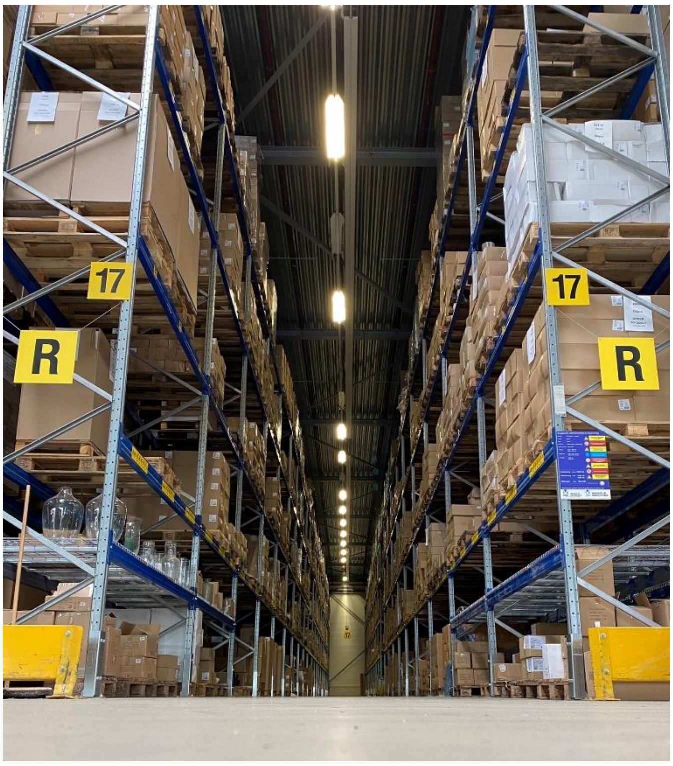

AN ITERATIVE APPROACH TO WAREHOUSE TACTICAL LEVEL DECISION MAKING

IMPROVING THE ORDER PICKING EFFICIENCY BY DIMENSIONING THE WAREHOUSE DESIGN, THE STORAGE METHOD AND STORAGE POLICY

ABSTRACT

This document reports a master thesis research about optimising the warehouse and logistic activities of B-Living in Hengelo to the extent of being able to in-house the logistic activities of Mars & More into the warehouse of B-Living as a result of the takeover in January 2023.

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UNIVERSITY OF TWENTE

MASTER INDUSTRIAL ENGINEERING & MANAGEMENT

Manufacturing Logistics and Supply Chain & Transport Management

AN ITERATIVE APPROACH TO WAREHOUSE TACTICAL LEVEL DECISION MAKING

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Date	09 May 2023
Version	1
Number of pages	94
Number of appendices	6

Management Summary

This report studies an order picking efficiency problem for home decoration wholesaler B-Living. B-Living is rapidly growing and with the acquisition of competitor Mars & More the logistics workload becomes too much for the logistics department to handle with the current logistic processes and operations.

Problem statement

After analysing the observed problem, we conclude that the order picking process is the bottleneck process within the logistics department. The core problem causing the order-picking process to be the bottleneck is the lack of strategy within the storage process. This problem results in the following research goal:

The goal is to find adaptations in the storage process and warehouse design at B-Living Hengelo that improve the order-picking efficiency.

Warehouse decision making

We conclude that improving the efficiency of the order picking process can be obtained by considering tactical level decisions regarding product allocation. After conducting literature research on the possibilities of improving the order-picking processes and the storage processes, we found methods which are able to solve this product allocation problem by improving the traveling times of picking orders. First, we research dividing the warehouse in functional areas by constructing an algorithm that assigns product flows to SKUs. This approach indicates whether separating the warehouse in different functional areas improves the order-picking efficiency and determines the dimension of these functional areas. Thereafter, we consider multiple storage policies and storage methods for this B-Living case and test these storage configurations by using the constructed SKU-to-location algorithm. Hence, we conduct research on three tactical decisions:

1. Functional area dimensioning
2. Storage method
3. Storage policy

Research approach

The warehouse of B-Living allows two types of functional areas: forward area and reserve area. A forward area is typically designed for efficient order picking and a reserve area for efficient storage of inventory. We research whether using functional areas will improve the order-picking efficiency, what dimensions of these areas are most efficient and which SKU inventory to assign (partly) to which functional area. We constructed a metaheuristics algorithm, that is able to calculate the impact of each decision. This algorithm assigns product flows to all SKUs and its objective is to minimise the total traveling time of picking orders. The solution from the flow-to-SKU algorithm is then used as input to test the impact of the storage method and policy decision. We researched the random storage method, the dedicated storage method and the class-based storage method. The random storage method is storing SKUs randomly within the warehouse. Dedicated storage is assigning SKUs to locations in the warehouse according to a certain storage policy. Class-based storage is assigning SKUs to classes and within these classes, store items at locations based on the storage policy.

Thereafter, we test and elaborate on the impact of two storage policies: ABC storage which is storing SKUs to locations based on the order picking frequency of the SKU and Cube per Order Index (COI) storage which is storing items to locations based on the inventory volume and the order picking frequency. We combine these storage methods and policies to 6 storage configurations. The impact of each storage configuration is then calculated by means of a constructive heuristic algorithm which assigns SKUs to locations within the warehouse. Hence, we constructed the flow-to-SKU algorithm

which measures the impact of functional area dimensioning decisions and the SKU-to-location algorithm to measure the impact of storage methods and policies decisions.

Results

We test a total of 7 functional area dimension interventions and 6 storage configurations for a total of 42 experiments. After 5 runs of updating the average traveling times per functional area, the updated traveling times parameters show no more changes. Hence, the flow-to-SKU algorithm finished updating the parameter from the SKU-to-location algorithm after 5 iterations. The final result of these tests show the best total traveling times are found by using 20% of the warehouse locations near the loading docks as forward area and the other 80% as reserve area. The results also show that dedicated storage method with the ABC storage policy shows the best results. This functional area dimension and storage configuration combination result in an estimated total traveling time reduction of 23.74% compared to 2022.

Another performance indicator is the number of picks from small-width aisles. The higher the number of picks from locations within these aisles, the higher the expected waiting time, as it is not possible to operate within these aisles with two or more vehicles simultaneously. The solution reduces the number of picks from small-width aisles by 27.79% compared to 2022.The solution requires a total of 3,093 replenishments per year. These replenishments are executed by the inbound employees that are out of scope for this research. However, as the solution of this research adds additional workload to the inbound employees, a trade-off might be considered.

It is estimated that the reduction of traveling time and the reduction of waiting times will improve the order picking process and that the 7 full time equivalent (FTE) that are currently required for order-picking pallet shipments can be reduced to 5.5 FTE. This reduction of FTE results in €60,080 of savings per year given the current average salary of warehouse employees. It is expected that the increasing workload for the inbound employees do not require additional FTE as it possible to execute the replenishments at moments the inbound employees are not busy with their current activities.

Conclusions and recommendations

Looking back at our research goal and results. We conclude that the solution shows improvements to the order-picking efficiency and is easy to implement. Hence, we would recommend the following:

- Functional area decision: Use the area before the cross aisle as forward area and the remaining as reserve area
- Storage method decision: Assign SKUs to fixed locations by using the dedicated storage method
- Storage policy decision: Assign the most frequently picked SKUs to the locations closest to the loading docks by using ABC storage

We recommend to regularly update the parameters and run the algorithms with these updated parameters as the demand of each SKU is influenceable by trends and collections which influences the picking frequency of SKUs and therefore the flow and/or location assignment. Thereafter change the fixed locations based on the outcome of the model. We also recommend using this model with the Mars & More data when integrating the logistic activities of B-Living and Mars & More.

Preface

This report presents my research study at B-Living in Hengelo. In the framework of completing my Master's studies at the University of Twente in Industrial Engineering & Management within the Production and Logistics Management orientation. With a lot of joy, I look back at my years studying at the University of Twente and doing research at B-Living. In this preface I would like to take the opportunity of thanking a number of people.

I want to thank all the employees of B-Living for cooperating with my research and their contributions. The culture of the company and the willingness to improve and change of the employees enabled me to quickly acquire knowledge about the company, the people and the processes. I especially want to thank my supervisor Ramon Jansen for his efforts during this research. With his company knowledge and expertise he provided me with everything that I needed for this research and always made time to help when I got stuck. I also would like to thank B-Living for giving me the opportunity to start my career at their organization and to start implementing the solutions from this research.

Secondly, I would like to thank my supervisors at the University Marco Schutten and Breno Alves Beirigo. They really helped me with my research by providing very pleasant feedback to improve my research and my report. I also want to thank Peter Schuur as my initial supervisor who guided me through the first phase of my thesis, the project plan.

At third, I want to thank Hein Langeveld and Niek Tijink from Bolk Business Improvement for helping me find the research assignment at B-Living and for helping me during this research. Hein and Niek are specialised in the field of logistics and warehousing and they provided me with a lot of insights and views on these fields during this research.

Finally, I would like to thank my family and friends for the support and their help to keep me motivated throughout my years of education.

Stijn Huuskes, May 2023

Table of Contents

List of figures

List of tables

Glossary

ABC	Classification based on usage values
COI	Cube per Order Index
ERP	Enterprise Resource Planning
I/O point	Starting and stopping point
KPI	Key Performance Indicator
NP	Non-deterministic Polynomial Time
OOS	Order Oriented Slotting
SKU	Stock Keeping Unit
WMS	Warehouse Management System
XYZ	Classification based on variability

1 Introduction

This chapter starts with a background description of the company and a brief description of the logistic department in Section 1.1. In Section 1.2 the motivation of the research is explained and the analysis of the problem and the core problems are described in Section 1.3. Section 1.4 states the research goal and Section 1.5 the research design consisting of the research questions. We elaborate on the research scope in Section 1.6. At last, Section 1.7 describes a summary from this chapter.

1.1 Company description

B-Living is the result of a merger between textile company Blyco Textile Group and glassware supplier Hakbijl Glass. As both companies are active in importing and exporting home decoration goods, the companies attended the same exhibitions and shared the same customers. This was the main motive for the merger. Instead of operating individually, both companies decided to continue as one company distributing from one location to reduce costs and improve market share. Hakbijl Glass was a distributor of glassware founded in 1930 and used to be the European leader in decorative glassware situated in Lelystad, The Netherlands. Blyco Textile group was a wholesaler founded in 1805 by the Blijdestein family in Enschede, The Netherlands, specialising in distributing, designing, developing and producing textile home decoration and in- and outdoor textile products. Since 2020, the headquarters and main warehouse of B-Living are located in Hengelo, The Netherlands. Another warehouse and the glass painting location are based in Poland and B-Living has an office in India that manages the purchasing and shipment of incoming goods exported to the European warehouses of B-Living. The company designs modern interior items and serves as a distributor for importing and supplying home decoration in the business-to-business sector. The products of B-Living are distributed to the customers by the logistic department in Hengelo.

LOGISTICS DEPARTMENT

The operations of B-Living 's logistic department are subdivided into main processes receiving, storage, order picking and shipping. The receiving activities consist of receiving and checking the items entering the warehouse. Incoming goods are shipped by either truck or container shipment. The items are then stored in the desired locations during the storage process. Thereafter the customer order is collected and assembled by means of order picking. And finally, the customer order will be controlled, prepared and shipped to the logistic partner or the customer. Figure 1 schematically displays the main logistic process flow.

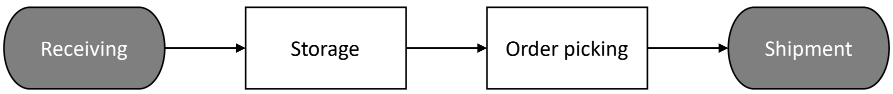

Figure 1 Main logistics process flow

These operations are executed in a building of about 10,000 m^2 of which 10% is utilised for sales and marketing purposes. The other space of the building is used by the logistic department as an office, assembly station and the warehouse. At this assembly station the value-adding activities such as cushion filling and labelling operate, at the logistics office, the receival and shipments are planned and the warehouse is used for distributing the products B-Living sells to its customers. Figure 2 shows the map of B-Living including its layout and layout specifics. The warehouse contains 15 wide aisles and 12 small aisles and the total number of pallet rack sections is 898. Each pallet rack section can contain up to three euro pallets every layer and is able dimension the layers up to a height of seven meters. The warehouse also contains shelve racks which are used to store rolls and foils that are not stored on pallets and 'piece shelve racks' which are used for the storage of single remaining pieces from picked pallets. Currently, the warehouse of B-Living contains 14,471 storage locations. We elaborate on all internal logistic activities and warehouse resources in Chapter 2.

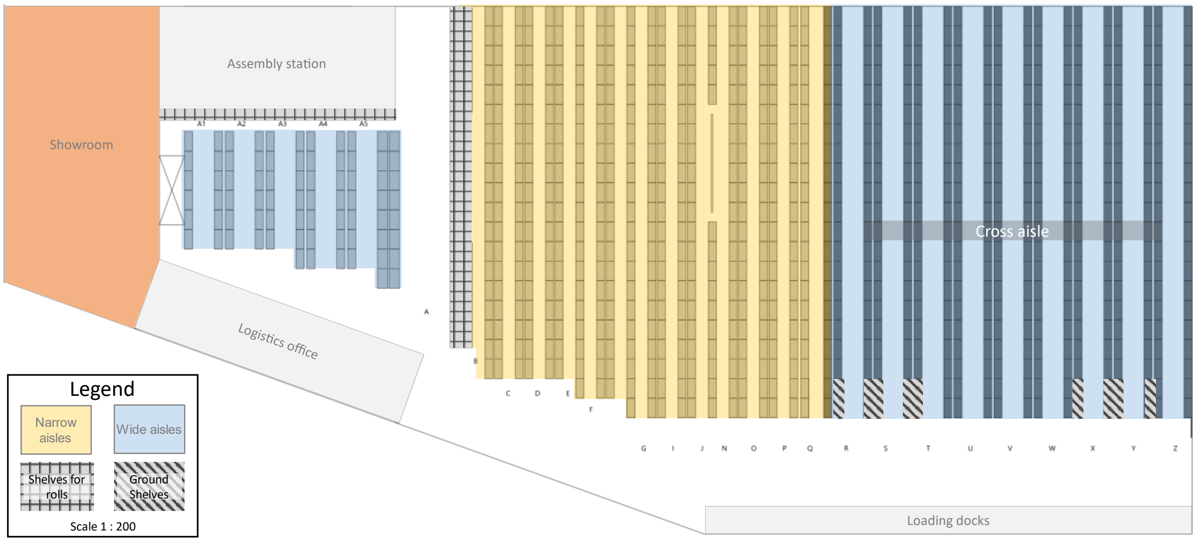

Figure 2 Warehouse layout of B-Living Hengelo

1.2 Research Motivation

The lockdown in the Netherlands during March and April of 2020 caused by the Covid-19 pandemic seemed to be a perfect moment to move all stock from the warehouses of Hakbijl Glass in Lelystad and Blyco Textile group in Enschede to the B-Living warehouse in Hengelo. It was a priority to move all stock to the warehouse in Hengelo as fast as possible to ensure a small operational break. In 2022, two years post the merger of Hakbijl Glass and Blyco Textile, the logistics department of B-Living still copes with the inefficiencies resulting from this fast relocation. As the company grows, the Hengelo warehouse utilisation and the workload of the logistics department in Hengelo are increasing, resulting in unfinished orders and working overtime. In 2023, B-Living is taking over the company Mars & More and B-Living would like to in-house all logistic activities of Mars & More to its warehouse in Hengelo. This means that even more pressure will be put on the logistics department of B-Living.

1.3 Problem statement

The internal logistic processes are executed experience-based without the use of strategies, policies and computer intelligence. This results in inefficient storage and inefficient order picking. The cause of this problem is the lack of focus that has been given to achieving an efficient warehouse and efficiently designed logistic processes during the merge of the two warehouses in 2020. Hence, during peak periods, which fluctuate daily and weekly, the logistics department struggles to finish the current order-picking workload. With the acquisition of Mars & More, additional logistic activities should be handled by the logistics department of B-Living. It is therefore not possible to handle the logistics activities of Mars & More by the logistics department of B-Living with the current way of working.

The B-Living warehouse in Hengelo can currently store up to 14,000 pallets in pallet the pallet racks with an average rack height of 1.88 meters (the average height of full pallets is 1.51 meters). With the current average warehouse utilisation of 88%, the amount of empty pallet places is less than 1,680. The warehouse of Mars & More uses more than 2,500 pallet places to store their products. Completely in-house the Mars & More stock into the current warehouse would lead to an average warehouse utilisation of over 105.8%.

To summarise: the logistics department of B-Living is currently unable to handle its own workload during regular working hours in peak periods, let alone the additional logistics activities of Mars & More. And direct integration of the additional stock of Mars & More to the warehouse of B-Living is not possible as the current warehouse utilisation does not allow that many empty locations in the pallet racks. Hence, the logistics department of B-Living and its warehouse currently does not have the ability to handle the workload nor the storage space to execute the logistics activities of Mars & More at the B-Living warehouse in Hengelo.

Core problem

We create a problem cluster to identify the core problems that are responsible for the logistics department of B-Living being unable of executing the logistics activities of Mars & More in the B-Living warehouse (1). This is the observed problem that initialized this research. Figure 3 displays the problem cluster.

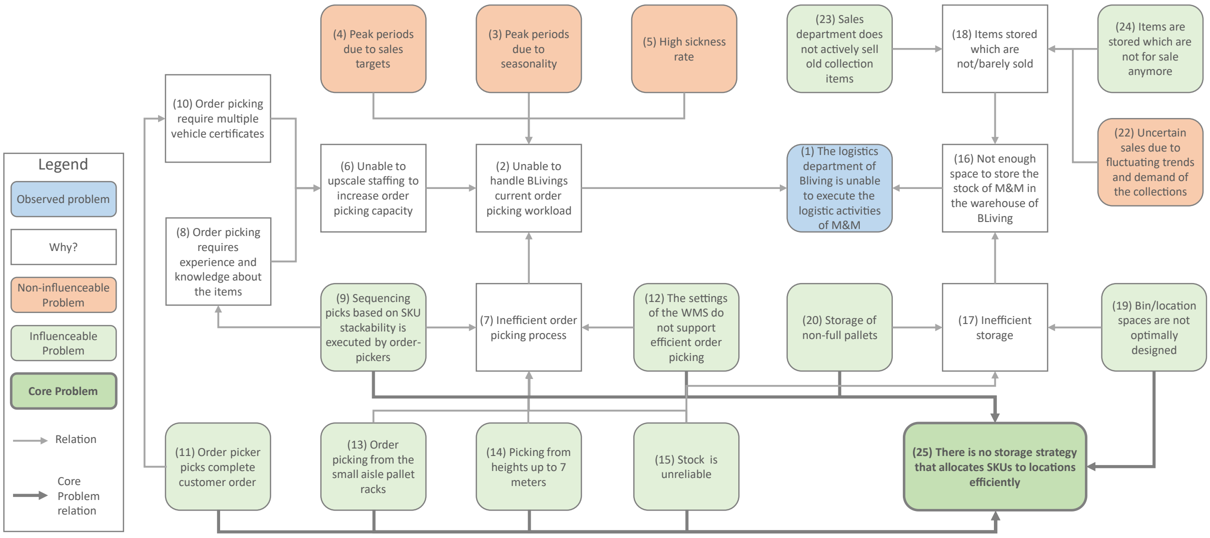

Figure 3 Problem cluster

1.3.1 Order picking efficiency problems

As mentioned before, the order-picking inefficiencies and storage capacity shortage causes the observed problem. The logistics department of B-Living is currently not able to pick all orders within regular working hours (2). This main issue is caused by peak demand periods due to seasonality (3) and sales advancing orders to meet their targets (4), understaffing due to high sickness rates (5), not being able to efficiently upscale staffing to increase the order picking capacity for short periods (6) and low output due to an inefficient order-picking process (7).

B-Living does not have deterministic demand. During peak periods, demand fluctuates daily. This causes problems since upscaling the staff is not effective for a couple of hours or days (6). Executing the order-picking process requires experience and knowledge that cannot be taught in a short period (8). The sequence that is picked is determined by how the order-picker things is best and not based on efficient order picking (9) and is the problem that causes this experience and knowledge to be required. Another problem concerning upscaling staff to increase order-picking capacity is the required skills and certificates (10). The order pickers of B-Living obtain pick lists containing a complete customer order (11). Since all items are stored in different storage locations and at different heights, the order picker should have the skills and certificates to operate three different vehicles to be able to pick all items.

The other problem which causes the logistics department of B-Living to be unable to handle its current order-picking workload is the inefficient order-picking process (7). One of the causes for this problem is that there is little logic in the order picking path as SKUs are to be sequenced due to their stackability (9), the WMS and its current settings that not supports the order-picker and the planning department to pick efficiently at the moment (12) which results in unnecessary movements. Orders are to be picked from small aisle locations as well which are not designed to order-pick from (13). Locations at 7 and 7.5 meters high are not excluded from picking (14). The order-picking vehicle can not reach these hights. Hence, this results in unnecessary vehicle changes. And the stock is unreliable (15). When the stock is not correct, the order-picker has to go to the logistics office to retrieve a new location. Hence, the order-picker has to travel from the picking location to the office and then back to a picking location to continue picking its order.

1.3.2 Storage space capacity problems

The storage space capacity of B-Living's warehouse is not sufficient to integrate all Mars & More stock into the Hengelo warehouse (16). The main causes of this problem are the inefficient storage of stock (17) and the storage of items that are not or barely sold (18). The locations and bins are not optimally designed for the products of B-Living (19) and storage and not replenishing non-full pallets (20) both cause this inefficient storage. It is even so that the WMS does not automatically assign non-full pallet locations to pick from. Hence, for some SKUs there are multiple non-full pallets in the warehouse that can be assembled to empty locations. Unreliable stock (15) is a problem that affects both the order-picking process as well as the storage process. Storing items that are not or barely sold is caused by the fluctuating trends and demand of the collections (22). This problem is not influenceable. However, the sales department does not actively sell these old collections (23) and many items are stored in the warehouse but are not even up for sale anymore (24).

There is a core problem which is connected to 8 out of 10 problems that are established. Solving this core problem will (partly) solve the problems that resulted in the observed problem. Hence, there is currently no storage strategy that allocates SKUs to locations efficiently (25).

1.4 Research goal

The research goal is set to tackle the observed problem of B-Living's logistics department not being able to operate the additional logistics activities of Mars & More with their current order-picking process and storage capacity. This goal can be obtained when the core problem stated in the previous section is solved. Hence, the following research goal is formulated:

The goal is to find adaptations in the storage process and warehouse design at B-Living Hengelo that improve the order-picking efficiency.

1.5 Research Design

The main research question is as follows:

How can the current order-picking efficiency be improved by adapting the storage process and the warehouse layout dimensions?

To answer this main research question, the following five research questions and the approach on how to answer these questions are formulated:

1. *What is the current situation of the logistics department at B-Living Hengelo?*
   Chapter 2 discusses the current situation at the warehouses of B-Living regarding…
    a. the overall operations of B-Living
    b. the warehouse resources that are used for the operations
    c. the storage process
    d. the order-picking process

e. the KPIs that are currently established

2. *What literature can support the improvement within the logistic department that support our research?*
   Chapter 3 describes our literature review and discusses scientific methods and tools on the following subjects:
   a. Warehouse characteristics and warehouse decision making
   b. Storage systems
   c. Warehouse design and product allocation
   d. Storage methods
   e. Reshuffling the SKUs and their locations
   f. Optimisation techniques
   g. Warehouse key performance indicators

3. *How can we improve the order-picking process and increase the warehouse storage efficiency?*
   Chapter 4 and 5 propose interventions that improve the order-picking process and increase the warehouse storage capacity resulting from the current situation analysis and the literature review. We separate both chapters as these chapters address different solutions which both contribute to the order picking efficiency and warehouse utilization efficiency.
   a. What alternatives are relevant to improve the order-picking process?
   b. What different storage methods are useful to store the products of B-Living in the Hengelo warehouse?
   c. What alternatives are relevant to better allocate the products to pick locations?
   d. How do the explored alternatives score on the case criteria?
   e. On the basis of these scores, which alternatives are worthwhile to examine as interventions in a simulation study?

4. *How can we validate and test (a combination of) the interventions applied to the different cases?*
   Chapter 6 evaluates the proposed interventions discussed in chapter four and five on the key performance indicators using a simulation study in case of each of the following interventions:
   a. What dimensions are most efficient to the functional area
   b. Which SKU to assign to which functional area
   c. Which storage method and policy to use to allocate the SKUs within the functional area
5. *How is B-Living able to integrate the findings within the current processes?*
   Chapter 7 elaborates on the implementation of the proposed interventions

1.6 Scope

Not all factors and variables can be taken into consideration due to time and data limitations. This research focuses on the internal logistics activities of B-Living. Hence, this research focusses on the logistic processes of storing the incoming goods and order picking. Out of scope are the logistic activities receiving and shipping and the value adding activities at the assembly station. This research also focuses on the order-picking output as the storage capacity output can be solved partly by solving the core problem and the other part can be solved by taking rather simple actions such as actively selling or disposing the out-of-collection items.

The Mars & More processes and SKUs are also out of scope as the acquisition of the company is a motive for this research, but not the core problem that causes the logistics inefficiencies of B-Living. B-Living has two types of outbound shipments which are courier and truck shipments. In Chapter 2 we elaborate on these shipment types to indicate the current situation at B-Living. However, the courier flow which is linked to the Mars & More flow is left out of scope as this flow will be integrated into the Mars & More flow. An area within the warehouse will be assigned to the courier and Mars & More flow. Which area is out of scope for this research is indicated in Figure 4. From this figure can be seen that the areas that are in scope are the 'narrow aisle' area and 'wide aisle', referred to as storage area and picking area respectively within this report.

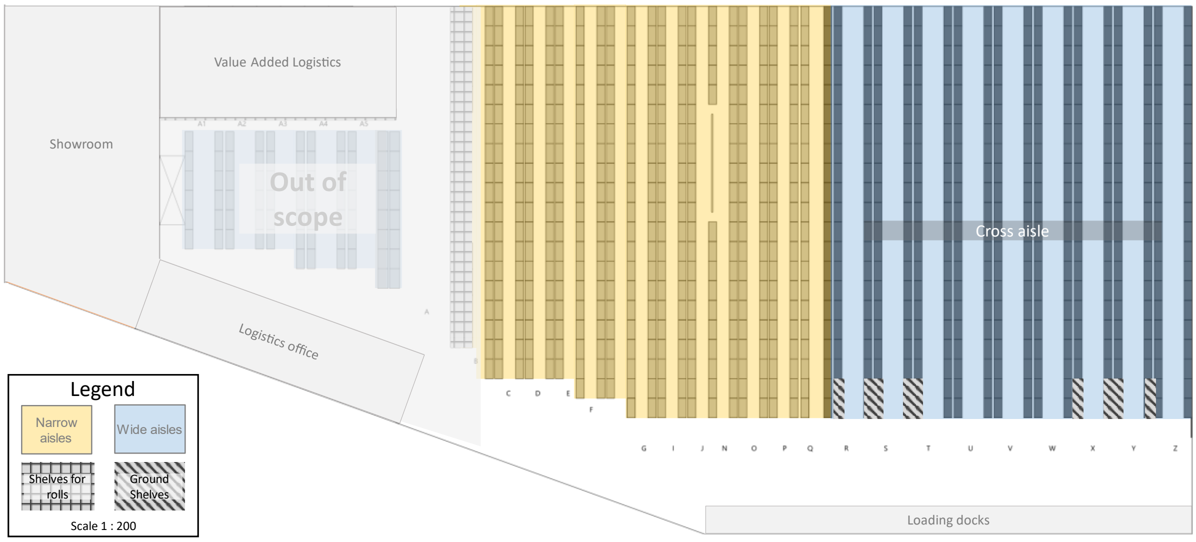

Figure 4 In-scope warehouse map

Finally, a proportion of the SKU collection is used due to data limitations. There is a 'Collection' product group of which most data that is required is known. The other product groups are 'Delete', which are items that are not sold anymore, 'Current Season', which are SKUs that are sensitive to trends and fashion. The latter product groups are out of scope due to their lack of data availability and insecure future demand.

1.7 Problem context summary

This chapter introduces the research by discussing the history of the company and the merger of two home decoration wholesalers in 2020. This merger caused inefficiencies to the logistic processes that up-to this day are not solved. The acquisition of Mars & More highlighted these inefficiencies as a problem which disables the logistics department to integrate the Mars & More logistics activities in the warehouse of B-Living. All inefficiencies are established within a problem cluster that concluded that there is one core problem which relates to 8 out of 10 inefficiencies. The core problem is that there is no storage strategy that allocates the SKUs and replenishes the SKUs efficiently. This problem resulted in the following research goal:

The goal is to find adaptations in the storage process and warehouse design at B-Living Hengelo that improve the order-picking efficiency.

To reach the goal of the research the current situation of the logistics department at B-Living is examined in Chapter 2. Thereafter, literature research is conducted in Chapter 3. In Chapter 4 and 5 we discuss the design of the research model that is able to find the storage process and warehouse design adaptations. Chapter 6 discusses the results of this design. How the model and the results from the model can be used by B-Living is elaborated on in Chapter 7. Finally, conclusions and recommendations are discussed in Chapter 8.

Within the research we scope due to time and data limitations. We used the product group 'Basic Collection' as the sample set because its data availability. We also limit the processes to the internal processes storage and order-picking as involving all other processes would make the problem to complex to solve within the time master thesis' frame.

2 Current Situation

This chapter analyses the current situation of the logistics department at B-Living. This chapter starts by elaborating the overall operations in Section 2.1. Thereafter, the resources that support the distribution activities of B-Living is described in Section 2.2. Section 2.3 elaborates on the supply of B-Living and the internal logistic activities that are currently executed during the storage process. The current outbound logistic process order-picking and the B-Living 's demand of SKUs is described in Section 2.4. And at last, the key performance indicators that are currently used and the conclusions of the current situation regarding the problem statement are formulated in Section 2.5 and Section 2.6 respectively.

2.1 Overall operations

The overall operations of the logistics department of B-Living are to receive and store items in the warehouse and distribute the items to the customers. In Section 1.1 we mentioned that this overall operation can be subdivided into four main processes receiving, storage, order-picking and shipping.

A trailer or container with the supplier's incoming SKUs arrives at the warehouse in Hengelo and is allocated to a loading dock. The incoming items are then unloaded based on their shipment type. Within trailer shipments, the incoming SKUs are always carried by pallets. Hence, the trailer shipments can directly be unloaded with pallet trucks. The incoming items that are transported via container shipments are not packed on pallets as container space is expensive. The incoming SKUs should therefore be unloaded on pallets first. The unloading of a container is physical work and is mostly executed by temporary workers.

After unloading the received items, the inbound employees check the items by taking a sample and inspecting the item and its quality. When the correct item is received and the quality is sufficient, the inbound employee places the SKU at a location or on a shelf within the warehouse based on what the inbound employee thinks is a good location for that SKU. A scanning device is used to register the item and its location for the warehouse management system (WMS).

Customer orders are transformed to pick lists by the administrative officer. The pick lists contain order lines that are to be picked. Each order line represents the purchased item and its quantity and the specific location to pick from. The order picker picks the entire pick list as it is not possible to order pick one pick list with multiple order pickers simultaneously. The shipment type determines the order-picking process. Small orders which do not transport per pallet are shipped by courier DPD. Order picking these pick lists enables order pickers to batch pick lists to pick up to four orders simultaneously. These orders are then prepared for shipment by putting the items of that order in a box and apply shipment labels to that box. Customer orders which do require pallet transportation are consolidated and when picked completely, the items are checked, the pallets are reorganised, sealed and labelled before being shipped to the customer or to the logistic partner. These logistic activities are displayed in the process flow of Figure 5. More detailed process flows of the inbound logistic processes and the outbound logistic processes are described in Section 2.2 and Section 2.3 respectively.

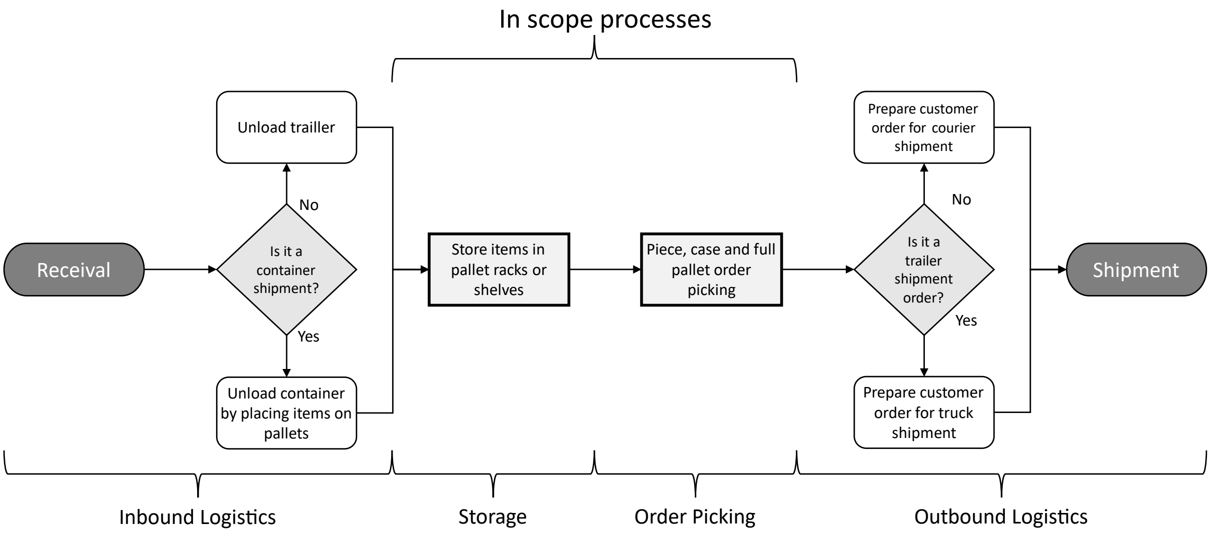

Figure 5 Logistics activities process flow

2.2 Resources of the logistic department

The logistics department uses resources to operate the activities discussed in Section 2.1. In Subsection 2.2.1 the current layout of the warehouse and information about the building is presented. Information about the storage locations is discussed in Subsection 2.2.2. Which warehouse management system (WMS) B-Living uses and some remarks on the application of the WMS is elaborated on in Subsection 2.2.3. In Subsection 2.2.4 the machinery that is used for warehousing purposes is described. And at last, Subsection 2.2.5. describes the logistics department's staff.

