University of Twente
Faculty of Behavioural, Management and Social Sciences

Industrial Engineering and Management

IMPROVING THE STORAGE ASSIGNMENT OF (SEMI-)FINISHED GOODS AT BOLLETJE

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UNIVERSITY OF TWENTE.

Bolletje®

Management Summary

To stay a competitive bakery and producer of affordable and tasty goods, Bolletje wants to make sure that their production lines produce a high quality product, at a constant level without major interruptions. In order to achieve this goal, goods from the production lines need to be stored at appropriate locations in the warehouse. The allocation of goods at the warehouse indirectly affects the goal of Bolletje to create affordable products. Costs of transporting, storing and retrieving goods from locations indirectly affect the cost-price of the goods.

We used a problem cluster to identify the core problem from the central (perceived) problem. The central problem is a feeling of inefficiency in the storage of goods at the warehouse. This is a result of a waste of (physical) man hours in the warehouse, this is caused by a waste of movements/driving time. The root cause of this waste is the core problem. Two (influencable) core problems were identified; no optimized picking policy and storage policy. The core problem we solve is the absence of an optimized storage policy. A rough estimate shows that the 66% to 78% of the hours spent in the warehouse can be attributed to the storage assignment policy of goods. The following (main) research question was formulated for this research:

How can the Warehouse and Distribution Department of Bolletje Almelo store its (semi-)finished goods in the warehouses in Almelo, such that the driving distance is minimized?

Data collection methods to describe the current situation include interviews and data analysis methods. The warehouse at Bolletje can be considered as a warehouse-system which consists of multiple sub-warehouses/halls. In these sub-warehouses, pallets are stored using block stacking, deep lane storage, pallet racks and shuttle systems. Products to be stored result from production in Almelo, Heerde and external suppliers. Standard (EUR & FIN) pallets are used to store the products using various types of material handling equipment. Besides regular pallet storing and picking, each packing happens at the Value-Added Services department and layer picking at the "pickplein". Pallets are currently stored based on their assigned zone. Zones consist of locations and products. A rough measure shows that on average, three to four pallets are stored/picked per hour.

Multiple methods in literature are found to classify stock and warehouses. Based on the literature, we decided to choose a binary integer non-linear model which creates classes consisting of products and locations. A class is a pre-determined zone (group of locations) where products, which are assigned to that class, can be stored. The model minimizes the class-based distance to store and retrieve all products. This is based on the average pallets to store and duration of stay (DoS). The pallets to store is based on the average of four-week period. The DoS is the expected number of weeks a pallet stays in the warehouse. We tried to solve it optimally, but due to the NP-hardness of the model, even for smaller benchmarks we were not able to solve it in a reasonable time. Therefore we decided to use a heuristic and meta-heuristic (simulated annealing). We splitted the warehouse-system in sub-warehouses, as shown in the first column of table 1. Per sub-warehouse we experimented with the number of classes in a range of [4,10] and location aggregations. Location aggregations include single, adjacent and technical zone. In single aggregation, each individual location is considered. The adjacent configuration combines individual adjacent locations. In the technical zone aggregation, locations with similar characteristics (e.g. height, type, width etc.) are combined. We used a heuristic which assigns products and locations to classes. This solution is improved using a meta-heuristic. The result from one run is a product- and location-to-class assignment, for each product and location in every time period (four weeks). The table below presents the number of classes per sub-warehouse.

Table 1: Number of classes per sub-warehouse

Sub-warehouse	Near optimum number of classes
Hal 16	7
VAS / Roggebrood	4
Extern	8
Banket	9
Oude Beschuit	3

We use the "VAS / Roggebrood" sub-warehouse to illustrate the solution of a sub-warehouse. In the Excel file, products and locations are assigned to classes per period (four weeks). The figure presents a sample of products and locations. Here, product 9 ("BOLLETJE Roggebrood Mild 250g X12") and 10 ("BOLLETJE Roggebrood Fries 250g X12") are assigned to class 3, which in turn consists of location 0 ("EX05-1") and location 1 ("EX05-2"), and others. The lines on the figure on the right hand-side demarcate the locations of the class in the sub-warehouse. The usage of different types of lines indicate the levels of the locations.

		1	2	3	4
50410388-VLEGELAAR Knackebrod Volkoren en Sesam 375g X24	0	2	2	2	2
50410465-RIVERCOTE Knackebrod Volk Goudb Sesam 375g X15	1	1	1	1	1
50410474-KEMPI Knackebrod Combi Sesam Volkoren 300g X24	2	4	4	4	4
50410360-TASTINO Knackebrod 4 pomp en 6 zonnebl 264g X10	3	1	1	1	1
50410618-TASTINO Crispbread Pumpkin and Sunflower CZ 264g x10	7	3	3	3	3
50410471-VLEGELAAR Knackebrod Combi Pompoen Zonnebloem 265g X10	8	4	4	4	4
50052080-BOLLETJE Roggebrood Mild 250g X12	9	3	3	3	3
50052070-BOLLETJE Roggebrood Fries 250g X12	10	3	3	3	3
50391104-BOLLETJE Graanrepen Amandel Havermout Displaydoos 10 st X7	13	4	4	4	4
50391105-BOLLETJE Graanrepen Hazelnoot Spelt Displaydoos 10 st X7	14	4	4	4	4

		1	2	3	4
EX05-1	0	3	3	3	3
EX05-2	1	3	3	3	3
FF06-2	23	1	1	1	1
FF07-1	24	1	1	1	1
FF07-2	25	1	1	1	1
FF08-1	26	1	1	1	1
FF08-2	27	2	2	2	2
FF09-1	28	2	2	2	2
FF09-2	29	2	2	2	2
FF10-1	30	2	2	2	2

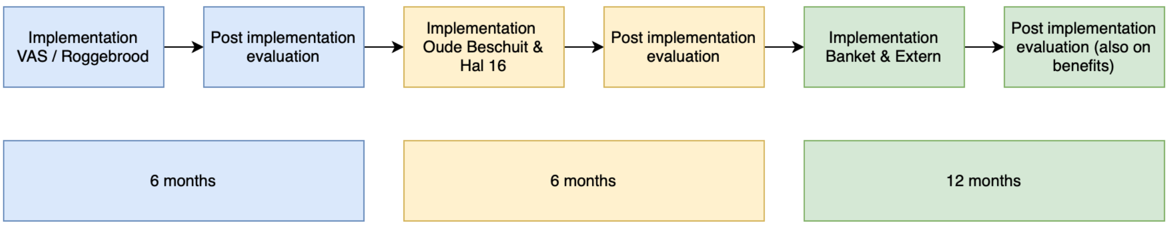
We used Monte-carlo simulation to study the robustness of the solutions and evaluate the effect of the two random parameters (average pallets to store and duration of stay). Six scenarios were evaluated. The "Likely" scenario slightly deviates from the reality. The "Medium" scenario evaluates strong deviations in the average pallets to store and duration of stay. The "High" and "Low" scenario adjust the parameters in higher and lower values, respectively. The "Pallets constant" keeps the pallets constant and changes the duration of stay. "DoS constant" scenario adjusts the number of pallets and keeps the duration of stay constant. Sub-warehouses which contain products with seasonal demand are less robust compared to sub-warehouses with more stationary demand. Table 2 presents the improvements (in distance) compared to the current situation.

Table 2: Improvements per scenario

Scenario (improvement in distance)					
Likely	*Medium*	*High*	*Low*	*Pallets constant*	*DoS constant*
27.3%	27.8%	52.2%	12.2%	30.5%	27.5%

To calculate the savings that can be obtained by implementing the alternative storage assignment policy, we used the total hours spent at the warehouse and savings in distance compared to the current situation. Only a portion (67%) of the hours spent at the warehouse can be attributed to the storage assignment policy.

We recommend Bolletje to do a phased implementation per sub-warehouse. The implementation can start with the "VAS / Roggebrood" sub-warehouse, because this is a relatively small sub-warehouse with little to no seasonal demand. After the implementation a post-implementation review is advised, to evaluate what went well and wrong. Afterwards, it is advised to continue with the "Hal 16" & "Oude Beschuit" sub-warehouses. These warehouses are larger in terms of number of locations, but do not yet contain seasonal demand. We advise to take into account the lessons learned of the "VAS / Roggebrood" sub-warehouse and start the implementation. These lessons do not affect the solution, but can affect the way of implementation. After the first three sub-warehouses are implemented, we recommend to start with the "Extern" and "Banket" sub-warehouses, which have a large number of pallets to store and strong seasonal demand. The figure below depicts the sequence and time frame in which the solutions can be implemented.



Preface

This report finalizes my master Industrial Engineering and Management at the University of Twente. In this section I want to express my gratitude to some people who helped my during the thesis but also during my entire studies.

First I would like to thank my supervisor. Robin, thank you for giving me the opportunity to do my graduation assignment at Bolletje, guiding me through the assignment and providing me with alternative views to the problem! I was not always able to conduct my research at the office on a daily basis due to COVID-19, but you provided me, whenever needed, a quick response. Without your positive support and optimism, I might have lost my own optimism.

Moreover, special thanks to my supervisors from the university. In face of the pandemic, it was still possible to help me through the process and providing me with constructive feedback and pleasant video calls.

Third, I want to thank my girlfriend for her support and enthusiasm towards both me and my graduation assignment.

Finally, I want to thank my parents for their mental and financial support during my studies. You helped me through ups and downs during my studies.

Enjoy reading this report!

Thijs Busger op Vollenbroek

January 26, 2021

List of Abbreviations

Abbreviation	Definition	Introduced on page
AS/RS	Automated Storage and Retrieval System	14
BOM	Bill of Material	18
CBS	Class-based storage	19
COI	Cube-per-Order Index	16
COL	Closest-open-location	16
DOS	Duration of Stay	16
DP	Dynamic Programming	20
ED	Extra Dock	9
ERP	Enterprise Resource Planning	4
FIFO	First-in-First-out	16
FTE	Full-time-equivalent	12
GBH	Graph-based-Heuristic	17
IFH	Interaction frequency heuristic	16
I/O	Input/Output	16
KPI	Key Performance Indicator	6
LD	Loading Dock	10
MTO	Make To Order	1
MTS	Make To Stock	1
OOS	Order Oriented Slotting	16
QAP	Quadratic assignment problem	19
SA	Simulated Annealing	19
SKU	Stock Keeping Unit	9
SLAP	Storage Location Assignment Problem	16
VAS	Value-Added-Services	1
WDD	Warehouse and Distribution Department	1
WMS	Warehouse Management System	14

List of Figures

Contents

1 Introduction

This report describes the result from the graduation assignment of the Master program Industrial Engineering and Management (IEM) at the University of Twente conducted at Bolletje B.V. This research describes the optimization of the material handling process at Bolletje. More specifically, it focuses on the improvement of the storage assignment of (semi-)finished goods at the warehouse of Bolletje.

This chapter starts in section 1.1 with an introduction of the company Bolletje and a description of the department where the research is carried out. Next, a research motivation is given in section 1.2. Section 1.3 covers the problem statement including a problem cluster and definition of the core problem. Section 1.4 states the research objective including the main research question and scope. Section 1.5 finalizes the chapter, here the research design, questions, approach and deliverables are described.

1.1 Company introduction

Bolletje is a Dutch industrial bakery founded in 1867. Bolletje operates two bakeries, located in Almelo and Heerde. In total the company employs around 400 people over the two locations. The company was founded by Gerardus Johannes ter Beek in 1867 as a bakery shop. In the 1920's, Gerardus' son, Bernard, started the bakery with a specialization in *beschuit*. In the thirties, the five sons and two daughters joined the company. Until 1952, the company was not yet named Bolletje, but as *Ter Beeks Eierbeschuit*. The products were mainly sold to bakeries, however, these did not like to sell it with the name of the bakery on the package, therefore Gerard and Jan invented a new name. Their new name originated from the little balls, *bolletjes*, used to produce the *beschuit*. They changed their name into Bolletje and the current slogan, which is still used in the '*Ik wil Bolletje!*' commercials. As the competition grew in the sixties, the fourth generation of the Ter Beek family realized that it was too risky to focus on a single product (*beschuit*), so they diversified their product range. Bolletje took over different segments of the market, in order to achieve this diversification in the form of extending the assortment. Nowadays, Bolletje produces over around 200 different products assorted into five segments. Next to its own products, Bolletje produces private label products. Besides the home market in the Netherlands, Bolletje exports their products all around Europe and countries with Dutch emigrants, such as the United States, Canada, Australia and New-Zealand (Bolletje B.V., 2020).

The research is carried out at the warehouse and distribution department (WDD). This department is a division of the Logistics department at Bolletje. The red-bordered part in figure 1.1 depicts the organizational structure of the WDD. This department is led by a manager (1 FTE) and foremen (3 FTE). Two foremen lead a team/shift of warehouse employees. The other foreman leads the Value-Added-Services (VAS) department. The freight planner plans the rides for the truck drivers (18.6 FTE), carried out by Bolletje. The truck drivers ensure the shipment of goods to the customers. Warehouse employees (23.6 FTE) receive, store, pick and shipment (together with truck drivers) goods. The planning division (4 FTE) takes care of a smooth planning of orders. The planning is done in a hybrid manner, meaning that some products are make to order (MTO) and some (MTS).

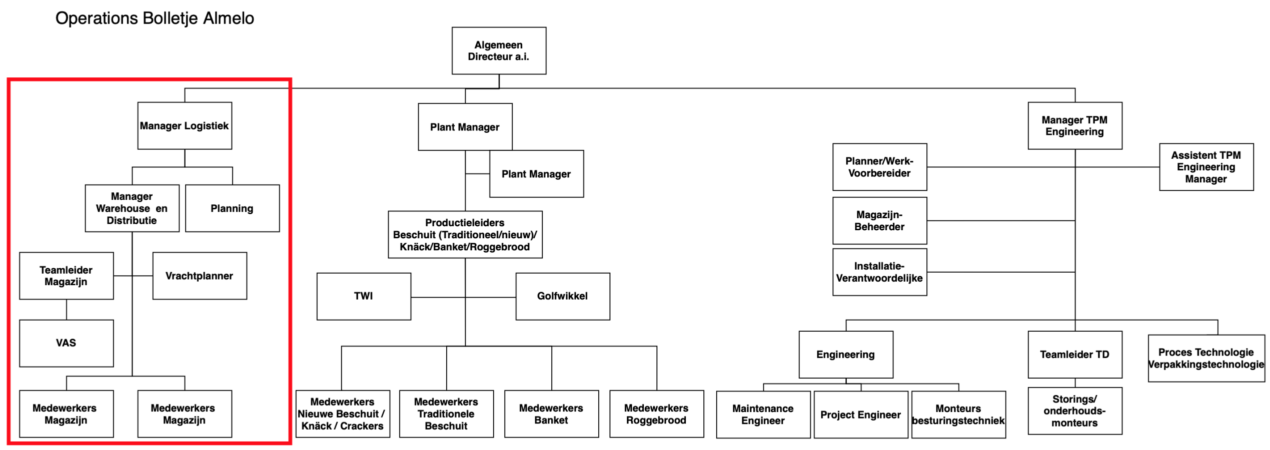


Figure 1.1: Organisational structure WDD

1.2 Research motivation

The overall goal of Bolletje in the coming years is to make sure that each production line can produce a high quality product, at a constant level without major interruptions, with a high utilization and increase in sales. Figure 1.2 displays the production amount in consumer units per year from 2013 to 2019 of all products. Based upon this figure, the growth in 2018 and 2019 is negative. The reduction results from the outsourcing of some products and decrease in market size of some products. Bolletje expects the average production growth of the last years to remain constant in the future and has therefore the challenge to use its storage capacity efficiently.

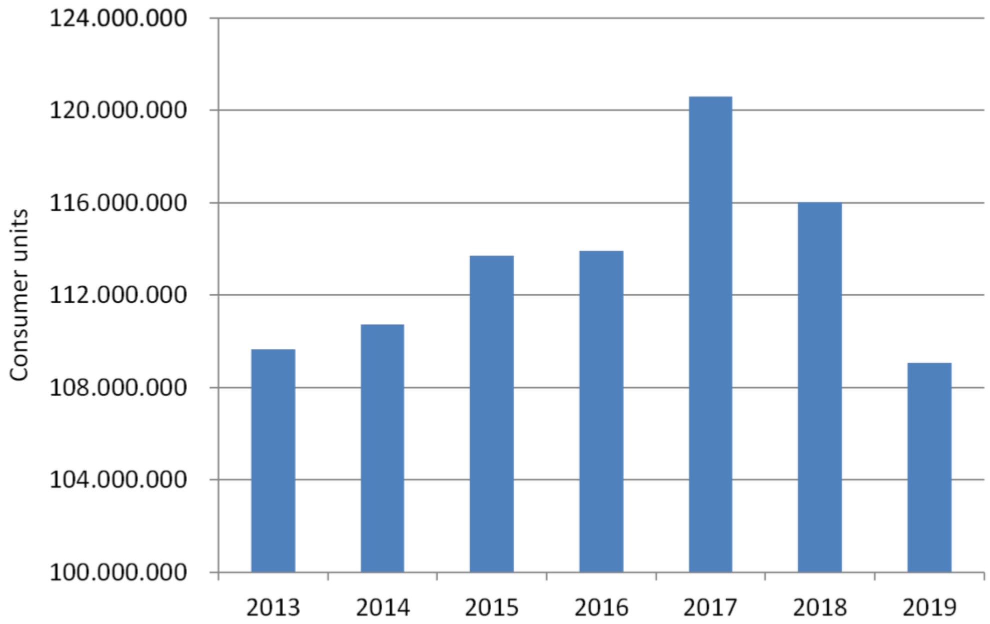


Figure 1.2: Production over the years (in consumer units)

The total production can be subdivided into four categories, these, and their respective relative contribution to the total production is shown in figure 1.3. All categories, except for the "Sint"-products show a similar (increasing and decreasing) pattern in demand distribution as shown in figure 1.2. The demand for "Sint"-products shows relatively stable pattern. The market share for "Ontbijt & Lunch" slightly decreased with 0.1%, whereas the "Sint" market share increased with approximately 0.6%. The market share of the other two categories slightly increased.

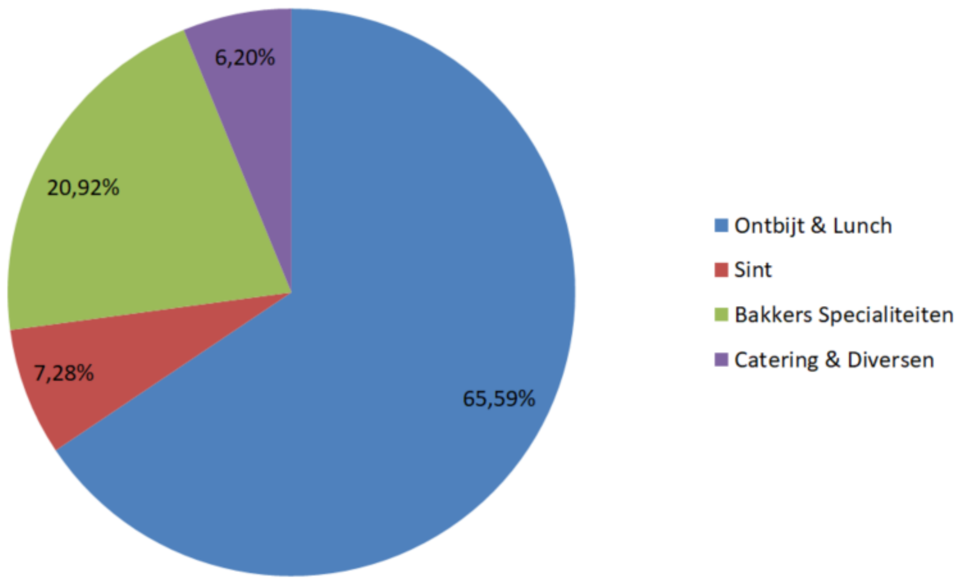


Figure 1.3: Production per category

In order to achieve this overall goal, the WDD has to make sure that the flow of goods in terms of storage and distribution is well connected. Being well connected means that the impact of the warehousing processes on the expenses, responsiveness and service is minimal.

Currently, the department has already implemented some redesigns in the lay-out of and pragmatic extensions to the warehouse. Some of the production lines got removed or replaced, this space is now used as storage space. However, some pallet racks (i.e. storage space) got removed in favor of new production lines. It is not clear how these modifications in lay-out and storage space affected the driving distance traversed by the warehouse employees.

As a result of the changes in the lay-out of the warehouse, there is a feeling of inefficiency to the internal departments of Bolletje. Obtaining a better or even optimal storage of goods, will result in a reduction of driving distance and therefore increase efficiency and decrease costs. Currently, there is no metric measuring the driving distance as a result of storing/picking pallets, however, the WDD distinguishes 11 types of activities which help to make a rough estimation of the costs attributed to driving distance as a result of picking (semi-)finished goods.

Table 1.1: Warehousing activities and hours spent in 2019

Activities	Unit	Norm/hour	Total units	Total Hours
1. Detailpicking salesorder	Carton	300	1006168	3354
2. Palletpicking salesorder	Pallet	16	120709	7544
3. Storing finished goods	Pallet	32	94332	2948
4. Receiving transferorders	Pallet	32	47441	1483
5. Receiving goods	Pallet	26	63176	2430
6. Loading 2nd ride and export	Truck load	1.25	1636	1309
7. Replenishment "Pickplein"	Pallet	22	10598	482
8. Ordercollection G&V	Pallet	22	29414	1337
9. Retour remaining pallet	Pallet	12	7664	639
10. Deposit residual goods	Container	20	68457	3423
11. "Milieuplein"	Hours	7.2	8088	1123

Table 1.1 depicts the activities and hours spent on activities in the warehouse. Activity one does slightly influence the distance to be traversed determined by the storage policy and is therefore out of scope. Activities two until eight can be attributed as hours that are influenced by the storage policy. Assuming that wages/hour are equal per activity, this results in an average of 70% attribution of costs that are caused by the storage policy. The norm per hour is the number of units (e.g. carton, pallet etc.) that should be done per hour. However, since 2020, the ratio partially lowered due to a new palletizer. Figure 1.4 depicts the total hours spent, number hours allocated as a result of the storage assignment policy and the percentage to the total hours. The data of 2018 was imputed using a weighted average, since it was not available.

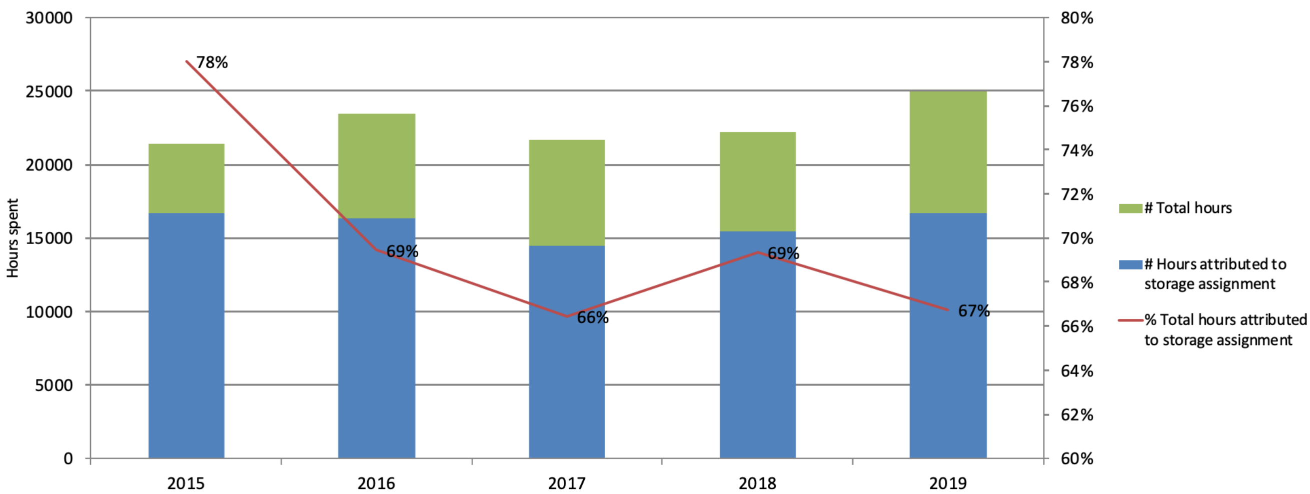


Figure 1.4: Hours attributed to storage assignment

1.3 Problem statement

With the use of a problem cluster, connections between (sub-)problems and core problems can be identified. This helps to connect the causal links between the various problems. The core problems are the root causes of the observed/central problem (Heerkens & van Winden, 2017). The main/central problem in this research is the feeling of inefficiency in the storage of goods at the warehouse. Figure 1.5 represents the problem cluster. The numbers in the figure are referred to in the explanatory text below. The green colored box is the central problem. The white, red and orange text boxes are causes, core influenceable and non-influenceable problems, respectively.

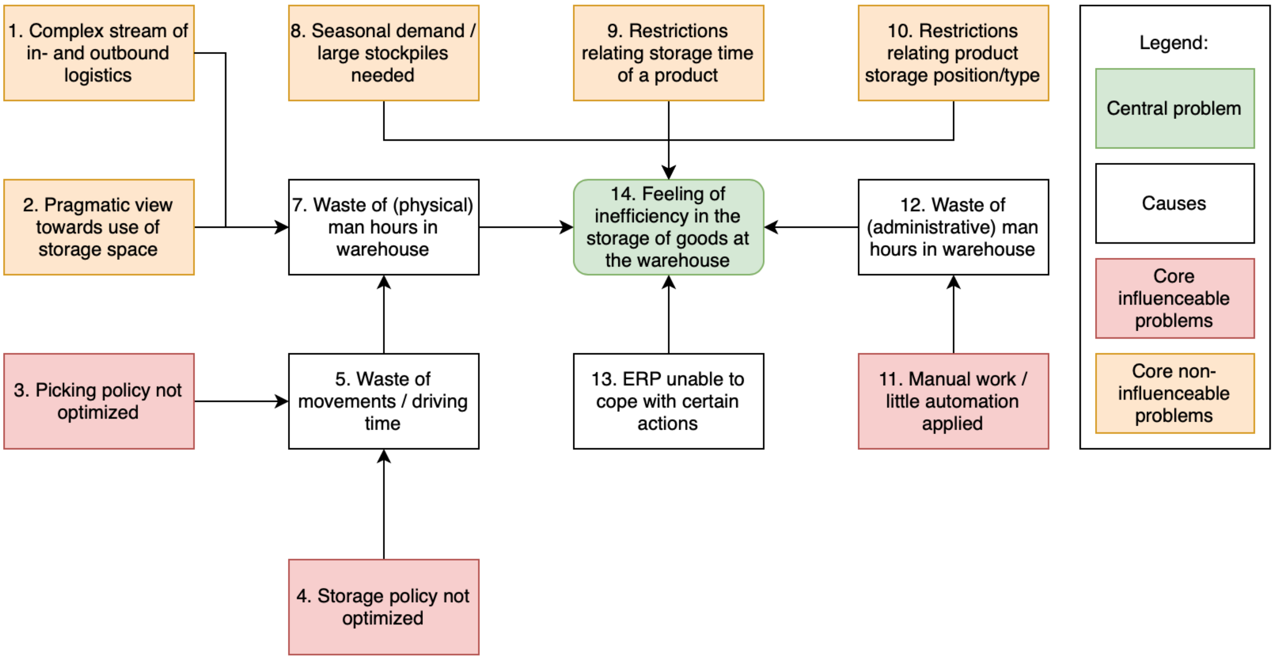


Figure 1.5: Problem Cluster

The central problem (14) is in the middle and marked green. At Bolletje there is a perceived inefficiency in the storage of goods at the warehouse. This perceived inefficiency is the result of multiple causes (white) and sub-causes (red and orange).

First, multiple complex streams of in- and outbound goods (1) and a pragmatic view towards the use of storage space (2) result in a waste of man hours in the warehouse (7). Due to the pragmatic view, changes in the lay-out of and allocation of products in the warehouse are made which are not necessarily better or optimal. These changes are based on a gut feeling and not on thorough rational quantitative analysis.

A waste in physical movements of the warehouse employees is caused by a waste of driving distance (5). The cause of this waste in movement is that there is no picking policy (sequence in which goods are picked) and therefore not optimized (3). Although this is usually the main contributor to the costs of a warehouse (according to van den Berg and Zijm (1999), Coyle, Bardi, and Langley (2003)), this is not the focus of this research. This is not the focus because usually one product is picked, transported to the truck dock and next a new product is picked, therefore there is no or a small sequence of products that need to be picked, which might not be very beneficial to optimize at this moment. Besides that, the efficiency of order picking is strongly affected by storage assignment rules (Le Duc & De Koster, 2005).

Due to the absence of a storage policy (4), products are not systematically stored at the optimal locations (relative to each other), this leads to a waste of movements and driving distance, besides that, it results in an inefficient use of storage space. This core problem will be solved in this research and will eventually help to solve the central problem.

