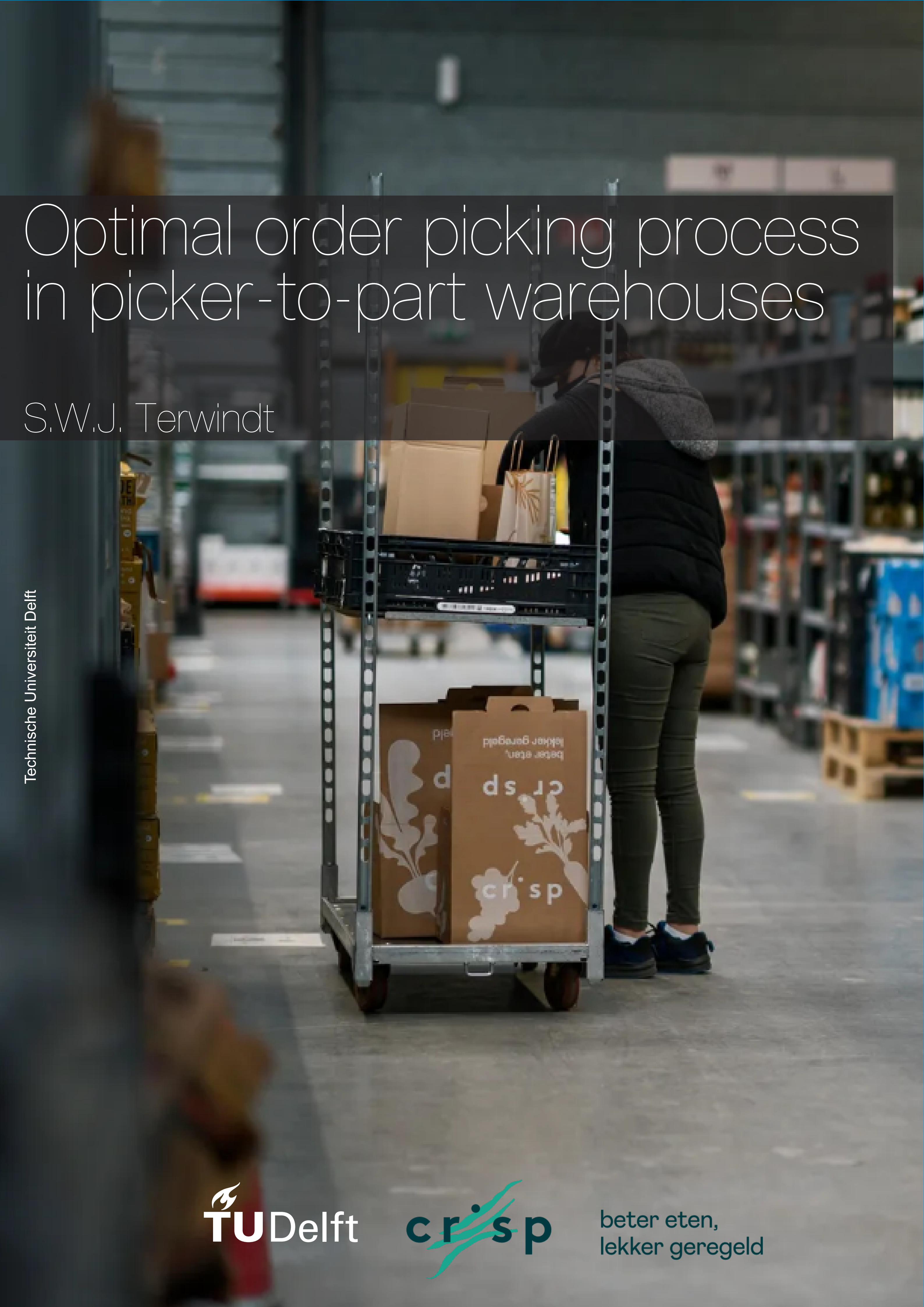

Optimal order picking process in picker-to-part warehouses

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TU Delft

crisp

beter eten,
lekker geregeld

Optimal order picking process in picker-to-part warehouses

by

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(*Cover image: [1]*)

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Preface

This thesis concludes my master program in Mechanical Engineering for the track Multi-Machine Engineering at Delft University of Technology. The research was performed in coöperation with Crisp B.V., a Dutch online supermarket specializing in daily fresh products. The topic of this research is optimizing the order picking process in a picker-to-parts warehouse.

For the last 11 months I have worked on this thesis. Between the start of the project and now, there were many ups and downs. But now the project is finished I can look back with pride on my work and process. Writing a thesis has been a very challenging project, from which I have learned a lot, both professionally as personally, but now it is finished I can only look back on it in a positive way.

This thesis wouldn't be in the current state as it is now without the support of some individuals. First of all I would like to thank Mark Duinkerken for willing to be my thesis supervisor at the university. If needed you were always easy reachable and able to provide me with valuable feedback on my work. I also want to thank Dr. Frederik Schulte for being the chair of my graduation committee. In the few meetings we had together you provided constructive feedback, which helped me to improve my work.

I would also like to express my gratitude to Justin Koekenbier, my supervisor from Crisp. You had to take over the supervision halfway during my thesis process and it is fair to say that you did really well. Your knowledge and expertise really helped me in my process and I really appreciated your involvement in my work. Also a big thanks to the rest of my team, Jesse, Laurens and Noortje. You all made my time at Crisp so much more enjoyable.

Finally, I want to thank my friends and family for their support during this project. Especially in the times when the stress got to me. You provided a welcome distraction and really helped me to clear my head time by time. Thanks for the support, distractions and also the time you took to discuss my thesis. A special thanks to Laurens, Martijn, Idse and Jenne for keeping up with me at home, cooking meals when I had a long day, letting me borrow your laptops to run my model and supporting me during this process. In addition I want to thank Jenne and Eric for the countless coffee and lunch breaks. It were refreshing moments during the day where I could clear my mind. Thank you all for your support and belief in me and this project.

Stijn Terwindt
Delft, February 2025

Abstract

Over the past decade, consumer shopping habits have increasingly shifted towards online grocery purchases, creating a growing demand for efficient and scalable warehouse operations. As order volumes and complexity rise, the optimization of warehouse processes has become essential to meet requirements while controlling operational costs. This study addresses the Joint Order Batching Picker Routing Problem (JOBPRP) by developing an exact optimization approach and examining the interdependencies among key warehouse processes, such as batching, routing, and product allocation. Using a case study of Crisp B.V., an online grocery retailer, the proposed algorithm was implemented to optimize configurations across multiple temperature-controlled zones with varying operational characteristics, such as differing pick densities and operational constraints. The research shows that all warehouse processes are interconnected and the best performing configuration is depending on the operational characteristics of the warehouse. The optimization approach achieved a 39.14% reduction in weekly travel distance compared to Crisp's current benchmark, highlighting its potential to significantly enhance travel distances. These findings highlight the significant impact of integrating order batching and picker routing on warehouse efficiency. The study not only demonstrates the critical correlation between warehouse processes but also provides actionable insights for optimizing order picking in high-density, large-scale warehouses.

Nomenclature

Abbreviations

Abbreviation	Definition
ACO	Ant Colony Optimization
ALNS	Adaptive Large Neighborhood Search
BPP	Bin-Packing Problem
COI	Cube-per-Order Index
C&TBSA	Correlated and Traffic Balanced Storage Assignment
DCP	Demand Correlation Pattern
DEPSO	Discrete Evolutionary Particle Swarm Optimization
FCFS	First-Come-First-Served
GA	Genetic Algorithm
JBP algorithm	Joint Order Batching and Picking algorithm
JOBPRP	Joint Order Batching and Picker Routing Problem
HMEA	Heuristically Modified Exact Algorithm
KPI	Key Performance Indicator
MIH	Minimum Increment Heuristic
MILP	Mixed Integer Linear Programming
MOEA	Multi-Objective Evolutionary Algorithms
OBP	Order Batching Problem
O/D	Origin-Destination
P&D (point)	Pickup and Delivery (point)
PRP	Picker Routing Problem
(Im)PSO	(Improved) Particle Swarm Optimization
SA	Simulated Annealing
SBP algorithm	Sequential Order Batching and Picking algorithm
SLAP	Storage Location Assignment Problem
SPD	Sum of Pairwise Distances
SSA	Scattered Storage Assignment
SPRP-SS	Single Picker Routing Problem with Scattered Storage
TS	Tabu Search
TSP	Travelling Salesman Problem
VRP	Vehicle Routing Problem
WMS	Warehouse Management System

Table 1: List of Abbreviations

List of Figures

List of Tables

Contents

1 Introduction

Over the past ten years, consumer shopping habits have transitioned from in-store to online purchases. The rapid expansion of internet capabilities has significantly contributed to this trend, resulting in a shift towards online shopping not only for typical parcels, like clothing and electronics, but also impacting the fast-moving consumer goods (FMCG) sector. Numerous supermarkets now operate online platforms with next-day delivery options for groceries. This new behavior in online shopping has increased the need to improve warehouse efficiency. As a vital component of the supply chain, warehousing plays a crucial role in supply chain effectiveness. Notably, the process of order picking accounts for approximately 55% of warehouse operating expenses. This process is particularly critical for FMCG warehouses tasked with handling larger orders for delivery. This thesis examines ways to improve the order picking process, which is performed in collaboration with Crisp, a Dutch online supermarket specializing in daily fresh products.

1.1. Introduction Crisp

This thesis will be carried out in collaboration with Crisp, an online grocery store that emphasizes sustainable and locally sourced products. As a result of this product focus, their assortment is smaller compared to that of larger supermarkets offering home delivery. Crisp carefully selects its assortment and usually does not stock the same product of different brands, a practice often seen in larger retail chains. Their logistics framework includes two warehouses designated for order picking and three hubs dedicated to cross-docking operations. The warehouses located in Breda and Amsterdam handle the order picking process. The daily order volume varies from 1500 to 3500. Approximately 70% of the orders are processed by the Amsterdam warehouse, while the Breda warehouse manages the remaining 30%. This graduation project will focus on the picking processes within their facilities. The Crisp warehouse is characterized as a low-level picker-to-parts warehouse. 'Low-level' indicates that all storage racks are accessible to pickers without any mechanical aid, while 'picker-to-parts' means that pickers physically retrieve products from their storage locations. The warehouses are divided into three zones, each with different storage temperature requirements: ambient, chilled, and frozen. Order picking is executed similarly across all zones; pickers navigate through a zone using a specialized picking cart. The number of parcels each cart handles and the picks per parcel vary between the different zones. In general, orders in the ambient zone contain the highest number of picks per order, followed by those in the chilled zone, and finally, the frozen zone has the least. Concerning the number of orders per picking cart, the frozen zone accommodates the most due to its typically smaller order sizes. The ambient zone compensates for the order size with larger carts and comes second. The chilled zone comes last with the fewest orders per batch. These operational differences between zones lead to slight variations in their operating strategies. Once the orders are picked from their respective zones, they are sorted and prepared for shipment. Since it is essential to maintain the temperature constraints of each zone's orders during delivery, orders that include products of multiple zones are managed separately by zone rather than combined. The orders are either loaded on large trucks outgoing to the hubs or directly loaded on delivery vans ready for delivery. This is an ongoing process that is active during the whole day, resulting in different due times for the orders.

1.2. Problem description

Due to the rapid growth in online shopping and at home delivery, extensive research has been conducted on warehousing as this is considered as a key component in the logistics chain. To meet increasing demand and rising competition in the industry, warehouse operations must perform all their processes with maximum efficiency [2].The warehouse processes; receiving, storing, order picking, and shipping are critical to each supply chain [3, 4]. Among these operations, order picking is the most expensive operation as it represents 55% of the total operating costs of a typical warehouse [5, 6], making it the central focus point of this thesis. Warehouses vary widely because they are tailored to specific performance needs and dimensions. Selecting the optimal configuration is complex and different per warehouse as many decisions regarding the configuration are interfering with each other. Key issues that influence the warehouse performance are: The layout, the routing policy, the product allocation plan, and the order batching. Due to the interactivity between these problems, it is challenging to find the optimal warehouse configuration. The layout sets the outline for the other processes and is generally the first decision to be made. The next three problems are all Non-Polynomial (NP) hard problems if formulated as a MIP model. Recently, there has been increasing interest in integrating these issues to enhance warehouse efficiency. Most approaches aim to minimize the total travel distance by solving the routing problem while considering other factors. The routing problem is a variant of the travelers salesman problem and can be solved with exact algorithms, meta heuristics or heuristics. The challenge for an efficient order picking process is the interplay among all decisions aimed at optimizing the order picking process. Each process or decision is interconnected, complicating the search for the ideal setup. The current order picking process at the Crisp warehouses remains quite simplistic and can potentially be improved to decrease operational expenses.

1.2.1. Current state and gap

The literature on the optimization of order picking has increased rapidly in the last decade. The tendency is that most research is focused on one specific problem, however the integration and solving two problems jointly has gained more attention the last years. Especially the integration of the batching and routing problem, known as the Joint Order Batching and Picker Routing Problem (JOBPRP), has been receiving more academical attention. There are multiple solutions proposed in the literature to solve this problem. The most common way to address the JOBPRP is to write the problem as a a mixed-integer programming model, where the batching and routing are then solved sequentially and iterative. To reduce the computation time both problems are often solved with a meta-heuristics. The batching is often solved with a Genetic Algorithm (GA) or a Particle Swarm Optimization (PSO), whereas the routing is often solved with a 2-opt heuristic or a Ant Colony Optimization (ACO). However, multiple other combinations of (meta-)heuristics have been used in the literature. Important papers that solve the JOBPRP are mentioned with their specifications in Table 1.1.

Papers	Batching	Routing	# Orders	# SKU's	Items/ order	orders/ batch	computation time
Tsai et al. [7]	GA	GA	250	400	10	kg based	600 s
Kulak et al. [8]	TS	Nearest neighbour+Or-opt heuristic Savings+2-opt heuristic	250	500	2	vehicle capacity	110 s
Chen et al. [9]	GA	ACO	8	12	10	5	N/A
Cheng et al. [10]	PSO	ACO	200	12	10	5	N/A
Kübler et al. [11]	DEPSO	Nearest neighbour+2-opt heuristic	200	7200	10	vehicle capacity	140 s

Table 1.1: Important papers on solving the JOBPRP

The work of Kulak et al. [8] presented a mixed-integer programming (MIP) formulation and then solved it with 2 different combination of heuristics. Their MIP formulation is used by other authors as a starting point, so did Chen et al. [9] and Cheng et al. [10] modify the model to address extra requirements. Chen et al. [9] added the due date of orders, which resulted in the total tardiness being the objective function. This model focuses on the minimizing this tardiness and not specifically on minimizing the travel distance. However minimizing the travel distance in the composed batches will have a positive effect on the total tardiness, as the composed batches are then picked more efficient and therefore faster. Cheng et al. [10] focus again on minimizing the total travel distance. They compare their model with the approach of Tsai et al. [7] and conclude that their model handles both small as large instances well. They conclude that their approach has a lower computation time and can handle larger instances better. However they do not include the due date in their model and suggest that adding this in a multi-objective model could be relevant for further research. The above mentioned researches only consider a random product allocation and do not study the effect of the product allocation.

Kübler et al. [11] differs in this as it uses a class-based storage in their work. Their approach is comparable with Cheng et al. [10] but in addition they calculate the relocation effort of a product and the gained reduction in travel distance by relocating. With a relocation they mean that a product is changed of class and therefore placed in a different location. This paper comes the closest to solving all three problems jointly. This paper does not take the due date of the orders in account or account for congestion.

Research on the relation between product allocation and solving the joint order batching and picker routing problem is still underrepresented. van Gils et al. [12] and van Gils et al. [13] did analyze the relation between the order picking problems and indicate that with solving the problems jointly significant benefits can be achieved. They do this with a full factorial ANOVA. They show that the product allocation has a clear relation with the routing and batching, however they do not propose any kind of optimization. Roodbergen [14] show different possible layouts for a class-based product allocation, such as the across-aisle or within-aisle storage. However, the effect of this allocation policy in combination with solving JOBPRP has not yet been researched.

In terms of an existing gap, there are a few possibilities. The first and foremost most clear gap is the size of the problem. Most research is applied to limited size warehouses. As can be seen from Table 1.1 the number of orders is around 250, which is roughly a factor 10 lower than for the case study of Crisp. It would be valuable to see if the model can be used for larger instances and keep the computation time to a minimum. Most of the available papers also assume that the products in the warehouse are distributed randomly. The effect of different storage policies in combination with the JOBPRP has not yet been researched. The effect of different storage policies on the travel distance is most likely to be enhanced by different layouts, however research that integrates the JOBPRP with design choices on the layout and the integration of a suiting storage policy is not presented.

1.3. Objective and research questions

Before defining the objective and the research questions, it is important to define the scope of the project. Because the project is conducted in cooperation with Crisp, the scope is related to their warehouse. This means the project will be specified to a low-level picker-to-parts warehouse with a single pickup and single delivery point. The objective of this research is to determine the effect of combining warehouse processes to find the best performing warehouse configuration. To integrate these processes, a model is developed that minimizes the total travel distance and is able to incorporate all warehouse processes. The model should be applicable to the warehouse of Crisp and thus able to handle large instances. This objective leads to the following research question:

How can the order picking process in a large scale low-level picker-to-parts warehouse be optimized by incorporating different due times, and what is the effect of the integration of multiple warehouse processes on the travel distance?

To answer this research question, it is supported by the following subquestions:

1. How is the current order picking process organized?
2. Which warehouse processes influence the order picking performance and which approaches can be used to enhance the order picking performance?

3. How can a model be designed to minimize travel distance while simultaneously meeting the due times of orders?
4. How can the developed model be applied to the Crisp warehouse using real-world data?
5. How do different warehouse processes affect the performance of order picking operations in a picker-to-parts warehouse?
6. For the low-level picker-to-part warehouse of Crisp, what are the optimal configurations for the different operational characteristics?

1.4. Thesis outline

The proposed approach of this thesis is visualized in Figure 1.1. It shows which subquestion is answered in each chapter and what the method per subquestion will be. Chapter 2 will contain the system analysis. In chapter 3 the relevant literature will be discussed. Chapter 4 will propose a mathematical model. Chapter 5 will give the validation of the proposed modal. Chapter 6 will propose the experimental plan and chapter 7 will display the obtained results. The thesis will conclude with the conclusion, discussion and recommendations.

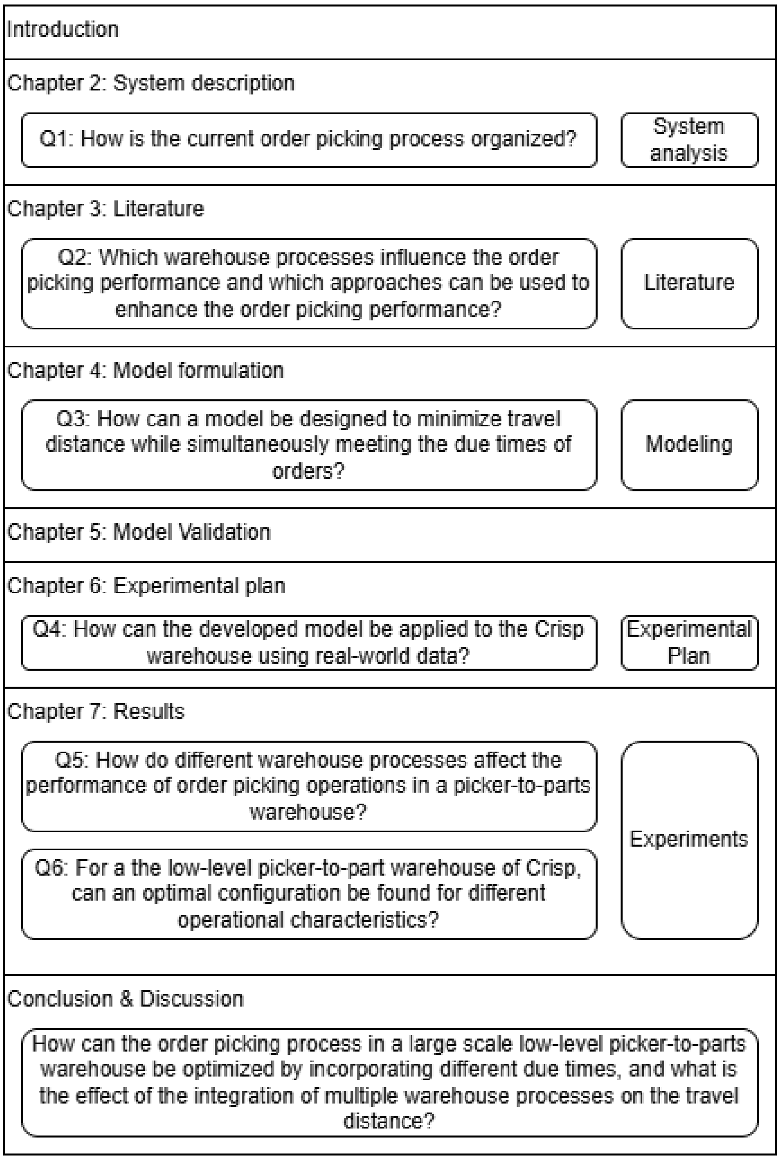


Figure 1.1: Structure of the research

2
System Description

This chapter provides a system analysis of Crisp's warehouse alongside its ongoing processes. It begins with a broad overview of warehouse procedures, followed by a detailed depiction of the present operation within Crisp's warehouse. It gives an answer to the first subquestion as it describes in dept how the current order picking process at Crisp is organized.

