the honeycombing effect and increasing the available pallet locations with 809. Figure 21 displays the daily occupancy rate of the initial and best configuration of the base scenario and the target occupancy rate. The occupancy rate is calculated in the same way as in Section 2.1.3. Figure 21 shows that over time the occupancy rate shows an upward trend and gets closer to the target occupancy rate. Moreover, it indicates a consistent improvement in the daily occupancy rate from initial to best, while being able to still allocate all inbound pallets during the time horizon.

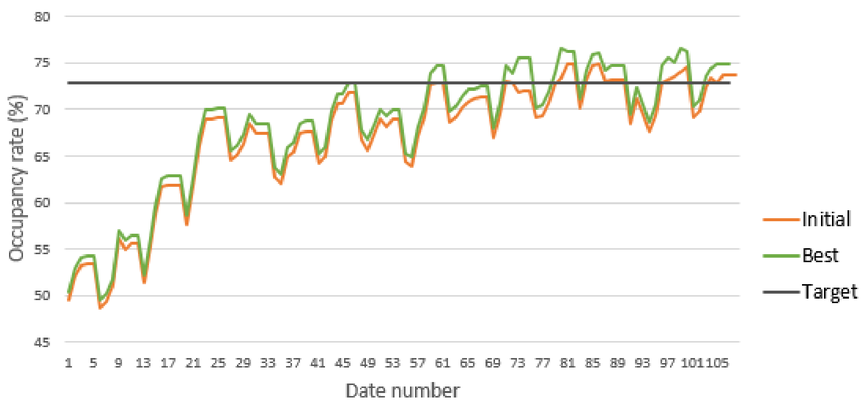

Figure 21: Daily occupancy rate initial versus best configuration, base scenario

5.5.2 Analysis solution space

This section analyses the solution space visited by the improvement heuristic. In a multi-objective optimization problem, there is no optimal solution, but rather a set of alternative solutions [1]. These Pareto optimal solutions are optimal since no other solution in the solution space dominates them. The problem owner can then decide on the most suitable solution [11]. The set of Pareto optimal solutions represents the trade-off between the objectives and shows what improving one objective does to another. Figure 22 displays a heat map of the objective function value against the block pallet capacity. The contrast shows the progress through the iterations, with darker dots indicating later iterations during the improvement heuristic. The graph shows that the improvement heuristic iteratively converges towards a region of better solutions near the best solution.

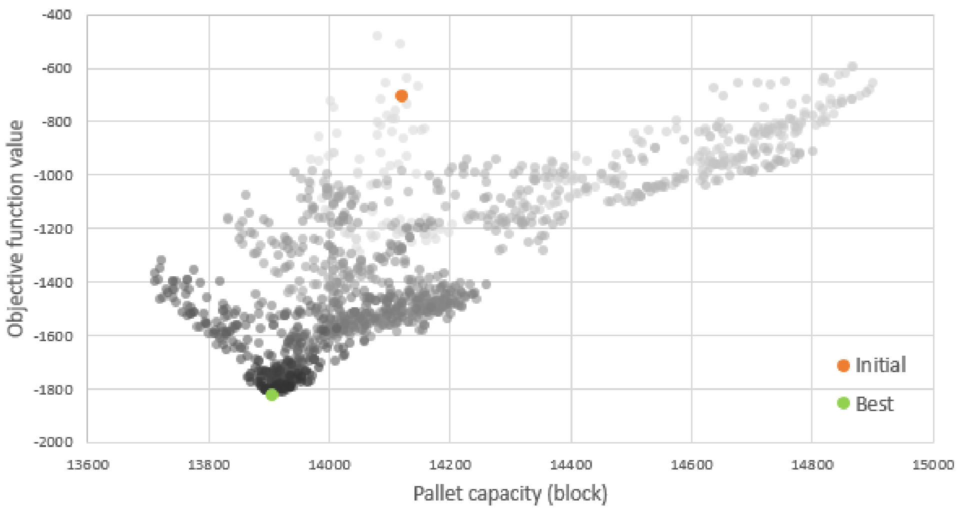

Figure 22: Heat map objective function value against pallet capacity

To find the Pareto optimal solutions, this section plots the block pallet capacity against the objectives of the objective function: average inbound pallets not possible to place per day, average available pallet locations, and required additional floor space. In these graphs, we project a Pareto front to identify the Pareto solutions [35]. In each graph, the initial solution is presented by an orange dot, and the best solution by a green dot. The graphs cannot show the complete solution space, because the improvement heuristic explores only certain parts based on the objective function.

Figure 23 plots the block pallet capacity against the average inbound not possible per day and projects the Pareto front on it. The figure shows that different configurations with equal pallet capacity can result in various values for the average inbound pallets not possible per day. Moreover, decreasing the block pallet capacity below 13,860 significantly increases the inbound pallets not possible. Table 23 shows the initial and best configuration and the configurations on the Pareto front when plotting the block pallet capacity against the average inbound not possible per day. Since a lot of Pareto configurations have zero inbound pallets not possible, the table only includes the configuration with the lowest capacity.

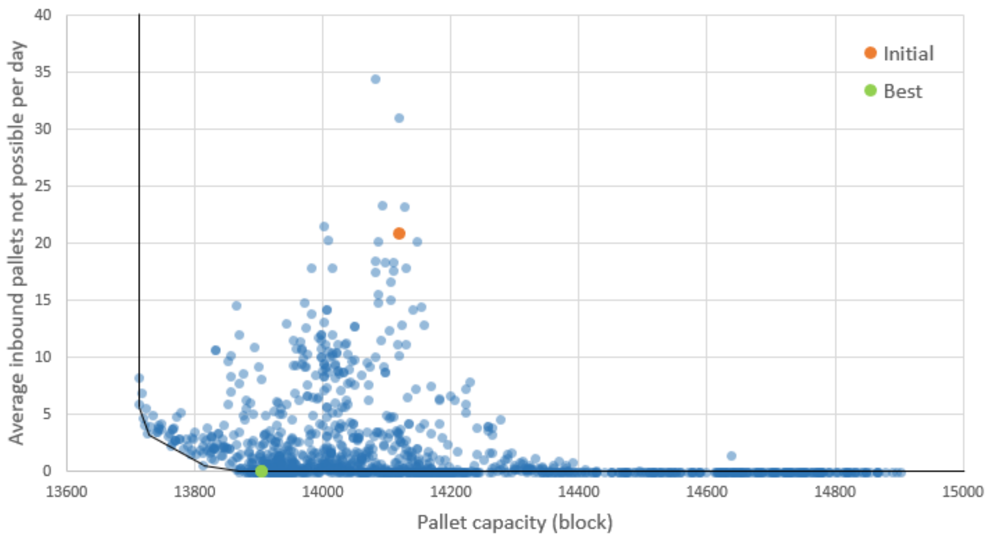

Figure 23: Pareto front inbound pallets not possible versus pallet capacity

Table 23: Configurations on the Pareto front inbound pallets versus pallet capacity

Configuration*	**Pallet capacity (block)**	**Inbound pallets not possible per day**	**Available pallet locations**	**Additional required floor space (in pallet depth)**	**Mean occupancy rate (%)**
Initial	14,121	20.8	1,017	0	66.9
Best	13,905	0	1,826	0.5	68.2
26-228-30-56-63-3-0	13,712	6.0	1,483	0	69.1
25-228-32-57-61-3-0	13,720	4.1	1,529	0.5	69.0
26-228-30-57-62-3-0	13,725	3.4	1,520	1.5	69.0
26-228-31-58-61-3-0	13,762	2.2	1,560	10.5	68.9
23-232-30-53-62-6-1	13,812	0.7	1,643	0	68.6
22-232-31-58-59-7-0	13,868	0	1,761	0.5	68.3
...	...	...	...	...	...

*Low long - Low normal - Low short - Low extra short - Single-deep - SBS/RS - Two half

The first five Pareto configurations have a significantly low pallet capacity, resulting in more inbound pallets not possible and fewer available pallet locations. However, they achieve higher mean occupancy rates. In general, these Pareto solutions show that a mean occupancy rate above 69% in combination with a low and inefficient pallet capacity leads to an increase in inbound pallets not possible. Table 23 also shows that adding capacity does not necessarily require more floor space. The last Pareto configuration has zero inbound pallets not possible and a higher number of available pallet locations, resulting in a lower occupancy rate than the other configurations shown in the table. The best configuration lies on the Pareto front with zero inbound pallets not possible to place in inventory. Compared to the best configuration, the last configuration has an equal required floor space, but underachieves in terms of the number of available pallet locations. Therefore, the best configuration offers a better balance between the pallet capacity and the utilization of the pallet locations. We can conclude from Figure 23 that many configurations exist with zero inbound pallets not possible that lie on the Pareto front.

Figure 24 plots the block pallet capacity against the average available pallet locations and projects the Pareto front on it. The figure shows that generally when increasing the block pallet capacity, thus the total number of pallet capacity, the available pallet locations increase as well. This is because the inventory stays the same. However, different configurations with equal pallet capacity can result in various values for the average available pallet locations. The figure also indicates that the improvement heuristic did not explore solutions with average available pallet locations below 992.