The Enterprise Resource Planning (ERP) system of Bolletje cannot cope with certain actions in terms of storing which leads to a feeling of inefficiency in usage of storage space. For example, if a storage location has space for 20 pallets and an order of 5 pallets of an arbitrary product (*e.g. product X*) is assigned to the location, the remaining 15 pallet places can no longer be utilized for the same product (or a different product, but that does not make sense), the storage location is blocked until the entire location is empty again. This also affects the utilization and can lead to an overoptimistic view concerning the utilization of storage space.

The storage space utilization is non-constant with respect to time. This is due to seasonality in demand patterns

(8), therefore large stockpiles are needed to comply with the demand. To comply with quality requirements, there is a limitation of the storage time of the products (9). Products can only be stored for one-third of their shelf life. For example, if the product has a shelf life of 180 days after the production date, the storage time of the product is 60 days. After this time is expired, the product can no longer be distributed because of these quality requirements. Restrictions relating to the product storage (10) can also result in a feeling of inefficiency. These restrictions refer to the possible storage locations per products. In order to prevent the deterioration products (e.g. chocolate products), some need to be stored in conditioned rooms relating to temperature. These three core (non-influenceable) problems lead to a feeling of inefficiency in the storage of goods at the warehouse.

Manual work due to little automation that is applied with respect to the tasks of warehouse employees (11) leads to waste of administrative man hours (12). A consequence of this waste in man hours is the central problem of a feeling of inefficiency.

The action problem resulting from the problem cluster is a storage policy which is not optimized. The owner of the problem is the WDD and the logistics manager. The discrepancy between norm and reality is that the driving distance within the warehouse is considered as excessive and needs to be reduced. There is no pre-defined norm in terms of driving distance as mentioned in section 1.2.

1.4 Research objective

Based on the problem description in the previous section, the main research objective is:

To find an automated storage policy of the (semi-)finished goods at Bolletje with the aim of reducing the driving distance within the warehouse.

Due to time restrictions, the research is scoped in different ways. First, as the WDD is the initiator of the research project, their view is used as guideline and the results will therefore mainly contribute to their department. Second, the storage of packages, raw materials and (semi-)finished goods in big bags will not be taken into account, since this will add more complexity relative to the benefits obtained by including them. Last, the solution resulting from this research should be applicable to the ERP-system.

1.5 Research design

The central problem is the result of multiple core problems as described in section 1.3, such as no optimized picking and storage policy. As a consequence, there is a feeling of inefficient usage of storage capacity and excessive driving distance. To achieve the objective of this research, described in the previous section, the research question is formulated as follows:

How can the Warehouse and Distribution Department of Bolletje Almelo store its (semi-)finished goods in the warehouses in Almelo, such that the driving distance is minimized?

To answer the main research question, the following knowledge questions have been defined:

1. **How is the current situation regarding the warehouse configured at Bolletje?**
    - 1.1. *What are characteristics about the products being stored at the warehouse?*
    - 1.2. *What is the current lay-out of the warehouse and how is the workforce organized?*
    - 1.3. *How are the in- and outbound logistic activities configured?*
    - 1.4. *How are (semi-)finished goods currently stored in the warehouse?*
    - 1.5. *What is known about the demand distribution of incoming and outgoing goods within the warehouse?*
    - 1.6. *What KPIs are currently in place?*
    - 1.7. *What is the current performance regarding the driving distance?*

    Chapter 2 covers the answer to question 1 and its sub-questions. In order to improve the storage of (semi-)finished goods, a clear overview regarding the current situation is required. The current situation includes a description of the products being stored, visualization of the lay-out explanation of workforce management, description of the in- and outbound activities, current storage policy and performance of the warehouse. The data collection takes place by means of interviews, relevant Bolletje documents and the ERP-system.

2. **What storage methods are available in the literature (and beyond) for production companies?**

   2.1. *How can the warehousing problem be characterized and what is important for storage policies?*

   2.2. *Which methods for inventory classification are available?*

   2.3. *Which storage methods are suitable for this problem?*

   2.4. *What performance measures are commonly used to optimize?*

   2.5. *What optimization techniques are available?*

   Chapter 3 presents a comprehensive literature review and answers question 2. By answering the second question, essential insights in available frameworks, methods and principles are obtained. First the important aspects relating to warehousing problems are identified. After that, possible methods for stock classification are reported. Next, a set of possible storage methods are discussed including their advantages and disadvantages. After that, performance measures which are commonly used are defined. Finally, optimization techniques are presented to solve a problem optimally or improve a possible solution.

3. **How can the storage policies found in the literature (and beyond) be applied to the Warehouse and Distribution Department?**

   3.1. *What elements from the literature can be used and applied for the situation at Bolletje?*

   3.2. *Which key performance indicator(s) should be included in the model and optimized?*

   3.3. *What are the solutions options?*

   3.4. *How should the solution be configured such that it is suitable for Bolletje?*

   Chapter 4 describes how the chosen storage policy found in the literature can be applied to the WDD at Bolletje. First, the elements needed for the policy are described, including how the formulated restrictions from Bolletje are taken into account. Next, the key performance indicator(s) (KPIs) included in the model are discussed. Finally, we elaborate on the contents of a solution how the solution should be configured to make it suitable for the problem Bolletje.

4. **What results can be expected when implementing the chosen storage method?**

   4.1. *How to conduct a pilot study at Bolletje?*

   4.2. *Which data should be used to conduct a pilot study?*

   4.3. *Which scenarios should be evaluated?*

   4.4. *What results can be expected when implementing the storage method at the Warehouse and Distribution department?*

   Chapter 5 presents the results that can be expected when implementing the solution at Bolletje. First the procedure to conduct a pilot study is elaborated on, this is based on a literature study and interviews. Next, the data used to conduct the pilot study and scenarios are described Finally, the expected results relating to the optimized key performance indicators when implementing the solution are discussed.

5. **How should the (new) storage method be implemented at the warehouse?**

   5.1. *What are critical success factors when implementing the solution?*

   5.2. *What activities should be executed in order to implement the (new) storage method?*

   5.3. *How should these activities be executed, and who is responsible for what activity?*

   Chapter 6 provides a plan of how the storage method can be implemented at the warehouse. First critical success factors are identified using literature to consider during the implementation. Next, taking into account the identified critical success factors, the activities to implement the (new) storage method are described. Finally, the sequence and responsibilities of the activities are described. The data is gathered using literature and interviews to determine a proper implementation plan.

2 Current situation

This chapter answers the first (1) research question stated in section 1.5 regarding the current situation at the warehouse of Bolletje. The organization of the chapter is as follows. First an introduction of the products portfolio and their characteristics is discussed. Next, Section 2.2 visualizes and describes the lay-out of the warehouse. Next, section 2.3 describes the in- and outbound activities in the warehouse. After the description of the lay-out and activities, section 2.4 covers the current storage method of the (semi-)finished goods, including a distribution of the incoming goods of the warehouse. Section 2.5 covers the current logistic performance after which section 2.6 finalizes the chapter with the conclusions.

2.1 Product characteristics

As mentioned in the previous chapter, Bolletje produces and distributes bakery products. These can be subdivided into seven categories, namely biscuits, rye bread, knäckebröd, sticks, seasonal products, (breakfast) cake and cookies. These seven categories are not used for warehousing purposes. Products belonging to the last category are mainly produced during and after the summer period and sold in the subsequent months. See figure 2.1 for an illustration of the products being produced. After a batch of products is finished, the products are stored in their storage locations according to the storage policy mentioned in section 2.4. Products have two types of dates which are relevant for the quality of the product. These are the "uiterste levercode (ULC)" (translated as utmost delivery date), and best before date. The ULC is used as the last date products can be shipped to the customers of Bolletje (distribution centres of retailers). The other date is the best before date. This date is relevant for consumers as it is guaranteed that products taste well before this date, this is also called the expiration date of the product. Section 2.4 elaborates further on this discussion. Besides the date, standard pallets are being used. These are described and illustrated in section 2.2.

Figure 2.1: Bolletje products

2.2 The warehouse and workforce management

The warehouse at Bolletje is split up in multiple halls distributed across the plant (i.e. there is no single building/room which consists of halls where products can be stored). The storage halls use different storage means and some halls are conditioned on temperature, this in order to retain the quality of the product (e.g. chocolate products). Figure 2.2 depicts an overview of the lay-out of the warehouse at Bolletje. The blue bordered rooms on the right hand-side are the conditioned rooms, the top room is soon to be replaced and therefore not considered in this research. The warehouse does not have a standard rectangular shape, which is commonly used in warehousing.

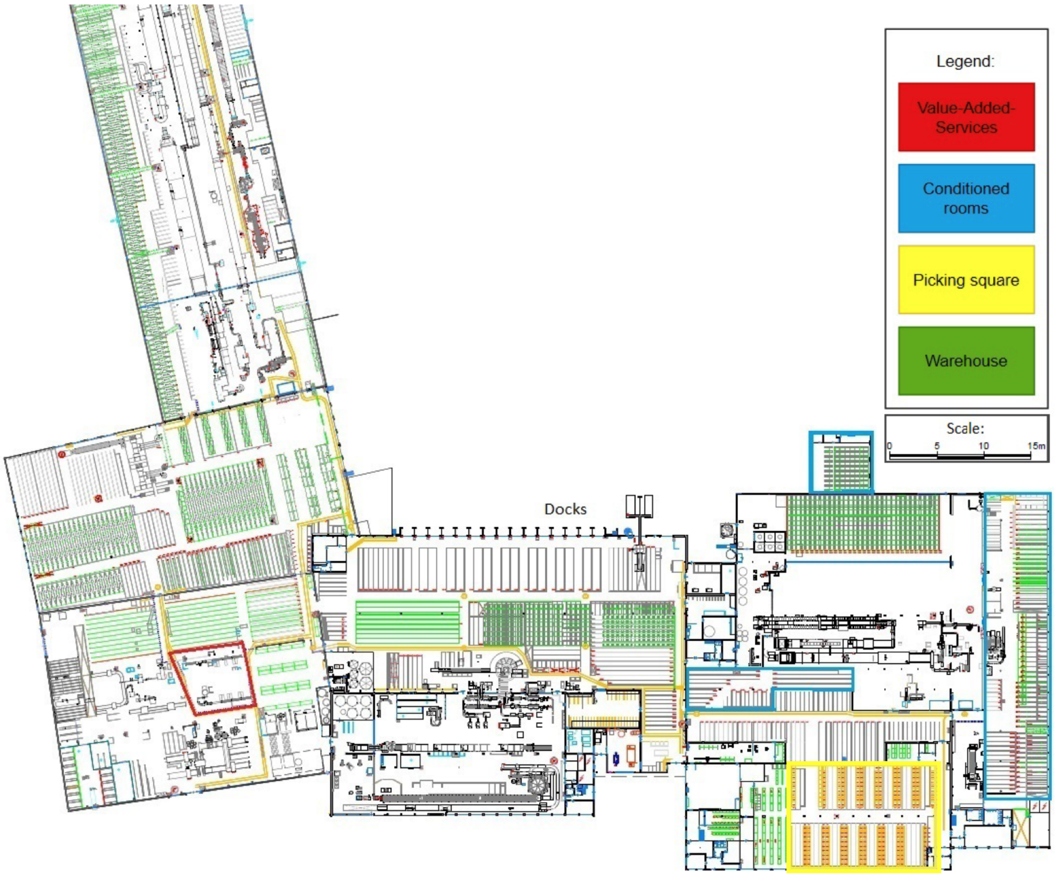
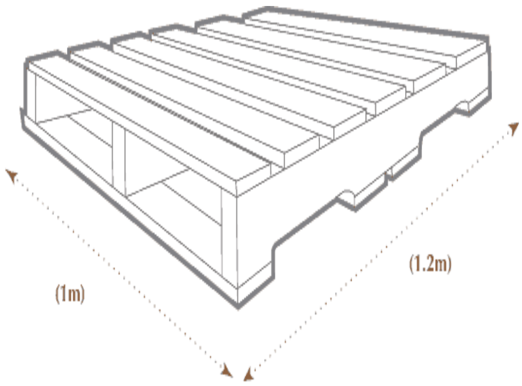
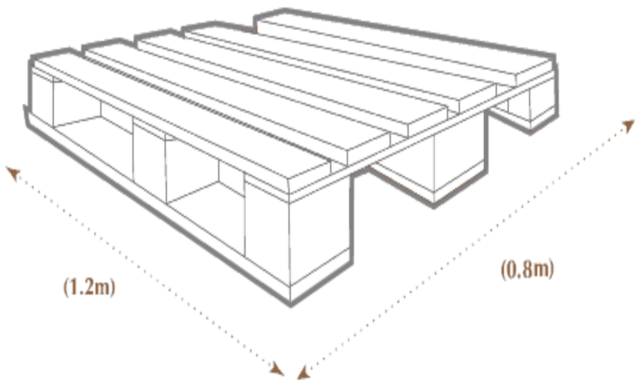


Figure 2.2: The warehouse lay-out

Standard FIN and EUR pallets are used to store the products on. Figure 2.3 depicts the dimensions of the pallets. These are used because of the convenience in storing, picking, loading and transporting the pallet. As these are based on the length and width of a standard truck.



(a) FIN pallet



(b) EUR pallet

Figure 2.3: Pallet dimensions

Bolletje makes uses of multiple different means of storage. Regular and deep lane pallet racks are used to store full pallets. Regular pallet racks can store a single pallet at its storage location, whereas deep lane pallet racks can store a batch of pallets, however, this has to be the same product from the same batch. Besides that, block stacking is used to store pallet of the same product, this storage means, as deep lane storage, requires the pallets to be stored to be the same. See 2.4a for the use of block stacking and 2.4b for the use of deep lane storage pallet racks. There is also the possibility of storing pallets in a pallet racks with a shuttle. This shuttle automatically transports pallets in a single lane. This is especially useful for large batches where many of the same pallets have to be stored. The length and width of storage locations are equal to the pallet dimensions displayed in figure 2.3, the height of the storage location however, is different for some locations and should be taken into account in the model.

(a) Block stacking

(b) Deep lane storage racks

Figure 2.4: Storage means

Bolletje currently organises its workforce in the warehouse in two shifts. The two shifts have two dedicated shift-times, the morning and afternoon. The morning shift starts at 7:00 and ends at 15:30, the afternoon shift starts at 15:30 and finishes at 23:00. In the time in between, the foremen of both shifts discuss issues regarding their shift. In the morning the foremen and WDD-manager organise a stand-up meeting where they discuss the following issues: Safety, Quality, On-time delivery and Processes and Flow. Bolletje partially carries out the transport to distribution centres and between plants. During the day, the transportplanner schedules these in- and outbound rides.

2.3 In- and outbound activities in the warehouse

There are three main inbound streams to the warehouse. These are the internally produced pallets, pallets resulting from the production location in Heerde (as there is no warehouse in Heerde, pallets are transported to Almelo) and from external suppliers other than Bolletje. Internally produced products arrive from multiple lines from different locations within the building (i.e. multiple input-locations). The goods from Heerde and external suppliers arrive at a single I/O-location, located at the "Docks" (see figure 2.2), these arrive on approximately a daily and weekly basis respectively. There is currently no truck-to-dock assignment policy (i.e. trucks are randomly assigned to available docks).

The production lines in Almelo produce approximately 1500 pallets per week, whereas Heerde and external suppliers deliver around 600 and 200-250 pallets to Almelo, respectively. Section 2.4 elaborates in more detail the distribution of incoming goods at the warehouse.

As mentioned in the previous section, the WDD uses two shifts per day. The morning shift usually stores the incoming products from the production lines and arrived trucks in the night/morning. After the truck arrives, products are temporarily stored on an extra dock (ED), the capacity on this extra dock is equal to one standard truck size. After that, a visual check is done and stickers attached on the pallets. Next, pallets are stored, see section 2.4 for the storage assignment policy of Stock-Keeping-Units (SKUs). Sometimes, the product is not stored at the location given by the hand-scanner, but at another location (close to the original location), this is due to the accessibility of assigned location, sometimes a bulk-low (low-level location) location might be more convenient than bulk-high (high-level location). The employee overrides the system, a new location is assigned to the pallet and saved in the system. A single command policy is used to store the products, meaning a product is stored and the employee returns to the I/O-location. However, whenever an employee has to traverse a long distance for storing a product, the department tries to use dual command if possible. Sometimes a pallet is directly needed at the production lines, then a pallet is directly stored at the production line instead of in the warehouse itself. The WDD uses a electrical trucks, electric hand pallet trucks and forklift trucks to transport its pallets. Figure 2.5 illustrates the types of material handling equipment. Besides the equipment to transport pallets, the WDD uses a hand scanner to scan stickers on pallets and locations in the warehouse.

(a) Hand pallet truck

(b) Standing electric reach truck

(c) Forklift truck

Figure 2.5: Material handling equipment

After the morning shift is finished, the afternoon shift picks the orders and loads them onto the load docks (LD) or into the trucks using single command. The national outbound logistics are carried out by Bolletje, however, international outbound logistics are carried out by an external carrier. The foreman of the evening shift assigns picking orders to its employees to pick them in the evening. Next, the employees retrieve pallets from their locations, book them off and load them onto the loading dock or, if available, load them directly into the trucks. The capacity of the loading dock is equal to one full truck size (33 EUR pallets), and each dock as one loading dock. The pallets to be picked and their respective locations are shown on a hand-scanner. As mentioned earlier, picking is usually the main contributor to the costs of a warehouse and is mainly and directly affected by the picking sequence. However, since usually one or at most two pallets are picked, it becomes irrelevant in what order they are picked. Because of this, better routing will not significantly decrease the driving distance. Smart assignment of goods to storage locations has a greater impact on picking distance and time.

Next to regular pallet picking, Bolletje also picks cases and layers in a forward picking area. Consumer-units are repacked at the Value-Added-Services department (VAS), see the red-bordered area in figure 2.2. Here, multiple different consumer-units are picked and consolidated in a single box (trade-unit) for the customer (see figure 2.6a for an illustration of each picking). The number of hours spent at VAS is not included in the activities as this is separate from regular (pallet) storing and picking in the warehouse. Case and layer picking happens at the "pickplein", this is the yellow indicated area on the bottom in 2.2 in section 2.2. At the "pickplein", multiple layers of trade units (cartons) are picked and consolidated on a pallet (see figure 2.6b for an illustration of layer picking). Layer picking is labor intensive as it accounts for approximately 10% to 15% of the hours spent in the warehouse and only a small portion of the total volume.

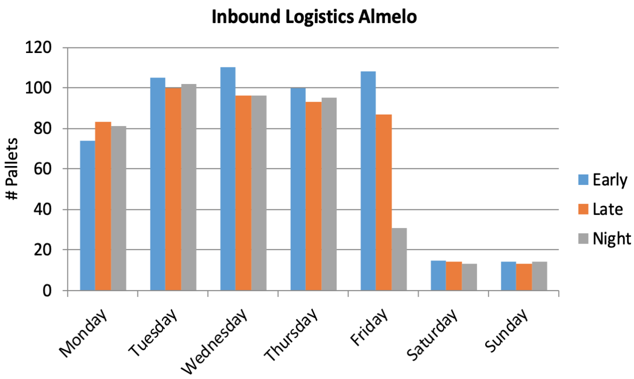
(a) Each picking and consolidation in carton

(b) Layer picking and consolidation on pallet

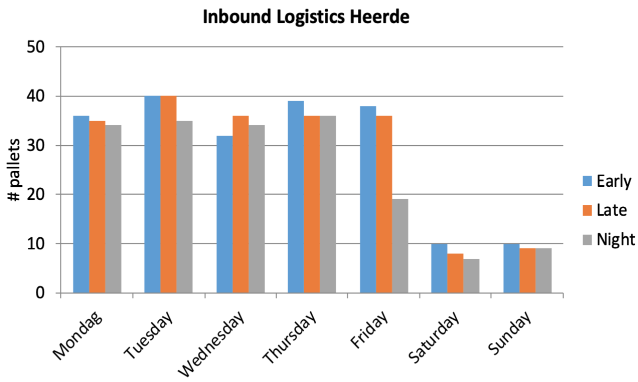
Figure 2.6: Each and Layer picking

2.4 Current storage assignment of (semi-)finished goods

The WDD currently allocates products based on their zonal location. The zones are not determined by an analysis but based upon experience of the WDD-manager. The halls in the plant are split up in multiple zones. The SKUs are divided into multiple categories, these categories belong to an attached storage zone in the warehouse. The system allocates the pallet that has to be stored to the first available location (i.e. closest open location) in the zone of the SKU, irrespective of the inbound location. The system allocates the SKU such that the entire order of that SKU can be stored. For example, if 20 pallets are produced, the system assigns the order to a storage location with a capacity of 20 or more. Besides the zonal allocation, the system does not allocate based on expiration date, this is illustrated by an example. Suppose an SKU is produced twice a week and has the same expiration date (recall from section 2.1), but a different production order, then the second order is not stored in the same storage location as the previous one if there is still space available to store the pallets of the second order. This yields a higher utilization of all storage locations together, but an increased driving distance because more and less favorable locations are used. Figure 2.7 depicts the to be stored products (i.e. products that are ready to be stored resulting from production lines in Almelo, Heerde and external suppliers). The dip in the Friday afternoon is explained by cleaning of the machines, therefore a lower production amount can be fabricated. External suppliers deliver in total approximately 200-250 pallets per week, the distribution over the workdays per week is approximately uniformly distributed. The pallets resulting from production in the weekend are stored in Monday, therefore Monday is the busiest day in terms of storing pallets.



(a) Pallets resulting from production in Almelo



(b) Pallets resulting from production in Heerde

Figure 2.7: Inbound pallets from different locations (week 1-38, 2020)

2.5 Current logistic performance

The KPIs that are currently in place are divided into two categories, namely the warehouse and transport. The warehouse measures the number of hours spent, number of pallets delivered and fraction of both (i.e. pallets delivered per hour). The number of used hours is also compared to the amount of norm hours. Transportation performance indicators deal with number of national rides and return rides where a load is included. These result in two main indicators, namely loading degree and % return loads. Figure2.8 shows the norm versus the used hours in the warehouse. In order to measure the strength of a relation between two continuous variables, the Pearson correlation coefficient (ρ) is used. There is a very high (nearly perfect) correlation between the two variables (ρ= 0.999). Figure 2.9 depicts the gross number of full-time equivalent (FTE) used compared to the number of pallets transported. There is little correlation between these variables (ρ=0.02). The number of pallets delivered per hour is relatively stable around 4, it is considered to be a surrogate/rough measuring, since it is based on the number of hours used and number of pallets transported. The increase in number of hours used in figure 2.8 and pallets transported in 2.9 is due to the large seasonal demand after the second-half of the year. During this time, especially "Sint"-related products are sold during this time of the year. Currently, as mentioned before, there is no metric in place measuring the driving distance available. In section 4.2 we elaborate on how the distance to and from locations is measured.

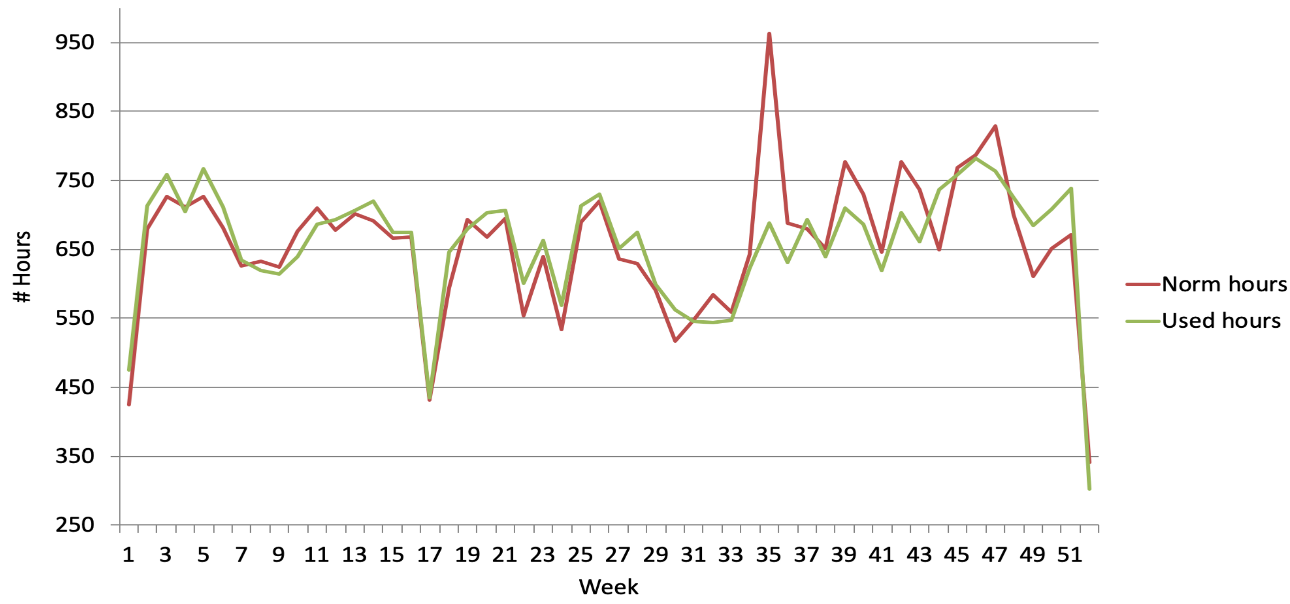


Figure 2.8: Norm versus used hours in 2019

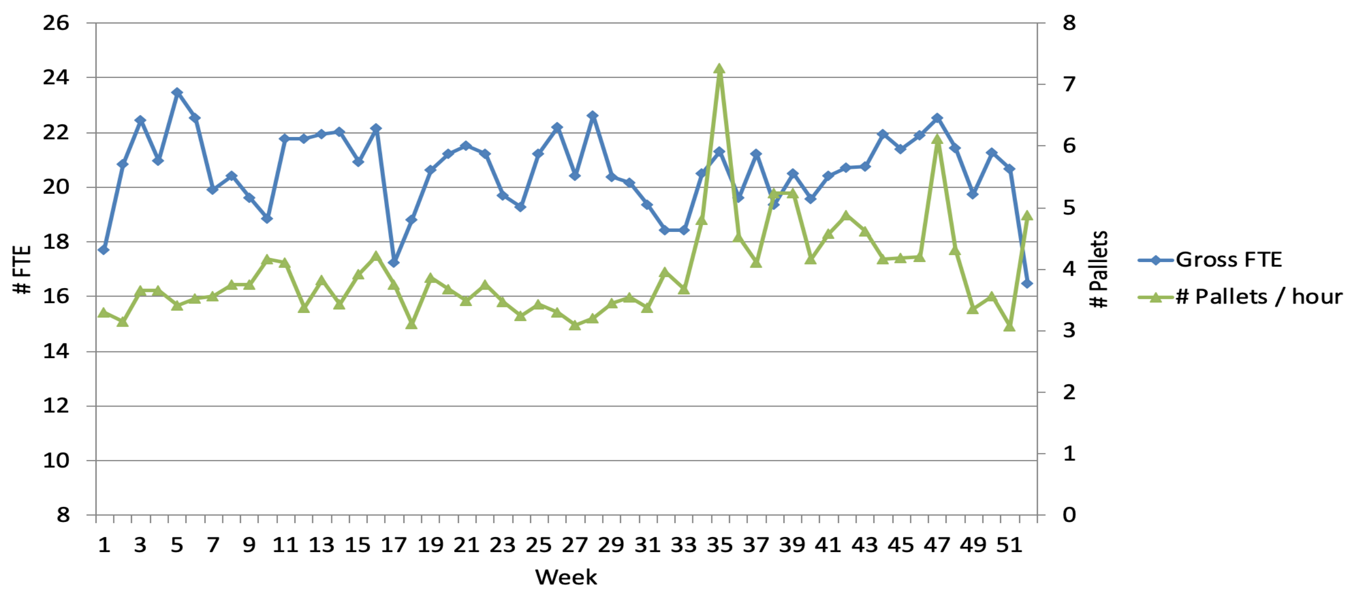


Figure 2.9: Gross FTE used versus pallets transported

2.6 Conclusions

This chapter provided insight in the current situation of the warehouse of Bolletje. Here the product characteristics, lay-out, flow of goods and performance indicators of the warehouse are discussed. It answered the following research question: *How is the current situation regarding the warehouse configured at Bolletje?*

Bolletje produces around 200 different products. These are subdivided into seven categories.

The warehouse is iteratively designed, meaning that storage locations are added and removed through the years in favor of and in contrast to the production lines. Multiple types of storage means are used, such as block stacking, pallet racks and shuttles. The goods have multiple inbound locations, namely the internal production lines and external deliveries from Heerde and other suppliers. On average, Almelo production lines deliver 1400 to 1500 pallets a week, Heerde on average 400-500 and external deliveries account for approximately 200 to 250 pallets a week.