2.1. General warehouse processes

This subsection provides a general overview of the product flow and the processes within a warehouse. Warehousing is a critical step in the supply chain. The simplest supply chain is depicted in Figure 2.1. This supply chain can be enlarged by incorporating more hubs in the process. These hubs can be located between the manufacturer and the warehouse but also between the warehouse and the customer. In both scenarios, the extra hubs are used for cross docking to realize a more efficient or sustainable delivery schedule.

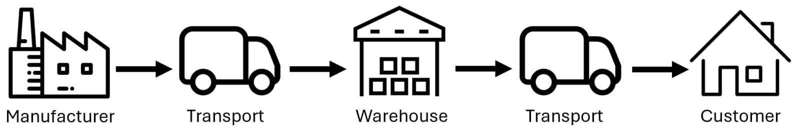


Figure 2.1: Simple supply chain

Within the warehouse, there are multiple sequential steps to go from the incoming products to the packed orders. The warehouse processes are quite straightforward and can be categorized into the following steps: receiving, storing, order picking, and shipping. [3, 4] This process flow is visualized in Figure 2.2. The process begins with the manufacturer who delivers the products to the warehouse. Upon the arrival the delivery is unloaded, identified and checked. The frequency of these deliveries varies depending on the product type. For instance, fresh products with short expiration dates are delivered more frequently than non-food items with longer expiration dates. Upon arrival, store keeping units (SKUs) are either stored in the back stock or placed directly in the front stock, depending on their specifications and circulation time. Depending on the characteristics of the warehouse the picking locations could be divided into multiple zones. Dividing the picking area in zones could be a hard or a soft decision. It is a hard decision if it leads to zone-specific storage technology (e.g. a refrigerated section). It is a soft decision if the decision is simply organizing similar storage locations [4]. In the case of a warehouse used in the FMCG sector there are most likely 3 'hard' zones with their own storage temperature. This is due to the different storage temperatures that are required for different products, resulting in a ambient, chilled and frozen zone. The order picking process consists of order pickers walking through the warehouse to pick the respective SKUs of each order. This picking can be done by picking single orders or picking multiple orders simultaneously. The preferred way of picking depends on the characteristics of the warehouse. For example a palletised warehouse will most likely use single pick tours, whereas warehouses used for single products will most likely pick multiple orders together.

The picked orders are then brought to the sorting area, here the orders are sorted and prepared for delivery. After which the orders are loaded onto the vans/truck and delivered to the customer or brought to cross docking hub.

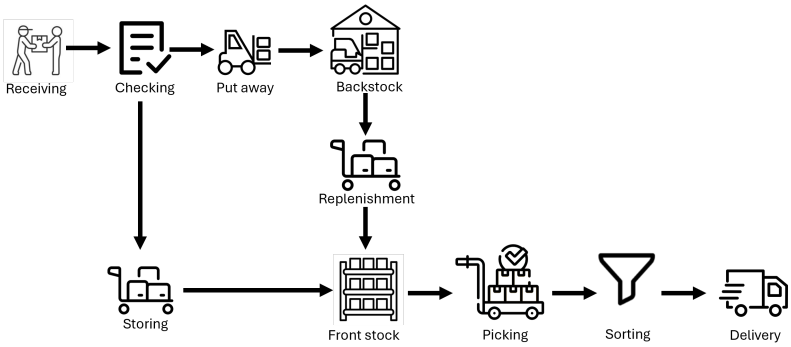


Figure 2.2: Warehouse process flow

2.2. Crisp specification

Where in the previous subsection the warehouse process is described for a general warehouse, this subsection will describe the current process at Crisp in detail. Crisp has two warehouses used for order picking, located in Amsterdam and in Breda. To ensure an efficient delivery schedule, they have 3 hubs used for cross docking. These are located in Delft, Utrecht and Aartselaar (Belgium). The way of operating in the order picking warehouses is identical, however the warehouses differ in size and layout. The number of orders fluctuates throughout the week as can be seen in Figure 2.3. Sunday and Monday are typical busy and Wednesdays have less activity. This is explainable as customers have preferences on which day they want their groceries delivered. The low peak for the Breda warehouse on Wednesday is also affected by the fact that Crisp does not deliver on Wednesdays in Flanders. This thesis will focus on the warehouse in Amsterdam as this warehouses handles the most capacity of the two. However due to the similarities between the two warehouses, this thesis will most likely also be applicable to the warehouse in Breda.

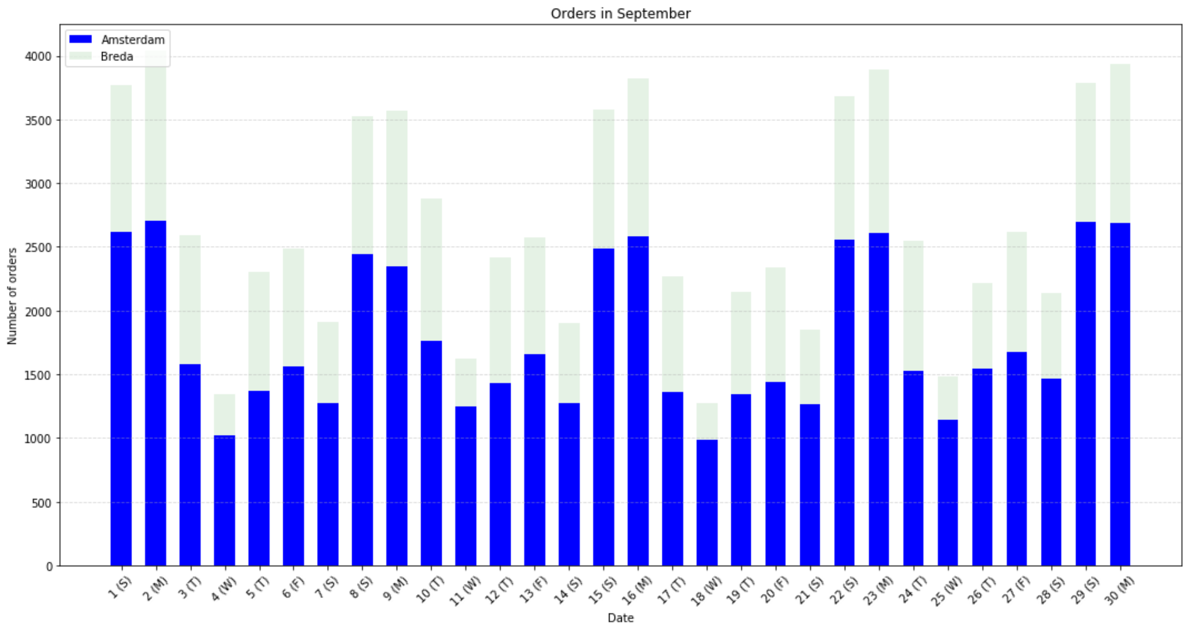


Figure 2.3: Orders in September 2024

2.2.1. Terminology

The orders visualized in Figure 2.3 represent the total customer orders in the month September. However, an order from a customer can consist of multiple containers. A container is the packaging that is used to pack multiple SKUs of the order. Per zone this is different; in the ambient zone this are cardboard boxes, in chilled zone this are cardboard boxes or paper bags and in the frozen zones this are plastic bags. In the ambient zone each cardboard box is considered to be a parcel, however in chilled and frozen, multiple paper or plastic bags can be placed in one parcel (an EPP box), Figure 2.8b and Figure 2.9b illustrate this. The total order structure can be seen in Figure 2.4 and the definitions in Table 2.1

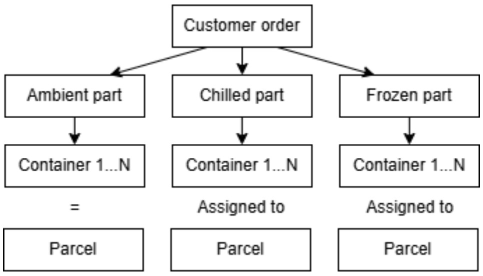


Figure 2.4: Order structure

Term	Definition
(Customer) Order	Full order of the customer
Container	Package used to pack SKUs out of the order. Can be a cardboard box, paperbag or plastic bag.
Parcel	In ambient this represents the cardboard box, in chilled and frozen this is the EPP box in which containers are placed.
Batch	All parcels that are placed together on a single picking cart

Table 2.1: Definitions of Warehouse Terms

2.2.2. Process flow for Crisp

As already described in section 2.1, the general warehouse process flow can be found in Figure 2.2. However in the process flow of Crisp there are some additional active processes. The total process flow can be seen in Figure 2.5. Crisp receives quite different products, which are delivered by different suppliers in different ways. Resulting that some SKUs will have to undergo an extra step, the prepicking. A simple example of such products are vegetables that are sold per weight instead of per piece. These vegetables are first weighed and then packed together, adding an extra step to the warehouse flow. For the replenishment of the front stock with SKUs from the back stock, Crisp does not only take the emptiness of the shelves in the front stock into account, but also uses a forecast to determine a potential increase in demand. The prep process that comes before the picking process is preparing the picking carts. This preparation consist of placing the parcels on the carts and labelling and linking them with the Warehouse Management System (WMS). After labeling each box, the picking carts get transported to the pickup point of the corresponding picking zone. So all carts, regardless their zone, are prepared at the same place and then moved to the P&D points of the corresponding zone. For the order picking, electronic scanners are used. Each location for a SKU is labelled with their own QR code. The picker must scan the corresponding QR code, before it can proceed to pick the products. As a check the picker must thereafter scan the box he's putting the SKU in to prevent mistakes. The order picker follows a S-shape heuristic through the warehouse, traversing all the storage places. The picked carts are then brought to the delivery point, where the boxes are prepared for delivery. With prepared for delivery is meant ensuring all products in the box are packed properly and closing the boxes. After this preperation process, the boxes are transported to the sorting area where the parcels are sorted per route. After the sorting, the parcels are brought to the loading area and loaded on the corresponding van out for delivery.

2.2.3. Layout

This subsection presents a detailed overview and illustration of the warehouse configuration. Crisp currently operates two warehouses involved in order picking activities. However, this thesis focuses on the Amsterdam location, hence only the Amsterdam warehouse layout will be addressed here. The general floor plan of the warehouse is shown in Figure 2.6. Several processes are carried out within designated areas in the warehouse. The left section is predominantly allocated for inbound logistics and backstock storage. However, there are specific sections allocated for pre-picking, cart preparation, a sorting area and last-mile operations. The pre-pick area is tasked with repackaging single-item deliveries into larger (or smaller) marketable units. For example, apples arriving in crates are re-packaged in quantities of four. The cart preparation area is where empty boxes are loaded

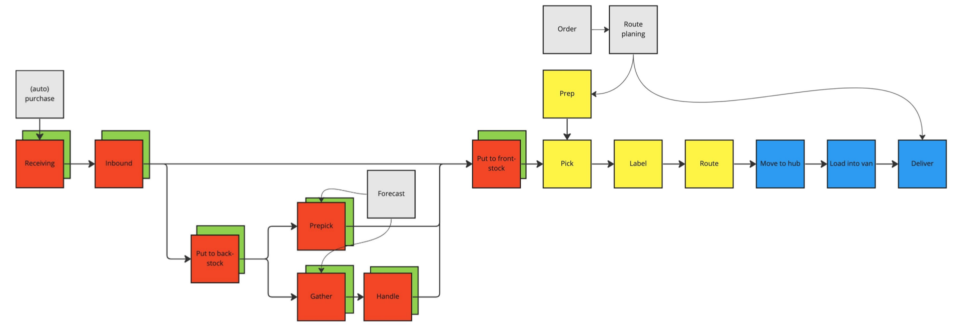


Figure 2.5: Process flow Crisp

onto carts and labeled. The loaded carts are then transported to the pickup point of the corresponding zones. After the picking process, the picked carts are transported to a sorting area. A customer order can consist of items from multiple zones. Due to the required temperature at delivery these distinct parcels are handled separately. So in the sorting process they are not combined, only placed together. In this area the parcels are sorted on the correct route, after completion they are transported to the last mile area. The last mile area is a small loading area where vans are loaded inside, although during peak times the loading extends to outside. This last mile area is also used as the storage ground for all organized orders. The order picking is carried out in the top right section, divided into three distinct zones, each varying in size and layout. The ambient zone, which is the largest, accommodates 3500 SKUs and includes the majority of the SKUs. The chilled area holds 2000 SKUs, while the smallest zone, the frozen section, has 500 SKUs. Each of the three zones has unique specifications and operational methods and are described below. Their specifications can be found in Table 2.2

Zone	Storage locations	# SKU's	Parcels per batch	Range picks/parcel	Average parcel size	Average picks/batch
Ambient	4800	3500	18	[1-25]	10	180
Chilled	3500	2000	6	[1-20]	15	90
Frozen	800	500	4	[1-35]	18	75

Table 2.2: Specifications per picking zone

Ambient

The Ambient zone is the largest area and hosts the highest number of SKUs. The layout of this picking zone is illustrated in Figure 2.7a. This area is a rectangular warehouse configuration with 8 aisles and 34 storage shelves. These racks can be designed to suit the size of various SKUs, each shelf thus holds different SKUs. Additionally, some spaces are occupied by pallets. Pallets and storage racks are similar in size; the key difference is the number of distinct SKUs they can hold. Both types of storage locations can be seen in Figure 2.7c and Figure 2.7d. Parcels in the ambient zone are packaged in either a small or large cardboard box, with the box size determined by the quantity and dimensions of the SKUs per parcel. Each picking cart can hold 18 parcels, regardless of the size of the box. The number of SKUs per parcel can vary greatly, typically ranging from 4 to 25 SKUs, with some exceptions with more or less products. The average SKUs per parcel in the ambient zone is 10 SKUs per parcel. A standard picking cart generally includes approximately 180 picks per route.

Figure 2.6: Floor map Warehouse Amsterdam

(a) Layout (b) Picking cart (c) Storage locations (d) Storage locations

Figure 2.7: Specification of the ambient zone.

Chilled

The primary distinction between the chilled and ambient zones is the batch size. In the ambient zone, carts can hold 18 parcels, whereas in the chilled section, each cart is restricted to 6 EPP (Exanded Polypropylene) boxes. Each box is capable of holding a single cardboard container box, whether small or large. Additionally, the chilled zone allows for very small orders, typically in the range of 1 to 3 products, to be picked using a paper bag. One EPP box is able to accommodate 3 paper bag containers. In theory, if each EPP box holds 3 small containers, a cart could carry 18 containers, but this scenario is uncommon. A single EPP box is in the chilled section considered as one parcel. The storage areas in the chilled section are similar to those in the ambient section. Most SKUs are kept in storage racks, although there are some palletised storage locations in the chilled section as well. The number of SKUs per parcel is higher compared to the ambient section. Due to the fact that the chilled zone holds less SKUs than the ambient zone, the layout is also smaller. It has only 4 aisles instead of 8 and has a comparable length. The chilled section can thus be considered a scaled-down version of the ambient zone, mainly differing in the number of parcels per batch. Due to the small batch sizes, and thus more batches, the chilled section is more sensitive for congestion than the other zones.

(a) Layout (b) Picking cart (c) Storage locations (d) Storage locations

Figure 2.8: Specification of the chilled zone.

Frozen

The layout and storage locations of the frozen section in the Crisp warehouse are the most unique. SKUs in this section are selected from a freezer that contains multiple SKUs. The design and routing within this area are distinct as well. Unlike the rectangular configuration seen in the ambient and chilled sections, this section is designed to the available warehouse space. Resulting in a longer first aisle compared to the second and third aisle. Also, in contrary to other areas where pickers pick on both sides of the aisle, in the frozen section the picker only picks from the right-hand side. Parcels in the frozen zone consists of a maximum of 6 containers per parcel. The picks per container are smaller in comparison with the containers in the other zones. On average each container consists of three picks, resulting in an average parcel size of 18. This allows carts to carry many containers at once, resulting in a lower number number of constructed batches in comparison with for example the chilled section. The containers in the frozen zone are plastic bags instead of the cardboard boxes used in the ambient and chilled section. The frozen zone is also the smallest zone, has the least storage locations and holds the least amount of SKUs.

(a) Layout (b) Picking cart (c) Storage locations (d) Storage locations

Figure 2.9: Specification of the frozen zone.

2.2.4. Current batching method

The order picking process at Crisp starts with assembling the picking carts. This process is done in a centralized place, where all the carts used for the different zones are prepared. A picking cart is loaded with multiple parcels, depending on the zone this number fluctuates. An ambient cart is loaded with maximum 18 parcels, a chilled cart is loaded with maximum 6 parcels and a frozen cart is loaded with maximum 4 parcels. The parcels are assigned to these carts following predefined rules. The carts are prepared based on the pick deadline. Meaning the parcels with the fastest pick deadline are placed on the first outgoing picking cart. If there are more orders with the same pick deadline, orders are assigned based on the following order:

1. Lowest hub building ID
2. Lowest route number (code)
3. Stop number/order ID
4. Parcel ID

Each hub used for cross docking has an ID number. The farthest hub will have priority over the nearest hubs. Within the parcels assigned to a specific hub, the lowest route numbers are assigned first. The orders of this route are then sorted by stop number/their order ID. This is implemented because this makes the loading process on the busses easier. The busses should namely be loaded in an order that is logic when unloading the bus. So the first stop should be easily accessible instead of being stored in the bottom. The last step in the order, the Parcel ID, is something that is almost never the deciding factor. This is the case when the last assigned order to the cart consists of 2 parcels. Then the first parcel will be placed on the first picking cart and the second parcel on the second picking cart. However the chances of this being the case are very low. These guidelines when assigning parcels to the picking carts thus do not take the resulting travel distance in account and are not batched based on characteristics of the parcels but based on these regulations. Because the due time of the orders is the main criteria to form batches, the batching strategy of Crisp can be compared with the FCFS (first comes, first served principle). These due times are related to the selected delivery time by the customer. When ordering, customers can select a specific time slot for their order to be delivered. They have the choice between a 1 hour, 2 hour and 4 hour time slot. These time slots result in a custom made delivery schedule to deliver all orders on time. Delivery vans therefore will have a strict departure time, resulting in the orders assigned to a specific van all have the same pick deadline.

2.2.5. Current routing and product allocation

After the parcels are batched on the carts, the actual order picking starts. The order pickers follow the S-shape heuristic trough the warehouse. Traversing the whole aisle and thus visiting each pick location per picking batch. The layout and walking directions per zone can be seen in the layout picture depicted in Figure 2.7a, Figure 2.8a and Figure 2.9a for the respective zones. As can be seen, all zones do not contain a middle cross aisle; the only way to traverse to the next aisle is by using the top or bottom cross aisle. In the ambient and chilled section the picker is able to pick SKUs from both sides of the aisle as in the frozen section the picker will only pick items at one side. The picker is guided by a electronic scanner which provides the picker with the next pick location. To reduce picking time, this scanner will tell the picker if the next pick location is the same as the previous, is nearby, farther away or in the next aisle. This reduces the search time of the picker.

At the Crisp warehouse, the allocation of products is determined by their stackability. Stackability refers to the rigidity of an SKU when putting products in an order box. Ensuring that products are not crushed during the picking process is crucial with respect to customer satisfaction. Products with a high stackability will therefore be picked first. These are therefore located in the first aisles of the picking area, this are for example canned products. The products with a low stackability are located in the last traversed aisles, this are products like strawberries or bread. This way of product placement ensures that the heavier products are picked first and the more fragile products are placed on top. Within these stackability classes, the SKUs are randomly assigned to fitting storage locations. So SKUs on pallets will be kept to pallet places. This only holds for the chilled and ambient zones; in the frozen zone all products have the same rigidity due to the fact that they are frozen. Because products come in different sizes, the shelves in the warehouse are adjustable. The non uniformity of the shelves makes the product allocation plan complicated as not all products can be stored anywhere. The fast moving products of Crisp are placed mostly at eye height to reduce the picking effort for the pickers. Because Crisp sells products with an expiry date and want to ensure no expired products are sold, they sort products in the warehouse on expiry date. This means that the same SKU, with a different expiry date, can have 2 distinct locations in the warehouse.