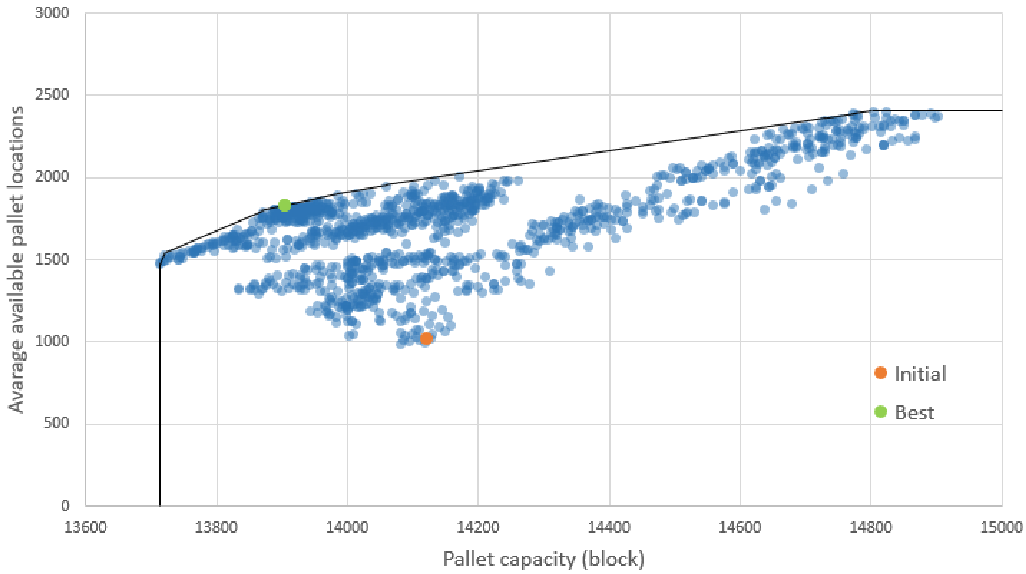

Figure 24: Pareto front available pallet locations versus pallet capacity

Table 24 shows the initial and best configuration and the configurations on the Pareto front when plotting the block pallet capacity against the average available pallet locations. The third Pareto configuration is close to the best configuration but balances the objectives a bit differently. It outperforms the best configuration on the required floor space, but 1.5 inbound pallets are not possible on average per day and it has 61 fewer average available pallet locations. Moreover, the bottom six Pareto configurations outperform the best configuration on the available pallet locations but require more floor space. A trade-off between the objectives should be made to make a decision on which configuration is more suitable. Additionally, the table shows that an increased mean occupancy rate decreases available pallet locations.

Table 24: Configurations on the Pareto front available pallet locations versus pallet capacity

Configuration*	Pallet capacity (block)	Inbound pallets not possible per day	Available pallet locations	Additional required floor space (in pallet depth)	Mean occupancy rate (%)
Initial	14,121	20.8	1,017	0	66.9
Best	13,905	0	1,826	0.5	68.2
26-228-30-56-63-3-0	13,712	6.0	1,483	0	69.1
25-228-32-57-61-3-0	13,720	4.1	1,529	0.5	69.0
21-233-31-59-57-7-0	13,870	1.5	1,765	0	68.3
21-233-31-60-57-7-0	13,888	0.8	1,809	0.5	68.2
23-233-31-58-58-5-2	13,943	0	1,853	11.5	68.0
25-233-32-60-58-3-3	14,059	0	1,951	41	67.4
30-233-31-48-66-5-3	14,169	0	2,007	64.5	66.9
24-263-20-42-59-4-4	14,729	0	2,352	173	64.4
26-262-21-42-59-3-4	14,772	0	2,393	181.5	64.2
18-272-26-32-62-3-6	14,823	0	2,401	200	63.9

*Low long - Low normal - Low short - Low extra short - Single-deep - SBS/RS - Two half

Figure 25 displays the relationship between the block pallet capacity and the required extra floor space and projects the Pareto front on it. The graph only shows non-negative values, because the extra floor space required is bounded to zero. Below a block pallet capacity of 13,712, no configurations are explored that require extra floor space. Above a block pallet capacity of 14,121, which is the initial pallet capacity, the improvement heuristic only explores configurations with a positive extra required floor space. In between both, the relationship between the pallet capacity and extra floor space required seems linear.

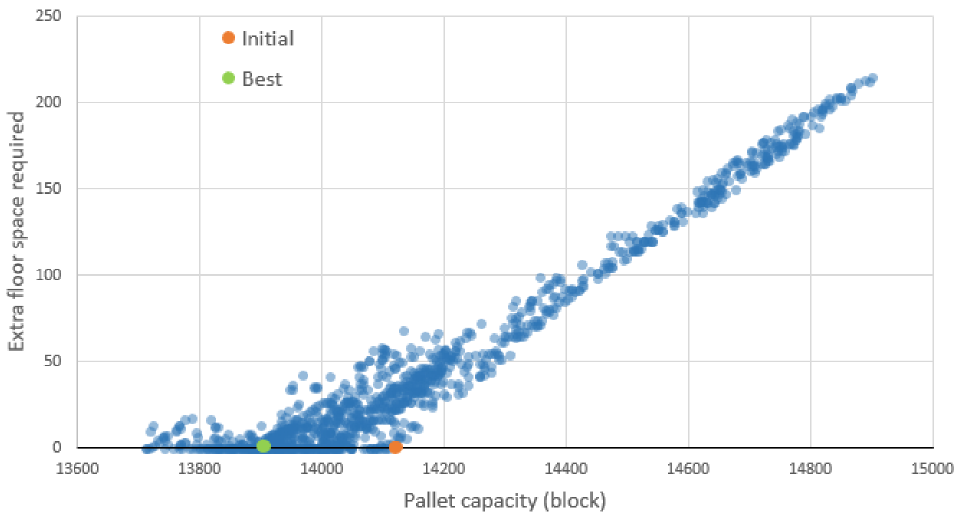

Figure 25: Pareto front (x-axis) additional required floor space versus pallet capacity

Generally, to increase the pallet capacity, additional floor space is required. However, different configurations with equal pallet capacity can result in various values for the additional required floor space. To achieve an equal pallet capacity with smaller pallet racking systems compared to larger pallet racking systems requires additional floor space. Figure 25 shows that the best objective does not lie on the Pareto front. It consists of pallet rackings that require additional floor space compared to the initial configuration. However, a value of 0.5 seems small and is compensated by the other penalties. If Riedel is not able to create the extra floor space, the problem owner should balance the objective penalties differently.

5.6 Sensitivity analysis

To evaluate the robustness of the improvement heuristic, this section performs a sensitivity analysis on the weights of the penalties of the objective function. It compares the differences in performance taking into account different values. Table 25 creates experiments with varying weights of the penalties for the sensitivity analysis. The weight of the available pallet rackings was set as a benchmark so it is fixed. Experiments 1 and 2 evaluate the impact of the penalty on the inbound pallets that are not possible to be placed. Experiments 3 and 4 evaluate the impact of the penalty on additional required floor space. Finally, experiments 5 and 6 test the impact of the penalty on available pallet locations by increasing or decreasing the other two penalties.

Table 25: Weights penalties objective value experiments

	Cost inbound pallet	**Cost/reward pallet racking**	**Reward available pallet location**
Current weights	15	8	1
Experiment 1	20	8	1
Experiment 2	10	8	1
Experiment 3	15	13	1
Experiment 4	15	3	1
Experiment 5	10	3	1
Experiment 6	20	13	1

Table 26 shows the configurations of the best objective function values of the experiments and Table 27 presents the corresponding output KPIs. Below these tables, the impact of each penalty is elaborated on based on these experiments.

Table 26: Best configurations experiments sensitivity analysis

	Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
Current weights	22	233	31	58	58	7	0
Experiment 1	17	234	43	57	59	5	0
Experiment 2	20	233	53	41	59	4	1
Experiment 3	13	234	37	56	59	11	2
Experiment 4	96	252	63	99	73	4	1
Experiment 5	74	253	80	71	59	30	1
Experiment 6	9	233	40	66	59	10	1

Table 27: Output KPIs experiments sensitivity analysis

	Pallet capacity (block)	**Inbound not possible**	**Extra floor space (in pallet depth)**	**Available pallet rackings**	**Honeycombing pallet locations**
Current weights	13,905	0	0.5	1,826	3,074
Experiment 1	13,912	0	8	1,928	2,989
Experiment 2	13,961	0	8	1,843	3,113
Experiment 3	13,828	0	0	1,800	3,017
Experiment 4	19,761	0	1,460	8,408	3,151
Experiment 5	19,491	0	1,403	8,372	3,085
Experiment 6	13,781	0	0	1,759	3,013

Penalty inbound pallets not possible to place
Experiments 1 and 2 in Table 26 and Table 27 reveal that increasing or decreasing the cost of one inbound pallet not possible by 5 has a minor impact on the results. Compared to the results of the current weights, the best configurations and output KPIs of experiments 1 and 2 differ slightly. If the inbound pallets penalty is more important (experiment 1), the heuristic ensures more flexibility causing an increase in available pallet rackings and thus fewer honeycombing pallet locations. However, this requires extra floor space compared to the situation of the current weights. Contrarily, if the penalty is less important (experiment 2) the system becomes less flexible and the honeycombing pallet locations increase compared to the situation of the current weights. However, the inbound pallets not possible is still zero, thus the improvement heuristic still gives a high priority to this penalty.

Penalty additional required floor space
Experiments 3 and 4 in Table 26 and Table 27 expose the importance of the penalty on additional required floor space. Compared to the results of the current weights, the best configuration and output KPIs of experiments 3 and 4 are quite different. If the penalty of additional required floor space is more important (experiment 3), the aim of the heuristic is to obtain zero additional floor space. This ensures that the pallet rackings from the configuration fit into the current floor space of the DC. However, if the penalty is less important (experiment 4), the heuristic is able to freely add pallet rackings causing the pallet capacity to increase majorly. This results in a substantial increase in available pallet rackings and additional floor space required. Since the heuristic has many options when allocating the inbound pallets, the honeycombing pallet locations have an insignificant increase.

Penalty available pallet locations
Experiments 5 and 6 in Table 26 and Table 27 reveal a crucial impact of the penalty on available pallet locations. If decreasing the other two penalties, thus making the available pallet locations penalty more important (experiment 5), the only aim of the heuristic is to create as many pallet rackings. Thus, like in experiment 4, the heuristic adds a huge amount of pallet rackings. However, in experiment 5 it gives a higher value to low-capacity pallet rackings, whereas in experiment 4 to high-capacity pallet rackings. The difference is that in experiment 5 also the weight of the inbound

pallets penalty has decreased, giving the available pallet penalty the highest priority. As can be seen in Table 27, low-capacity pallet rackings create less honeycombing, thus generate a higher percentage of available pallet locations from the total pallet capacity. If increasing the other two penalties, thus making the available pallet locations penalty less important (experiment 6), the heuristic puts the focus on allocating all inbound pallets to pallet rackings that fit within the current floor space of the DC. Compared to the best configuration of the current weights, adding more low-capacity pallet rackings causes a decrease in available pallet rackings and honeycombing pallet locations. It shows that a lower pallet capacity and fewer available pallet locations can result in more efficient utilization of the pallet rackings.