The core problem is to design a storage policy such that the travelling distance is minimized. Currently, the warehouse allocates pallets based on their zonal location (class based policy). Within these zones, the closest open location is chosen to store the pallets. This yields a high utilization of the first available locations, however, also leads to excessive driving distance by not efficiently zoning and allocating the products to the zones.

An analysis based on historic performance showed that a large part of the spent hours are caused by the storage assignment policy the warehouse uses. On average, three to four pallets are stored/picked per hour.

3 Literature review

This chapter covers the answer to the second (2) question stated in section 1.5, concerning a literature review regarding state of the art storage methods for production companies. Section 3.1 first describes methods for classifying warehouses (including relevant aspects for storage policies) and inventories are described. Next, we aim to thoroughly discuss possible storage heuristics, policies and rules for allocating products to storage locations in section 3.2. Section 3.3 covers commonly used performance measures to optimize including constraints. Section 3.4 describes optimization techniques to further improve a current solution, these include mathematical models and local search methods. Section five finalizes the chapter with conclusions.

3.1 Warehouse and inventory classification

According to Gu, Goetschalckx, and McGinnis (2007), warehouses are considered as an essential component of any supply chain. There are multiple reasons why to have a warehouse, these reasons include the following uses:

- Match supply with customer demand
- Consolidation of products to reduce transportation costs
- Product mixing
- Cross-docking

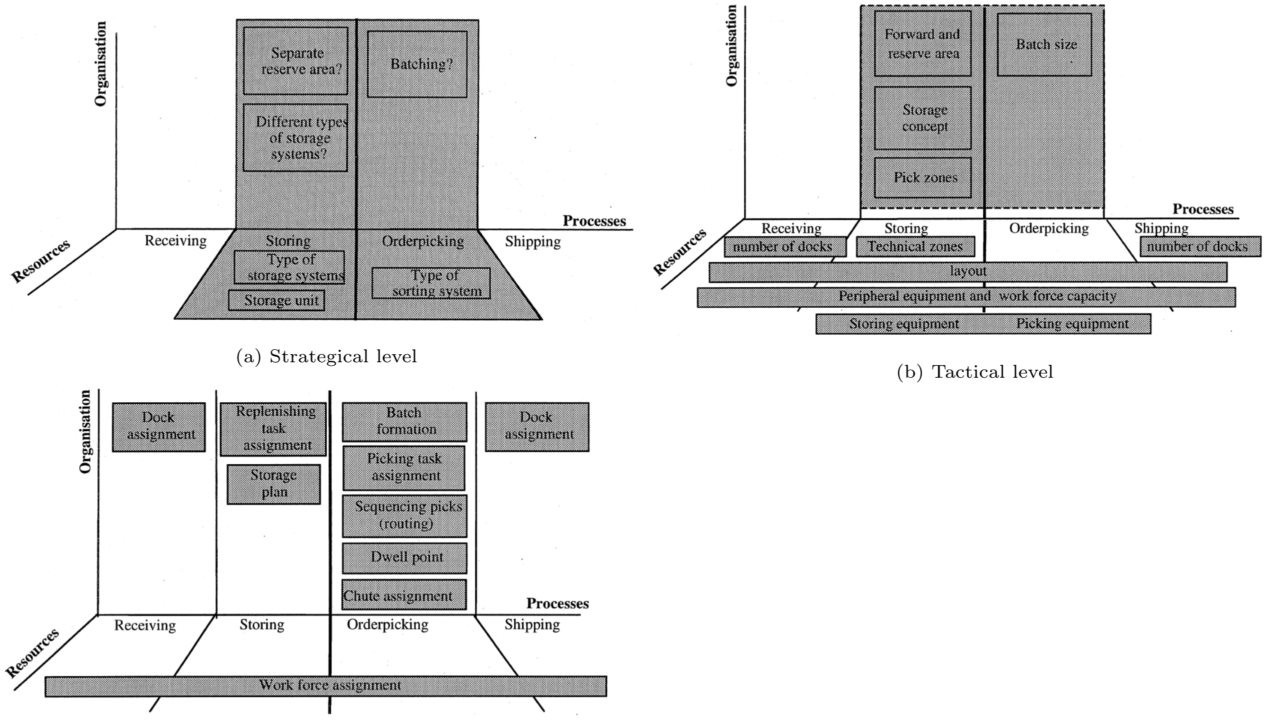
Three types of warehouses may be distinguished, these are distribution, production and contract warehouses. In distribution warehouses, products from multiple suppliers are collected for delivery to the customers. Production warehouses store raw materials, semi-finished and finished products. A contract warehouse conducts the warehouse operation for its customers. The warehouse usually performs the following four types of activities (Richards, 2011), (Bartholdi & Hackman, 2019):

- Receiving: at the receiving stage, goods are delivered at the *receiving docks*. Ensuring the correct product, right amount and right quality arrived is crucial. After that, products are stored at a location - usually determined by a Warehouse Management System (WMS).
- Storage: three key aspects have to be determined in advance when storing products, how much of the product should be stored with which *storage mean* at which location. Sometimes the storage area is split up into a *reserve area* (most economical way) and *forward area* (easy retrieval).
- Order-picking: at this stage, items are retrieved from their storage locations using material handling equipment, usually in a pre-determined sequence. After picking the items, they are sometimes sorted and *consolidated* (grouping items for the same customer). According to Drury (1988), this is the most costly activity.
- Shipping: products are consolidated into larger storage packages, checked, packed and finally loaded and transported, sometimes using multiple *transportation modalities* (train, trucks, aircrafts, boats etc.).

Besides the process angle, Rouwenhorst et al. (2000) view the warehouse from a resource and organizational perspective, many resources and organizational structures can be distinguished, the main resources and organizational decisions are:

- Type of *storage unit* (e.g. pallet, tote) and in which *storage system* (e.g. shelves, pallet racks, Automated Storage and Retrieval Systems(AS/RS)) that product is stored.
- *Picking equipment* (e.g. reach truck) and *order-pick auxiliaries* (e.g. bar code scanner).
- *Warehouse Management System (WMS)* to make sure processes run smoothly and activities are carried out correctly. The main benefits are increased efficiency, speed and order/inventory accuracy. (Min, 2007)
- *Truck assignment policy* at receiving process, *storage policy* at storage process, *picking policy* at picking activity and *sorter lane assignment, dock assignment and operator/equipment assignment policies* at the final shipping stage.

Warehousing problems can be further distinguished by hierarchical level. Literature commonly differentiates three different levels, namely strategic, tactical and operational. Warehousing decisions at strategic level have a long term impact and considerable investments. The two main groups of decisions are the design of the process flow and types of warehousing systems. The tactical level considers medium-term decisions and have to be based on the outcomes of the preceding level. Key decisions including the dimensions of resources, determination of the lay-out and some organizational issues. The main issues at the short-term operational level are the assignment and control problems of people and equipment. Figure 3.1 depicts the strategic (3.1a), tactical (3.1b) and operational (3.1c) decisions to be made by a warehousing department based on the three different angles (resources, process and organization) discussed earlier in this section.



(a) Strategical level

(b) Tactical level

(c) Operational level

Figure 3.1: Warehousing decisions per hierarchical level (Rouwenhorst et al. (2000))

Inventory classification methods can be divided into two categories, namely qualitative and quantitative (Silver, Pyke, & Thomas, 2016). The main purpose of these classifications is to manage control effort of the stock keeping units (SKUs). Qualitative classification methods are:

- Functional: classification based on the function of the inventory (cycle, safety, anticipation and pipeline stock).
- Product life cycle: classification based on the phase of the product life cycle (start-up, rapid growth, maturation and decline).

Quantitative methods the classify inventory include the following:

- ABC-analysis: classifies SKUs based on annual sales value, other relevant characteristics can also be included, such as criticality and number of customer transactions (Ng, 2007). In order to include multiple characteristics, weighted linear optimization can be used (Ramanathan, 2006).
- Forecasting and Stock control: classification of SKUs based on demand interval, size and coefficient of variation of demand size (used for non-normal demand patterns) (Boylan, Syntetos, & Karakostas, 2008).
- Inventory theory: classifies SKUs based on demand rate D_i, holding costs h_i and lead time L_i, SKUs should be ranked according to the ratio: $\frac{D_i}{h_i^2 L_i}$ (Zhang, Hopp, & Supatgiat, 2001).
- Total cost minimization: classifies SKUs based on demand rate D_i, holding costs h_i, lot size Q_i and shortage costs b_i, SKUs should be ranked according to: $\frac{b_i D_i}{h_i Q_i}$ (Teunter, Babai, & Syntetos, 2010).
- Fill rate: use demand-weighted average fill rate FR_{2T}, price p_i and demand weighted price p_T, rank them according to the ratio: $(1 - FR_{2T})\frac{p_i}{p_T}$ (Teunter, Syntetos, & Babai, 2017).

3.2 Storage methods

This section thoroughly discusses the storage location assignment problem (SLAP) (Charris, Rojas-Reyes, & Montoya-Torres, 2018). This problem is also referred to as product allocation, storage location/space, reserve/space allocation and slotting/warehouse layout problem. Storage policies are methods to assign SKUs to storage locations. These policies can be split up into three types of broad categories, namely: Haphazard, shared/class-based and dedicated storage (Bahrami, Piri, & Aghezzaf, 2019). Figure 3.2 depicts an overview of storage assignment policies. Haphazard storage and dedicated storage are two opposites of each other, class-based storage is a mixture of these two (C. G. Petersen & Aase, 2004). In the next three subsections, an in depth explanation of storage policies belonging to the aforementioned categories is given, including their pros and cons.

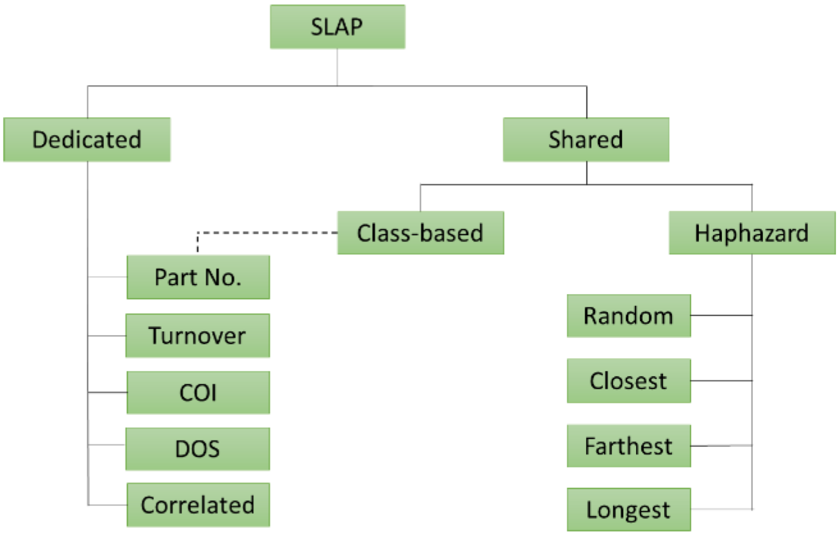


Figure 3.2: Classification of storage policies (Bahrami, Piri & Aghezzaf (2019))

3.2.1 Haphazard storage

In haphazard storage, the only information needed to implement is whenever a storage location is available or not. An individual SKU can be stored at any *available* storage location. In practice, products are usually stored at the closest-available slot and retrieved first-in-first-out (FIFO), this is called *closest open location* (COL) storage (G., 1999). This strategy minimizes the building costs (less space needed), yields a uniform utilization of storage space and aisle congestion is reduced (de Koster, Le-Duc, & Roodbergen, 2007). However, this strategy maximizes handling costs due to the possibility of large travel times and control is more difficult compared to dedicated storage due recording SKUs at the locations for retrieval purposes (Choe, 1990). Farthest open location policy allocates the most distant free location from the I/O-point to the SKU. SKUs can also be assigned to locations based on the time the locations are not occupied, called the longest open location policy.

The main advantages of haphazard storage policies are its simplicity, space utilization, uniform use of storage locations and aisles leading to lower congestion and resistance to demand fluctuations and assortment changes. However, the lack of a systematic view and non-utilization of process and product information leads to a declined performance (D. M.-H. Chiang, Lin, & Chen, 2011).

3.2.2 Dedicated storage

Dedicated storage methods allocate a predetermined and fixed number of slots assigned to each SKU, this is the opposite of randomized storage. This system is particular useful for warehouses with a large throughput. The main idea behind dedicated storage policies is that fast-movers should be located at easily accessible areas close to the Input/Output-point (I/O-point). In literature, many dedicated storage policies can be found. Usually, an allocation policy is based on compatibility, complementary, popularity and space (Kallina & Lynn, 1976). The item-oriented policies discussed here are Part number, Turnover based, Duration of Stay (DOS) and the Cube-per-Order-Index (COI) rule. The order oriented slotting (OOS) heuristics such as correlation based and Interaction Frequency Heuristic (IFH) are discussed afterwards.

One of the first policies used in warehousing was assigning SKUs to storage locations based on their part number. This helps storekeepers to easily find and retrieve SKUs from their dedicated position in the warehouse. Currently it is considered to be an obsolete and old-fashioned method (Brynzer & Johansson, 1996).

The most popular dedicated storage assignment method is based on the (full-)turnover, volume-based or demand rate of products. Here, the most wanted products (i.e. fast-movers) are placed at the most accessible locations and slow-movers are placed at remote locations (de Koster et al., 2007). One problem with this allocation is the assortment and demand fluctuations.

Duration of Stay (DOS) assigns locations to product units based on their duration in the warehouse. The shorter the DOS in the warehouse, the better location the product unit get assigned (i.e. closer to the I/O-point). The DOS-approach needs the most and precise data in comparison to the other policies. In case of absence of accurate data, it is still possible that DOS-based storage can be beneficial (Suby, 1975). The quality of the solution is based on the balance of the system (Goetschalckx & Ratliff, 1990). A *perfectly balanced* system requires the number of departing and arriving units with a DOS of p to be equal for any period t. The number of arriving units in period t with DOS of p is denoted by $n_p(t)$, implying that $n_p(t) = n_p(t+p)$. A system is *balanced* if the aggregate input is equal to the aggregate output. It is shown that whenever the system is perfectly balanced, an optimal shared policy can be obtained by the individual duration of stay. As a perfect balanced system is unrealistic, two heuristics are provided, a greedy heuristic (GREEDY) with a restrictive condition and an adaptive one. The greedy heuristic maximizes the number of items stored at the most accessible locations. The items with the earliest departure times are stored at the COL, ties are broken up by the non-decreasing order of arrival times. The adaptive shared storage algorithm is shown in appendix A. Langevin, Riopel, Montulet, and Chen provide a problem formulation for an AS/RS-system which can be generalized for regular warehouses. See appendix B for the description of the mathematical model. Due to the excessive use of binary variables for a realistically sized problem, large computational effort is needed to solve the problem. Therefore, the authors developed a graph-based heuristic (GBH) and compared it to GREEDY from Goetschalckx and Ratliff (1990). A storage graph $\boldsymbol{G=(V,C,A)}$ is defined as:

- $\boldsymbol{V}$ is the set of time V={1,2,...,T+1} nodes. The first node is the source and node T+1 the sink.
- $\boldsymbol{C}$ is a set of directed connection arcs between the nodes in $\boldsymbol{V}$.
- $\boldsymbol{A}$ a set of directed storage arcs, starting from the arrival time a_i and ending at the departure time d_i (i.e. DOS) for each product i.

The heuristic consists of three steps and is based on the longest-path method:

While $\boldsymbol{A} \neq \varnothing$ do

1. Identify longest path p in graph $\boldsymbol{G}$ from source to sink
2. Allocate unit loads of path p to the COL
3. Delete the arcs of path p from graph $\boldsymbol{G}$

Figure 3.3 illustrates the directed acyclic storage graph and longest path from source to sink. Here, unit loads s_1 and s_4 are assigned to the COL and deleted from the graph. Figure 3.4 depicts a comparison for a toy-problem between GREEDY and the GBH from Langevin et al.. The authors conclude that their heuristic performs 0.56% to 2.13% and 2.01% to 7.50% better in terms of travel time and space requirements, respectively.

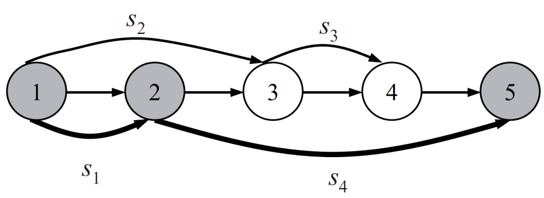


Figure 3.3: Longest path p in a storage graph (Langevin et al. (2008))

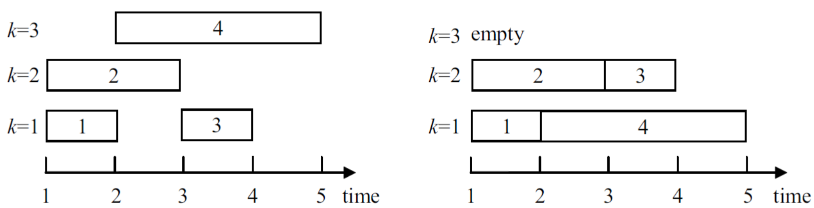


Figure 3.4: Comparison between GREEDY and GBH (Langevin et al. (2008))

One of the main problems with GBH is the computation of the longest path p for reasonably sized instances. The Longest path is NP-Hard and its decision problem: "*Does there exist a simple path in a given graph with at least k edges?*" NP-complete (Cormen, Leiserson, Rivest, & Stein, 2001) (Pardalos & Migdalas, 2004).

The cube per order index (COI) is a single command policy. It assigns storage locations to SKUs based on the ratio of required storage locations and the number of in/out trips of storage per period (i.e. popularity) (Heskett, 1963). Here, SKUs with the lowest COI are placed at the most favorable locations (i.e. closest to the I/O point). The COI-strategy uses the following parameters and variables:

$$\begin{aligned}
q &= number\ of\ storage\ locations \\
n &= number\ of\ SKUs \\
m &= number\ of\ I/O\ points \\
S_j &= number\ of\ storage\ locations\ required\ for\ SKU\ j \\
T_j &= number\ of\ trips\ inout\ of\ storage\ for\ SKU\ j\, that\ is,\ throughput\ of\ SKU\ j \\
p_i &= percentage\ of\ travel\ in/out\ of\ storage\ to/from\ I/O\ point\ i \\
d_{ik} &= distance\ required\ to\ travel\ from\ I/O\ point\ i\, to\ storage\ location\ k
\end{aligned}$$

Next, the COI-method ranks every location in non-decreasing order based on the expected travel distance (assuming multiple I/O locations) from location k to the docks:

$$f_k = \sum_{i=1}^{m} p_i d_{ik} \qquad \forall k \tag{3.1}$$

The lowest f_k is the best location, next, items are ordered based on their COI:

$$COI_j = \frac{T_j}{S_j} \qquad \forall j \tag{3.2}$$

Finally, SKUs are sorted based on 3.2 in non-increasing order. The first item is then stored at the best location(s) based on the 3.1. The method was initially conceived as a heuristic, but some authors showed that it yields an optimal solution under certain environmental conditions. The COI-approach is considered to be an item-oriented solution suitable for single command situations. Usually multiple items are picked during a tour (i.e. multi-command). Mantel, Schuur, and Heragu show that in a multi-command situation, item-oriented strategies perform worse than order-oriented strategies (de Ruijter, Schuur, Mantel, & Heragu, 2009). Schuur (2015) has proven that, given an arbitrary parameter p, COI can be *p-fold* worse than the optimal slotting configuration in terms of order picking travel time.

Whereas the above described policies mainly focus on single-command modes and ignore possible associations between the SKUs. The following policies include possible correlation of items that might be picked together in the same order and are order oriented. Correlated storage (clustering / family-grouping) considers products which are complementary to each other and probably need to be picked simultaneously. This is a hybrid between item-oriented and order-oriented policies. This policy requires an estimation of the correlation among the items to be stored in the warehouse. Dependent demand of a higher level items in the bill of material (BOM) is easily recognized, these interrelations become more complex in a distribution warehouse. The slotting problem here is two-fold, first clusters with items have to be identified, next the clusters need to be assigned to storage regions (Bahrami et al., 2019). In literature, multiple methods are proposed by authors to solve the problem. E. A. Frazelle and Sharp (1989) propose a two-stage heuristic. First correlated items are grouped using conditional probabilities and an independence hypothesis test. Next, clusters are assigned to storage locations based on popularity, similar to COI. Rosenwein formulate the clustering problem as the p-median problem. However, he does not propose a solution for the allocation of clusters with items to storage regions. Amirhosseini, Sharp, and Subramanian present the *order-satisfying correlation measure*, which measures the degree of correlation within two or more products in the warehouse or customer orders. The correlation metric of Liu is similar to but more flexible than the one proposed by Rosenwein. The similarity of product i and j is calculated as follows: $c_{ij} = \frac{1}{|Q|} \sum_{q \in Q} \frac{min[u_q^i, u_q^j]}{max[u_q^i, u_q^j]}$. Here, Q is the set of orders, u_q^i is the amount of items required for order q. $|Q|$ is the cardinality of set Q

Order oriented slotting (OOS) is proposed by Mantel, Schuur, and Heragu. These authors also consider the routing policy when slotting items. Two parameters are presented, namely:

f_{i0} = *popularity*, the number of orders that require SKU i

f_{ij} = *interaction frequency*, number of orders that require both SKU i and j

The reasoning behind that is, in order to minimize the effort needed to pick orders, two conditions must hold. SKUs with a high interaction frequency must be stored close to each other. Second, popular SKUs need to be placed close to the I/O-point. The OOS is probably for the majority routing policies an NP-hard problem, therefore, the authors proposed four heuristics. The first one is random, which allocates the SKUs randomly. Popularity heuristic is the second one, here the SKUs are allocated based on their popularity (f_{i0}) COI-concept. The third heuristic is called Interaction Frequency Heuristic (IFH). IFH first allocates singles based on their popularity. Next, interactions (f_{ij}) are sorted in decreasing order. If SKU i and j neither have yet been allocated, they are assigned as close as possible and the distance is in accordance with the popularity. If only one of the SKUs has to be stored, then they need to be stored as close as possible to the other and such that the distance is in accordance with the popularity. The last formulation the authors provide is based on the Quadratic assignment Problem (QAP). The heuristic minimizes the following sum:

$$\min_{a\in S} f^0(a) = \sum_{i=1}^{I-1}\sum_{j=i+1}^{I} f_{ij}d_{ij}(a) + \alpha\sum_{i=1}^{I} f_{i0}d_{i0}(a) \tag{3.3}$$

In 3.3, S is the set of storage assignments. d_{ij} and d_{i0} are the distance between SKU i and j and the distance between SKU i and the I/O point, respectively. The α value denotes the relative weight to the objective of frequently demand items close to the I/O and has to be determined empirically. As the QAP is an NP-hard problem, optimal solutions are hard to obtain (Sahni & Gonzalez, 1976). Due to the structure of the problem (S, f^0), efficient search methods can be used such as simulated annealing (SA) (de Ruijter et al., 2009). With a toy example, the authors showed that a reduction of 16% can be obtained with OOS compared to COI. Besides the heuristics, the authors also propose two routing policy dependent mathematical models. Figure 3.5 depicts a comparison between COI and OOS in reduction of travel distance.

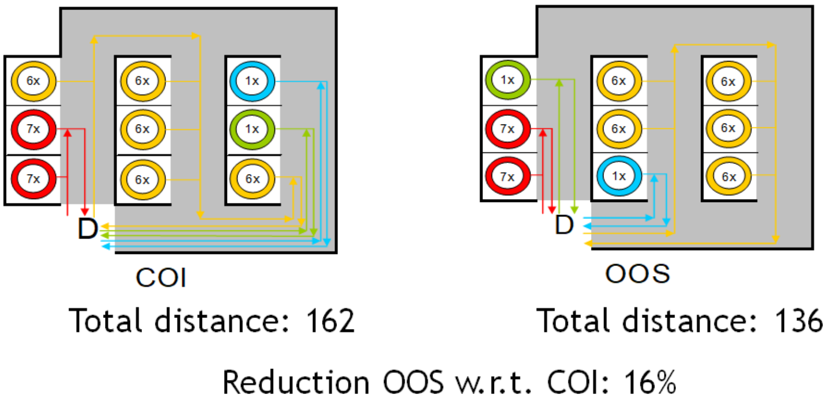


Figure 3.5: Comparison between COI versus OOS (Mantel, Schuur & Heragu (2007))

Van Oudheusden, Tzen, and Ko (1988) consider the problem of slotting and routing simultaneously. Most methods do not take into account the sequence in which two SKUs of the same order are picked. The authors propose a method to minimize the total distance traversed taking into consideration the direct link frequencies (i.e. how often SKU i is picked after or before SKU j).

In general, dedicated storage policies require allotted space for each SKU at its maximum inventory level. This leads to a low utilization of the warehouse in comparison to haphazard storage. Besides that, as items with a low COI and high turnover rate are concentrated near to the I/O, there will be congestion in popular aisles in a multi-picker situation (Caron, Marchet, & Perego, 1998).

3.2.3 Class-based storage

Class-based storage (CBS) is a balance between haphazard and dedicated storage policies. It classifies SKUs into classes based on product characteristics such as DOS, volume or usage rate. The SLAP becomes a problem of assigning SKUs to classes and subsequently classes to storage regions. Within the class, items are positioned with a haphazard rule such as COL storage or random. Haphazard with one single class can be considered as CBS and every SKU a single class as dedicated storage (Gu et al., 2007). Often three classes are used and this is referred to as ABC storage (Roodbergen & Vis, 2009). The main advantages of CBS are is its ability to deal with demand variations, changes in the product assortment, simple implementation and maintainability. CBS outperforms haphazard storage in terms of travel distance and in convenience compared to dedicated storage. Most research has been done on automated warehouse environments and little on predominant manual storage/picking environments (D. E. H. Frazelle, 2016). CBS does take advantage of the logic of dedicated storage, whereas it avoids the exhaustive side of it (C. G. Petersen & Aase, 2004). The most common CBS classification criterion used in turnover rate (D. Chiang, Lin, & Chen, 2014), however, other criteria may be used as well, such as the ones indicated by the dashed line in figure 3.2.

Conventional research shows that there is an inverse relation between the average travel time and the number of classes. However, Yu, De Koster, and Guo (2015) found that there is an optimum number of classes. Meaning that the average travel time increases after a certain number of classes. See figure 3.6 for an illustration of this principle. The authors show that between 3 to 10 classes is optimal. Fewer or more classes results in inferior solutions. Another main outcome of the research is that the average travel time is insensitive to the number of classes in a wide range. This gives flexibility in designing classes for a CBS-policy.

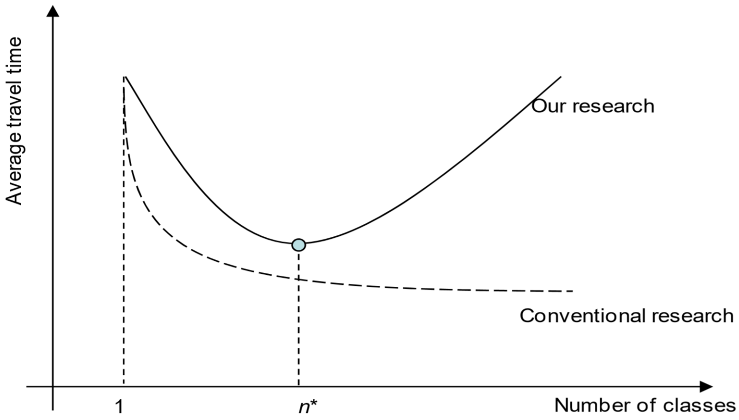


Figure 3.6: Relation between travel time and number of classes (Yu, De Koster & Guo (2015))

Muppani and Adil (2008) propose a model for the formation of storage classes for the SLAP. Literature primarily focuses on order-picking costs whereas their model considers the storage-space costs. See Appendix C for the mathematical model the authors developed. Due to the non-linearity in the objective function and large number of binary variables, reasonably sizes problems become intractable to solve. To solve the problem, the meta-heuristic SA algorithm is used (see section 3.4 for a thorough description of meta-heuristics and SA). The neighbourhood structure consists of the storage classes with their respective parts. The move-operator is used to visit a neighbour solution. Two randomly selected classes k and l such that $k \neq l$ are selected from the current solution. Next, a random part p_i is selected and moved from class k to class l. After the part is moved, a mathematical allocation model is solved to obtain the neighbour solution value.

Berg (1996) proposes a class-based storage allocation model in single command mode with space constraints. The author proposes a dynamic programming (DP) algorithm which finds a class allocation such that the total single command cycle travel time is minimized. The advantage of their model is that it holds for many warehousing systems, as it is independent of the demand curves, travel metric, warehouse lay-out and position of the I/O-point. The drawback is that the DP-algorithm computationally intensive (i.e. large problems pose computational difficulties in terms of computation time) and a maximum of one I/O-point can be considered.