2.3. System Analysis

This section provides the system analysis. The system is both explored with a black box analysis as a CATWOE analysis. It highlights the key elements of the system and their relations.

2.3.1. Black box analysis

A black box model outlines the inputs, outputs, requirements and the KPI's of the process. This framework helps in understanding the order picking process and gives the relation between the inputs and output while taking the requirements and KPI's into account. The black box analysis can be seen in Figure 2.10. The system's inputs and outputs resolve around picking multiple SKUs into orders ready for delivery. Workers pick single SKUs and put them in boxes that will be delivered to the customer. The generated waste of the process will consist of products with an expired delivery date and bulk packaging material used to pack multiple SKUs in one tray. With respect to the requirements it is important that the picking process can be executed safely. To ensure the safety of everybody on the work floor, multiple rules are implemented. Besides the safety, it is important that the picking is accurate. Customer satisfaction is very important for Crisp, so orders should be complete and not miss any products.

The order picking can be measured on different Key Performance Indicators (KPI's). The accuracy rate and the packing quality are related to the customer satisfaction. The orders should be complete and the products should be neatly packed. The pick rate represents the speed of the pickers. Due to the fact they pick multiple orders at once, defining a time per order is challenging. The pick rate is measured in the average time it takes to perform a single pick. The pick rate is highly correlated with the travel distance. An as low as possible travel distance will namely improve the pick rate. The travel distance is in this thesis the most important KPI. As the order picking process represents 55% of the total operating costs [5, 6], the costs are also an important KPI. The order picking costs are related to the performance of the order picking process and thus are related to the travel distance KPI.

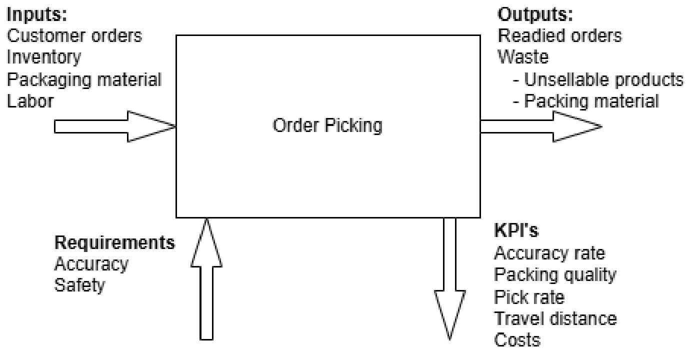


Figure 2.10: Black box model of the order picking process

2.3.2. CATWOE

CATWOE is an acronym that stands for Customers, Actors, Transformation, Worldview, Owners and Environment. A CATWOE analysis helps to identify the key elements of a process and is a simple checklist that helps to find solutions to problems. For a order picking process, the CATWOE analysis can be found below.

- **Customers:** The customers are the customers of Crisp, the people who order groceries at Crisp.
- **Actors:** The actors are the employees that are working in the warehouse. This include the order pickers but also the managers, planners and inbound/outbound managers.
- **Transformation:** The core process of the order picking process is converting the input stock into outgoing orders. Orders specify the items and quantity, which is subsequently picked and prepared for delivery.
- **Worldview:** The worldview on the order picking process involves efficiency, accuracy, supply chain continuity and cost reduction. Effective and accurate order picking is crucial to maintaining customer satisfaction and operational efficiency. Having an efficient as possible order picking process will reduce costs and ensure a smooth continuity in the supply chain.
- **Owners:** The owners are the warehouse management team that is responsible for the process and has the authority to make changes regarding the process. The end ownership will lie with the board of Crisp.
- **Environment:** The environmental constraints include picker speed, suppliers, fluctuations in order volume, regulations regarding Fast Moving Consumer Goods (FMCG). The punctuality of suppliers and the picker speed will affect the efficiency. The fluctuations will put pressure on the picking process. The regulations are to be incorporated in the picking process.

2.4. Conclusion

This chapter provides a comprehensive analysis of the Crisp warehouse operation, outlining the different stages from receipt to delivery. It explains the existing operational methods in the warehouse and provides an overview of the processes. Within the Crisp warehouse, multiple processes are employed between the receiving of product until the delivery. Products are received, occasionally pre-picked, stored, picked, and prepared for delivery. Orders are picked in three distinct zones, categorized by picking temperature. The picking process in each zone varies by parcel size and batch size, yet all are picking following to the S-shape heuristic. This chapter answers subquestion 1 as it explains the current order picking process.

3

Literature review

The literature review chapter examines the key concepts regarding optimizing a picker-to-part warehouse. This aims to provide a comprehensive understanding on all the relevant aspects of warehouse optimization. Not all warehouses are the same, as they are specified to their required performances and dimensions. Among the warehouse processes (receiving, storing, order picking and shipping), order picking is the most costly operation as it takes 55% of the total operating costs for a typical warehouse [5, 6]. This literature chapter will only evaluate the performance of the order picking, however warehouses could also improve its performance by better alignment of the processes or improve the performance of other warehouse processes. The decisions regarding the order picking process can be categorized on a strategic, tactical and operational level. [15, 16], which will be examined in respectively section 3.1, section 3.2 and section 3.3.

3.1. Strategical level

At the strategic level, we consider decisions that have a long term impact and are mostly associated with high investments [16]. The decisions refer to policies and plans for using the resources in order to fulfill the long term competitive strategy [15]. This encloses the level of automation, equipment selection and the picking policy [16].

3.1.1. Level of automation

The level of automation, is as the name already implies, the level of automation in the warehouse. It refers to the extent to which manual processes within the warehouse are replaced by automated systems. This can range from no automation, where all tasks are performed manually to a fully automated process where all tasks are performed by machines. Automating a warehouse requires large investments as these machines are expensive. With today's digitization, a certain level of automation is quickly achieved. For example using a Warehouse Management System (WMS), which almost every warehouse uses, is a form of automation.

3.1.2. Equipment selection

The selection of the equipment is quite depending on the level of automation. If the warehouse is fully automated, the selected material will be quite different than a manually operated warehouse. However assuming a manual picker-to-part warehouse, the most important equipment is the picking cart. Picking carts can be customized on size, amount of places for an order, weight, drivetrain etc. Besides the picking cart, the picking device that guide the order pickers are also of importance. Having a device that is able to scan products will enhance the efficiency compared to checking off products of a list with pen and paper. Choosing suitable racks is also part of the equipment selection and requires large investments. It is important to determine to decide between low-level and high-level shelves. Low-level means that the picker can reach all the items himself without needing additional equipment, whereas high-level means the SKUs can be stored in higher racks not reachable without additional equipment. Selecting a low-level or high-level will result in needing different equipment for the order picking process.

3.1.3. Picking policy

The picking policy refers to the way orders are picked. When designing a warehouse, decisions on how to pick orders have to be made. Dallari et al. [17] presented five different picking policies, which are shown in Figure 3.1. These different picking policies are scaled on their level of automation. The applied picking policy has a direct link with the level of automation and the selected equipment. Nonetheless, applying different picking policies require different equipment or levels of automation.

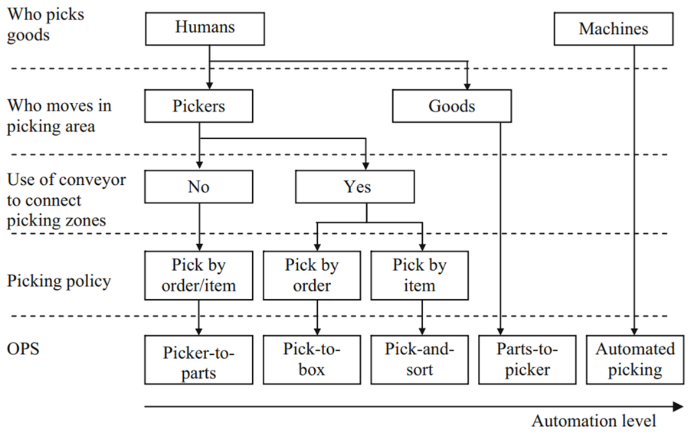


Figure 3.1: Classification of order picker systems [17]

3.2. Tactical level

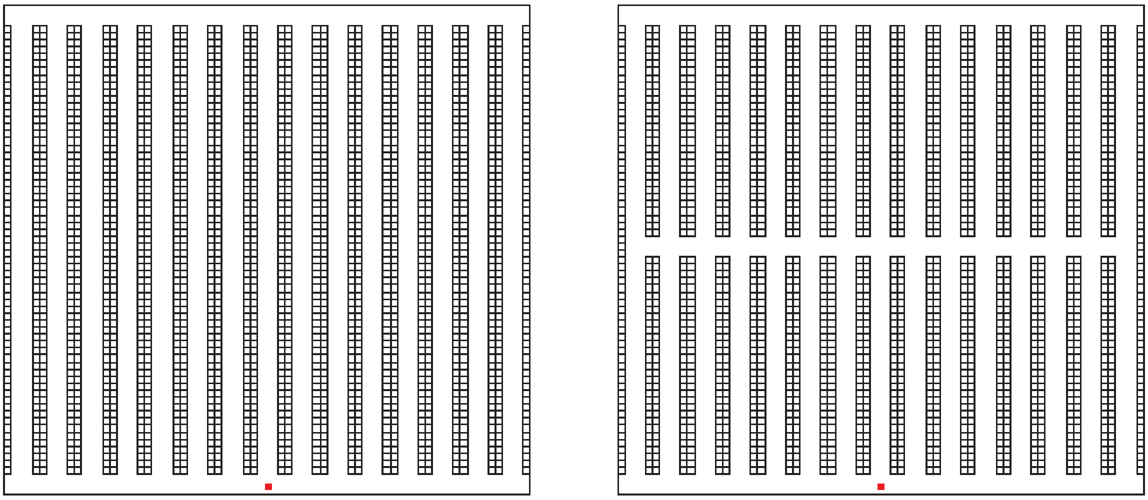
At the tactical level, decisions are made that impact the medium term [15], based on the outcomes of the strategic decisions [16]. Tactical decisions typically concern the dimensions of resources (e.g. storage size, storage capacity, number of employees), the determination of the layout and storage assignment [16].

3.2.1. Dimensions of the resources

The dimensions of the warehouse are bound by the physical walls of the warehouse, as these will determine the total size of the warehouse. However the warehouse is divided in multiple zones with specific tasks. Decisions on how large each zone should be are typical tactical level decisions. This include the dimensions of the picking zones, outbound, inbound, backstock etc. Opting for a specific size of the picking zone will directly influence the storage capacity, after all a larger picking zone will result in more storage space. In addition to the division of the warehouse space for each zone, the number of equipment and personnel is also divided under dimensions. The number of pickers and the number of material handling equipment should be decided to ensure an efficient process. Having a surplus on any of these two will not specifically improve the process, as too many carts will have to be stored somewhere and working with too many workers will lead to a crowded warehouse and potential congestion during picking.

3.2.2. Layout

The layout of the warehouse is a key component of warehouse operations and has a significant impact on order picking and traveling distances in the warehouse [6]. The warehouse layout design is one of the most important parts of warehousing as it is a crucial component of increasing the productivity of warehouses [18]. It demarcates the dimensions for the other warehouse operations. Warehouse design is a highly complex task with many trade-offs between conflicting objectives and a large number of feasible designs [19]. Because of these trade-offs it is favorable to start with a defined layout. There are two types of layout decision problems that can be distinguished [20]. The first problem is called the facility layout problem. This concerns the decisions about where to locate various departments (receiving, picking, storing, sorting, shipping, etc.) inside the warehouse. Using the activity relationship between the departments, a warehouse block layout is derived. The common objective is to minimize



(a) Conventional warehouse layout, single block

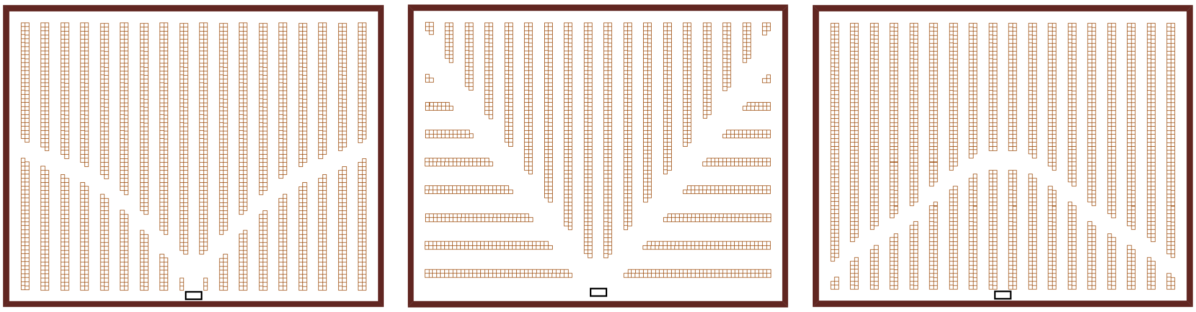
(b) Warehouse layout with middle cross aisle, multi-block

Figure 3.2: Conventional layouts with a single P/D point (adapted from: [26])

the handling cost (travel distances) between the different departments. The second problem is usually called the internal layout design or aisle configuration problem [20]. It concerns the placement of equipment and storage space (number, width and length of aisles) within the departments [20, 19].

The aisle configuration can have a significant effect on order picking and the travel distances [6]. A conventional layout is shown in Figure 3.2a. Defining the optimal layout is hard as it is affected by the strategic and operational decisions [21]. Adding cross aisles to the warehouse is a commonly used method to reduce the travel distance. Cross aisles are perpendicular to the picking aisles as can be seen in Figure 3.2b. Creating a warehouse with (multiple) cross aisles is called a multi-block layout [19]. Adding cross aisles in a warehouse layout has been researched in various studies. Roodbergen et al. [22] concluded that, apart from special cases with a very high picking density, it is always favorable to have a multiple block layout. The research done by Ertek et al. [23] presented a detailed discussion of the impact of cross aisles on a rectangular warehouse. They defined the optimal amount of cross aisles with respect to the amount of aisles and the length of the aisles. They also analyzed both equally and unequally spaced blocks. They concluded that establishing cross aisles can bring significant travel-time savings and that it is more desirable to establish only equally spaced cross blocks than unequally spaced cross blocks. This is in contrary to the research by Küçük [24], which concluded that a lower number of unequally spaced cross aisles provide the same travel distance reductions due to a higher number of equally spaced cross aisles. Therefore less number of unequally spaced cross aisle provide savings on warehouse size and achieve the same travel distance reduction. Additionally, this research found an interesting pattern of storage block lengths with respect to pick densities. If the pick density increases, the middle storage block gets longer to provide maximum travel distance reduction. Berglund and Batta [25] presented a method for calculating the maximal efficient cross aisle positions for a picker-to-parts warehouse. The proposed method is suitable for multiple warehouse sizes, different storing policies and can vary the amount of cross aisles.

Besides the conventional rectangular warehouse designs, some authors study the effects of non-conventional layouts. Gue and Meller [26] proposed two new different designs; the flying-V layout and the Fishbone layout as can be seen in Figure 3.3a and Figure 3.3b. Where Gue and Meller [26] only considers one pickup and delivery (P&D) point, Gue et al. [27] presented a modified version of the flying-V layout for multiple P&D points In their work they also proposed another layout, the inverted-V layout (visualized in Figure 3.3c), nevertheless they also concluded that the modified flying-V layout always outperforms the inverted-V layout. Pohl et al. [28] compare the flying-V layout with the conventional layouts of Figure 3.2 under turnover-based storage assignment. They concluded that a flying-V layout will always outperform conventional layouts under random storage assignment. These researches only focus on unit load warehouses. Here pickers only perform a single or dual pick per route, the effect of an order picking process with multiple picks is still underrepresented. Dukic and Opetuk [19] analyzed and compared the fishbone layout with a random storage policy to a conventional layout. They concluded that the fishbone layout results in a longer travel distance compared to a traditional layout with a middle cross aisle for an order size between 10 and 30 picks. However, the fishbone layout does perform slightly better than a conventional layout without a middle cross aisle. Çelik et al. [29] compared the fishbone layout with a conventional layout with two middle cross aisles. Their study finds that the conventional layout will outperform the fishbone layout for all orders with 3 or more picks. Çelik and Süral [30] continue on the research of Çelik et al. [29] by changing the storage policy to a turnover-based storage. They concluded that if the demand is very skewed (e.g. 20/80) the fishbone layout will outperform the conventional layout for orders with up to at least 30 picks.



(a) Flying V layout [26] (b) Fishbone layout [26] (c) Inverted V layout [27]

Figure 3.3: non conventional layouts (adapted from: [6])

Besides the configuration of the racks, the dimensions such as the length and width of the aisles are also important parameters. Hwang and Cho [31] developed an algorithm to find these optimal parameters. They first solve for the minimum number of aisles and then find the optimal size of the aisle. Derhami et al. [32] presented a simulation-based optimization algorithm to optimize the utilization of storage space and the transportation costs in the layout. It is important to design the width of the aisles in such a way that workers are able to surpass each other, otherwise this will lead to congestion in the warehouse. Choosing for an aisle width where the aisles are wide enough for pickers to surpass each other easily could lead to a two way warehouse. Pickers are able to enter and leave the aisle from both sides, the downside of a two way aisle is that the pickers will have more interactions with other pickers and it will be more chaotic. If the aisle is too narrow to turn, the routing will also be limited as the picker is then forced to enter the aisle and leave the aisle on the other side. Increasing the width of the aisles too much will affect the travel distance as well. The picker has to cross the aisle to pick from both sides which will increase the travel distance. Table 3.1 displays the advantages and disadvantages of each warehouse configurations. In Table E.1 the reasoning behind the table is given. The table indicates that there is a relation between the space utilization and the congestion. The most important one is if the space utilization increases, the congestion will decrease. However using more space, will increase the warehouse size and therefore be more expensive.

A different decision that affects the order picking process is the amount of P&D points. Multiple papers investigate the effect of multiple P&D points in a warehouse. Many of these papers focus on multiple P&D points in non-conventional warehouses. Examples are the studies of Gue et al. [27] and Mesa and Masel [33] that evaluate the effects of multiple P&D points on non-conventional warehouses. Having multiple P&D points will avoid congestion and facilitate flow through receiving and shipping docks [34]. Nevertheless every P&D point will use additional space and will complicate the warehouse logistics in comparison to warehouses with only one sorting or loading location. The location of the P&D point is often in the left bottom corner or in the bottom middle. The location of the P&D point is of importance as it will affect the routing policy by its location; a P&D point in the middle will already have different routing results than a P&D point in the bottom corner.

[1] The fishbone layout is the only non conventional layout that is evaluated as the flying-V and inverted-V layouts are comparable with a multi-block layout

Layout	Aisle width	Space utilization	Congestion	Routing	Allocation impact
Single block	Narrow	+ +	- -	-	- -
	Double	-	+	-	-
Multi-block	Narrow	+	-	+	+
	Double	- -	+	+	+ +
Fishbone [1]	N/A	- -	+	-	+

Table 3.1: Relations regarding the warehouse layout

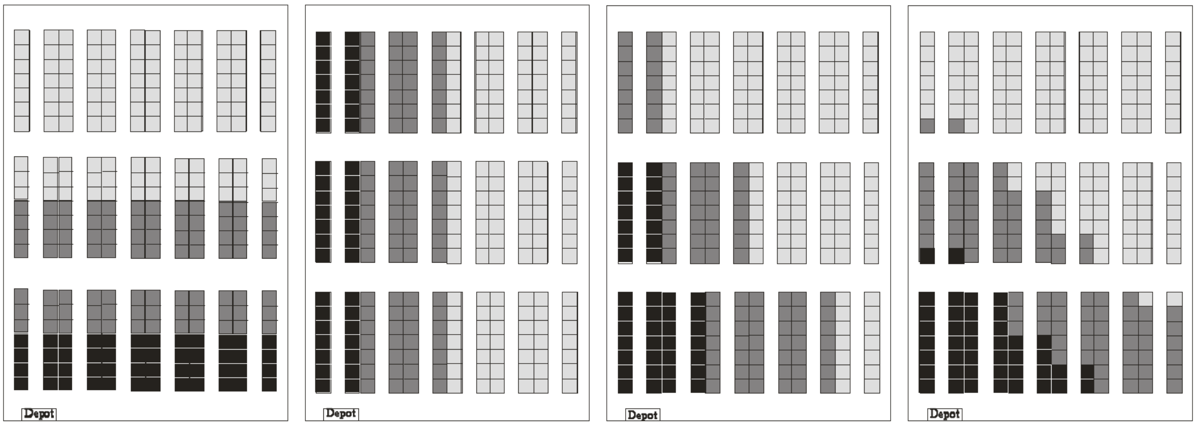
3.2.3. Product allocation

There are numerous ways to store products within the warehouse. The effect of the product allocation policy is related to the routing policy. Some combinations of strategies reinforce each other, whereas other combinations have little effect. The simplest storage method is the *random storage policy*. In this policy the Storage Keeping Units (SKUs) are assigned to a location in the warehouse that is selected randomly from all eligible empty locations with equal probability [20]. The random storage policy makes high use of the space since one storage location may be shared by different items, but leads to a lower performance in the order-picking operation [35]. The random storage policy only works in a computer-controlled warehouse that randomly assigns the location per product. If the order pickers can choose the location themselves, the order picker will probably pick the first encountered empty location which is known as the *closest open location policy*. This policy is thus in most aspects similar to the random storage policy, the only difference is which empty location is selected. Selecting the closest open location will result in a more concentrated distribution around the P&D point in comparison with the random storage policy [20].