2.2.1 Warehouse information

The warehouse of B-Living which is located in Hengelo has 10,000m^2 surface and the ceiling has a height of 9 meters. The warehouse in-houses the storage areas containing 14,471 locations, the showroom, offices above the showroom, the assembly station, the logistics office and the loading docks in front of aisles N-Z. The WMS divides the storage areas of the warehouse into zones that corresponds to the layout of the warehouse. Figure 6 shows the warehouse including the assigned zone codes. Each zone represents their own product groups and functions. The 'Bulk Glass' and 'Bulk Textile' zones contain conventional pallet racks with small aisles. These locations are designed for bulk storage and thus full pallet movements. The 'Pick Wide' zone contains conventional pallet racks with wide aisles and a cross-aisle. This zone is designed for order picking as the wide aisles' widths allow vehicles to pass each other and therefore enable multiple vehicles to operate in the same aisle simultaneously. The 'Other' and 'Pick Foil' zones are assigned to store resources such as boxes, seals and foil that are used for ancillary purposes.

Figure 6 Warehouse layout with storage zones

The area with small aisles is designed to store bulk and the area with wide aisles area is designed for order-picking. As replenishment and reshuffling is not part of the logistic activities, order pickers still pick from the area with small aisles and the wide aisle area still has bulk storage. Elaboration on these storage and order picking processes is formulated in Section 2.3 and 2.4 respectively.

The zones whose data is reliable enough to analyse are the 'Bulk Textile', 'Bulk Glass' and 'Pick Wide' zones. Currently, these warehouse zones have a utilisation rate of respectively 92.28%, 94.79% and 78.19%. An expert assumption with regards to the utilisation rates of the other zones is at least 90%. Hence, the utilisation rate is high and therefore does not grant a lot of space for peak periods.

2.2.2 Storage locations

The storage type and dimensions of the storage location are different for each zone code as some of the zone codes are assigned to certain product groups. B-Living uses conventional pallet racks of three euro-pallets width, one euro-pallet depth and a maximum rack height of 7.5 meters for aisles A-F and 7 meters for all other aisles, as two different pallet rack brands are used. Items that do not meet these measurements are stored in special locations. In total, there are 14,471 storage locations of which 96.30% are assigned to pallet storage and 3.70% of the locations are assigned to shelf storage.

Pallet storage system

The dimensions of the conventional pallet locations all have the same width and depth of one euro pallet, respectively 0.8 and 1.2 meters. The height of the locations and the height of the bins vary for each aisle. The purchasing department of B-Living has a policy that incoming pallets have a height limit of 1.3 meters in order to stack two pallets in the trucks. However, receiving pallets with heights of over 1.3 meters is sometimes necessary or more beneficial due to customer preferences, SKU measurements or bulk discounts. The bins of the warehouse therefore have different height dimensions. Table 1 shows the different bin heights and the percentage of total bins that measure these corresponding heights. The top rack locations occupy the bins on top of the pallet racks at 7 meters or above. The height of these locations is limited by the ceiling which is at 9 meters high. What relation these bins have to the pallet heights is discussed in the current situation about storage of the inbound logistics in Section 2.3.

Table 1 Bin height and the percentage of the total number of bins that correspond to these bin heights

Bin height	% Of total bins in warehouse
0.5 meter	0.87%
1.5 meter	26.15%
1.8 meter	19.38%
2.0 meter (of which 19.92% are top locations)	44.06%
2.5 meter	8.47%
3.0 meter	1.07%
Total	**100%**

SHELF STORAGE SYSTEM

SKUs which are not beneficial to store on pallets are stored on shelves. Such as small rolls of fabric or foil with a length of 0.8 meters. These SKUs are stored in the fabric and foil roll shelves (rack AV) that is displayed in Figure 9a as the stock of these rolls are too little for pallet storage. The number of locations that are assigned to these shelves sums to 145. Another product type that requires special location are large rolls of foil and fabric. These storage locations relate to three-meter-deep shelves for rolls larger than 1.2 meters (the standard euro pallet length). Figure 9b shows that the ground locations of aisles A and B are connected and therefore capable to store items larger than 1.2 meter up to 3 meters. In total these locations amount to 288 shelf locations. Leftover pieces or cases are stored at shelves at ground locations in the first four pallet racks of aisles R-T, X and Z as is displayed in Figure 9c. The inbound employee places items on those shelves when leftover pieces are found in bins of that aisle. A total of 108 locations are assigned to these shelves. However, most of these items are never sold as most SKUs are only sold per case. Elaboration on these outbound items is described in Section 2.4.

Figure 9a Shelf storage for small rolls

Figure 9b Side view of shelf storage for large rolls

Figure 9c Shelfs for leftover pieces

2.2.3 Warehouse Management System

Microsoft Dynamics is used as the Enterprise Resource Planning (ERP) system of B-Living. This system connects purchasing orders and sales orders with the warehouse management system (WMS) that is used by the logistics department to support the logistic activities of B-Living. Data that is used for this WMS is transferred by scanning devices.

The WMS is crucial for order picking because no SKU is stored at an assigned location. Hence, what arrives and leaves the warehouse and each movement should be exactly tracked to have a working process. Although each movement is to be registered, experiences show that B-Living 's stock is unreliable. Unreliable stock is one of the problems as described in Section 1.3. Resolving unreliable stock is a non-value-adding process that is time-consuming for the order-picking process and therefore a cause of inefficiency. Elaboration on what effect unreliable stock has on the order-picking process is described in Section 2.4.

The WMS transforms customer orders into pick lists with small adjustments of the administrative employee. This pick list contains details on what to pick, how many pieces to pick and what location to pick from. The customer order determines what items to pick. How many items to pick at what location is based on the available stock at the locations. The WMS uses prioritisation parameter to determine the picking location. Each location has a priority code that is a manually imported parameter. This also implies that pick lists may contain multiple locations per SKU pick. Order details do not consist of other information such as item weight, volume and quantities per case.

2.2.4 Machinery

Machinery and vehicles are operated by the logistic department to support B-Living 's internal logistic processes. As different activities require specific handlings, multiple vehicles and machines are present in the warehouse. Two seal robots, two weighing machines and one cleaning machine represent the machinery of the warehouse. The seal robots and the weight measuring machines are part of the control stage during the outbound logistics process. In addition to these machines, internal logistics vehicles are used to execute the inbound, storage, order-picking and outbound processes.

To support the inbound logistics process, electric pallet jacks and pump pallet jacks are used to unload the truck. These pallets are then stored with small aisle reach trucks and wide aisle reach trucks into the pallet racks. The order picker then operates the high-level order picker, the wide aisle pallet truck and the small aisle pallet truck to assemble the customer order depending on the picking location and volume of the pick. The order-picker accordingly uses the electric pallet jacks to check the order and prepare it for shipment during the outbound process.

As pallet racks reach heights of 7.5 meters and aisles do not have the same widths. Operating storage and order picking activities in this environment requires in total 8 different types of internal transportation machines. Which machines are used, a description of the machines, what the machines are used for and the quantity of each machine that is currently available in the warehouse is shown in Table 2.

Table 2 Internal logistics vehicle information

Machine	*Description*	*Used for*	*Qty*
High Level Order picker	Man-up pallet truck, where both pallet and person can reach up to 7m	Piece/collo order picking	9
Rider electric pallet Jack	Electrical pallet truck jack can be driven	Ground pallet transportation	3
Walking electric pallet jack	Electric pallet jack which is operated by walking	Ground pallet transportation	2
Order assembly truck	Vehicle that can carry two pallets simultaneously	Ground piece/collo order picking	4

Reach truck small aisles	Reach truck with a seven-meter reach that is able to pick pallets on both sides in small aisles	Pallet storage in pallet racks and pallet picking	2
Reach truck wide aisles	Reach truck with a seven-meter reach that can only pick pallets in wide aisles	Pallet storage in pallet racks and pallet picking	3
Forklift trucks	Pallet truck with a reach of 5 meters	Pallet storage in pallet racks and pallet picking	2
Pump pallet jack	Nonelectric pallet jack	Ground pallet transportation	10

2.2.5 Logistics department staffing

The logistics department staff 21 employees consisting of 3 truck drivers for in-/outbound logistics, 7 order pickers for regular transport, 1 order picker for courier transport and 5 employees working at the assembly station. In Figure 10 the structure of the logistic department staff is shown. During the Covid-19 pandemic, the logistic department started working in groups to minimise the risk of contamination during start-ups and breaks. Surprisingly, this change showed increasing warehousing performance and it is thereafter decided to remain a two-shift department each working 8 hours every Monday to Thursday. The first shift starts at 7.30 AM and the second shift starts at 8.30 AM. On Friday, the entire department starts at 8.00 AM and finishes at 3.00 PM. Hence, the full-time employment is 38 hours per week. During weekends and national holidays, the logistics department is not operating.

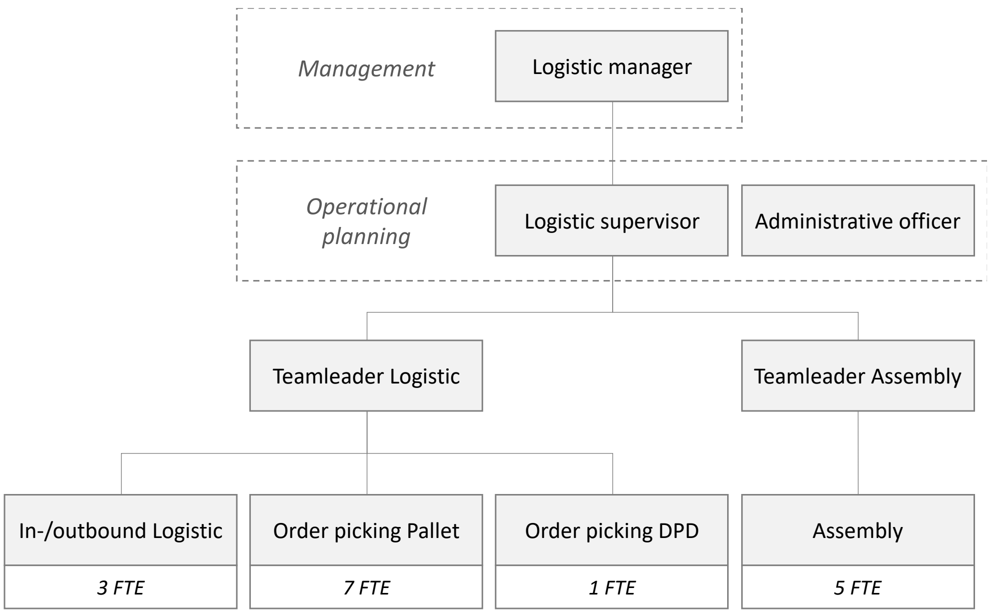

Figure 10 Logistic department staff structure

An interesting statistic which is causing problems for the logistic department especially during peak periods is the sickness rate. Over a period of 10 months from January until October 2022, the average sickness rate was 9.99%. This is surprisingly high as the average sickness rate in The Netherlands in the first half year of 2022 was 5.9% according to Statistics Netherlands (CBS).

One of the core problems is working overtime during peak moments as described in Section 1.3. as the order-pickers are sometimes not able to finish their workload in regular working hours. Upscaling staff for order picking is difficult as operating 6 different vehicles is required for the order picking process and operating these vehicles requires specific certificates. This factor is rarely taken into consideration in the existing literature and therefore with the current employment scarcity a problem for the logistics department. New employees are trained to achieve these certificates, but this training process takes a couple of days. Upscaling is only necessary during peak moments when additional order-picking staff is required for a short period. Hence, B-Living finds it not worth the effort to train a temporary worker for these short periods. On the other hand, B-Living fails to find employment agencies that employ people who possess the required certificates and are willing to work temporarily for B-Living.

Spreading the workload across the staff members is also not possible. The assembly staff does not have the required skills to help with logistic activities, the courier order pickers do not have the skills to do pallet order picking and the workload of the in-/outbound logistics during peak periods does not allow the in-/outbound logistics staff to order pick as well. It is therefore not possible to upscale the order picking capacity for short periods during peak periods, which results in working overtime being the only option to finish the workload. Analysis of working overtime during 2022 is elaborated on in Appendix A.

The logistics department experienced that hiring temporary workers to order-pick is not possible. The temporary workers which meet the order-pick requirements mentioned in the previous alinea are scarce and not willing to work for a short period (at most a week). However, temporary workers are hired for unloading container shipments as this process is time-consuming and physically exhausting labour which is easy to learn and execute. Therefore, temporary workers are deployed to execute this work and decrease some of the workload for the regular logistics staff. In 2022, temporary workers were deployed 30.70% of working days for unloading container shipments only.

2.3 Inbound logistics

This is an informative section that elaborates on the current situation of the inbound logistics of B-Living and highlights the issues and important findings that were found during the analyses of the supply of SKUs and the storage process of B-Living. The inbound logistics consists of the supply of goods that is explained in Subsection 2.3.1. and the operational activities receiving and storage which are elaborated on in Subsection 2.3.2.

2.3.1 Supply

B-Living counts a total of 129 suppliers that supplied B-Living at least once between January 2021 and September 2022. These suppliers are from 38 countries of which 22 countries are located within Europe and 16 outside Europe. B-Living ’s office in India arranges the supply from Asia and the procurement department of B-Living in Hengelo arranges the purchasing activities of suppliers from other continents. The supply flow of B-Living can be divided into the container shipment flow and the truck shipment flow. All supply that is shipped from European countries is transported by truck and all supply from other continents is transported by ship.

The surface of a general truck used for supplying B-Living can store up to 33 euro pallet places and the height of the truck is 2.8 meters. Hence, the truck can store up to 66 pallets that are stackable and have heights up to 1.3 meter, which is the desired height of the purchasing department (Discussed in Section 2.2). SKUs from this truck are currently stored at locations within the warehouse with the quantities per pallet used by the supplier. These quantities per full pallet are a parameter in the ERP that is used for purchasing and sales purposes.

The container sizes differ per purchasing order. Most shipments are transported with 40-foot containers, but it sometimes occurs that a 20-foot container or even a part of a container is used for B-Living’s supply. To utilize container space efficiently, the supplied cases are stacked from the bottom to the top of the container to avoid transporting air. This is cost efficient but requires the extra handling of sorting and stacking on pallets in comparison to truck shipped supply. Since no robust stacking rules apply to this process, the quantity per pallet differs for each pallet. Hence, the quantity per pallet parameter is not accurate.

Whilst truck shipments arrive almost daily, container shipments arrive once, rarely twice per week. However, the workload and volume per container shipments are generally much more than truck shipments. In 2022, 62.69% of received procurement orders were truck shipments and 37.31% of receiving shipments were container shipments. Whereas 52.69% of the workload in terms of storage movements derives from the container shipments and 47.31% from truck shipments. The total workload for container shipments requires even more additional work compared to truck shipments as all items are randomly stored in the container and are to be sorted and placed on pallets before being able to store them.

Figure 11 displays the storage movements per week over 2022. Within this data analysis, the distinction between container and truck shipments has been made. This graph shows that the receiving workload fluctuates a lot for both shipment types. E.g., week 31 of 2022 required a little less than 100 movements and the next week (week 32 of 2022) required more than 500 movements, which is five times as much.

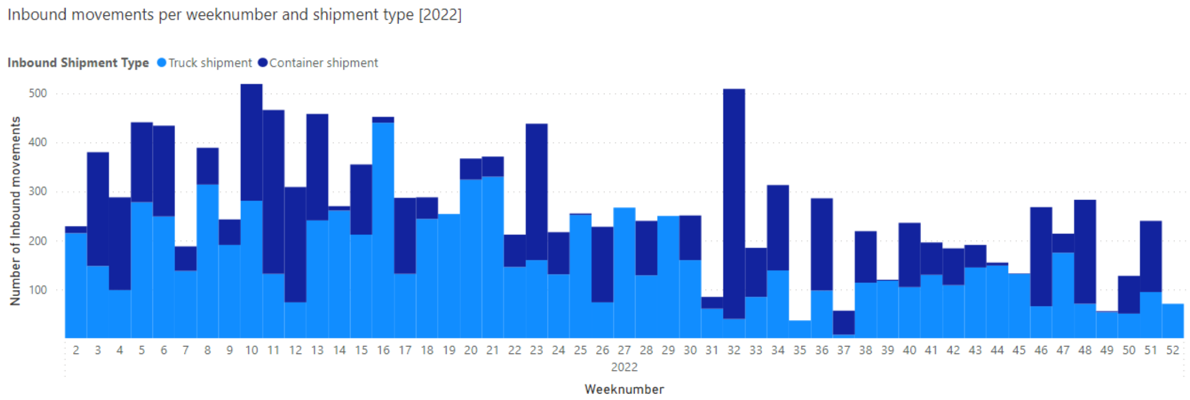

Figure 11 Inbound workload per week number in 2022

This analysis gives insights in the workload over the year and shows the fluctuation of inbound workload per weak. From this graph can be seen that in the first half of the year much more inbound movements occurred.

B-Living's collection consist of 4 main product categories. This collection originates from the two merged companies. Blyco's products can be subdivided to the categories textile, big and small rolls of cloth, door curtains and some slow-moving product types grouped as categories other. Hakbijl has one product type which is glassware. The share of inbound movements per product category is shown in Figure 12. This figure distinguishes the truck and container shipments and displays a total of three pie charts of which one shows the share of inbound movements disregarding the type of shipment. From this analysis can be concluded that the inbound of glassware products are responsible for more than 2/3 of the total inbound movements share.

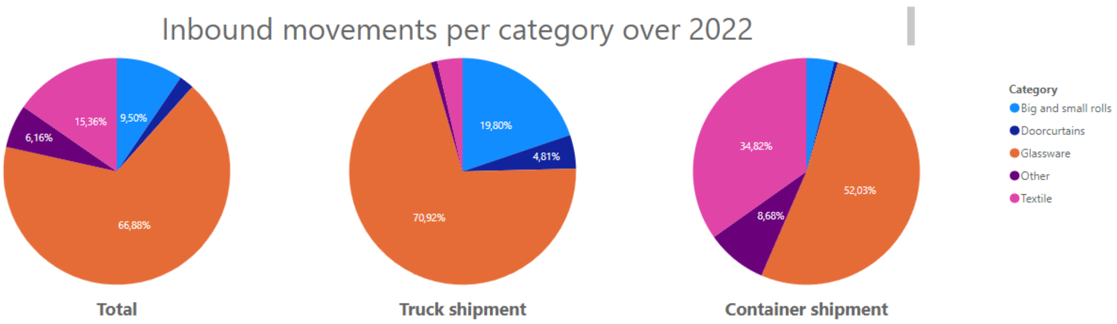

Figure 12 Inbound movements per product category and shipment type in 2022

B-Living has a manufacturing plant in Poland for painting glasswork operations that is called Logomar. This plant is considered a supplier of B-Living for this research as this production plant is responsible for 17.40% of the inbound volume for B-Living in 2022. With this volume, Logomar is considered B-Living 's top supplier as it supplies about 2.5 times as much as the second-best supplier in terms of volume. As can be seen from Figure 12 the glassware category 'DECO GLASS AND ACC' has a little over 2/3 share in terms of storage movements. Then the textile category 'HOMEDECO TEXTILES'. The other categories all sum up to 18.43% of share in storage movements. These graphs shows that the main product categories are still textile and glassware as is discussed in Chapter 1. The share of inbound movements per product category over the year is displayed in Figure 13.

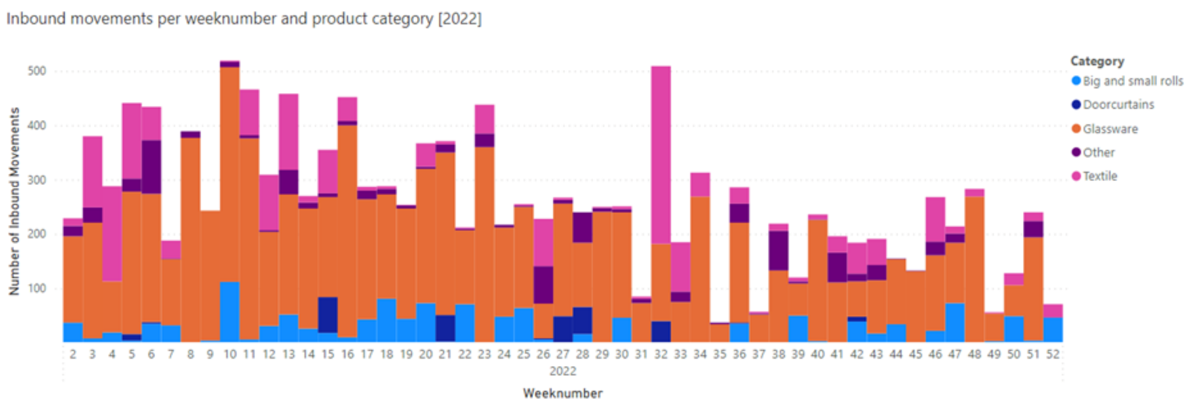

Figure 13 Inbound movements per category and week number in 2022

2.3.2 Storage

After unloading, checking for quality and counting, the inbound employees who are responsible for in & outbound logistics store the pallets to locations within the warehouse. The inbound employee uses the small aisle reach trucks when the pallet is stored in the small aisle pallet racks. Otherwise, the inbound employee uses a reach truck as these trucks are faster and more user-friendly to store the inventory to locations.

The WMS of B-Living is used to control stock levels. Items and their quantities are scanned onto the locations once they are stored by the inbound employee. At what location to store the SKU is based on what the inbound employee thinks is a suitable location. The logic at which location the SKU is stored is elaborated on later this section. However, the inbound employee is free to store the item at any place. Hence, experience and knowledge about the warehouse are important traits for the inbound employees as efficient storage of items depends on their logic.

Storage system

The current storage policy is to place the small roll items on the small roll shelves and the large roll items on the large roll shelves. All other receivals are stored in pallet bins, where the policy is to place the pallet based on whether it is a bulk or pick pallet. Hence, when 6 pallets of a single SKU enter the warehouse, the inbound employee considers part of this inventory as pick pallets and the remaining as bulk pallets. The width of the narrow aisles does not allow two vehicles to operate in the same aisle. Hence, it is not desirable to piece and case order pick in narrow aisles. Bulk pallets that are not supposed to be used for piece and case order picking is therefore placed at a location in the narrow aisle pallet racks. Pallets with items that are to be piece or case picked are placed at a location in the wide aisle pallet racks.

Whether to place the items in the narrow or wide aisle pallet picks depends on the product type. From the merger in 2020, the policy of storing glasswork at the left side of the wide aisle area and textile products at the right side of the wide aisle area still holds. This policy is constructed to support stackability and therefore an efficient order picking path going from the left side to the right side in the picking area. For the narrow aisle areas it is the opposite. The left and right side are divided in zones to consolidate both product groups. There was no strategy behind dimensioning these zones other than dividing both product groups within a reasonable area for the total inventory.

Another policy is to place identical items near each other, of which the thought is to minimise the distances between these items. The inbound employee uses two scanning devices during the storage process. One scanner is used to scan the item onto the location it is stored. The other scanner is used to track the location of the same item that is already stored in the warehouse. Hence, when an item is to be stored, the inbound employee checks whether that item is already stored in the warehouse. When the item location is known, the inbound employee places the SKU inventory at that location or at an empty location near the location of the found item.

The stored items should be allocated according to these policies. However, these policies are often not taken into consideration during the storage process as this takes more time than randomly store the items. Nonetheless, the storage process steps including its policy decisions are displayed in the flow chart of Figure 14.

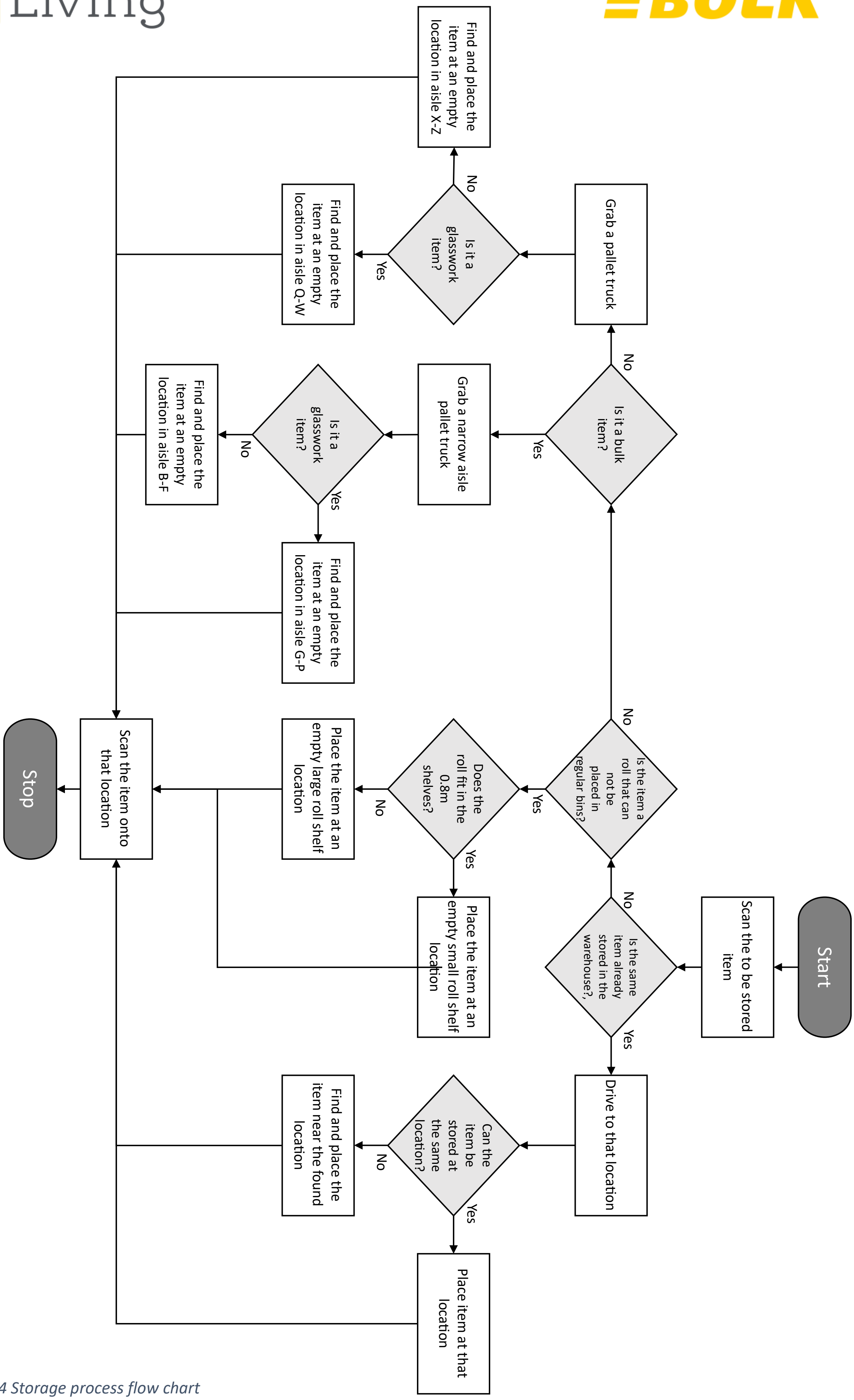

Figure 14 Storage process flow chart

The majority of pallets that enter the warehouse have a maximum height of 1.3 meters as this is a requirement for B-Living's suppliers. Surprisingly, the bin heights differ from this requirement. Table 3 shows the percentage of total bins per corresponding height and the percentage of received pallets with that corresponding height and an additional 0.15 for storage and retrieval space (thus a pallet with a height of 1.4 meters will be counted for as 1.55 meters and therefore not fit the 1.5-meter bin). Hence, it can be concluded from this graph that storing 'air' is inevitable with the current designed bin heights. In total the average amount of height that is not occupied when storing a pallet is 0.63 meters, which is half the average pallet height of 1.26 meters. Hence, it can be concluded that the pallet bin heights are not dimensioned efficiently.

Table 3 Bin height and inbound pallet height comparison

Bin height	*% Of total bins in warehouse*	*% Of received pallets that fit bin height*
0.5 meters	0.87%	0.38%
1.5 meters	26.15%	89.27%
1.8 meters	19.38%	0.35%
2.0 meters (of which 19.92% are top locations)	44.06%	1.80%
2.5 meters	8.47%	7.75%
3.0 meters	1.07%	0.45%
Total	**100%**	**100%**

STORAGE MOVEMENTS

An analysis of the storage movements is conducted to find the locations that are mostly used for the storing of pallets. Generally, the incoming goods arrive per full pallets. Rolls of fabric and foil and some exceptional items do not arrive per full pallet and require extra handling to store as these items are stored by hand instead of by reach truck. As these flows consist of different items and different handling, both incoming flows are analysed based on the storage movements within the warehouse. The storage registration data from 2021 until September 2022 is used for these analyses.

The storage per height analysis from the order picking data of January 2021 until September 2022 is displayed in Figure 15. The number of locations for the 0-, 1.5-, 3-, 5- and 7-meter height bins are respectively 2,662, 2,556, 2,611, 2,468 and 2,170. This figure shows both the analyses of the actual picks per bin height and a normalised display, as the number of locations is not equally distributed over all heights. This analysis shows that the bins in the middle of the pallet rack are surprisingly underrepresented. This is unexpected, as with the current storage policy we would expect an equal distribution over all heights as working from the beginning of the aisle towards the end would assume that a higher bin would be stored before storing in any bin at the next pallet rack. Another more applicable distribution than the current distribution would be that the distribution descends from bottom to top as it is more logical for the inbound staff to store the items at the bottom of the pallet racks first before storing them at higher layers.

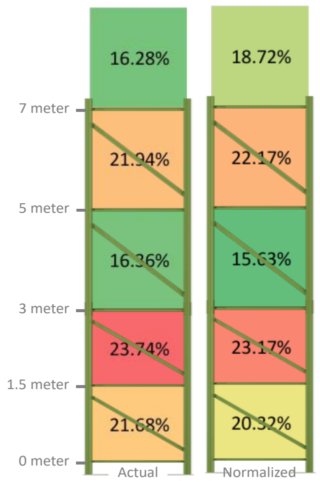

Figure 15 Full pallet Storage per bin height frequency

Figure 16 shows a heatmap of B-Living 's warehouse with the frequency of full pallet storage per location generated from the same dataset as the storage per bin height analysis of Figure 15. The red marked pallet racks are pallet racks which show the most storages frequency and the green marked pallet racks show the pallet racks with the least storage frequency. The heatmap displays that aisles R and S as the most represented aisles for the storage of full inbound pallets. The items that are mostly stored in these aisles are glasswork items from top supplier Logomar as is elaborated on in Subsection 2.3.1. Interesting about this heatmap is that the narrow aisles, which are designed to store especially bulk pallets, are almost never used for full pallet storage.

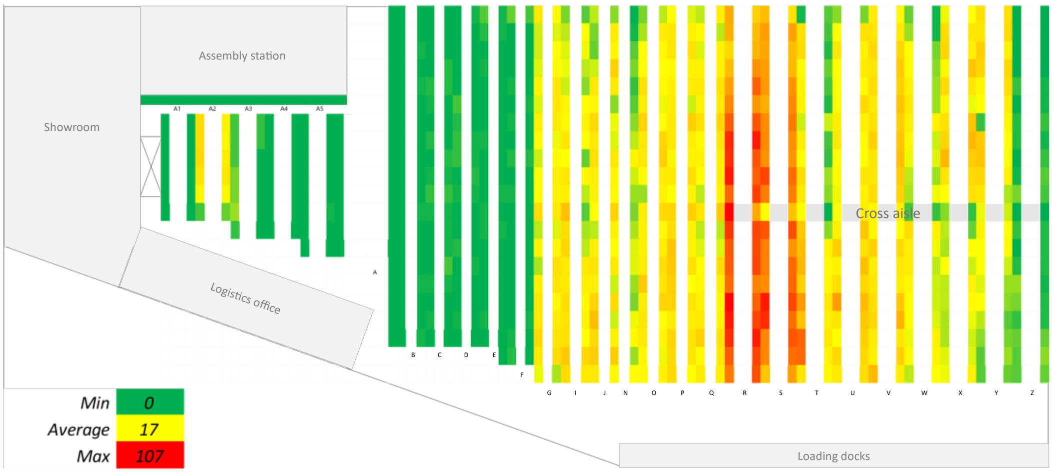

Figure 16 Warehouse heatmap of full pallet storage movements

The same analysis from the same dataset is conducted for the piece/case storage. The storage per bin height analysis is displayed in Figure 17. This analysis shows a more expected distribution in comparison to the full pallet storage per height analysis, where the bottom locations are more popular than the top locations and the popularity of bin height storage is descending from bottom to top.

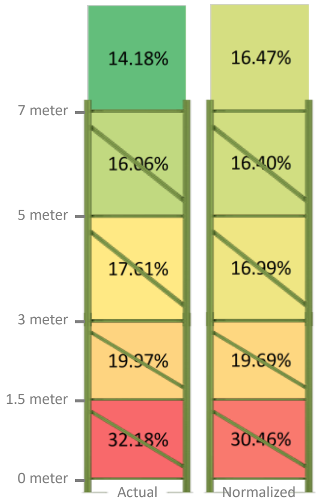

Figure 17 Storage per bin height frequency

Figure 18 shows a heatmap of B-Living 's warehouse with the frequency of piece/case storage per location. This analysis shows that piece/case storage are mostly represented in the foil and roll storage locations and that the other storages are almost equally distributed over the warehouse storage locations. The overrepresentation of rolls and foils makes sense as rolls and foils are never supplied per full pallet. It is also interesting to see that the number of piece/case storage are well spread over all other locations.

Figure 18 Warehouse heatmap of piece/case storage movements

2.4 Outbound Logistics

This section discusses the current situation and the issues regarding the demand of B-Living and the order-picking process. Information and analyses about B-Living 's demand is described in Subsection 2.4.1. The outbound logistic activity order picking is elaborated on in Subsection 2.4.2.

2.4.1 Demand

The week number demand graph of Figure 19 shows that the overall outbound of B-Living vary from 1,000 to 3,500 movements per week. The graph shows that there are a lot of fluctuations per week showing peaks at the end of the winter period and the end of the summer period (from week 7 and from week 34 respectively). Another finding is the difference between truck and courier shipment movements. The graph shows that the outbound movements per truck shipments are much larger than the outbound movements of the courier shipments except from the summer period. During the summer period (week 16 to week 32) the number of outbound movements per courier shipments increases while the number of outbound movements per truck shipment show a decreasing trend.