To conclude, changing the weight of the inbound pallets penalty has a minor impact on the results, but can influence the flexibility and honeycombing pallet locations slightly. Contrarily, the weight of the penalty of additional required floor space has a major impact. When this weight gets less priority, the heuristic is able to freely add pallet rackings causing the pallet capacity to considerably increase. The same holds for giving more priority to the weight of the available pallet locations penalty. However, when this penalty is less important, the heuristic puts the focus on allocating all inbound pallets to the pallet rackings that fit within the current floor space of the DC. It shows that a lower pallet capacity and fewer available pallet locations can result in a more efficient utilization of the pallet rackings.

5.7 Conclusion

This chapter answers research question *'What are possible improvements to the design of the pallet rackings within the DC?'* by simulating the WMS with different configurations of the pallet racking systems using the improvement heuristic developed in Chapter 4. The chapter explores different designs of the pallet racking systems to search for improvements. The simulation design consists of the following four steps.

Step 1: Weighing the objective function
This step weights the penalties of the objective function. The cost of not placing one inbound pallet in inventory over the time horizon (C_i) gets a weight of 15, whereas the reward of one available pallet location over the time horizon (R_a) is set to 1 to serve as a benchmark. The cost of one pallet depth of additional floor space (Cp) gets a weight of 8 to make sure that the cost of one additional pallet racking is always more than the reward of the available pallet locations of one pallet racking.

Step 2: Parameter tuning SA
This step tunes the parameters of the SA to balance intensification and diversification. The decrementing rule of Gonzales et al. [78] is selected and adjusted to the following rule with T_k the temperature level at the k-th Markov chain, α the decrementing parameter and I the length in iterations of the constant part of the rule.

$$T_k = \begin{cases} T_0 & k < I \\ \alpha * T_k & k \geq I \end{cases}$$

The start temperature and initialization length are found by experimenting with values of the start temperature with a fixed stop temperature of 50, Markov chain length of 50, and alpha of 0.9. By analyzing the acceptance ratio of the experiments, we select a start temperature of 350 and an initialization length of 300. Then, experiments are performed to determine the other parameters of the cooling scheme. We select the experiment with the best balance between the run time and the best objective function value. This results in the following cooling scheme: initialization length 300, start temperature 350, alpha 0.8, stop temperature 10, and Markov chain length 100.

Step 3: Analyse heuristic results
This step analyses the results of the improvement heuristic for the base scenario on the best configuration and the complete solution space. Table 28 shows the best configuration of the base scenario. The best configuration results in a consistent improvement in the daily occupancy rate based on the past demand data from January until April 2024. Resulting from the analysis on the solution space, the best configuration performs well in all three output KPIs from the penalties. The inbound pallets not possible is zero, thus lies on the Pareto front. The number of available pallet locations is 1,826 and also lies on the Pareto front. Contrarily, this configuration requires 0.5 extra floor space so it does not lie on the Pareto front, but this value seems small and is compensated by the other penalties. The best configuration results in an improvement of the mean occupancy rate of 1.3%.

Table 28: Base scenario, best configuration

Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
22	233	31	58	58	7	0

The results suggest the following possible improvements to the design of the pallet racking systems.

- Build 18 low long pallet rackings to cope with larger batches.
- Remove 50 low normal pallet rackings.
- Build 7 low short and 34 low extra short pallet rackings to increase flexibility.
- Introduce the SBS/RS by rebuilding 7 low normal pallet rackings.

Step 4: Sensitivity analysis
This step performed a sensitivity analysis on the weights of the penalties of the objective function to evaluate the robustness of the improvement heuristic. Changing the weight of the inbound pallets not possible has a minor impact on the flexibility and honeycombing effect. Contrarily, giving the penalty of additional required floor space less priority or giving the available pallet locations penalty more priority, the heuristic freely adds pallet rackings. It shows that a lower capacity and fewer available pallet locations result in a more efficient utilization of the pallet rackings.

6 Scenarios of future product portfolios

This chapter develops scenarios of future product portfolios. These scenarios capture the uncertainty in demand of the base scenario. The chapter compares and analyses the results of the improvement heuristics for the future scenarios, and answers the following research questions.

7. What are relevant scenarios on the future product portfolio to investigate?

8. How do the improvements influence the occupancy rate in different scenarios?

Section 6.1 explains the first future scenario assuming an increased volume, but the same initial inventory. The future scenario in Section 6.2 also assumes an increased volume, but an increased initial inventory as well. Section 6.3 elaborates on the future scenario of adding low volume SKUs to the product portfolio. Section 6.4 explains the future scenario of splitting a percentage of the current SKUs in the product portfolio on their volume. Section 6.5 gives the results of the future scenarios and compares them to the base scenario and each other. Section 6.6 reflects on the accuracy of the improvement heuristic by elaborating on the verification and validation.

6.1 Scenario 1: Increased volume, same initial inventory

The first scenario assumes an increased volume of inventory over the time horizon compared to the base scenario but takes the same initial inventory as the past inventory input data. This indicates that the safety stock at the start does not increase. This scenario reflects how the improvement heuristic deals with a gradual increase in the volume of inventory over time. It indicates what is needed to have more flexibility to store additional inventory of the SKUs of the current product portfolio.

To increase the volume over the time horizon, Algorithm 3 receives modified input data of the InboundPallets and OutboundPallets tables. The batch sizes of the inbound process are increased by 5%. This percentage can be adjusted in future research. Then, the differences in the number of pallets of the batch sizes are added to the orders of the outbound process. The heuristic randomly distributes these outbound pallets over the existing outbound orders with an equal batch number. Moreover, it makes sure that the outbound date is not before the inbound date.

6.2 Scenario 2: Increased volume, increased initial inventory

The second scenario assumes an increased volume of inventory over the time horizon compared to the base scenario and an increased initial inventory. This indicates that the safety stock of the start inventory also increased. This scenario reflects how the improvement heuristic copes with a sudden increase in inventory levels. It shows what is needed to quickly improve the configuration of pallet rackings within the DC to adapt to sudden changes in the inventory. Scenario 1 is optimistic and assumes no safety stock, whereas scenario 2 is pessimistic and deliberately takes a high safety stock. In reality, the safety stock will probably be in between these two scenarios.

To increase the volume over the time horizon, Algorithm 3 receives modified input data of the InboundPallets and OutboundPallets tables. The volumes of the inbound and outbound pallets are increased by 5%, following the same method that is applied in scenario 1. The percentage can be adjusted in future research. Additionally, in scenario 2, the initial inventory is increased by modifying the Rackings input data. The heuristic empties all pallet rackings, increases the initial inventory of each batch, and reallocates the batches to the pallet rackings. Then, it adds the extra initial inventory to the OutboundPallets table, in the same way as adding the extra inbound pallets.

6.3 Scenario 3: Adding low-volume SKUs

The third scenario adds SKUs with low volume to the product portfolio. This scenario reflects on the impact of an increase in the variety of SKUs rather than an increase in the volume or inventory of existing SKUs. The DC has many drive-in pallet rackings that are mainly used for the storage of SKUs with large volumes, as Section 3.1.2 explains. This future demand scenario researches what is required for managing a larger variety of SKUs, such as the need for other types of pallet racking systems.

To integrate low-volume SKUs into Riedel's product portfolio, Algorithm 3 receives modified input data of the InboundPallets and OutboundPallets tables including the additional SKUs. These additional SKUs are not incorporated into the initial inventory, thereby leaving the Rackings input data unchanged. The characteristics of the additional SKUs are based on existing low-volume SKUs that had inventory during the time horizon of the historical data from the base scenario. To select existing SKUs to base the additional SKUs on, those with fewer than three batches during the time horizon are excluded. This decision is made to ensure that the additional SKUs make an impact. Then, the heuristic sorts the SKUs in ascending order based on the mean batch size and selects 5% of the SKUs with the lowest volume. This percentage can be adjusted in future research. The heuristic generates additional low-volume SKUs based on the following characteristics of the selected SKUs.

- Date number of the first batch.
- Number of batches over the time horizon.
- Mean and standard deviation of the batch size.
- Mean and standard deviation of the days between the batches.
- Number of orders over the time horizon.
- Mean and standard deviation of the order size.
- Mean and standard deviation of the length of stay.

For each additional low-volume SKU, the heuristic adds batches to the inbound process and orders to the outbound process as follows. First, it generates an article number, pallet height, and pallet type and determines the date and batch number of the first batch. After that, it generates batches iteratively. The number of batches is based on the number of batches of the existing SKU. The size of a batch and the days between the previous batch and the current batch are calculated by generating a normal random variable. The following formula is used, with normal random variable X, standard normal random variable Z, mean σ, and standard deviation μ [51].

$$X = \sigma Z + \mu$$

For each inbound batch of the additional SKUs, the heuristic generates outbound orders. The heuristic ensures that the first order of a batch is after the inbound date of the batch. The number of orders per batch is based on the characteristics of the existing SKU. The order size and length of stay are also calculated by generating a normal random variable using the mean and standard deviation. Using this information, the heuristic generates orders of the outbound process of which the total number of pallets does not exceed the number of inbound pallets of the batch. In general, the heuristic makes sure that the inbound batches and outbound orders are not generated on a Saturday or Sunday, because then the factory and DC are closed.

6.4 Scenario 4: Split SKU volumes

The fourth scenario splits SKUs by halving the volume of existing SKUs and redistributing these volumes to newly created SKUs. This scenario explores the impact of having a larger product portfolio of SKUs with lower volumes. In this scenario, the total volume remains equal to the base scenario, unlike in scenario 3, which experiences an increase. Despite the unchanged volume, the increase in the variety of SKUs and thus the variety of batches might require other types of pallet racking systems.

To get a larger product portfolio of lower volume SKUs by splitting existing SKUS, Algorithm 3 receives modified input data. The Rackings table remains the same, but the InboundPallets and OutboundPallets tables are adapted. The heuristic halves the volumes in terms of the number of inbound and outbound pallets of 5% of the existing SKUs. This percentage can be adjusted in future research. One-third of the selected SKUs have a high volume, one-third a medium volume, and one-third a low volume. Then, it creates additional SKUs that receive the other half of the volume of the existing SKUs and their characteristics. Thus, the total volume remains unchanged.