Unlike the *random- and closest open location policy*, dedicated storage policies store SKUs at their dedicated place. The disadvantage of this is that a location is also reserved for products that are out of stock, which leads to the lowest space utilisation among all policies [20]. Advantages of this policy are that pickers get familiar with the layout, products can be easily grouped and the dedicated storage can be useful if products have different weights. Heavier products can be stored in the lower racks and in locations that are visited first in the sequence, preventing damage to lighter products by crushing them. Within the dedicated storage, choices can be made on which location stores specific SKUs, leading to different configurations. Based on these choices, specific SKUs are located at the easiest accessible locations, usually near the depot at eye high. Choices can be made on popularity, turnover, volume, pick density, Cube-per-Order Index (COI), correlation or by specific algorithms used to determine the optimal place [36].

The *class-based storage policy* combines the random and dedicated storage policies. It first divides all SKUs in several classes, often the number of used classes is three [20]. A classical way for dividing items into classes is Pareto's method, where the idea is that the fastest moving class contains 15% of the products that contributes 85% to the turnover [20]. Each class is dedicated to a specific area of the warehouse where the storage of SKUs is done randomly. The classes can be defined on the same criteria as the dedicated storage. The difference between both policies is that in the class-based policies all SKUs are classified and then randomly stored in their section, whereas in the dedicated storage policy each SKU is assigned to a specific location. The fastest moving class is often called class A, the next fastest class is called B, etc. In assigning the classes to an area in the warehouse multiple configurations are possible as shown in Figure 3.4. The across-aisle storage policy stores the A-items in the front locations of the warehouse. The within-aisle policy places same class items in the same aisle, with class A closest to the depot. In the nearest-sub aisle storage policy it is assumed that a sub aisle contains only one class and the distance between the center of the sub aisle and the depot determines the class. This policy is only suitable for multi-block layouts, as for a single-block layout the configuration is exactly the within-aisle storage. The nearest-location storage determines the distance between each location and the depot and places the A-items in the closest single locations.

The previous discussed ways of storing products all consider one place per SKU, however storing SKUs in multiple locations could be advantageous. This storing policy is called the scattered storage assignment (SSA) policy, here individual items are intentionally distributed to multiple positions in the picking area to increase the probability that items belonging to the same order are located at nearby positions [37]. A scattered storage is shown to reduce unproductive picker travel because there is always some item close by irrespective of the current picker position [38]. A scattered storage is especially suited if each order demands just a few items. Scattered storage also heavily influences the picker routing as SKUs are available at multiple storage locations. The downside is that opting for a SSA policy increases the space utilization and can complicate the storing process.



(a) Across-aisle storage (b) Within-aisle storage (c) Nearest-subaisle storage (d) Nearest-location storage

Figure 3.4: class-based storage assignment configurations; *Black boxes are class A, Dark grey boxes are class B, Light boxes are class C* (taken from: [14])

Figure 3.5 presents an overview of the different storage policies. Which storage policy is preferable differs per warehouse and is dependent on the other active warehouse processes such as the routing, order size and batching. In terms of space utilization, the random storage policy has the lowest space requirement, so could be useful for warehouses with a space shortage. Dedicated storage has the highest requested space as it has to reserve storage locations for possible obsolete SKUs. The class-based policy is somewhere between the dedicated and random policy. The dedicated storage policies have the advantage that the picker will get familiar with the location of the SKU. The main disadvantage of the dedicated storage is that it reserves a spot for a SKU even if the SKU is out of order. This could turn out disadvantageous with high seasonal products. The class-based and the dedicated storage are in essence very comparable. The best classified products are in the easiest accessible locations, the difference is the final determination of the location. The dedicated storage has to evaluate and place each specific item, whereas the class-based randomly locates the SKUs per class. These similarities result in comparable results for both policies. As the implementation of a dedicated storage is harder than a class-based storage [39], the class-based storage policy is preferable.

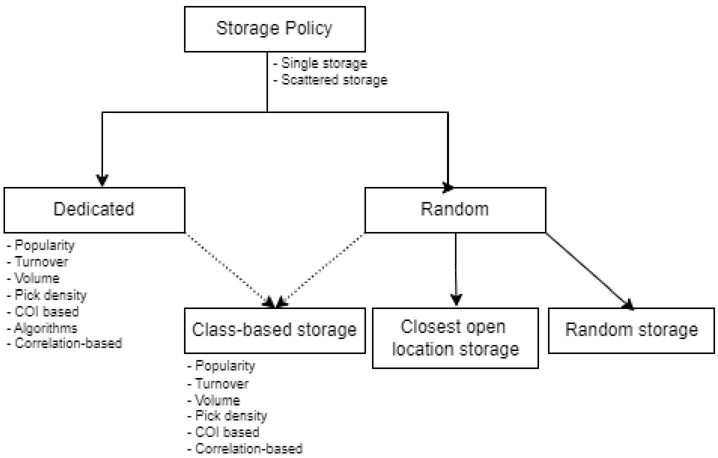


Figure 3.5: Diagram of storage location policies

Table 3.2 illustrates the differences between the different storage policies. The full reasoning of the scores in Table 3.2 can be found in Table E.2. It evaluates the difference between a single and scattered storage and evaluates the four storage policies. While random storage is the most space-efficient, dedicated and class-based storage policies generally improve picker performance and travel distances. Dedicated storage returns the highest picker performance, but suffers from low space utilization. Class-based storage strikes a balance between the two, offering a compromise in both space efficiency and travel distance reduction.

	Space utilization	Picker familiarity	Routing	Difficulty to implement	Congestion	Precedence constraints
Single	+	+	-	+	-	+
Scattered	-	-	+	-	+	+
Random	+ +	- -	- -	+	+ +	- -
Closest open location	+ +	- -	-	+ +	+	- -
Dedicated	- -	+ +	+ +	- -	- -	+ +
Class-based	+	+	+	-	-	+

Table 3.2: Evaluation of different policies

For multi-picker warehouses with a class-based or dedicated storage policy it is important to consider congestion. Where the random storage assignment generates a uniformly distributed activity over the picking area, the other storage assignment policies tend to concentrate picking operations. Therefore, traffic may become congested. The level of congestion depends on which class-based storage policy is used and how the skewness of the classes is determined.

3.3. Operational level

At the operational level, processes have to be carried out within the boundaries set at the strategic and tactical level. The decisions typically concern daily operations such as job assignment, batch formation and the routing.

3.3.1. Job assignment

Job assignment is quite straightforward, it means which order/batch is assigned to which worker. If the workers are all performing the same task, the assigned job will most likely the one with the earliest due time. However for specific reasons there could be decided to deviate from this policy and assign specific orders to a specific picker.

3.3.2. Batch formation

When orders are large, in relation to the capacity of the picking cart, the orders are picked separately. This way of order picking is referred to as single order picking policy. However, if orders are smaller, multiple orders can be picked in the same tour and thereby reducing the total travel distance. Order batching is the method of grouping a set of orders to be retrieved in a single picker tour. According to Choe and Sharp [40] there are two criteria for batching: the proximity of pick locations and time window batching. Proximity batching assigns each order to a batch based on the proximity of its storage locations to those of other orders. Under the time window batching, all orders arriving during the same time interval (a time window) are grouped as a batch. If all the information about the orders is available when the batching and picking process starts, the problem is considered offline and can be considered a static problem. With an online batching problem, the problem is considered dynamic. Orders can be added throughout the process, needing the batching method to reevaluate constantly.

The Order Batching Problem (OBP) is the grouping of a given set of customer orders into feasible picking orders such that the objective function is minimized. This objective function is often to reduce travel distance, but could also focus on different parameters such as picking time, costs, tardiness or completion time [41]. Each batch is restricted to contain a maximum capacity that might be measured in: weight, volume, number of items, or number of orders [41].

When solving the order batching problem exact, it can be considered as a NP-hard problem and many studies focus on developing algorithms or (meta-)heuristics for solving it. In these approaches two different types can be distinguished; a seed algorithm and a saving algorithm. A seed algorithm selects an initial single seed order in the batch and then adds more orders according to a route closeness criterion until no more orders can be added due to a capacity constraint [20]. A savings algorithm starts by assigning each order to a separate batch. The algorithm then iteratively selects a pair of batches to be combined based on the saving of combining them until no more batches can be combined due to the capacity constraint [4]. The batching can also be done based on a priority rule. This means orders are prioritized and assigned to pick lists based on their priority (e.g. first-come-first-served) [12]. By following the priority rule, the results will turn out less than optimal but can be useful if specific orders are time bound.

3.3.3. Routing

In every picker-to-part warehouse, an order picker must follow a route to visit all pick up locations. Routing will impact the order picking performance as it directly impacts the travel distance. The routing plays a role in almost every study related to warehouse optimization as most of the objectives are directly linked with the travel distance. Some researchers estimated that travel time accounts for 50% of the total order picking time [20, 42]. The picker routing problem (PRP) is a variant of the vehicle routing problem (VRP) [2]. It uses an origin-destination (O/D) matrix that results from the structure of the warehouse, which means the solution is bound to the specific layout. In a warehouse all storage locations and P&D points are considered as a node. The O/D matrix includes the shortest distances between all nodes and is necessary to solve the PRP. The algorithm used to solve the routing problem can be classified in three general types; an exact algorithm, heuristics, and meta-heuristics [43]. Exact algorithms will find an optimal solution to a PRP. Heuristics are problem dependent algorithms built according to the specifications, with the result often not being optimal. Meta-heuristics are high-level problem-independent algorithms that provide a set of guidelines or strategies to find an approximate solution for the problem [43].

Heuristics

Where exact algorithms find the shortest possible route for the picker routing problem, heuristic algorithms tend to find solutions less than optimal but are easy to apply. For a single-block warehouse with narrow aisles there are 5 *basic* heuristics defined in literature. Hall [44] proposed the *traversal (S-shape)*, the *midpoint* and the *largest gap* heuristic. Petersen [45] added the *return* and the *composite* heuristic. An general description is given below. Because this thesis will use the S-shape heuristics, the S-shape heuristic is also visualized in Figure 3.6

- **Traversal (S-shape):** In the traversal policy the picker follows a S-shape throughout the warehouse. If the aisle has at least 1 pick, the picker will traverse the aisle entirely. If the aisle has no pick, the picker will skip the aisle and continue with the next one [2].
- **Mid-point:**. The warehouse is divided into two equal halves. Picks located at the top- or bottom part of the warehouse are picked from their respective top or bottom cross aisle. The picker leaves the aisle on the side where the picker entered the aisle
- **Largest gap:** In the largest gap policy, the picker avoids the largest gap. There are three possible gaps: (1) the distance between the top cross aisle and the first pick location in the aisle, (2) the distance between two middle pick locations, and (3) the distance between the bottom cross aisle and the last pick location[2, 20]. If the largest gap is between two pick locations, a return route to either the top- or bottom cross aisle is used.
- **Return:** The picker will enter and leave the aisle from the same (most often the front) aisle. Once the picker have picked all the picks in the aisle, the picker will return to the front end and continues to the next aisle with picks. This heuristic is mostly effective if most of the pick locations are on one end of the aisle [2].
- **Composite (combined):** This strategy combines the S-shape and the return policy. The entered aisles are either traversed entirely or a return method to were the picker entered the aisle is used, depending on which heuristic gives the shortest travel distance to the next pick. For each aisle, the choice is made by using dynamic programming[2].

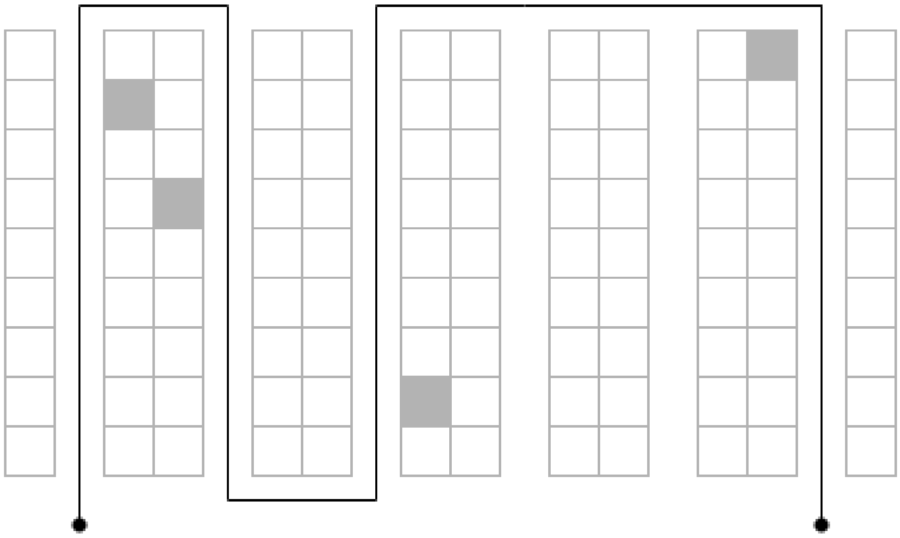
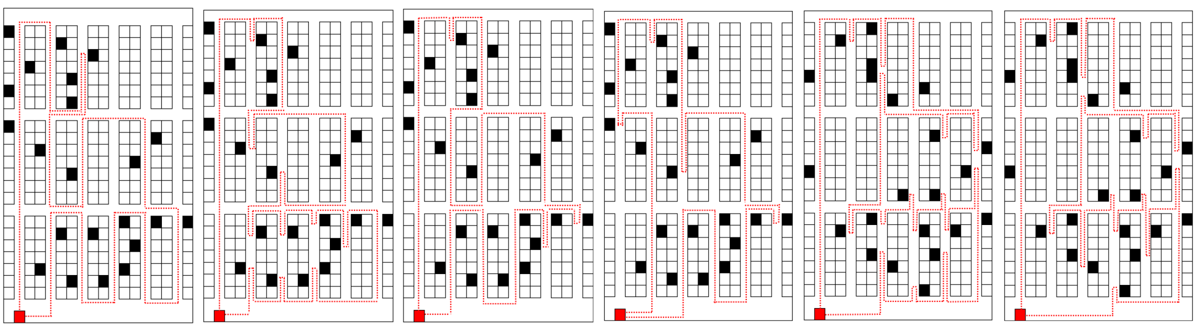


Figure 3.6: S-shape heuristic

The *basic* heuristics were originally developed for a single block layout, nevertheless multiple studies extended these heuristics to a multiple block layout and defined new heuristics. Roodbergen and De Koster [46] extended the largest gap and S-shape heuristic to a multi-block layout. They also proposed two new routing heuristics which they called *combined* and *combined+*. The proposed routing heuristics have a strong correlation with the heuristics for a single block warehouse, but do come with some additional conditions. Roodbergen and De Koster [46] located the pickup/delivery point in the bottom left corner. The S-shape, largest gap and combined heuristic all travel all the way up to the farthest block by using the first encountered aisle that contains requested items. Then it solves each block separately, starting with the farthest block and each iteration moving a block (with picks) back to the pickup/delivery point. The combined+ heuristic improves on this condition as it able to access the furthest block by not using specifically the first aisle that contains picks, but can use the first sub aisle per block that contains a pick to travel upwards. The proposed heuristics and their routes are visualized in Figure 3.7.

Vaughan and Petersen [47] developed the aisle-by-aisle heuristic. This heuristic starts in the left bottom of the warehouse and ends in the right bottom of the warehouse. The heuristic proceeds from left to right under the condition that each aisle containing picks has to be visited only once. A dynamic programming approach is used to determine the best cross aisle to use for moving from one picking aisle to the next to minimize the travel distance. Shouman et al. [48] proposed two new heuristics. the *block-aisle 1* and *block-aisle 2* heuristic. Both heuristics split each block in the middle into an upper and lower part. The upper and lower part are then picked using the return policy. The difference between the two heuristics is that in the *block-aisle 2* heuristic the upper part also contains the next adjacent storage location of the lower part if that specific location contains a pick.



(a) S-shape (b) Largest gap (c) Combined (d) Combined+ (e) Block-aisle 1 (f) Block-aisle 2

Figure 3.7: Heuristics for a multi-block layout (taken from: [43])

The previously mentioned heuristics for multi-block layout can be classified as simple heuristics, the second category is called the improvement heuristics. These heuristics try to improve an initial solution generated by a heuristic. Often used improvement heuristics are the *2-opt* and the *3-opt* local searches as well as the *Lin-Kernighan-Helsguan (LKH)* TSP heuristic. The 2-opt and 3-opt local search algorithms iterative improve an initial solution by swapping respectively 2 or 3 edges to reduce the travel distance. In each iteration, the algorithm evaluates in the current route whether swapping the edges would result in a shorter route. The LKH is a local optimization algorithm that takes an initial tour and then repeatedly exchanges some edges in the tour with other edges that are not in the tour (based on the λ-opt algorithm presented in Lin [49]) to reduce the distance of the current tour [43]. Where the 2-opt and 3-opt algorithms are fixed to swapping 2 or 3 edges, the LKH can dynamically change the number of swapped edges up to 5 edges [50].

Exact algorithms
Exact algorithms tend to find an optimal solution to the PRP. The work of Ratliff and Rosenthal [51] is seen as a seminar work. The warehouse in the work of Ratliff and Rosenthal [51], is a narrow, single block low-level picker-to-parts warehouse with a single depot in the front cross aisle. Ratliff and Rosenthal [51] proposed an algorithm to pick orders in minimum time, with a time complexity that is linear in the number of aisles. The algorithm of Ratlif and Rosenthal has been extended in multiple researches. The downside of their algorithm is that it lacks flexibility and is fixed to the warehouse configuration. Therefore multiple researches extended their research to different warehouse configurations.

Ratliff and Rosenthal [51] is specified to a single block warehouse, so multiple authors extended the algorithm to a multiple block warehouse. Roodbergen and De Koster [52] were the first to extend the research to a conventional warehouse with a middle cross aisle. They assumed that the cross aisles do not contain any storage locations. Goeke and Schneider [53] proposed a compact formulation of the PRP based on the work of Ratliff and Rosenthal [51] and is able to solve large problem instances within short runtime. Their work is also able to address scattered storage, decoupling of the picker and cart and includes multiple depots.

Besides extensions on the work of Ratliff and Rosenthal [51], there are also multiple studies that are self contained and no extension on their work. Chabot et al. [54] used a branch-and-cut algorithm to solve the order picking problem with precedence constraints. They proposed two algorithms, a capacity-indexed algorithm and a two-indexed flow formulation. They concluded that both the exact algorithms are performing better than heuristics, but have longer computational times. The study of Theys et al. [55] is in essence quite similar. The study applied an exact algorithm and compared the results to heuristics. The exact results are obtained by using the exact Concorde TSP algorithm [56], which uses a branch-and-cut algorithm to find the shortest route. Matusiak et al. [57] used the A* algorithm, which is based on dynamic programming, to solve the combined precedence-constrained order picker routing and order batching problem. The A* algorithm is first introduced by Hart et al. [58] and is in the work of Matusiak et al. [57] used for the routing, where the batching is solved by a simulated annealing algorithm. The mentioned studies concluded that solving the order picking problem with (meta-)heuristics have a lower computation time and for that reason could be preferable. Su et al. [59] proposed two mathematical optimization formulations for the multi-block layout with Mixed Integer Linear Programming (MILP). For which the scale and solution time are independent of the number of cross aisles. For a single block warehouse Su et al. [59] evaluated their algorithm to the algorithm of Scholz et al. [60] and for the multi-block layout to the two algorithms of Pansart et al. [61]. The algorithm of Scholz et al. [60] models the PRP as a classic TSP, but takes into account that pickers can only change the aisle by using the cross aisles.

Meta-heuristics
Meta-heuristics are mostly used to solve a combination of multiple order picking problems at once. The most commonly used meta-heuristics are[43]: *Genetic Algorithms (GA), Simulated Annealing (SA), a Tabu Search (TS), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO)* and *Adaptive Large Neighborhood Search (ALNS)*. Meta-heuristics typically return results comparable to results provided by exact algorithms, but in general use less computation time and find near optimal solutions instead of the optimal solution.