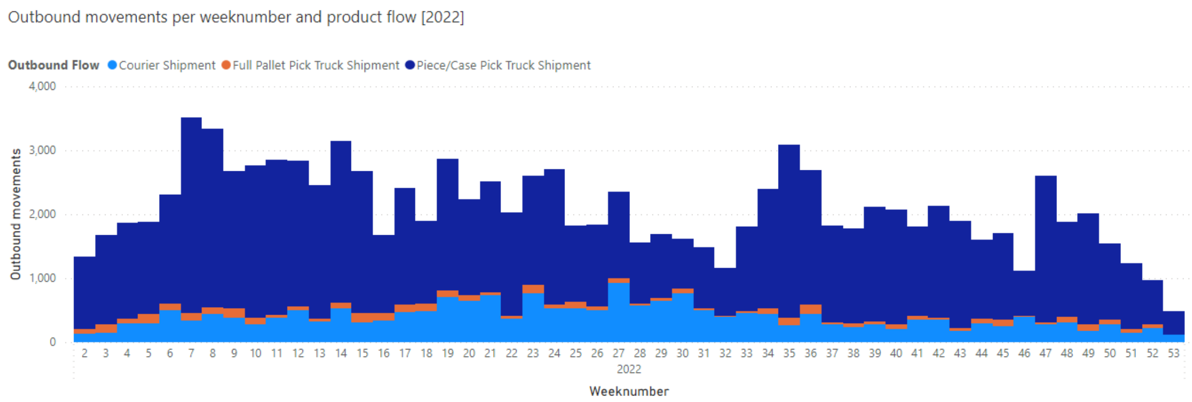

Figure 19 Weekly demand per shipment type

An insight into the product types per shipment type is shown in Figure 20. This graph shows that the truck shipments product category demand differs from the courier type product category demand. The main product category within the truck shipment type is glassware which is responsible for more than half the total outbound movements. 'Homedeco Textiles' which are textile products is responsible for over a quarter of the outbound movements. The graph of courier shipment outbound displayed in Figure 20 shows that this flow consists of 87.15% of product types door curtains and rolls of foil and PVC.

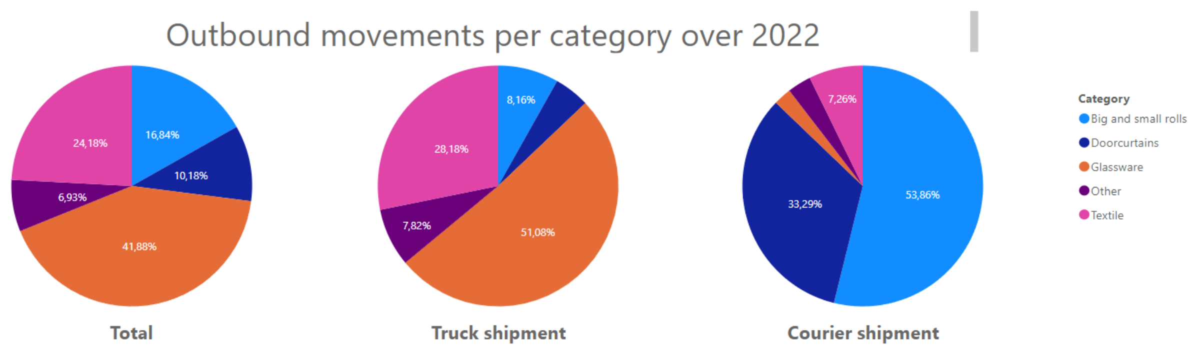

Figure 20 Outbound movements per product category for truck shipment and courier shipment

We can conclude that the two shipment types are different in terms of product demand and workload. It can also be concluded that B-Livings demand is influenced by seasonality. We therefore constructed a graph displayed in Figure 21 that shows the outbound movements per week over the year 2022 per product category. Analysing the top 5 categories it can be stated that door curtains have a peak demand in the spring and summer period and that it is barely sold in the autumn and winter period. Textile and Glassware show peaks during the autumn and winter periods. This graph gives an impression of the product groups of B-Living and how these groups contribute to the workload of the order-pickers.

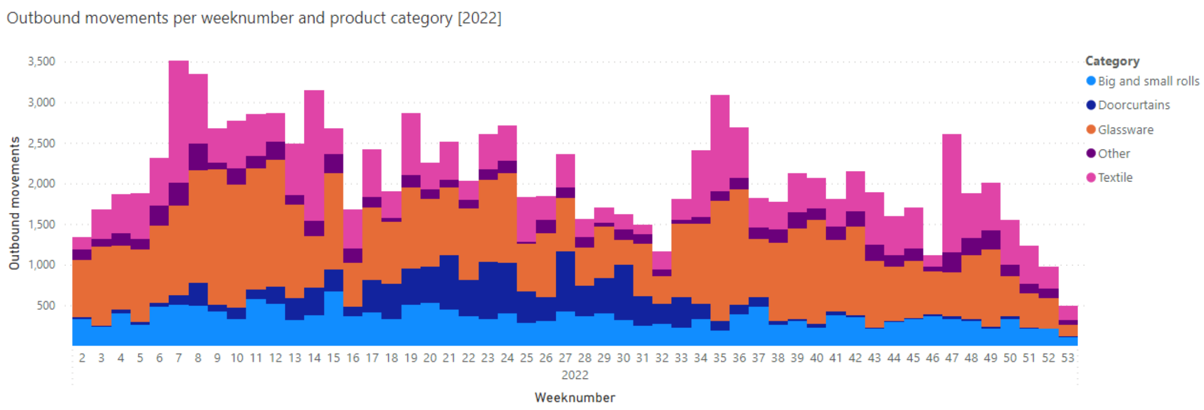

Figure 21 Weekly demand per product category 2022

SKU THROUGHPUT

To have information about the throughput of B-Livings products we analysed the SKUs that are currently stored in the warehouse on their demand. A total of 8,4481 SKUs is currently stored in the warehouse. What is interesting about the inventory of B-Living is that most of the items are barely or not sold. This is due to new collections and fashion trends. To cope with this problem, B-Living works with item attribute codes. The main item attribute codes that are used are ‘Collection’, ‘Current Season’ and ‘Delete’. The ‘Collection’ items are items that are not really sensitive to fashion trends and can also be referred to as the basic collection items. The ‘Current Season’ items consist of items that are currently fashionable, but when the season is finished, the demand on those items will decrease. Items which are sensitive to seasonality but not sensitive to fashion trends such as basic door curtains are assigned to the ‘Collection’ class. When the demand is low and the item is not sold anymore, the SKU receives the ‘Delete’ item code.

Figure 22 shows a graph of the number of times SKUs that are currently stored at the warehouse are picked in the past year. In this graph is shown that SKUs of B-Living are not picked very often. 37.62 % of relevant SKUs are stored in the warehouse, but not sold. 16.18% of relevant SKUs are sold only once in the year 2022. Hence, more than half of relevant SKUs sold one time at most in the past year.

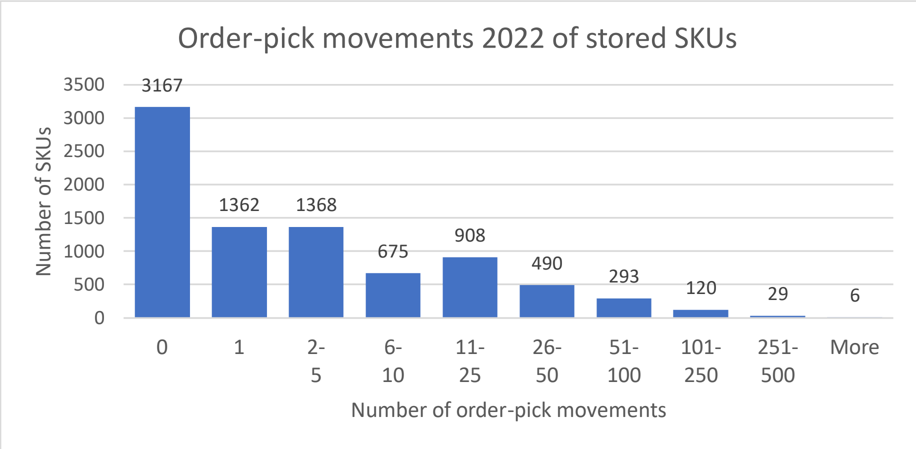

Figure 22 Order-pick movement frequency of all stored SKUs in 2022

In total 5,251 SKUs are sold the past year. Classify these items into five classes, where class E represents the slow-moving items and class A-D represents the fast-moving items. When an item is picked on average once every ten or more working days, the SKU is characterised as a slow-moving item. This results in class A SKUs representing the top 5% of total picks, class B SKUs representing the next top 10% of total picks, class C SKUs representing the next top 15% of total picks, class D SKUs representing the next top 34% of total picks and class E, the slow-moving SKUs, representing the remaining 36% of total picks. For each class, the number of SKUs, the number of maximum picks that class, the number of minimum picks that class, the number of SKUs that are sensitive to seasonality and the number of SKUs that are not sensitive to seasonality are shown in Table 4.

Table 4 Classification of SKUs based on pick frequency

Class	*% of top picks*	*#SKUs*	*Max #picks*	*Min #picks*	*Seasonality*	*No Seasonality*
A	0-5%	12	841	241	9	3
B	5-15%	62	241	117	14	48
C	15-30%	169	116	67	38	131
D	30-64%	828	67	26	393	435
E	64-100%	4,280	25	1	6,120	285

The table shows that 20.02% of SKUs are classified as A, B, C and D SKUs, which are SKUs that are sold on regular basis (on average at least once every two weeks on average).

2.4.2 Order picking process

A customer places an order which is then converted by WMS and the administrative employee to a warehouse pick order. Paper pick lists are then printed by team leader logistic and handed to the order pickers individually one order at a time. The size of the order determines the shipment type. Either the order is shipped by truck or by courier. Small orders which are not profitable using pallet transportation are shipped by courier shipment and pallet transportation orders are always shipped by trucks. Relationships between the type of shipment and the type of order picking are illustrated in Table 5. When dividing the orders, a distinction is made between truck and courier shipment orders. Hence, a courier shipment order picker only picks pieces and cases, whilst the truck shipment order picker might have to pick full pallets. In 2022, the ratio between truck and courier shipment orders have been 82.74% and 17.26% respectively.

Table 5 Order picking flow per shipment time

	Piece picking	*Case picking*	*Pallet picking*
Truck Shipment	X	X	X
Courier Shipment	X	X	

Quantities on the pick lists are indicated per pieces. The order picker uses a basic calculator to calculate how many cases should be picked from that item. Full pallet orders are mostly highlighted by the administrative officer.

The courier shipment order picking process is the same as the piece and case order picking of truck shipment orders. However, the only difference is that multiple courier shipment orders can be picked by one order picker simultaneously. The order picker uses a cart containing four separate areas to pick up to four different orders. The order picking process of both truck and courier shipment orders is described in the flowchart displayed in Figure 23.

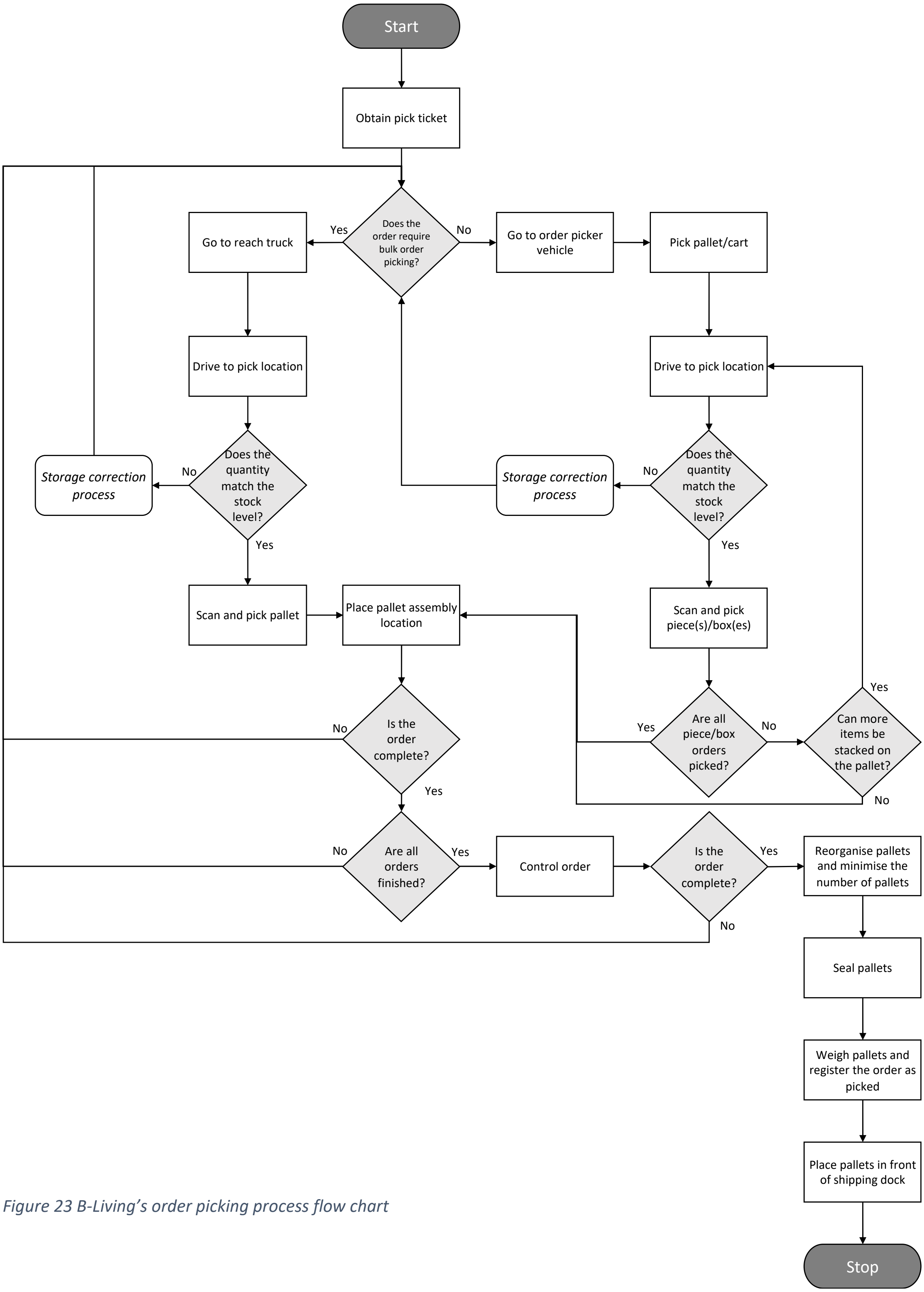

Figure 23 B-Living's order picking process flow chart

2.4.2.1 Order picking issues

In the problem statement of Chapter 1 we stated some of the problems that contribute to the observed problems of which some have relations to the core problem 'there is currently no storage strategy that allocates SKUs to locations efficiently'. Some of these problems concern the order-picking process.

Pick lists are handed out by the logistics supervisor based on the features of their order details and characteristics of the order picker. Picking orders containing heavy items will mostly be handed out to physically strong order-pickers and picking orders containing picks from locations at 7.5 meters will mostly be handed out to tall order pickers. Another factor is the skills of the order picker. Pick lists containing full pallet picks are handed out to order pickers who have reach truck certificates.

When the stock level of a location does not match the WMS stock level, order pickers have to go to the logistics office to indicate to the supervisor that there is a difference between the physical and digital stock level. Both the supervisor and the order picker are then going back to the corresponding location to check if there is a difference and what the difference is. After checking the difference, they both go back to the logistics office to correct the system and to find another location with that item. The order picker then picks the item at a new location and continues picking its order. This system correction process requires many movements and is therefore time consuming for the order picker. This process however occurs often as B-Living 's stock is unreliable. Stock reliability is difficult to measure, but an expert estimation is that one out of ten order lines involve different stock levels.

The order picking locations on the pick lists are sequenced ascending. Hence, the route of picking according to the sequence of the list is going from front to end of the aisle starting at the most left aisle location of the pick list to the upmost right aisle location. Truck shipment order picking can either be pallet or piece/case picking. When an order picker starts with its picking list, pallet picking is done at the beginning. So first, the order picker picks the full pallets with the reach truck. Then the other picker changes its vehicle to an order picking vehicle to pick the piece/case pick orders. Reasoning behind this policy is to minimise the vehicle changes.

Another order picking policy for piece/case picking is picking according to stacking order. As the products of B-Living contain mostly glasswork and textile, the order of stacking is important. There is a big variety in strength and weight of the pieces and cases of B-Living s' items. Heavy items should not be stacked on top of fragile pieces or boxes as the pallet might collapse or the products might get damaged. The pick list does not indicate information which determines the strength and weight of the product. Hence, this policy requires knowledge and experiences of the order picker. Reasoning behind this policy is to minimise the damage of the products and minimise the workload of restacking the pallet.

Order lines with the same items are picked sequentially. A picking list may contain two order lines of the same article of which the sum of quantities does not add up to a full pallet or more than a full pallet. The WMS selects the locations based on location priority. Hence, the location at which the SKU is stored with a high priority code is always automatically allocated by the WMS. The administrative employee sometimes changes the picking locations to decrease the number of movements. Hence, when a full pallet is ordered, the WMS allocates the location with the highest priority code first disregarding the quantity that is on that location. Hence, most of the time the WMS allocates multiple locations to the full pallet pick.

2.4.2.2 Order picking movements

The order picker receives its picking list at the beginning of aisle M at the left side of the loading docks. Then the order picker travels to its picking locations to pick the entire order. When pallets are stacked, the order-picker consolidates these pallets at the ending point in front of aisle Z near the sealing station (indicated with O). When the order is picked completely, the order-picker prepares the order for shipment and starts again at the starting point at the starting point I. An example of a picking route in the warehouse is shown in Figure 24.

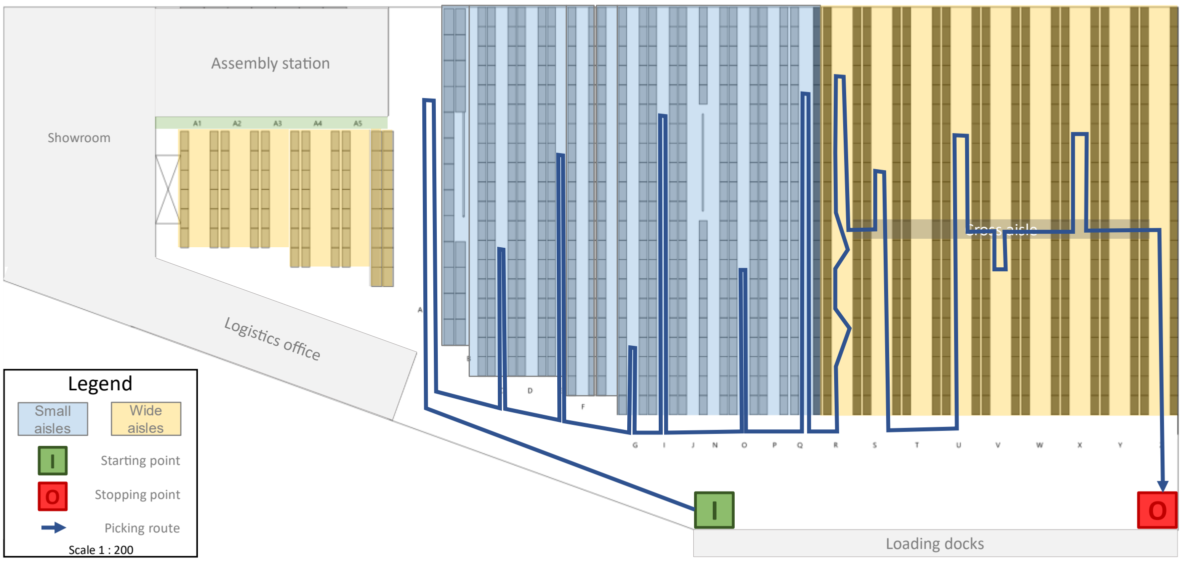

Figure 24 Picking route example

The routing of an order is important to the order picker as the traveling times between locations has a big impact on the total order picking time. The example route in Figure 24 shows a route which has a structured path starting at the left side of the picking areas and ending at the right side.

To indicate the inefficient storage and therefore inefficient order-picking movements we analysed the movements per location. Within this analysis we made a distinction between full pallet picks and piece/case picks as these types of picks require different vehicles and different handling. As discussed earlier this section, the amount of piece/case to full pallet movement ratio is approximately 20:1.

Figure 25 shows a heatmap of order picking, where each location is highlighted with a colour and each colour corresponds with the order picking frequency at that location. The colour scale is from red to green, where the locations which are highlighted red are picked from the most and locations highlighted with green picked from the least. Interesting about this graph is that aisle A, R, S and T shows a heated area. Aisle A is dedicated to Big rolls SKUs as these locations are shelves. Aisle R and S are stored with glassware products. And aisle T is dedicated to door curtains. This map also shows that the picking frequencies are evenly distributed over the other locations.

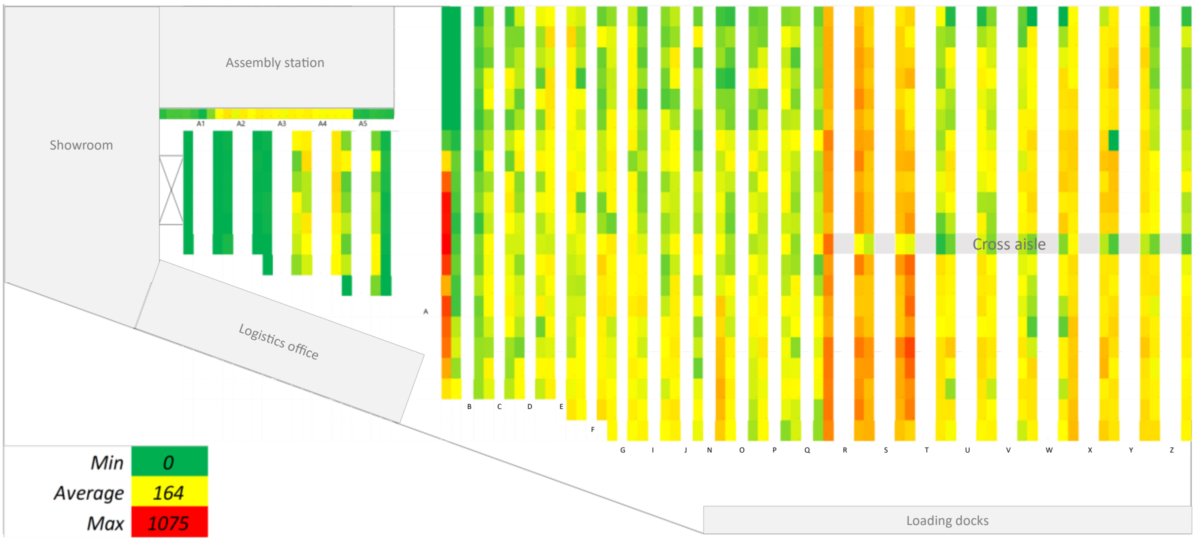

Figure 25 Order picking heatmap for truck shipment per location of 2022

To indicate the picking frequency at the different height locations, we analysed the number of picks per location height for both piece pick and pallet pick. These distributions of these order picks are visualised in Figure 26. From this figure can be seen that the picks per height is evenly distributed for the bottom four location heights with a small difference between locations above and below 3 meters. The top locations, which are difficult to pick from as is elaborated on in Subsection 2.4.2.1. show the least number of picks. However, picking from these locations is still hold a normalised share of 7.65%, which is undesirable.

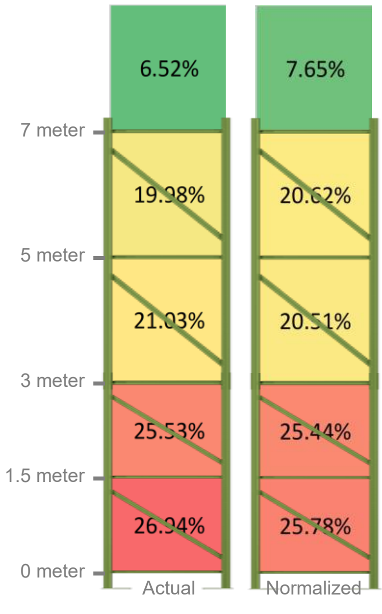

Figure 26 Height order picking heatmap of 2022

2.5 Key Performance Indicators (KPIs)

KPIs are currently not used by the logistics department for planning or performance measures. Overall revenue and incoming shipments are the only indicators that are currently used. The overall revenue is used to indicate the workload of the order-pickers and incoming shipments is used to indicate the inbound workload. For the description of the current situation in this chapter, revenue is not used to indicate the workload of the logistics department as revenue is typically not an accurate indicator of workload in comparison to storage and order-picking movements.

Planning uses the incoming shipments to measure the workload one week prior and uses the overall revenue to measure the workload for the next day. Hence, there is little insight into the order-picking workload of the department over a longer period than the next day and no insight into mid-term and long-term planning for the entire logistics department. Experience is the only indicator, as the department assumes that May, September, October and December are busy months in terms of order picking, which is not specifically true looking by means of inbound data and demand data respectively displayed in Figure 11 and Figure 21 respectively.

The performance of the logistics department is determined based on whether the orders are finished and the incoming shipments are stored in the warehouse from the previous day.

2.6 Conclusions

This chapter describes the current situation of the logistics department and concludes that there are multiple inefficiencies regarding activities in the warehouse. This is surprising as we conclude that the logistic departments resources show potential for an efficient warehouse. The layout of the warehouse has multiple areas with multiple purposes. Two storage systems are used that both fit specific product categories best as textile rolls are stored in shelves and SKUs that are packed in cases or boxes are stacked on pallets and stored in pallet racks.

Within the pallet rack areas a distinction is made between a storage area and a picking area. The difference between those areas are the aisle widths. The aisle widths of the storage area are designed to maximally utilise the area with storage locations. This resulted in 33% more storage capacity. The drawback of this area compared to the picking area is that storing and receiving pallets from locations within these aisles are only possible with a small-aisle reach truck, there is no cross-aisle which can be used to move between aisles and that it is not possible for multiple vehicles to operate in a single aisle The picking area has wide aisles and a cross aisle and does not have the drawbacks of the storage area. However, the perks of both areas are only beneficial when the areas are used to their purposes.

We conclude that the WMS, the machinery and the staff do not lack capacity and can be used to improve the order-picking process when used correctly. These resources are currently not used efficiently as the processes are unstructured.

The efficiency of this process is determined by the location of the to be picked items. Hence, where to place the SKUs is important to the order-picking process. We conclude that the current storage strategy is dividing the glassware products and the textile products. The SKU that is received from the supplier is then partly stored at the picking area and partly stored at the storage area. However, there is no replenishment, and therefore picking from the storage area is inevitable which is proved in Figure 25 and Figure 26. We also conclude that most of the stored SKUs within the warehouse there is no to little movement. It is therefore interesting to research placing these SKUs at more efficient locations. Hence, we use literature to research improving the storage process and using the warehouse resources to its full potential in Chapter 3.

3 Literature review

The current situation described in Chapter 2 concluded that multiple aspects of the current way of working should be addressed to improve the order-picking process and the storage capacity of B-Living. This chapter consults literature review that designs a conceptual framework for our research. First, literature about the characteristics of a warehouse, overall warehousing issues and decision-making on how to improve the warehouse activities is elaborated on in Section 3.1. Literature review on strategic level decisions about storage systems is described in Section 3.2. Literature review on the tactical-level decisions of dimensioning the warehouse areas is described in Section 3.3. Section 3.4 and Section 3.5 describes literature review conducted on operational level about storage methods and reshuffling respectively. Section 3.6 elaborates on optimisation techniques and the optimisation techniques that are used in this research. In Section 3.7, key performance indicators about warehousing performance are discussed. And at last, conclusions about the used literature are described in Section 3.8.

3.1 Warehouse characteristics

The internal logistics activities of a warehouse can be distinguished into the four basic processes receiving, storage, order-picking and shipping (Gu et al., 2007) as described in the current situation of Chapter 2. Rouwenhorst et al (2000) developed a framework which provides a structured approach to decision-making at the strategic, tactical and operational levels. Rouwenhorst et al (2000) state that each individual decision influences the constraints and requirements on lower levels. It is therefore important to research decision-making sequentially starting with strategic level decisions, tactical level decisions and operational level decisions in that order. Within these three levels, the framework shows decisions that are to be made on different characteristics of a warehouse.

Rouwenhorst et al (2000) discusses the warehouse processes, resources and organisation as the three angles on which the warehouse may be viewed. The processes of a warehouse consist of the receiving, storing, order-picking and shipping processes. This structure is also used for the description of the current situation in Chapter 2. Where the *receiving* process consist of the activities of handling the arrived items until it awaits the next process. *Storage* of these items may be placed in two types of areas. The reserve area, which is the most economical type of storage. And the forward area, which is used for easy retrieval by an order picker. As is described in Section 2.1, currently all items are placed in a reserve area as B-Living does not allocates a forward area. Hence, replenishment, which is moving items from the reserve to the forward area is currently not applicable. Elaboration on forward area and replenishment is described in Section 3.3. Retrieving the items from the storage location and transporting these items to the sorting and consolidation process is referred to as *order picking*. This process can be performed manually or (partly) automated. Currently, this process is performed manually and order consolidation and sorting are executed while picking the customer's order. Elaboration on the order picking process is described in Section 2.4. Finally, the orders are checked and prepared for shipment during the *shipping* process. For this research, the focus lies on improving the order-picking process and storage capacity by finding improvements in the storage process and the order-picking process. Hence, adaptations and decision-making on the storage and order-picking processes are discussed and the receiving and shipping processes are not discussed. The receiving and shipping processes are nevertheless still in scope as these processes might be influenced when changing the storage and order picking processes. Based on these processes, Rouwenhorst et al (2000) proposed a framework on each strategic, tactical and operational level, where different decisions are made on the organisation of the warehouse and the warehouse resources.

3.1.1 Strategic-level decision making

Each decision on the strategic level influences the constraints and requirements on the tactical and operational levels. Hence, improvements on the strategic level are important to research first.

Decisions on this level are considered to have a long-term impact. There are two main groups of warehouse decisions: warehouse organisation decisions and warehouse resource decisions. The warehouse organisation decisions concern the design of the warehouse. In order to improve the order picking process, Heragu et al (2005) discusses four order picking flows concerning cross-docking or reserve and/or forward areas. In Section 3.3 we elaborate on these warehouse design alternatives. Whether to batch orders is also one of the questions that are to be answered on this strategic level. Currently, the customer orders that are shipped by courier are batched by means of obtaining and picking multiple pick lists simultaneously. Customer orders that are shipped by truck are not batched as one order picker collects one complete customer order.

Warehouse resource design decisions on this level considers the systems that are to be used to improve the processes. Rouwenhorst et al (2000) describe the use of storage systems to improve the storage and order-picking process. Elaboration on storage systems is described in Section 3.2. The organisation and resource decisions are interrelated as the decisions influence each other. What decisions are applicable to B-Living depends on the technical capabilities and what decisions are interesting for B-Living depends on the economic considerations. The technical capabilities are discussed in Chapter 4 and the economic considerations are optimised and tested by means of optimisation techniques and a simulation study in. More literature about optimisation techniques is discussed in Section 3.6.

3.1.2 Tactical-level decision making

Decisions on the tactical level follow up the strategic level decisions. Tactical level decisions are medium term decisions that are based on the outcome of the strategic level decisions. These decisions do not have as much impact as the strategic level decisions but do require investments. Hence, these decisions should not be reconsidered too often. Tactical level decisions that are applicable to this research is the dimensioning of the pick and storage zones. The paper of Heragu et al (2005) is used as the basis of this section. Heragu et al. (2005) describe basic flows regarding the handling of items in the warehouse in the functional cross-docking, reserve and forward areas. Section 3.3 elaborates on the space allocation of the warehouse and the dimensioning of these functional areas.

Another tactical-level decision regards the methods on how to store and retrieve B-Living s items. The received items at the warehouse are currently stored on pallets randomly in the pallet racks or on shelves randomly at the roll and foil shelves. The independency of placing an item at a random location benefits the utilisation of the warehouse with the usage of the “closest-open-location” rule (Hausman et al., 1976). Other storage methods according to Gu et al. (2010) and Hausman et al. (1976) are assigned storage and class-based storage. By means of simulation and analytical models the random storage, assigned storage and class-based storage are compared by Gu et al. (2007). Hausman et al. (1976) and Graves et al. (1977). The results of these models conclude that assigned storage and class-based storage with few classes show significant reductions in travel time for both single command and dual command AS/RS systems in comparison to random storage (Gu et al., 2010). It is therefore interesting for B-Living to argue which storage method is most desired for the storage and order-picking processes. In Section 3.4 literature review on different storage methods is described in more detail.

3.1.3 Operational-level decision making

This research focuses more on the strategic and tactical-level decisions. However, the operational activities and operational-level decisions are strongly influenced by the decisions that are made in upper levels. Decisions that are to be made on the operational level are concerned with control and assignment issues. Rouwenhorst et al. (2000) formulated these operational-level decisions within their framework. The order-picking operational issues regard batch formation and order sequencing according to the tactical-level decision about batching orders and batch sizes. Other issues concerning the order-picking process on an operational level are the assignment of picking tasks to order pickers, the sequencing of picks per order, the dwell point for idle order picking equipment and the assignment of sorter lanes.

For the storage process, operational-level decisions regard the assignment of replenishment tasks to the logistics staff and the storage plan. Hence, the operational issues regarding storing and replenishing items to free locations according to the storage concept that is determined on the tactical level.

An operational-level decision which is not mentioned by Rouwenhorst et al (2000) about repositioning SKUs by moving them sequentially to improve the warehouse performance (Pazour & Carlo, 2015).Reshuffling is moving and changing the location of items within the warehouse to reduce movements or distance between picks. This activity is used to improve the order picking performance. This is interesting for B-Living as the items are sensitive to seasonality and therefore both fast and slow-moving items depending on the period it is to be picked. Elaboration on literature regarding reshuffling and systems to enable this reshuffling is described in Section 3.5.

3.2 Storage systems

The warehouse of B-Living contains mostly pallet racks and some shelve locations for items which are not stored on pallets as described in Section 2.1. In the new situation, where the logistic activities of Mars & More might be executed by the logistics department of B-Living, another storage system might be efficient. This acquisition increases the share of courier customer orders. This process is different from the truck customer orders. The possibility of designing and using a separate area for courier customer order picking might therefore improve the order picking system. As these orders consist of many different SKUs and low picking volumes, another storage system than pallet racking might be more desired. Deciding which storage system to use can be complex as there are many various storage systems and storage capacity and throughput of the items that are stored in the warehouse influence this decision (Zaerpour et al., 2019).