6.5 Results and comparison between scenarios

This section analyses the results of the future scenarios and compares them with the base scenario and each other.

6.5.1 Characteristics scenarios

Table 29 presents the characteristics of the base scenario and the scenarios of future product portfolios. These characteristics are parameters from Table 17 that are experimented on. Table 29 shows that the number of SKUs in the base scenario is 240, whereas Section 2.2 determines that the product portfolio of Riedel in March 2024 consisted of 287 ambient SKUs. Thus, not all SKUs from the product portfolio were in inventory during the time horizon because they have seasonality during the summer and/or around Christmas time. This is also the reason for fixing the high normal and high extra short pallet racking systems, as Section 4.3.4 explains. Moreover, Table 29 shows that scenario 3 (adding low-volume SKUs) and scenario 4 (split SKU volumes) have 12 additional SKUs, which is 5% of the total number of SKUs. This also results in an increase in the number of batches. The initial inventory of scenario 2 (increased volume, increased initial inventory) is 4.9% higher than the base scenario. This difference is caused by rounding the inventory of each batch separately.

The average inbound and outbound pallets per day of each scenario is higher than the base scenario, except for scenario 4 (adding low-volume SKUs), in which the volume is only split amongst SKUs. Compared to the base scenario, the inbound pallets of scenario 1 (increased volume, same initial inventory) and scenario 2 (increased volume, increased initial inventory) increased by 4.8%. This difference is caused by rounding the pallets of each batch separately. With 0.8%, the inbound pallets of scenario 3 (adding low-volume SKUs) slightly increase because of adding low-volume SKUs. The outbound pallets of scenario 1 (increased volume, same initial inventory) increase by 4.9%, again with a rounding difference, and in scenario 2 (increased volume, increased initial inventory) by 5.7%. This extra 0.8% is caused by the increased initial inventory. Scenario 3 (adding low-volume SKUs) has a smaller increase of the outbound pallets of 0.4% because in general low-volume SKUs have small orders.

Table 29: Characteristics base and future scenarios

	Base scenario	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
Number of SKUs (S)	240	240	240	252	252
Number of batches (B)	1,001	1,001	1,001	1,047	1,056
Initial pallet inventory ($\sum_{j,b} I_{j3b}$)	7,152	7,152	7,502	7,152	7,152
Average daily demand inbound pallets ($\sum_{t,b} \frac{d_{tb}}{T}$)	503	527	527	507	503
Average daily supply outbound pallets ($\sum_{t,b} \frac{o_{tb}}{T}$)	474	497	501	476	474

6.5.2 Comparison results

Table 30 shows the initial configuration (current configuration in the DC) and the differences to the best configuration of all scenarios. The initial configuration is the same in the base and future scenarios. It shows that the heuristic removes 50 low normal drive-in pallet rackings in all scenarios, except for scenario 3 (adding low-volume SKUs) in which it removes 48. As with the base scenario, the heuristic adds low long pallet rackings to cope with the large batches that do not fit into the low normal pallet rackings anymore. In scenario 1 (increased volume, same initial inventory), the heuristic adds an equal number of low long pallet rackings as in the base scenario because the initial inventory and the number of batches are equal to the base scenario. However, in scenario 2 (increased volume, increased initial inventory) the heuristic adds one more low long pallet racking to handle the additional initial inventory. In scenario 3 (adding low-volume SKUs) and scenario 4 (split SKU volumes), it adds less low long pallet rackings because of the increase in the number of low-volume batches. Therefore, the heuristic gives priority to pallet rackings with a lower capacity.

Compared to the base scenario, in the future scenarios, the heuristic adds substantially more low short pallet rackings and a varying number of low extra short pallet rackings. The difference in the number of single-deep pallet rackings in each scenario is around zero because removing one does not gain a reward, and adding one takes up an adequate amount of aisle space. Moreover, the heuristic exchanges low normal pallet rackings with SBS/RS rackings, but not with two half rackings since with equal costs the SBS/RS rackings have more capacity and flexibility.

Table 30: Initial configuration and differences to best configurations base and future scenarios

	Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
Initial	4	283	24	24	59	0	0
Base scenario	+18	-50	+7	+34	-1	+7	0
Scenario 1	+18	-50	+40	+10	-3	+4	0
Scenario 2	+19	-50	+22	+29	-1	+8	0
Scenario 3	+12	-48	+31	+39	0	+5	0
Scenario 4	+5	-50	+41	+23	+1	+5	0

The best configuration of each scenario results in the penalties and objective values displayed in Table 31 with the output KPIs of Table 32. Appendix C shows the heat maps of the objective function of each future scenario. These heat maps indicate that the improvement heuristic iteratively converges towards a region of better solutions near the best solution. Table 31 shows that the initial objective function value of each of the future scenarios is higher than the base scenario. The performance of the initial configuration of scenario 4 (split SKU volumes) is the closest to the base scenario since the initial penalties on the inbound and available rackings of the other scenarios are higher. This is because scenario 1 (increased volume, same initial inventory), scenario 2 (increased volume, increased initial inventory), and scenario 3 (adding low-volume SKUs) have an increased number of inbound and outbound pallets. Additionally, the initial objective function value of increasing the volume (and initial inventory) is better than when adding low-volume SKUs. Thus, the initial configuration is more suitable for an increase in volume than an increase in the number of low-volume SKUs. However, the difference between scenario 1 (increased volume, same initial inventory) and scenario 2 (increased volume, increased initial inventory) is relatively small, thus the additional initial inventory does not have much impact on the efficiency of the pallet rackings. The reason for this is that at the start of the time horizon, there is a lot of space left for additional inventory and it is gone before the DC gets full. Therefore, the penalty for inbound not possible does not differ much.

Table 31 also indicates that with the current configuration adding low-volume SKUs is worse than splitting SKUs. The difference is major, because scenario 3 adds only low-volume SKUs, whereas scenario 4 splits high, medium, and low-volume SKUs. When only splitting low-volume SKUs, the expectation is a decrease in the initial objective function value of scenario 4 since they cause more honeycombing.

Table 31: Penalties objective function base and future scenarios

		Penalty inbound not possible to place	**Penalty available rackings**	**Penalty floor space required**	**Objective value**
Base	Initial	311	-1,016	0	-705
	Best	0	-1,826	4	-1,822
	Difference	-311	-810	+4	-1,117
Sc1	Initial	2,299	-636	0	1,664
	Best	94	-1,618	424	-1,100
	Difference	-2,205	-982	+424	-3,764
Sc2	Initial	2,485	-459	0	2,026
	Best	28	-1,556	732	-796
	Difference	-2,457	-1,097	+732	-2,822
Sc3	Initial	4,358	-419	0	3,939
	Best	16	-1,914	944	-954
	Difference	-4,342	-1,495	+944	-4,893
Sc4	Initial	1,183	-792	0	391
	Best	6	-1,633	8	-1,619
	Difference	-1,177	-841	+8	-2,010

Table 32: Output KPIs base and future scenarios

		Capacity (block/Euro)	**Mean inventory**	**Mean available locations**	**Mean honeycombing locations**
Base	Initial	14,121 / 18,069	9,665	1,017	4,074
	Best	13,905 / 17,785	9,689	1,826	3,074
	Difference	-216 / -284	+24	+809	-1,000
Sc1	Initial	14,121 / 18,069	9,911	636	4,042
	Best	14,150 / 18,054	10,063	1,618	3,132
	Difference	+29 / -15	+152	+982	-910
Sc2	Initial	14,121 / 18,069	9,962	459	4,152
	Best	14,262 / 18,216	10,132	1,556	3,235
	Difference	+141 / +147	+170	+1,097	-917
Sc3	Initial	14,121 / 18,069	9,658	418	4,377
	Best	14,302 / 18,288	9,960	1,914	3,132
	Difference	-181 / -219	+302	+1,496	-1,245
Sc4	Initial	14,121 / 18,069	9,607	792	4,289
	Best	13,839 / 17,681	9,689	1,633	3,176
	Difference	-282 / -388	+82	+841	-1,113

The best objective function value of each future scenario is worse than the base scenario (Table 31). However, each scenario shows improvement from the initial to the best objective function value. The best solution value of scenario 4 (split SKU volumes) is the closest to the base scenario, requires the least floor space and has the lowest number of inbound pallets that are not possible to be placed. However, Table 32 shows that the best configuration of scenario 3 (adding low-volume SKUs) has more available pallet locations which is caused by a higher pallet capacity and lower mean inventory. The number of available pallet locations of scenario 3 even exceeds the base scenario, but requires the most additional floor space of all scenarios. Additionally, scenario 1 (increased volume, same initial inventory) and scenario 2 (increased volume, increased initial inventory) have slightly fewer available pallet locations while having to cope with around 400 additional mean inventory, which is mainly caused by an increase in pallet capacity. Despite the increase in pallet capacity in scenarios 1, 2, and 3, the heuristic is not able to allocate all inbound pallets. The best configuration of all future scenarios results in more honeycombing than the base scenario, which is caused by either an increase in batches or volume.

6.5.3 Improvement occupancy rate future scenarios

Figure 26 displays the daily occupancy rate of the initial and best configurations of the future scenarios, just as in Figure 21 for the base scenario. Table 33 shows the initial, best and difference in the mean occupancy rate of the base and future scenarios. Appendix D shows the mean occupancy rates per pallet type. In the base scenario, the occupancy rate of the best configuration lies slightly higher than the occupancy rate of the initial configuration with a mean difference of 1.3%, indicating a consistent improvement. For each scenario, Table 33 and Figure 26 are analyzed.