Larson, March, and Kusiak (1997) provide a three-stage heuristic for the lay-out of class-based warehouse based on the warehouse capacity, number of SKUs, inventory levels and popularity of SKUs. First the aisle layout and dimensions are determined, here slot dimensions, storage zone length and mediums are determined.

The implementation and problem of finding class regions is studied by multiple authors. Hausman, Schwarz, and Graves proposed an L-shaped model which is optimal for Chebyshev distances in single command mode. In dual command mode, this policy is not necessarily optimal (Graves, Hausman, & Schwarz, 1977). C. Petersen and Schmenner provide four aisle-dependent variations on the formation of classes in the warehouse on turnover-based storage. Figure 3.7 depicts the L-shaped class formation and the other four aisle-dependent variations on CBS.

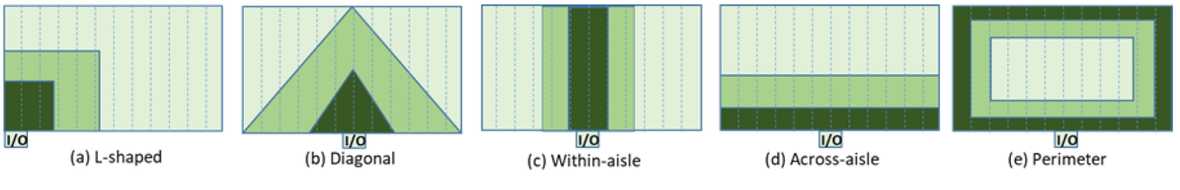


Figure 3.7: Class formations (Bahrami, Piri & Aghezzaf (2019))

3.3 Performance measures and constraints

Many KPIs can be distinguished to optimize. Charris et al. provide a thorough overview of the optimized performance measures in literature. The authors proposed a classification of the performance measures in multiple categories. Figure 3.8 depicts an organization of the categorized performance indicators. The most commonly used categories are "Space and distance", "Time", "Operational efficiency" and "costs", respectively. Travel distance and time were the most used performance indicators.

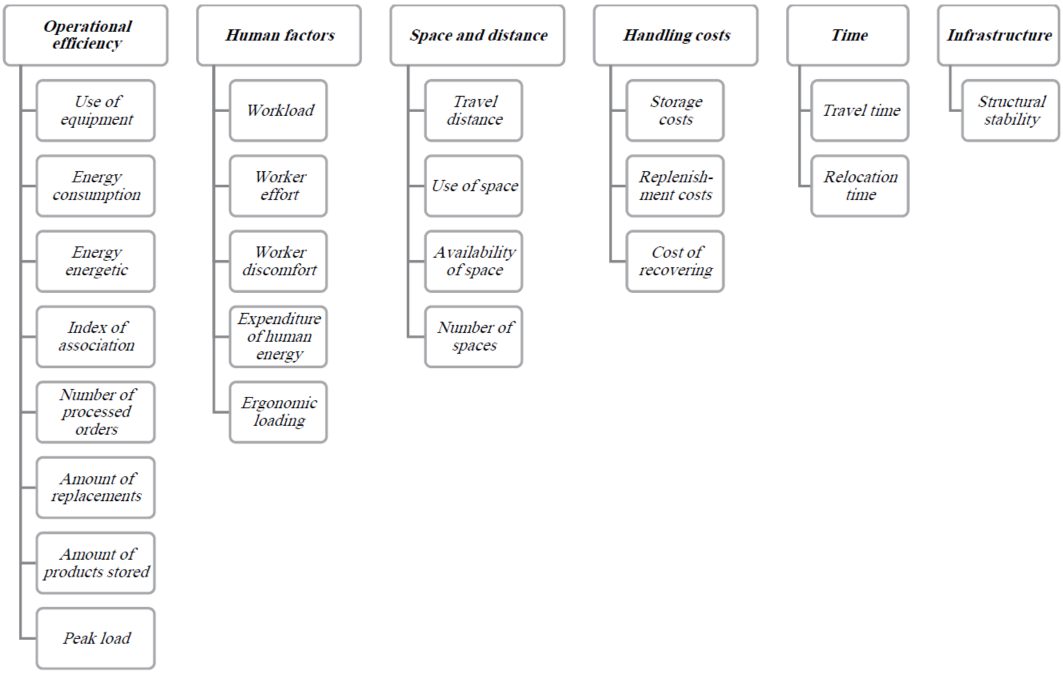


Figure 3.8: Categorization performance indicators (Charris et al. (2018))

Common constraints used in optimization models include are the ones related to the capacity and conditions of the warehouse, market and characteristics of the products. Capacity-related constraints deal with the capacity of the entire warehouse and storage locations themselves, whereas the conditions restrict some products not to be located together or at some places in the warehouse (e.g. due to temperature conditions) at all. Market constraints address issues such as demand rate, duration of stay and seasonality. Characteristics constraints concern aspects such as association, correlation, compatibility and expiration.

3.4 Optimization techniques

Many techniques to obtain an optimal solution or improve a current solution are described in literature. This section describes mathematical models, local search techniques (including approximation algorithms) and simulation (including simulation optimization).

3.4.1 Mathematical models

Mathematical models (queuing, stochastic optimization, linear programming) can be used to solve problems to optimally. In linear programming, the objective function and requirements (i.e. constraints) of a problem are described in (linear) functions. A special class of linear programming models are integer and binary programming models. The main advantage of such models is that they can describe many real-life situations (Winston, 2004). However, due to non-convexity, problems of a realistically sized problem becomes intractable and cannot be solved within a reasonable amount of time. Karp found that these kind of models are NP-complete. The previous section described several mathematical models. An optimization model usually consists of the following elements:

- Objective function: maximization or minimization, problem-dependent
- Decision variables: decisions to be made expressed in variables
- Constraints: restrict the decision variables only to attain certain values

3.4.2 Local search and approximation algorithms

Due to NP-completeness, many integer programming models cannot be solved efficiently. Therefore, two kinds of solutions exist, namely local search methods and approximation algorithms. Local search tries to sequentially explore the solution space. It visits "neighbour" solutions and evaluates their solution values (Kleinberg & Tardos, 2005). Two categories within approximate methods can be distinguished, approximation algorithms and heuristics. Approximation algorithms guarantee an upper or lower bound from the global optimum for an minimization and maximization problem respectively (Coffman, Garey, & Johnson, 1996). This means that the algorithms will perform at most a factor ϵ worse compared to the best solution value (Vazirani, 2003). Heuristics provide good, but not bounded solutions to a problem.

One of the most popular local search methods is SA. This algorithm is used to escape from local optima and systematically find better solutions. The SA method is based on statistical mechanics. Here, the annealing process requires a substance to be heated first and then slowly cool in order to get a strong crystalline structure (Talbi & El-Ghazali, 2009). The algorithm starts with an initial solution, including a starting temperature T, cooling factor α. Next, a new solution (N) is created by slightly adjusting the current solution (C). If the solution is better, it is accepted, else the solution is accepted based on a Boltzmann probability distribution ($e^{\frac{N-C}{T}}$). After L neighbour solutions are evaluated (i.e. Markov Chain Length), the temperature T is decreased with factor α. In the beginning, whenever the temperature is high, many solutions are accepted, also the inferior ones (i.e. diversification). When the temperature is low, generally only better solutions are accepted (i.e. intensification). See figure 3.9 for a summary of the algorithm.

Simulated annealing algorithm

```
Select the best solution vector x0 to be optimized
Initialize the parameters: temperature T, Boltzmann's constant k, reduction factor c
while termination criterion is not satisfied do
    for number of new solution
        Select a new solution: x0+Δx
            if f(x0+Δx) > f(x0) then
                f_new = f(x0 + Δx); x0 = x0 + Δx
            else
                Δf = f(x0 + Δx) − f(x0)
                random r(0, 1)
                if r > exp(−Δf/kT) then
                    f_new = f(x0 + Δx), x0 = x0 + Δx
                else
                    f_new = f(x0),
                end if
            end if
        f = f_new
        Decrease the temperature periodically: T = c x T
    end for
end while
```

Figure 3.9: Pseudo code simulated annealing

As there are no rules of thumb for determining the parameters in the algorithm, one has to determine them empirically. The only criterion which must be met is that the acceptance ratio (i.e. number of accepted solutions compared to the total visited ones) must equal one at the start of the algorithm.

3.4.3 Simulation

The third method in this chapter is simulation. Simulation is a useful technique to imitate real-world processes or facilities. The process/facility of interest is called *system* and the relation, assumptions and mathematics of the system constitute the *model*. Simulation is particularly useful to evaluate various interventions in the system under various scenarios, this is more cost and time efficient than evaluating such interventions in a real system. In order for the simulation model to be representative, the conceptual model should be verified and model results be validated with the real world results.

Another possibility is the use of simulation optimization. With simulation optimization, a combination of input factors are found such that an output factor (e.g. utilization or costs) is optimized. The idea is to sequentially decide on the system configuration and change the experimental factors based on the result of previous simulated configurations. In order to investigate the high dimensional solution space, heuristics and local search methods such as response surface methodology and simulated annealing should be used (Law, 2015).

3.5 Conclusions

This chapter presented a literature review regarding state-of-the-art stock classification, storage assignment models for warehouses, performance measures and optimization techniques. These included single, dual and multi command models, also item and order oriented methods are discussed. Commonly used performance measures and optimization techniques are also included.

The storage assignments models can be classified into three categories, namely haphazard, dedicated and class-based storage. Haphazard models include farthest location, random, and closest open location. Dedicated storage models dedicate a fixed set of storage places for each SKU. Many models are described, such are Cube-per-Order index and Order-oriented Slotting. Methods used for class-based storage are usually based on an indicator, such as turnover, duration of stay and correlation. The main advantage of class-based storage over the other two is that it utilizes the logic of dedicated storage, but not its restrictive dedicated part, as it stores the SKUs in a storage zone on a haphazard rule.

Performance measures often used in warehouse are based on space and distance. Distance-related models often relate to the distance traversed in a warehouse to store and retrieve goods from their storage locations. Time is also an indicator which is used regularly. Optimization models comprise of mathematical models, approximation algorithms and heuristics. Mathematical models are usually suitable to solve to optimality, however, large problems with many integer and binary variables become intractable. Approximation algorithms are guaranteed to perform at most a factor ϵ worse than the optimal solution. Heuristics provide good but usually not optimal solutions. Local search can help with improving approximation algorithms and heuristics. Local search improves the current best solution by slightly alters the current solution by using an operator, such as move or swap. In the case of a warehouse, a current allocation might be improved by switching SKU A and B from their respective classes.

Simulation models can be used to model a warehouse and its stochastic processes, such as demand and duration of stay. Besides that, it can also be used to to evaluate various interventions in storage assignment on the performance on the aforementioned indicators. For example, simulation optimization tries to alternate configurations of classes based on the previous configuration. In this manner, changes in policies can be compared and subsequently optimized.

Based on the literature review, we conclude that a mathematical model, heuristic and meta-heuristic are can be used to solve our problem. Specifically, we use a class-based allocation model which assigns both products and locations to classes.

4 Solution design

This chapter answers research question 3 stated in section 1.5, regarding the application of the storage methods found in literature to the situation at Bolletje. The first section 4.1 discusses the situation at Bolletje, the requirements and constraints. Section 4.2 covers a toy problem and mathematical model which assigns products and locations to classes. Section 4.3 discusses the results and provides an analysis. The chapter is finalized in section 4.4 with conclusions.

4.1 Bolletje situation, requirements and constraints

The warehouse at Bolletje cannot accommodate a dedicated storage policy, because there is not enough capacity for each SKU to store at its maximum inventory level. Haphazard storage does not seem to be suitable as well, as it does not directly minimize the distance to traverse. Because of the sparse capacity, we choose a class-based storage allocation model to be the most appropriate in this case. Recall from 3.2.2 the four determinants: Compatibility, Complementary, Popularity and Space (Kallina & Lynn, 1976). There is no issue with compatibility, as products are packed such that the substances do not interfere. This simplifies the problem because pallets can be placed in adjacent locations. Complementarity is not an issue either, because pallets are picked using single-command mode. Popularity is a suitable determinant which needs to be incorporated, there are different ways to express popularity, such as demand size and DoS. The fourth determinant, space, also needs to be incorporated due to the limited storage capacity of the warehouse and height of both the pallets and storage locations. The items to be stored are assumed to be in unit load on full pallets. In consultation with the management we decided to split the warehouse system in sub-warehouses. This in order to reduce the problem size and obtain the formulation of a tractable problem. Based on discussions with and between the warehouse manager and foremen, a pre-determined zonal assignment is established. These zones are based on the distance of their inbound locations and the capacity needed for these inbound locations. The next section discusses a mathematical model.

4.2 Alternative storage assignment policy

4.2.1 Toy problem - mathematical model

Before we proceed to the formulation and explanation of the mathematical model, we provide a small example of the problem we try to solve with the mathematical model. In the problem, we try to assign products and locations to classes such that the distance to store and retrieve these products is minimized. The problem is illustrated in figure 4.1. Here a rectangular warehouse with unit distances is depicted. The warehouse contains 10 aisles with 15 locations each. The value in the colors of the locations indicate the capacity per location. The other values represent the unit-distance to a location from the I/O-point. Each location can be accessed from the left side of the location. Recall that we want to form classes which contain locations and SKUs. Figure 4.1 depicts three zones with a corresponding capacity. Each zone (red, orange and yellow) can accommodate all of its pallets needed to store/retrieve the SKUs from its class. SKUs with a higher turnover rate are assigned to classes with locations close to the I/O, whereas slow-movers are assigned to classes with more distant locations. The next section elaborates of the formulation and explanation of the mathematical model.

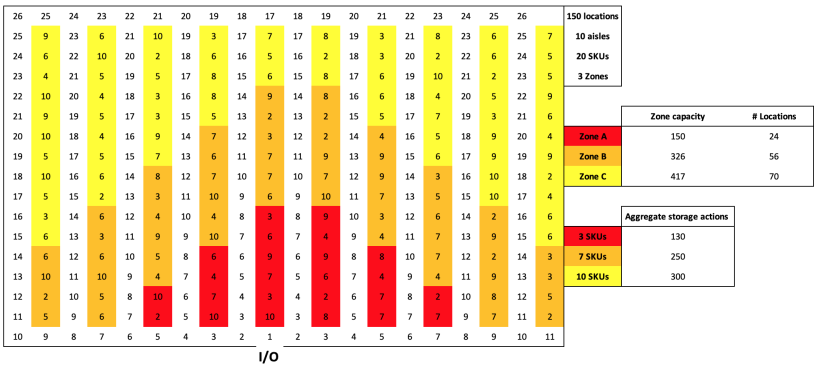


Figure 4.1: Toy problem

4.2.2 Mathematical model

We propose a mathematical model in order to solve the storage and zonal allocation problem. This model is based on the one proposed by Muppani and Adil. However, the model is slightly adjusted to make it suitable for the problem Bolletje faces (see Appendix C for the original model). The model allocates products to classes and locations to classes, such that the distance to store and retrieve these products is minimized. We first introduce and describe the *sets*, followed by the *parameters*, where-after the *decision variables* are reported. Finally, the model, including the objective function, constraints and assumptions, is formulated and explained afterwards.

Set	**Description and indice(s)**
I	Set of SKUs to be allocated (i ∈ I)
L	Set of locations to be assigned to classes (l ∈ L)
T	Set of time periods (t ∈ T)
K	Set of classes (k ∈ K)

Parameter		**Description**
$s_{i,t}$	=	Pallets of SKU i to store in period t
c_l	=	Capacity (unit-load) of location l
d_l	=	Distance (metres) to location l
$dos_{i,t}$	=	Expected Duration of Stay (weeks) of SKU i in period t
p_l	=	Penalization factor for location l
$a_{i,l,t}$	=	$\begin{cases} 1, & \text{if SKU } i \text{ can be assigned to location } l \text{ at period } t \\ 0, & \text{otherwise} \end{cases}$

Decisions		**Description**
$X_{i,k,t}$	=	$\begin{cases} 1, & \text{if SKU } i \text{ belongs to class } k \text{ at period } t \\ 0, & \text{otherwise} \end{cases}$
$Y_{l,k,t}$	=	$\begin{cases} 1, & \text{if location } l \text{ belongs to class } k \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$

Objective function:

$$Min\ z = \sum_t \sum_k \left\{ \frac{\sum_l (c_l * d_l * Y_{l,k,t})}{\sum_l (c_l * Y_{l,k,t})} \sum_i \frac{X_{i,k,t} * s_{i,t}}{dos_{i,t}} \right\} \tag{4.1}$$

Subject to:

$$\sum_i X_{i,k,t} * s_{i,t} \leq \sum_l Y_{l,k,t} * c_l * p_l \qquad \forall k \in K, t \in T \tag{4.2}$$

$$\sum_k Y_{l,k,t} = 1 \qquad \forall l \in L, t \in T \tag{4.3}$$

$$\sum_k X_{i,k,t} = 1 \qquad \forall i \in I, t \in T \tag{4.4}$$

$$X_{i,k,t} * s_{i,t} \leq \sum_l a_{i,l,t} * Y_{l,k,t} * c_l * p_l \qquad \forall i \in I, k \in K, t \in T \tag{4.5}$$

$$\frac{\sum_l (c_l * d_l * Y_{l,k,t})}{\sum_l (c_l * Y_{l,k,t})} \leq \frac{\sum_l (c_l * d_l * Y_{l,k+1,t})}{\sum_l (c_l * Y_{l,k+1,t})} \qquad \forall t \in T, k = 1, ...K-1 \tag{4.6}$$

$$X_{i,k,t},\ Y_{k,l,t}\ \in \mathbb{B} \tag{4.7}$$

It is assumed that storage and retrievals are done using single command (see section 2.4). We also assume no congestion and loads not to be relocated. The objective function 4.1 minimizes the demand and location-capacity weighted distance to be traversed. The function is minimized over $|T|$ time periods and $|C|$ classes.

The first term in the function approximates the distance to a class. This distance is based on the capacity of the locations and their distance. The reasoning behind this, is that locations with a higher capacity are accessed more frequently than locations with a lower capacity. However, based on the formulation, it is assumed that the positions within the locations are uniformly utilized.

The second term ensures that products with many pallets to store (i.e. sales-based) are placed in classes with favorable locations. To account for the problem that some products have a high sales-rate but a long duration of stay (compared to other SKUs), the term is divided by the expected duration of stay. See table 4.1 where the principle is based upon. Here, products with a high sales-rate and low duration of stay will be assigned to the best locations. Products with either a high sales-rate and high duration of stay or low sales-rate and low duration of stay get good, but less favorable locations. Finally, products with a high duration of stay and low sales-rate will receive bad locations. Here the quality of the location is determined by the distance to the I/O point.

		Pallets to store	
		Low	High
Duration of Stay	Low	*Good Locations*	*Best Locations*
	High	*Bad Locations*	*Good Locations*

Table 4.1: Location determination based on SKU characteristics

The above presented principle is based on Little's law. This law states that the average number of customers L, is equal to the product of the arrival rate λ and time a customer spend in a system W. In our problem, λ is the storage rate and is equal to number of pallets present in the warehouse/system ($s_{i,t}$) divided by the duration of stay in the warehouse ($dos_{i,t}$).

Thanks to constraints 4.2, classes get an appropriate size in terms of capacity. This means every class k should hold at least the capacity to accommodate the total (of all products) requested storage demand for each period t. However, the problem that arises here is that at most one SKU can utilize a location, instead of multiple SKUs. We propose to penalize the locations based on their capacity. The logic behind penalizing locations based on their capacity is that locations with a higher capacity can usually not be entirely utilized, whereas a location with a capacity of one can always be entirely utilized by an SKU. The locations are linearly penalized.

Constraints 4.3 restrict each location l to be assigned to exactly one class at every time period t. Every product i should be allocated to a single class at each period t. This is established by constraints 4.4. Due to the structure of the warehouse, size of pallets and properties of some products, not all pallets can be placed at each location. For example, a pallet containing chocolate products needs to be stored in temperature-conditioned rooms during the summer period (see sections 2.1 and 2.2). The right hand-side ensures that there are enough feasible locations having enough capacity to accommodate the total storage requirements by product i, see constraints 4.5. Constraints 4.6 make sure that preceding classes are better in terms of distance than subsequent classes. The final set of constraints 4.7, ensure the binary property of the variables.

We assume that pallets are transported based on unit load (i.e. all items are moved, stored and controlled as a single entity). The assumption is valid for most products. In order to overcome the problem where it does not hold, the parameter $a_{i,l,t}$ is introduced, to restrict some products not be placed on some locations.

As mentioned in the previous section, the warehouse system at Bolletje is divided into multiple sub-warehouses to simplify and create a tractable problem. The distances are based on the distance from inbound location to the storage location plus the distance from storage location to the outbound docks. The logic behind this is that it is assumed that a warehouse employee starts at the inbound location to store the product. To retrieve the product from storage, the employee has to traverse from the outbound position to the storage location and next travel to the outbound location again.

The distance is measured using a blue print of the warehouse with fixed routes. As mentioned before, locations get a pre-defined zone based on the inbound location. The distance to a location is based on the inbound location and outbound dock (we assume that each retrieval action from a location is carried out to the same (centered) dock). With this assumption (uniform utilization of docks), we are on average 5 metres off of the true distance to a dock. The distances are measured twice and independently to ensure the reliability.

4.3 Results and analysis

This section describes the results and provides an analysis. We start by solving a toy problem with intuition, followed by a test problem to test the mathematical model. Next we provide our solving approach, including neighbourhood-operators and experimental factors. The final subsection presents the results per sub-warehouse.

4.3.1 Solving a toy problem

To illustrate the problem, we provide a small problem with a solution (classes consisting of locations and products). In this toy problem with exclude the penalties (i.e. all p_l values are equal to 1) and the time set T (i.e. one period). We have 4 products and 5 locations to assign to two classes. Table 4.2 depicts the two parameters per period {Average pallets to store, Duration of Stay} in the left table. The right table shows the capacity and distance per location respectively. The optimal allocation would be to assign products A and D to the best class 1 and products B and C to class 2. Locations 1,2 and 3 belong to the first class and the remaining to the second class.

Product	*Characteristics*
A	{12,2}
B	{2,5}
C	{10,7}
D	{4,1}

Location	*Capacity*	*Distance*
01	5	4
02	5	8
03	10	12
04	10	16
05	10	20

Table 4.2: Product and location characteristics

4.3.2 Solving a test problem

In order to solve the mathematical model from the previous section we use Python. Specifically, we tried using multiple libraries (PuLP, Gurobi and MIP), however, all of these packages could not cope with the non-linear objective function 4.1. The model could not compile (due to the non-linearity in the objective function, i.e. division by decision variables was not possible) and therefore not be solved in these Python-specific libraries. AIMMS was used as next tool to model the mathematical program.

In order to check whether the model works correctly, a small example is used. Three time periods {1,2,3} were used in our example. Table 4.3 depicts product characteristics, these include the average pallets to store and duration of stay per time period and are indicated by {Pallets to store, Duration of Stay} in the table. We made sure that each possible product classification was included (see table 4.1). The locations have two characteristics, namely distance and capacity, these are shown in table 4.4.

Product/Time	*1*	*2*	*3*
A	{3,9}	{5,9}	{3,9}
B	{10,4}	{12,4}	{11,3}
C	{2,3}	{2,2}	{2,3}
D	{4,3}	{4,4}	{5,4}
E	{9,4}	{8,4}	{9,3}
F	{12,8}	{10,10}	{14,9}

Table 4.3: Test problem: Product characteristics

Location	*Capacity*	*Distance*
A01	12	50
A02	5	59
A03	9	32
A04	7	51
A05	8	20
A06	3	60
A07	13	27
A08	12	50
A09	9	56

Table 4.4: Test problem: Location characteristics

The model was not able to solve to optimality in reasonable time. However, the optimality gap (here defined as difference between discrete {0,1} problem solution and continuous [0,1] problem solution) was almost 1%, however, this was after 600 seconds. After some trial-and-error, we figured that main difficulty arises from the class capacity-weighted distance in the objective function. The model can easily be solved for a larger number of products (e.g. 20 to 30 products), but whenever the number of locations gets increased after 7, the model cannot quickly be solved to optimality. Because of the difficulty in solving the problem, we use a meta-heuristic. Recall that SA is a meta-heuristic for solving combinatorial optimization problems (Koulamas, Antony, & Jaen, 1994). We will elaborate on the how the problem is solved in the next subsection.

4.3.3 Solving approach

As mentioned in the previous subsection, it became clear that it is difficult to solve the problem for a reasonable size. Therefore, the meta-heuristic SA is used to solve the problem. Recall from section 3.4.2 that SA can be used to escape from local optima and systematically find better solutions. Here, better solutions are always accepted, whereas inferior solutions are accepted based on a Boltzmann probability distribution. Figure 4.2 depicts the solving approach and is two-fold. The initial solution, required by SA is created with AIMMS. The green indicated steps refer to the creation of the initial solution in AIMMS, whereas the the blue marked steps refer to simulated annealing in Python.

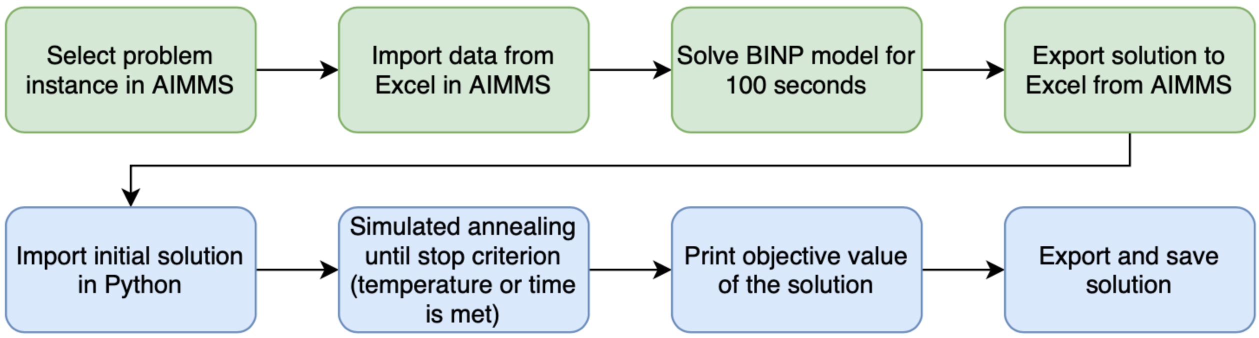


Figure 4.2: Solving approach

First a problem instance is selected, this means a sub-warehouse and configuration (we will later elaborate on the possible configurations) is chosen to optimize. Next, the instance-specific data is imported from an Excel-file into AIMMS after which the model is solved for 100 seconds (to get a feasible initial solution). After the optimization in AIMMS is finished, the solution is imported as initial solution in Python. Next, simulated annealing is done until a stop criterion is met after which the objective value is printed. Finally, the solution is exported to an Excel file and saved.

As mentioned before, the model is based on the paper of Muppani and Adil. They provide means of generation of neighbour solutions. Our approach is based upon theirs but extended. We either generate a neighbour solution using the products or the locations. Besides that, two operators are used, namely the move- and swap-operator. We now illustrate the generation of neighbour solutions using an example. Figure 4.3 illustrates a possible class formation consisting of 9 locations. We randomly select two classes k and l such that $k \neq l$ and that the number of locations in each class is at least 1. Within these classes, we randomly select a location. In the figure we chose location 4 in class 1 and location 7 in class 2. We swap these locations and get a new formation of classes. This action can also be done for products. Next we check whether the solution is feasible and if so, evaluate it.

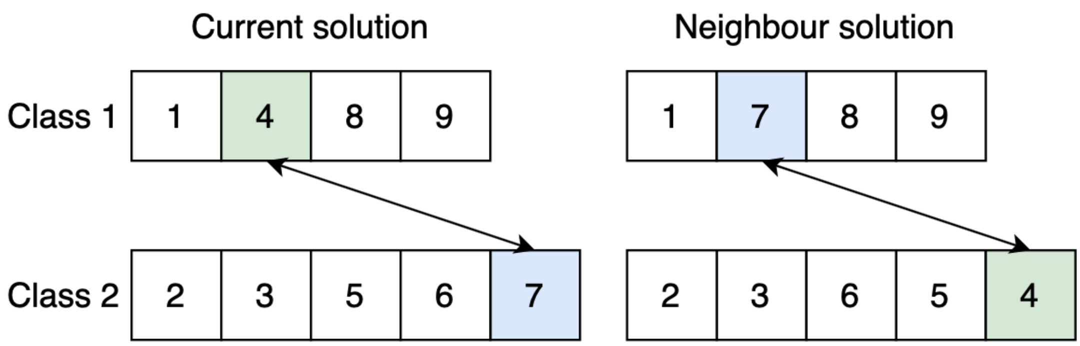


Figure 4.3: Swap operator: location swap

Figure 4.4 illustrates a product move. Here, two random classes k and l are drawn such that $k \neq l$ and the number of products in the first class is greater than 1. Next, a product from the first class is randomly drawn to be moved (product C in this case). The product is moved to the other class and the solution is checked on feasibility. Afterwards, if the solution is feasible, the solution is evaluated.