Zaerpour et al. (2019) compared different manual and automated storage systems and constructed a decision support system (DSS) that supports managers in choosing the best type of storage system. Manual storage systems utilise a combination of labour and handling equipment (Ashayeri & Gelders, 1985). B-Living currently uses only manual storage systems as the order pickers use order-pick trucks to assemble a customer order. According to Ashayeri & Gelders (1985) is automated storage systems on the other hand used to minimise labour as much as possible by substituting equipment capital investment. Currently pallet racks are used and require therefore no investments. According to Zaerpour et al. (2019) is pallet racks the most cost-efficient type of storage system for pallet storage (low capacity and low throughput). The courier flow, however, is currently stacked on pallets to store in pallet rack locations. Storing these items in case/bin storage locations requires a case/bin storage system. Zaerpour et al. (2019) conclude that for a low capacity and medium throughput (courier flow), case flow racking is five times as cost-efficient as the other two types in terms of case/bin storage. Hence, case flow racking might be interesting storage system for the B-Living ’s courier flow.

3.3 Warehouse Space Allocation

Proposing a warehouse design with its functional areas is a strategic level decision. This decision is interrelated with the warehouse product flows and the activities of B-Living

3.3.1 Warehouse product flows

Heragu et al (2005) state that temporary storage and providing value added services are the two primary functions of a warehouse. The area can therefore be divided into the reserve, forward and cross-docking area to achieve efficient execution of these functions. B-Living ’s warehouse and its processes are currently designed for the reserve area storage type. Heragu et al (2005) determined four flows of items that enter and leave the warehouse (see Figure 27). Items that flow through the warehouse by means of flow 1 are cross docked. By means of cross-docking, the item will not be stored at storage locations. Hence, the items enter and directly leave the warehouse reducing handling and movements to and from storage locations. Cross docking provides a fast product flow (Bartholdi & Hankman, 2017). Reserve storage flow regard items that are stored in the reserve area after being received and picked directly from the reserve area before shipment. Reserve storage is commonly used for bulk storage and replenishment of the forward area to ensure high space utilisation (J. P. van den Berg et al., 1998). This flow is the current flow of all B-Living ’s items. Walter et al (2013) state that to reduce labour-intensive and costly order-picking activities, using a combination of reserve and forward areas is implemented by many distribution centres. Where the forward area is used for convenient picking and the bulk area used for replenishment of the forward area and bulk storage (J. P. van den Berg et al., 1998; Walter et al., 2013). This is an interesting approach for B-Living to improve its overall logistic performance. Which product to store in what area is known as the forward reserve problem (J. P. V. den Berg & Zijm, 1999) that is elaborated on in detail in Section 3.5. Products that are received and then directly placed in the forward area follow the fourth flow. This flow is commonly used in supplier warehouses or in warehouses that consolidate large orders (Heragu et al., 2005).

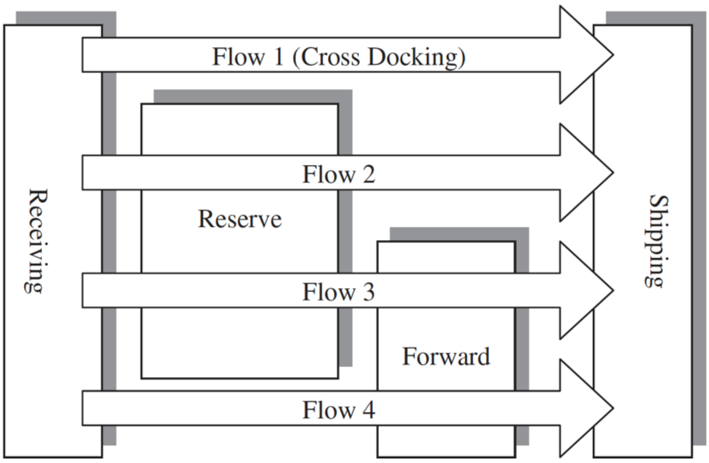

Figure 27 Typical product flows in a warehouse (Heragu et al., 2005)

The items of B-Living move currently according to flow three. This flow is the least favourite flow for the order picking process as picking from the reserve area is most expensive. Proposing other flows for certain items might therefore be interesting to improve thee order picking process. As B-Living has more than 14,000 SKUs with each its own supply and demand, it is assumed that more than one flow applies to the items of B-Living. The mathematical model from Heragu et al (2005) can be used to determine the flow of each item and eventually calculate the size of the functional areas within the warehouse.

3.3.2 Dimensioning the warehouse

In the paper of Horta et al.(2016), it is argued that most literature on warehouse layout design mainly focuses on the storage and order picking of product. As just-in-time delivery is increasing, more cross-docking is operated by distribution centres. This applies to B-Living as well. Cross-docking still occurs rarely, but B-Living is trying to cooperate more with their suppliers to achieve more cross-docking. Especially for B-Living ’s production plant in Poland. This production plant is one of the biggest suppliers to the warehouse. As B-Living is in control over the delivery of this supply, it might be interesting to allocate space to cross-docking as this is currently not allocated to the warehouse.

The mathematical model of Heragu et al (2005) can be used to dimension the warehouse with the requirement of some parameters. The total available storage space is required as input to the model. Another parameter that is required for the mathematical model is the dwell time. This parameter refers to the expected time an item spends on the shelves. The handling cost for each item in each flow is known. The relation between the dwell time and the handling cost is linear. Hence, when the dwell time increases, the handling cost increases as well. The annual demand rates of each item are required. And finally, the storage policy and material-handling equipment are known and affect the handling and storage costs. This mathematical model calculates with by means of linear programming which item should be assigned to which flow and what proportion of total available space should be assigned to the functional areas cross-docking, reserve and forward. The mathematical model formulation of Heragu et al. (2005) and an explanation of the objective value, the parameters and the constraints can be found in Appendix C.

3.4 Storage methods

Storage methods can be divided into the following three groups as is described in Section 3.1.2: random storage, assigned storage and class-based storage. Each storage method has its benefits and characteristics which will be elaborated on in this section.

3.4.1 Random storage

Random storage is the currently used storage method at B-Living. The random storage method implies that each SKU can be assigned to each location within the warehouse (Petersen, 1999). Petersen (1999) states that using the random storage method results in a uniformly utilisation of the warehouse and reduced aisle congestion but that it increases the possibility of larger travel times and longer pick routes in comparison to other storage methods. However, Malmborg (1996) analysed the space and retravel efficiency of random storage in comparison with assigned storage. In this paper Malmborg stated that, when the level of variation in retrieval demand is below a certain level, random storage can yield lower average retrieval costs than assigned storage.

3.4.2 Assigned storage and policies

Assigned storage is the opposite of storing items at random storage locations as every item is assigned to specific locations (Gu et al., 2010). The principle of assigned storage is placing fast-moving items in easily accessible areas. Multiple storing policies regarding assigned storage can be found in literature. For this research, the ABC and cube per order index (COI).

The most well-known storage policy is the ABC-policy. With the ABC-policy items are classified in the three classes A, B and C based on their demand volume, where class A consists of the SKUs with the highest demand volume and class C consist of SKUs with the lowest demand volume (Teunter et al., 2010). Another interesting classification for B-Living is the XYZ- classification. The XYZ- classification classifies SKUs based on the coefficient of variation of each SKU (Scholz-Reiter et al., 2012). The coefficient of variation is the ratio of the SKUs demand standard deviation over a period and its average demand. The study of Sholz-Reiter et al. (2012) integrates the XYZ-technique in the ABC-technique. This ABC-XYZ classification shows might be an interesting classification approach for B-Living, as B-Living has many seasonal influenced SKUs. As weight is an important factor for the order-pickers to sequence their order picks in order to load heavy items on the bottom of the pallet and light items on top of the pallet, it might be interesting to integrate weight into the classification as well. No literature about integrating weight classification to other classification techniques in order to improve the warehouse performances is found.

Heskett (1963) introduced the COI of an SKU as the number of location ratios assigned to the SKU and its pick frequency. Hence, this means that the items with a low ratio of the required storage space to the order frequency are assigned to the locations nearest to the starting and ending (I/O) point. The locations are all ranked based on the distance to the I/O points. The storage location with the lowest f_k is the best location in terms of travel distance. f_k can be calculated by using the following formula with m as the number of I/O points, p_i as the percentage of travel to the I/O point i, and d_{ik} as the distance from I/O point i to storage locations:

$$f_k = \sum_{i=1}^{m} p_i d_{i,k}$$

The most important item is the item with the highest COI. To calculate the most important items, the COI uses the variables S_j as the number of storage locations that are required for SKU j, and T_j as the throughput of SKU j. COI_j which is the COI of product j can be calculated by means of the following formula:

$$COI_j = \frac{T_j}{S_j}$$

A study that revised the optimality COI of Malmborg and Bhaskaran (1990) assignment policy concludes that the COI assignment policy yields an optimal layout.

3.4.3 Class-based storage

Class-based storage is a mixture of both random storage and assigned storage, as it assigns SKUs randomly to storage locations within storage zones according to pick activity (Petersen et al., 2004). Hausman et al. (1976) concluded that class-based assignment policies show significant potential reductions in travel times in comparison to random storage.

Most assigned storage policies can be used within the class-based storage method to allocate SKUs to classes. Hence, the COI and ABC-XYZ techniques can be used to form the classes. Within these classes allocating an SKU to a location within that class is random.

3.5 Reshuffling

Warehouse reshuffling is an approach to reposition items inside the warehouse to improve picking and put-away performances (Pazour & Carlo, 2015). Warehouse reshuffling becomes necessary for some companies as demand of each SKU might fluctuate massively throughout a certain period. B-Living also copes with this problem as the demand of many SKUs are sensitive to seasonality due to the collections and trends. Hence, an SKU can be a slow-moving item for some period and then become a fast-moving item for another period. Dedicate this item based on its demand during a certain period might therefore not be efficient for another period. To this extent, Christofides and Collof (1973) proposed warehouse rearrangement, referred to as the reshuffling concept. As the seasonal collections divide the year in two periods of which fast moving items become slow-moving items and vice versa, it might be interesting for B-Living to have two reshuffle moments per year.

3.6 Optimisation techniques

There are multiple techniques that can be used for optimisation or improvements problems. This section elaborates on linear programming, heuristic repair algorithms, constructive heuristics and metaheuristics.

3.6.1 Linear programming

Mathematical problems can be solved to optimality by using linear programming. This mathematical optimisation technique is a common technique that is used to solve many practical problems as is stated by Buriol et al. (2020). Linear programming uses linear relationships to maximise or minimise the objective functions by using a set of constraints. Without the set of constraints a lower bound is found for a minimisation problem. However, as this solution might not meet all constraints, it is likely that the lower bound solution is infeasible.

3.6.2 Heuristic repair algorithm

The heuristic repair algorithm is a technique that we use to repair an infeasible solution. Cao et al (2023) applied this technique to find and remove conflicted pairs within the solution and remove the conflict by changing the variables. The technique starts with an infeasible solution and applies modifications to the solution until the solution satisfies the set of constraints. We use this technique to find a feasible solution to the flow-to-SKU problem elaborated on in Chapter 4.

3.6.3 Constructive heuristic

Another approach to construct a feasible solution is by applying a constructive heuristic. A constructive heuristic generates a feasible solution by iteratively adding building blocks to the solution step by step starting from an empty or partial solution (Rader, 2010). Rader(2010) states that the basic principles of a constructive heuristic consist of three parts:

1. The incremental approach, which is generating a complete solution one element at a time from nothing.
2. Selection, which is selecting the building block to add to the solution based on a priority function. Greedy algorithm is a constructive algorithm that adds the building block that yields the greatest improvement.
3. No backtracking, which is to not reconsider the added building blocks. Hence, once a building block is assigned it can not be removed or replaced.

This approach is used in Chapter 5 to construct solutions to the SKU-to-location problem.

3.6.4 Simulated annealing algorithm

Approximation algorithms are used to systematically evaluate larger problems. One of the most popular approximation heuristics is the Simulated Annealing algorithm (Delahaye et al., 2019). This technique is used by Heragu et al. (2005) to find good solutions for larger instances as solutions to the warehouse space allocation problem for larger instances require too much computational time to generate with the initial linear programming approach. We use this approach to improve the feasible solution generated with the heuristic repair algorithm described in Subsection 3.6.2.

Simulated annealing starts with an initial solution S_i which is set as the current solution S_c. The best solution S_b is initialised and every time S_c has a better objective value than S_b, S_c is stored as S_b. Each iteration the algorithm considers a neighbour solution S_n and compares that solution to S_c. When S_n has a better objective value than S_c, S_n is accepted and used as S_c. When S_c is worse than S_n, the solution is accepted with a certain probability. Hence, simulated annealing uses a probability at which it accepts or declines S_n as S_c when the objective value of S_n is worse. This probability is based on the temperature of the model and the difference between the objective value of the S_c and S_n.

The temperature T starts at a starting temperature T_{start}, and decreases every k iterations by multiplying T with decrease factor α until it reaches the stopping temperature T_{stop}. To determine the probability of accepting a worse solution, the following formula is used for a minimisation problem:

$$P(T) = \begin{cases} 1, & when\ S_n \leq S_c \\ e^{\frac{S_c - S_n}{T}}, & otherwise \end{cases}$$

Hence, when the temperature gets lower, the probability of accepting worse becomes less likely. The probability of accepting worse becomes more likely when the difference between S_c and S_n are low. The algorithm is summarised in the following pseudo code for a minimisation problem:

$Set\ T_{start}, T_{stop}, \alpha,\ k$
$Set\ T = T_{start}$
$Set\ S_c = S_{start}$
$Set\ S_b = S_c$
$\boldsymbol{while}\ T > T_{stop}$
$\quad \boldsymbol{for}\ i = 1\ to\ k$
$\quad\quad S_n = FindNeighbour(S_c)$
$\quad\quad \boldsymbol{if}\ \exp\frac{\min(S_c - S_n, 0)}{T} \geq randbetween(0,1)$
$\quad\quad\quad S_c = S_n$
$\quad\quad\quad \boldsymbol{if}\ S_c \leq S_b$
$\quad\quad\quad\quad S_b = S_c$
$\quad \boldsymbol{next}\ i$
$\quad T = \alpha T$
$\boldsymbol{loop}$
$\boldsymbol{result}\ S_b$

A good T_{start} and T_{stop} are important to the simulated annealing algorithm performance as is stated by Prepah et al. (2017). A good T_{start} is the temperature at which the acceptance ratio is close to 1. And a good T_{stop} is when the acceptance ratio is close to 0. The acceptance ratio is the ratio at which the S_n is accepted compared to the total number of proposed S_n.

An approach to approximate the T_{start} and T_{stop} is by using the formula derived from Ledesma et al. (2008). The formula is as follows, where Δ is the average difference between S_c and S_n:

$$T_{start/stop} = \frac{-\Delta}{\ln\left(start/stop\ acceptance\ ratio\right)}$$

3.7 Key performance indicators

This chapter described models and theories that improve warehouse performances. However, when these models and theories are to be applied to the warehouse of B-Living it is important to test the performance of the designed layouts and processes. This section describes some KPIs from literature that quantifies warehouse performance and therefore enables testing. A recent paper about a framework for warehouse management systems of KPI evaluations is constructed by Faveto et al. (2021). Faveto et al. (2021) identified KPIs based on systematic literature review, ranks these KPIs based on the frequency they are used in literature and classifies these KPIs based on the impact domains economic, social and environmental. Social and environmental classed performance indicators are out of scope for this research as they do not measure the performance of the storage and order picking processes and the warehouse capacity. However, Faveto et al. (2021) proposed three subclusters that are in scope for this research as they measure the warehouse processes and capacity performances of the proposed interventions and the related cost:

- Generic performance
- Time related performance
- Cost performances

The performance indicators classified per subcluster are shown in Table 6 to 8, where the unit of measure, the relative frequency (f_θ^r), weighted frequency (f_θ^w), global frequency (G_θ) and hierarchy level (S: strategic, T: tactical & O: operational) of the KPIs of the in total 203 reviewed articles are displayed. We want to reduce the time of order-picking and therefore picking time, travel time and waiting time are the most important KPIs for this research as well as replenishment which might be an additional activity.

Table 7 Generic performance indicators (Faveto et al., 2021)

	unit	$f_\theta^r(\%)$	$f_\theta^w(\%)$	$G_\theta(\%)$	
Throughput	*LU/min*	24.14	32.64	91.15	T
Area occupation	*m²*	14.29	39.66	79.59	S
Receptivity	*LU*	20.20	20.49	67.67	T
Capacity Flexibility	-	20.20	16.79	63.01	S
Travel Distance	*m*	17.24	17.54	57.83	O
Resource Utilization	*%*	12.32	19.55	50.15	O
Shelf Occupation	*%*	5.91	5.08	18.64	O
Critical WIP	*LU*	7.39	2.01	17.83	T
Machine Collision	*1/hour*	5.42	1.69	13.36	O
Unoccupied Space	*%*	4.43	2.13	11.87	O
Vehicle Capacity	*LU*	3.45	2.76	10.62	O
Inventory Turnover	*days*	3.45	2.01	9.67	S
Object Misplacement	*%*	3.45	1.88	9.51	T
Selectivity	*%*	3.94	0.94	9.35	T
Positioning Accuracy	*%*	1.97	1.25	5.66	O
Number of Failures	*1/year*	1.48	1.13	4.48	T
Bottleneck Rate	*LU/min*	1.97	0.19	4.32	T
Peak Utilization	*%*	0.99	0.81	3.07	T
Unprocessed Order	*%*	0.99	0.63	2.83	T
Picking Accuracy	*%*	0.99	0.13	2.20	O
Stock Balance	-	0.49	0.19	1.26	T
Warehouse/Exposition	*%*	0.49	0.00	1.02	S

Table 8 Time related performance indicators (Faveto et al., 2021)

	unit	$f_\theta^r(\%)$	$f_\theta^w(\%)$	$G_\theta(\%)$	
Cycle Time	*min*	19.70	36.09	86.31	T
Picking Time	*min*	14.29	35.03	73.75	O
Order Elabor.Time	*min*	14.29	33.33	71.61	O
Travel Time	*min*	19.70	17.92	63.41	O
Queue Waiting Time	*hours*	10.84	11.84	37.38	T
Task Time	*min*	10.84	10.40	35.56	O
Planning Time	*hours*	2.46	21.80	32.59	T
Storage Time	*min*	6.90	8.65	25.19	O
Retrieval Time	*min*	5.91	6.77	20.78	O
Inventory Time	*days*	6.40	4.32	18.72	T
Lead Time	*days*	7.39	5.89	22.73	T
Makespan	*hours*	2.46	6.02	12.68	T
Charging Platform Av.	*%*	2.46	1.44	6.92	O
Packing Time	*min*	1.97	1.57	6.06	T
Warehouse Av.	*%*	0.99	1.69	4.17	T
Charging Time	*hours*	1.48	0.69	3.93	O

Table 6 Cost performance indicators (Faveto et al., 2021)

	unit	$f_\theta^r(\%)$	$f_\theta^w(\%)$	$G_\theta(\%)$	
Management Cost	*€/year*	11.82	14.10	42.26	S
Storage Cost	*€/task*	8.37	6.14	25.09	T
Retrieval Cost	*€/task*	6.40	3.95	18.24	T
Inventory Cost	*€*	3.45	8.08	17.33	S
Holding Cost	*€/day*	4.93	2.57	13.44	T
Direct Labor Cost	*€*	3.45	2.01	9.67	S
Indirect Labor Cost	*€*	1.97	2.26	6.93	S
Maintenance Cost	*€/year*	1.48	0.13	3.22	S
Space Cost	*€/m²*	0.49	0.00	1.02	S

3.8 Conclusions

This chapter describes the used literature for this thesis. We first evaluated warehouse decision making and determined three different levels of decision making, which are strategic, tactical and operational. Within the strategic level decisions we reviewed storage types and concluded that for this research, the pallet bin storage type and the shelf storage type are most applicable to the type of products within B-Living's portfolio. We conclude that for the big and small rolls product group, shelf storage is an effective storage type and that for all other product types, pallet bin storage is an effective storage type.

Within the tactical level decisions from literature we conclude that the order-picking efficiency can be improved by means of three decisions:

1. Make use of product flows and functional areas?
2. Which storage method to apply?
3. Which storage policy to apply?

To find the best decisions for B-Living, we are making use of a heuristic repair algorithm, constructive heuristic and metaheuristic approach. We concluded from the successful application of Heragu et al. (2005) that simulated annealing is a good technique to solve the functional area decision (question 1). The approach to find the decision is elaborated on in Chapter 4. To find the best decision on question 2 and 3 we use a constructive heuristic, as we conclude that this decision does not have to be solved to optimality. The explanation of this decision and the approach for finding the best decisions on question 2 and 3 are discussed in Chapter 5. As key performance indicators we conclude that picking time and waiting time can not be measured and analysed accurately as these times are very different and very dependent by each order-picker. Hence, we conclude that in order to measure order-picking efficiency, traveling time is an effective performance indicator and therefore the main objective. Waiting time while picking the order and the number of replenishments are indicators which we will use for conclusions and recommendation purposes discussed in Chapter 8.

4 Flow-to-SKU algorithm

This chapter addresses the core problem that is formulated in Chapter 2 and elaborates on how to solve the problem by using a mathematical model. First, we describe the problem context in Section 4.1 which elaborates on using the model of Heragu et al. (2005) as the basis of the product assignment model that is used during this research. The model of Heragu et al. (2005) and the modifications that are made to the model to fit the B-Living case we elaborate on in Section 4.2. Section 4.3 elaborates on why we use simulated annealing as our optimization technique to solve the model by clarifying the choices and assumptions that are made, discussing the parameter data that is used and how to obtain that data. The section also discusses the neighbour solutions and the process of generating new solutions by swapping and moving operators and finally the cooling parameters that are used for the simulated annealing algorithm. Conclusions of this chapter are then discussed in Section 4.4.

4.1 Problem context

The goal of the research is to increase the output of B-Living by improving the warehousing activities. The order-picking process is the bottleneck within the warehousing activities of B-Living that causes the entire department to not be able to finish the workload during peak periods. Within the process analysis, we concluded that product allocation is the core problem and we expect that allocating products more efficiently will improve the order picking output.

The layout of the warehouse was designed in 2020 to store bulk at the narrow aisle pallet racks and pick from the wide aisle pallet racks. Hence, the warehouse layout is designed to operate with a reserve and forward area. The movement of products to the warehouse in Hengelo during the merger in 2020 caused this inefficient allocation of products, as the only policy that is currently applicable to product placement is the product type. The companies that merged had both its product types. Hakbijl was a wholesaler of glassware home decoration products and Blyco was a wholesaler of textile home decoration products. The policy that applies to the product placement is to place the glassware products on the left side of the narrow aisle area and on the left side of the wide aisle area and textile products at the right side of both the narrow aisle area and the wide aisle area. Which pallet to place in which area is based on intuition of the inbound employees.

As glass products are heavier, more stackable and therefore first to be put on pallets before textile products, the policy is to start order picking at the left side of the wide aisle area and end at the right side of the warehouse. The layout design of the warehouse and the order picking flow are displayed in Figure 28.

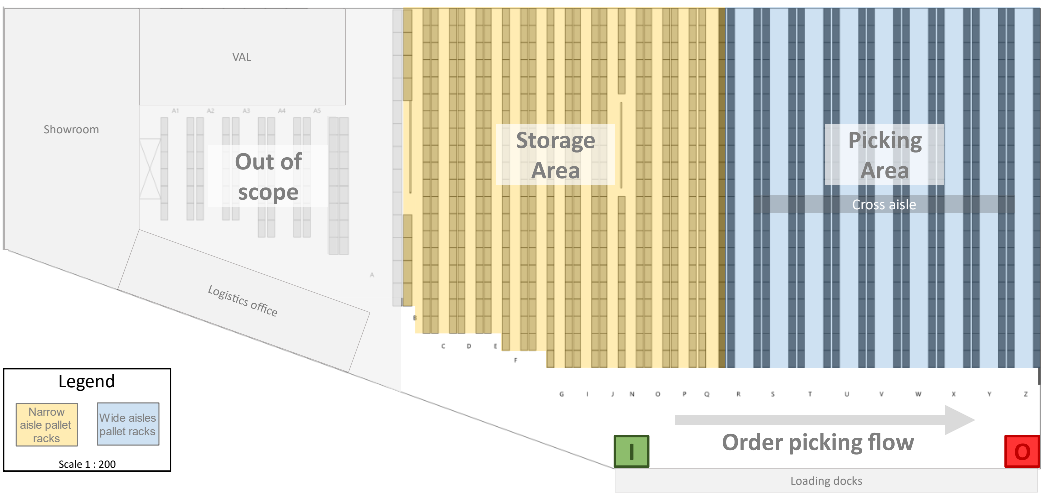

Figure 28 Designed layout and order picking flow of B-Living

The storage area is designed to efficiently use the space for storage purposes as the narrow aisles consume little surface and therefore more pallet racks are stored within this area. The height of the pallet racks is 7.5 meters which is operatable for the reach trucks and allows to place pallets close to the ceiling which is at 10 meters. The picking area on the other hand is designed for efficient order picking flow. This area has wide aisles which allows multiple vehicles to operate in an aisle as they can pass each other and the picking area also contains passages at the bottom two layers of the middle pallet rack sections that form a cross-aisle that can be used to reduce travel times between locations. However, these areas are not used this way as is discussed in Section 2.4. Hence, the layout of the warehouse shows potential for improving the order picking process.

4.1.1 Interventions

The layout of the warehouse is already designed with a picking and storage area. We propose 7 interventions of using the picking area as a forward area. We conclude that the complexity of the order picking process discussed in Section 1.3 causes the logistics department to struggle achieving the required output during demand peaks. Order-pickers require multiple vehicle certificates to order-pick in the warehouse of B-Living as the locations require height picking. Picking from the bottom two locations (the ground location and the location at 1.5-meter height) is possible with a cart or a pallet jack. Hence, when items are picked from ground locations, staff can be upscaled without requiring certificates. The main argument for B-Living to pick from the bottom (two) locations is the ability to use double pallet trucks. As is described in Section 2.2, B-Living already has two double pallet trucks that are currently not used. The double pallet trucks can hold two pallets, hence for multi-pallet orders, the double pallet truck requires less movements to and from the O-point to store the pallet and therefore less traveling time. The results of using a double pallet truck are further discussed in Chapter 6.

We considered the 7 interventions (labelled I0, I2,…,I6) which are tested to find an optimal dimensioning of the picking area. In Figure 29 we illustrate the side view of an aisle for using the locations within the picking area as forward area of I0 to I6. Intervention (I0) is assigning zero locations to the forward area. Interventions I1, I2, and I3 consist of using one, two, and all rack layers before the cross aisle as the forward area. Conversely, interventions I4, I5, and I6 consist of using one, two, and all rack layers of the total picking area as forward area. To test which locations to dedicate to which functional area, we made two distinctions. One of those distinctions is using the entire area (I4, I5 and I6) or using the area before the cross aisle (I1, I2 and I3) for forward order picking and storage purposes. Reasoning behind this distinction is the trade-off between the availability of space for forward area purposes and pick activity at the reserve area. Using the space behind the cross aisle for reserve area purposes might result in better solutions, we therefore want to test these interventions.

The other distinction that is made is about using the bottom layer, bottom two layers or all layers of the pallet racks to dedicate to the forward area. Again, the trade-off between space assigned to the forward and reserve area and picking activity is relevant to this distinction. However, we also want to test using the double pallet truck as is mentioned in the beginning of this subsection. It is preferable to pick from the bottom layer location as this vehicle does not have the ability to go up. Picking from the bottom two layers is also possible as the vehicle contains a step which can be used to pick from 1.5-meter locations, this only increases the order picker handling steps at the locations. Hence, picking from the bottom layer is assumed to show the least traveling times, then picking from the bottom two layers and picking from all layers is assumed to show the longest traveling times. With the proposed interventions we are able to test these assumptions.

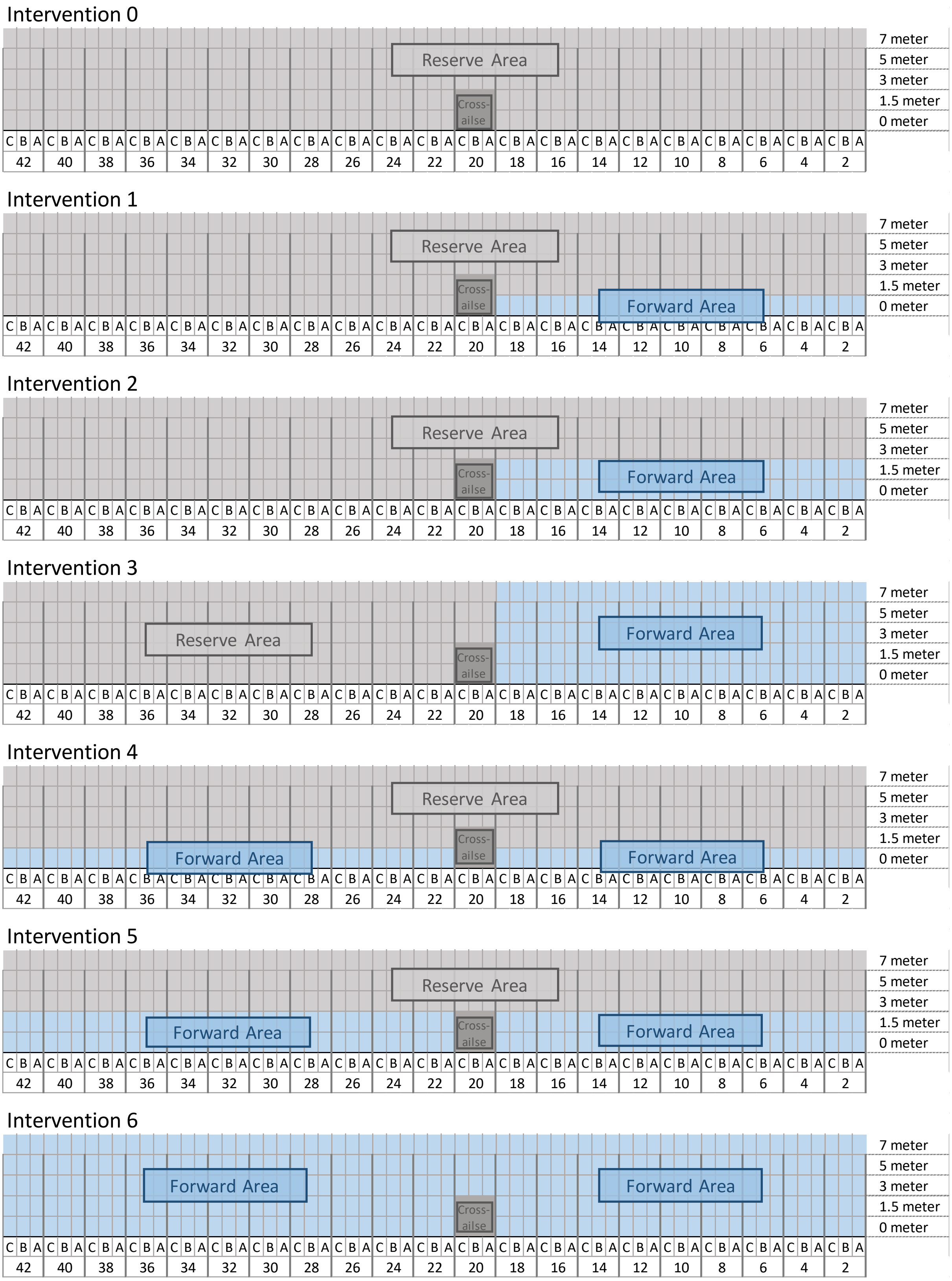

Figure 29 Side view of pallet racks within an aisle and the assignment of locations to the functional areas for all 7 interventions

4.1.2 Product-to-flow assignment

Conventional warehouses typically consist of three functional areas which are the crossdocking, forward and reserve area. Cross-docking is a process that reduces the handling time of a product as the incoming unit is not stored. Therefore, storing and receiving takes little handling when using the cross-docking method. Cross-docking is not possible for all products as it requires a short stay at the storing location because the area that is used for cross-docking is not designed for storing inventory. The demand of B-Living's SKUs is uncertain and the space in front of the loading docks that should be partly used for cross-docking is not available. Hence, cross-docking is not an option for B-Living.

The functional areas that are applicable to B-Living are the forward and reserve area. Making a distinction between forward and reserve areas can improve the order-picking process as picking from forward areas will reduce traveling times if executed properly. This research is about using both areas within the warehouse to reduce travel times between locations. Finding an improved product placement therefore requires assigning products to the functional areas.

Which item to assign to which area can be determined by using the paper of Heragu et al. (2005) about warehouse design and product assignment. The design of the warehouse layout already provides potential for using both areas. However, the size of the forward and reserve area depends on which SKU to store at which functional area. For our research we differentiate three flows at which a product enters and leaves the warehouse. These flows are illustrated in Figure 30.

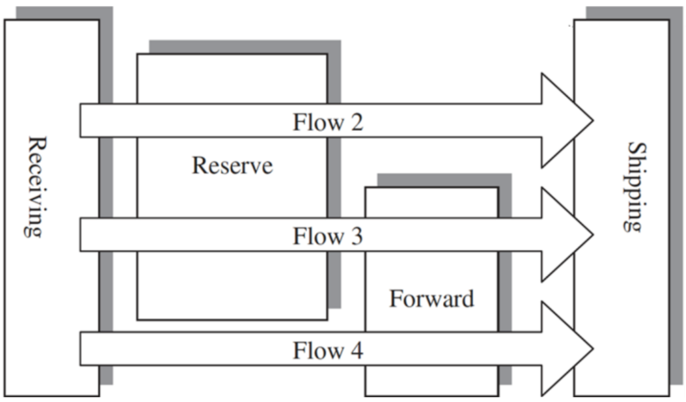

Figure 30 Typical product flows in a warehouse (Heragu et al., 2005)

The flows that can apply to the products of B-Living when using a forward and reserve area are reserve storage flow 2, 3 and 4. The products of B-Living are currently only handled by reserve storage flow and forward storage flow as the incoming goods are stored at locations within the picking and storage area and received from those locations when order-picking. Reserve-forward storage flow uses bulk storage in the reserve area, replenishment to the forward area and picking from the forward area location. This flow enables little storage in the forward area as the entire SKU inventory is divided over the forward and reserve area. However, this flow does require replenishment and therefore more handling.