Scenario 1 (increased volume, same initial inventory)
Table 33 shows that the increase in volume results in higher occupancy rates compared to the base scenario. However, the difference between the initial and best occupancy rate of scenario 1 is slightly smaller than in the base scenario. In scenario 1, the improvement of the occupancy rate is not caused by an increase in pallet capacity (Table 32), thus it is caused by an increased inventory level. Figure 21 shows that the difference between the occupancy rate of the initial and best configuration is after date number 60 (29th of February). Then, the initial daily occupancy rate flattens, whereas the best daily occupancy rate keeps increasing. Thus, as of March the initial configuration reaches the maximum utilization of the pallet rackings, which prevents the inventory from increasing. Therefore, not all inbound pallets fit into the DC anymore. Hence, the best configuration of pallet rackings allows the mean inventory to increase from March onwards, causing the occupancy rate to improve.

Scenario 2 (increased volume, increased initial inventory)
Table 33 shows that the increase in volume and initial inventory results in an even higher initial occupancy rate than in scenario 1. Because of the compatible best occupancy rates of scenarios 1 and 2, the difference between initial and best in scenario 2 is less than in scenario 1. In scenario 2, the heuristic increases the pallet capacity from the initial to the best configuration (Table 32). Therefore, before date number 60 (29th of February), Figure 21 shows a minor difference between the occupancy rate of the initial and best configuration in favor of the initial configuration. After February, the difference is significantly higher and shifted in favor of the best configuration, because in the initial situation the maximum utilization of the pallet rackings is reached. Thus, the best configuration of pallet rackings allows the mean inventory to increase, which improves the occupancy rate despite the expanded pallet capacity.

Scenario 3 (adding low-volume SKUs)
Table 33 shows that adding low-volume SKUs results in an initial mean occupancy rate similar to the base scenario. However, we expect the initial occupancy rate of

scenario 3 to be slightly higher than the base scenario due to a small inventory increase. Nevertheless, Figure 26 indicates that the initial occupancy rate of scenario 3 flattens. Compared to the base scenario, many inbound pallets cannot be placed in the DC resulting in a lower inventory (Table 33). The best configuration of scenario 3 solves this by balancing the types of pallet rackings while decreasing the pallet capacity (Table 32). Therefore, the graph of scenario 3 in Figure 26 resembles scenario 2, but with lower values and a larger difference between the initial and best configuration.

Scenario 4 (split SKU volumes)
Table 33 shows that splitting the volume of SKUs results in an initial mean occupancy rate slightly below the base scenario. The total volume remains equal, but the additional batches of scenario 4 prevent some inbound pallets from being placed, causing the mean inventory to drop (Table 33). Scenario 4 shows the largest difference between the initial and best occupancy rate because of a significant reduction in pallet capacity (Table 33). Just as in the other future scenarios, Figure 33 shows the largest difference after date number 60 (29th of February) because in the initial configuration the maximum utilization of the pallet rackings in the DC is reached.

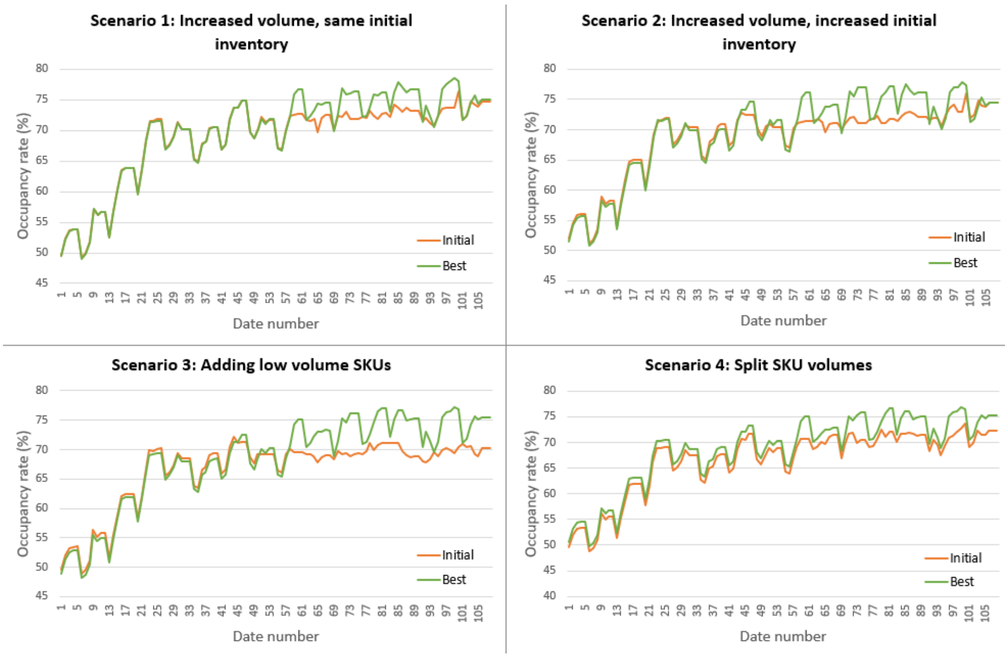

Figure 26: Daily occupancy rate initial versus best configuration, future scenarios

Table 33: Initial, best and difference mean occupancy rate base and future scenarios (in %)

	Initial mean occupancy rate	**Best mean occupancy rate**	**Difference mean occupancy rate**
Base	66.9	68.2	+1.3
Scenario 1	68.7	69.6	+0.9
Scenario 2	69.0	69.5	+0.5
Scenario 3	66.9	68.1	+1.2
Scenario 4	66.5	68.5	+2.0

6.6 Verification and validation

This section determines whether the improvement heuristic is an accurate representation of the real world. Banks [5] proposes principles on how to do so, consisting of verification and validation.

6.6.1 Verification

Verification is determining whether the problem formulation is transformed into an executable computer program as intended [5]. During the development of the improvement heuristic, tracing and debugging techniques are used to detect logical errors. We traced several inbound batches to ensure that the built-in WMS allocates them as intended. Moreover, several outbound orders were traced to test whether the WMS selects the correct pallets. The inbound and outbound processes are both converted to flowcharts to accommodate as an extra intermediate step before developing the model in the computer program. Besides that, debugging the creation of the future scenarios verifies whether the scenarios present possible real-world situations. They should be realistic and relevant to the research. Section 6.5.1 reflects on the quantitative characteristics of the scenarios to investigate whether the improvement heuristic generates the expected scenarios.

6.6.2 Validation

Validation is determining whether the model behaves with accuracy consistent with the study objectives [5]. The improvement heuristic is a simplification of the real world and we should be able to make decisions on it. The validity of the improvement heuristic can be tested by offering it the current configuration of the pallet rackings and evaluating whether the results resemble the performance of the real world. Section 4.4 compares the output KPIs of the improvement heuristic on the base scenario with the performance of the real world. It observes some differences between the performance of the improvement heuristic and the real world. However, the differences seem small and explainable, thus with a high certainty we can assume it will not be practically impactful. Therefore, this validates that the heuristic aligns well with the real world.

6.7 Conclusion

This chapter answers research question *'What are relevant scenarios on the future product portfolio to investigate?'* by determining the following four scenarios on the future product portfolio.

- Scenario 1: increased volume, same initial inventory. This reflects on a gradual increase in volume without increasing the safety stock. This scenario is implemented by increasing the batch sizes by 5%.
- Scenario 2: increased volume, increased initial inventory. This scenario also increases the safety stock, thus scenario 1 is optimistic and scenario 2 is pessimistic. Just as the volume, the heuristic increases the inventory by 5%.

- Scenario 3: adding low-volume SKUs. This reflects on the impact of an increase in the variety of SKUs rather than an increase in the volume or inventory of existing SKUs. The heuristic generates the inbound and outbound pallets of 5% additional SKUs by using the mean and standard deviation of characteristics of the existing low-volume SKUs.
- Scenario 4: split SKU volumes. This explores the impact of having a larger product portfolio of SKUs with lower volumes, but an unchanged total volume compared to the base scenario. The heuristic halves the number of inbound and outbound pallets of 5% existing high-volume, medium-volume, and low-volume SKUs and creates additional SKUs that receive the other half of their volume.

Additionally, this chapter answers research question *'How do the improvements influence the occupancy rate in different scenarios?'* by analyzing the results and comparing them to the base scenario. The best configurations of the future scenarios are quite in line with the best configuration of the base scenario. However, in scenarios 3 and 4, the best configuration gives more priority to low-capacity pallet rackings. With the current configuration, splitting high, medium, and low-volume SKUs performs best, because the total volume remains equal to the base scenario. Additionally, increasing the volume (and initial inventory) of the complete product portfolio performs better in allocating inbound pallets than adding low-volume SKUs to the product portfolio. Each scenario shows improvement from the initial to the best objective function value. However, in each scenario, the best configuration results in inbound pallets that are not possible to be placed. Scenario 3 has a higher number of available pallet locations compared to the base scenario, but it requires the most additional floor space of all scenarios. Scenario 1 and 2 also require a lot of extra floor space, whereas scenario 4 only requires an additional pallet depth of 1 but has a low number of available rackings compared to the base scenario while it has an equal total volume.

The best configurations of the future product portfolio scenarios allow the inventory to increase, resulting in improved daily occupancy rates. The improvement of the heuristic is mainly observed after date number 60, where the initial configurations reach the maximum utilization of the pallet rackings in the DC. Therefore, the initial configurations observe inbound pallets not possible after date number 60. However, the best configurations can manage higher inventory levels. Thus, despite a potential increased pallet capacity, this results in improved occupancy rates between 0.5 and 2%.

Finally, this chapter evaluated whether the improvement heuristic gives an accurate representation of the real world. On the one hand, to verify the improvement heuristic, this research uses tracing and debugging to identify logical errors. On the other hand, to validate the improvement heuristic, this research assesses its performance against real-world historical data.

7 Conclusions and recommendations

In this research, an improvement heuristic is developed to improve the occupancy rate of the pallet rackings in the DC. It searches for a configuration of pallet rackings that is able to allocate the inbound pallets within the floor space of the DC while keeping sufficient available pallet locations. The uncertainty in demand is simulated by creating scenarios of future product portfolios. This research answers the following main research question.

How should the occupancy rate of the DC be optimized to reach the target service level for possible future product portfolios?

Section 7.1 concludes the research and Section 7.2 lists the recommendations that should be implemented to reach the target service level in the future based on the base and future scenarios. Section 7.3 explains the contribution to practice and scientific literature. Finally, Section 7.4 discusses the limitations to the research and further research that derives from them.