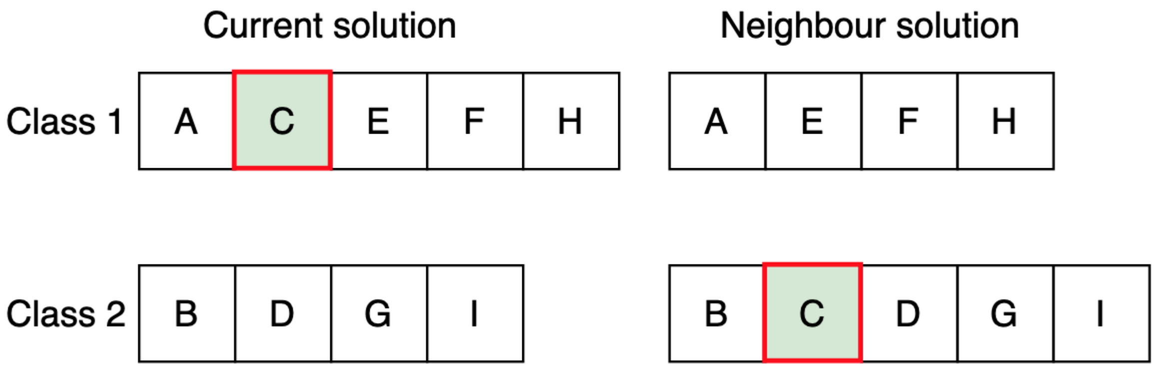


Figure 4.4: Move operator: product move

The third and final operator we use is a simultaneous change of products and locations. Figure 4.5 illustrates the operator use. We randomly select a product from the available products with class l and select a class k such that $l \neq k$. The product (E in this case) is moved to the class k. Next, feasible locations are moved to the other class to accommodate the increase in required storage capacity in class k. In this case locations 7 and 9 are feasible locations to move, these are moved to class k. Thus, we simultaneously move a products and locations from one class to another.

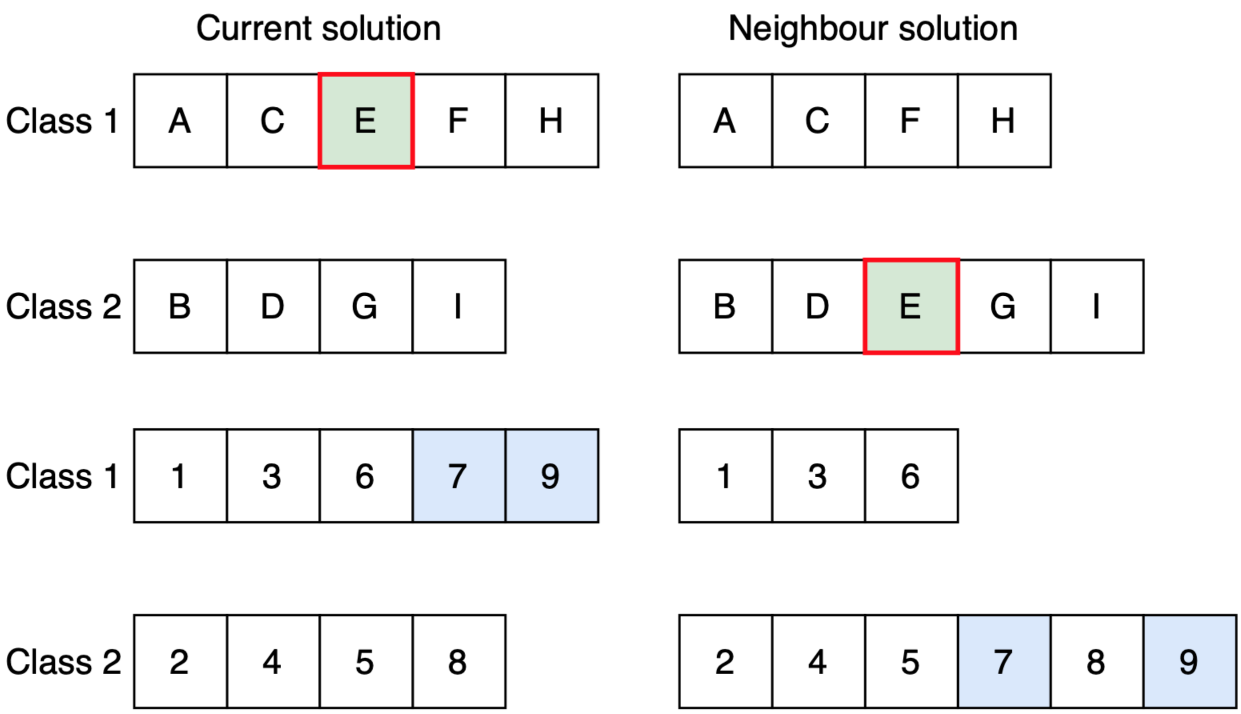


Figure 4.5: Simultaneous move operator use

Since the problem is difficult to solve, we propose to experiment with different warehouse configurations. A configuration is the level of aggregation of locations. We experiment with three types of (location) configurations, see figure 4.6 for an illustration of the different configurations. The first configuration is the initial one, here all locations are considered to be single. Thus, every single location has to be assigned to a class. The second configuration is to combine adjacent locations. The intuition behind this configuration is that adjacent locations will probably be put in the same class without deteriorating the solution. Three adjacent locations are combined and their capacity weighted distance is used to determine the distance. The third and final configuration aggregates locations such that technical zones are created. This is the highest aggregation level.

In this configuration, locations are combined based on similar characteristics (i.e. height, level, type etc.). The solutions of the aggregated configurations (i.e. configuration two and three) are afterwards dis-aggregated and evaluated. The dis-aggregation is such that individual locations have the same class assigned to as its aggregated location. The sub-warehouse of the "VAS / Roggebrood" already has a small number of locations in the adjacent form, therefore we will not experiment with technical zones, the same holds for the Banket sub-warehouse and Oude Beschuit sub-warehouse. The number of classes per warehouse system is an arbitrary choice, therefore we also experiment with this factor. Recall the relation between the average travel time and number of classes in section 3.2.3. We experiment in a range of [4,10] number of classes.

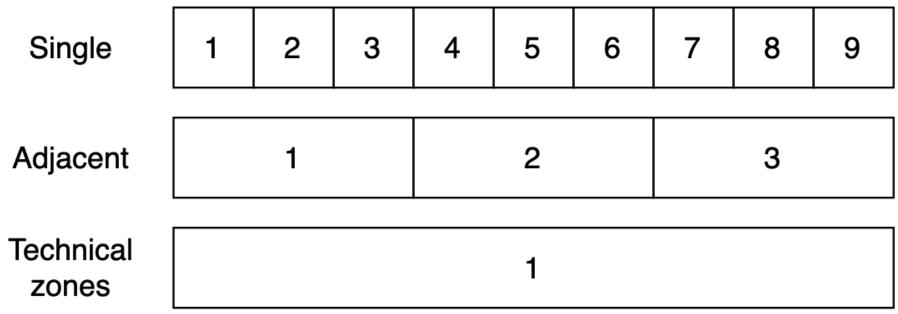


Figure 4.6: Aggregation of locations

4.3.4 Analysis

Recall from the section 4.1 that we divided the warehouse system into five sub-warehouses. We refer to them as follows: "Hal 16", "VAS / Roggebrood", "Extern", "Banket" and "Oude Beschuit". We refer to the storage rate as ($\frac{s_{i,t}}{dos_{i,t}}$). Appendix D contains figures of the splitted warehouses. Here, three types of lines are used. The lines indicate the level of the location, these are dashed, solid and dotted. These represent base level, first-level and second-level locations respectively.

After experimenting with the first warehouse (Hal 16), we conclude that we cannot obtain a reasonable solution with the mathematical model. We experimented with multiple options (e.g. multistart: "hotstart", maximum number of workers, long runtime, technical zones, omitting time horizon etc.) in AIMMS, but this did not yield a reasonable initial solution. The initial solution we got from AIMMS was one which assigns all products and locations to a single class, we do not consider this as a reasonable solution. Therefore we use a constructive heuristic to create an initial (reasonable) solution. The heuristic assigns for each period t the products with the highest storage rate to the total required closest feasible locations in the class. A new class is created whenever one of the following three conditions hold: 1) after the assigned locations to the class is greater than $\frac{numberoflocations}{numberofclasses}$, or 2) the number of products assigned to a class is greater than $\frac{numberofproducts}{numberofclasses}$, or 3) the distance to the next feasible location to assign for the product is greater than 20 compared to the last assigned location. If there are no more locations for a class to assign, the product is assigned to the class with the closest locations with enough remaining feasible capacity. The closest feasible locations are allocated to class for the product. The heuristic assigns all products to a class for each period.

Whenever a neighbour solution is created, it is checked for feasibility based on the constraints of the mathematical model before evaluating the objective. We tried to include a penalty-term in the objective to allow infeasible solutions to be accepted. However, we did no longer get a feasible solution afterwards. Due to time limitations, we did not investigate this further and therefore discarded the created (infeasible) neighbour solution. All constraints except 4.6 is kept. After some trial-and-error, we found that the move-operator (see figure 4.4) improves the solution most often, therefore, this operator has a higher chance of being used to create a neighbour solution compared to the other two. The swap- and simultaneous-operator perform approximately equal. A starting temperature of 10,000,000 and α of 0.9 (geometric approach) with Markov chain length of 10,000 are appropriate parameters for the meta-heuristic. For simulated annealing to work properly, the acceptance ratio should start at 1 and decrease monotonically with the temperature. The acceptance ratio is the number of accepted solutions divided by the number of proposed solutions. Figure 4.7 depicts the acceptance ratio and temperature decrease. When the temperature is high, we accept many solutions (i.e. exploration of solution space) and after it decrease, we accept less solutions (i.e. exploitation).

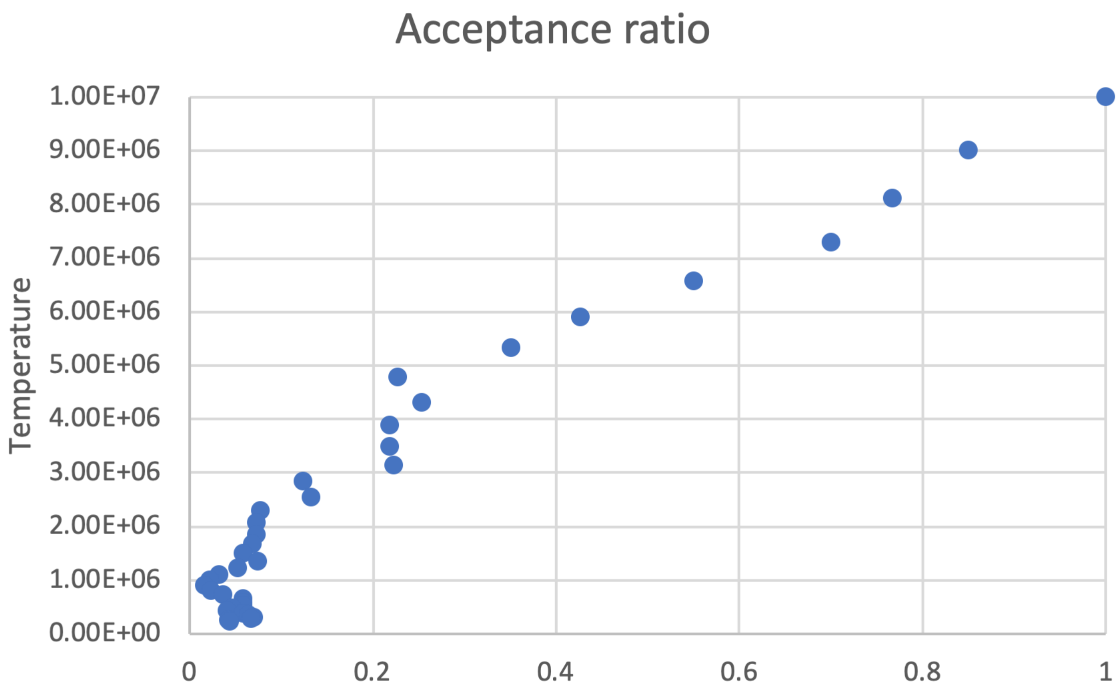


Figure 4.7: Acceptance ratio

Simulated annealing improves the solutions of the constructive heuristic between 2% to 25%. Figure 4.8 presents the objective value for the different configurations in "Hal 16". After the annealing, each initial solution got improved. The search method increased the the average number of class changes for both the product and locations. The aggregation of locations in the adjacent form improves the solution over all single configurations. Due to the aggregation the meta-heuristic method was better able to improve the solution. The technical zone configuration did improve, but was not always better. As expected, using more classes results in a decreased (class-based) distance to traverse, up to a certain number (recall the results from Yu et al. and figure 3.6). In the case of of Hal 16, 7 classes results in the least amount of travel distance to traverse.

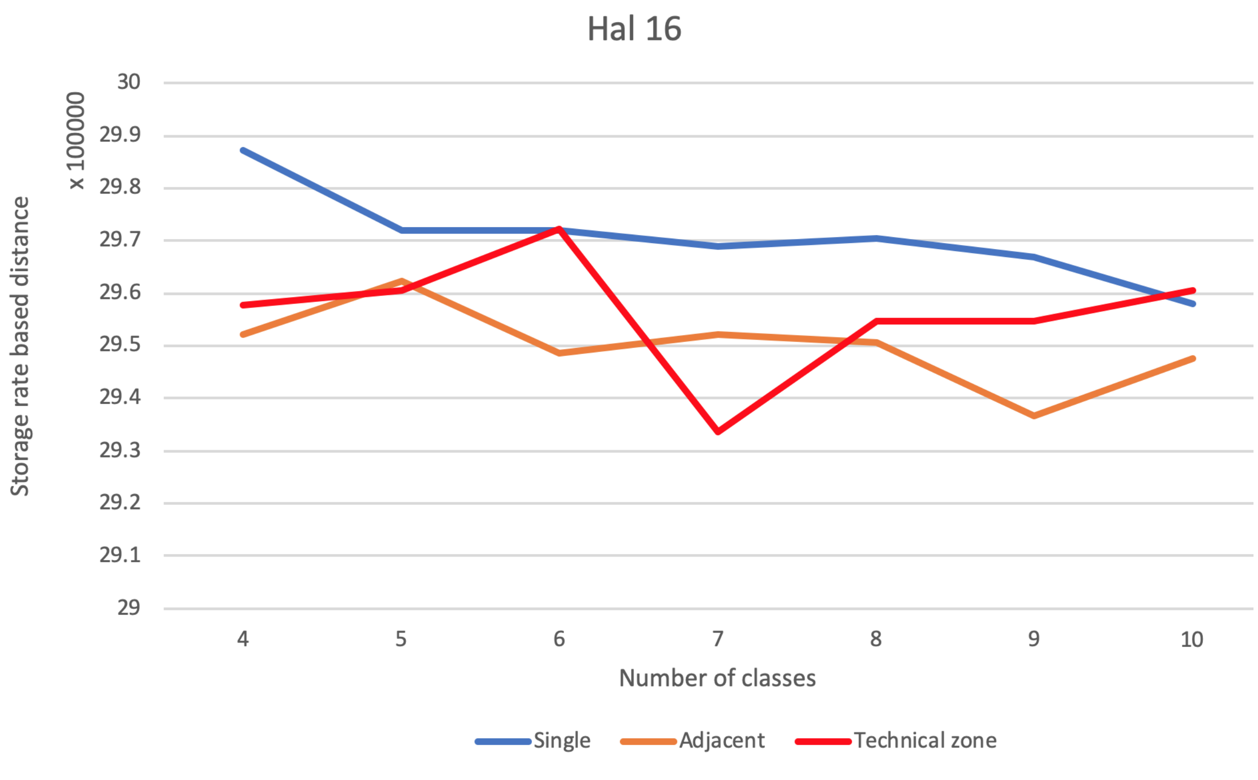


Figure 4.8: Distance comparison Hal 16

Products with stable demand and duration of stay do not change much per time period. Products with seasonal demand change more often between classes over time. Locations which are more distant than others also change more between classes than close locations, this is because in some periods the required storage capacity is lower than the available capacity and therefore distant locations do not need to be utilized and are assigned to higher (less favorable) classes. Figure 4.9 illustrates the assigned locations to classes for the 7-class configuration of technical zones. As the locations and products can change over time, we used the mode class (most often assigned class). For the different location levels, dashed, solid and dotted lines are used to indicate the base, first and second level of the locations.

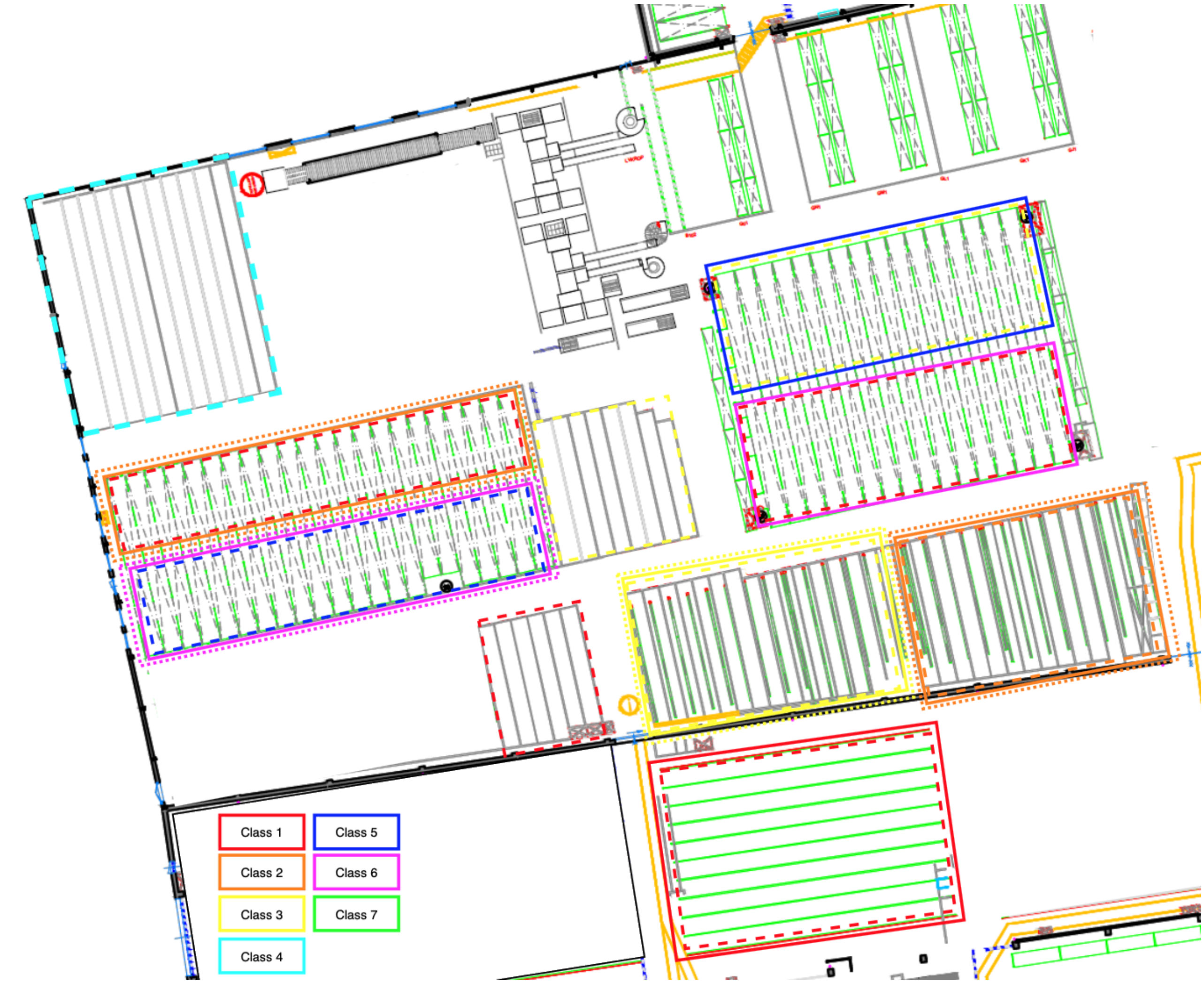


Figure 4.9: Warehouse hal 16

As mentioned before, some zones contain locations which cannot store the products because of their height and are therefore placed in classes which do not contain products. Examples of these are locations on the second level. Therefore, these are used for other sub-warehouses.

The Banket sub-warehouse contains products with seasonal demand. These products have a high number of pallets to store over the periods, but also a high duration of stay (recall the "Sint" category from section 1.2). The seasonal demand for these products occurs after half a year, however, the pallets are produced at the beginning of the year. Due to the lower storage rate (compared to other products), these products are not assigned to the closest locations. Figure 4.10 illustrates the objective function for the different configurations and number of classes. The adjacent configuration with 9 classes has the lowest objective function. Often, locations with the lowest distance have a low height and can therefore only be utilized by a small number of products. The close locations are in some periods used in other classes to reduce their (class-based) distance, however, no products can be stored in these locations and are therefore superfluous. As with the "Hal 16" sub-warehouse, sometimes enough capacity is available with close locations and distant locations are not needed, these were placed in classes with no products.

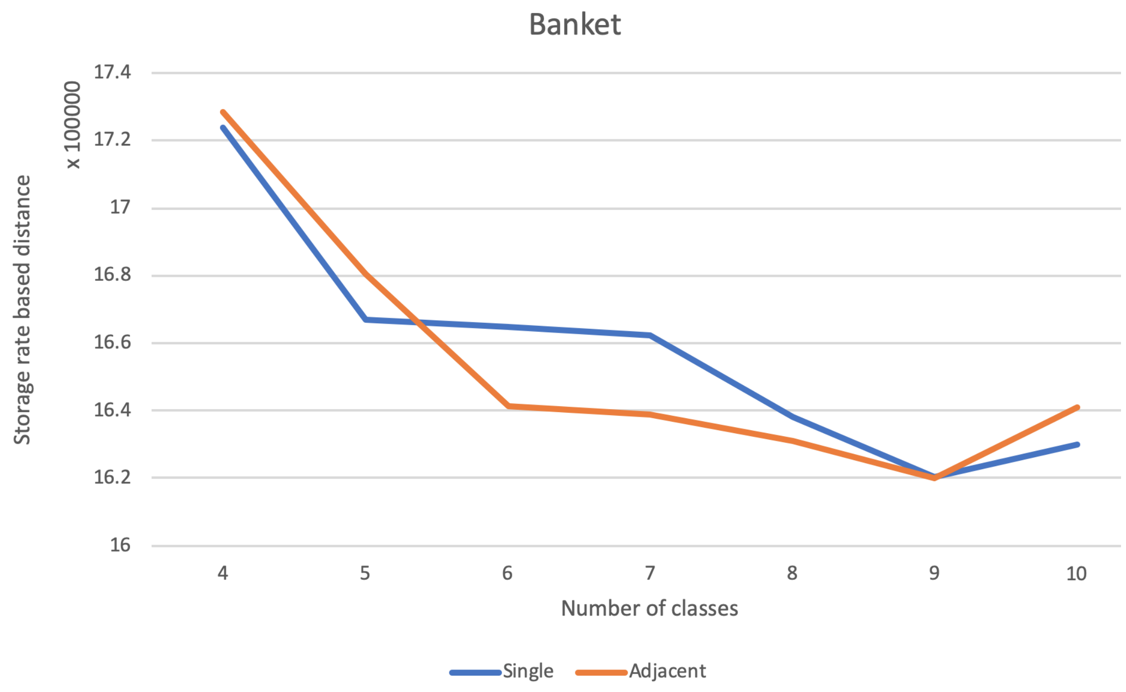


Figure 4.10: Distance comparison Banket

Appendix E illustrates the seasonality over the year. Here the storage rate is visualized over the thirteen periods. After the second period (2), seasonal products get classes with more favorable locations assigned than some regular products with a low storage rate. In the first class, products are assigned with low pallets heights, these are also products with a high storage rate. Appendix F illustrates the warehouse and the classes, here we used to mode-class over the periods for each location.

Figure 4.11 illustrates the changes of products between classes over time. Five products with non-overlapping class in a period were chosen to illustrate class changes over time. The "BOLLETJE Kruidnoten Naturel 200g x24" and "AH Kruidnoten Naturel 500g X12" have a high average number of pallets to store after the second period and therefore get classes assigned with reasonably close locations (whereas in the beginning of the year they get higher classes). "BOLLETJE Pepsels Pinda115g X15" has the characteristic that the pallet has a low height and is therefore assigned to class 1, which contains locations with a low height.

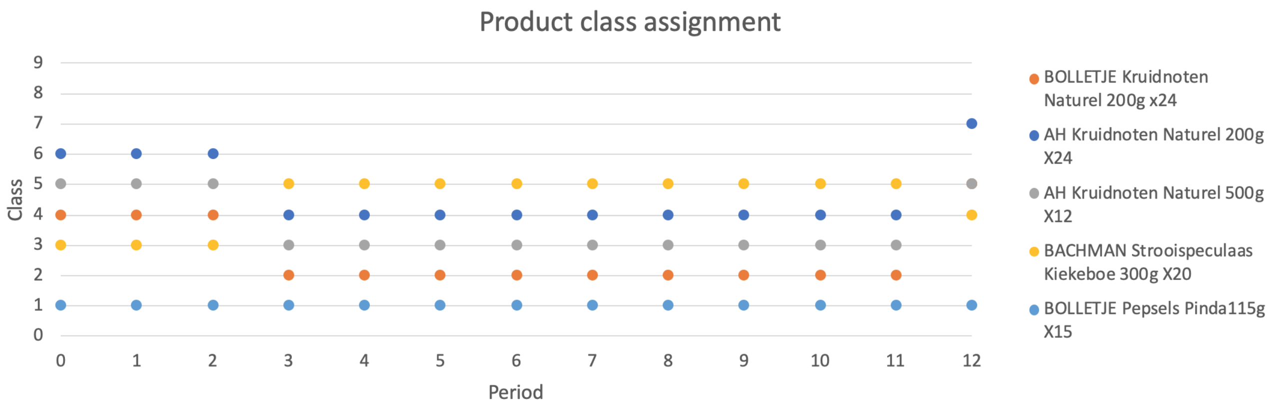


Figure 4.11: Banket product to class assignment

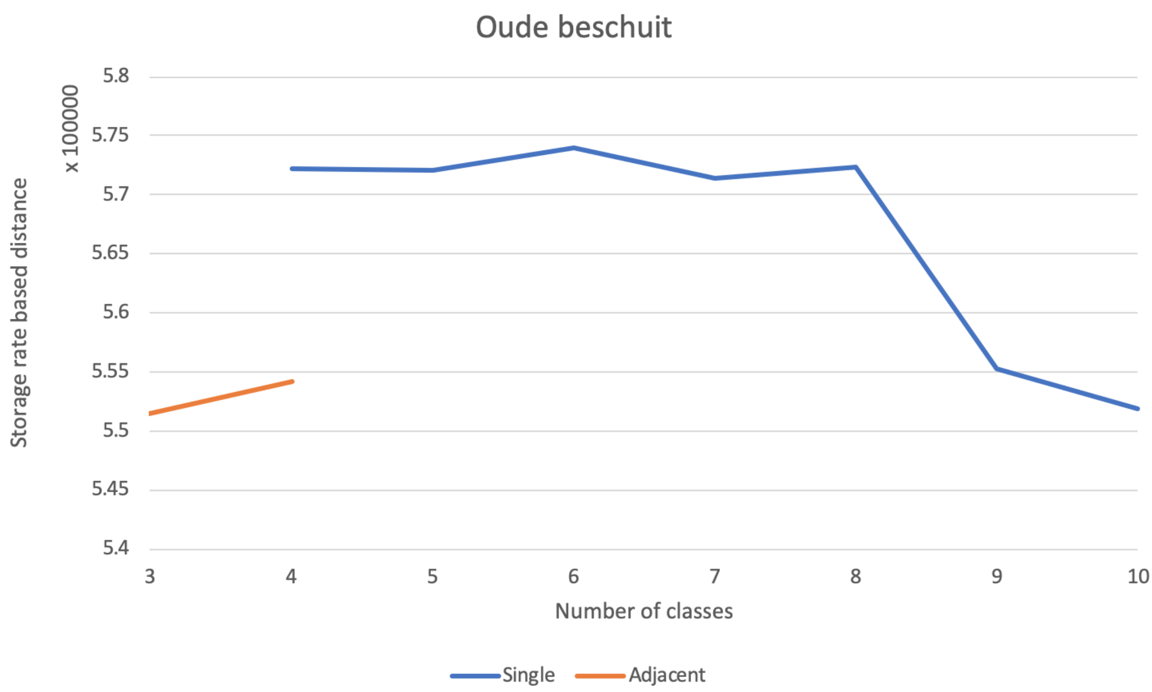


Figure 4.12: Distance comparison Oude Beschuit

Figure 4.12 illustrates the results from the "Oude Beschuit" sub-warehouse and its configurations. We were not able to obtain a feasible solution for the adjacent configuration for the classes 5 till 10. This can be explained by the small number of products and that when using more classes, each product gets a dedicated locations, where there is not enough capacity to accommodate this policy. Therefore we included three classes in the adjacent configuration. The adjacent configuration with three classes yields the lowest objective function. There is little seasonal demand (compared to e.g. thee "Banket" subwarehouse) and therefore the products and locations do not often change between classes over time. Figure 4.13 illustrates the mode-class per location. Note that close locations (yellow) are placed in a lower class, this is due to the feasibility of these locations. Products with a high storage rate could not be placed at those locations and are therefore placed at a different class.