Tsai et al. [7] proposed a multiple-GA method consisting of two separate GA's, one for the batching and one for the TSP. The GA for the batching finds the optimal batch plan by minimizing the sum of the travel costs and considering the earliness and tardiness penalties. The GA is inspired by the natural selection mechanism where stronger individuals are more likely to survive. It defines potential solutions in the form of chromosomes and starts by creating an initial population by randomly generating feasible solutions. Offspring solutions are then produced through crossover and mutation. The fitness of each solution can be related to the objective function value. In the GA for the TSP, each gene denotes a picking location that has to be visited, the order of the genes is the visiting sequence in the batch. By reflecting back to the objective function it finds the most effective travel path in a batch by minimizing the travel distance. Kordos et al. [62] also uses two GA's in their study. Where Tsai et al. [7] used it for the routing and the batching, they applied it to the product placement and routing. They concluded that using the GA's simultaneously reduces the travel costs to 26% in comparison with only using the routing GA. Lin et al. [63] studied a comparable problem as in the study of Tsai et al. [7], but used a PSO approach. They modify the PSO proposed by Selvakumar and Thanushkodi [64] to solve the routing problem for a batch. PSO imitates the movement of a population of particles seeking the optimal solution. In each iteration of the PSO, each particle moves towards the optimal solution by updating its own velocity and position on the basis of the past good experience of the particle and the global good experience of all particles [63]. Ho and Tseng [65] studied the order picking routing by updating the results of the largest gap heuristic by a SA approach. SA is an optimization technique that allows non-improving moves in its local search process to ensure the solution does not get stuck in a local optimum. Chen et al. [66] applied an ACO approach for two order pickers to a multi-block layout while taking congestion into account. Later they modified their previous work to multiple order pickers in Chen et al. [67]. An ACO is a meta-heuristic algorithm which simulates the behavior of ant colonies in nature as they forage for food and find the most efficient routes from their nests to food sources and is commonly used to solve the TSP [66]. Chabot et al. [54] used an ALNS to solve the order picking problem with respect to precedence constraints. The ALNS uses destroy and repair operations to improve the solution in each iteration. A destroy operation removes nodes from the pick sequence, while the repair operation inserts them at potentially better positions [43]. Cortés et al. [68] studied the order picker routing problem with constraints of the inventory availability and considering an order is not allowed to be split. The problem is solved by using a generic TS and using two hybrid variants of the TS, called TS 2-Opt Insertion and 2-Opt Exchange. They evaluated the results of these 3 meta-heuristics and compared the results with a SA and GA approach. A generic tabu search implements a tabu list, which records the movements applied in previous solutions. This tabu list prevents returning to the most recent visited solutions in order to avoid cycling and promotes searching in other zones of the solution space that have not yet been explored [68]. Swap and shift movements are implemented to obtain new routes. In a swap movement, two storage locations are interchanged, whereas in a shift movement, one location is selected and inserted into a new position in the route [68].

The Joint Order Batching Picker Routing Problem

The Joint Order Batching and Picker Routing Problem (JOBPRP) means as the name already suggest, integrating order batching and picker routing problems to enhance the performance. The PRP and OBP are strongly linked, since the OBP needs to be solved to provide an input for the PRP while the PRP has to be solved to evaluate the performance of the OBP. The JOBPRP can be addressed using two main approaches: integrating both into one optimization problem or solving them sequentially and iteratively.

Ene and Öztürk [69] represent the JOBPRP with an integer programming formulation. Due to the need for short computation time, they solve this problem by using a genetic algorithm to approximate the results. They first determine the location of the products and then apply their GA to solve the joint batching and routing problem. They integrated both problems in the integer programming formulation. Lin et al. [70] simultaneously determines the optimal order batching and the shortest picker routing. The work used the Manhattan distance between picks to obtain an *'order center'*, which can be seen as the location with the lowest average distance to all the picking locations in that order. These order centers are then linked to the nearest *'batch center'* and used to solve the routing problem. By changing the location of these 'batch centers' in the algorithm, different batches are formed and different results for the routing are found. This is done with an improved PSO (ImPSO). Which improves the PSO by updating on basis of the previous best and worst experiences of particles.

Won and Olafsson [71] proposed two different heuristics to solve the JOBPRP. Their solution is based on combining a Bin-Packing Problem (BPP) with a TSP. The first heuristic is the Sequential Order Batching and Picking (SBP) algorithm. It is sequential in the sense that it first solves the batching problem and then solves the picking problem for these batches. The second heuristic, the Joint Order Batching and Picking (JBP) algorithm, simultaneously constructs batches and tours. In contrary to the SBP, this heuristic also relaxes the constraint that each picker should always pick the maximum capacity of the cart. In both cases, the routing is solved by a 2-opt heuristic. Their numerical results show that considerable improvements can be achieved by solving the problem jointly.

Tsai et al. [7] proposed a multi-GA method to solve the JOBPRP. It consists of two genetic algorithms, one for the batching and one for the routing. In the first stage of the GA, the order batches that are required for picking are identified. The second GA searches for the most effective travel path for the batch by minimizing the travel distance. These results are then used again as starting point of the first GA, until the maximum iteration number is reached.

Scholz and Wäscher [72] integrated multiple routing heuristics into an iterated local search approach to solve the batching problem. They combined the iterated local search with the following routing heuristics: S-shape, largest gap, aisle-by-aisle, combined+ and the heuristically modified exact algorithm (HMEA). They showed it is possible to solve the JOBPRP with multiple heuristics, and showed the potential of the JOBPRP instead of solving the problems separately.

3.4. Conclusion

This chapter answers subquestion 2. It showed all aspects that influence the warehouse performance. There are four main aspects found that have a significant influence of the warehouse operations; The layout, the product allocation, order batching and the routing. The configuration of the racks will set the physical outline for the rest of the warehouse processes and therefore has a high influence on the order picking performance. Adding cross aisles to a single block warehouse is a trade-off between the reduction of travel distance and the required space for a cross aisle. The layout will affect all other processes in the warehouse and is therefore of high influence.

How and where products are placed can influence the performance by placing specific products in the most easily accessible locations. Each policy has its own strengths and weaknesses. While random storage is the most space-efficient, dedicated and class-based storage policies generally improve picker efficiency and travel distances. Dedicated storage returns the highest picker efficiency, but suffers from low space utilization. Class-based storage strikes a balance between the two, offering a compromise in both space efficiency and travel distance reduction.

With order batching, a given set of customer orders is batched into a feasible batch such that the objective function is minimized. Which orders are batched together depends on the storage allocation and the routing method. The batching method groups orders in a batch, functioning as the input for the routing problem. The batching problem thus directly affects the routing problem and is therefore most relevant to be solved in combination with the routing problem.

When improving the warehouse efficiency, reducing the total travel distance is often the objective. The routing can be solved in three different ways, with heuristics, an exact algorithm or by using meta-heuristics. Heuristics are rules of thumb that aim to find good solutions to the routing problem. The exact algorithm gives the optimal solutions to the routing problem but is a NP-hard problem, so for large instances the computing time exponentially increases. Meta-heuristics are mostly used in a high order problem and used to solve multiple order picking problems at once. The results obtained from a meta-heuristic approach are comparable with exact algorithms, but in general use less computation time. With the use of meta-heuristics, larger instance can be solved in a feasible time. Different meta-heuristics have proven to be applicable to solve the JOBPRP. There is no research conducted in which meta-heuristic is the best performing, however many authors propose a Genetic Algorithm. An overview of the relevant literature that integrates multipe warehouse processes can be found in Table 3.3, it also shows this work.

Reference	Objective	Layout		Allocation			Routing			Batching		Characteristics		
		Si	Mu	R	D	C	E	H	MH	B	JB	O	S	P
[22]	A statistical estimate for average travel distance for different layouts	X	X	X				X				-	-	-
[23]	Finding optimal multi-block layouts		X	X			X					-	-	-
[25]	Finding optimal placements of cross-aisles		X			X		X				-	-	-
[35]	Assign SKUs to locations based on order pairs	X			X		X					-	-	-
[51]	Solving the picker routing problem with an exact algorithm	X			X		X					-	-	-
[46]	Developing new heuristics for the routing problem		X	X				X				-	-	-
[2]	Finding optimal routing policies and comparing to heuristics		X	X			X	X				14	450	30
[73]	Solving a combined precedence-constrained routing and order-batching problem.	X			X	X					X	100	3000	3
[55]	Comparing the LKH-heuristic to TSP heuristics and evaluating the effect of midaisles.	X	X	X		X	X	X			X	100	500	80
[7]	Proposes a batch picking model that considers not only travel cost but also an earliness and tardiness penalty	X		X					X		X	250	400	60
[63]	Investigates the JOBPRP by using a PSO	X		X					X		X	100	16	4
[67]	Proposes a hybrid algorithm for the JOBPRP	X		X					X		X	200	10	4
[69]	Designing a storage alocation plan and order picking system for the automotive industry		X			X			X		X	45	400	3
[70]	Solving the JOBPRP with a 'batch center'	X		X					X		X	100	16	4
[72]	Solving the Order Batching and the Picker Routing Problem in a more integrated way for different heuristics		X	X				X	X		X	80	3000	80
[8]	Solving the JOBPRP for multiple-cross-aisle warehouse systems		X	X					X		X	250	500	20
[11]	Solving the JOBPRP combined with the allocation policy		X	X		X		X	X		X	200	7200	100
[74]	Uses a grouped genetic algorithm to solve the JOBPRP	X		X				X	X		X	50	2000	50
This research	Examine the relation between warehouse processes and find the optimal configuration	X	X	X		X		X			X	12000	64000	200

Abbreviations: Si: Single-block, Mu: Multi-block, R: Random policy, D: Dedicated policy, C: Class-based policy, E: Exact algorithm, H: Heuristics
MH: Meta-Heuristics, B: Batching only, JB: Joint Batching with routing, O: number of Orders, S: Number of SKUs, P: Pick density (picks per batch)

Table 3.3: An overview of the literature reviewed on the optimizing the travel distance by integrating multiple warehouse processes processes

4
Model development

This chapter will discuss the JOBPRP model. The JOBPRP model described in this chapter is specified to the system in chapter 2. The chapter will explain the model objective, input and output and the assumptions and simplifications made to accurately represent the system of chapter 2. Finally, the mathematical model is presented and explained. The mathematical model is based on the works of Kulak et al. [8] and Cano et al. [74]. This chapter will provide an answer to the third subquestion.

4.1. Model objective

The goal of this thesis is to define the best performing orderpicking operation in the Crisp warehouse. The literature review in chapter 3 outlined four main aspects of warehouse optimization; the layout, the product allocation, the batching method and the routing. The effect of each process will be evaluated and the best performing configuration will tried to be found. The layout and the product allocation are considered as input for the JOBPRP model, which combines the other two aspects. The objective of the model is to minimize the total travel distance of the picking carts. With the total distance is meant not the routes per picker, but all routes combined. The model will find the optimal batching strategy to minimize this travel distance. The outcome of the model will be in the form of the constructed batched and the to be walked routes by these batches. Figure 4.1 gives a black box representation of the JOBPRP model. The blackbox depicted in Figure 4.1 can be seen as a sub process in the total order picking blackbox that is depicted in Figure 2.10. Where Figure 2.10 depicts the whole system, Figure 4.1 depicts only the JOBPRP model.

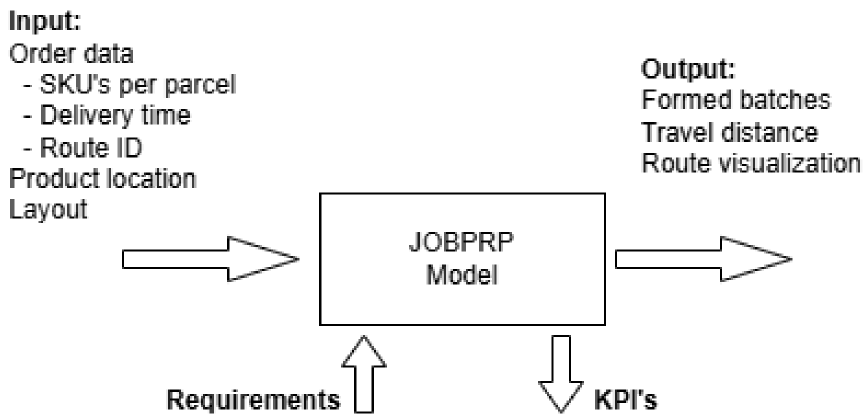


Figure 4.1: Blackbox representation of the JOBPRP model

4.2. Performance indicators

The main performance indicator of the JOBPRP model is the computation time. Due to the NP-hard complexity of the JOBPRP, the computation time quickly rises as the number of parcels increases. To ensure the model's practical applicability, extended computation times, spanning several hours, are undesirable. This makes the computation time a key performance indicator.

4.3. Requirements

The model should be a valid representation of reality as presented in chapter 2, giving it a few requirements is should meet. The requirements are the following:

- A parcel should be picked entirely in a single batch, it can not be splitsed.
- Each picking zone has an unique maximum capacity of parcels per batch.
- Each order should be picked before their pick deadline.
- The route visits the locations only one time, so no detours are allowed.
- The aisles have directional traffic and follow the S-shape heuristic.
- In a batch, the maximum time difference between the pick deadline of 2 parcels is 2 hours.
- To reduce the complexity in the rest of the supply chain, parcels on the same delivery route are batched as much as possible together

These requirements are either addressed by the constraints within the mathematical model or managed through the relevant input data. The subsequent subsections will elaborate on this.

4.4. Input

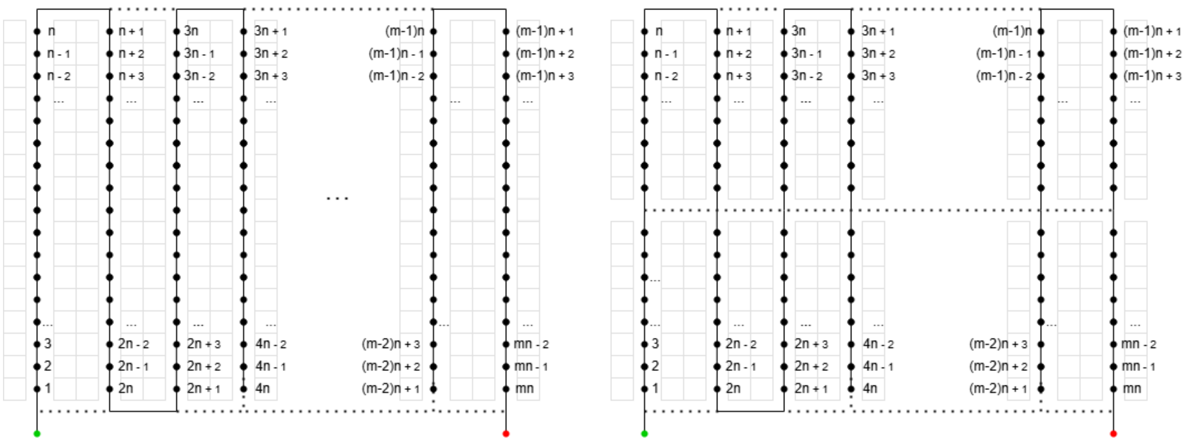
The input for the JOBPRP model can be divided in two main categories, the actual data of the parcels and the locations and layout of the warehouse. The layout of the warehouse is depicted in the distance matrix, which maps the distance between different locations in the warehouse. The locations used in the input data are the locations of the distance matrix.

4.4.1. Layout and distance matrix

The distance matrix, denoted as $d_{i,j}$, quantifies the travel distance between nodes i and j. A node displays a location in the warehouse related to a shelf. The distance matrix displays the layout of the warehouse. The node representation of a rectangular single-block warehouse layout is visualized in Figure 4.3a. m represents the number of aisles and n represents the number of locations per aisle. It is assumed that the distance between two adjacent nodes in the same aisle is 1 meter. The distance to cross to the next aisle is assumed to be 3 meters. The picker is only able to cross to the next aisle using the physical cross aisles. The layout and the one-directional aisles have their influence on the distance matrix. To compensate for the one directional aisles, the distance between location i and j for $j < i$ is modeled as M, with M a large value. This large value implies that traversing back in an aisle is impossible. The picking tour starts and ends in the P&D point. In the distance matrix, the pickup and delivery points are represented as a single node. Despite being distinct in reality, this simplification is possible because they serve as the start and end points. By adjusting the distances of all nodes to the delivery location, assuming it is positioned at its actual location, the matrix maintains its validity. To create a cross aisle, the distance between two shelves is increased to create a cross aisle. Creating this cross aisle, will increase the distance between the nodes located next to the midaisle to a distance of 2 meters instead of 1. The distance matrix is of size $nm + 1 \times nm + 1$ and is in the form of Figure 4.2. Due to the one-directional aisles, if an aisle is entered, the entire aisle is traversed. This makes it possible to model all the nodes in one aisle as 1 node, nevertheless, all nodes in that aisle are visited. This simplification reduces the size of the distance matrix, meaning the JOBPRP model has less locations to reconsider which will improve the computation time. The simplified node representation can be found in Figure 4.4. The verification of this simplification is provided in subsection 5.1.1

$$d_{ij} = \begin{bmatrix} d_{PD,PD} & d_{PD,1} & d_{PD,2} & d_{PD,3} & \cdots & d_{PD,nm} \\ d_{1,PD} & d_{1,1} & d_{1,2} & d_{1,3} & \cdots & d_{1,nm} \\ d_{2,PD} & d_{2,1} & d_{2,2} & d_{2,3} & \cdots & d_{2,nm} \\ d_{3,PD} & d_{3,1} & d_{3,2} & d_{3,3} & \cdots & d_{3,nm} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{1,PD} & d_{nm,1} & d_{nm,2} & d_{nm,3} & \cdots & d_{nm,nm} \end{bmatrix} \sim \begin{bmatrix} 0 & d_{PD,1} & d_{PD,2} & d_{PD,3} & \cdots & d_{PD,nm} \\ d_{1,PD} & 0 & d_{1,2} & d_{1,3} & \cdots & d_{1,nm} \\ d_{2,PD} & M & 0 & d_{2,2} & \cdots & d_{2,nm} \\ d_{3,PD} & M & M & 0 & \cdots & d_{3,nm} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{1,PD} & M & M & M & \cdots & 0 \end{bmatrix}$$

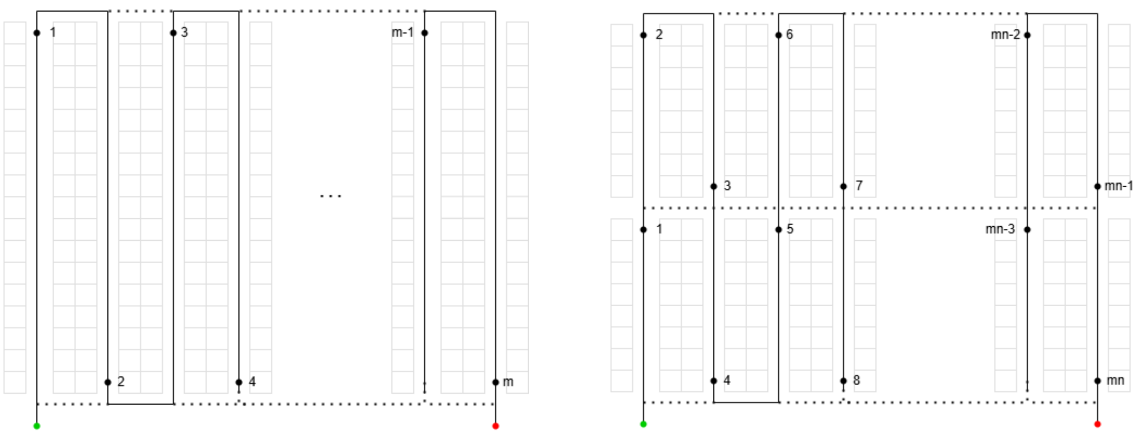
Figure 4.2: Distance matrix



(a) no midaisle

(b) with midaisle

Figure 4.3: Node representation of the locations in the warehouse



(a) no midaisle

(b) with midaisle

Figure 4.4: Simplified node representation of the locations in the warehouse

4.4.2. Parcel data

The JOBPRP model is applied to the warehouse of Crisp and therefore will use their actual picking data. For this data to be useful in the JOBPRP model, some data processing steps have to followed. The data processing steps are described in Appendix B. The input data for the JOBPRP model will be in the form of Table 4.1. The data is sorted per 'parcel_ID', with each 'Stock_Location' indicating a stock location the parcel must visit. These 'Stock_Locations' are represented by a 'Location_Number'. This transformation associates each stock location with a position in the distance matrix, which makes it suitable as input for the JOBPRP model. The data necessary for JOBPRP can be found in the final three columns of Table 4.1. An important step in the data processing steps, is sorting the data by 'Delivery_Time' and 'Delivery_route'. This ensures that the data is sorted per route on ascending delivery time.