7.1 Conclusions

This research solves the core problem "The optimal occupancy rate for future product portfolios is unknown". The analysis on the current situation in the DC showed that Riedel uses a single-deep pallet racking system and five different drive-in pallet racking systems with different heights and lengths. The pallet racking systems result in a total pallet capacity of 14,121 block pallets and 18,069 Euro pallets, and a target maximum occupancy rate of 72.8%. The actual occupancy rate over 2022 and 2023 fluctuates between 40% and 80% with some peaks above the target maximum occupancy rate. Moreover, it highlighted that the product portfolio consists of twice as many SKUs as 4.5 years ago, indicating an increasing SKU variety.

The literature review provided knowledge on the different types of pallet racking systems. It suggested that drive-in pallet racking systems are mainly used for the storage of SKUs with larger volumes because one pallet racking can store one batch. This commonly creates honeycombing which decreases the occupancy rate. Therefore, the observed increase in SKU variety denotes a shift in the capacity and utilization requirements of the DC. These requirements depend majorly on the types of pallet racking systems, thus the developed improvement heuristic searches for a better configuration of pallet racking systems. The literature review positioned the problem in literature on a strategic and tactical level. The problem concerns managing the multiple product inventories over a time horizon by allocating the pallets containing the products to storage systems that are identified from multiple racking options with varying capacities.

The base scenario is based on the demand in the DC from January until April 2024. The results show that the three output KPIs of the best configuration of the base scenario lie on or close to the Pareto front. A sensitivity analysis on the base scenario evaluated the robustness of the weights of the penalties of the objective function. This indicated that the penalties have a major impact on the pallet capacity of the best solution. When changing the priority, the improvement heuristic freely adds pallet rackings which significantly increases the additional required floor space and available pallet locations. Since the future product portfolio and demand are unknown, we set up the following four scenarios to simulate this uncertainty.

1. Increased volume, same initial inventory
2. Increased volume, increased initial inventory
3. Adding low-volume SKUs
4. Splitting SKU volumes

Based on the results of the base and future product portfolio scenarios, we can conclude the following.

- Without bypassing the allocation suggestions of the WMS, the current configuration of pallet rackings does not provide all inbound pallets with a pallet location in the base scenario. The improved configuration is proposed to decrease the probability of a stock out by being able to place all inbound pallets (See Table 34).

Table 34: Base scenario, best configuration

Low long	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/RS**	**Two half**
22	233	31	58	58	7	0

- With the current configuration of pallet rackings, splitting the volumes of 5% of the high, medium, and low volume SKUs performs best because the total volume remains equal to the base scenario. However, compared to the base scenario, more inbound pallets do not fit into the pallet rackings, and the honeycombing effect increases. If only splitting low-volume SKUs, the expectation is that the honeycombing effect increases substantially. When the total volume increases, Riedel can rather increase the volume (and initial inventory) of the current product portfolio by 5% than adding 5% SKUs with a low volume. The former has fewer honeycombing locations and inbound pallets that do not fit than the latter. This indicates that the type of pallet racking used in the DC is better utilized by a larger volume than by a higher SKU variety. Thus, the current types of pallet rackings cannot cope with the increasing variety of SKUs.
- The proposed configurations of pallet rackings of the future product portfolio scenarios align closely with the proposed configuration of the base scenario. This suggests that the proposed configuration for the base scenario is robust and adaptable to potential changes in the product portfolio. Therefore, Riedel can be confident that adapting the layout using the proposed configuration continues to meet the needs with a changing product portfolio. However, if the total volume increases, either by increasing the volume (and initial inventory) of the current product portfolio by 5% or adding 5% SKUs with a low volume, Riedel requires additional floor space to cope with it.

- The results of the base and future product portfolio scenarios indicate a need for more low-capacity drive-in pallet rackings to decrease the honeycombing effect and increase the inventory. Drive-in pallet rackings with a lower capacity have a smaller depth, thus require more aisle space per pallet location. Therefore, within the current floor space, the total pallet capacity will decrease. The results indicate that a configuration of pallet rackings with more low-capacity pallets rackings, thus a reduced pallet capacity and increased flexibility, in combination with a higher occupancy rate improves the utilization of the pallet rackings while still being productive. Table 35 shows the improvement in the mean occupancy rate in each scenario. This research improved the mean occupancy rate on average by 1.2%, which ensures flexible storage prepared for the future.

Table 35: Improvement mean occupancy rate per scenario (in %)

Base	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
+1.3	+0.9	+0.5	+1.2	+2.0

After conducting this research, we can conclude that a solution has been found to the core problem. The proposed configuration of pallet rackings adapted to the future product portfolios improves the occupancy rate and space utilization of the DC. In the scenarios, the improvement heuristic is able to place almost all inbound pallets over the time horizon. The proposed configuration of pallet rackings increases the occupancy rate from March onwards, which results in a lower probability of a stock out in the months after. Therefore, the research partially solves the gap between the norm and reality of the action problem 'The service level of Riedel decreases from Pentecost and Ascension Day until the summer period'.

7.2 Recommendations

The insights gained from the scenarios provide Riedel with the following recommendations.

Optimize layout DC
This research results in an improved configuration of the pallet rackings in the DC of Riedel, derived in Chapter 5 for the current product portfolio and in Chapter 6 for the future product portfolios. Riedel should ensure that the improved configuration of pallet rackings fits into the DC or within the expansion possibilities by planning and implementing a warehouse layout design. A detailed analysis of the available floor space along with the improved configuration of pallet rackings can maximize the utilization of space in the DC. The optimized layout of the DC ensures better allocation of pallets to increase the utilization and occupancy rate of the pallet rackings. Despite the lower pallet capacity, the improved occupancy rate allows a larger inventory in the DC due to more inbound pallets possible to be placed. A larger inventory means more products available at a certain moment in time resulting in a decrease in the probability of a stock out. The additional inventory serves as a buffer for demand uncertainty from the customer. Moreover, the improved configuration increases flexibility within the DC allowing a higher variety of SKUs. However, if the total volume of the product portfolio increases significantly, an expansion of the DC

is required.

Make decision on expanding DC
The scenarios of future product portfolios from Chapter 6 exposes the impacts of increasing the volume and/or SKU variety of the current product portfolio by 5%. On the one hand, if the total volume of pallets flowing through the process remains equal, even with an increased variety of SKUs, there is no need to expand the DC. However, to be able to fit all inbound pallets required for inventory and to increase flexibility, the improved configuration should be implemented. On the other hand, if Riedel has the need to manage an increased volume or variety of SKUs with an increased total volume, expansion of the DC is required. The current floor space is not sufficient to accommodate the increase in demand. When expanding the DC, a thorough analysis is needed on the floor space requirements of the improved configuration of the future product portfolio.

Upgrade the WMS
To implement the improved configuration and optimized layout of the DC, Riedel should upgrade their WMS. This enables the correct allocation of pallets to the additional pallet rackings and the new structure. The implementation of an improved allocation algorithm of the WMS ensures a higher utilization of the pallet rackings. The WMS should accurately track the pallets through the DC. We recommend implementing a mechanism that discovers when and in what situation pallets are not possible to be placed in the pallet racking suggested by the WMS. This supports Riedel in recognizing the areas of improvement.

Extend data storage
Currently, the complete inventory data from the WMS is stored for two months after which part of it is removed. The inventory data that is stored long-term consists of the number of pallets stored in certain pallet rackings. However, it does not include SKU-specific information. Thus, the inventory of a certain SKU longer than two months ago is unknown so tracking and analyzing the information of SKUs is not feasible. Riedel should ensure that the long-term data is extended to allow better decision-making by performing analysis on the SKUs-specific inventory.

7.3 Practical and scientific contribution

This research is performed at Riedel. The contribution to the company is the insights into the impact of the configuration of the number of pallet rackings per type on the occupancy rate. The improvement heuristic developed simulates the WMS of the DC by managing the inventory of pallets. It searches for better configurations to cope with the demand of the DC. It ensures that all demand is placed in the DC at any time with a high flexibility without an expensive investment of expanding the DC. The uncertainty of the demand input is experimented on by creating scenarios of future product portfolios. Using the results, Riedel understands the required actions to improve the occupancy rate of the pallet racking systems in the DC. This ensures a higher service level throughout the peak in demand resulting in satisfied customers.

The scientific contribution lies in the uniqueness of the problem. Generally, the occupancy rate is a less studied topic and the impact of the pallet racking configuration on the occupancy rate is even less explored. Kimball [40] determines the percentage of utilized pallet locations at peak inventory levels of some types of pallet racking systems individually. However, the impact of several combinations of different pallet racking systems is barely researched. Mital et al. [48] propose an algorithm to identify all configurations of the MHS that are Pareto-optimal, but do not take the occupancy rate into account. Additionally, they organize the warehouse from scratch, whereas the improvement heuristic developed in this research takes the initial configuration into account to keep the investment costs to a minimum.

7.4 Limitations and further research

This research has the following limitations due to a bounded scope that can be further researched.

- As mentioned in Section 7.2, there is a limited availability of data. This research uses inventory data over the months of January until April 2024. Therefore, this research cannot guarantee the same results for the rest of the year. Section 1.2.1 determined that the drop in service level is caused because of Pentecost and Ascension Day. This research includes the months leading to these holidays, which is the most crucial period of the year for managing the inventory. Furthermore, since multiple SKUs that are put on high pallets have seasonality, we fixed the number of high pallet racking systems. Further research should also take into account the number of high pallet rackings to investigate whether they are efficient. However, the SKUs in the current product portfolio that are put on low pallets do not have seasonality.
- The configuration of pallet rackings is limited to seven types. Further research can look into other types of pallet rackings with different capacities.
- Section 5.2 explains that the reward of removing pallet rackings is bounded for each type of pallet racking. The results show that for the low normal pallet rackings the improvement heuristic deletes exactly the given bound. If Riedel decides to completely redesign the DC, further research can ignore these bounds to discover the optimal number of low normal pallet rackings.
- Scenarios 3 and 4 are not completely comparable because scenario 3 adds only low-volume SKUs, whereas scenario 4 splits high, medium, and low SKUs, as mentioned in Section 6.5.2. Further research can discover the impacts of splitting only low-volume SKUs.