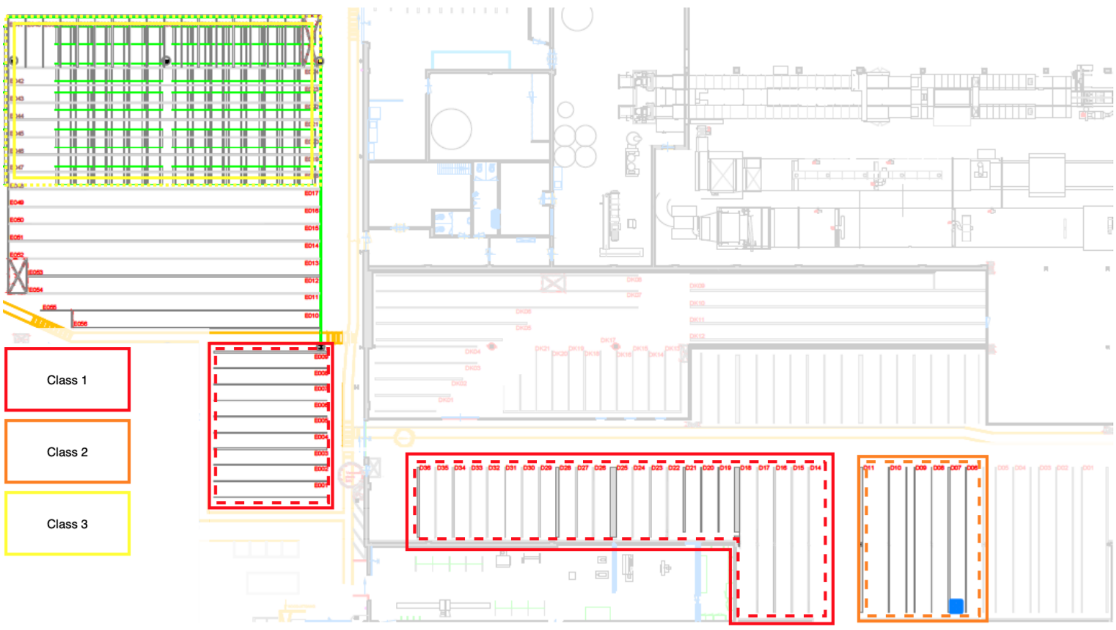


Figure 4.13: Warehouse Oude Beschuit

Figure 4.14 illustrates the results for the "VAS / Roggebrood" sub-warehouse. Compared to the other sub-warehouses, the single configuration yields a better objective than the adjacent form. This can be explained by the little number of locations and products pertaining this sub-warehouse. The 4-class configuration yielded the lowest objective function value.

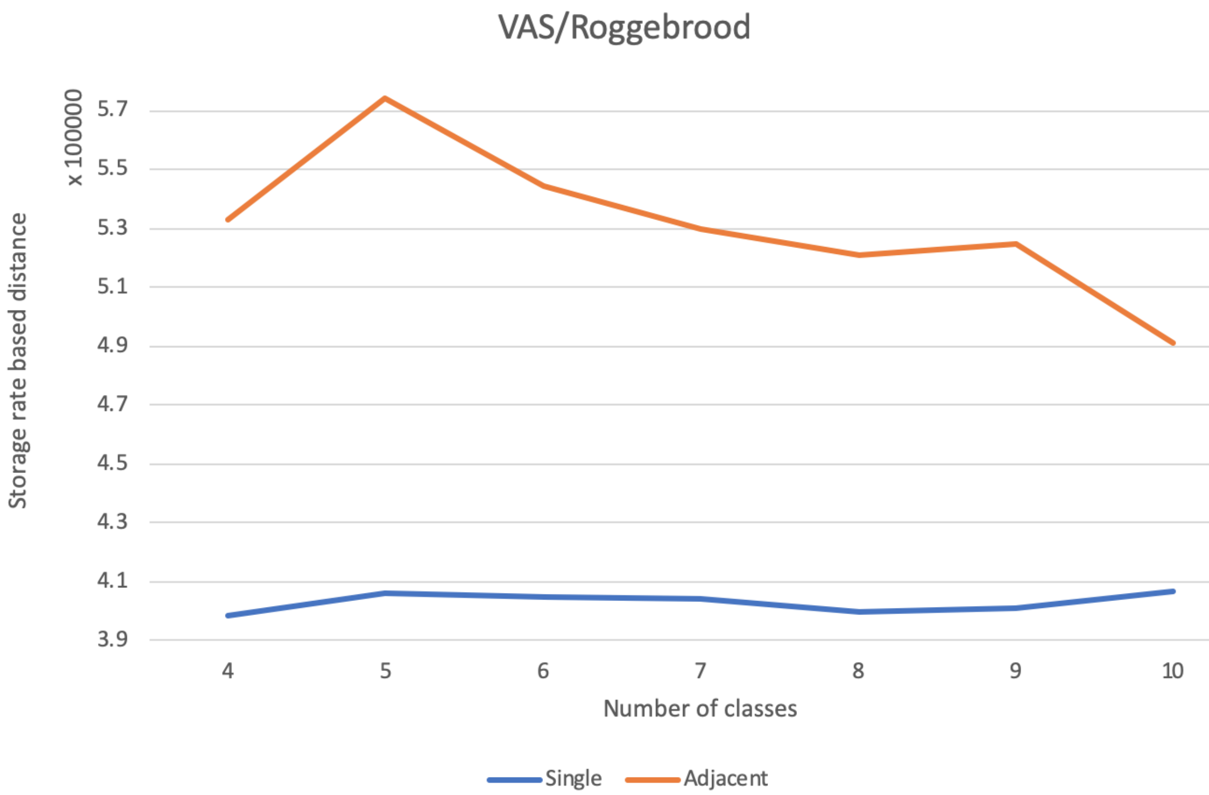


Figure 4.14: Distance comparison Roggebrood/VAS

This sub-warehouse also consists of close locations with a low height. In the solution we see whenever there is enough capacity in the class with low-height locations, redundant locations are assigned to classes which contain products it cannot store. This makes sense from a mathematical point of view, as the (close, low-height) locations reduce class-based distance, however, from a practical point of view it is not useful as these locations cannot be utilized by the products in this class (due to their height). Therefore we slightly adjusted the solution to make it more useful in a practical context. As the average number of pallets to store and their respective duration of stay is rather constant, product and locations do not change between classes over time. In the adjacent configuration, the meta-heuristic found many improvements, usually between 22% and 25%.

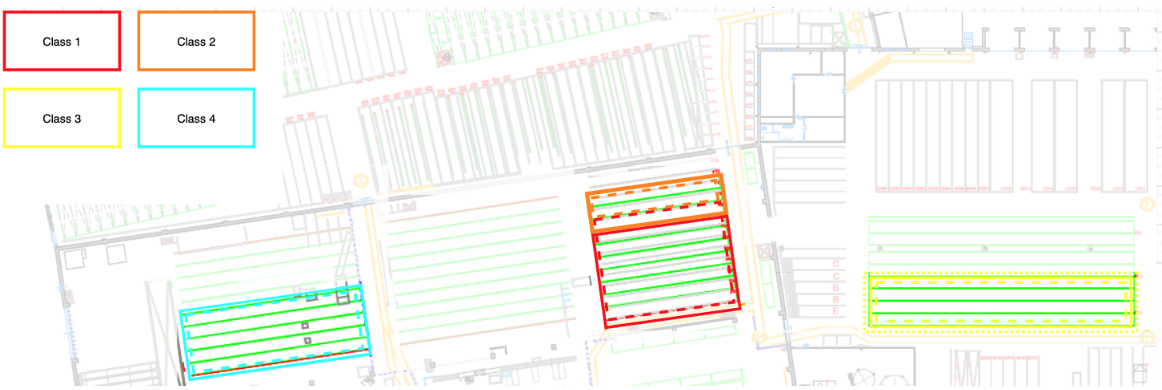


Figure 4.15: Warehouse VAS / Roggebrood

The sub-warehouse "Extern" contains products with the requirement of being stored in conditioned rooms which complicates the product & location to class assignment. The initial heuristic did not yield a feasible initial solution. The heuristic did not obtain a feasible solution because of the way the assignment of products was done. The heuristic sequentially assigns products with the highest storage rate to the best locations. In the period 4 till 10, some products have a strict restriction of being stored in conditioned rooms. During period 4 till 10, the heuristic assigns products who can, but not necessarily have to, to classes with locations in conditioned rooms because of the close distance of these locations. However, whenever the heuristic needs to assign products with a requirement of being stored in conditioned locations, there are no more feasible locations left, since these are already occupied by others. The second problem that occurred at this sub-warehouse is the feasibility of products relating to the pallet-height and locations-heights. In this assignment, some products have a small number of feasible locations and also a low storage rate, meaning that the products are assigned to lower classes with more distant locations. However, distant locations are often not feasible due to their height, therefore, no more remaining capacity is available to store the products.

Because of the inability to create a feasible initial solution, the heuristic is modified. We first assign products that need to be stored in conditioned rooms, these are also stored in separate classes. The next modification is as follows. While there is enough feasible capacity to store the remaining "high" products, we assign products in the aforementioned manner (i.e. based on highest storage rate and closest feasible and available locations). Else, if there is only the required storage capacity left for the "high" products, assign the high products including the feasible locations to the current class. High products are products with a height greater than 1900 mm, the reasoning behind this is that the majority of the (unconditioned) locations are at most 1900 mm high.

The heuristic was not able to obtain a solution for the technical zone configuration, because there is not sufficient capacity to accommodate the required storage requirement and storage capacity. This is because technical zones are assigned to a class to accommodate the total storage capacity of some or all products, however, there are not enough feasible zones left for products which are assigned to latter classes.

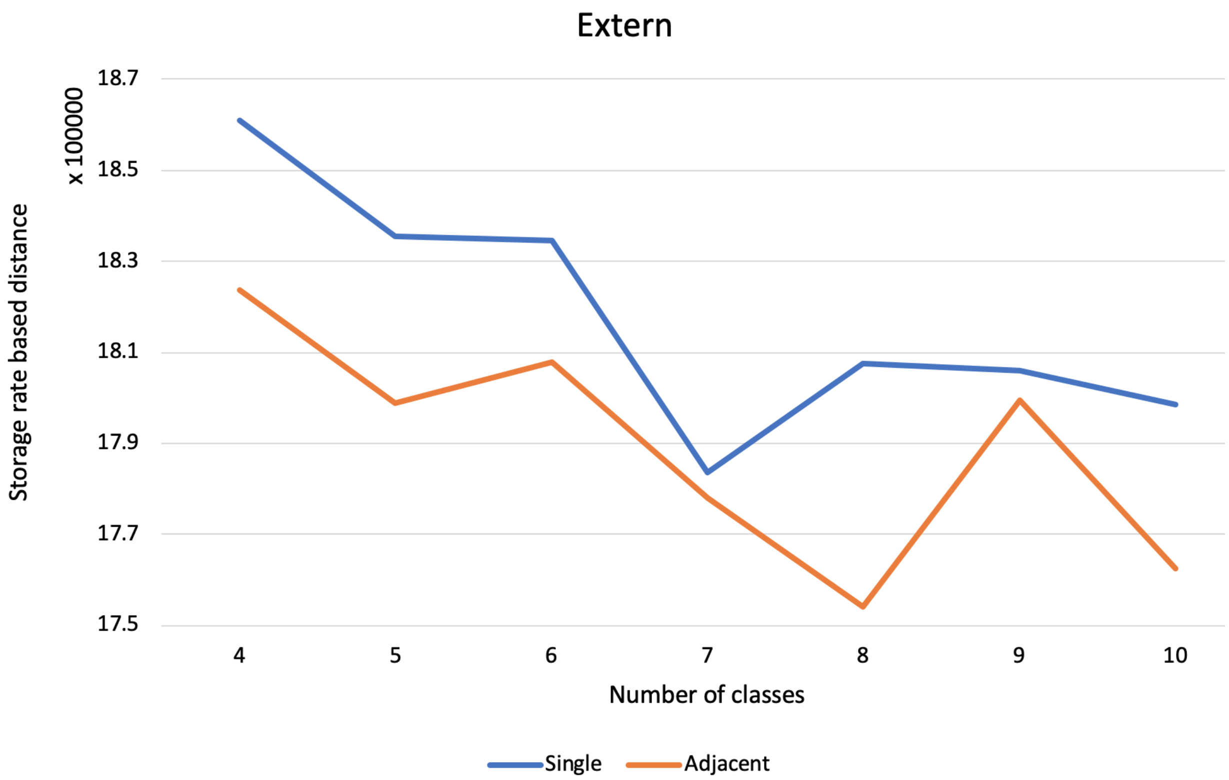


Figure 4.16: Distance comparison Extern

Figure 4.16 illustrates the objective function values over the different classes for the "Extern" sub-warehouse. The adjacent configuration with 8 classes yields the lowest objective function value. As with the other warehouses, we use the mode-class over time per location to illustrate the location distribution over classes. Appendix G contains the "Extern" sub-warehouse.

The limitation of the solutions is for new products, as these are not yet assigned to classes over the periods. We propose to assign them to classes over the periods based on the forecast and expected duration of stay. The product can be assigned in a period to the class with the lowest Δ (Δ = average storage rate - storage rate new product). Since the proposed solution is based on deterministic parameters, whereas the reality is stochastic, we want to evaluate how our solutions perform under stochastic conditions. To incorporate stochasticity and evaluate the robustness of solutions, simulation is a suitable analysis tool to use (Goetschalckx, 2018). The main source of stochasticity is in the number of pallets to be stored and their duration of stay, we will model different scenarios for the aforementioned solution configurations. Solution robustness and comparisons with the current solution are done in the next chapter.

4.4 Conclusions

This chapter answered research question 3: *"How can the storage policies found in the literature (and beyond) be applied to the Warehouse and Distribution Department?"*

A class-based policy is the most suitable model for Bolletje to store its products as it benefits from the logic of dedicated storage and flexibility of haphazard storage. Popularity and space are relevant determinants of the storage policy and taken into account in the model. To simplify the model and create a tractable problem, we split the warehouse-system at Bolletje into 5 sub-warehouses. These are "Hal 16", "VAS / Roggebrood", "Extern", "Banket" and "Oude Beschuit" and visualized in the chapter.

To introduce the mathematical model, a toy problem with a solution is presented to visualize a possible solution. Next, a mathematical model is presented. This model forms classes consisting of products and locations assigned to it. The objective of the model is to minimize the capacity weighted distance to store and retrieve pallets in the time horizon. Classes must be formed such that they can accommodate the aggregate pallets to be stored of all SKUs in the specific class. Besides that, each location and product must be assigned to exactly one class. Any restriction is the space of the pallets, some locations cannot store the pallets due to the height of pallets. Therefore a class must hold enough feasible locations to store a specific product.

We figured, on a test problem, that the model was hard to solve, therefore a meta-heuristic was used to improve a solution. However, after trying out the model on the real situation, the solver was not able to create reasonable solution. Therefore, we used a constructive heuristic. Next the solution was used in simulated annealing as initial solution. Three types of operators were used, in this way, each possible solution in the solution space can be accessed. The swap and move operator are used for both the locations and products. With the swap operator, we interchange two locations or products from different classes. The move operator switches a location or product from its current class to another class. The third operator simultaneously changes products and locations, here a random product is selected, moved to another class including feasible locations. As the main difficulty arises from the capacity-weighted distance in the objective function, we aggregated locations. We aggregated the locations on three levels, namely single, adjacent and technical zones. In single mode, each location has to be assigned to a class. The adjacent configuration combines three adjacent locations. Technical zones are zones which include locations based on similar characteristics such as height, name, storage means and capacity.

The model provided some interesting insights. For example, whenever there is enough capacity in the classes to accommodate the required storage capacity, distant locations who not need to be utilized are placed in classes which contain little to no products. Also, sometimes close locations got assigned to classes which cannot utilize them due to feasibility. From a mathematical point of view this makes sense as it reduces the class-capacity weighted distance. From a practical point of view, this does not work and therefore the solutions got slightly modified. Infeasibility of solutions created by initial heuristic got resolved by modifying the heuristic. Table 4.5 depicts the number of classes per sub-warehouse and their best location-aggregation form. This reduces the total storage rate based travel distance. Sub-warehouses which contain products with little seasonality in their demand pattern, also have little location and product changes between classes over the periods. The "Banket" warehouse contains products which have a strong seasonality pattern and therefore there are class changes for the products over the periods. The same holds for the "Extern" sub-warehouse.

Table 4.5: Classes per sub-warehouse

Sub-warehouse	*Location aggregation*	*Number of classes*
Hal 16	Technical zone	7
VAS / Roggebrood	Single	4
Extern	Adjacent	8
Banket	Adjacent	9
Oude Beschuit	Adjacent	3

5 Solution test

This chapter answers research question 4: "What results can be expected when implementing the chosen storage method?", stated in section 1.5. Here we evaluate the solutions from the previous chapter. Specifically, we evaluate how our solution performs under stochastic conditions. The analysis is first described in section 5.1, including the scenarios to evaluate. Afterwards, section 5.2 elaborates on the robustness of the solutions under stochastic conditions and compares it to the current configuration in the warehouse. The chapter is finalized in section 5.3 with conclusions.

5.1 Stochastic analysis and scenario descriptions

In order to evaluate the solutions given by the previous section, we use a simulation model. Our problem is partially characterized by static input parameters, i.e. input which is known beforehand, and partially by random variables. The realization of these random variables is not known beforehand but revelead during the months in the year. Static parameters include the number of locations, type and number of products, capacity and distance of locations. Stochastic parameters include the number of pallets to store in a period and their duration of stay. Table 5.1 illustrates the characterization of our problem. Pillac, Gendreau, Guéret, and Medaglia (2013) describe a characterization of the problem based on the information evolution and information quality. The problem we are interested in is a static and stochastic problem. The goal of the simulation model is to investigate the effect of stochasticity on the distance to be traversed.

		Information quality	
		Deterministic input	Stochastic input
Information evolution	Input known beforehand	*Static and deterministic*	*Static and stochastic*
	Input changes over time	*Dynamic and deterministic*	*Dynamic and stochastic*

Table 5.1: Characterization of uncertainty (Pillac, Gendreau, Guéret and Medaglia (2013))

The method we use to investigate the effect of stochasticity is Monte-carlo simulation. This technique is useful as we want to evaluate how our solution performs under different scenarios. The technique is efficient and gives reliable results (Kroese, Brereton, Taimre, & Botev, 2014). Besides that, different scenarios can be quickly evaluated and analysed. Recall the main source of stochasticity is the number of pallets to store and their duration of stay. We model these two random parameters and evaluate the robustness of the solutions. Figure 5.1 illustrates the Monte-carlo process we follow per sub-warehouse. We start by defining a domain of possible inputs. Next, based on the domain of the inputs, we generate an instance of the random parameters (i.e. values for the number of pallets to store and duration of stay). Subsequently, a deterministic computation is performed on the problem instance. Finally, the results (i.e. objective value) are stored and a new instance is generated, evaluated and stored.

Figure 5.1: Monte-carlo simulation process

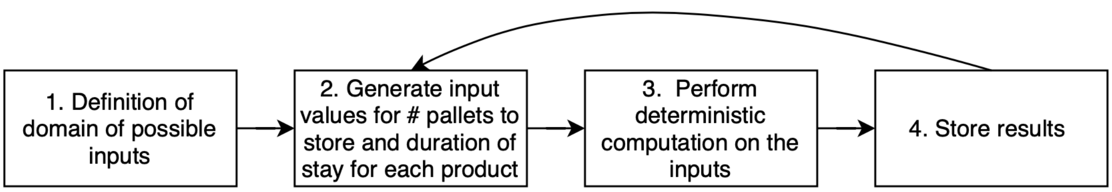


Table 5.2 depicts the different scenarios we evaluate, including the multiplication-factors. We evaluate an expected scenario, which corresponds to the data set but is slightly adjusted, this scenario is likely to happen. The medium scenario is also a probable to happen, the values are more severely adjusted than the "Expected" scenario. High and low scenarios are improbable but relevant to evaluate, these scenarios represent a high and low demand scenario. We also evaluate two deterministic/stochastic scenarios where either the number of pallets to store or duration of stay is constant and the other one is varied, to investigate the effect of either of

the two. The values for the different scenarios are based on standard deviations of the data. The values for both the number of pallets to store and duration of stay for an instance are adjusted by values in the range from the table multiplied by the parameter specific standard deviation of the product. For example, if a product in period one has an average number of pallets to store and standard deviation of 20 and 4, respectively, the new value (in a high scenario) can be 20+2*4 = 28. Suppose the DoS and standard deviation of the DoS of that product are 1.5 and 0.25, the new value for the DoS of that instance (high scenario) can be 1.5-2*0.25 = 1. For each sub-warehouse defined in the previous chapter, a Monte-carlo run is carried out.

Table 5.2: Multiplication factors per scenario

Scenario number	Scenario name	*# Pallets to store*	*Duration of Stay*
1	*Expected*	[-0.2, 0.2]	[-0.5, 0.5]
2	*Medium*	[-0.5, 0.5]	[-1, 1]
3	*High*	[1, 2]	[-2, -1]
4	*Low*	[-2, -1]	[1, 2]
5	*Pallets deterministic*	[0, 0]	[-2, 2]
6	*DoS deterministic*	[-2, 2]	[0, 0]

5.2 Solution evaluation and comparison

Per sub-warehouse and scenario we generate 1,000 instances and evaluate the objective of the instances. Figure 5.2 illustrates the storage rate based distance for sub-warehouse "Hal 16" for the six scenarios. Here, we show the results with a box and whisker plot. This warehouse, has little seasonal demand (compared to the "Extern" and "Banket" sub-warehouse). Except for the high and low scenarios, the solution is rather robust to small changes in either the average number of pallets to store and duration of stay. The duration of stay has a stronger effect on the storage rate than the change in number of pallets and therefore stronger influences the storage rate class based distance to traverse.

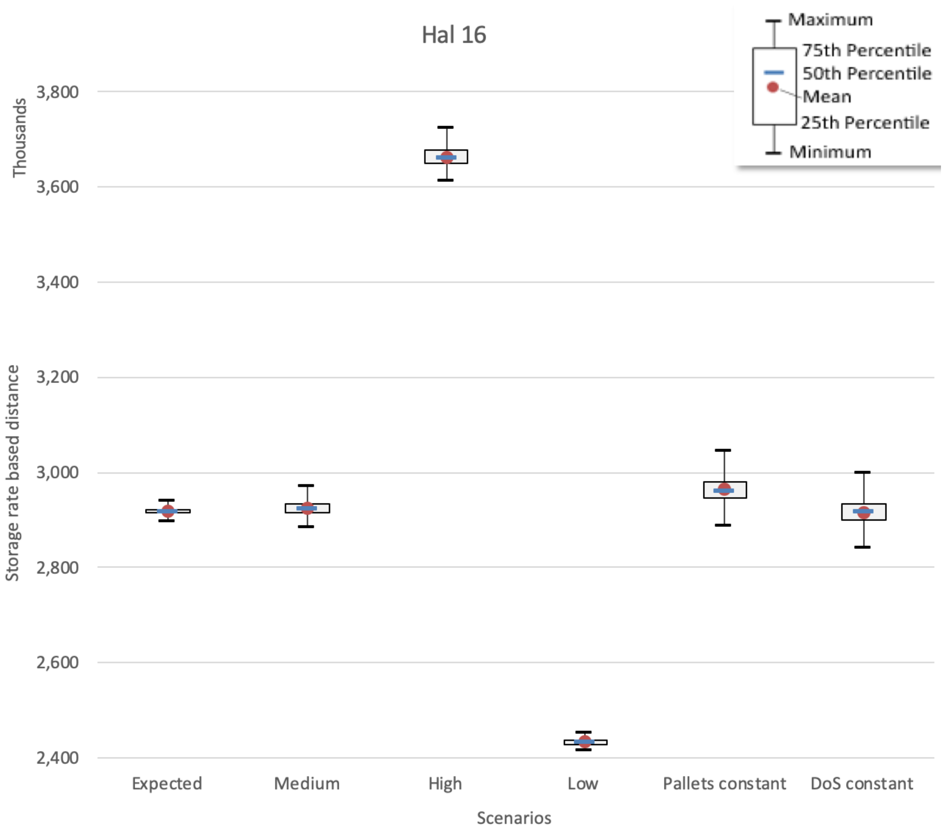


Figure 5.2: Hal 16 scenario results

The "VAS / Roggebrood" sub-warehouse is a relatively small sub-warehouse (compared to the other sub-warehouses). Besides that, most locations are close to each other. These aspects affect the robustness of the solution in a postive manner. Figure 5.3 illustrates the scenario results for this sub-warehouse. Here, the range of the means [399 thousand, 407 thousand] for the different scenarios are close to the expected mean (402 thousand). However, in the "High" and "Pallets constant" scenario, the solutions show some outliers to above, which is caused by the change in duration of stay, which results in a higher storage rate.

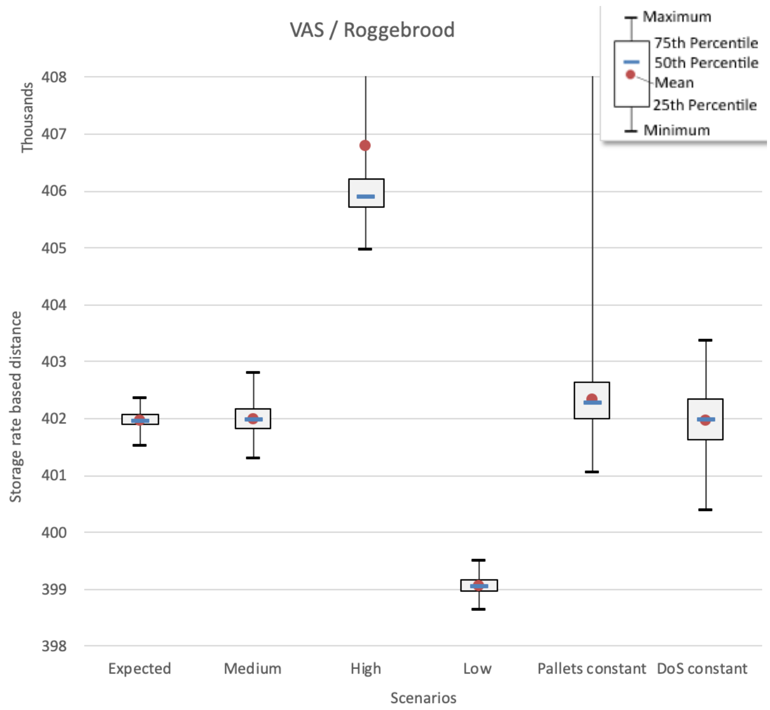


Figure 5.3: VAS / Roggebrood scenario results

Figure 5.4 show the results for the "Extern" sub-warehouse. Here a strong influence of the seasonal demand can be observed. In the 'high'-scenario, the range of values is very high compared to the other scenarios. The medium and Pallets constant scenario constant show some outliers. The main cause of these outliers is due to the variance in duration of stay with strongly influences the storage rate based distance.