We used the approach of Heragu et al. (2005) to research which SKUs to assign to which functional area and what fraction of inventory of those SKUs to place at both functional areas. This approach assigns SKUs to the product flows given certain SKU characteristics and warehouse functional area space limits.

4.2 Mathematical model

The calculation of the forward and reserve area and the assignment of SKUs to product flows can be solved by using the mathematical model constructed by Heragu et al. (2005). The mathematical model is formulated as an integer programming model (IP model). The IP model consists of three components: objective value, decision variables and constraints. This section elaborates on the model formulation and a simplification of the model.

The model that is proposed in the paper of Heragu et al. (2005) is a generic model that can be applied to multiple cases. However, some changes are made to this model to fit the B-Living case. As mentioned in the previous section, cross-docking cannot be integrated into the warehouse of B-Living. Thus, this option is not considered. Flow 1, decision variable cross-docking proportion α and cross-docking space in the functional area a are therefore left out of the model formulation. Additional adaptation to the objective function and the constraints are made to simplify the model for the B-Living case.

The objective value proposed by Heragu et al. (2005) minimises the costs of handling and the costs of storage. However, the objective for this research is to reduce the travel time of the order-picking process. It is therefore not necessary to calculate the cost of handling and the storage costs. Hence, the objective function changes to minimising the traveling time instead of minimising handling and storage costs. Applying the adaptations to the general model formulation by Heragu et al. (2005) results in the formulation of the mathematical model that is used for assigning product flows to SKUs.

Indices of sets:

i	number of SKUs, i =1, 2,…, n (where n is the total number of SKUs),
j	type of material flow, j = 2, 3, 4,

Parameters:

T_F	average travel time in the forward area per pick,
T_R	average travel time in the reserve area per pick,
N_i	number of picks per year of product i,
S	total available storage space,
Q_i	order quantity for product i (in unit loads),
F_i	quantity of product i spends in the forward area if product is assigned to material reserve-forward storage flow,
P_i	quantity of product i per pallet unit,
L_F	upper storage space limit for the forward area,
L_R	upper storage space limit for the reserve area.

Decision variables:

X_{ij}	1 if product i is assigned to flow type j; 0 otherwise,
β, γ	proportion of available space assigned to each functional area β = reserve and γ = forward.

Objective function:

$$\min \sum_{i=1}^{n} \sum_{j=3}^{4} T_F N_i X_{ij} + \sum_{i=1}^{n} T_R N_i X_{i2}$$

Constraints:

$$(1) \sum_{j=2}^{4} X_{ij} = 1 \qquad \forall i$$

$$(2) \sum_{i=1}^{n} \left(\frac{Q_i}{P_i} X_{i2}\right) + \sum_{i=1}^{n} \left(\frac{(Q_i - F_i)}{P_i} X_{i3}\right) \leq \beta S$$

$$(3)\ \sum_{i=1}^{n}\left(\frac{F_i}{P_i}X_{i3}\right)+\sum_{i=1}^{n}\left(\frac{Q_i}{P_i}X_{i4}\right)\leq \gamma S$$

$$(4)\ \beta+\gamma=\ 1$$

$$(5)\ \beta S<L_R$$

$$(6)\ \gamma S<L_F$$

$$(7)\ \beta,\gamma\geq 0$$

$$(8)\ X_{ij}=0\ or\ 1 \quad \forall i,j$$

Constraint (1) constraints SKUs to be assigned to multiple flows. By applying constraint (2) and (3), the proportion of the functional areas space are calculated and constraint (5) and (6) limit these proportions to the set upper limits for the functional area space. Since the assessment of this research is not to design the warehouse layout, but use the current design to its potential, the total space of the warehouse is known. The unit of measure used for this model is pallet places. Hence, the model uses the order quantity divided by the quantity per pallet of an SKU to determine the amount of space that is required to store the SKU. The last two constraints ensure that the proportions of functional space β and γ cannot be negative and decision variable X_{ij} is a binary value.

4.3 SKU to functional area heuristic

This section elaborates on the algorithm that is used to solve the SKU to functional area problem for B-Living that is described in Section 4.1. The modified approach on how we solve this problem is discussed in Section 4.2. Which optimisation technique to use for this approach is therefore first described this section. Thereafter, we elaborate on how the algorithm is constructed.

4.3.1 Choices and assumptions

As data is not available for all SKUs and as SKUs are added to and removed from the collection frequently, we consider 1,306 SKUs that belong to the 'basic' collection for this research. These SKUs can all be assigned to all three flows. However, the number of SKUs over the entire collection is 8,567 SKUs and the merger of Mars & More will add 2,948 SKUs to this collection. An optimisation technique that is able to solve instances of more than 10,000 is therefore recommended as upscaling is desired. Heragu et al. (2005) propose multiple optimisation techniques for this. The objective values for small instances (up to 3000 SKUs) are solved to optimality by using linear programming. Solving larger instances with linear programming requires too much computational time and we therefore choose heuristics to be the appropriate optimisation technique for this research. The heuristic algorithm consists of 6 steps:

1. Calculate the lower bound. Hence, the SKU will be assigned to the flow that has the least traveling times for order picking.
2. The proportions of the functional area are calculated,
3. Check whether the upper limit proportions calculated in step 2 do not exceed the upper bounds. When the upper bounds are not exceeded, the solution is feasible and therefore an optimal solution is found. When the upper bounds are exceeded and the solution is therefore infeasible, we move to step 4.
4. Calculate the differences between the functional areas upper bound and the proposed solution. The functional area with the most space left is set as l^* and the functional area with the least space left is set as k^*.
5. We then swap the SKU that has the least impact on the total traveling time from k^* to l^*.

6. We review the feasibility of the solution. When the solution is feasible, the algorithm stops and the found solution is accepted, otherwise return to step 2.

We start at a lower bound which is infeasible and apply changes to the lower bound found in step 1 until the heuristic repairs and a feasible solution is generated. However, the heuristic repair algorithm does not have a function to improve the feasible solution. Assuming that the heuristic solution can be improved, we choose to use a simulated annealing approach as optimisation technique to solve the SKU to functional area problem. Since the heuristic does find a feasible solution, we choose to use this solution as initial solution to the simulated annealing.

4.3.2 Parameter data

This subsection elaborates on the input of the model and how this data can be obtained. The first two parameters are the average order-picking travel time in the forward area T_F and the average order-picking travel time in the reserve area T_R. We measured the traveling time from the beginning of the aisle to every location within that aisle which we described in Section 2.2. These traveling times to locations are used to calculate the average traveling times per functional area. These average traveling times per functional area are different to all interventions as each intervention has a different set of locations. The average traveling times per functional area per intervention is shown in Table 9. These averages are based on measurements to the centre of the functional area.

Table 9 Average traveling times per intervention and functional area

	Forward area Traveling Time (seconds per pick)	*Reserve area Traveling Time (seconds per pick)*
No-forward intervention	-	73.65
Bottom-layer-before-cross-aisle intervention	23.36	73.55
Bottom-two-layers-before-cross-aisle intervention	28.87	74.69
Before-cross-aisle intervention	46.39	75.59
Bottom-layer intervention	39.47	74.64
Bottom-two-layers intervention	44.98	76.36
Full-forward intervention	61.60	71.90

The number of picks for each SKU N_i are derived from past years' order details. The total available storage space S is known as it is the number of pallet places within the storage and picking area. Using the total space that is currently used to store the SKUs considered for this case sums up to a total of 5,266 pallet places. The parameter order quantity per SKU Q_i is derived from the master data and purchasing orders. Parameter F_i is a set parameter as it is desired for the top 10% of SKUs in terms of required volume per year to store 2 pallets in the forward area and 1 pallet to the forward area for the remaining 90% of SKUs.

The quantity per pallet of each SKU PQ_i is generally known and for this research, the data is derived from B-Livings' master data. The final parameters, upper bound values of the forward area UL_F and reserve area UL_R, depend on the intervention. The upper bounds (UB) for each functional area per intervention are shown in Table 10.

Table 10 Number of locations per functional area per intervention

	Forward Area UB (pallet places)	*Reserve Area UB (pallet places)*
No-forward intervention	0	5,266
Bottom-layer-before-cross-aisle intervention	194	5,072

Bottom-two-layers-before-cross-aisle intervention	350	4,916
Before-cross-aisle intervention	1,027	4,239
Bottom-layer intervention	451	4,815
Bottom-two-layers intervention	762	4,504
Full-forward intervention	2,179	3,087

4.3.3 Neighbour solutions

A simulated annealing algorithm tries to find improvements by comparing neighbour solutions. Multiple methods can be used to generate these neighbour solutions. Insert and delete operators are not possible for this problem as the solution requires every SKU to be assigned to one flow (Constraint 1). Move and swap operators are applicable to our model. We want to start with more diversification and we therefore use the swap operator at the start of the algorithm run as this operator applies two changes each iteration. At some point we want to end with more intensification and therefore switch to the move operator as this operator applies one change when generating the neighbour solution. However, as the solution is constraint to upper space limits for the reserve and forward area, the feasibility of the swap and move is to be considered. Using the proposed calculations of Heragu et al (2005) by summing over all SKUs for every swap or move requires too much computational time and would make the model (especially when upscaling the number of SKUs) inefficient. We therefore use temporary calculations. Instead of summing over all SKUs, the model subtracts calculations of the to be set to 0 decision variable X_{ij} and adds the calculations of the to be set to 1 decision variable X_{ij}. This temporary solution is then checked for its feasibility. If the temporary solution is feasible, it is accepted as new possible solution. Otherwise, the temporary solution will be deleted and the model tries to find a new feasible temporary solution. This process is the same for both the swap as the move operators.

The algorithm starts by swapping two neighbours as we want to generate many different solutions. We do the swapping operation until the temperature reaches half the starting temperature as we then want to decrease the number of changes per solution. The flow of this swap and move process is displayed in the flowchart of Figure 31.

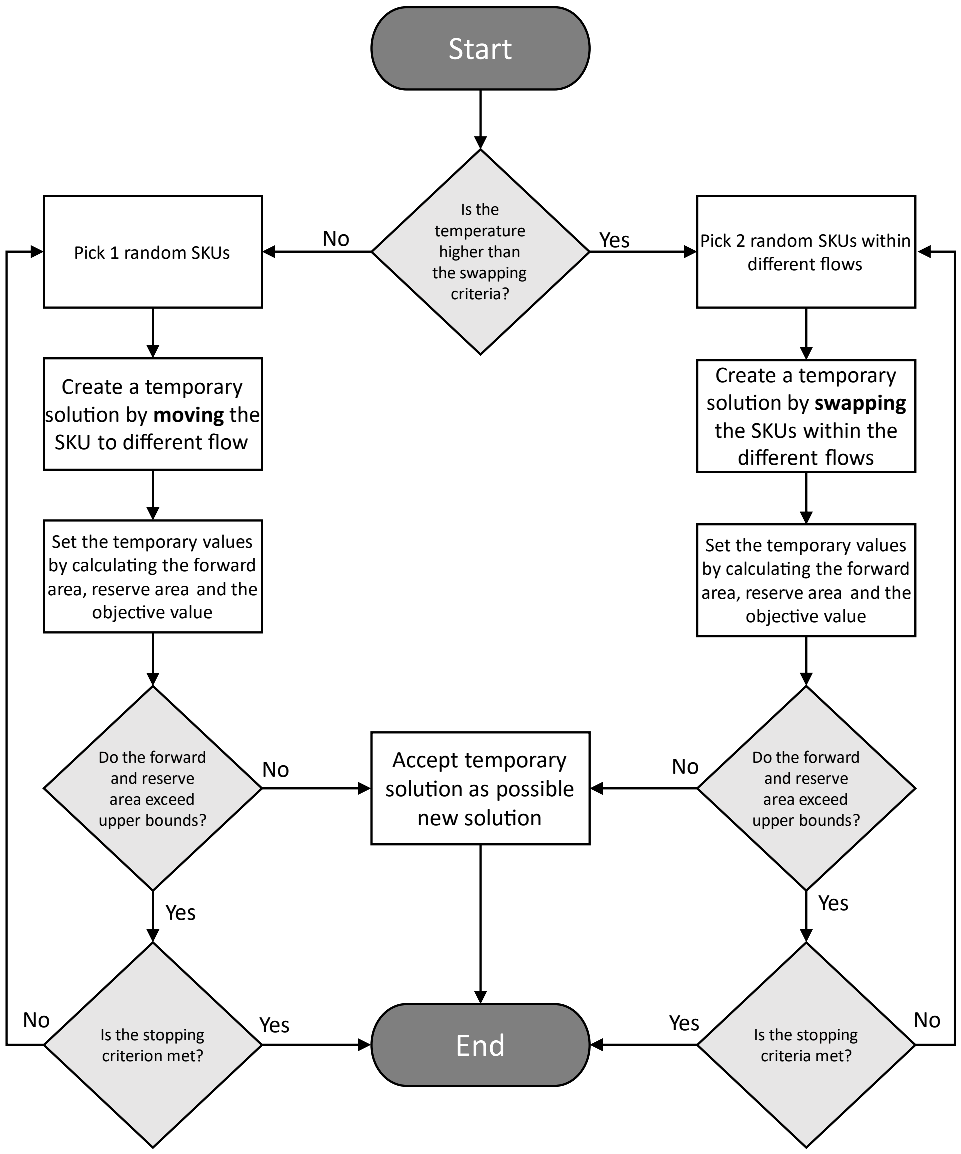

Figure 31 Swap and move operator function flow chart

The solution is accepted when the objective value of the new solution is better than the objective value of the current solution. However, the solution is not always declined when the new solution is worse than the current solution. Due to the hill-climbing ability of the simulated annealing approach, the worse solution can also be accepted. With a certain probability, simulated annealing accepts a worse solution to climb from a local optimum. This probability is determined by the simulated annealing's temperature and declines every time the temperature is updated.

4.3.4 Cooling parameters

The cooling scheme for the simulated annealing consists of the starting temperature, the temperature lower bound at which the algorithm stops, the Markov chain length and the decrease factor of the temperature.

4.3.4.1 Starting temperature

As we discussed in the previous section, the temperature and the solution change set the probability of accepting or declining a worse solution. At the beginning of the run, we want the simulated annealing to accept worse solutions to explore the possibilities. The starting temperature should therefore be set to a value at which the acceptance ratio is close to 1. This acceptance ratio is calculated by the ratio of accepting a worse solution. We calculate the acceptance ratio of multiple starting temperatures to find a fitting starting temperature which is displayed in Figure 32. This figure shows that at a temperature of around 20,000, the acceptance ratio starts to decline.

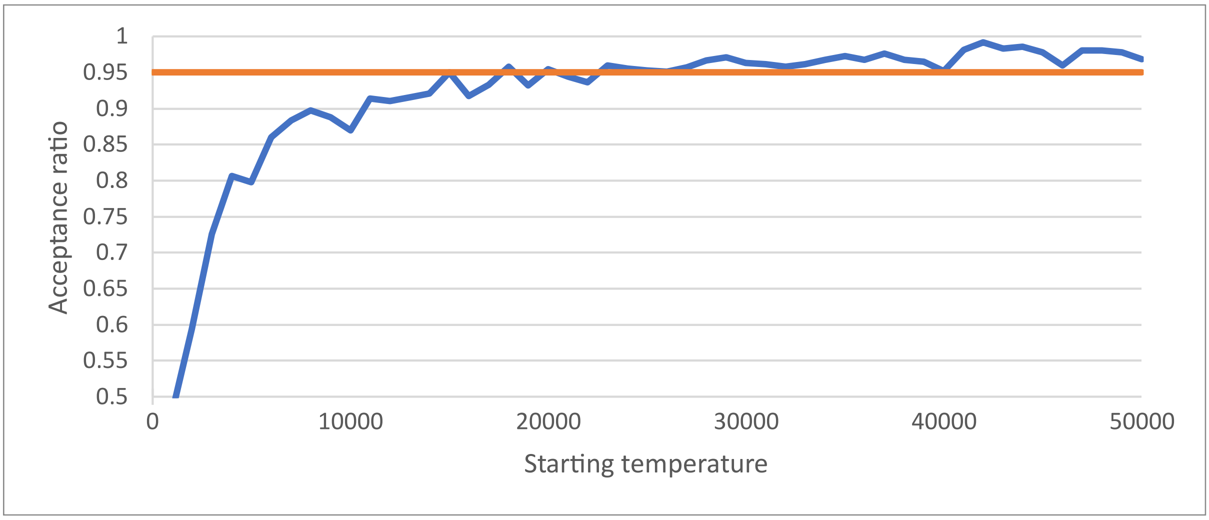

Figure 32 Acceptance ratio graph per starting temperature

4.3.4.2 Temperature lower bound

The temperature lower bound is calculated the same way. As we want to stop the simulated annealing when the acceptance ratio is close to 0, we analyse the stopping temperature which we display in the graph of Figure 33. As can be seen from this figure, the acceptance ratio drops below 0.01 at a temperature around 200.

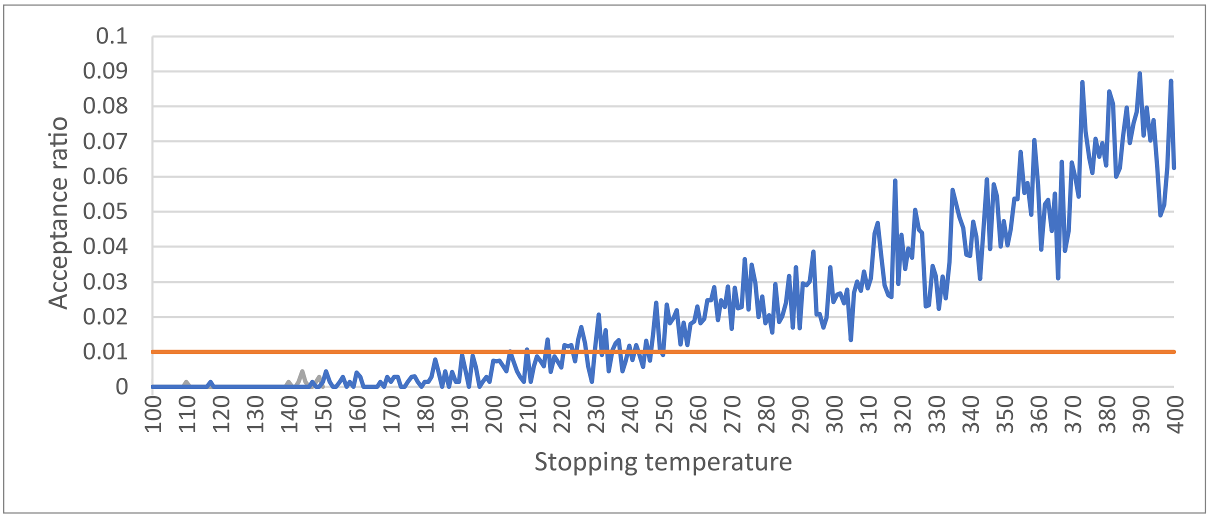

Figure 33 Acceptance ratio per stopping temperature

4.3.4.3 Markov chain length and decrease factor

The Markov Chain length and the decrease factor determine the speed at which the temperature decreases until the stopping criteria and therefore determine the speed of the model. Concluding which Markov Chain length and which decrease factor to use for our model is therefore a trade-off between the computational time and both parameters. Using the starting and stopping temperatures found this section we try to find the most suitable parameters by doing multi-factorial experiments. We tested the decrease factors 0.9, 0.95, 0.99, 0.995 and 0.999 and Markov chain lengths of 250, 500, 750, 1,000, 1,500. The results of the experiments shows that the decrease factor that is closest to 1 shows the best results and that a larger Markov chain length shows little improvements. However, the computational time of these parameters have great impact on the computational time. We make a trade-off between solution improvements and computational time and we decide to limit the computational time per experiment to a maximum of 60 seconds as we conduct the simulated annealing algorithm for multiple experiments and as the solution improvements are neglectable. The top 5 configurations in terms of the objective value are displayed in Table 11. To decrease the risk of randomness we took an average objective value and CPU time of 3 experiments per configuration.

Table 11 Top 5 configurations in terms objective value

Rank	*Decrease factor*	*Markov Chain Length*	*CPU time (seconds)*	*Total Traveling Time (seconds)*
1	0.995	500	46.39	2,670,351
2	0.99	1000	46.62	2,671,313
3	0.99	750	34.01	2,672,661
4	0.99	500	23.16	2,686,990
5	0.995	250	26.10	2,689,522

The third configuration from Table 11 with a decrease factor of 0.99 and a Markov chain length of 750 has an acceptable objective value, which is 0.087% higher as the ranked 1 configuration, but has a computational time of 26.69% less. We therefore choose this configuration to be the best fit to this research.

4.3.5 Results

The simulated annealing tries to find improvements of the total traveling times based on the assignment of products to each flow. The found parameters that best fits our model are a starting temperature of 19,604, a stopping temperature of 218, a decrease factor of 0.99 and a Markov chain length of 750. With these parameters, the simulated annealing algorithm is able to find an improved solution while still having computational time within the limits that are stated.

The first run of the simulated annealing uses the average traveling times found in Subsection 4.3.2. These traveling times are based on single-command order picking. We used these averages as is it is unable to calculate multi-command order picking traveling times for both functional areas as the current flow is only reserve storage flow (reserve area order picking). However, in order to find realistic averages of order picking traveling times per functional areas to make the model more accurate, we allocated the SKUs to specific locations within these functional areas in Chapter 5 and calculate the average traveling times based on all orders of the year 2022. The model constructed in this chapter is then executed with the new averages, which makes the model iterative and more accurate. Chapter 5 elaborates on the allocation of SKUs within their assigned functional areas by making use of different storage policies.

4.4 Conclusions

The goal of this research is to improve the order picking process by storing SKUs to efficient locations within the warehouse. Concluded from Chapter 3 we found that making a distinction between a forward area and reserve area is a good approach for improving the order picking process by reducing the traveling time of the order pickers. However, what locations should be used for both functional areas and which SKU to store in these areas are to be determined. This chapter proposes a simulated annealing approach for solving the SKU to functional area assignment problem. This problem is about assigning SKUs to flows and therefore the inventory of the SKUs to the functional reserve and forward areas to dimension these areas. Which SKU to assign to which functional area(s) is based on the desired flow of the SKU.

The proposed model by Heragu et al. (2005) is modified to the case of B-Living by solving the model with the objective to minimize the order-picking traveling time. The algorithm is constructed to solve the problem for multiple area upper bounds. We therefore apply the algorithm to 7 functional area interventions of which a trade-off will be made between storage space per functional area and traveling times. Which SKU to dedicate to which flow is determined by the SKU popularity and the SKU inventory parameters which are interrelated. The result of this algorithm is then used as the input to the SKU to picking location assignment of Chapter 5.

5 SKU-to-location algorithm

Where to store each SKU within these functional areas is determined by the storage policy and storage method. We therefore propose an SKU-to-location assignment algorithm to test which storage policies fits best to the B-Living case. This chapter discusses the approach that is used to measure the impact of using the different storage policies on the order-picking traveling time. The chapter first starts with an introductory section describing the problem context, the storage policy configurations that are tested and the design assumptions that are used in Section 5.1. Thereafter, Section 5.2 elaborates on how to calculate the traveling times between locations in the warehouse. The heuristic approach to place SKUs at specific locations within the warehouse according to the storage policy configurations described in Section 5.1 is discussed in Section 5.3. The heuristic approach of the order-picking paths, the traveling time calculations and the integration of the Chapter 4 model and the model constructed this chapter is discussed in Section 5.4. Finally, Section 5.5 conclusively describes the findings of this chapter.

5.1 Problem context and design assumptions

The model constructed in Chapter 4 assigns flows to SKUs and therefore assigns the SKUs to functional areas. The algorithm uses estimated traveling times per functional area based on measurements to the centre of the functional area. We constructed an algorithm that is able to calculate the traveling times of picking orders from 2022 using the solution of the flow-to-SKU algorithm and using different storage methods and storage policies. The algorithm that is able to construct this path assigns SKUs to locations and calculates the traveling time between picks. Results of these calculations can then be used to update the estimated traveling time per functional area per pick of the flow-to-SKU algorithm.

The SKU-to-location algorithm uses the solution of the flow-to-SKU algorithm described in Chapter 4. Hence, the solution of Chapter 4 is used as input to the model of this chapter. And as we calculate the traveling times per pick of the 2022 orders with the SKU-to-location algorithm, we are able to use the calculated traveling times per functional area and update the parameters of the SKU-to-flow algorithm. Hence, the model becomes iterative to make the flow-to-SKU assignment more accurate and to find a better solution. Figure 34 displays how the models of Chapter 4 and Chapter 5 are iterative and which results are used for bootstrapping.

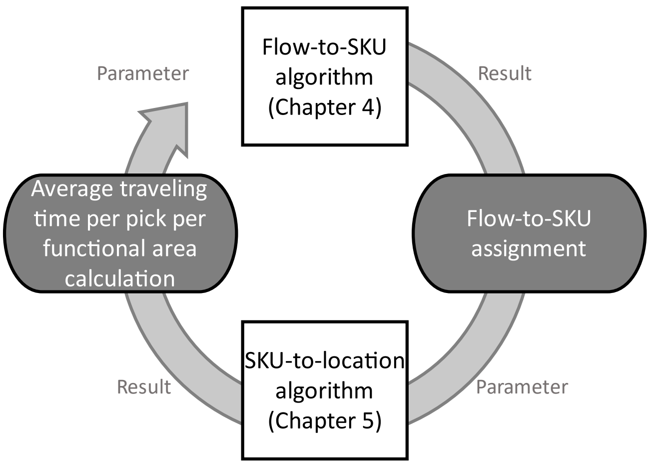

Figure 34 Integration of model Chapter 4 and model Chapter 5

5.1.1 Storage configurations

Where to place the SKUs within these functional areas depend on the storage method and the storage policy. We distinguished the storage methods random storage, dedicated storage and class-based storage. As the stackability of SKUs is a priority rule when picking an order we choose classing the SKUs based on their stackability for the class-based storage method. The specific locations within the assigned area are determined by storage policies. We therefore test the impact of 6 configurations to find the most an improved storage method and storage policy based on all orders of the year 2022. These configurations are shown in Table 12.

Table 12 Storage configurations that are tested

	Storage method	*Storage policy*
Configuration 1	Random	Random Storage
Configuration 2	Dedicated	Cube per Order Index
Configuration 3	Dedicated	ABC (number of picks)
Configuration 4	Stackability Class-Based	Random Storage
Configuration 5	Stackability Class-Based	Cube per Order Index
Configuration 6	Stackability Class-Based	ABC (number of picks)

5.1.2 Design assumptions

As is discussed in Subsection 4.3.1, the basic collection of 1,306 SKUs is used in the first model constructed in Chapter 4 due to the data availability and the stability of the SKUs. As we use a part of the collection for this model, we use part of the warehouse as well to make a more realistic simulation. Hence, we used a random sample of the locations within the functional areas. Which locations to use and how the sample is drawn is elaborated on in Section 5.2.

Because we use the basic collection instead of the entire collection during this research, the exact location of the SKUs is not the objective of this model. The specific allocation of SKUs to locations is only used for calculation purposes. Where to place the SKUs within the functional areas is a result from the used method and policy. This result does however give an accurate indication of the functional area traveling times and of the most applicable storage method and policy in terms of reducing the order-pick traveling times.

5.2 Locations and distances

The SKU-to-location assignment continues with the seven interventions discussed in Subsection 4.1.1. As stated, the total space used to store the basic collection of B-Living is 5,266 locations denoted by set L. These locations are divided over the functional areas, where each functional area intervention has a certain sample size for both the forward and reserve functional area. The locations of this sample size are randomly drawn from the total number of functional area locations.

We transform the currently used location codes to align these location codes to the input parameters we use in the traveling time calculations. Location codes used in the warehouse within the bulk area and the picking area consists of 6 digits. In Figure 35 we displayed a location card as example. The first digit indicates the letter of the aisle. The second and third digits indicate the pallet rack section within that aisle. The fourth and fifth digits indicate the height number of the location where the height is indicated in decimetres and the sixth digit indicates the bin within the pallet rack section. Hence, the location card of Figure 35 displays the location of bin A on 1.5-meter height in pallet rack section 4 of aisle E.

Figure 35 Location card. The code addresses bin A at 1.5-meter height in pallet rack section 4 of aisle E.

As all required information is readily available within each location code, we transform the aisle letter to the corresponding X coordinate and we divide the pallet rack section by 2 and round it down to zero decimals to set the corresponding Y coordinate. We elaborate on these coordinates later this section. The height of the location is used for the height traveling time purposes and the bin letter is neglected for the traveling time calculation as the traveling time differences between bins are neglectable.

To calculate the traveling time between two locations in the set of L, we are able to separate the height traveling time from the ground traveling time. For every pick at a location higher than 1.5 meter, the order picker has to go down first to travel to the second location. Hence, there is no relation between two locations and the height traveling time. Figure 36 displays a side view of an aisle and all its locations, where the beginning of the aisle is at the right side. The pallet rack sections codes are denoted by 2, 4, 6 … 42, the bins within these sections are denoted by A, B and C and the layers of the pallet racks is denoted by 0, 1.5, 3, 5 and 7 meters. Hence, traveling from the beginning of the aisle to the top location of pallet rack section 42 and back is measured to take approximately 97 seconds.

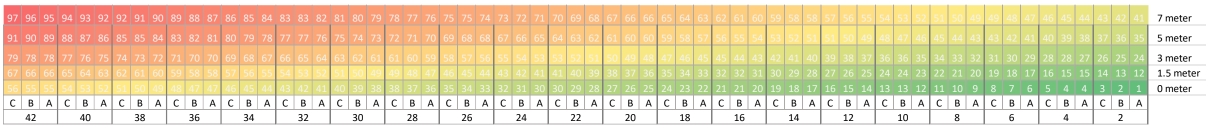

Figure 36 Side view of an aisle with the traveling times per locations in seconds

We use a matrix that stores the traveling time values of the closest path between two ground locations. The other traveling time parameter that is used is the traveling time of picking from higher locations. Hence, in order to calculate the traveling times between locations i and j, we use the following formula:

$$TotalTravelingTime_{i,j} = TravelTime_{i,j} + HeightTravelTime_i + HeightTravelTime_j$$

5.2.1 Height traveling time

The order picker moves from one place to another and goes up and down to the location to pick from. The locations consist of an aisle letter, a pallet rack section code, the height of the location and the bin code. The traveling times between locations are calculated with this information. The height at which a pallet is picked from is not influenced by the pervious location or the next location. Hence, the height parameter to pick from location l is:

$$HeightLocation_l \qquad \forall l \text{ in set } L \ (5{,}266 \text{ locations in total})$$

This parameter stores values in the range of 1 to 5 for each l, stating the level at which the location is at. The height location level and its corresponding picking height and traveling times to go up and down to that location is displayed in Table 13. The height traveling time parameter is denoted by:

$$HeightTravelTime_h \qquad \forall h \text{ in set } H \ (5 \text{ height locations in total})$$

These traveling times are measured by means of timing the order picker and the traveling time it takes to go up and down the height is the same at each location with that corresponding height.

Table 13 Traveling times per location height

Picking height	$HeightLocation_l$	$HeightTravelTime_{HeightLocation_l}$
0 meter	1	0 seconds
1.5 meter	2	11.02 seconds
3 meters	3	23.03 seconds
5 meters	4	34.47 seconds
7 meters	5	40.52 seconds

5.2.2 Ground traveling time

The order picker must move from one ground location to another while picking the order. This ground traveling time between locations are also measured and calculated. To simplify this parameter, we decreased the number of ground locations by grouping 6 locations from the set of L to 1 ground locations. This grouping can be done since the differences are neglectable picking from the left location within the aisle or picking from the right location within the aisle and picking from bin A, B or C. This results in a total of 21 aisles and 21 locations per aisle as is shown in Figure 37. Hence, we calculate the distances between the 21 X-coordinates and the 21 Y-Coordinates. Some coordinates do not store locations as can be seen from the bottom left side of the warehouse in Figure 37. However, this does not affect the algorithm that uses these traveling times as these locations are not in the set of L locations.

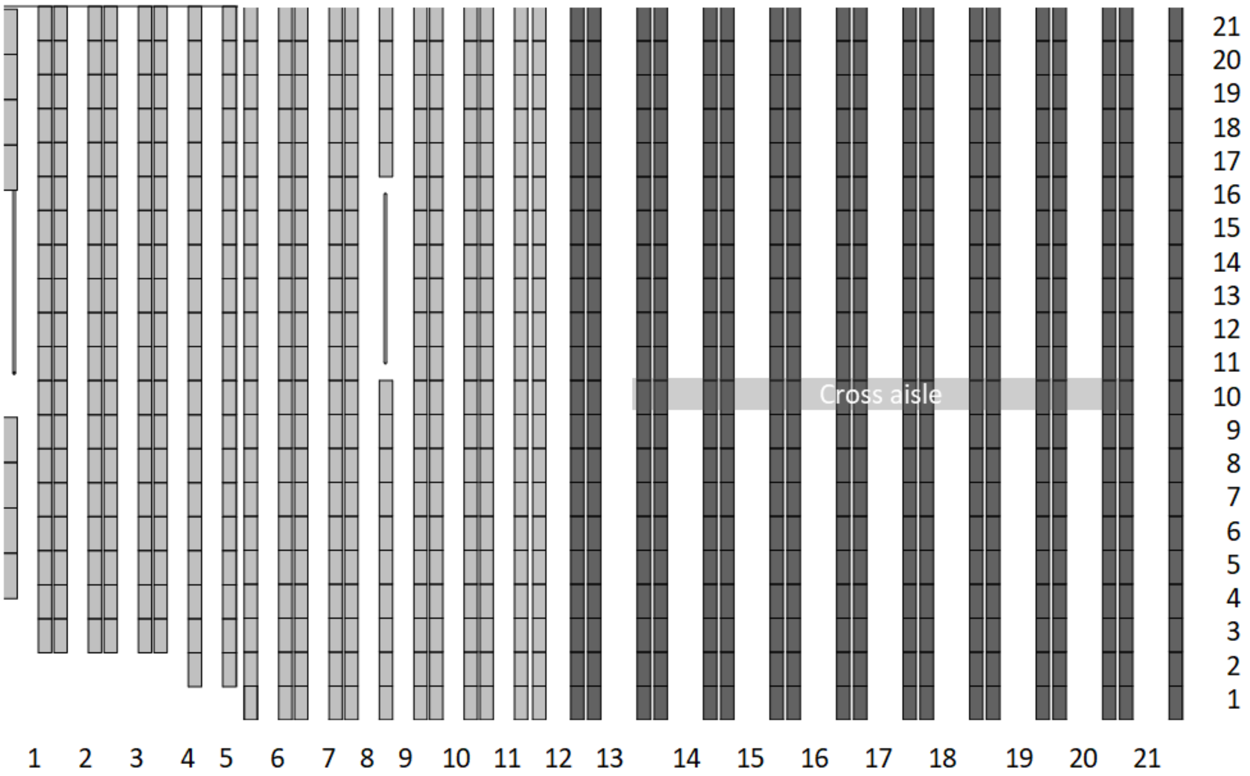

Figure 37 Warehouse coordinates

In total there are 441 (21*21) different ground locations that will be used for traveling time calculations. The ground locations are denoted by the parameter:

$$GroundLocation_g \qquad \forall l \text{ in set of } L \text{ (5,266 locations in total)}$$

The ground location parameter stores a value within the range of 1 to 441 for each location l. This value is derived from the X and Y coordinates. To calculate the traveling times between two locations we use the height traveling times as mentioned above and the traveling times between origin and destination locations i and j. The parameter that stores these traveling times is denoted by:

$$TravelTime_{i,j} \qquad \forall i,j \text{ in the set of } G \text{ (441 ground locations in total)}$$

The traveling time values between ground locations are set to a traveling time matrix which stores the traveling time of going from and to all possible ground locations. Hence, this matrix consists of 177,241 (441*441) values. The traveling times between these locations are calculated by using the X and Y coordinates. When an order-picker has to move from ground location α to ground location β, the calculations are based on the X_i, Y_i, X_j and Y_j coordinates. These distances are then multiplied by the traveling time per coordinate which are $t_X = 2.306$ seconds and $t_Y = 1.341$ seconds to find the total traveling times between ground locations.