A Current layout DC

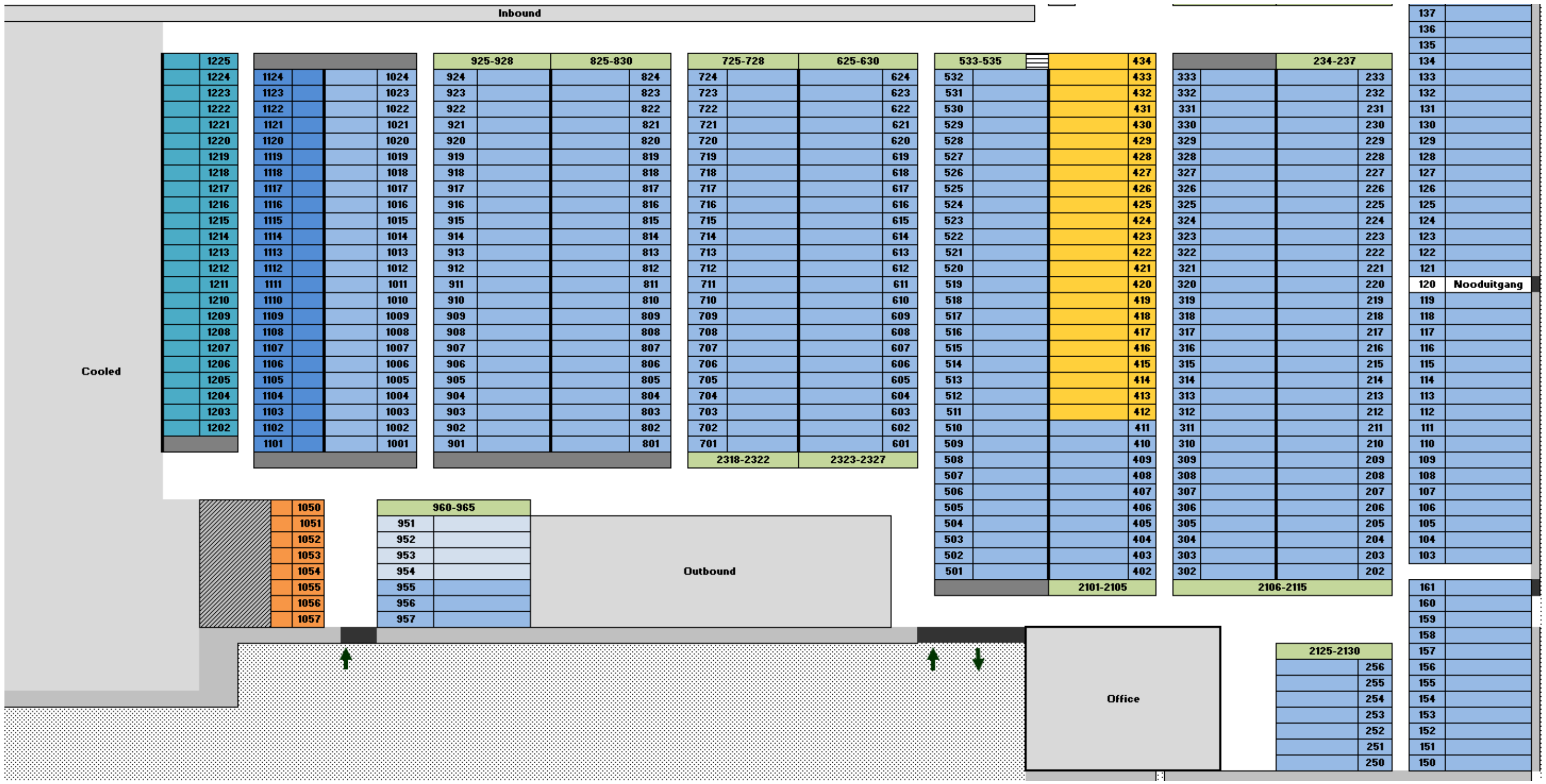

Figure 27: Current layout DC

B Flowcharts algorithm inbound and outbound

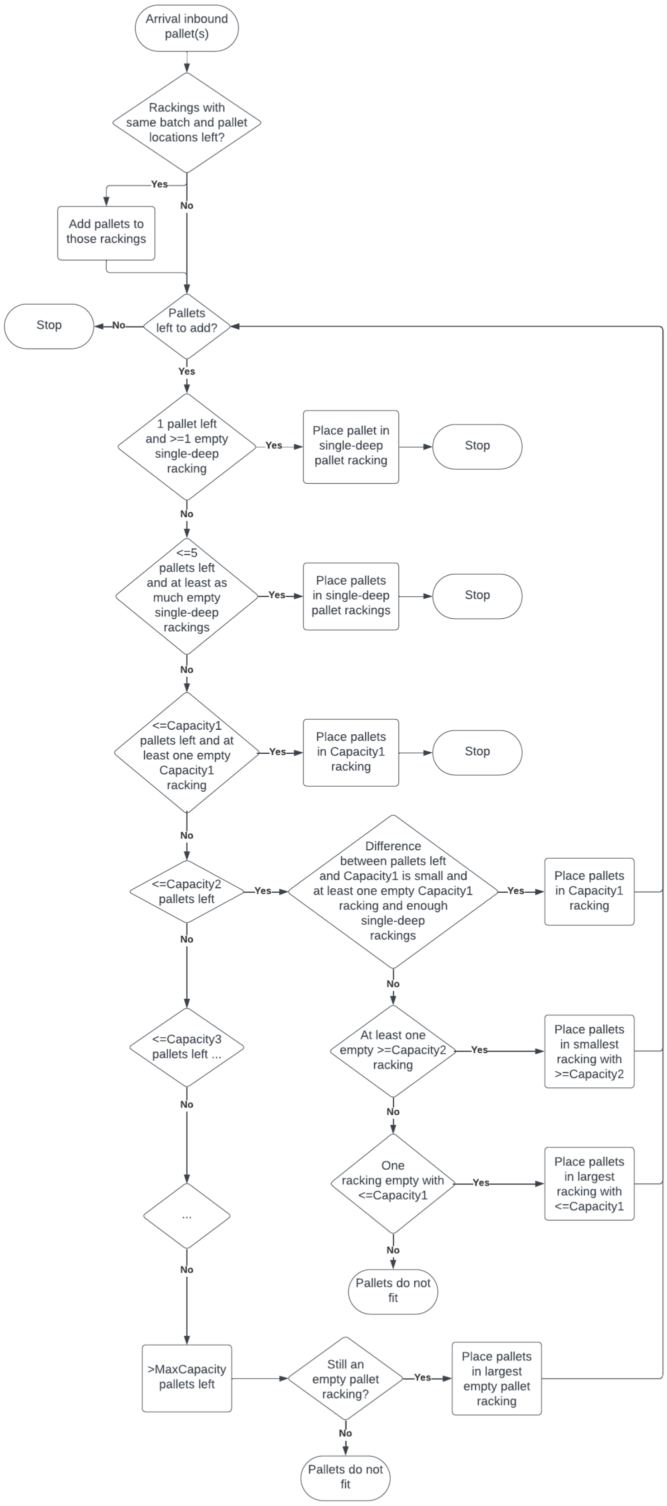

Figure 28: Flowchart inbound process

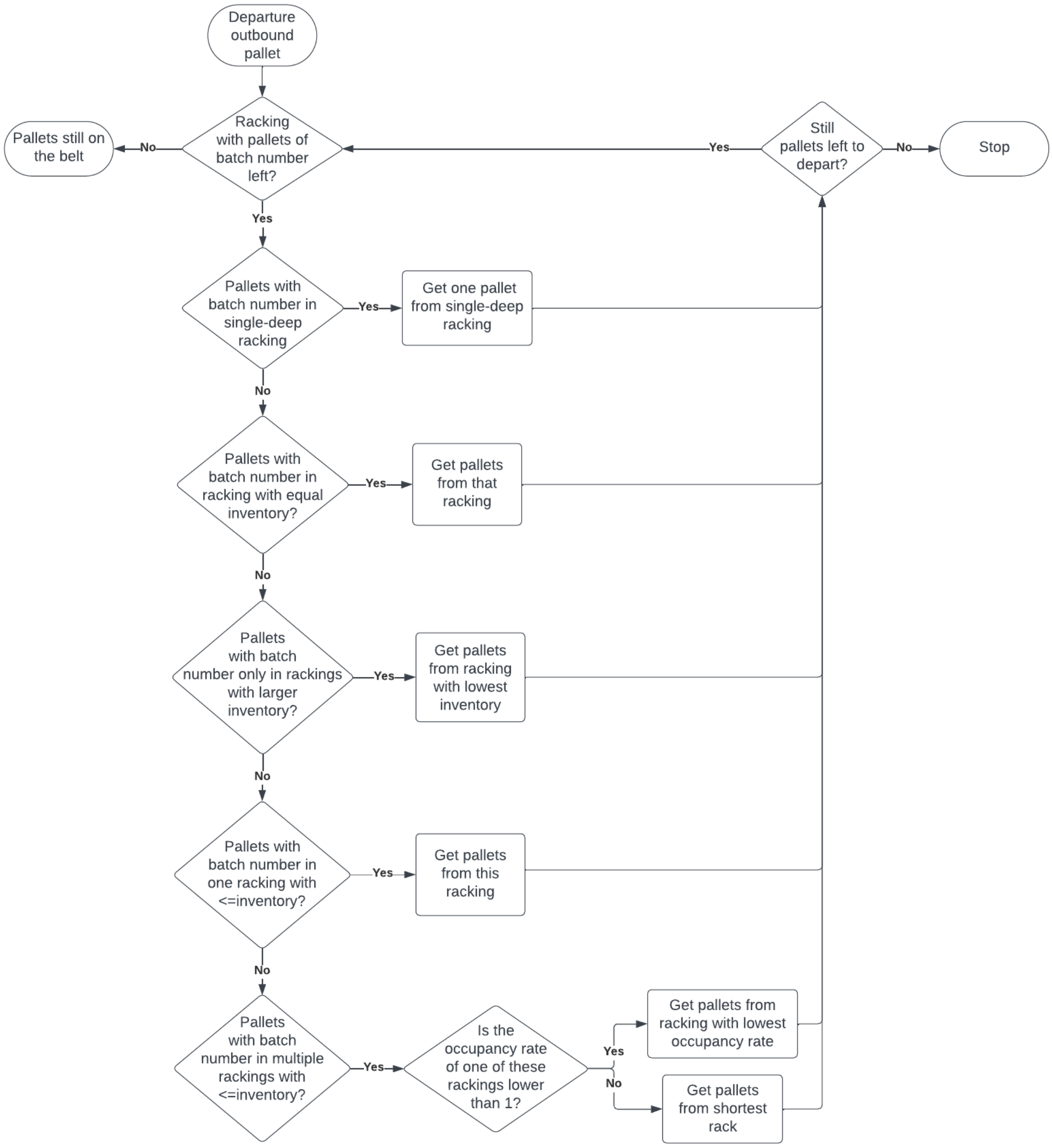

Figure 29: Flowchart outbound process

C Heat maps objective function value against pallet capacity, future product portfolio scenarios