Order_id	Parcel_ID	Zone	Delivery_Time	route_id	Stock_Locations	Location_Numbers	Order_number	W_o
nl-212473086	nl-33824995	chilled	10-15-2024 22:00:00	nl-201273	A-936-1, D-360-2, B-711-1, D-531-1, B-420-1, C...	1, 2, 3, 4	1	4
nl-212473086	nl-33825071	ambient	10-15-2024 22:00:00	nl-201273	Y-711-2, S-379-1, V-815-1, Z-822-2, X-795-1, V...	1, 4, 5, 6, 7, 8	2	4
nl-212473086	nl-33825083	frozen	10-15-2024 22:00:00	nl-201273	G-464-1, L-386-1, L-512-2	1, 3	3	4
nl-212492445	nl-33825074	ambient	10-15-2024 22:00:00	nl-201273	W-760-2, U-740-4, V-287-4, U-707-2	3, 4, 5	4	4
nl-212492445	nl-33825081	chilled	10-15-2024 22:00:00	nl-201273	A-350-1	1	5	4
nl-212492445	nl-33825084	frozen	10-15-2024 22:00:00	nl-201273	G-480-1, G-310-1, G-368-4	1	6	4
nl-212500356	nl-33825001	chilled	10-15-2024 22:00:00	nl-201273	D-236-2, D-240-2, B-406-2, B-745-1, C-885-3, D...	1, 2, 3, 4	7	4
nl-212500356	nl-33825057	ambient	10-15-2024 22:00:00	nl-201273	V-207-1, Y-736-4, Y-400-1, V-236-4, S-355-1, X...	1, 3, 4, 6, 7	8	4
nl-212500356	nl-33825082	frozen	10-15-2024 22:00:00	nl-201273	H-444-2, L-512-2	2, 3	9	4
nl-212549874	nl-33825004	chilled	10-15-2024 22:00:00	nl-201273	C-866-2, C-291-1, B-420-1, C-340-1, D-781-1, C...	2, 3, 4	10	4
…	…	…	…	…	…	…	…	…
nl-212749269	nl-33834484	frozen	10-16-2024 18:20:00	nl-201288	G-310-1, H-436-2, H-278-1	1, 2	3529	4
nl-212750376	nl-33834444	chilled	10-16-2024 18:20:00	nl-201288	C-846-2, D-305-3, A-915-3, D-737-4, C-737-3, D...	1, 2, 3, 4	3530	4
nl-212750376	nl-33834474	ambient	10-16-2024 18:20:00	nl-201288	Y-750-4, V-205-3, W-754-3, S-539-1, W-309-1, V...	1, 4, 5, 7	3531	4
nl-212750376	nl-33834484	frozen	10-16-2024 18:20:00	nl-201288	G-416-1, H-334-1	1, 2	3532	4
nl-212763309	nl-33834450	chilled	10-16-2024 18:20:00	nl-201288	C-260-1, A-906-4, C-500-1, B-730-1	1, 2, 3	3533	4
nl-212763309	nl-33834461	ambient	10-16-2024 18:20:00	nl-201288	W-389-1, S-439-1, W-323-4, W-439-4, U-745-3, Z...	1, 3, 5, 7, 8	3534	4
nl-212763309	nl-33834479	frozen	10-16-2024 18:20:00	nl-201288	L-366-1, L-478-1	3	3535	4
nl-212770896	nl-33834453	chilled	10-16-2024 18:20:00	nl-201288	D-325-3, C-790-1, C-707-4, C-820-4, C-711-1	3, 4	3536	4
nl-212770896	nl-33834466	ambient	10-16-2024 18:20:00	nl-201288	Y-710-2, W-309-1	5, 7	3537	4
nl-212770896	nl-33834482	frozen	10-16-2024 18:20:00	nl-201288	L-368-1, L-270-1	3	3538	4

Table 4.1: Input data for the JOBPRP model on 16-10-2024

4.5. Assumptions and simplifications

The requirements presented in section 4.3, set the boundaries for the JOBPRP model. The JOBPRP model should be as close to the real system described in chapter 2 as possible, however to model the real situation some assumptions are made. This is because modeling the actual situation is too complex and can be simplified with a few assumptions. The first assumptions are related to the product allocation. The Crisp warehouse consists of shelves that contain multiple SKUs. In theory each SKU can be modeled with their own product location. However, this would unnecessary complicate the model and, therefore, is chosen to model each shelf as a separate location, as visualized in Figure 4.3. This means that a location can hold multiple different SKUs. This is not far away from reality as the picker will most likely park their picking cart in front of the shelf and pick all products in that shelf before moving to the next location. The picker is also able to pick from both sides of the aisle, the extra travel distance these movements create is not taken into account in this model. When reallocating SKUs in a new storage policy, it is assumed that the SKUs are uniform. This means we do not incorporate the size differences between SKUs in the new defined storage policies. In Figure 2.7-2.9 the difference between multiple locations is clearly visible. It is thus assumed that each shelf/location is is uniform and is able to hold multiple SKUs. The different storage sizes are neglected in this model.

The next assumption is related to the parcels. The composition of which containers are assigned to which parcel is considered fixed. It could be beneficial to interchange specific containers to a different parcel in the chilled and frozen zone. However it is assumed that the parcels are fixed as changing container between parcels is undesired for the rest of the supply chain.

chapter 3 showed there are multiple possible ways to solve the routing problem; With heuristics, exact algorithms or with meta-heuristics. Due to the operational complexity to change away from the S-shape heuristic, it is assumed the S-shape heuristic is used for the routing.

The last assumption is has to do with the due time of the parcels, because parcels with a time difference more than 2 hours are not allowed to be batched together. The input data sheet is sorted on the delivery time. To decrease the computation time, the JOBPRP model takes small chunks as input based on the maximum parcels per batch. Because the data is sorted on delivery time, the first parcel will always have the earliest delivery time. If a subsequent parcel within the chunk size has a delivery time with a difference of more than two hours, the chunk is considered full and a new chunk is started. In bullet-points this are the made assumptions and simplifications:

- The routing considered is the S-shape (traversal) heuristic
- Product locations are considered per shelf instead of single locations
- Travel distances between the picking cart and the shelves are neglected
- For the reallocation of SKUs, the SKUs are assumed to be uniform
- We consider parcels as they are, containers are not interchanged
- The chunks of inputdata do not contain parcels with a delivery time with a difference of more than 2 hours.

4.6. Model formulation

The mathematical model is based on the works of Kulak et al. [8] and Cano et al. [74]. Which provide the basis of this mathematical model and provided the first 5 constraints. The last two constraints are designed to fit the configuration for Crisp.

Sets and Indices

- $b \in B$: Set of Batches
- $p \in P$: Set of Parcels
- $i, j \in L$: Set of storage locations
- $I_p \subset L$: Set of storage locations per parcel $\quad \forall p \in P$

Parameters

- Q : Max batch capacity
- W_p : Weight per parcel $\quad \forall p \in P$
- $d_{i,j}$: Distance matrix between i and j

Binary decision variables

$$x_{i,j,b} = \begin{cases} 1 & \text{if the route for batch } b \text{ goes from the location to perform pick operation} \\ & i \text{ to the location to perform pick operation } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_{p,b} = \begin{cases} 1 & \text{if parcel } p \text{ is performed by batch } b \\ 0 & \text{otherwise} \end{cases}$$

The objective function is:

$$\text{Min} \sum_{b \in B} \sum_{(i,j) \in L} d_{ij} x_{i,j,b} \tag{4.1}$$

The objective function minimizes the total travel distance for all batches. The function calculates the total distance traveled by all batches by multiplying the distance $d_{i,j}$ between each constructed route between location i and j constructed in this batch.

s.t.

1. **Each parcel is assigned to one batch only:**

$$\sum_{b \in B} y_{p,b} = 1 \quad \forall p \in P \tag{4.2}$$

This constraint ensures that for each parcel p, there is only one value of $y_{p,b}$ equal to 1. Assigning a parcel p to only one batch b.

2. **Each route starts and ends in the P&D point:**

$$\sum_{j \in L} x_{0,j,b} = 1 \quad \forall b \in B \tag{4.3}$$

$$\sum_{i \in L} x_{i,0,b} = 1 \quad \forall b \in B \tag{4.4}$$

These two constraints ensure the routes of each batch starts and ends in the P&D point. Equation 4.3 ensures that for each batch b the route between node 0 (P&D point) and a single location is equal to 1. Meaning the picking route starts at the P&D point. Equation 4.3 ensures that for each batch b the route between a single location and node 0 is equal to 1. Meaning the picking route will end at the P&D point.

3. **A visited pick location in batch b should also be left by batch b:**

$$\sum_{j \in L} x_{i,j,b} = \sum_{j \in L} x_{j,i,b} \quad \forall i \in I, \forall b \in B \tag{4.5}$$

Constraint 4.5 ensures that a visited location by a batch is also left by the same batch. The left hand side of the equation represents the number of times batch b leaves location i and travels to any location $j \in L$. This is equal to the right hand side which represent the number of times batch b arrives at location i from any location $j \in L$.

4. **Each batch has a maximum capacity:**

$$\sum_{p \in P} W_p \cdot y_{p,b} \leq Q \quad \forall b \in B \tag{4.6}$$

This constraint ensures that the constructed batches not do exceed the maximum capacity of the pick carts. For each batch b it must hold that the assigned parcels p do not exceed the maximum batch capacity Q. The left hand side of the equation calculates the total weight of all parcels assigned to a batch which cannot exceed the batch capacity.

5. **Subtour elimination:**

$$x_{i,j,b} = 0 \quad \forall b \in B, \forall i \in L, \forall j \in L \setminus \{0\} \text{ and } j \leq i \tag{4.7}$$

Equation 4.7 ensures the one directional flow in the warehouse, the picker is due to this constraint not allowed to move back to previous locations or visits itself. For each batch b the route $x_{i,j,b}$ from a location $i \in L$ to a location $j \in L \setminus \{0\}$ for $j \leq i$ is 0. Due to the constraint of Equation 4.4 the value 0 (the P&D point) is excluded from the set of locations for this constraint, as this would make the model infeasible. Besides that the route should always end in the P&D point, this also allows to construct empty batches. The condition $j \leq i$ makes traversing back to previous aisles impossible. This constraint is also handled in the distance matrix with the large M value, however adding the constraint in this way, improves computation time.

6. **If parcel p is assigned to batch b, all pick locations of parcel p are visited by batch b:**

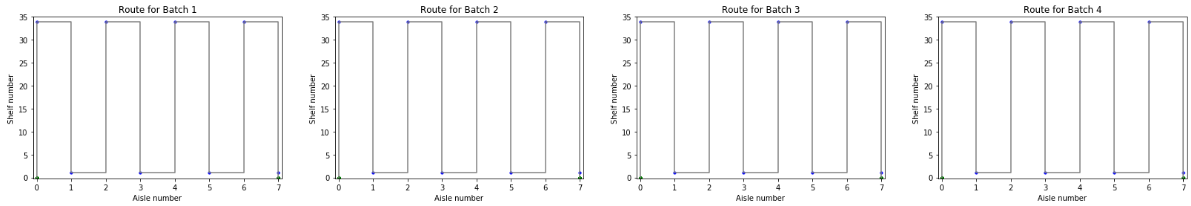
$$y_{p,b} \leq \sum_{j \in L} x_{i,j,b} \quad \forall p \in P, \forall b \in B, \forall i \in I_p \tag{4.8}$$

This constraint ensures that if a parcel p is assigned to a batch b, so $y_{p,b} = 1$, the right hand side of the equation should also be 1. Resulting that for all locations that must be visited by this parcel $i \in I_p$ the value of $x_{i,j,b}$ is equal to 1, assuring the route visits all necessary locations. If parcel p is not assigned to batch b, $y_{p,b}$ will be 0 and there is no requirement to visit the locations of this parcel. However if another parcels assigned to this batch does have to visit this location, the $\leq$ sign allows for this to be possible.

4.7. Output

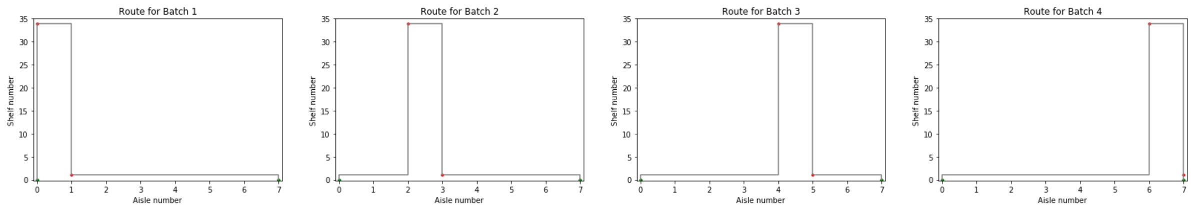
The output of the JOBPRP model can be split into two main important outputs; the travel distance and the formed batches. To minimize the total travel distance is the objective function of the JOBPRP model, so this value represents the performance of the model. The JOBPRP model will reduce the travel distance by making batches with a lower travel distance. To implement these constructed batches it necessary to know which parcel is assigned to which batch. This is therefore the other important output. To obtain a clear understanding of the JOBPRP model, it should also be possible to visualize the constructed batches. Nonetheless, this is not necessarily the primary output of the JOBPRP model.

As the visualization of the constructed routes for each batch is one of the desired outputs, this will be used to create a clear understanding of the JOBPRP model. To visualize the working of the JOBPRP model a straightforward example will be used dedicated to the ambient zone described in chapter 2. For this example it is assumed that each batch can contain 8 parcels which all consist of 1 single location. For the batches constructed without the JOBPRP model it is assumed they will all traverse a full route through the warehouse. These routes are depicted in Figure 4.5 and have a total travel distance of 1156 meter (equal to four full routes of 289 meter). If the JOBPRP model is applied to this example, the routes of Figure 4.6 are constructed which have a total travel distance of 364 meters (91 meter per route). The blue dots in these figures imply that this location is to be visited for one parcel, the red dots imply that this location is to be visited for multiple parcels. As can be seen in Figure 4.5 and Figure 4.6 the JOBPRP model batches all parcels that must visit the same location together to obtain the lowest travel distance. This example is quite straightforward, but underlines the working of the JOBPRP model. Simply put, the JOBPRP model evaluates all possible batches and their corresponding travel distance. The JOBPRP model then will find the solution that minimize the total travel distance by finding batches that are able to take a shortcut.



(a) Batch 1 (b) Batch 2 (c) Batch 3 (d) Batch 4

Figure 4.5: Constructed routes without applying the JOBPRP model



(a) Batch 1 (b) Batch 2 (c) Batch 3 (d) Batch 4

Figure 4.6: Constructed routes with applying the JOBPRP model

4.8. Conclusion

This chapter discusses the JOBPRP model, whose objective is to minimize the total distance traveled by the picking carts. First, the model objective, KPI's and requirements are stated. After which the input to the JOBPRP model is described. The assumptions and simplifications that are made to represent the system described in chapter 2 are explained. After all necessary inputs are decribed, the mathematical model is provided and is explained. It ends with a description of the outputs of the JOBPRP model. The chapter explains the development of the model and how the due time of the orders are incorporated in the model, thereby providing an answer to subquestion 3

5

Verification and validation

The JOBPRP model presented in section 4.6 must be verified and validated before experiments can be carried out. A series of tests will be conducted to determine whether the model implementation is correct and is generating the expected results. The JOBPRP model is solved with the solver Gurobi, version 9.1.2. on a computer with a 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHZ with 4 cores CPU and 16 GB of RAM. Solving the JOBPRP model on a computer with more cores will most likely improve the computation time of the JOBPRP model, as this provides the calculating power of the computer.This chapter will provide the validation and verification of the JOBPRP model.

5.1. Verification

Verification is determining that a simulation computer program performs as intended [75]. To verify the JOBPRP model, multiple tests are performed to check if the outcomes are as expected. First, the simplification of the distance matrix is verified. Subsequently, the computational limitations are considered. Finally, several scenarios are evaluated to validate the outcomes alongside their related hypotheses. The JOBPRP model is verified using the characteristic of the ambient zone, described in chapter 2, as input, however the verification also holds for the chilled and frozen zone.

5.1.1. Simplified distance matrix

The first check of the JOBPRP model is related to the distance matrix. As explained in section 4.5 the layout of the warehouse is simplified. It is important to check if this simplification is rigid and returns the same results as the non-simplified version. This has to be verified for both the situation with and without a midaisle. This is done by verifying if both matrices return the same result with the same input data and by comparing the distances of single (predefined) routes. The visualization of all the tests can be found in section C.1 The used input data for the full set are 90 parcels with all 4 picks/parcel. The data file can be found in Table E.3. For this experiment, the warehouse configuration depicted in Figure 6.1a, which is a rectangular layout with 8 aisles and 34 shelves per aisle, is used.

Test	Midaisle	Travel distance non-simplified	Travel distance simplified	Verified
Full data set (C.1)	no	735	735	✓
Full route (C.2b)	no	289	289	✓
One aisle (C.3)	no	91	91	✓
Full data set (C.4)	between 9-10	727	727	✓
Full data set (C.5)	between 17-18	747	747	✓
Full route (C.2c)	between 17-18	297	297	✓
One full aisle (C.6a)	between 17-18	93	93	✓
One half aisle (C.6c)	between 17-18	57	57	✓

Table 5.1: Verification of simplification distance matrix

Table 5.1 confirms the simplification of the distance matrix. It evaluates for different scenarios if the simplified distance matrix and returns the same results as the non-simplified distance matrix. The verification is applied to a full data set, a single full route and a route that only visits a single aisle. For the route that visits only a single aisle and has a midaisle, both the situation with a pick below and above the midaisle are verified. Implementing this simplification is expected to reduce computation time positively and will be taken as standard. Further details related to the computation time are provided in subsection 5.1.2.

5.1.2. Computational limits

Due to the NP-hard complexity of the JOBPRP, the computation time becomes a crucial factor. First, the influence of reducing the number of nodes in the the distance matrix on the computation time will be demonstrated. Also the effect of the number of picks per parcels is evaluated. Subsequently, the impact of varying input size of number of parcels and thus constructed batches on both computation time and objective value will be discussed.

Effect simplification warehouse nodes

Simplifying the distance matrix decreases the number of possible locations in the model, leading to a reduction in computation time. Table 5.2 shows the contrast in computation times between the simplified and non-simplified matrices. These results are obtained with the first four columns of the dataset provided in Table E.3, resulting in 4 SKUs/parcel. The results align with expectations. Due to the simplification, the number of locations are reduced from 273 to either 9,17 or 25, depending on the presence of one or two midaisles. This reduction reduces the computation time because the model has fewer calculations to perform. In the non-simplified matrix, the number of locations remains consistent regardless of a midaisle, resulting in similar computation times. However, when a midaisle is added in the simplified matrix, additional locations emerge, consequently increasing computation time. For instances with up to 60 parcels, the computation time between a single and double midaisle are comparable, however increasing the number more, will result in divergent computation times.

# Parcels	Non-simplified			Simplified		
	No midaisle	midaisle location 25	midaisle location 25&32	No midaisle	midaisle location 25	midaisle location 25&32
10	0.7 s	0.9 s	1.0 s	0.01 s	0.02 s	0.01 s
20	16 s	18 s	19 s	0.1 s	0.3 s	0.2 s
30	25 s	28 s	32 s	0.3 s	0.4 s	0.5 s
40	1260 s	1480 s	1700 s	0.5 s	2 s	3 s
50	2800 s	3610 s	4425 s	0.6 s	5 s	5 s
60	–	–	–	3 s	224 s	238 s
70	–	–	–	4 s	201 s	432 s
80	–	–	–	16 s	632 s	6545 s
90	–	–	–	23 s	1045 s	–
100	–	–	–	181 s	–	–
110	–	–	–	1160 s	–	–
120	–	–	–	950 s	–	–

Table 5.2: Computation time of the simplified and non-simplified distance matrix, with a maximum of 2 hours (7200s)

Effect number of SKUs per parcel

The values shown in Table 5.2 are derived from parcels containing 4 SKU per parcel. The computation time is also influenced by parcel size due to the number of viable solutions and the behavior of the Gurobi solver. For parcels with approximately 4 SKUs, multiple solutions offer optimal performance, which all must be analyzed by Gurobi. However,when the number of SKUs per parcel increases, the chances of discovering shortcuts diminish, and consequently, the number of well performing solutions decreases. This implies that the computation time is influenced not just by the number of parcels and locations, but also by the composition of the parcels.