The shortest distances of two ground locations depend on where the points are located within the warehouse. The cross aisle has influence on the traveling distance between locations as the order picker does not have to return to the beginning of the aisle to go to another aisle. For some instances, the other aisles can therefore be reached more efficiently by using the cross aisle. Hence, the first distinction that is made is between the storage and pick area. There are a total of 5 possible paths which of which examples are shown in Figure 38.

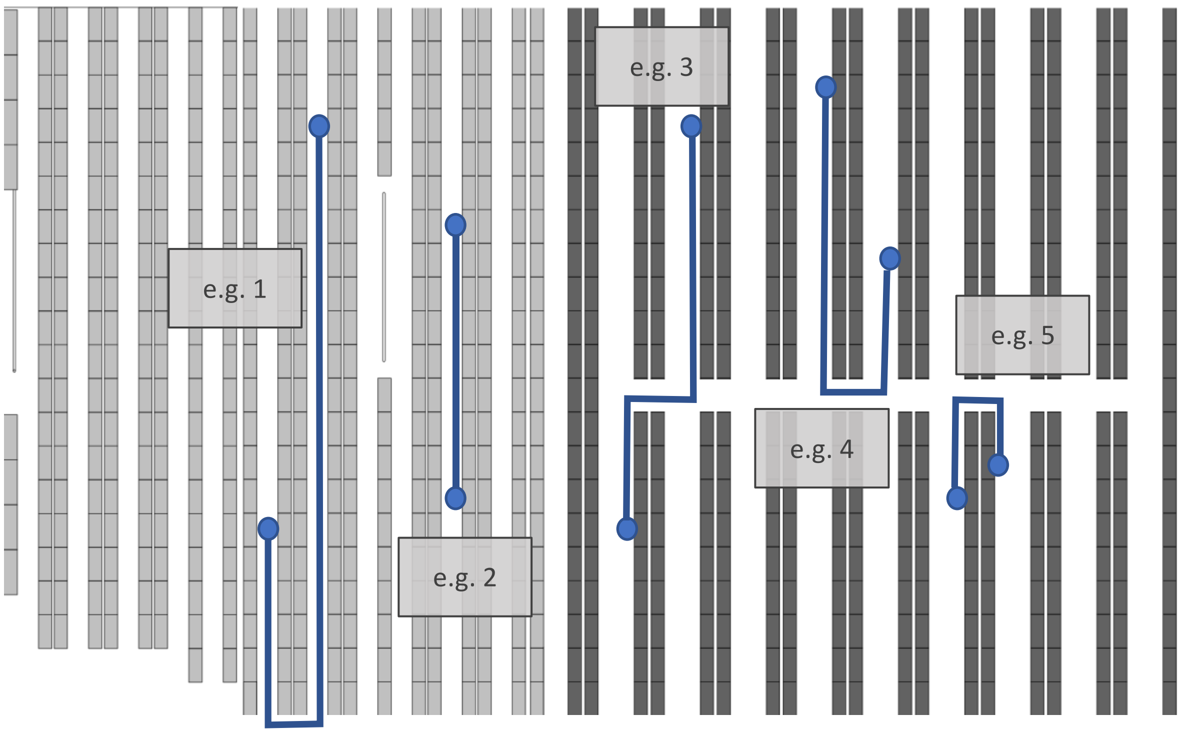

Figure 38 Examples of the 5 possible travel paths between locations

When the traveling time between two points of which at least one point is located in the small aisle area is to be determined, the order picker has to travel to the beginning of the aisle every time the order picker travels to another aisle (e.g. 1 of Figure 38) . The order picker starts at point Y_i, leaves aisleX_i, travels to the aisle of point Y_j and travels to the Y_j coordinate. Hence, the calculation of the route is $TravelTime_{i,j} = (Y_i + Y_j)t_Y + |X_i - X_j|t_X$. When the order picker has to pick from the same aisle (no matter what area), the distance between both Y_α and Y_β is the distance between the locations (e.g. 2 of Figure 38). Hence, $TravelTime_{i,j} = |Y_i - Y_j|t_Y$.

However, when both locations are located in the pick area and in different aisles, the calculation process is more extensive. When one of the points is located before the cross aisle and the other point is located after the cross aisle, the distance between the Y-coordinates of the two points and the distance between the X-coordinates of the two points is the total distance (e.g. 3 of Figure 38). Hence, the formula is $TravelTime_{\alpha,\beta} = |Y_\alpha - Y_\beta|t_Y + |X_\alpha - X_\beta|t_X$. When both points are located after the cross aisle, the path with the least distance between the two points is always by using the cross aisle (e.g. 4 of Figure 38). The formula for calculating this distance is therefore $TravelTime_{\alpha,\beta} = (Y_\alpha - 10)t_Y + (Y_\beta - 10)t_Y + |X_\alpha - X_\beta|t_X$. Finally, when the two points are both located before the cross aisle, the path with the least distance depends on whether to use the cross aisle or to return to the beginning of the aisle (e.g. 5 of Figure 38). Both distances are therefore calculated and the path with the least distance is then chosen to be the shortest path. The formula is stated as follows: $TravelTime_{\alpha,\beta} = t_Y * \min\left((10 - Y_\alpha) + (10 - Y_\beta)\ , Y_\alpha + Y_\beta\right) + |X_\alpha - X_\beta|t_X$. Setting the values of the matrix $TravelTime$ with traveling times for each location α to each location β is as stated in the following pseudo code:

For $\alpha = 1\ to\ GroundLocations$
  For $\beta = 1\ to\ GroundLocations$
    If $X_\alpha = X_\beta$ *#both points are located at the same aisle*
      $TravelTime_{\alpha,\beta} = |Y_\alpha - Y_\beta|t_Y$
    ElseIf $X_\alpha\ or\ X_\beta$ ***in*** $BulkArea$ *#at least one point is located in the wide aisles*
      $TravelTime_{\alpha,\beta} = (Y_\alpha + Y_\beta)t_Y + |X_\alpha - X_\beta|t_X$
    Else *#both points located at the narrow aisles and not at the same aisle*
      If Y_α and Y_β ***behind*** $CrossAilse$ *#both points located after cross aisle*
        $TravelTime_{\alpha,\beta} = (Y_\alpha - 10)t_Y + (Y_\beta - 10)t_Y + |X_\alpha - X_\beta|t_X$
      ElseIf Y_α and Y_β ***before*** $CrossAilse$ *#both points located before cross aisle*
        $TravelTime_{\alpha,\beta} = t_Y * \min\left((10 - Y_\alpha) + (10 - Y_\beta)\ , Y_\alpha + Y_\beta\right) + |X_\alpha - X_\beta|t_X$
      Else *#one point is located before and one point is located after the cross aisle*
        $TravelTime_{\alpha,\beta} = |Y_\alpha - Y_\beta|t_Y + |X_\alpha - X_\beta|t_X$

5.3 Product Allocation parameters

In the previous section we elaborated on how to obtain the traveling times between locations which are required for the traveling time calculations of path order picking. These traveling times between locations and the flow-to-SKU algorithm parameters and results from in Chapter 4 are used as parameters to the SKU-to-location algorithm constructed in this chapter. This section elaborates on all SKU-to-location parameters of the heuristic algorithm.

The algorithm dedicates SKUs to specific locations according to the storage configuration. Each configuration has a different approach on which SKU to allocate to which location, but there are some general SKU-to-location algorithm parameters. The first general parameter that is discussed in this subsection is the traveling time distances, then the construction of the functional area location subsets is elaborated on, thereafter the flow-to-SKU assignment, then the SKU inventory to store at the functional areas and the orders of year 2022 is discussed as final general parameter. Furthermore, there are some parameters used for specific policies which are discussed at the last part of this subsection. The configurations

5.3.1 Functional area location subsets

Each intervention has a different subset of functional area locations, but the subsets are the same for all policies. To construct these subsets, we use the intervention input that is elaborated on in Subsection 4.3.2 about the sample that is derived from the total set of locations. This resulted in the number of locations for each subset stated in Table 14.

Table 14 Number of locations per functional area per intervention

Intervention	*Forward Area UB (pallet places)*	*Reserve Area UB (pallet places)*
No-forward	0	5,266
Bottom-layer-before-cross-aisle	194	5,072
Bottom-two-layers-before-cross-aisle	350	4,916
Before-cross-aisle	1,027	4,239
Bottom-layer	451	4,815
Bottom-two-layers	762	4,504
Full-forward	2,179	3,087

For each intervention, we drew the locations from locations set L randomly up to the number of locations from each functional area as is stated in Table 14. These locations are the same for each calculation within that intervention, so that the objective value of each test is not influenced by randomness.

Each location is assigned to a functional area based on the intervention that is used. Hence, which location to add to which subset is fixed for each intervention. Since the set of locations is sorted from closest to the I and O point to furthest from the I and O point, we add the locations to the subsets sequentially. This process results in constructed subsets of both functional areas sorted ascending from closest to the I and O point to furthest from the I and O point.

5.3.2 Flow-to-SKU assignment

Another general parameter that is used for all storage policies is the Flow-to-SKU assignment. This parameter is the outcome of the algorithm from Chapter 4. During this algorithm, the model finds an improved assignment of SKUs to product flows by focusing on minimising the traveling times. Hence, the results of Chapter 4 decide which SKU to dedicate to which flow and therefore dedicates the inventory to a single or to both functional areas. These results are different for all interventions. Whether an SKU is assigned to a flow, is stated with the binary variable X_{ij}, where this variable is 1 if SKU i is assigned to flow j. Only 1 flow is assigned to each SKU. Chapter 4 elaborates on how the flow is assigned to the SKU.

5.3.3 SKU inventory per functional area

We use the inventory parameters of Section 4.2 to calculate the amount of inventory of SKU i to allocate to the functional areas. The following parameters are used for this calculation:

Q_i	order quantity for product i (in unit loads),
F_i	quantity of product i spends in the forward area if product is assigned to material reserve-forward storage flow,
Q_i	quantity of product i per pallet unit
X_{ij}	SKU i to flow j assignment

To calculate the number of locations to use from the functional area subsets k to store SKU i, we use a different formula for each flow that is assigned to the SKU. We therefore create the parameter $Inventory_{i,k}$ that sets the number of locations required for storing SKU i in functional area k. We use the following formulas to calculate the number of locations to use per functional area subset for an SKU i:

$$Inventory_{i,reserve} = \frac{Q_i}{Q_i} X_{i2} + \frac{Q_i - F_i}{P_i} X_{i3}$$

$$Inventory_{i,forward} = \frac{F_i}{P_i} X_{i3} + \frac{Q_i}{P_i} X_{i4}$$

5.3.4 Stacking priority

As the SKUs have different characteristics in terms of firmness and weight, we scored each SKU based on their stackability. The prioritising rules that hold since the merger of 2020 is picking glassware first and stack textile on top. However, as B-Living has grown adding other product types to their collection and since not all glass products and textile products are even stackable, we prioritised the SKUs based on their product category. There are in total 35 categories within the basic collection and every category has a priority code assigned to it, with code 1 being the best stackable category and therefore first to pick, code 3 is the least stackable category which is to be picked at last and code 2 being in the middle of SKUs with code 1 and 3. This way, SKUs are to be picked in the sequence of priority 1 first, 2 second and 3 at last. Which priority code is assigned to which category is shown in Figure 56that is displayed in Appendix D. The parameter of the stackability of SKU α is denoted by $Stackability_{\alpha}$

5.3.5 2022 sales orders

To verify our outcome and to calculate realistic traveling times, we used a full year of sales data from 2022. By using the SQL Server of B-Living, we were able to extract historical data of orders and the order details of year 2022. We limited these orders to the sample of SKUs we used for this research. Hence, all SKUs that are not from the basic collection (which is the sample used) are extracted from the sales data. The order details consist of the order number which is an identical number for each order placed, the location of the pick, the SKU number and the quantity that is picked. This resulted in a dataset of 3,934 orders consisting of 36,471 order details in total.

We modified this dataset to simulate the paths of which the orders are picked. We first consolidated each order number and added an I at the beginning of each order and a O at the end of each order to create an order picking batch. Thereafter, we sort the orders ascending by the locations at which they were picked last year, picking from the left to the right side of the warehouse. This results in the shortest traveling path for each order using the current picking policy. Finally, we prioritised the SKUs within the orders based on their stackability which is a parameter that is elaborated on earlier in this section. The priority codes are 1,2 and 3 of which the SKUs are to be picked in that order.

To summarise the actions taken, the complete dataset consists of all orders consolidated, starting at the I-point, ending at the O-point and sorted by means of the order picking policy. Which is prioritising the stackability of items first and then picking from the left side of the warehouse to the right side of the warehouse. This results in a total of 44,339 locations that are travelled to in 2022. An example of how an order within this dataset looks like after all actions taken is shown in Figure 39.

Order number	SKU number	Priority code	Location picked from
VO-2200017	Start	Start	I-Point
VO-2200017	20651	1	I2315A
VO-2200017	19252	2	R0630A
VO-2200017	20692	2	R2530B
VO-2200017	8852	2	R3330C
VO-2200017	8854	3	R3450B
VO-2200017	End	End	O-Point

Figure 39 Order path of a single order in 2022

5.3.6 Storage policy and storage method parameters

The general parameters calculated this section are used for all policies. However, each policy has its specific parameters to use. The parameter that is used for the ABC policy is the popularity of the SKUs based on picking frequency. We therefore use the number of picks per year of the SKU (N_i) based on historical data. This parameter is known and used for the algorithm of Chapter 4. How this data is obtained is already discussed in Section 4.2.

Storage policy Cube per Order Index (COI) uses the COI parameter, which is a calculation consisting of the picks per year N_i, the order quantity Q_i and the quantity per pallet PQ_i. All these parameters are already used for the algorithm of Chapter 4 and discussed in Section 4.2. The formula that calculates the COI is as follows: $COI_i = \frac{N_i}{\left(\frac{Q_i}{P_i}\right)}$, where $\frac{Q_i}{P_i}$ is the number of pallets to store of SKU i.

For the Order Oriented Slotting (OOS) policy, we use the popularity f_{i0} parameter and the interaction frequency parameter f_{ij}. Where f_{i0} is the popularity parameter of SKU i by means of picking frequency. And f_{ij} the frequency that SKU i and SKU j are in the same orders. At last, the random storage policy has randomness as its parameter that is used to place an SKU within the warehouse.

5.4 Experimental design

This section discusses the storage allocation of SKUs to different storage policies and methods. We test all configurations discussed in Section 5.1 for all interventions to find the most efficient storage configuration and intervention for B-Living. Subsection 5.4.1 discusses the heuristic algorithm that allocates the locations from each functional area to the SKUs. Thereafter, Subsection 5.4.2 elaborates on how each storage configuration is applied to the product allocation heuristic. In Subsection 5.4.3, the calculation of the total traveling time is discussed. The storage configurations which we will test the impact to the total traveling times is displayed in Table 15.

Table 15 Brief description of the storage configurations used for the experiments

Storage configuration	*Description*
Random storage	allocate SKUs to random locations within its assigned functional area
ABC-assigned storage	allocate SKUs based on order picking frequency within its assigned functional area
COI-assigned storage	allocate SKUs based on order picking frequency and inventory volume within its assigned functional area
Class-based random storage	allocate SKUs to random locations within its assigned functional area and stackability class. This storage configuration is currently applied to the storage process.
Class-based ABC storage	allocate SKUs based on order picking frequency within its assigned functional area and stackability class
Class-based COI storage	allocate SKUs based on order picking frequency and inventory volume within its assigned functional area and stackability class

5.4.1 Storage allocation heuristic algorithm

Although storing an SKU at a certain location depends on the storage configuration, the functional area locations and the assignment of each location to the SKUs is the same for all policies. As is described in Section 5.3, we constructed subsets of locations for each functional area given the number of locations that are available considering the intervention. From these subsets we draw locations to allocate to the SKUs by taking the storage configuration into consideration.

In order to allocate the SKUs to the locations within the subsets, we want to sort the subset from closest to the IO points to furthest from the IO point. So that if we apply a storage configuration, we can allocate the SKUs to the location sequentially drawing the locations from the subset. Which locations are most preferable to use depend on the distance to the IO point. However, we do not have a single IO point in the warehouse of B-Living. The locations closest to the IO point should therefore be calculated. As all orders start at the I point and end at the O point, we do not prioritise the I point over the O point or vice versa. Therefore, to determine the traveling distance to the IO point of location γ we use the formula:

$$\frac{\left(TravelTime_{I_{point},i}+TravelTime_{j,O_{point}}\right)}{2} + HeightTravelingTime_j$$

The parameters used for this formula are already calculated in Section 5.2 and the formula is applied to all locations within the total subset of locations. We then sort these locations ascending from closest to the IO point to furthest from the IO point.

The next step is sorting the SKUs according to the storage configuration. How these sets are sorted is elaborated on in the next subsection. When this sorting process is executed, we have a set of sorted SKUs and two subsets of sorted locations from closest to furthest from the IO point. The heuristic algorithm then loops over all SKUs checking at each SKU which flow is assigned to that SKU by the algorithm of Chapter 4. And sequentially adding the locations from the corresponding subsets to the SKUs. When a location is added to the SKU, the location is then removed from the subset to avoid assigning a location to multiple SKUs. The process of allocating the SKUs to the locations is displayed in the following pseudo code:

```
SortedSetOfSKUs #use a set of SKUs sorted according to the storage configuration from first to last
ForwardLocationSubset.copy #use a copy of the forward area subset
ReserveLocationSubset.copy #use a copy of the reserve area subset

For α = 1 to NumberOfSKUs #loop over all SKUs
    β = SortedSetOfSKUs_0 #set β as the variable that stores the next to place SKU according to its policy
    SortedSetOfSKUs_0.delete #delete the SKU from the sorted set of SKUs
    If FlowSKU_β = 2 #when the flow of the SKU is 2 (reserve area only)
        PickLocationSKU_β = ReserveLocationSubset_0 #set top location from the subset as picklocation
        For i = 1 to Inventory_β,reserve
            ReserveLocationSubset_0.delete #delete number of required locations from subset
    ElseIf FlowSKU_β = 3 #when the flow of the SKU is 3 (forward and reserve area)
        PickLocationSKU_β = ForwardLocationSubset_0 #set top location from the subset as picklocation
        For i = 1 to Inventory_β,reserve
            ReserveLocationSubset_0.delete #delete number of required locations from subset
        For i = 1 to Inventory_β,forward
            ForwardLocationSubset_0.delete #delete number of required locations from subset
    Else FlowSKU_β = 4 #when the flow of the SKU is 4 (forward area only)
        PickLocationSKU_β = ForwardLocationSubset_0 #set top location from the subset as picklocation
        For i = 1 to Inventory_β,forward
            ForwardLocationSubset_0.delete #delete number of required locations from subset
```

After each iteration, the number of SKUs and the number of locations in the subsets decrease until all SKUs have a picking location. The has now assigned the required number of locations to the SKUs. However, we only use 1 location that we use for the traveling time calculations. This picking location is denoted by $PickLocationSKU_\beta$ in the pseudo code.

5.4.2 Storage configuration application

The heuristic approach that is used to allocate SKUs to locations in the previous subsection requires a sorted set of SKUs. This sorted set of SKUs stores all SKUs sorted according to the storage configuration. As discussed in Section 5.1 we test 6 configurations for all interventions. How each storage configuration is applied to the heuristic will be discussed in this subsection.

5.4.2.1 Random allocation

The way we applied random storage policy is by randomly assigning a location to a SKU while taking the assigned functional area into consideration. Hence, no logic is used while assigning locations to SKUs. By making use of randomness, we constructed a random set of SKUs and assigned each SKU randomly to the locations within its functional area.

5.4.2.2 Dedicated storage

The ABC storage policy dedicates an SKU to the locations based on its popularity. As our popularity parameter, we chose to use the frequency of orders that the SKU is in. This parameter is commonly used to quantify the popularity of an SKU according to Mantel et al. (2007).

Just like the ABC storage policy, the COI storage policy dedicates the SKUs to the locations by means of its COI. This parameter and how it is obtained is already discussed in Section 5.3.

5.4.2.3 Class-based storage

The class-based storage method divides the area in different classes and allocates the SKUs within their classes based on a certain parameter as described in Section 3.4. The classes we use for the B-Living case is the stackability of items. This is the only parameter of importance for our order-picking path, as SKUs that have a stackability score of 1 should be placed first on the pallet, thereafter SKUs with a stackability score of 2 and at last with a stackability score of 3. We can therefore divide the functional areas in three classes at which the SKUs with the corresponding stackability score can be placed.

As we use different interventions and as the product assignment solution is not a fixed solution, we do not have a fixed number of locations that are required for each class. Hence, the number of locations per class is to be determined for every intervention and every solution resulting from the algorithm of Chapter 4.

For the random and assigned storage methods, we used two subsets of locations which descend from the functional areas. As we now use three classes per functional area, the number of subsets become 6 in total. Hence, we construct subsets: reserve1, reserve2, reserve3, forward1, forward2, forward3. These subsets contain all locations the aisles that will be assigned to each class. Hence, we calculate the required number of locations per class, find the number of aisles that we therefore need to dedicate to each class and then add those locations within that aisle to the subsets. How the subsets are constructed is displayed in the following pseudo code. The pseudo code is partly displayed, as the follow up is evident.

$forward1$ # $subset\ containing\ locations\ of\ forward\ area\ class\ 1$
$forward2$ # $subset\ containing\ locations\ of\ forward\ area\ class\ 2$
$forward3$ # $subset\ containing\ locations\ of\ forward\ area\ class\ 3$
$reserve1$ # $subset\ containing\ locations\ of\ reserve\ area\ class\ 1$
$reserve2$ # $subset\ containing\ locations\ of\ reserve\ area\ class\ 2$
$reserve3$ # $subset\ containing\ locations\ of\ reserve\ area\ class\ 3$

For $\alpha = 1\ to\ NumberOfSKUs$ #$loop\ over\ all\ SKUs$
  If $FlowSKU_\alpha = 2$
    If $Stackability_\alpha = 1$
      For $i = 1\ to\ Inventory_{\alpha,reserve}$
        $reserve1\ .add$ #$add\ number\ of\ required\ locations\ to\ subset$
    If $Stackability_\alpha = 2$
      For $i = 1\ to\ Inventory_{\alpha,reserve}$
        $reserve2\ .add$ #$add\ number\ of\ required\ locations\ to\ subset$
    If $Stackability_\alpha = 3$
      For $i = 1\ to\ Inventory_{\alpha,reserve}$
        $reserve3\ .add$ #$add\ number\ of\ required\ locations\ to\ subset$
  ElseIf $FlowSKU_\alpha = 3$
    If $Stackability_\alpha = 1$
      For $i = 1\ to\ Inventory_{\alpha,reserve}$
        $reserve1\ .add$ #$add\ number\ of\ required\ locations\ to\ subset$
      For $i = 1\ to\ Inventory_{\alpha,forward}$
        $forward1\ .add$ #$add\ number\ of\ required\ locations\ to\ subset$

$Proceed\ this\ process\ for\ SKUs\ with\ flow\ 3\ and\ stackability\ 2\ \&\ 3\ and\ for\ SKUs\ with\ flow\ 4.$

By applying this code, we constructed the subsets that we need sorted from closest to furthest from the IO point. Hence, the allocation of SKUs follows the same process as elaborated on in Subsection 5.4.1 by allocating the SKUs to locations corresponding with the assigned subsets, but now using 6 subsets instead of 2. Within the class-based storage method we also tested applied the random storage policy, the ABC policy and the COI storage policy by using the same approach as discussed in this subsection.

5.4.3 Travel path and traveling time calculations

By applying the storage allocation heuristic algorithm and the storage configuration approach discussed earlier this section, we assigned an order pick location to each SKU α with the variable $PickLocationSKU_\alpha$. As we now have the order pick location, all orders of year 2022 and the traveling times between locations. We can construct a path picking all orders of 2022 and calculate the total traveling time of year 2022. How we execute this calculation is by means of a function that requires the parameters:

$PickLocationSKU_\alpha$	$\forall\ \alpha\ in\ the\ set\ of\ SKUs\ A\ (1{,}306\ in\ total)$
$Order_o$	$\forall\ o\ in\ the\ set\ of\ order\ year\ 2022\ O\ (44{,}339\ in\ total)$
$TravelTime_{g,g+1}$	$\forall\ g\ in\ the\ set\ of\ ground\ locations\ G\ (441\ in\ total)$
$HeightTravelTime_h$	$\forall\ h\ in\ the\ set\ of\ height\ locations\ H\ (5\ in\ total)$
$GroundLocation_l$	$\forall\ l\ in\ the\ set\ of\ locations\ L\ (5{,}266\ in\ total)$
$HeightLocation_l$	$\forall\ l\ in\ the\ set\ of\ locations\ L\ (5{,}266\ in\ total)$

As this is not an optimisation algorithm, we find the objective value by means of a heuristic calculation. The objective value of this calculation is the total traveling times for the year 2022. This calculation consists of the total traveling times of height picks and the total traveling times of the order paths. To construct the path of orders in year 2022, we create two subsets denoted by $groundPath_l$ and $heightPath_h$ consisting of all ground locations l and height locations h that are to be travelled to pick all orders from subset $Order$. This subset $Order$ is constructed in Section 5.3 and consists of all individual orders from 2022, starting with at the I point, then the SKUs of that order and ending at the O point. With the SKUs of each order sorted ascending by picked location and sorted ascending by stackability code (see Figure 39).

Both subsets are derived from this $Order_o$ subset containing also 44,339 values in total, where the path location l is the picking location of the SKU that is in the $Order$ subset. How the locations are added to the $groundPath$ subset and the $heightPath$ subset is by the applying the following pseudo code:

$groundPath_i = subset\ of\ the\ total\ ground\ locations\ path\ where\ i\ is\ 1\ to\ 44{,}339$
$heightPath_i = subset\ of\ the\ total\ heights\ path\ where\ i\ is\ 1\ to\ 44{,}339$

For $i = 1\ to\ O$ $\#loop\ over\ all\ order\ lines\ (44{,}339\ lines\ in\ total)$
$groundPath_i = GroundLocation_{PickLocationSKU_{Order_i}}$ $\#construct\ a\ path\ of\ ground\ picking\ locations$
$heightPath_i = HeightLocation_{PickLocationSKU_{Order_i}}$ $\#construct\ a\ path\ of\ height\ picking\ locations$

With the result of both subsets, we can calculate the total traveling times by means of the objective function. The objective function is as follows:

$$Total\ Traveling\ Time = \sum_{o=1}^{O-1} TravelTime_{groundPath_o, groundPath_o+1} + HeightTravelTime_{heightPath_o}$$

Hence, the total traveling time is found by calculating the travel time of the ground path and calculate the travel time of the height path. The calculation iterates until $O - 1$. However, this does not influence the calculation of the final $HeightTravelTime_{heightPath_O}$ variable, as this value is 0.

5.5 Conclusions

This chapter elaborates on the algorithm that assigns the SKU-to-locations. This constructive heuristic algorithm proposes three storage policies and three storage methods which result in a total of 7 configurations:

1. Random storage
2. ABC-dedicated storage
3. COI-dedicated storage
4. Random class-based storage
5. ABC class-based storage
6. COI class-based storage

The solution of the Flow-to-SKU algorithm discussed in Chapter 4 assigned flows to each SKU and therefore the SKUs to the functional areas. This SKU to functional area assignment is then used as input to the SKU-to-location algorithm. The 6 storage configurations decide which SKU to place at which location within the functional area that is assigned to that SKU. Then a path is constructed which picks all orders of 2022 from the picking locations that are assigned to the SKUs by each storage configuration. With the location distances, the traveling times and the constructed path, the average traveling time per forward are pick, the average traveling time per reserve area pick and the total traveling time for the orders of 2022 can be calculated. The average traveling times per functional area are then used as updated parameters to the Flow-to-SKU algorithm. Hence, the solution of both algorithms is used as input to the opposite algorithm which results in an iterative approach. When the solutions do not improve anymore, the expected total traveling time for the orders of 2022 for all storage configurations are compared to the actual total traveling time of 2022 in Chapter 6.

6 Experimental Results

This chapter discusses and evaluates the results of the computational experiments. We start with a chapter introduction which briefly describes how we computed the results in Section 6.1. Thereafter, we describe the computational results in Section 6.2. In Section 6.3 we analyse the limitations and robustness of the algorithms and we discuss the key findings and conclusions in Section 6.4.

6.1 Introduction

This section briefly elaborates on the goal of the algorithms, the purpose of the flow-to-SKU algorithm, the purpose of the SKU-to-location algorithm and how the results of both algorithms are used as parameters for both algorithms making it an iterative process.

6.1.1 Algorithm result goals

The goal of the algorithm results is finding the functional area intervention and the storage configuration that is expected to have the least traveling time when order picking. Forward area and reserve area are the considered functional areas. However, we want to test different functional area layouts with different dimensions as it is expected that the dimension of the intervention has a big influence on the total traveling time of picking orders. We therefore created 7 functional area interventions. The functional area interventions that are considered are extensively described in Section 4.1, but to recall we briefly described these interventions in Table 16. The no-forward intervention is the baseline, which currently applies.

Table 16 Functional area interventions description

Functional Area intervention	*Description*
No-forward intervention (I0)	This intervention reproduces the current situation at B-Living, not making use of a forward area. Hence, locations are assigned to the reserve area.
Bottom-layer-before-cross-aisle intervention (I1)	This intervention sets the bottom layer locations of the picking area before the cross-aisle as forward area and all other locations as reserve area
Bottom-two-layers-before-cross-aisle intervention (I2)	This intervention sets the bottom two-layer locations of the picking area before the cross-aisle as forward area and all other locations as reserve area
Before-cross-aisle intervention (I3)	This intervention sets all locations of the picking area before the cross-aisle as forward area and all other locations as reserve area
Bottom-layer intervention (I4)	This intervention sets all bottom layer locations of the picking area as forward area and all other locations as reserve area
Bottom-two-layers intervention (I5)	This intervention sets all bottom two-layer locations of the picking area as forward area and all other locations as reserve area
Full-forward intervention (I6)	This intervention sets all locations of the picking area as forward area and all other locations as reserve area

With these 7 interventions, we test a total of 6 storage configurations which are extensively described in Section 5.1. Table 17 briefly describes these storage configurations considered. There is currently not a default storage policy, but based on the current storage process, we use class-based random storage as the base line storage policy.

Table 17 Brief description of the storage configurations used for the experiments

Storage configuration	*Description*
Random storage	allocate SKUs to random locations within its assigned functional area
ABC-assigned storage	allocate SKUs based on order picking frequency within its assigned functional area
COI-assigned storage	allocate SKUs based on order picking frequency and inventory volume within its assigned functional area
Class-based random storage	allocate SKUs to random locations within its assigned functional area and stackability class. This storage configuration is currently applied to the storage process.
Class-based ABC storage	allocate SKUs based on order picking frequency within its assigned functional area and stackability class
Class-based COI storage	allocate SKUs based on order picking frequency and inventory volume within its assigned functional area and stackability class

6.1.2 Flow-to-SKU algorithm

To test which functional area intervention and storage configuration best fits B-Living we use two algorithms that are related to each other. The first algorithm constructed in Chapter 4 assigns product flows to SKUs. For this flow-to-SKU assignment we have three possible product flows:

- **The reserve storage flow**, where the SKU is received, stored at the reserve area, picked from the reserve area and shipped to the customer
- **The reserve-forward storage flow**, where the SKU is received, stored at the reserve area, replenished to the forward area, picked from the forward area and shipped to the customer
- **The forward storage flow**, where the SKU is received, stored at the forward area, picked from the forward area and shipped to the customer

Assigning a product flow to the SKU assigns (part of) the inventory to functional areas. Within this research there are two functional areas, which are the forward and reserve area. All inventory of the SKU is stored at the reserve area when the reserve storage flow is assigned to the SKU. When the forward storage flow is assigned to an SKU, all of its inventory is assigned to the forward area. When the reserve-forward storage flow is assigned to the SKU, a fraction of the SKU inventory that will be used for order-picking is assigned to the forward area and the remaining inventory is placed at the reserve area. The inventory at the forward area is then replenished from the reserve area when it reaches a certain stock level.

We elaborate on the construction and details of the flow-to-SKU algorithm and how we are able to compute results in Chapter 4. However, important for this chapter are the input parameters of the algorithm average traveling times per functional area. These averages are based on the centre location of the functional area and the starting and stopping locations within the warehouse and not based on traveling times between locations. As these average traveling times are not realistic, we constructed the SKU-to-location algorithm that uses the flow-to-SKU assignment to compute actual average traveling times per functional area based on the sales orders of 2022. Hence, the solution of the flow-to-SKU algorithm is used as parameter to the SKU-to-location parameter

6.1.3 SKU-to-location algorithm

With the assignment of product flows to SKUs and with the set of locations per functional area we are able to assign SKUs to locations based on storage configurations. For each storage configuration, the SKU-to-location algorithm assigns SKUs to specific locations. With these locations we construct paths of picking the sales orders from 2022. We then calculate the average order picking traveling times for both functional area and the total order picking traveling time of 2022. These average traveling times are more realistic and more accurate than the used average traveling time parameter of the flow-to-SKU algorithm. Hence, to compute more accurate results with our flow-to-SKU algorithm, we update the average travel time per functional area parameter with the results from the SKU-to-location algorithm.