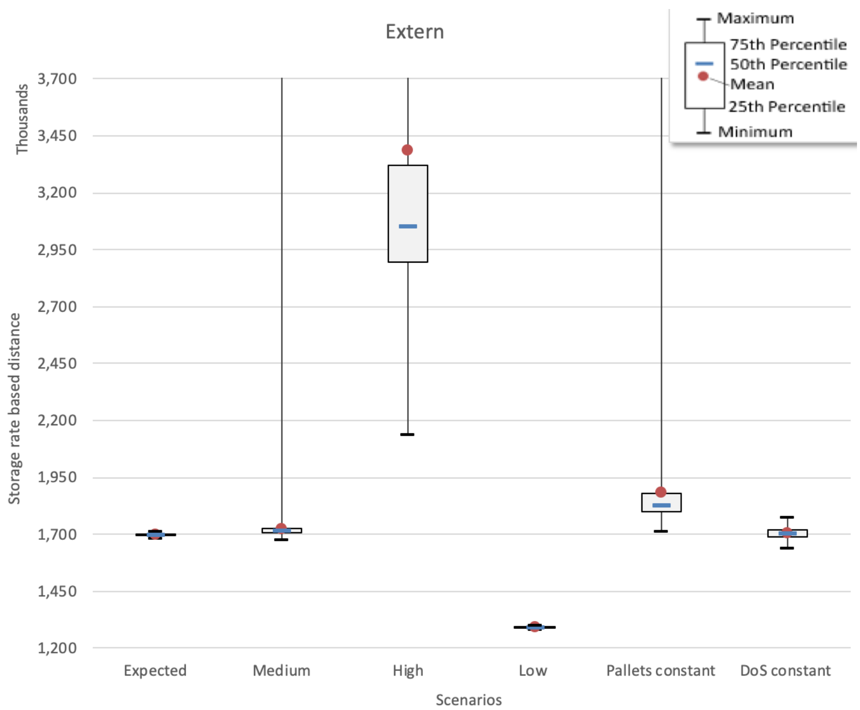
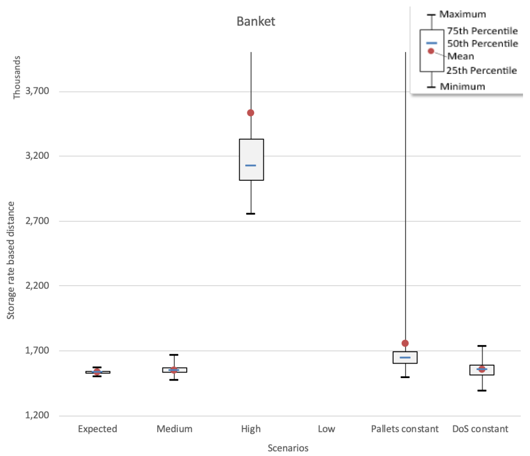
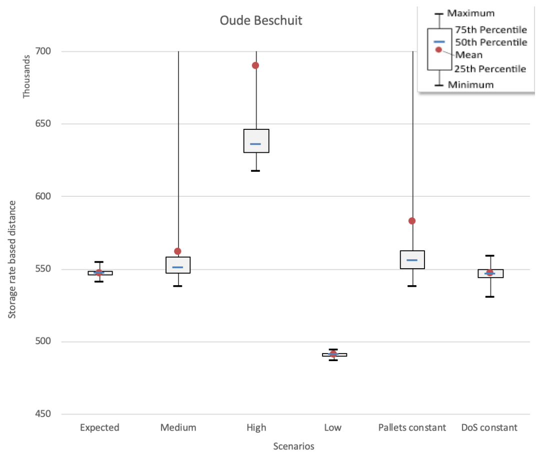


Figure 5.4: Extern scenario results

The last two sub-warehouses show a similar pattern to the sub-warehouses discussed before, therefore we combine them in a single figure. Figure 5.5a represents the results for the "Banket" sub-warehouse, figure 5.5b illustrates the results for the "Oude Beschuit" sub-warehouse. As with the "Extern" sub-warehouse, the "Banket" sub-warehouse contains of products with seasonal demand. In the "Pallets" constant, the duration of stay strongly influences the objective value. The "Oude Beschuit" sub-warehouse contains has a stable demand and duration of stay pattern. For the different scenarios, the solution looks robust as it does not vary widely, except for the high and low scenario.



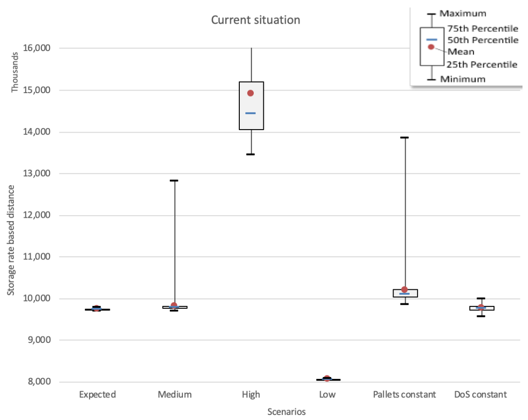
(a) Banket



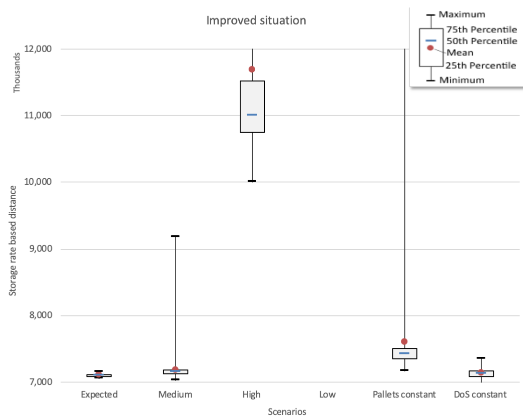
(b) Oude Beschuit

Figure 5.5: Scenario results

In order to compare the solution to the current way products are stored at the warehouse, we need to compare it on warehouse-system level instead of on sub-warehouse level, as the warehouse system is not splitted in a similar fashion in the current situation. Currently, the entire warehouse system consists of 14 classes consisting of locations and products. The distribution of locations over classes can be seen in Appendix H. Figure 5.6 illustrates the results for both the current (5.6a) and improved situation (5.6b). For all scenarios, the improved (class-based) storage policy performs better than the current policy.



(a) Current situation



(b) Improved situation

Figure 5.6: Comparison current situation versus improved situation

Table 5.3: Improvement per scenario

Scenario (improvement in distance per scenario)					
Expected	*Medium*	*High*	*Low*	*Pallets constant*	*DoS constant*
27.3%	27.8%	52.2%	12.2%	30.5%	27.5%

Table 5.3 presents the percentage improvements per scenario. This is the average difference between an instance in the current situation and improved situation. The improved situation performs better for each scenario. We also see the strong effect of the stochasticity stemming from the duration of stay in the 'high' and 'pallets constant' scenario.

Recall from section 1.2 that approximately 67% of the hours can be attributed to the storage assignment policy in 2019 (see figure 1.4). Based on figure 2.8, the average number of hours used per week are 637. 67% of these hours are affected by the storage assignment policy, these can (theoretically) be reduced by 27.3%. This means that the WDD can reduce the total number of hours used by approximately 18.7%.

5.3 Conclusions

This chapter answered the following research question: *"What results can be expected when implementing the chosen storage method?"*. In this chapter we used a stochastic analysis to investigate how the solution performs under stochasticity. The problem is characterized as static and stochastic problem, as some of the input is known beforehand and some is stochastic. Monte-carlo simulation was used to create instances, per scenario, 1,000 instances were created. These instances were based on the average and standard deviations of the two stochastic parameters.

Three of the five sub-warehouses are robust against changes in either the average number of pallets to store or duration of stay. The sub-warehouses which have products with a seasonal demand pattern ("Extern" and "Banket") are less robust against these changes. The "VAS / Roggebrood" sub-warehouse performs well and is also very robust against changes in either of the stochastic parameters.

The improved solution performs better for each scenario. Depending on the scenario, the scenario improves by a certain percentage compared to the current situation. We compared the solution of the aggregate of sub-warehouses (i.e. sum of all sub-warehouses) to the current configuration. Improvements in distance ranged, depending on the scenario, between 12.2% and 52.5%. The expected reduction in travel distance (based on the "Expected" scenario) is 27.3%. In a "High" and "Low" scenario, the improvements were 52.5% and 12.2% respectively. For the "Medium", "Pallets constant" and "DoS constant", the improvements were similar to the "Expected" scenario.

6 Solution implementation

This chapter answers the fifth research question: "How should the (new) storage method be implemented at the warehouse? The first section briefly describes relevant success factors when implementing strategies, a new storage policy in this case. Next, an implementation plan is presented to implement the results found in the previous chapters. This includes a way how the solution should be read and a plan of approach for implementation. The chapter is finalized with conclusions.

6.1 Success factors in implementation of storage policies

Literature revealed there are a number of common factors which influence the success or failure of an implementation. We briefly describe these factors in this section and use them in the subsequent section to give the WDD guidance in the implementation of the storage policy. Below we briefly discuss the relevant success factors for the implementation of the storage policy.

Top management support: The management of a company needs to support the proposed changes and make sure these are aligned with strategic business goals. Active commitment/involvement in the project is also a critical success factor for the success of an implementation. (Motwani, Mirchandani, Madan, & Gunasekaran, 2002)

Proper project management: The project should have a clear distinction in terms of roles & responsibilities. One of the roles is the "project champion", this member should have leadership, business and technical competencies. (Nah, Lau, & Kuang, 2001)

Phased implementation: A phased implementation can help structure and achieve the goals of the project. These phases (if possible) should have a formal start and closure. The closure of the project can be a clear and measurable target to achieve, such as an improvement in a performance indicator or project plan. These phases consist at least of a clear purpose, activity blocks and a critical (time) path. Training of human resources and planning of their capacity should also be taken into account, as a project is a temporary effort to create a (new) product or service, with a predetermined start and end date. (Mandal & Gunasekaran, 2003)

Management of change: Properly managing the change in the project is one of the main critical success factors. It refers to the need of preparing and helping employees in the change program. One key aspect is the actively inform and build user acceptance of the project, this can be done by informing the proposed benefits and how it affects these to them. (Nah et al., 2001)

Post-implementation evaluation and information: Post implementation allows the project team to reflect on the positive outcomes of the project. Besides that, negative outcomes can be evaluated and taken into account after the implementation. The results and evaluation should be communicated to other relevant stakeholders. (Nah et al., 2001)

These factors help us shape an implementation plan. If these are taken into account, a successful implementation can be achieved. The next section describes how the solution should be read and the guidance how to implement it.

6.2 Solution and implementation plan

This plan helps Bolletje to implement the chosen solution from the previous chapters. We illustrate how the solution stored in Excel should be read, afterwards a brief plan is described to give Bolletje guidance in the implementation.

We use an Excel workbook and placed the solution for each sub-warehouse ("Hal 16", "VAS / Roggebrood", "Extern", "Banket", "Oude Beschuit") on a sheet. These sheets contain both the product and location assignment (to classes). Figure 6.1 illustrates what the solution looks like for sub-warehouse "VAS / Roggebrood". The light-green filled cells are the periods (4 weeks) of the year (1-13), these represent the t index of our model. The blue part are the products from the sub-warehouse. Their assignment is shown in the light-red part on the right-hand side. For example, product 9, which is the "BOLLETJE Roggebrood Mild 250g X12", belongs to class 3 in period 2 (and all other periods), illustrated with a red circle. Below the product assignment, the location assignment is illustrated. The gray-filled cells indicate the locations. As before, the light-green cells represents the time periods (4 weeks). The yellow cells denote the class to which the location pertains. For example, location 0, which is "EX05-1", belongs to class 3 in period 0 (and other periods), see the red circle in the yellow area. The same illustration was done for the other sub-warehouses with the same colors. For the sub-warehouses that have seasonality in their demand pattern, frequent changes in locations and products can be observed. In sub-warehouses where we used a adjacent or technical zone configuration, the solution is dis-aggregated on single location level.

		1	2	3	4	5	6	7	8	9	10	11	12	13
50410388-VLEGELAAR Knackebrod Volkoren en Sesam 375g X24	0	2	2	2	2	2	2	2	2	2	2	2	2	2
50410465-RIVERCOTE Knackebrod Volk Goudb Sesam 375g X15	1	1	1	1	1	1	1	1	1	1	1	1	1	1
50410474-KEMPI Knackebrod Combi Sesam Volkoren 300g X24	2	4	4	4	4	4	4	4	4	4	4	4	4	4
50410360-TASTINO Knackebrod 4 pomp en 6 zonnebl 264g X10	3	1	1	1	1	1	1	1	1	1	1	1	1	1
50410615-TASTINO Crispbread Pumpkin and Sunflower 264g X10	4	4	4	4	4	4	4	4	4	4	4	4	4	4
50410616-TASTINO Knackebrod Pumpkin and Sunflower IT/DK 264g X10	5	4	4	4	4	4	4	4	4	4	4	4	4	4
50410617-GRAFSCHAFTER Knackebrod Sonnenblumkerne Kürbiskerne 264g X10	6	4	4	4	4	4	4	4	4	4	4	4	4	4
50410618-TASTINO Crispbread Pumpkin and Sunflower CZ 264g x10	7	3	3	3	3	3	3	3	3	3	3	3	3	3
50410471-VLEGELAAR Knackebrod Combi Pompoen Zonnebloem 265g X10	8	4	4	4	4	4	4	4	4	4	4	4	4	4
50052080-BOLLETJE Roggebrood Mild 250g X12	9	3	3	3	3	3	3	3	3	3	3	3	3	3
50052070-BOLLETJE Roggebrood Fries 250g X12	10	3	3	3	3	3	3	3	3	3	3	3	3	3
50052169-BOLLETJE Roggebrood Fries Kuip 500g X12	11	3	3	3	3	3	3	3	3	3	3	3	3	3
50052180-AH Roggebrood Fries Kuip 500g x12	12	3	3	3	3	3	3	3	3	3	3	3	3	3
50391104-BOLLETJE Graanrepen Amandel Havermout Displaydoos 10 st X7	13	4	4	4	4	4	4	4	4	4	4	4	4	4
50391105-BOLLETJE Graanrepen Hazelnoot Spelt Displaydoos 10 st X7	14	4	4	4	4	4	4	4	4	4	4	4	4	4

		1	2	3	4	5	6	7	8	9	10	11	12	13
EX05-1	0	3	3	3	3	3	3	3	3	3	3	3	3	3
EX05-2	1	3	3	3	3	3	3	3	3	3	3	3	3	3
EX05-3	2	3	3	3	3	3	3	3	3	3	3	3	3	3
EX06-1	3	3	3	3	3	3	3	3	3	3	3	3	3	3
EX06-2	4	3	3	3	3	3	3	3	3	3	3	3	3	3
EX06-3	5	3	3	3	3	3	3	3	3	3	3	3	3	3
EX07-1	6	3	3	3	3	3	3	3	3	3	3	3	3	3
EX07-2	7	3	3	3	3	3	3	3	3	3	3	3	3	3
EX07-3	8	3	3	3	3	3	3	3	3	3	3	3	3	3
EX08-1	9	3	3	3	3	3	3	3	3	3	3	3	3	3
EX08-2	10	3	3	3	3	3	3	3	3	3	3	3	3	3
EX08-3	11	3	3	3	3	3	3	3	3	3	3	3	3	3
FF01-1	12	1	1	1	1	1	1	1	1	1	1	1	1	1
FF01-2	13	1	1	1	1	1	1	1	1	1	1	1	1	1
FF02-1	14	1	1	1	1	1	1	1	1	1	1	1	1	1
FF02-2	15	1	1	1	1	1	1	1	1	1	1	1	1	1
FF03-1	16	1	1	1	1	1	1	1	1	1	1	1	1	1
FF03-2	17	1	1	1	1	1	1	1	1	1	1	1	1	1
FF04-1	18	1	1	1	1	1	1	1	1	1	1	1	1	1
FF04-2	19	1	1	1	1	1	1	1	1	1	1	1	1	1
FF05-1	20	1	1	1	1	1	1	1	1	1	1	1	1	1
FF05-2	21	1	1	1	1	1	1	1	1	1	1	1	1	1
FF06-1	22	1	1	1	1	1	1	1	1	1	1	1	1	1
FF06-2	23	1	1	1	1	1	1	1	1	1	1	1	1	1
FF07-1	24	1	1	1	1	1	1	1	1	1	1	1	1	1
FF07-2	25	1	1	1	1	1	1	1	1	1	1	1	1	1
FF08-1	26	1	1	1	1	1	1	1	1	1	1	1	1	1
FF08-2	27	2	2	2	2	2	2	2	2	2	2	2	2	2
FF09-1	28	2	2	2	2	2	2	2	2	2	2	2	2	2
FF09-2	29	2	2	2	2	2	2	2	2	2	2	2	2	2
FF10-1	30	2	2	2	2	2	2	2	2	2	2	2	2	2
FF10-2	31	2	2	2	2	2	2	2	2	2	2	2	2	2
FH06-1	32	4	4	4	4	4	4	4	4	4	4	4	4	4
FH06-2	33	4	4	4	4	4	4	4	4	4	4	4	4	4
FH07-1	34	4	4	4	4	4	4	4	4	4	4	4	4	4
FH07-2	35	4	4	4	4	4	4	4	4	4	4	4	4	4
FH08-1	36	4	4	4	4	4	4	4	4	4	4	4	4	4
FH08-2	37	4	4	4	4	4	4	4	4	4	4	4	4	4
FH09-1	38	4	4	4	4	4	4	4	4	4	4	4	4	4
FH09-2	39	4	4	4	4	4	4	4	4	4	4	4	4	4
FH10-1	40	4	4	4	4	4	4	4	4	4	4	4	4	4
FH10-2	41	4	4	4	4	4	4	4	4	4	4	4	4	4

Figure 6.1: Product and location to class assignment for sub-warehouse "VAS / Roggebrood"

In terms of properly managing the implementation of the results, it is recommended to show what the benefits and changes of the implementation are. Specifically, we recommend to communicate why the solution performs better than the current situation. The main reason for this is the way of assigning products and locations to classes. In the solution, the products and locations are assigned based on the storage rate and distance, respectively. In the current solution, products and locations are less based on these and more on convenience (e.g. storing all private label "Knackebrod" products together, i.e. based on product clusters with similar characteristics) at a zone with feasible locations. For the sub-warehouses that have products with seasonal demand, the main improvements stem from the change in classes for these products over the time periods.

We recommend Bolletje to do a phased implementation per sub-warehouse and start with the "VAS / Roggebrood" sub-warehouse, as this is a small sub-warehouse compared to the other sub-warehouses. Besides that, there is little seasonal demand in this sub-warehouse, which simplifies the solution implementation. We also recommend to work with this sub-warehouse for half a year before implementing the other solutions, this in order to get employees can get used to the different way products are being stored. After half a year, a post implementation evaluation is recommended and discuss results and feedback. The next phase is the implementation of the class-based storage policy in the "Hal 16" & "Oude Beschuit" sub-warehouses. These are larger warehouses in terms of capacity, but do not yet contain product with a strong seasonal demand pattern. For these sub-warehouses, we recommend a post-implementation evaluation as well. To reflect on the positive outcomes and possible negative outcomes. After these three solutions are implemented, we recommend to start at the beginning of the year with the implementation of the "Extern" and "Banket" sub-warehouse, because of the seasonality. Here an emphasis should be placed on the changes and reasoning behind this.

6.3 Conclusions

In this section we presented (relevant) success factors when implementing a new storage policy. Moreover, an implementation plan is presented. Relevant success factors for the implementation are include, but are not limited to, top management support, proper project management, phased implementation, management of change and post-implementation evaluation and information.

The solution for each sub-warehouse is visualized in Excel using the products, locations and periods of the sub-warehouse. Different colors are used to indicate a specific assignment of a product or location in a time period.

We recommend to do the implementation in series. This means that the all solutions of the sub-warehouses should not be implemented simultaneously. The smallest sub-warehouse in terms of number of locations is the "VAS / Roggebrood" sub-warehouse. Besides the size of the sub-warehouse, there is little to no seasonality in the demand pattern, which simplifies the implementation. Following the implementation, we advise to do a post-implementation review. This to evaluate what went well and wrong in the implementation. A similar approach is recommended for the "Oude Beschuit" & "Hal 16" sub-warehouse. These are greater in number of locations and pallets to store, but do not yet have a strong seasonal demand pattern. Finally, we suggest Bolletje to start with the implementation of the "Oude Beschuit" & "Banket" sub-warehouse and finalize the implementation.

7 Conclusions and recommendations

This chapter finalizes the report. In this chapter, conclusions are drawn in the first section. Next, recommendations are given based on the results stemming from the research. These recommendations are relevant for the WDD of Bolletje. The chapter is finalized with suggestions for further research. Topics for further research may be used for future researchers in both the warehousing field and at the company, this section finalizes the chapter.

7.1 Conclusions

This section draws conclusions based on the research carried out at Bolletje. Using a problem cluster, a core problem of the central problem was found. The core problem tackled in this research is the absence of an optimized storage policy. An analysis reveals that approximately 66% to 78% percent of the spent hours at the warehouse can be attributed to the storage assignment policy. The research objective, formulated in section 1.5 and deducted from the core problem and objective is formulated as follows:

How can the Warehouse and Distribution Department of Bolletje Almelo store its (semi-)finished goods in the warehouses in Almelo, such that the driving distance is minimized?

Bolletje has two production locations, one in Almelo and the other one located in Heerde. The produced from Heerde are transported to the warehouse in Almelo, as there is no warehouse in Heerde. The warehouse in Almelo can be considered as a warehouse-system, as it is spread over the entire plant. Standard FIN and EUR pallets are used to store the products. Block stacking, deep lane storage racks and shuttles are examples of the different storage means that are used in the warehouse. The production location in Almelo and Heerde account for approximately 65% and 25% of the pallets to store, the remaining 10% comes from external suppliers. On average, based on the total hours spent, three to four pallets are stored/picked per hour.

In a literature review, state-of-the-art warehouse/stock classifications, storage assignment models for warehouses, performances measures and optimization techniques were found. The problem is classified as the Storage Location Assignment Problem (SLAP). Storage methods get be categorized into three categories; haphazard, dedicated and class-based storage. Haphazard stores products based on some pragmatic rule, e.g. closest open location. Dedicated storage reserves a fixed set of locations for each SKU. Class-based storage uses the logic of both, here a zone of locations is reserved for a set of SKUs. Performance measures often used relate to space and distance traversed in the warehouse. Optimization models include (but are not limited to) mathematical models, approximation algorithms and (meta-)heuristics. Simulation is a technique that can be used to model stochastic processes.

Popularity and space are two relevant determinants for the storage policy. Popularity can me expressed in multiple ways (e.g. demand size, DoS, turnover etc.). Space relates to the feasibility of locations with respect to the product. A toy problem was used to illustrate the problem the model tries to solve. The simplify the model and create a tractable problem, we splitted the warehouse, based on the inbound location, in five sub-warehouses: "Hal 16", "VAS / Roggebrood", "Extern", "Banket" and "Oude Beschuit". The model is a mathematical model which minimizes the class capacity-weighted distance times the storage rate of all products over the entire time horizon. Constraints relate to the size of a zonal-capacity and feasibility of the locations. Besides that, each product and location should be assigned to a class in every period. Due to NP-hardness of the model, we are not able to solve the problem within reasonable time, also no reasonable initial solution. Therefore, we proceeded using a heuristic and (meta-)heuristic. The heuristic assigns products to classes including feasible locations until some condition is met, then a new class is created. We experimented with the number of classes in a range of [4,10] and location configurations (single, adjacent, technical zones). In the meta-heuristic, the following three operators were used; move (i.e. move product or location to other class), swap (i.e. swap products or locations between classes) and a simultaneous operator (i.e. move both product and feasible locations to other class). The next table depicts the results per sub-warehouse, these comprise of the location aggregation and number of classes.

Sub-warehouse	*Location aggregation*	*Number of classes*
Hal 16	Technical zone	7
VAS / Roggebrood	Single	4
Extern	Adjacent	8
Banket	Adjacent	9
Oude Beschuit	Adjacent	3

The problem is characterized as a static and stochastic problem, as input is known beforehand and some parameters are stochastic. Monte-carlo simulation is used to simulate realizations of the random parameters. This technique is suitable as it efficient and gives reliable results. The following six scenarios were evaluated: expected, medium, high, low, pallets deterministic and DoS deterministic. The sub-warehouses that have products with seasonal demand ("Extern" and "Banket") are not very robust against changes in number of pallets to store or duration of stay. The table below depicts per scenario the improvement between the current situation and the improved situation.

Scenario (improvement in distance per scenario)					
Expected	*Medium*	*High*	*Low*	*Pallets constant*	*DoS constant*
27.3%	27.8%	52.2%	12.2%	30.5%	27.5%

Only a portion (67%) of the total hours spent at the warehouse can be attributed to the storage assignment policy. These hours are based on activities that are affected by the storage assignment policy. These saving exclude practicalities as these are hard to estimate.

7.2 Recommendations, limitations and scientific contributions

In order for Bolletje to utilize the results from the research, they should implement to class-based storage policy proposed in this report. The implementation itself does not require a high investment. However, employees which store & retrieve the products in & from the warehouse need to get used to a different way of storing products.

We recommend Bolletje and specifically the WDD to do a phased implementation of the solutions. The WDD can start with the implementation of the solution in the "VAS / Roggebrood" sub-warehouse, as this is a small (oversee-able, in terms of locations and products) warehouse and does not have strong seasonal demand. After the implementation at this sub-warehouse, a post-implementation evaluation is recommended, to evaluate what went well and wrong. Next, proceed with the implementation of the solution "Hal 16" and "Oude Beschuit" and take into account the feedback from the implementation at the "VAS / Roggebrood" sub-warehouse. These sub-warehouses are chosen as next phase because they are greater in terms of locations and number of pallets to store, but do not yet contain seasonal demand. For this phase, a post-implementation evaluation is also recommended. Finally, we recommend to start with the implementation of the solution of the sub-warehouses of "Banket" & "Extern" at the start of the year (because of the seasonal demand).

The solutions also have some assumptions/limitations. Even though the capacity of a class is based on the expected amount of pallets to store, it is still possible that the required storage capacity exceeds the the allocated capacity. In such a situation, multiple alternative storage possibilities are available. One can store the product at the closest location in another class, class with the most capacity left or lowest fill rate. The fill rate option might be the best, but it is not easy for an employee to figure out which class has the lowest fill rate. Therefore we recommend to store it in the closest open feasible location in another class due to the ease of use and small chance of happening (as it is based on the expected storage requirement).

Recall from section 1.3 the problem of storing some of the same products in the same location. In the solution, we assumed that products in a planning period can be stored at the locations irrespective of the batch number. In reality however, some additional "overflow" might be needed to accommodate different batches. Another limitation of the solution is that there might be infeasible locations in a class. Some locations can be feasible for product X but not for product Y. To overcome this problem we recommend to store the product at the lowest possible location in the class. In such a way, products which require high locations remain unoccupied until there is such a product to store. In the future, new products can be introduced who are not yet assigned to classes. We propose to assign these to classes based on the lowest delta (Δ = average storage rate - storage rate new product). In case of adding/removing several products, Bolletje can assign the products based on storage rate to the class with the lowest delta and move products to lower classes of there is not enough capacity. In case of a removal we recommend to not make changes to products and locations.

We presented a modification to solving the product and location to class assignment problem. The modification is in the mathematical model. Specifically, we presented a mathematical model that is generalized and can be used for other warehouses who want to implement a class-based storage policy and have feasibility constraints. The other contribution is the heuristic and additional operator. To the best of our knowledge, we presented a new heuristic. The (simultaneous) operator is new and not used before.

7.3 Suggestions for further research

First, as mentioned in the recommendations section, the solutions of the "Extern" and "Banket" warehouse are sensitive to stochasticity (i.e. they are not robust). It might be beneficial for Bolletje to further investigate how more robust solutions for these sub-warehouses can be build.

Second, from the problem cluster, it can be interesting for Bolletje to automate tasks in the warehouse. For example, some tasks of the inbound process are standard and repetitive. This is an automation possibility.

Third, currently there is no truck-to-dock assignment in place. It can be beneficial for Bolletje to investigate the effect of smarter assignment of trucks to docks.

Fourth, some locations are infeasible for most products due to their height. Specifically, locations with a height of at most 1500 mm cannot accommodate the storage of most products. It can therefore be interesting to research what the effect is of having 2 levels instead of 3 levels of locations, such that there are more feasible locations.

Lastly, recall the other core (influencable) problem from the problem cluster, no optimized picking policy. This problem also affects the the waste of movements / driving time, therefore, improving it can contribute to the reduction in waste.

A Adaptive algorithm

Algorithm 1 ADAPTIVE algorithm

for each duration of stay p **do**
  $n_p = 0$
end for
for each product i **do**
  for each item k=1,...,q_i in batch of product i **do**
    $p = k * dit_i$
    $n_p = n_p + 1/(q_i * dit_i)$
  end for
end for

for for each duration of stay p **do**
  $z_p = n_p * p$
end for

Cumulative remainder = 0, prev bound = 0, zone = 0
for each duration of stay p **do**
  Cumulative remainder = Cumulative remainder + z_p
  if Cumulative remainder $>$ 1 **then**
    zone = zone + 1
    zone size (zone) = round to integer (cumulative remainder)
    lower dos (zone) = prev bound + 1
    upper dos (zone) = p
    Cumulative remainder = cumulative remainder-zone size (zone)
    prev bound = p
  end if
end for

Figure A.1: Adaptive algorithm

B Model SLAP

The following sets and parameters are defined in the model.