# SKUs/parcel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Computation time [s]	1	51	111	201	166	95	105	60	68	45	25	30	10	15	6	8

Table 5.3: Computation time for 70 parcels for a simplified distance matrix with a midaisle at location 25

Relation objective value

As shown in Table 5.2, increasing the number of parcels, and subsequently the number of formed batches, will increase the computation time. It is crucial to assess whether an increased number of parcels within the JOBPRP model also impacts the objective value. The hypothesis for this is that for larger instances, the model can identify superior solutions. With the increase in number of parcels, the search space enlarges, and more potential routes with shortcuts are likely to be discovered. This verification uses Crisp's pick data from 16-10-2024. By alternating the chunk size of the JOBPRP model to multiples of full batches, the model returns various objective values, as illustrated in Figure 5.1. The chunk sizes are multiples of 18 parcels (full batches) because a single (full) batch will always outperform multiple (half full) batches. The results confirm the hypothesis; for larger instances, the JOBPRP model finds better solutions, applicable to layouts both with and without a midaisle. Figure 5.1 also depicts the link between computation time and larger instances, which is consistent with the observations in Table 5.2. This serves to verify that improving the size of the chunk size of the JOBPRP improves the outcome but comes with a higher computation time. Furthermore, it demonstrates that smaller instances, which require less computation time, can also lead to improved solutions. Allowing the JOBPRP model to operate with smaller instances to decrease computation time for specific experiments.

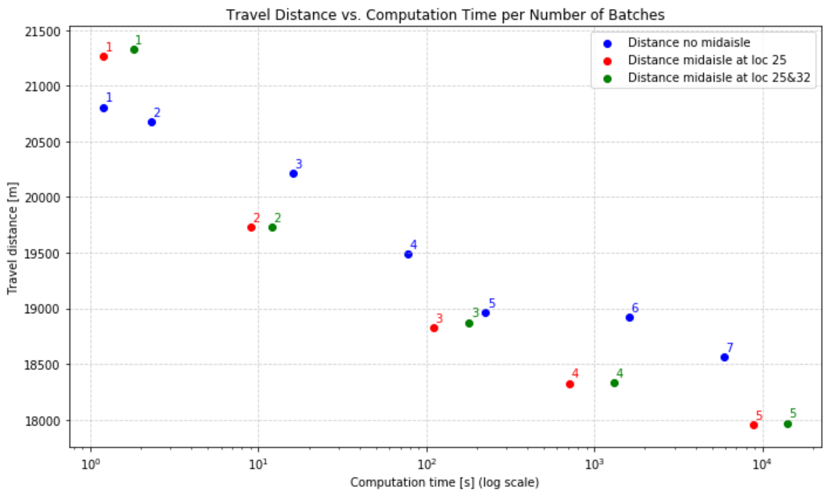


Figure 5.1: Travel distance versus computation time for different full batches

5.1.3. Scenario testing

Verifying the model involves assessing whether it accurately represents the intended system and produces the output as intended, this is achieved by scenario testing. Predefined data sets are used as input for the JOBPRP model to determine whether the outcomes align with the hypotheses. This can be divided into two categories, instances that should return an anticipated outcome and instances that specifically test the constraints of the model.

Boundary scenarios

To test the JOBPRP model, various scenarios with distinct hypotheses are examined. The model should return the expected routes, as outlined by the hypotheses. The description of the performed experiments and results of the experiments focusing on these scenarios are described in Table 5.4. The visualization of the routes are depicted in section C.2. These visualizations are a clear way of understanding the output of the JOBPRP model. The returned values and outcomes of the JOBPRP model all met their hypothesis, verifying these boundary scenarios.

Input data	Hypothesis	Result	Verified	Visualization
3*18 times the same parcel, with picks only in one specific aisle	The model should only pick the same parcel in each separate batch, as this will return the lowest travel distance	The model returns 3 batches that only pick the same parcels	✓	(C.7)
18 parcels that are located in a specific aisle, the rest of the parces are not located in that aisle.	1 of the formed batches should handle all the parcels that are located in the specific aisle, the rest of the parcels should be picked by the other batches	The model returns one full batch in the specific aisle and the other parcels are placed in another batch	✓	(C.8)
All parcels have only picks in the bottom part of the warehouse	The route should only visit the bottom part of the warehouse	The route only visits the bottom part of the warehouse	✓	(C.9a)
All parcels have only picks in the top part of the warehouse	The route should only visit the top part of the warehouse	The route only visits the top part of the warehouse	✓	(C.9b)
The data from the above two are used as input together	Instinctively we would say nothing changes and the output will be the same as the two above, however the hypothesis is that one batch will pick the stops in the first 4 aisles and the second batch will pick the stops in the last 4 aisles.	One batch picks all items in the first aisles, the other batch picks all items in the last aisles	✓	(C.9c)
The number of picks per parcel are fluctuated, the used values are 1,4,8,12 and 16 picks/parcel	The lower the number of picks per parcel, how more freedom the model has to define optimal routes. So increasing the number of picks will result in a larger travel distance	For increased picks/parcel the travel distance increases	✓	(C.10-C.14)

Table 5.4: Verification of the applied constraints

Constraint verification

To verify if the JOBPRP model meets the applied constraints, experiments with specific input data are performed to verify the performance of the model. The performed experiments that focus on checking the applied constraints, are described in Table 5.5. The experiments confirmed their hypotheses, indicating that the constraints were applied correctly.

Input data	Which constraint	Hypothesis	Result	Verified
The maximum number of parcels for the number of batches	Capacity	The model should return only full batches	The model returns only full batches	✓
A single parcel has an weight higher than then the capacity	Capacity	The model should become infeasible	Infeasible model	✓
The total weight of all the parcels is higher than then the total capacity	Capacity	The model should become infeasible	Infeasible model	✓
Each parcel has an weight of 0	Capacity	The model should be able to batch all parcels in one single batch	Only one batch is returned	✓
Various data files	A parcel can only be in one batch	The model should place parcels in one batch only	Parcels are assigned to a single batch	✓
Preformed batches with a few locations	A batch must visit all the locations of the batched parcels	The route should visit all the locations of the batched parcels	The formed routes visit all the locations	✓

Table 5.5: Verification of the applied constraints

5.2. Validation

After the verification of the model, the next step is to validate the model. Validation is the task of demonstrating that the model is a reasonable representation of the actual system: that it reproduces system behavior with enough fidelity to satisfy analysis objectives [75]. The validation is applied to the Crisp orderpicking process. Because there is no real-world data that incorporate the JOBPRP model it is not possible to compare the results to other models. However, the output of the JOBPRP model can be compared to the current travel distance, derived from the real world data of Crisp. For the actual constructed batches, the real travel distance is compared to the calculated travel distance for each zone. For the real travel distance, the special picking carts for parcels with missings are not considered. Traversing a full route in the ambient, chilled and frozen zone in the actual warehouse is equal to respectively 340, 180 and 160 meters, whereas a full route composed by the distance matrix for the JOBPRP model are respectively 289, 161 and 156 meter. This difference in the length of a full travel route result in the differences in daily travel distances depicted in Figure 5.2. The travel distance correlates with the distance matrix. The modeled distance between consecutive shelves is set at 1 meter. In the actual Crisp warehouse, shelf widths can vary between 1 meter and 1.30 meters, resulting in a difference in travel distance per full route. For simplicity the distance between each shelf in the JOBPRP is considered to be 1 meter. As the benchmark of the model is also calculated with the same distance matrix, this simplification is still rigid. Although there are some differences between a full modeled route and a actual full route, the essence of the model is the same and therefore a validated representation of reality. A similar approach is applied to the distance involved in applying a cross aisle, moving to the next aisle, and the distance to and from the P&D point. Skipping a cross aisle has a modeled distance of 1 meter, implying a cross aisle width of 1 meter. Although this could be larger in the actual setting, the model remains an accurate reflection of the real-world scenario. The assumed distances for moving to the next aisle and reaching the depot in the model are set at respectively 3 meters and 2 meters, aligning well with reality. The picker will travel also from the shelf to the pick cart and vice versa. These extra travel meters are not incorporated in the model; it models the travel distance of the picking cart and ignores these extra travel movements.

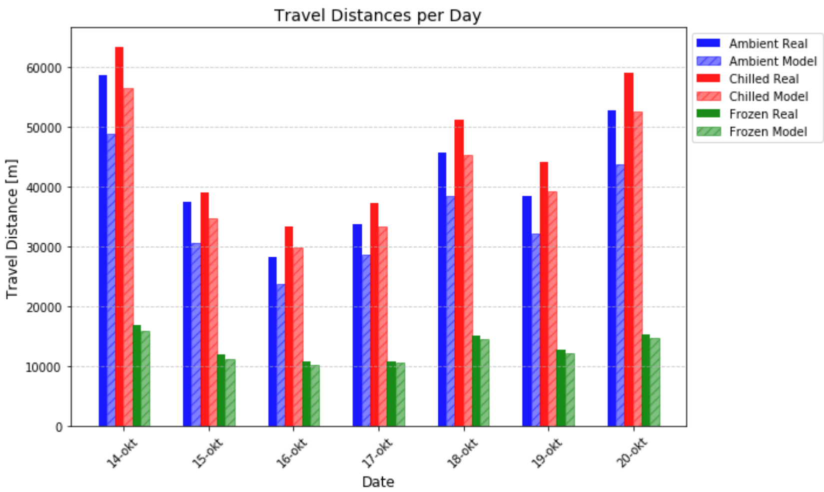


Figure 5.2: Validation of weekly travel distances

For the storage allocation policy, the SKU's are all considered to be uniform. Meaning that each product is modeled to have the same dimensions. However in reality, this is not the case as some SKU's are stored in pallets and some in the shelves. Also some SKUs will need a larger shelf space than others. In the modeled situation, this distinction between SKUS is not incorporated. This makes the applied storage policy for some shelves not realizable in reality, as the size of the assigned SKU exceeds the shelf size. For both the defined storage policies, this could return slightly different results but in essence the modeled storage policies are a sufficient representation of reality. Although the modeled situation differs on two aspects slightly from reality, the model is still a very good representation of reality and therefore can be validated.

5.3. Conclusion

In this chapter, the JOBPRP model has been verified and validated. The verification process ensures that the simplification of the distance matrix is rigid. Various hypotheses and scenario tests were employed to verify the model's behavior. Additionally, the model proves capable of finding improved solutions even for smaller cases. Which reduces the computation time and could be advantageous if many experiments are needed.

For validation, the model's outcomes are compared with the actual travel distances observed at the Crisp warehouse. Assumptions in the distance matrix and the SKU uniformity reflect minor deviations from reality, yet the model remains an accurate representation.

6 Experimental set up

This chapter will provide an experimental plan that answers subquestion 4. Because all warehouse processes highlighted in chapter 3 are interconnected, it is important to define a clear experimental plan. The changes made to adjust the model to the specific zones are also described.

6.1. Experimental plan

Because all warehouse processes are interconnected, it is challenging to find the best performing warehouse configuration with respect to the travel distance. The first importance step, is to define a benchmark result. This is the total travel distance of the current situation and will be used to compare the different warehouse configurations. To objectively compare the results between the different processes, all should be tested individually. After which specific combinations can be tested. Due to the differences per zone, the experiment plan is performed to all three zones separately. In chapter 3 the choices regarding warehouse optimization are evaluated. The choices per process are summarized in Table 6.1 and also shows which configurations are considered in this thesis.

For the layout, 3 configurations are considered; a single-block layout (no midaisle), a 2-block layout (1 midaisle) and a 3-block layout (2 midaisle). Other layouts are not considered due to the scares warehouse space and overhauling costs. Adding 3 or more midaisle will use to many space in the already dense warehouse. Overhauling Crisp's entire warehouse to a non-conventional layout is costly, making such changes impractical and therefore not considered. For the product allocation policy three configurations are considered; the actual storage policy (random policy), an within-aisle policy and an across-aisle policy. Both policies are independent of the location of the midaisles in a layout and thus suitable to be evaluated for multiple layouts. The nearest-subaisle and nearest-location policy are specified to the layout, meaning that with a change in layout the allocation policy is also changed. Making the evaluation impractical. The routing is assumed to be the S-shape heuristics and is in each configuration the same. For the batching, configurations with optimal batches and the current batches are considered. Combining the layout, the allocation and the batching in all possible ways will result in seventeen distinct configurations. To reduce computation time, some experiments will first be performed for a specific scenario with a small data set, after which the most promising instances will be explored in dept. This be mostly useful for determining the best performing layout, as with 2 midaisles this leads to many configurations. The used scenarios will be explained in section 6.2. The performed experimental plan to find the optimal warehouse configuration can be summarized as found below:

1. Determine benchmark results
2. Determine results of the single warehouse process
    - Layout
    - Product allocation
    - Batching
3. Determine results of a combination between two warehouse process
    - Layout & Product allocation
    - Layout & Batching
    - Product allocation & Batching
4. Determine results of the combination of all warehouse processes
    - Layout, Product allocation & Batching

Warehouse process	Configuration	Design choice	Considered?
Layout	Single-block	no midaisle	X
	Multi-block	1 midaisle	X
		2 midaisles	X
		n midaisles	
	Non-conventional	Fishbone	
		Flying V	
		Inverted V	
Allocation	Dedicated	Multiple classifications	
	Random	Random	X
		Closest open location	
	Class-based	Across-aisle	X
		Within-aisle	X
		Neareset-subaisle	
		Neareset-location	
Routing	Heuristics	S-shape	X
		Mid-point	
		Largest gap	
		Return	
		Composite	
		Combined+	
	Exact algorithm	Linear programming	
	Meta-heuristics	GA	
		SA	
		TS	
		PSO	
		ACO	
		ALNS	
Batching	Unit load	Single orders	
	OBP	Seed algorithm	
		Savings algorithm	
	JOBPRP	Exact	X
		Meta-heuristic	

Table 6.1: Different configurations as found in chapter 3

6.2. Different scenarios

As input for the JOBPRP model, a full week of data is considered. The used data is from the actual picking data from Crisp in the week of 14 October 2024-20 October 2024. This is an average week, without any promotional actions that may influence costumer behavior. Special action promotion weeks generate a distorted picture of reality, as it highly affects customer behavior. In a week typically Monday and Sunday are the busiest days and handle the most orders. This is caused by the costumer preference for their groceries to be delivered on this day. Wednesdays are typically the days with the lowest number of orders. Each day can be seen as a different scenario used as input in the JOBPRP model. The scenarios vary on their size and probably also the ordered products. Orders on a Monday and Sunday will most likely consist groceries for a whole week, whereas orders for a Friday typically consist of more luxurious products. Table 6.2 gives a summary of the input for each scenarios. It shows the number of total orders and the number of handled parcels per zone for that day. A given configuration might be ideal for one particular day, but be less performing on other days. Finding a configuration that reduces the weekly travel distance is preferable over identifying a configuration suitable for just a single day. Weekly datasets suggest consistent patterns, which indicate that the optimal configuration will yield the best outcomes on a monthly scale as well. Daily orders provide a reasonable representation of weekly orders, enabling the identification of optimal configurations while reducing computation time.

Scenario	# Orders	# Parcels Ambient	# Parcels Chilled	# Parcels Frozen
14-Oct (M)	2253	2518	2064	398
15-Oct (T)	1414	1570	1272	282
16-Oct (W)	1117	1256	1085	251
17-Oct (T)	1304	1488	1198	261
18-Oct (F)	1647	1974	1634	363
19-Oct (S)	1409	1670	1428	300
20-Oct (S)	2056	2316	1921	364
Full week	11200	12792	10602	2219

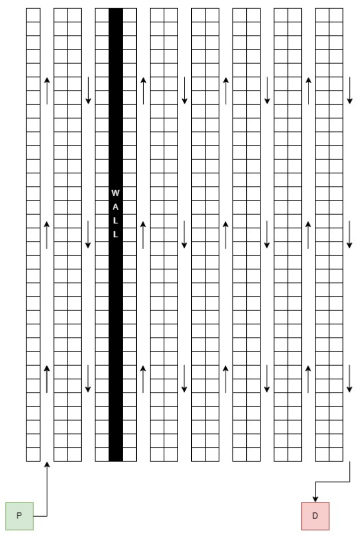
Table 6.2: Weekly number of orders

6.3. Adjustments to Crisp warehouse

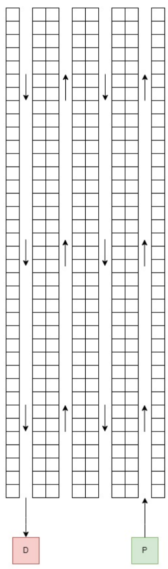
Each zone in the Crisp warehouse has different specifications, demanding slight adjustments for each zone to be a representation of reality. The different specification are already explained in chapter 2. The summary is given below in Table 6.3 and the layouts are shown in Figure 6.1. The biggest differences are the number of parcels per batch and the layout. The number of parcels per batch is an easily changeable parameter in the JOBPRP model, however for the different layouts a specific distance matrix is used. Due to the similarities between the ambient zone and chilled zone with respect to the layout they are explained together. The frozen zone is explained separately.

Zone	Storage locations	# SKU's	Parcels per batch	Range picks/parcel	Average parel size	average picks/batch
Ambient	4800	3500	18	[1-25]	10	180
Chilled	3500	2000	6	[1-20]	15	90
Frozen	800	500	4	[1-35]	18	75

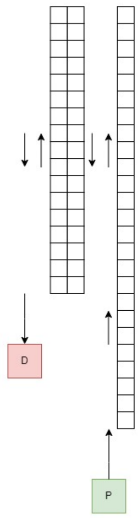
Table 6.3: Specifications per picking zone



(a) Ambient



(b) Chilled



(c) Frozen

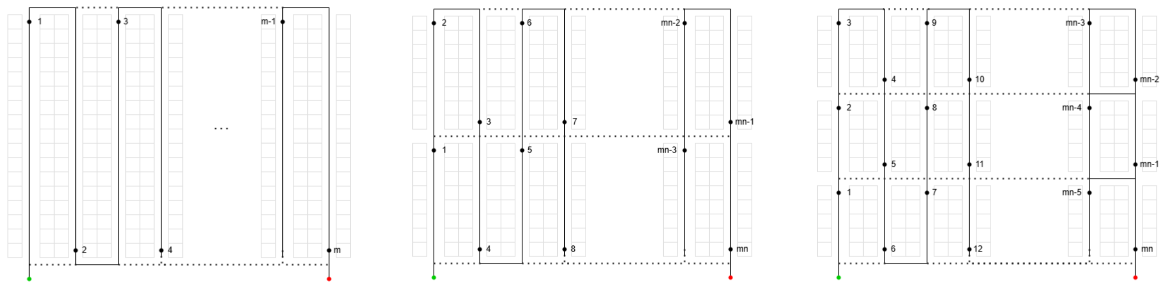
Figure 6.1: Layout for different zones

Ambient and chilled

The ambient and chilled zone can both be approached as an rectangular warehouse. The simplified node representation presented in Figure 4.4 is therefore applicable. The difference between the zones is in the number of aisles and pick locations per aisle. The ambient zone has 8 aisles with 34 pick locations and the chilled zone has 4 aisles with 38 locations. The number of (simplified) nodes are related to the number of aisle and the number of applied midaisles. The number of nodes in the layout and thus in the distance matrix are calculated by Equation 6.1. The plus 1 at the end represents the P&D point.

$$N_{nodes} = N_{aisles} * (1 + N_{mid_aisles}) + 1 \tag{6.1}$$

The resulting matrices for the ambient zone with respectively zero, one and two midaisles will thus be 9×9, 17×17 and 25×25. For the chilled zone the distance matrix will be respectively; 5×5, 9×9, 13×13. The location of the midaisle determines which shelves correspond to a node in the warehouse layout. Changing the location of the midaisle will thus not only have change the distance between the nodes, but also realize changes in which shelf is represented by which node. The distance matrices for the ambient zone are depicted in Figure 6.3 and the chilled zone is depicted in Figure 6.4. The ambient distance matrix also takes the wall between pick aisle 2 and 3 into account by changing the distance between the points in aisle 1 and 2 and the rest of the aisles.