6.1.4 Iterative approach

The assignment of flows to SKUs as a result of the flow-to-SKU algorithm is used as parameter to the SKU-to-location algorithm and the average traveling times per pick resulting from this SKU-to-location algorithm is then used as input to the flow-to-SKU making it an iterative process as is shown in Figure 40. This iterative approach calibrates the input parameters up to a steady state at which the parameters changes are neglectable.

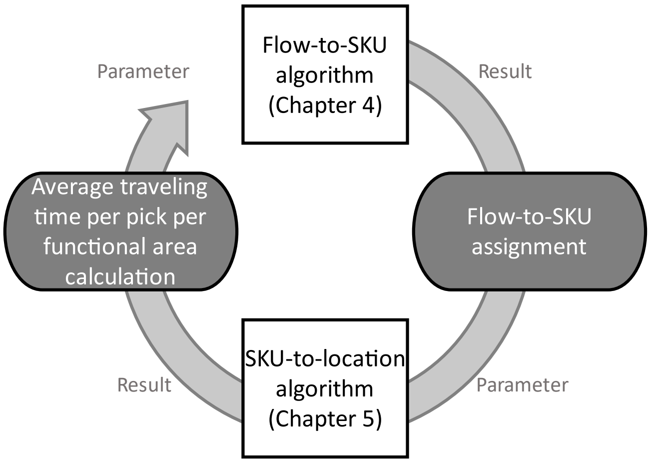

Figure 40 Integration of model Chapter 4 and model Chapter 5

6.1.5 Experimental factors

The experiments that are conducted are multi factorial. Using the historical sales data we are able to construct a realistic sequence of SKUs to pick and form a path based on the SKU picking locations. The multi factorial experiments consist of two factors which have influence on the total traveling time. These two factors are the functional area intervention and the storage configuration. These 7 functional area interventions and 6 storage configurations sum up to 42 combinations which we test the impact of to the total traveling times.

A factor which we exclude from the experimental design is the vehicle factor. There were two vehicles considered from the start of this research. Order-picking can be executed with the long order-picking vehicle, which is able to carry two pallets or carts simultaneously or order-picking can be executed with the height order-picking vehicle, which is able to pick from height locations. It is assumed that using the long order-picking vehicle reduces the traveling time per order as the operator is able to carry two carts or pallets simultaneously. However, this vehicle is can only pick from bottom layer locations as it does not have the ability to go up. As picking from the bottom locations only is not possible, we were able to exclude this factor

6.1.6 Key performance indicators

The objective of both algorithms constructed in Chapter 4 and 5 is to minimise the total traveling time of order picking. However, the algorithm from Chapter 4 improves the total traveling times by focussing on assigning SKUs to product flows and the algorithm constructed in Chapter 5 improves the total traveling time by using different storage method and policy combinations. Hence, the focus of the Flow-to-SKU assignment lies in efficiently assigning (part of) the SKU inventory to functional areas and the focus of the SKU-to-location algorithm is about efficiently placing SKUs to locations within those functional areas. We therefore use different performance indicators to evaluate the results of both algorithms.

The objective of this research is to minimise the total traveling time of picking orders. However, assigning flows to SKUs have some trade-offs. We therefore use three performance indicators which are taken into account when concluding the best fit functional area intervention and storage configuration for B-Living.

The total traveling times is the objective of this research and therefore the most important KPI. Furthermore, allocating the SKUs to the reserve storage flow has a downside. The reserve storage product flow means storing the entire inventory in the reserve area. The majority of the reserve area locations are within the small aisle area and as it is only possible for one vehicle to operate in a small aisle, it is undesired to pick many SKUs from the locations in small-aisles. We therefore consider the expected number of picks from locations in the small aisles as a performance indicator.

Another performance indicator to consider for the Flow-to-SKU assignment is the number of replenishments. Using the reserve-forward storage flow has the benefit of placing most of the SKU inventory to the reserve area while still picking from locations within the forward area. Hence, it uses both areas to its design purposes. However, the picking locations within the forward area are to be replenished to benefit from both advantages and these replenishments requires extra handling for the inbound logistics employees. The workload of the inbound logistics employees is out of scope, but as determining which functional area intervention and storage configuration is best for B-Living, we will take the additional workload of the inbound logistics employees into account. Hence, the Flow-to-SKU assignment results is measured with KPIs:

- Total traveling time (objective)
- Number of picks in the small-aisle area
- Number of replenishments.

6.1.7 Optimisation technique

The algorithm constructed in Chapter 4 dedicates SKUs to flows based on the expected traveling times per functional area, the SKU picking frequency, the volume of the SKU inventory and the functional area limits. We tested the heuristic repair algorithm and the simulated annealing optimisation techniques to solve this problem and generate improved flow-to-SKU solutions. Three storage flows are considered which are storing the entire inventory in the reserve area using reserve storage flow, storing a proportion of the inventory in both functional areas using storage reserve-forward storage flow and storing all inventory of an SKU in the forward area using forward storage flow. To generate multiple forward and reserve area options we considered 7 functional area interventions described in the previous section.

Each intervention has upper limits for the number functional area locations. By assigning SKUs to certain flows the algorithm tries to find improved solutions by changing the assigned flows of the SKUs. Optimisation technique results. We used the heuristic repair algorithm and simulated annealing as is described in Chapter 4 to improve the flow-to-SKU assignment.

The heuristic repair algorithm starts at an infeasible lower bound at which all flows with the least expected traveling times per pick to are assigned to the SKUs. It then changes the flow of an SKU that reduces the total traveling time of order picking the least. This changing of flow process repeats until a feasible solution is found.

The simulated annealing approach starts at a feasible solution and tries to improve this solution by swapping flows of SKUs and moving a flow of an SKU. Using the heuristic repair algorithms approach and the simulated annealing approach with parameters T_{start}, T_{stop}, $\alpha = 0.99$ and $M = 750$ we generate the results per intervention displayed in Figure 41.

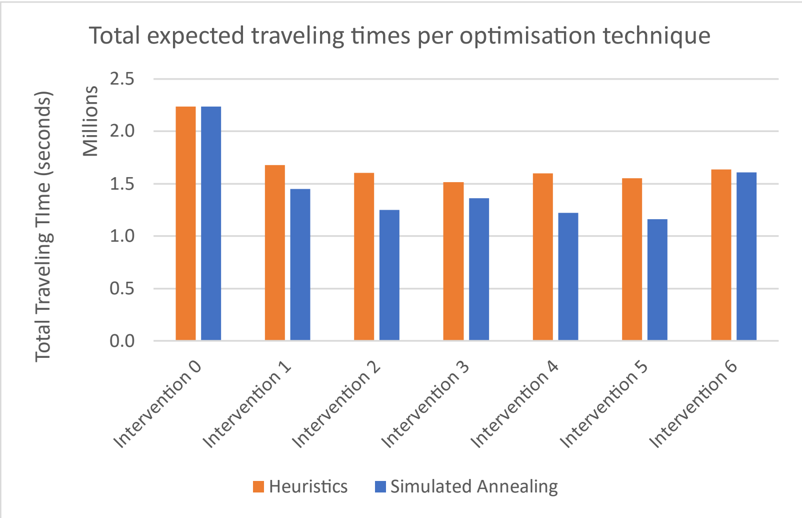

Figure 41 Total expected traveling times generated with the heuristic repair algorithm and the simulated annealing algorithm

With the set simulated annealing parameters, the algorithm run requires on average 34.01 seconds computational time. The heuristic repair algorithm requires on average 5.15 seconds computational time. We argued in Chapter 4 that a CPU time of less than 60 seconds is reasonable for executing the 2-factorial experiments for multiple instances. Hence, the simulated annealing approach shows the best objective value and meets the maximum CPU time requirement.

6.2 Computational results

This section evaluates the results of the experiments. The section starts with a calibration of the input parameters in Subsection 6.2.1. Changing the parameters of the simulated annealing model requires updated starting and stopping temperatures. These updated values are elaborated on in Subsection 6.2.2. Thereafter, the results from the flow-to-SKU algorithm are evaluated in Subsection 6.2.3, and the results from the SKU-to-location algorithm are evaluated in Subsection 6.2.4.

6.2.1 Average traveling time parameter calibration

Every iteration, the algorithm updates the input parameters average forward area traveling time and average reserve area traveling time per pick. After some iterations, the input variables enter a steady state at which they remain consistent. To find the number of iterations which are required to enter the steady state, we run the two-factorial experiment for 10 iterations. Each iteration, the lowest traveling times per functional area are set as the new parameter The results of these iterations are shown in Figure 42. As can be seen from these graphs, the average order picking traveling times reach a steady state at iteration 5 for both functional area average traveling times per pick at each intervention.

Figure 42 Updated average traveling times per functional area in seconds

6.2.2 Simulated annealing updated starting and stopping temperature

After calculating the new average forward traveling time and average reserve traveling time per pick. As the parameters have new values, the starting and stopping temperature which are determined in Section 4.3 are not applicable anymore as the average traveling times per pick per functional area decrease. The difference between S_c and S_n are less and using the set T_{start} and T_{stop} with the updated average traveling times per pick will therefore result in inefficient algorithm runs. To update these values we use the approximation formula $T = \frac{-\Delta}{\ln(acceptance\ ratio)}$ from Ledesma et al. (2008). In Section 4.3 we elaborate on this approach.

We use the acceptance ratio of 0.95 for setting the starting temperature and an acceptance ratio of 0.01 for the stopping temperature. Results of these update temperatures per iteration are shown in Figure 43. As can be seen from this graph the steady state is reached at iteration 5 as was already concluded this section.

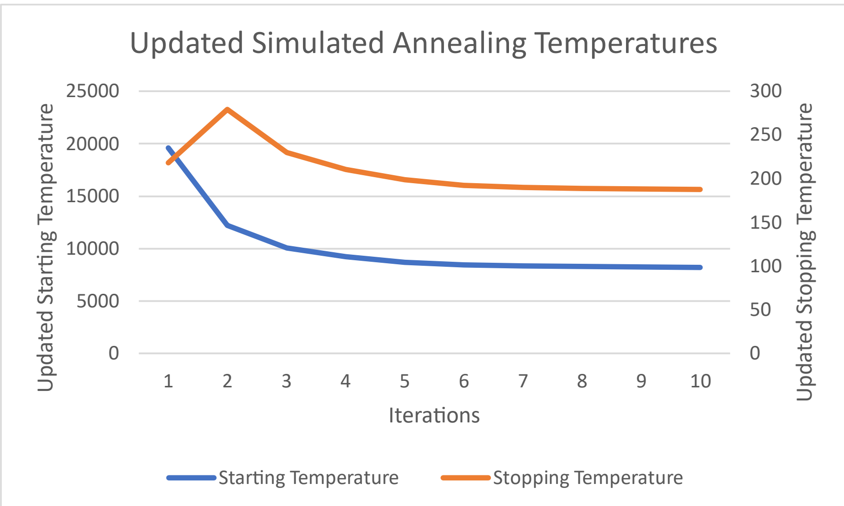

Figure 43 Simulated Annealing updated Starting and Stopping temperature per iteration

6.2.3 Flow-to-SKU algorithm results

Using the simulated annealing algorithm, we are able to find an improved flow-to-SKU assignment. Which SKUs to store at which functional area is determined by the assigned flow. Table 18 shows the proportion of space per functional area per intervention and the percentage of SKUs that are assigned to each flow.

Table 18 Intervention space proportions and Flow-to-SKU proportions

	Reserve area space proportion	Forward area space proportion	% of SKUs to the reserve storage flow	% of SKUs to the reserve-forward storage flow	% of SKUs to the forward storage flow
No-forward intervention	100%	0%	100%	0%	0%
Bottom-layer-before-cross-aisle intervention	96%	4%	88%	10%	2%
Bottom-two-layers-before-cross-aisle intervention	93%	7%	79%	18%	4%
Before-cross-aisle intervention	80%	20%	43%	44%	13%
Bottom-layer intervention	91%	9%	73%	23%	3%
Bottom-two-layers intervention	85%	15%	56%	37%	7%
Full-forward intervention	57%	43%	22%	44%	34%

The reserve-forward storage flow and the forward storage flow both benefit from the forward area order-pick perks, and with the assignment of flow-to-SKUs, the algorithm assigns around three times as many SKUs to the relative space in the forward area. E.g. for bottom-layer-before-cross-aisle intervention, with a forward area proportion of 4% we are able to dedicate the picking locations of 12% of SKUs to this area.

The impact of this assignment of Flow-to-SKU can be measured based on the objective value total traveling time for order-picking and performance indicators number of replenishments and the number of picks from the small-aisle area. The numerical results of these KPIs for all interventions are shown in Table 19. This table shows that before-cross-aisle intervention and the bottom-two-layers intervention have the lowest total traveling times, but that they also require the most replenishments.

Table 19 Numerical results of the Flow-to-SKU algorithm for all interventions

	Total Traveling Time (seconds)	*Number of replenishments*	*Number of picks from small-aisle area*
No-forward intervention	2,345,963	0	50,115
Bottom-layer-before-cross-aisle intervention	2,114,354	770	32,030
Bottom-two-layers-before-cross-aisle intervention	1,967,335	1,309	24,539
Before-cross-aisle intervention	1,772,416	3,093	9,193
Bottom-layer intervention	1,912,029	1,751	20,441
Bottom-two-layers intervention	1,746,037	2,828	11,988
Full-forward intervention	1,982,638	2,395	5,427

By scoring the interventions on all three KPIs we generated radar charts of all interventions displayed in Figure 44. Within these charts the KPIs get a score of 1 which is the least favourable result up to 5 which is the most favourable result. From these graphs it can not be concluded that a specific intervention has a better score than the other interventions or that one intervention can be completely left out of the considered options during the experiments of the SKU-to-location assignment in Section 6.3. However, we conclude that all proposed interventions are more beneficial than the current situation, which is the no-forward intervention.

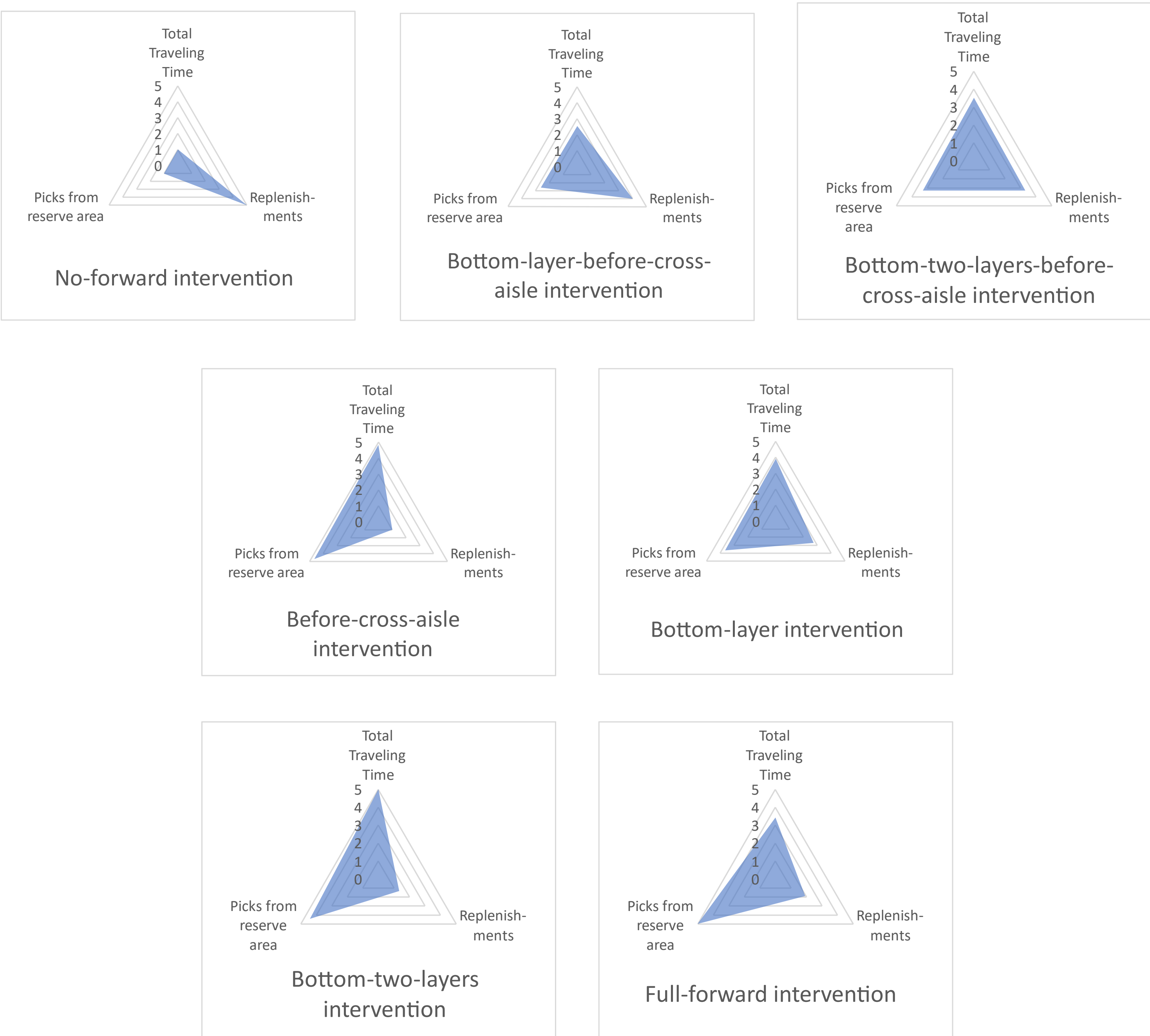

Figure 44 Radar charts per functional area intervention of the Flow-to-SKU assignment algorithm

6.2.4 SKU-to-location algorithm results

This subsection elaborates on the impact of the storage configurations to the total traveling times of order-picking. The experiments constructed in this subsection follow from the solution of the Flow-to-SKU assignment algorithm conducted in the previous section. The solution dedicates Flow-to-SKUs and therefore (partly) to the functional forward and reserve areas. From this SKU to area assignment, the storage configurations allocate the SKUs to specific locations. After allocating the SKUs within specific locations in the warehouse, we have all SKUs assigned picking locations. Using the set of orders from 2022 and the picking locations of each SKU, we are able to generate order picking paths which are used to calculate the order picking traveling times between picks.

The 2-factorial experiments are executed to find the best storage configuration for B-living. The results of these experiments show that for each intervention, the ABC and class-based ABC storage configurations score best as is displayed in Figure 45. The ABC storage policy for both assigned as class-based storage has a total traveling time of 20.43% less than the random storage policy and 31.76% less than the COI storage policy.

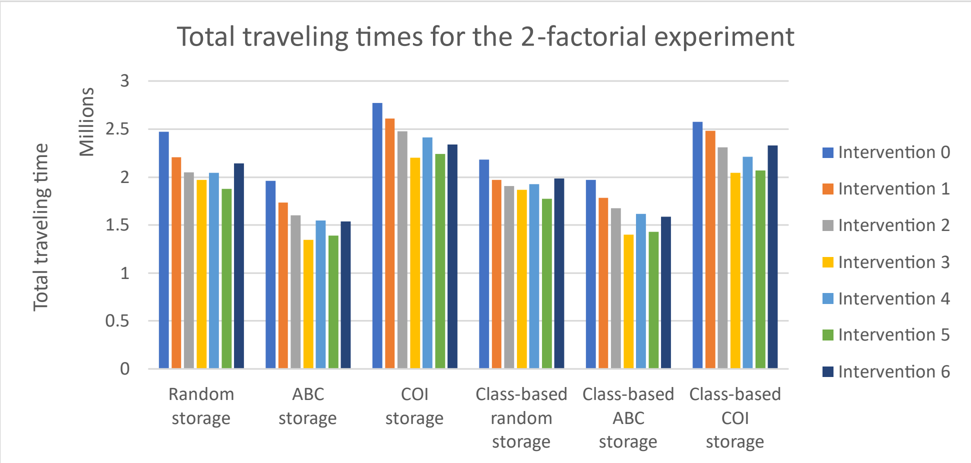

Figure 45 Total traveling times for the 2-factorial experiment

The graph shows as well that the total traveling times of COI storage is the worst out of all storage policies tested. This is interesting, as this storage configuration is similar to the ABC policies as both policies use picking frequency as its popularity parameter. The difference between ABC and COI storage policy is the volume parameter. ABC storage does not use the SKU inventory volume as a factor for assigning an SKU to a location and COI does use this parameter as a factor. This result therefore concludes that using volume as a factor for assigning SKUs to location has a negative influence on the total travel time of the order picker.

Another finding is that the class-based methods have better total traveling times than the assigned methods for both the random and COI storage policies as we show in Figure 45. The class-based random storage has a total traveling time of 7.82% less than random storage and class-based COI has a total traveling time of 6.05% less. It is interesting that the ABC policy has a better total traveling time when it is assigned instead of class-based assigned. The class-based ABC storage has a total traveling time of 3.11% longer than the ABC assigned storage configuration. Hence, it can not be concluded that the class-based storage method is better or worse than the storage assignment method

To find how much each intervention influences the storage configuration we displayed the boxplots of Figure 46 for the results of each storage configuration for each intervention. These boxplots show that the deviation between interventions per storage configurations show big differences. The ABC storage policies have a minor difference between the lowest obtained value and the first quartile. This implies that multiple interventions are interesting for the ABC storage policies as the deviation of the top 25% of the results (the bottom line of the ABC storage and Class-based ABC storage boxplots) is short.

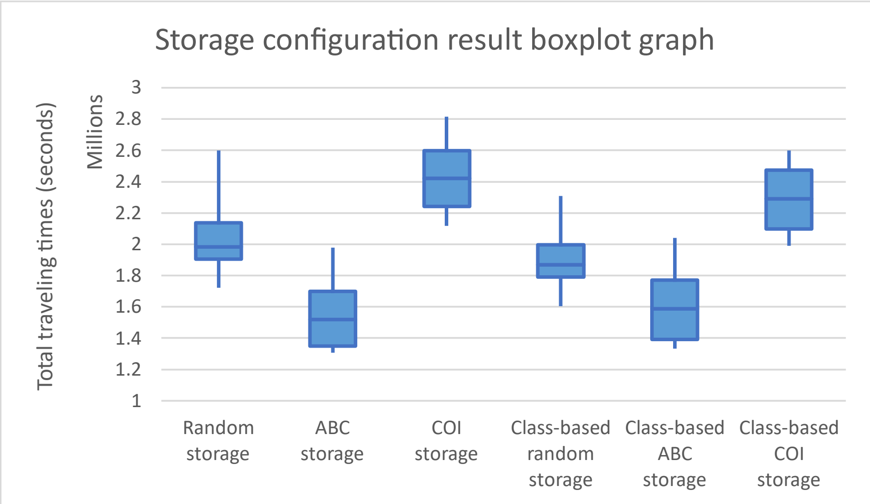

Figure 46 Total traveling time results of each storage configuration for all functional area interventions

From all these findings can be concluded that the ABC storage policy has the best total traveling times of all policies considered. Table 20 shows top 5 storage configuration and functional area intervention combinations in terms of total traveling time of order-picking. These results show that the ABC-assigned storage shows the best storage configuration results.

Table 20 Top 5 objective value combination of experimental factors

Rank	*Order-Picking vehicle*	*Intervention*	*Storage configuration*	*Total traveling times (seconds)*	*Intervention overall score*
1	Height order picker	3	ABC	1,327,668	3.50
2	Height order picker	5	ABC	1,340,404	3.59
3	Height order picker	5	CB-ABC	1,370,646	3.59
4	Height order picker	3	CB-ABC	1,370,967	3.50
5	Height order picker	4	ABC	1,497,556	3.43

6.3 Sensitivity analyses

There are two uncertainties regarding the input parameters of the algorithms which endanger the robustness of the results. The first uncertainty is the input parameter average traveling times per functional area per pick. We use these parameters to assign flows to SKUs. To reduce the sensitivity of the algorithms due to these parameters, we make the algorithms iterative. Hence, we update the parameters every iteration with realistic and accurate measures, improving the robustness of the flow-to-SKU algorithm. To evaluate the sensitivity of this algorithm we constructed a graph containing the results of the simulated annealing objective value in Figure 47. The results from this graph show that the objective value does not change much after the calibration period of 5 iterations.

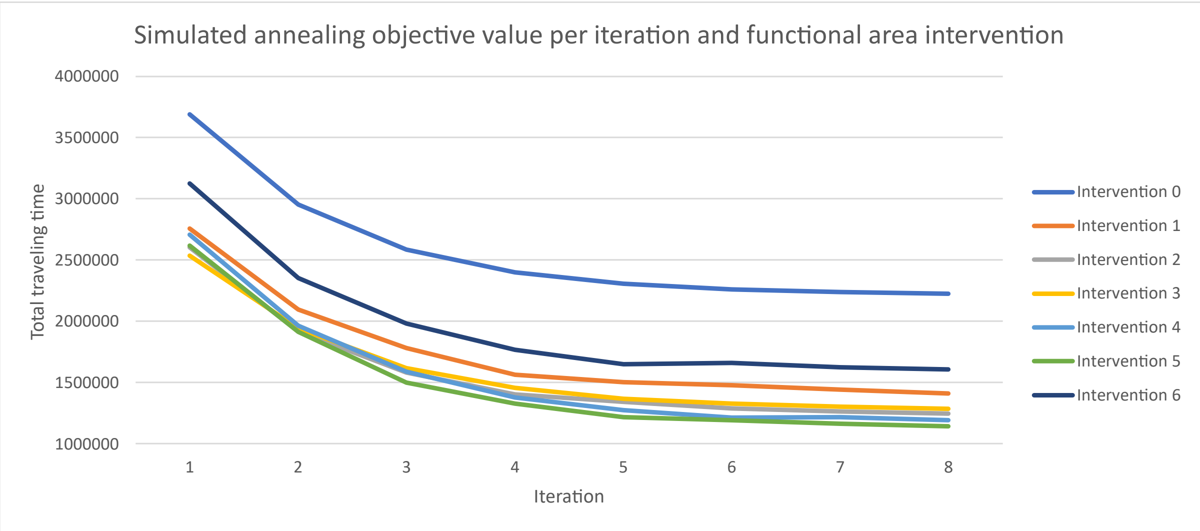

Figure 47 Simulated annealing objective value per iteration and for all interventions

The second uncertainty regarding the robustness of the algorithm is the set of orders. The set of orders we use are the 2022 sales data. With SKU-to-location algorithm we use this set of orders to construct order picking paths which we use to calculate the traveling times between picks. To test the sensitivity of this parameter we shuffled the sequence of order picking, creating three order sets from the orders of 2022 with different picking sequences. The calculated total traveling times of these three instances are displayed in Figure 49a and Figure 49b for both the ABC storage configuration and the class-based ABC storage configuration respectively. From this graph can is concluded that the differences of results are neglectable and that the algorithm results are not sensitive to randomness or picking sequences.

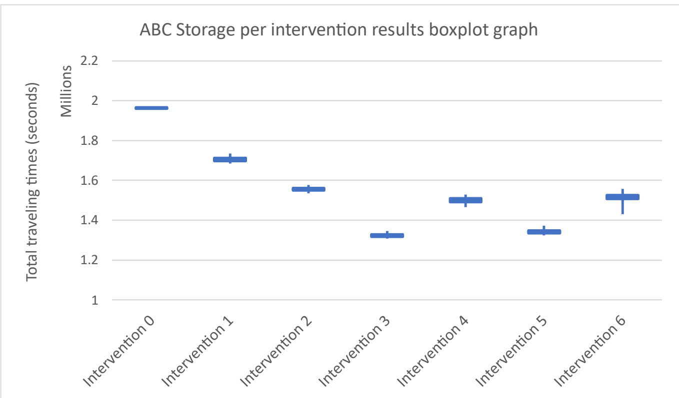

Figure 49a ABC storage per intervention boxplot graphs

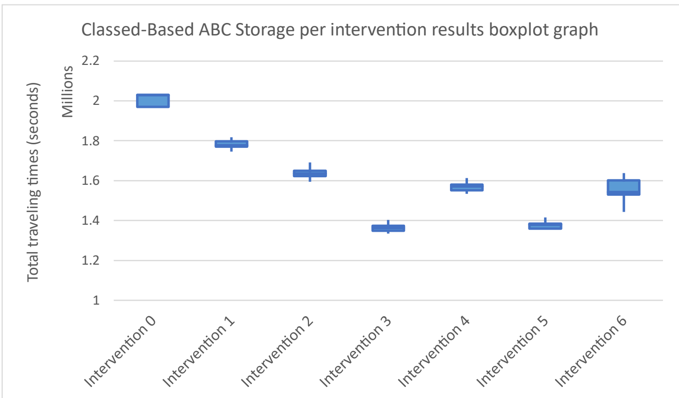

Figure 49b Class-based ABC storage per intervention boxplots

6.4 Key findings and conclusions

A multi-factorial experiment has been conducted to evaluate the factors order-picking vehicle, functional area intervention and storage configuration. By simulating an order-picking path, we evaluated 6 proposed storage configurations and 7 functional area interventions which sum up to 42 combinations. We tested these combinations for multiple iterations and updated the average traveling times per functional area each iteration to find better solutions.

From the experimental results we conclude that picking all SKUs from the bottom layer is not possible for the B-Living case. Hence, the option of using the long order-picking vehicle to reduce traveling times by being able to carry two pallets or carts simultaneously is excluded from the options.

The final result of these tests shows the best total traveling times is by picking with the regular order picking vehicle, assigning the functional area according to before-cross-aisle intervention and applying ABC assigned storage. Hence, assigning the entire picking area before the cross-aisle as forward area or assigning the bottom two layers of the picking area as forward area and applying assigned storage with an ABC-storage policy suits B-Living best for picking with the regular order picker.

Applying this combination of factors result in a total traveling time of 1.340 million seconds. This is a reduction of 23.74% compared to the 2022 total traveling times for the same instance, as this traveling path resulted in a traveling time of 1.757 million seconds. The results on all performance indicators of the top combinations are shown in Table 21.

Table 21 Top results for the Flow-to-SKU and the SKU-to-location algorithm

Intervention	*Storage configuration*	*Total traveling time (seconds)*	*# Replenish-ments*	*# Small-aisle area picks*
Historical performance	-	1,757,655	0	12,731
Before-cross-aisle	ABC	1,327,668	3,093	9,193
Bottom-two-layers	ABC	1,340,404	2,828	11,988

The results in the table show that the number of replenishments for this sample set are estimated in a range of 2,800-3,100 times and the number of small-aisle area picks are estimated in a range of 9,000-12,000 times. Compared to the current number of picks in the small area which is 12,731 picks, this is an improvement of up to 27.79%.

The experimental results show that the updated traveling times improve the Flow-to-SKU algorithm objective value with on average 50.11%. However, this flow-to-SKU assignment that results from the algorithm with the updated values show neglectable changes to the SKU-to-location assignment. Hence, with the updated traveling times, the result of the simulated annealing becomes more accurate. After 4 iterations the input average traveling times become steady and we therefore use a calibration of 4 iterations.

Using the interventions and storage configurations from the top 2 combinations displayed in Table 21 we generated a heatmap consisting of all locations and there picking frequencies. Figure 50 and Figure 53a respectively display the warehouse layout heatmap and the height picking heatmap of the before-cross-aisle intervention with the ABC storage configuration. Figure 51 and Figure 53b respectively displays the warehouse layout heatmap and the height picking heatmap of the bottom-two-layer intervention with the ABC storage configuration. These graphs conclude that the picking frequency in the forward area is a lot more than in the reserve area for both interventions and that the popular locations are at the beginning of the aisle reducing when heading towards the end of the aisles.