N	=	Number of unit loads
K	=	Number of locations
i,j	=	Index of unit load
$[a_i,d_i]$	=	Arrival and Departure time of SKU i
c_k	=	One way travel time to location k

$$w_{ij} = \begin{cases} 1, \ a_i \geq d_j \ or \ a_j \geq d_i, \quad i,j = 1,...,N, \quad i \neq j \\ 0, \ \text{otherwise} \end{cases}$$

Here, each unit load i has a DOS_i in an interval $[a_i, d_i]$. w_{ij} is an NxN-matrix to indicate whether two unit loads can be assigned to the same location. The following decision variables are used:

x_{ik}= 1, if unit load i is stored in location k, 0 otherwise

y_{ijk}= 1, if unit load i and j are stored in the same location k, 0 otherwise

The objective B.1 of the following model is to minimize the total travelling time associated with four one-way trips (store/retrieve).

$$\min \sum_{i=1}^{N} \sum_{k=1}^{K} 4c_k \cdot x_{ik} \tag{B.1}$$

Subject to:

$$\sum_{k=1}^{K} x_{ik} = 1, \qquad i = 1,...,N \tag{B.2}$$

$$y_{ijk} + 0.5 \geq 0.5(x_{ik} + x_{jk}), \qquad i,j = 1,...,N, \quad k = 1,...,K \tag{B.3}$$

$$(1 - w_{ij})y_{ijk} = 0, \qquad i,j = 1,...,N, \quad k = 1,...,K \tag{B.4}$$

$$x_{ik}, y_{ijk} \in \{0,1\} \tag{B.5}$$

Constraints B.2 ensure the assignment of each SKU to a single location. Set B.3 ensures that $y_{ijk} = 1$ whenever i and j are placed in the same location k. Constraint set B.4 restricts y_{ijk} to be 0 whenever $w_{ij} = 1$. The last set, B.5, ensure the binary property of the decision variables.

C Model Storage Classes

The following notation is used in the mathematical model:

Indices:

c	*(c=1,2,...,C)*	For classes
l	*(l=1,2,...,L)*	For the storage/retrieval locations
p	*(p=1,2,...,P)*	For SKUs/products
t	*(t=1,2,...,T)*	For time periods

Parameters:

a_l	=	Area of location l
d_l	=	distance of location l from I/O point
D_p	=	Total retrievals of product p
f	=	Space cost per unit of area
f_p	=	Area required to store product p
h	=	Picking costs per unit of area
I_p^t	=	Total inventory in unit loads of product p in period t

Decision variables

$$x_{pc} = \begin{cases} 1, & \text{if product } p \text{ is assigned to class } c \\ 0, & \text{otherwise} \end{cases}$$

$$y_{lc} = \begin{cases} 1, & \text{if location } l \text{ is assigned to class } c \\ 0, & \text{otherwise} \end{cases}$$

The model is formulated as follows:

$$z = f\sum_c\sum_l(a_l \cdot y_{lc}) + 2h\sum_c\left[\left\{\frac{\sum_l(a_l \cdot d_l \cdot y_{lc}}{\sum_l(a_l \cdot y_{lc}}\right\}\sum_p D_p \cdot x_{pc}\right] \tag{C.1}$$

Subject to:

$$\sum_c x_{pc} = 1 \qquad \forall p \tag{C.2}$$

$$\max_t\left[\sum_p(I_p^t \cdot f_p \cdot x_{pc})\right] \leq \sum_l(a_l \cdot y_{lc}) \qquad \forall c \tag{C.3}$$

$$\sum_c y_{lc} \leq 1 \qquad \forall l \tag{C.4}$$

$$x_{pc}, y_{lc} \in \{0,1\} \qquad \forall p, c, l \tag{C.5}$$

The objective C.1 is to minimize the use of storage space and total order picking cost. Constraints C.2 ensure that each product is allocated to exactly one class. Constraint set C.3 makes sure that the storage space of class c is large enough to accommodate the inventory at its highest level of all products p in class c. Thanks to constraint set C.4, storage locations can only be, if assigned at all, to at most one class. The last constraint set C.5 impose the variables to only attain binary values.

D Warehouse splitting

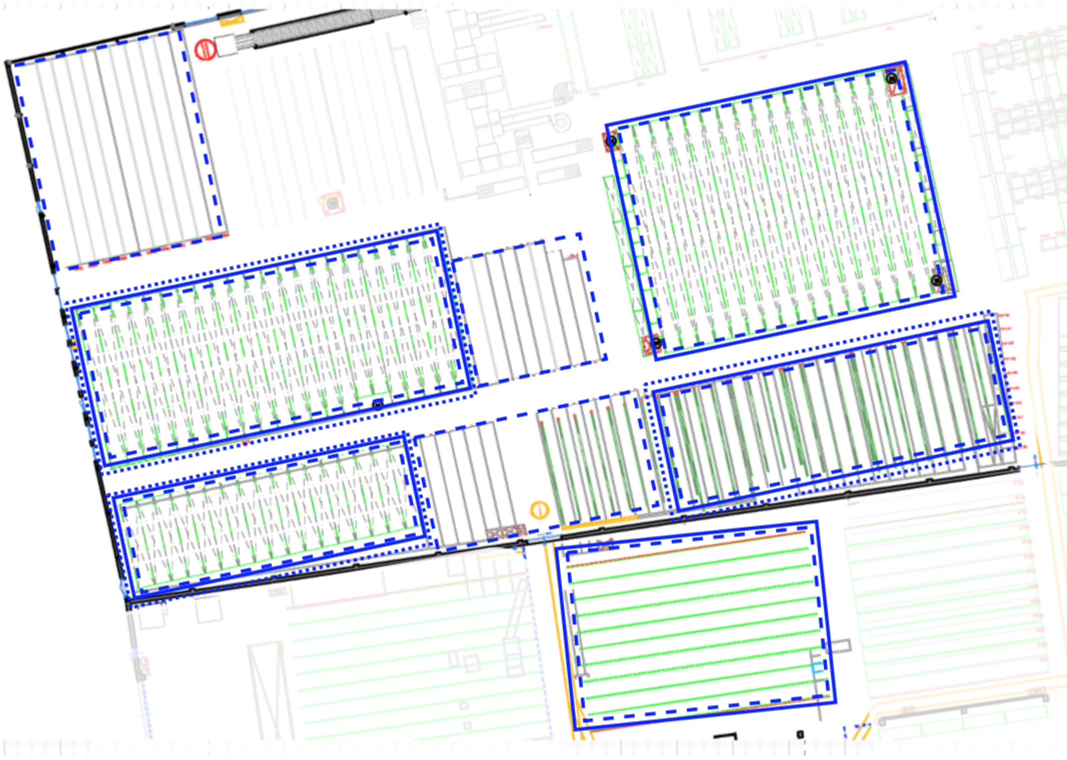


Figure D.1: Hal 16 sub-warehouse

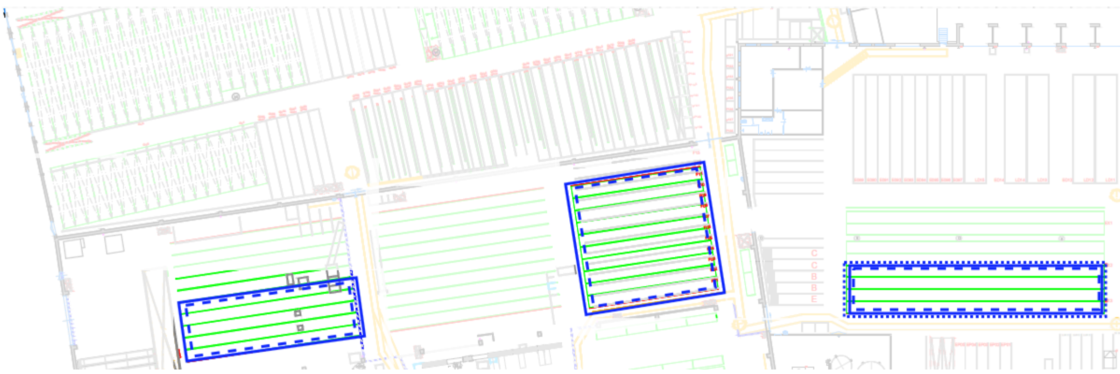


Figure D.2: Roggebrood / VAS sub-warehouse

Figure D.3: Extern sub-warehouse left

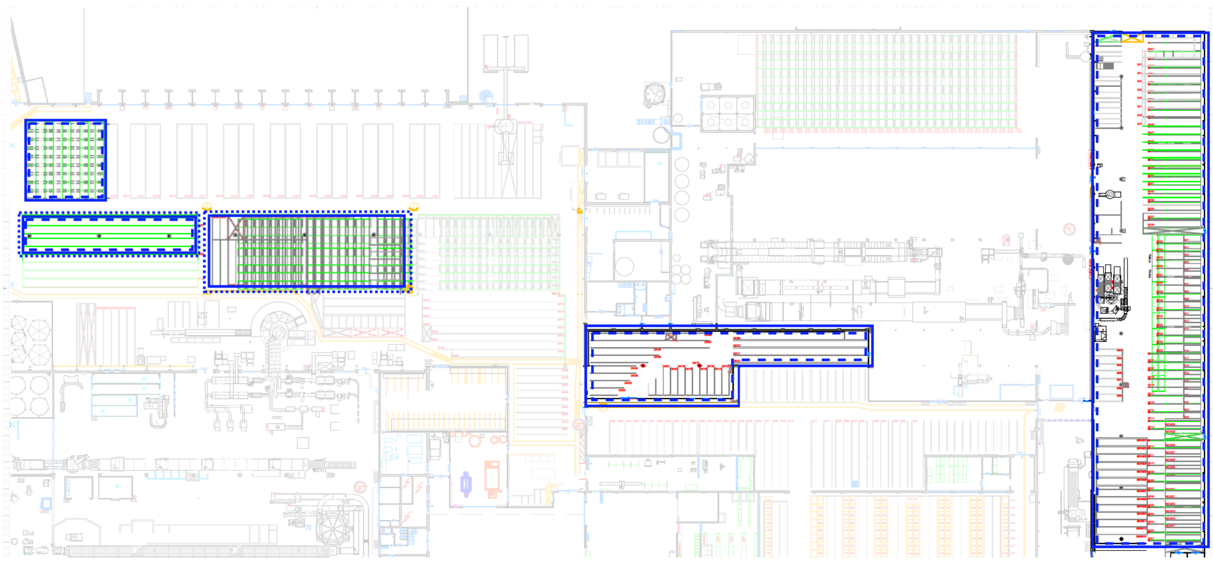


Figure D.4: Extern sub-warehouse right

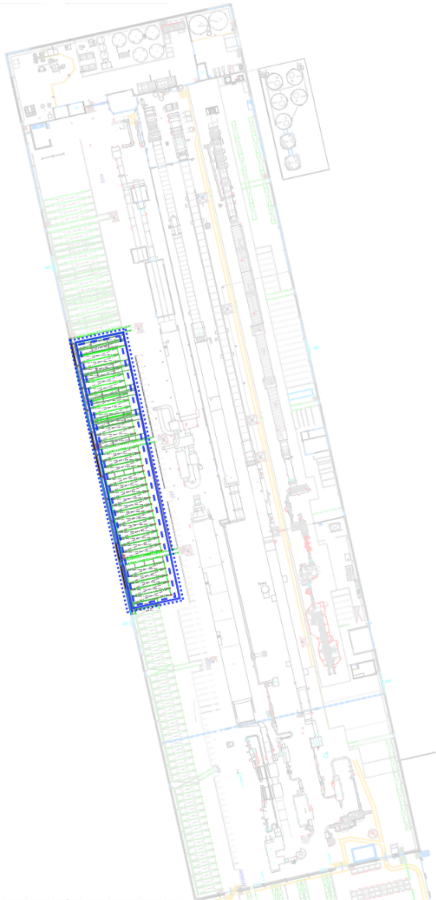


Figure D.5: Banket sub-warehouse left

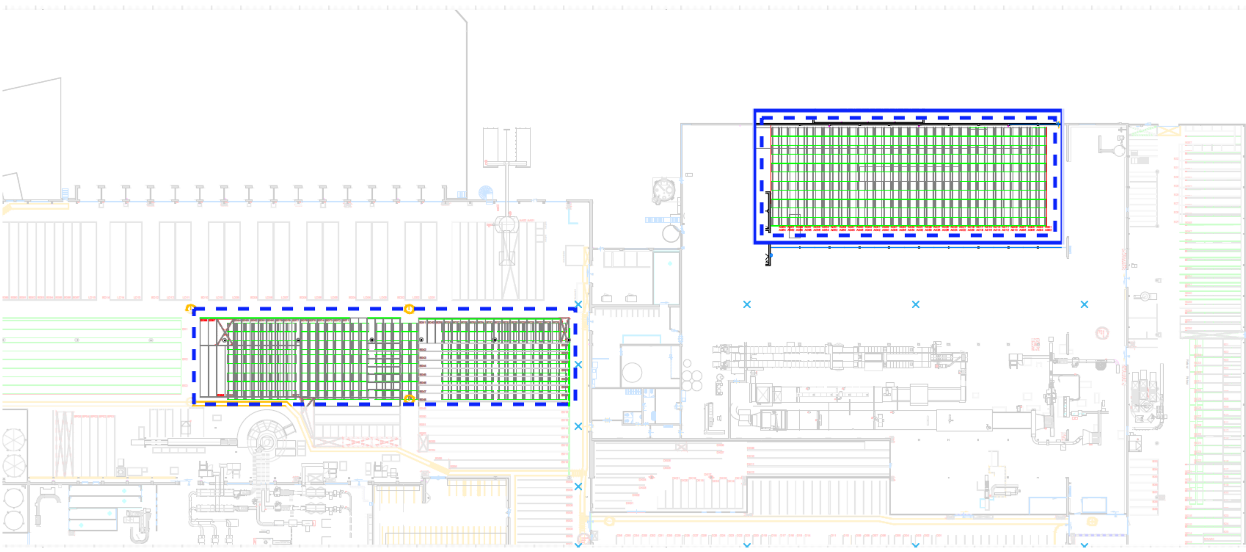


Figure D.6: Banket sub-warehouse right

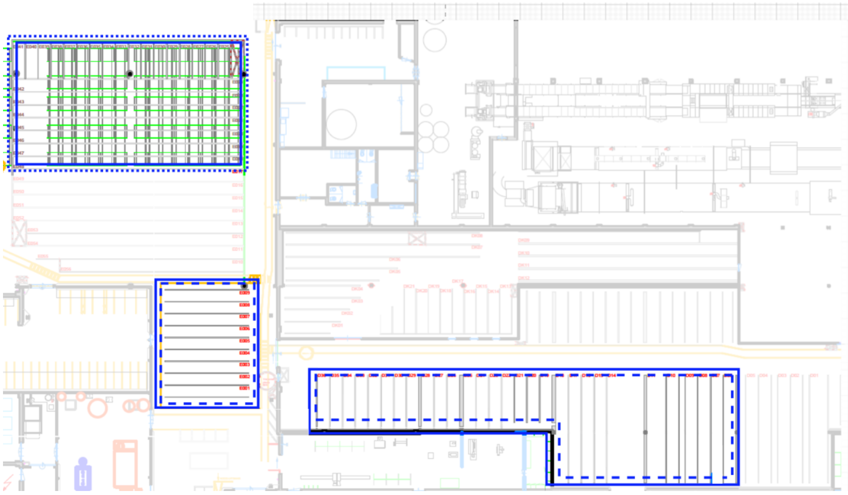


Figure D.7: Oude beschuit sub-warehouse

E Seasonality Banket products

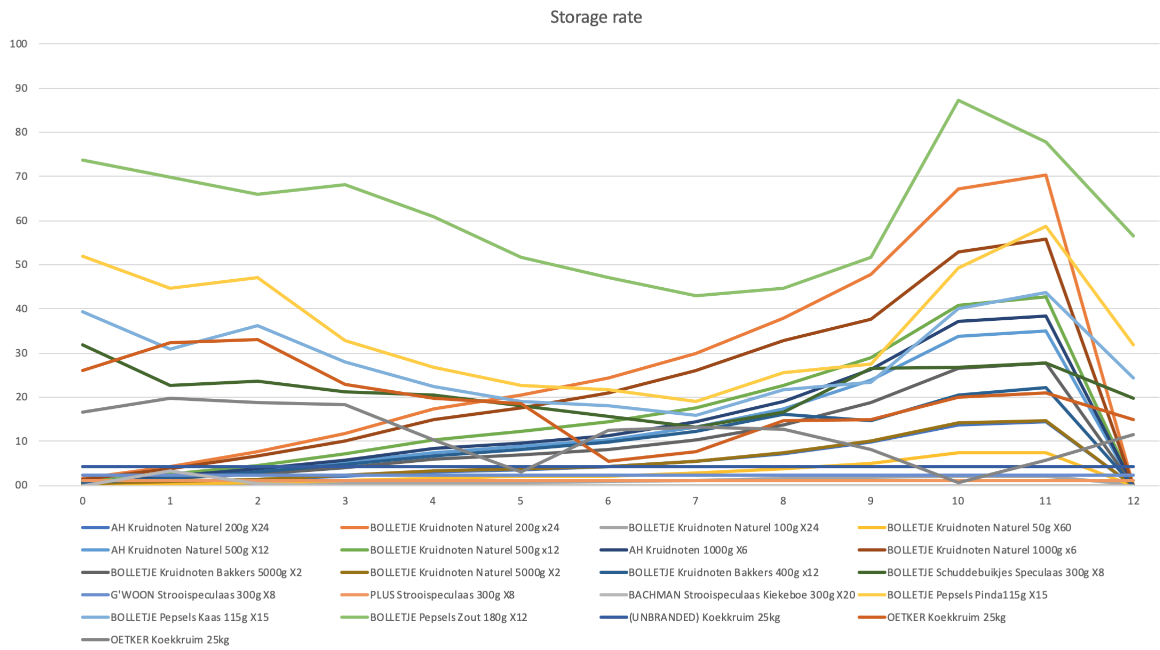


Figure E.1: Seasonality Banket

F Banket warehouse

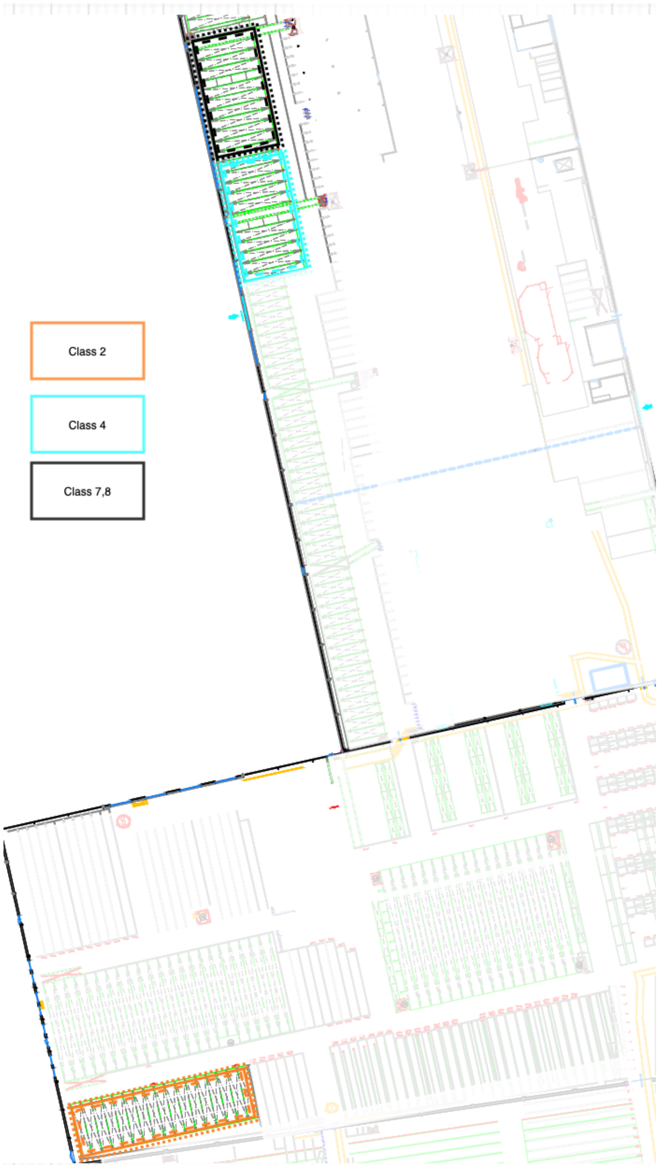


Figure F.1: Banket (optimized) sub-warehouse left side

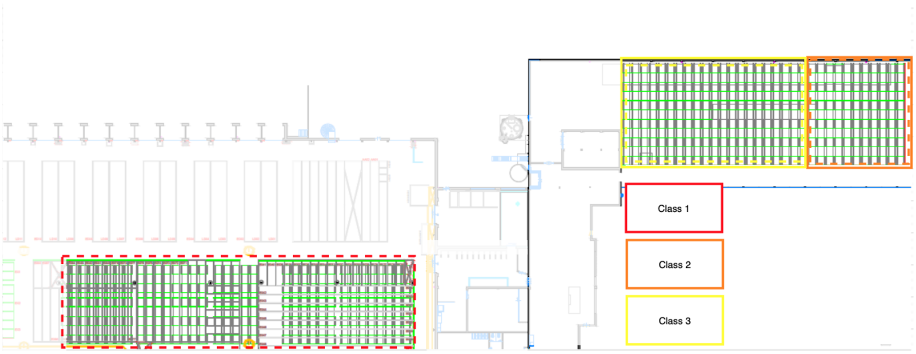


Figure F.2: Banket (optimized) sub-warehouse right side

G Extern warehouse

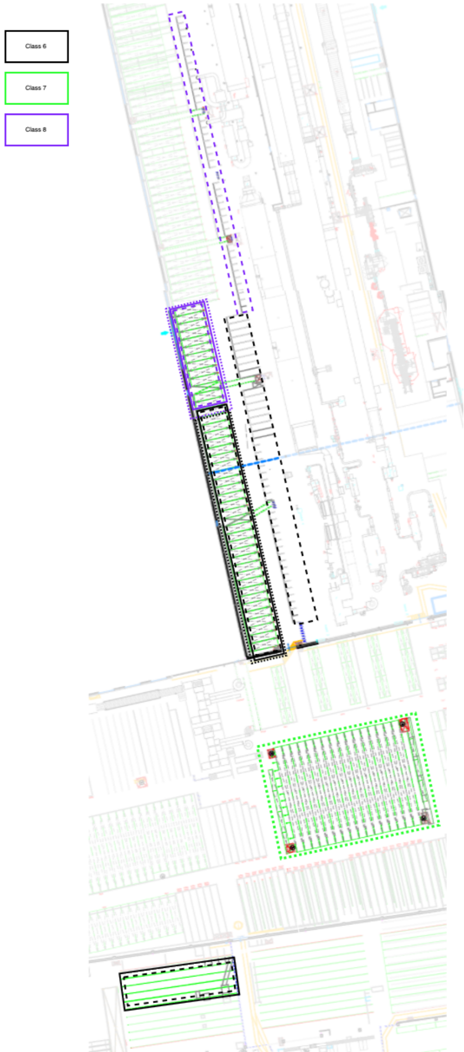


Figure G.1: Extern (optimized) sub-warehouse left side

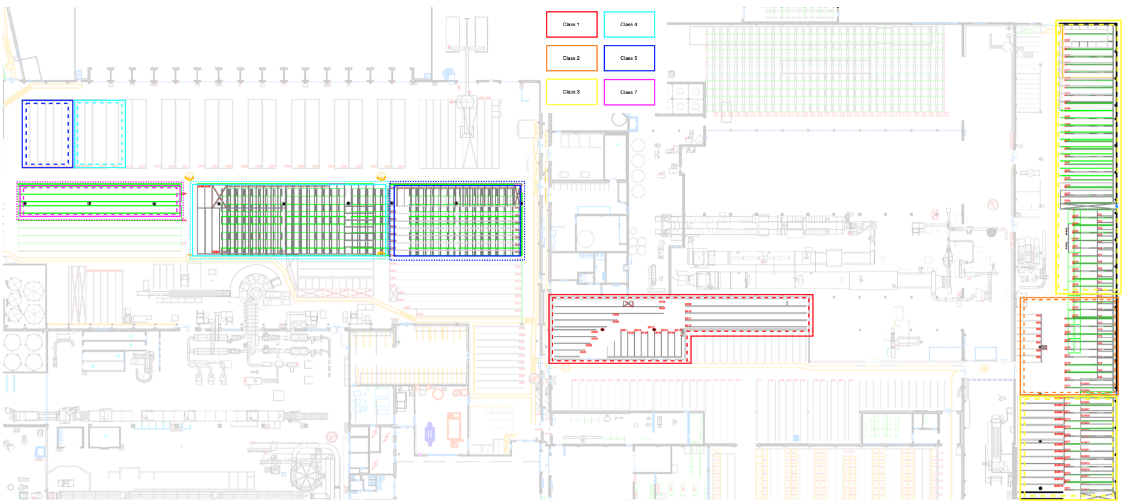


Figure G.2: Extern (optimized) sub-warehouse right side

H Current location assignment

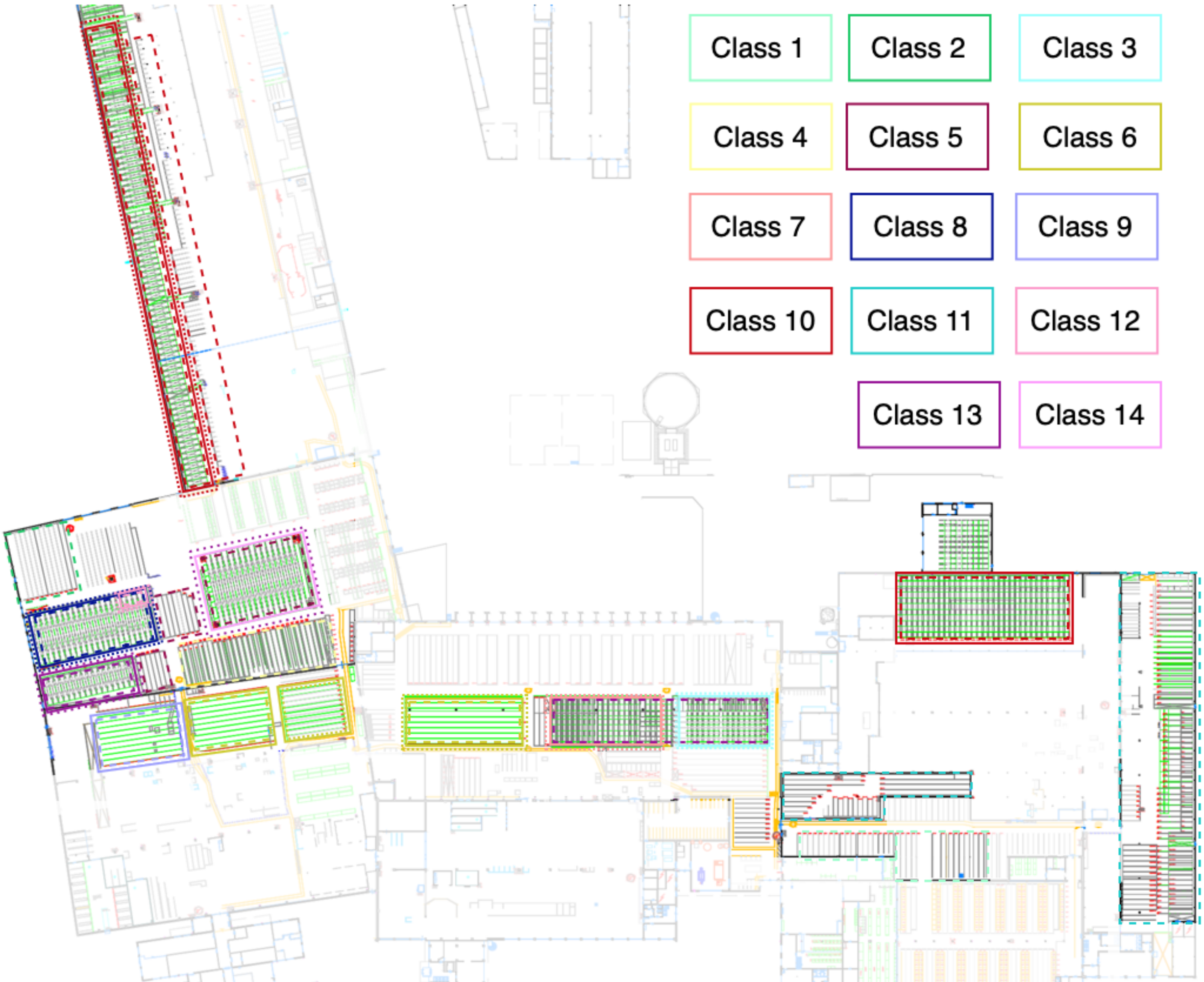


Figure H.1: Current location to class assignment

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