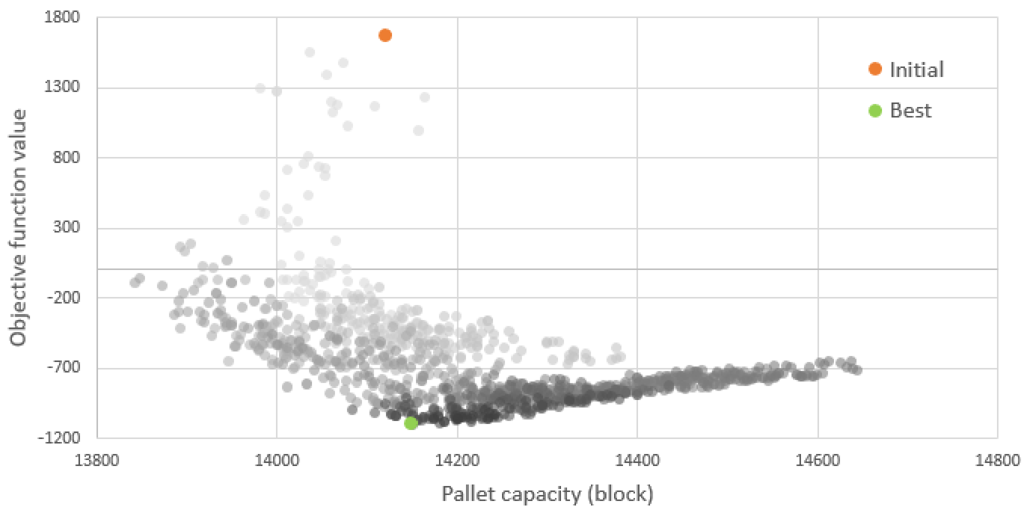

Figure 30: Scenario 1, heat map objective function value against pallet capacity

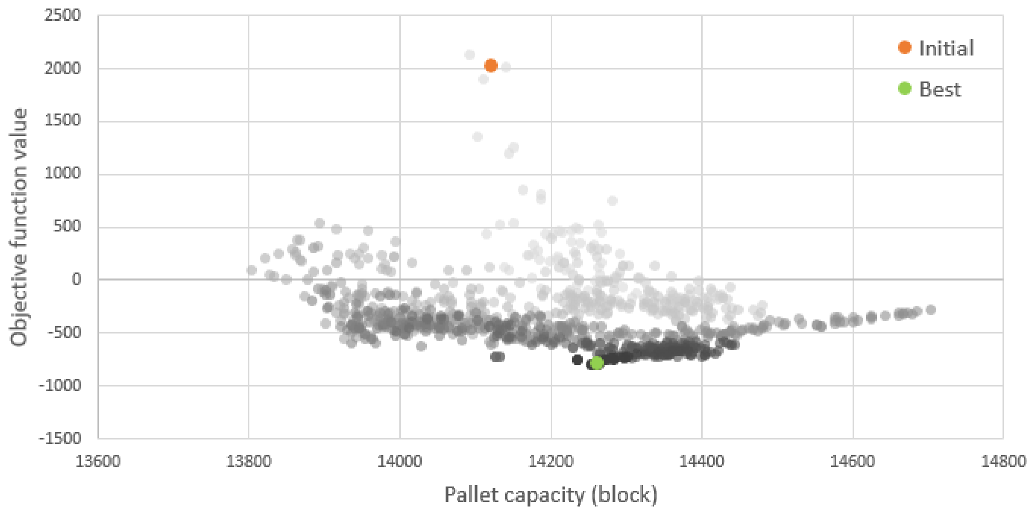

Figure 31: Scenario 2, heat map objective function value against pallet capacity

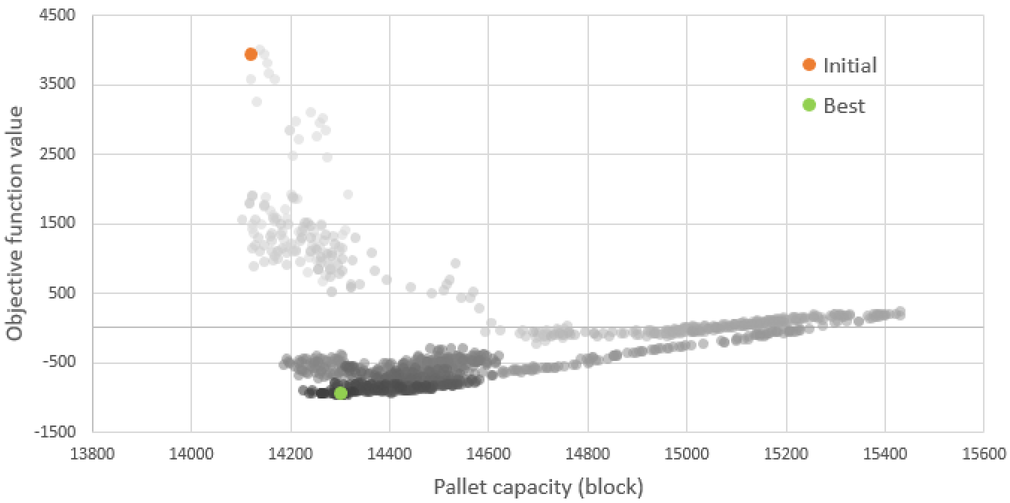

Figure 32: Scenario 3, heat map objective function value against pallet capacity

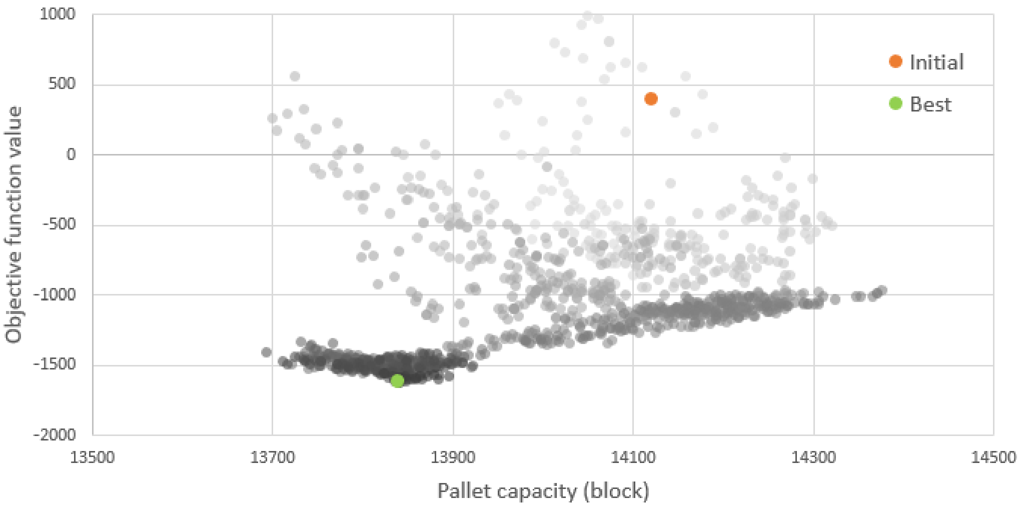

Figure 33: Scenario 4, heat map objective function value against pallet capacity

D Occupancy rates base and future scenarios

Table 36: Total occupancy rate and mean per pallet racking type base and future scenarios

		Total (block/Euro)	**Low long**	**Low normal**	**Low short**	**Low extra short**	**Single-deep**	**SBS/ RS**
Base	Initial	0.684 / 0.535	0.809	0.668	0.630	0.581	0.781	-
	Best	0.697 / 0.545	0.771	0.693	0.695	0.615	0.639	0.628
	Difference	+0.013 / +0.010	-0.038	+0.025	+0.065	+0.034	-0.142	-
Sc1	Initial	0.702 / 0.548	0.796	0.685	0.603	0.598	0.817	-
	Best	0.711 / 0.557	0.761	0.716	0.610	0.626	0.679	0.707
	Difference	+0.009 / +0.009	-0.035	+0.031	+0.007	+0.028	-0.138	-
Sc2	Initial	0.705 / 0.551	0.788	0.684	0.651	0.599	0.834	-
	Best	0.710 / 0.556	0.766	0.701	0.677	0.644	0.741	0.735
	Difference	+0.005 / +0.005	-0.022	+0.017	+0.026	+0.045	-0.093	-
Sc3	Initial	0.684 / 0.534	0.789	0.664	0.625	0.553	0.850	-
	Best	0.696 / 0.545	0.759	0.700	0.641	0.614	0.667	0.677
	Difference	+0.012 / +0.011	-0.040	+0.036	+0.016	+0.061	-0.138	-
Sc4	Initial	0.680 / 0.532	0.807	0.664	0.599	0.560	0.805	-
	Best	0.700 / 0.548	0.766	0.710	0.606	0.625	0.692	0.696
	Difference	+0.020 / +0.016	-0.041	+0.046	+0.007	+0.065	-0.113	-

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