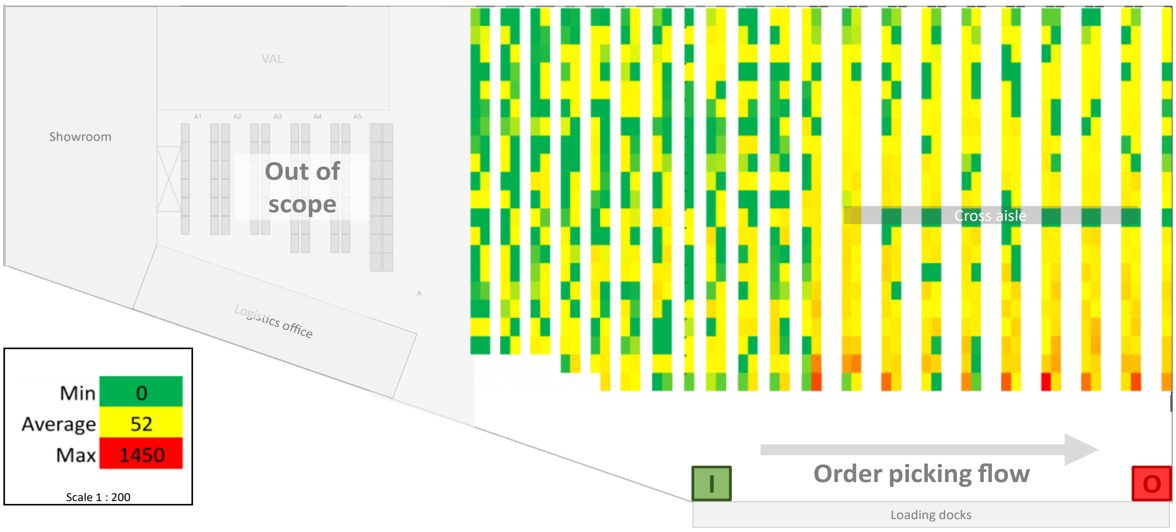

Figure 50 Warehouse order picking heatmap for storage configuration ABC and the bottom-two-layer intervention

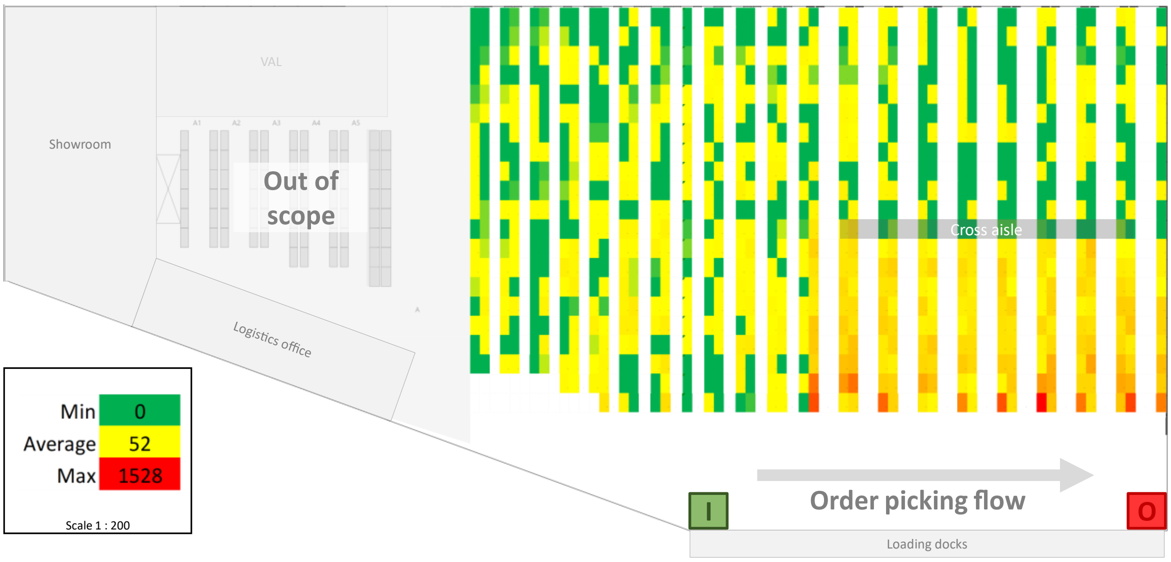

Figure 51 Warehouse order picking heatmap for storage configuration ABC and the before-cross-aisle intervention

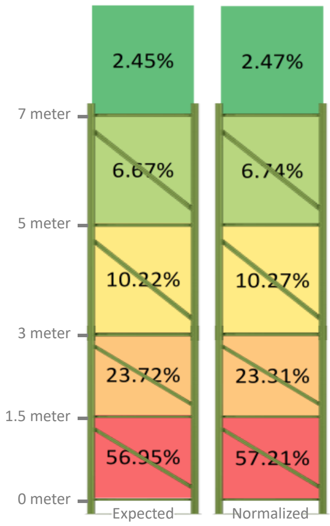

Figure 53a Height picking heatmap of ABC storage and the before-cross-aisle intervention

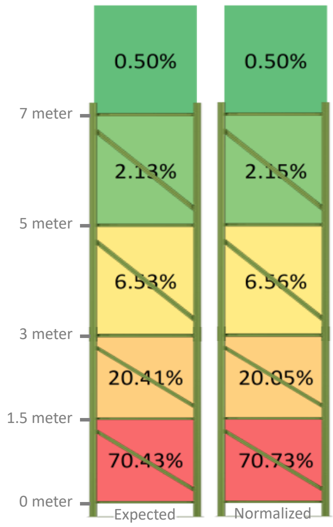

Figure 53b Height picking heatmap of ABC storage and the bottom-two-layers intervention

7 Implementation

This chapter describes how the solution can be applied to the storage and order picking process of B-Living by changing the WMS parameters and the internal logistic processes. We used the Microsoft systems Microsoft Dynamics, Power-BI, Microsoft SQL Server and Excel to obtain and analyse the data. The system used by B-Living is Microsoft Dynamics. All departments and employees work with this system and the data that is available can be found by using this system. Changes to the WMS parameters are discussed in Section 7.1. However, all data is stored in databases on an SQL server. With Microsoft SQL Server we are able to extract the required data by using queries. Extracting data with Microsoft SQL Server is discussed in Section 7.2. Data from these databases are also used for analysis that are required to cope with B-Livings exceptions. A practical approach to dashboard these analysis on a frequent basis can be constructed with the Power BI tool which is elaborated on in Section 7.3. Training the logistic staff is discussed in Section 7.4.

7.1 WMS adjustments

Microsoft Dynamics, the WMS of B-Living, has features that enable the application of the flow-to-SKU solution of this research with simple adjustments. Parameter settings of SKUs and of locations that should be adjusted are:

The ‘Fixed’ setting, which assures that an SKU is fixed to a certain location. When receiving this SKU it will be appointed to this location. Hence, in case of dedicating an SKU to a location, this setting should be used.

The ‘Min Quantity’ and ‘Max Quantity’ settings. These settings enable replenishment. Hence, when a location is to be replenished (when the stock of an SKU at its fixed location is below the ‘Min Quantity’) the WMS automatically proposes a replenishment command. The ‘Max Quantity’ setting can be used to command not to place an SKU to the fixed location as this location reached its maximum quantity. Hence, this way the WMS does not command an inbound SKU to a location that is full already.

The ‘Storage Location Sequence’ setting determines the sequence of assigning SKUs to locations. Hence, this setting is a priority code which prioritizes one location over another. Hence, a picking location should have a higher priority than a storage location.

We use Microsoft SQL Server to obtain data that is required for setting the parameters.

7.2 Microsoft SQL Server Management

The results from Chapter 6 show that the best storage configuration for B-Living is ABC storage. ABC storage is based on allocating the most picked SKUs at the top locations. The top locations can be determined based on the location distance to the I/O point and to the height of the location. How to calculate the top locations is discussed in Section 5.2.

The picking frequency per SKU can be determined by means of warehouse movements. ‘Warehouse Entry’ which is the table that consists of all warehouse movements is used to find the number of movements per SKU of the ‘Collection’ type SKUs. By using Microsoft SQL Server manager we were able to subtract the warehouse movement data by means of queries. The queries we used for the parameters and the analysis are:

- SKU information
- Inbound information
- Stock information
- Outbound information
- Warehouse movements

The query codes of these used sets of data are written in Data Analysis Expressions (DAX) language stated in Appendix E. These codes can be modified to subtract desired data.

7.3 Power BI

Microsoft Dynamics has many features that enable storing according to the desired storage configuration. However, forecasting and replenishing based on that forecast is not possible. Using Power BI as a tool to cope with these exceptions is therefore recommended. Using the DAX codes of Appendix E acquire all data sets required. Power BI is a tool which is able to connect to the database and subtract the real-time information that is inserted in Microsoft Dynamics. Power BI is easy to use and with the features of Power BI, data sets can be linked and dashboards can be created with the required output. To show the replenishment based on forecasting problem, we stated a case at which B-Living requires customisation which is easy to execute with Power BI:

Some customers have multiple stores at different locations. These stores, which are the customers, order individually the same products. E.g. 15 customers order 6 cases of SKU X. Hence, on that day 90 cases of SKU X are required. SKU X is assigned to the reserve-forward storage flow and is therefore picked from the forward area and replenished from the reserve area. The quantity per pallet is 30 and the set Min and Max of X are respectively 2 and 30 cases. Microsoft Dynamics is currently not customised to spot this exception and to handle accordingly by suggesting a replenishment of 3 full pallets before picking the orders. By using the Power BI tool, B-Living is able to construct a dashboard that provides this information.

This case is the exception which require customisation that is currently foreseen. However, we believe that when the solution is implemented, there are some more exceptions of which Power BI is able to provide insights.

7.4 Training the logistics department staff

To successfully implement this solution, the logistics department staff is to be trained. The administrative officer has to know how to provide replenishment proposals. The regular replenishment proposals according to the Min and Max of an SKU are automatically generated, but have to be manually assigned to an employee. And the exceptional replenishments provided by the Power BI dashboard should be manually drafted.

Having sufficient data is very important for a successful implementation. The purchasing department and the logistic employees responsible for inbound should therefore be trained to provide the required data to Microsoft Dynamics and to act when data is incorrect. E.g. the max depends on the quantity per pallet. If that data is incorrect in Microsoft Dynamics, the WMS is not able to provide efficient replenishment proposals.

7.5 Conclusions

From this chapter we conclude that the solution can be implemented by adjusting the WMS settings, bypassing the WMS by using Power BI for the exceptions and training the staff to execute replenishments and obtain SKU and location data. The combination of these adjustments results in a successful implementation of the solution.

8 Conclusions and recommendations

This chapter elaborates on the follow-up conclusions and recommendations. In Section 8.1 we discuss the conclusions of this research. In Section 8.2 the scientific contribution of this research is discussed. The limitation of this research is elaborated on in Section 8.3. Thereafter, we state recommendations for practice in Section 8.4. At last, we discuss some recommendations for further research in Section 8.5.

8.1 Conclusions

B-Living is able to reduce the traveling distance per pick and improve the order-picking efficiency by implementing a storage policy, storage method and by dividing the warehouse into reserve and forward areas. Making a distinction between forward and reserve area shows improvements for all tested interventions in comparison to the current situation, which is not having a forward area. And applying the ABC storage policy for either dedicated storage or class-based storage also improves the order-picking efficiency compared to the current storage configuration, which is class-based random storage. This conclusion meets the research goal:

The goal is to find adaptations in the storage process and warehouse design at B-Living Hengelo that improve the order-picking efficiency.

In the literature review from Chapter 3, we made a distinction between warehouse decision making on strategic, tactical and operational level. This research focussed on the tactical decisions of choosing a storage method, storage policy and decisions regarding product flows. These tactical decisions can be accomplished by adapting the way of working and the WMS. Hence, in order to improve the order picking efficiency, B-Living does not have to make an investment or apply changes to the warehouse layout or locations.

We conclude that B-Living lacked the data to obtain accurate results with a single algorithm and we therefore constructed another algorithm which iteratively updates the input data to generate accurate and realistic results. This bootstrapping approach enables the algorithms to learn from their solutions improve their results.

The solution that showed the best results was the storage configuration ABC dedicated storage. This storage configuration assigns the most frequently picked SKUs at locations closest to the IO point. These locations are situated at the beginning of the aisles in front of the loading docks. How this policy can be implemented is by assigning the SKUs based on their historical order frequency. The WMS has a feature that provides this SKUs to locations assignment and proposes replenishments and storage of incoming goods to the assigned locations. The other storage configurations scored less than ABC storage. The results of ABC class-based storage were a little less than the ABC dedicated storage, but showed improvements compared to class based random storage which is the current storage policy. The Cube per Order Index (COI) policy is the worst policy compared to the random and ABC storage policies.

The results of the experiments showed that using a forward and reserve area improves the order-picking efficiency compared to the current situation. In the current situation, this functional area distinction is not made. The before-cross-aisle intervention scored best out of all 7 tested interventions. This intervention uses the wide aisle area before the cross-aisle as forward area and the remaining storage area as reserve area. Hence, the SKUs assigned to the reserve-forward product flow and the SKUs assigned to the forward product flow should be placed in this area which stores 20% of the total number of locations within the storage areas. The current WMS has features that enable this distinction between forward and reserve area and to implement this functional area distinction to the storage and order-picking process, it is required to change the location parameters in the WMS.

Which SKU to assign to which functional area is the result from the flow-to-SKU algorithm. This algorithm assigns flows to SKUs based on the picking frequency and the volume of the inventory. We distinguish three product flows, the reserve flow, the reserve-forward flow and the forward flow. With the before-cross-aisle intervention the results show that 43% of SKUs are assigned to the reserve flow, 44% of SKUs assigned to the reserve-forward flow and 13% of SKUs assigned to the forward flow. Hence, 57% of SKUs are picked from the forward area, which represents 20% of the entire area.

The theoretical improvements of the total traveling times when applying ABC dedicated storage and using the wide aisle area before the cross-aisle as forward area results in a 23.74% improvement compared to the current situation. The difference in the total traveling time between the before cross aisle intervention and the bottom two-layer intervention is 0.95%. Hence, using the bottom two location intervention might be a consideration after researching dimensioning these bottom two locations. We elaborate on this option at the recommendations for further research in Section 8.5. The number of small-aisle area picks improves with a reduction of up to 27.79%. A practical note is the number of replenishments. However, there are currently no replenishments thus this an additional activity to the logistics activities.

8.2 Scientific contributions

Literature found on product placement and warehouse dimensioning generally addresses a single warehouse problem. However, for most warehouse problems, the observed problem is interrelated with other problems and solving one problem would therefore not provide the desired solution. When we conducted this research we found out that this was the problem for B-Living as well. We therefore combined three tactical level decisions into a single model consisting of two interrelated algorithms. Hence, we fine-tune our solutions whilst in literature the focus is on the assignments instead of using feedback to update the solution.

Small and medium-sized enterprises often not possess important data to find solutions to tactical level decisions as required data is not accurate or not readily available in most cases. This research contributes to the decision-making process of these small and medium-sized enterprises by making decisions with data that is not readily available, but is generated by an algorithm that uses historical data as its parameters.

Furthermore, the algorithms constructed in this research are applicable to other cases than the B-Living case. The only adaptations that should be made or the parameter data of the SKUs and the locations that are considered. How to obtain these parameters for the flow-to-SKU algorithm is elaborated on in Chapter 4 and for the SKU-to-location algorithm is elaborated on in Chapter 5.

8.3 Limitations

The main limitation to this research is the data validity of the SKU set and the forecasting of sales. By shuffling the 2022 sales orders to generate different sets of order we tried to minimise the risk of invalid results due to randomness. As B-Living is a company which is highly influenced by trends and fashion, a limitation to this research is the usage of historical data to make decisions that influence the future efficiency of the logistic processes. However, as we used the 'Basic Collection' dataset of which is forecasted to show similar demand as in the current situation. The algorithms constructed this research can also be executed at different periods per year with updated data to generate a more up-to-date solution.

Another limitation to this research is the researched number of functional area interventions and the number of storage policies considered. This subset is chosen as it is more intuitive for the company and the subset already showed the best solution for B-Living. SKUs from other subsets are irrelevant to the research as these SKUs are not or barely sold in the future as these SKUs will be replaced with 'new collection' SKUs. What interventions or policies are interesting to research are described in Section 8.5.

8.4 Recommendations for practice

By implementing the solution of this research, B-Living is able to improve the order-picking efficiency. However, there some problems described in the problem statement of Section 1.3 which can be solved that align with the implementation of the research solutions.

To achieve a smooth picking flow, we recommend B-Living to scope the activities when order-picking. The current process is picking the order SKUs with up to three different vehicles, then restacking the order when the complete order is picked, finishing with preparing the order for shipment by sealing and processing within the WMS. Instead, we recommend the logistics department to separate the customer orders in full pallet pick orders and case pick orders. By applying this change, the order-picker does not have to change its vehicle which requires a long time. Then during peak periods, it is recommended to separate the order-picking and preparing for shipments activities. Hence, the order pickers only retrieve SKUs from the assigned locations and another employee controls and prepares the order for shipment by restacking, sealing and labelling the order. This will result in a decreasing workload for the order-picking process which is currently the bottleneck during peak periods.

8.5 Recommendations for further research

It is recommended to research a method for using the double pallet order picker. It is assumed that picking with the height order picker requires more handling per pick and a longer average traveling time per pick. There are two main reasons behind these assumptions.

1. The order picker has to perfectly place the vehicle next to the picking location as the order picker is not able to leave the vehicle when picking with the height order picker.
2. The ability to transport two pallets or carts in a single run. Hence, the average traveling time per pick is assumed to reduce when picking two pallets are carts simultaneously.

Another recommendation is adding other variables to the objective function of the flow-to-SKU algorithm. This algorithm only minimises the traveling time as this is the scope of the research. However, we argue that for the overall performance of the logistics department, it is beneficial to include other time variables such as storage, replenishment, preparing for shipment or restacking times.

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Appendix A | Working overtime

WORKING OVERTIME

Regular ending times of the first and second shifts are 4.30 PM and 5.30 PM respectively. However, these ending times vary as the workload is not spread evenly over the days and weeks. The number of days a person of the logistic department staff (excluding management, team leaders and planning) has to work at least one hour of overtime per week is visualised in Figure 54. This graph shows that in 42.31% of weeks, working overtime occurs at least one day. And that the average working overtime hours on days the logistics department could not finish the work in regular working hours is 1.8 hours. This graph also shows that the weeks in which working overtime occurred are not spread evenly over the year, but that it shows periods with consecutive weeks of working overtime and periods where working overtime does not occur. This enhances the statement of B-Living having to deal with workload seasonality.

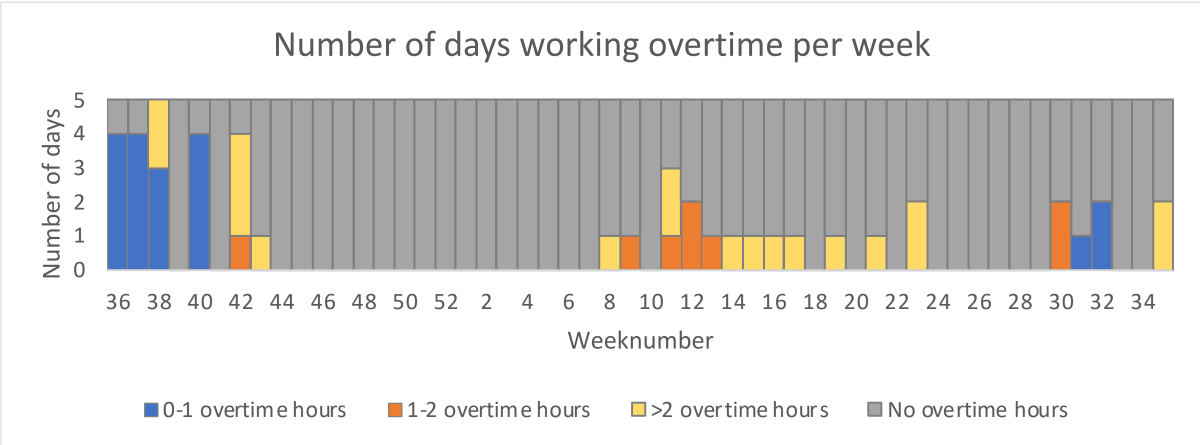

Figure 54 Number of days working overtime per week (week 36 of 2021 until week 35 of 2022)

Appendix B | Full pallet and courier picks per location

Full pallet picks are single command, which means that the order-picker moves empty from the loading docks towards the picking location on a reach truck vehicle, picks the pallet from that location and moves back to the loading docks to consolidate the pallet. The full pallet pick heatmap is shown in Figure 55. What can be concluded from these graphs is that full pallet picks are most of the time glassware products from aisle R and T. The full pallet pick heatmap has similarities to the piece/case pick heatmap as aisle R and T show heated locations. However, the full pallet picks show few to zero movements at the locations left to aisle G.

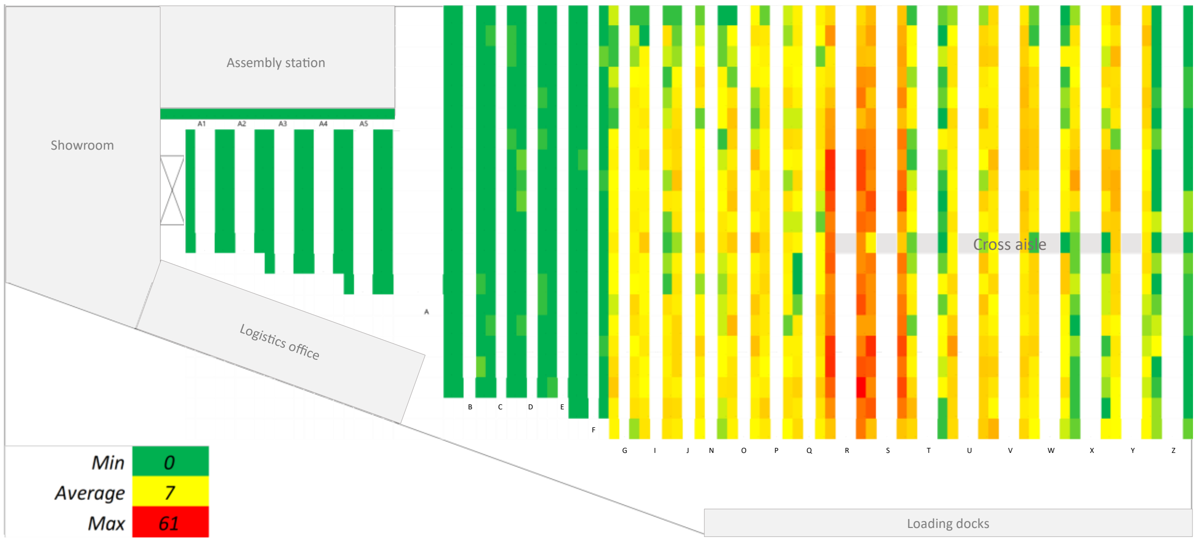

Figure 55 Pallet picks for truck shipment per location

Appendix C | Model Heragu et al. (2005) explained

The objective function of the model is to minimise the total handling and storage costs of all SKUs. The total handling costs is the sum of the annual demand and its handling costs for the assigned flow for all SKUs. The handling costs per flow and the annual demand should therefore be known for each SKU. The total storage costs are the sum of the costs of storing a unit load of product at the assigned functional area and its order quantity. The storage cost of each SKU and each flow and the order quantity should therefore be known.

Both the material handling costs and storage costs differ for each flow. Cross-docking is a flow that has minimal handling costs but requires expensive space occupation in general. Reserve storage flow, which is storing and receiving from the reserve area shows little storage costs as the reserve area is designed to store many items. However, order picking from the reserve area is therefore less efficient and the handling costs of using reserve storage flow are therefore relatively high. Reserve-forward storage flow has both the relatively low storage and handling costs. A drawback to this flow is the extra handling of replenishing items from the reserve area to the forward area to make use of both perks. The fourth flow does have relatively low handling costs but is expected to have expensive storage costs as the forward area in general has higher storage costs than the reserve area.

The total handling costs are therefore based on handling a unit of SKU and its demand. Hence, when the demand of an SKU is high, it is beneficial to dedicate this SKU to a flow that has little handling costs. The same holds for the storage costs. When the order quantity of a product is high, the model assumes that the average space that is required for this SKU is also high and therefore storing this item at a low storage cost area is beneficial. However, both costs are interrelated as the functional areas that have low handling costs have high storage costs in general and vice versa. The relation between the handling and storage costs are displayed in Table 22.

Table 22 Handling and storage cost relation between functional areas

	Handling costs	*Storage costs*
Cross-docking area	Low	High
Forward area	Middle	Middle
Reserve area	High	Low

Decision variables

The decisions that are to be made are which flow to assign to the SKUs and the dimensions of the functional areas. Decision variable X_{ij} is a binary variable which is 1 when flow j is assigned to SKU i and 0 otherwise. The dimensions of the functional areas are calculated as proportions of the total space of the warehouse. The proportion of the cross-docking area is denoted by α, the proportion of the reserve area is denoted by β and the proportion of forward area is denoted by γ.

Model formulation

The model is then formulated as a linear programming model that is divided into sets, parameters, decision variables, objective function and constraints.

Indices of sets:

i	number of SKUs, i =1, 2,…, n (where n is the total number of SKUs),
j	type of material flow, j = 2, 3, 4,

Parameters:

λ_i	annual demand rate of product i in unit loads,
A_i	order cost for product i,
P_i	price per unit load of product i,
p_i	average percentage of time a unit load of product i spends in reserve area if product is assigned to material reserve-forward storage flow,
$q_{ij} = 1$	when product i is assigned to material flow j = 2 or 4; $[d_i]$ + 1 when product i is assigned to flow j = 3, where d_i is the ratio of the size of the unit load in reserve area to that in forward area and $[d_i]$ is the largest integer greater than or equal to d_i,
b, c	levels of space available in the vertical dimension in each functional area b = reserve and c = forward,
r	inventory carrying cost rate,
H_{ij}	cost of handling a unit load of product i in material flow j,
C_{ij}	cost of storing a unit load of product i in material flow j per year,
S_i	space required for storing a unit load of product i in material flow j per year,
TS	total available storage space,
Q_i	order quantity for product i (in unit loads),
T_i	dwell time (years) per unit load of product i,
LL_F, UL_F	lower and upper storage space limit for the forward area,
LL_R, UL_R	lower and upper storage space limit for the reserve area.

Decision variables:

X_{ij}	1 if product i is assigned to flow type j; 0 otherwise,
β, γ	proportion of available space assigned to each functional area β = reserve and γ = forward.

Objective function:

$$\min 2 \sum_{i=1}^{n} \sum_{j=2}^{4} q_{ij} H_{ij} \lambda_i X_{ij} + \sum_{i=1}^{n} \sum_{j=2}^{4} (q_{ij} C_{ij} Q_i X_{ij}/2)$$

Constraints:

$$(1) \sum_{j=2}^{4} X_{ij} = 1 \quad \forall i$$

$$(2) \sum_{i=1}^{n} \left(\frac{Q_i S_i X_{i2}}{2}\right) + \sum_{i=1}^{n} \left(\frac{p_i Q_i S_i X_{i3}}{2}\right) \leq b\beta TS$$

$$(3) \sum_{i=1}^{n} \left(\frac{(1-p_i) Q_i S_i X_{i3}}{2}\right) + \sum_{i=1}^{n} \left(\frac{Q_i S_i X_{i4}}{2}\right) \leq c\gamma TS$$

$$(4) \beta + \gamma = 1$$

$$(5) LL_R < b\beta TS < UL_R$$

$$(6) LL_F < c\gamma TS < UL_F$$

$$(7) \beta, \gamma \geq 0$$

$$(8) X_{ij} = 0 \text{ or } 1 \quad \forall i, j$$

The first constraint ensures that all SKUs are assigned to one flow. The second constraints calculates the space of the reserve area considering all SKUs assigned to flows 2 and 3 and this constraint therefore calculates the proportion of total space that is required for the reserve area: decision variable β. Constraint (3) sets decision variable γ, which is the proportion of total space that is required to store all SKUs assigned to reserve-forward storage flow and 4. For both constraint (2) and (3), a percentage of space is used when an SKU is assigned to reserve-forward storage flow as this flow requires space in both the forward area as the reserve area. Constraint (4) sets all functional area space proportions to be equal to 1. Thus, the total space is assigned to all functional areas. Constraint (5) and (6) ensures that the functional space proportions do not exceed the upper limits of those functional areas. Constraints (7) ensures that the proportions are nonnegative and constraint (8) sets the decision variable X_{ij} to be binary.

Appendix D | Priority codes per product category

Category	Code
CUSHIONS	3
VASES RECYCLED	3
SELF ADHESIVE FOILS	3
CARPETS	3
PVC TABLECLOTH	1
STATIC FOILS	2
KITCHEN TEXTILES	3
HOMEDECO TEXTILES	2
PLAIDS	2
OUTDOOR	2
CHAIR CUSHIONS	2
VASES COLOURED	2
MISCELLANEOUS	2
MOSQUITO CURTAINS	2
DECO STRING CURTAINS	2
TRANSPARENT FOILS	3
CURTAINS	2
PVC LACE	2
CANDLE HOLDERS	2
VASES CLEAR	2
KITCHEN GLASSWARE	2
BOWLS	1
BOTTLES	1
DECO GLASS AND ACC	1
WEIGHTS AND CLAMPS	2
FLAMERTD. ON ROLL	1
DISPLAY PLANTERS	1
DISPLAY VASE	1
DISPLAY ESSENTIALS	1
SCENTED CANDLE	1
DISPLAY BANNERS	1
CYLINDERS	2
PLANTERS	1
VASES BUBBLES	2
HOME ACCESSORIES	2

Figure 56 Priority code per SKU category

Appendix E | DAX codes for Microsoft SQL Management Server

The codes in this appendix can be used to subtract the data with Microsoft SQL Management Server that is used for this research and can be useful with the implementation of the research results.

SKU information

```
SELECT
       IV.[Value]
       ,I.[No_]
       ,I.[Description]
       ,I.[Search Description]
         ,I.[Item Category Code]
       ,I.[Parent Category]
       ,I.[Parent Category 2]
       ,I.[Base Unit of Measure]
         ,IUM.[Qty_ per Unit of Measure] as 'Qty per pallet'
       ,I.[Unit Price]
       ,I.[Unit Cost]
       ,I.[Vendor No_]
       ,I.[Vendor Item No_]
       ,I.[Lead Time Calculation]
       ,I.[Reorder Point]
       ,I.[Reorder Quantity]
       ,I.[Country_Region of Origin Code]
       ,I.[Lot Size]
       ,I.[Minimum Sales Quantity]
       ,I.[Safety Stock Quantity]
       ,I.[Reordering Policy]
       ,I.[Base Amount for Surcharges]
       ,I.[Surcharge Model Indirect Cost]
       ,I.[Fixed Sales Lot Size]
  FROM [dbo].[B Living$Item] I
      Left join [B Living$Item Attribute Value Mapping] IM On I.[No_] =
IM.[No_]
      Left Join [B Living$Item Attribute Value] IV On IM.[Item Attribute
Value ID] = IV.[ID]
      Left join [B Living$Item Unit of Measure] IUM on I.[No_] =
IUM.[Item No_]
      Where IM.[Item Attribute ID] = '1' and IV.[Value] <> 'Delete'
and (IUM.Code = 'Pallet' or I.[Base Unit of Measure] = 'MTR1')
"])
```

Inbound

```
     SELECT
       [Item No_]
              ,[Description]
       ,[Posting Date]
       ,[Document No_]
       ,[Quantity]

  FROM [dbo].[B Living$Item Ledger Entry]
  where [Location Code]='B Living' and [Posting Date]>='2021-01-01' and
[Quantity]>0 and [Document No_] like '%ONTV%'
  order by [Posting Date] desc
  "])
```

Stock

```
WITH cte_check

AS(SELECT
       [Bin Code]
       ,[Item No_]
       , sum([Quantity]) as 'Stock'
         , max([Registering Date]) as 'Last Mutation'


  FROM [dbo].[B Living$Warehouse Entry]
where [Location Code] = 'B LIVING'
Group by [Bin Code], [Item No_]
)

Select *
From cte_check
where [Stock] >0
Order By [Bin Code]
```

Outbound

```
 SELECT
  sh.No_ As 'DocumentNumber',
  sl.[No_] AS 'ProductNumber',
    sl.[Description] as 'ProductName',
  sl.[Location Code],
  sh.[Sell-to Customer No_] As 'CustomerNumber',
  sh.[Sell-to Customer Name] as 'CustomerName',
  sl.[Quantity],
  sh.[Shipping Agent Code],
  sh.[Order Date],
  sl.[Unit of Measure Code]

  FROM [dbo].[B Living$Sales Header Archive] sh
      LEFT JOIN [B Living$Sales Line Archive] sl
            ON sh.[No_] = sl.[Document No_]
      where sh.[Order Date] >= '2021-01-01' and sh.No_ like '%VO%'
      order by sh.[Order Date] desc
```

Warehouse Movements

```
Declare @startDate varchar(10) = '2021-01-01';
WITH CTE_SOURCE AS
(
    SELECT
        MIN([Registering Date]) as [Date],
        [Item No_],
        'TRANSFER' as [Movement Type],
        [Source No_],
        [Source Line No_],
        [Reference No_],
        [User ID]
    FROM
        [B Living$Warehouse Entry]
    WHERE
        [Reference No_] like 'M-VERPL%' AND
        [Registering Date] >= @startDate
    GROUP BY
        [Item No_],
        [Source No_],
        [Source Line No_],
        [Reference No_],
        [User ID]
)
SELECT
    cte.[Date],
    cte.[Item No_],
    CAST((SELECT SUM([Quantity]) FROM [B Living$Warehouse Entry] w1
WHERE w1.[Reference No_] = cte.[Reference No_] AND w1.[Quantity] > 0)
As INT) as [Quantity],
    cte.[Movement Type],
    (SELECT TOP 1 [Bin Code] FROM [B Living$Warehouse Entry] w1 WHERE
w1.[Reference No_] = cte.[Reference No_]AND w1.[Quantity] < 0) as
[From],
    (SELECT TOP 1 [Bin Code] FROM [B Living$Warehouse Entry] w1 WHERE
w1.[Reference No_] = cte.[Reference No_] AND w1.[Quantity] > 0) as
[To],
    cte.[Source No_],
    cte.[Source Line No_],
    cte.[Reference No_],
    cte.[User ID]
FROM
CTE_SOURCE cte
UNION ALL
select
    [Registering Date] As [Date],
    [Item No_],
    ABS(CAST([Quantity] as INT)) As [Quantity],
    'INBOUND' as [Movement Type],
    NULL as [From],
    [Bin Code] as [To],
    [Source No_],
    [Source Line No_],
    [Reference No_],
    [User ID]
from
    [B living$Warehouse Entry]
where
    [Registering Date] >= @startDate and
```

Appendix F | Order Oriented Slotting

The paper of Schuur (2015) argues if allocating SKU according to COI is the most optimal allocation strategy for the performance of order picking multiple SKUs per order. Schuur even states that the worst-case behaviour of COI is infinitely bad. Hence, other SKU allocation strategies might be more efficient to the B-Living case as multiple SKUs are to be picked per order. Order-oriented slotting (OOS) of Mantel et al. (2007) is such a strategy that includes SKU relations per order as OOS aims to store the SKUs based on orders instead of COI where the SKUs are stored based on the frequency they are picked. OOS stores the items in such a way that the picking time of the orders is minimised by means of an Integer Linear Programming (ILP) model. The interaction between SKUs is incorporated by Mantel et al. (2007) by using the variable f_{i0}, which is the number of orders that require SKU i, and the variable f_{ij}, which is the number of orders that require SKU i and SKU j. An illustration in the paper of Mantel et al. that shows the comparison of COI and OOS for a small example is displayed in Figure 57. OOS shows the better performance in this example. However, this example is simplified as all orders are disjoint.

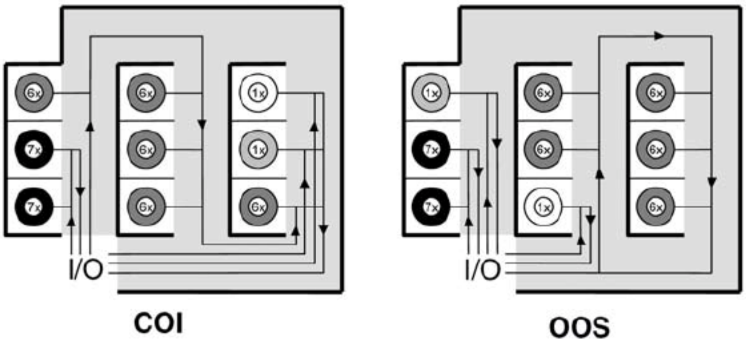

Figure 57 Visualised comparison of COI and OOS for a small example (Mantel et al., 2007)