(a) no midaisle (b) with midaisle (c) with 2 midaisles

Figure 6.2: Simplified node representation of the locations in the warehouse

$$\begin{bmatrix}
0 & 35 & 71 & 41 & 77 & 47 & 83 & 53 & 89 \\
56 & 0 & 36 & 72 & 108 & 78 & 114 & 84 & 120 \\
20 & M & 0 & 36 & 72 & 42 & 78 & 48 & 84 \\
50 & M & M & 0 & 36 & 72 & 42 & 78 & 48 \\
14 & M & M & M & 0 & 36 & 72 & 42 & 78 \\
44 & M & M & M & M & 0 & 36 & 72 & 42 \\
8 & M & M & M & M & M & 0 & 36 & 72 \\
38 & M & M & M & M & M & M & 0 & 36 \\
2 & M & M & M & M & M & M & M & 0
\end{bmatrix}$$

(a) No midaisle

$$\begin{bmatrix}
0 & 18 & 36 & 55 & 37 & 24 & 42 & 61 & 43 & 30 & 48 & 67 & 49 & 36 & 54 & 73 & 55 \\
39 & 0 & 18 & 37 & 19 & 38 & 56 & 75 & 57 & 44 & 62 & 81 & 63 & 50 & 68 & 87 & 69 \\
57 & M & 0 & 19 & 37 & 56 & 74 & 93 & 75 & 62 & 80 & 99 & 81 & 68 & 86 & 105 & 87 \\
38 & M & M & 0 & 18 & 37 & 55 & 74 & 56 & 43 & 61 & 80 & 62 & 49 & 67 & 86 & 68 \\
20 & M & M & M & 0 & 19 & 37 & 56 & 38 & 25 & 43 & 62 & 44 & 31 & 49 & 68 & 50 \\
33 & M & M & M & M & 0 & 18 & 37 & 19 & 38 & 24 & 43 & 25 & 44 & 30 & 49 & 31 \\
51 & M & M & M & M & M & 0 & 19 & 37 & 56 & 38 & 25 & 43 & 62 & 44 & 31 & 49 \\
32 & M & M & M & M & M & M & 0 & 18 & 37 & 19 & 38 & 24 & 43 & 25 & 44 & 30 \\
14 & M & M & M & M & M & M & M & 0 & 19 & 37 & 56 & 38 & 25 & 43 & 62 & 44 \\
27 & M & M & M & M & M & M & M & M & 0 & 18 & 37 & 19 & 38 & 24 & 43 & 25 \\
45 & M & M & M & M & M & M & M & M & M & 0 & 19 & 37 & 56 & 38 & 25 & 43 \\
26 & M & M & M & M & M & M & M & M & M & M & 0 & 18 & 37 & 19 & 38 & 24 \\
8 & M & M & M & M & M & M & M & M & M & M & M & 0 & 19 & 37 & 56 & 38 \\
21 & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 18 & 37 & 19 \\
39 & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 19 & 37 \\
20 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 18 \\
2 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0
\end{bmatrix}$$

(b) Midaisle at loc 17

$$\begin{bmatrix}
0 & 18 & 27 & 37 & 48 & 37 & 37 & 24 & 33 & 43 & 54 & 43 & 43 & 30 & 39 & 49 & 60 & 49 & 49 & 36 & 45 & 55 & 66 & 55 & 55 \\
39 & 0 & 9 & 19 & 30 & 19 & 19 & 38 & 47 & 57 & 68 & 57 & 57 & 44 & 53 & 63 & 74 & 63 & 63 & 50 & 59 & 69 & 80 & 69 & 69 \\
48 & M & 0 & 10 & 21 & 10 & 28 & 47 & 56 & 66 & 77 & 66 & 66 & 53 & 62 & 72 & 83 & 72 & 72 & 59 & 68 & 78 & 89 & 78 & 78 \\
58 & M & M & 0 & 11 & 20 & 38 & 57 & 66 & 76 & 87 & 76 & 76 & 63 & 72 & 82 & 93 & 82 & 82 & 69 & 78 & 88 & 99 & 88 & 88 \\
47 & M & M & M & 0 & 9 & 27 & 46 & 55 & 65 & 76 & 65 & 65 & 52 & 61 & 71 & 82 & 71 & 71 & 58 & 67 & 77 & 88 & 77 & 77 \\
38 & M & M & M & M & 0 & 18 & 37 & 46 & 56 & 67 & 56 & 56 & 43 & 52 & 62 & 73 & 62 & 62 & 49 & 58 & 68 & 79 & 68 & 68 \\
20 & M & M & M & M & M & 0 & 19 & 28 & 38 & 49 & 38 & 38 & 25 & 34 & 44 & 55 & 44 & 44 & 31 & 40 & 50 & 61 & 50 & 50 \\
33 & M & M & M & M & M & M & 0 & 9 & 19 & 30 & 19 & 19 & 38 & 15 & 25 & 36 & 25 & 25 & 44 & 21 & 31 & 42 & 31 & 31 \\
42 & M & M & M & M & M & M & M & 0 & 10 & 21 & 10 & 28 & 47 & 20 & 16 & 27 & 16 & 34 & 53 & 26 & 22 & 33 & 22 & 40 \\
52 & M & M & M & M & M & M & M & M & 0 & 11 & 20 & 38 & 57 & 30 & 22 & 17 & 26 & 44 & 63 & 36 & 28 & 23 & 32 & 50 \\
41 & M & M & M & M & M & M & M & M & M & 0 & 9 & 27 & 46 & 19 & 11 & 22 & 15 & 33 & 52 & 25 & 17 & 28 & 21 & 39 \\
32 & M & M & M & M & M & M & M & M & M & M & 0 & 18 & 37 & 10 & 20 & 31 & 20 & 24 & 43 & 16 & 26 & 37 & 26 & 30 \\
14 & M & M & M & M & M & M & M & M & M & M & M & 0 & 19 & 28 & 38 & 49 & 38 & 38 & 25 & 34 & 44 & 55 & 44 & 44 \\
27 & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 9 & 19 & 30 & 19 & 19 & 38 & 15 & 25 & 36 & 25 & 25 \\
36 & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 10 & 21 & 10 & 28 & 47 & 20 & 16 & 27 & 16 & 34 \\
46 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 11 & 20 & 38 & 57 & 30 & 22 & 17 & 26 & 44 \\
35 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 9 & 27 & 46 & 19 & 11 & 22 & 15 & 33 \\
26 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 18 & 37 & 10 & 20 & 31 & 20 & 24 \\
8 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 19 & 28 & 38 & 49 & 38 & 38 \\
21 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 9 & 19 & 30 & 19 & 19 \\
30 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 10 & 21 & 10 & 28 \\
40 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 11 & 20 & 38 \\
29 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 9 & 27 \\
20 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0 & 18 \\
2 & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & M & 0
\end{bmatrix}$$

(c) Midaisles at loc 17 and 25

Figure 6.3: Distance matrices for the ambient zone, with M representing a very large value.

$$\begin{bmatrix} 0 & 39 & 79 & 45 & 85 \\ 48 & 0 & 40 & 80 & 46 \\ 8 & M & 0 & 40 & 80 \\ 42 & M & M & 0 & 40 \\ 2 & M & M & M & 0 \end{bmatrix}$$

(a) No midaisle

$$\begin{bmatrix} 0 & 18 & 40 & 63 & 37 & 24 & 46 & 69 & 43 \\ 27 & 0 & 22 & 45 & 19 & 38 & 28 & 51 & 25 \\ 49 & M & 0 & 23 & 41 & 60 & 46 & 29 & 47 \\ 26 & M & M & 0 & 18 & 37 & 23 & 46 & 24 \\ 8 & M & M & M & 0 & 19 & 41 & 64 & 38 \\ 21 & M & M & M & M & 0 & 22 & 45 & 19 \\ 43 & M & M & M & M & M & 0 & 23 & 41 \\ 20 & M & M & M & M & M & M & 0 & 18 \\ 2 & M & M & M & M & M & M & M & 0 \end{bmatrix}$$

(b) Midaisle at loc 17

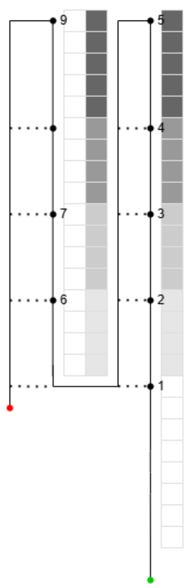
$$\begin{bmatrix} 0 & 18 & 27 & 41 & 56 & 37 & 37 & 24 & 33 & 47 & 62 & 43 & 43 \\ 27 & 0 & 9 & 23 & 38 & 19 & 19 & 38 & 15 & 29 & 44 & 25 & 25 \\ 36 & M & 0 & 14 & 29 & 10 & 28 & 47 & 20 & 20 & 35 & 16 & 34 \\ 50 & M & M & 0 & 15 & 24 & 42 & 61 & 34 & 30 & 21 & 30 & 48 \\ 35 & M & M & M & 0 & 9 & 27 & 46 & 19 & 15 & 30 & 15 & 33 \\ 26 & M & M & M & M & 0 & 18 & 37 & 10 & 24 & 39 & 20 & 24 \\ 8 & M & M & M & M & M & 0 & 19 & 28 & 42 & 57 & 38 & 38 \\ 21 & M & M & M & M & M & M & 0 & 9 & 23 & 38 & 19 & 19 \\ 30 & M & M & M & M & M & M & M & 0 & 14 & 29 & 10 & 28 \\ 44 & M & M & M & M & M & M & M & M & 0 & 15 & 24 & 42 \\ 29 & M & M & M & M & M & M & M & M & M & 0 & 9 & 27 \\ 20 & M & M & M & M & M & M & M & M & M & M & 0 & 18 \\ 2 & M & M & M & M & M & M & M & M & M & M & M & 0 \end{bmatrix}$$

(c) Midaisles at loc 17 and 25

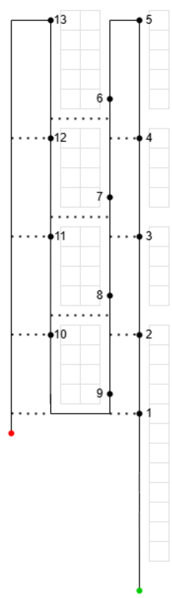
Figure 6.4: Distance matrices for the chilled zone, with M representing a very large value.

Frozen

The frozen zone is in terms of layout quite different than the ambient and chilled zone. This is because the frozen zone is not a standard rectangular warehouse. It is built using the available space and therefore differs with respect to the other two zones. The picking strategy is also quite different, where in the ambient and chilled zone the picker picks on both sides of the aisle, the picker in the frozen zone only picks at the right hand side. This means that when moving from the first to the second aisle, the picker will not be bound by midaisles, they can just cross anywhere they like. Moving from the second to the third aisle however, is again bound by the physical midaisle. The simplified representations are shown in Figure 6.5. If there is no midaisle, the locations in the first and second aisle are modeled at one node. This can be seen with the hatching in Figure 6.5a. Figure 6.5b shows all possible locations of the midaisle, however only 1 or 2 at the time are evaluated. Instead of the used shelves as in the other zones, now freezer units are used. The length of these freezers is 2 meters, resulting in a difference of 2 meters to an adjacent location. The resulting distance matrices are found in Figure 6.6. By the addition of a midaisle, the nodes representation changes from 9 to 13 nodes, however in contrary to the other zones, the distance matrices for 1 or 2 midaisles have the same size as by the addition of a second midaisle, no extra nodes arise.



(a) no midaisle



(b) with midaisle at any location

Figure 6.5: Simplified node representation of the locations in the frozen zone

$$\begin{bmatrix} 0 & 18 & 26 & 34 & 42 & 52 & 29 & 37 & 45 & 55 \\ 5 & 0 & 8 & 16 & 24 & 34 & 11 & 19 & 27 & 37 \\ 13 & M & 0 & 8 & 16 & 26 & 19 & 27 & 35 & 45 \\ 21 & M & M & 0 & 8 & 18 & 27 & 35 & 43 & 53 \\ 29 & M & M & M & 0 & 10 & 35 & 43 & 51 & 61 \\ 39 & M & M & M & M & 0 & 45 & 53 & 61 & 71 \\ 10 & M & M & M & M & M & 0 & 8 & 16 & 26 \\ 18 & M & M & M & M & M & M & 0 & 8 & 18 \\ 26 & M & M & M & M & M & M & M & 0 & 10 \\ 36 & M & M & M & M & M & M & M & M & 0 \end{bmatrix}$$

(a) No midaisle

$$\begin{bmatrix} 0 & 16 & 24 & 32 & 42 & 52 & 63 & 51 & 41 & 33 & 30 & 38 & 48 & 58 \\ 8 & 0 & 8 & 16 & 26 & 36 & 47 & 35 & 25 & 17 & 14 & 22 & 32 & 42 \\ 16 & M & 0 & 8 & 18 & 28 & 39 & 27 & 17 & 9 & 18 & 26 & 24 & 34 \\ 24 & M & M & 0 & 10 & 20 & 31 & 19 & 9 & 17 & 26 & 34 & 16 & 26 \\ 34 & M & M & M & 0 & 10 & 21 & 9 & 19 & 27 & 36 & 44 & 18 & 28 \\ 44 & M & M & M & M & 0 & 11 & 19 & 29 & 37 & 46 & 54 & 28 & 38 \\ 33 & M & M & M & M & M & 0 & 8 & 18 & 26 & 35 & 43 & 17 & 27 \\ 25 & M & M & M & M & M & M & 0 & 10 & 18 & 27 & 35 & 9 & 19 \\ 15 & M & M & M & M & M & M & M & 0 & 8 & 17 & 25 & 35 & 45 \\ 7 & M & M & M & M & M & M & M & M & 0 & 9 & 17 & 27 & 37 \\ 10 & M & M & M & M & M & M & M & M & M & 0 & 8 & 18 & 28 \\ 18 & M & M & M & M & M & M & M & M & M & M & 0 & 10 & 20 \\ 28 & M & M & M & M & M & M & M & M & M & M & M & 0 & 10 \\ 38 & M & M & M & M & M & M & M & M & M & M & M & M & 0 \end{bmatrix}$$

(b) Midaisle at second location

$$\begin{bmatrix} 0 & 16 & 24 & 34 & 44 & 54 & 65 & 53 & 43 & 33 & 30 & 40 & 50 & 60 \\ 8 & 0 & 8 & 18 & 28 & 38 & 49 & 37 & 27 & 17 & 14 & 24 & 34 & 44 \\ 16 & M & 0 & 10 & 20 & 30 & 41 & 29 & 19 & 9 & 18 & 16 & 26 & 36 \\ 26 & M & M & 0 & 10 & 20 & 31 & 19 & 9 & 19 & 28 & 18 & 16 & 26 \\ 36 & M & M & M & 0 & 10 & 21 & 9 & 19 & 29 & 38 & 28 & 18 & 28 \\ 46 & M & M & M & M & 0 & 11 & 19 & 29 & 39 & 48 & 38 & 28 & 38 \\ 35 & M & M & M & M & M & 0 & 8 & 18 & 28 & 37 & 27 & 17 & 27 \\ 27 & M & M & M & M & M & M & 0 & 10 & 20 & 29 & 19 & 9 & 19 \\ 17 & M & M & M & M & M & M & M & 0 & 10 & 19 & 9 & 19 & 29 \\ 7 & M & M & M & M & M & M & M & M & 0 & 9 & 19 & 29 & 39 \\ 10 & M & M & M & M & M & M & M & M & M & 0 & 10 & 20 & 30 \\ 20 & M & M & M & M & M & M & M & M & M & M & 0 & 10 & 20 \\ 30 & M & M & M & M & M & M & M & M & M & M & M & 0 & 10 \\ 40 & M & M & M & M & M & M & M & M & M & M & M & M & 0 \end{bmatrix}$$

(c) Midaisles at the first and second location

Figure 6.6: Distance matrices for the frozen zone, with M representing a very large value.

6.4. Conclusion

This chapter introduces the experimental plan to evaluate the correlation between the warehouse processes. It shows how the JOBPRP model can be applied to the Crisp warehouse and which adjustments should be made and thus answers subquestion 4. This experimental plan will be used to provide an answer to subquestion 5 and 6, which are described in chapter 7.

7

Results

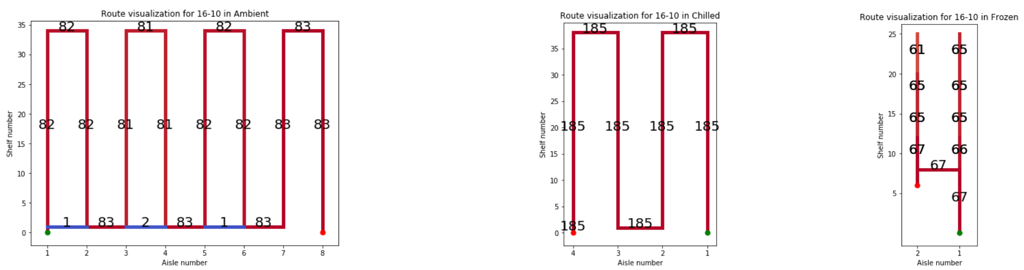
With the model validated and verified and the experimental plan outlined in chapter 6, this chapter presents the results. It will address subquestions 5 and 6. The findings are presented for each stage of the experimental plan for all separate zones. For each combination of warehouse processes, for the best performing configurations, the visualization of the scenario of 16-10 are depicted in Appendix F to visualize the effect of different configurations

7.1. Benchmark results

The benchmark results are constructed from the actual formed batches. The total distance traveled by these batches is the benchmark. The warehouse of Crisp and their order picking process can be compared to a single block low-level picker-to-parts warehouse with a First-Come-First-Served (FCFS) batching policy, S-shape routing heuristic, and random product allocation policy. In daily operations, Crisp encounters what is called 'missings', which occur when a SKU is out of stock at the time a batch reaches the SKU's location. The parcel with a missing SKU is then placed on a new special "missing pick cart', which solely retrieves the missing SKU once it is restocked. This leads to additional travel distance. However, when computing benchmark results, these 'missings' are not considered. The benchmark assumes a scenario in which there are no missing SKUs, as this aspect is also excluded from the JOBPRP model. Both the real traveled distance as the distance without these 'missings' are given in Table 7.1. For the scenario of 16-10-2024, the visualization is depicted in Figure 7.1. The numbers on each aisle represent the number of times these aisles are traversed during the day.

Zone	14-Oct	15-Oct	16-Oct	17-Oct	18-Oct	19-Oct	20-Oct	Total
Ambient (real)	53107	33428	26021	30777	41133	34320	47086	265872
Ambient (no missing)	48784	30668	23723	28545	38330	32129	43673	245852
Chilled (real)	60679	38248	31621	38456	49422	42830	56554	317810
Chilled (no missing)	56376	34715	29785	36124	45354	39149	52586	294089
Frozen (real)	17744	12196	10414	10890	15312	12808	15476	94840
Frozen (no missing)	15944	11222	10154	10532	14446	12208	14756	89262
Total (real)	131530	83872	68056	80123	105867	89958	119116	678522
Total (no missing)	121104	76605	63662	72330	98130	83486	111015	626332

Table 7.1: Benchmark travel distance for a full week in meters



(a) Ambient

(b) Chilled

(c) Frozen

Figure 7.1: Benchmark visualization of the routes on 16-10 for each zone

7.2. Single warehouse process

In this subsection, the results of step 2 of the experimental plan are presented. A single warehouse process is assessed per zone to distinctly observe its impact. Each zone is independently analyzed for this step.

7.2.1. Layout

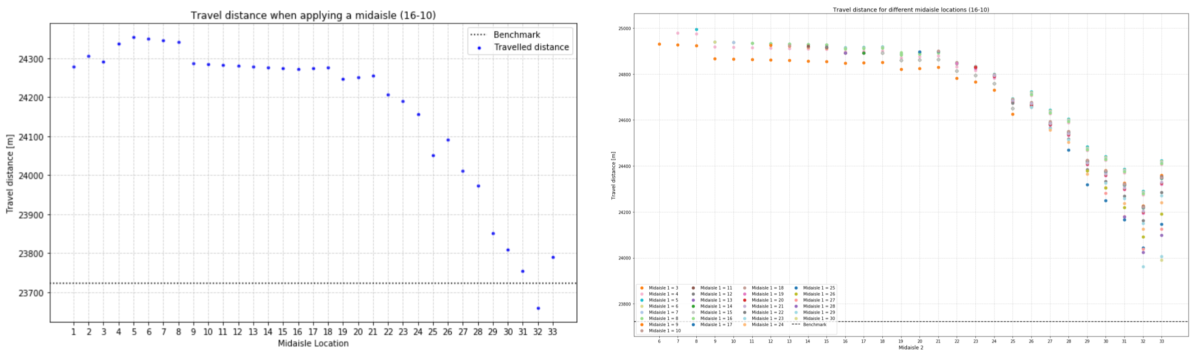
Modifying the warehouse layout can enhance travel efficiency by enabling order pickers to use shortcuts. To evaluate the influence of the layout, two configurations are examined: a rectangular warehouse with one or two midaisles. These results are compared with the standard, a rectangular single block layout, which is applicable to both the ambient and chilled zones. For the frozen zone, layout adjustments differ, as they are specified to the layout of the frozen zone. As discussed in subsection 3.2.2, non conventional warehouse layouts exist; however, the study of Çelik et al. [29] indicates that a rectangular multi-block warehouse will outperform non conventional layouts for orders with 3 or more picks. Additionally, overhauling Crisp's entire warehouse is costly, making such changes impractical.

Ambient zone

The results for a single midaisle are shown in Figure 7.2a, while those for two midaisles are depicted in Figure 7.2b. These figures demonstrate that introducing a midaisle, without taking other warehouse processes into account, does not improve the travel distance. There is only one instance, with a single midaisle on location 32, that improves the travel distance. However, the improvement is only 60 meters, which is considered negligible. The results pictured in Figure 7.2 are derived from the data from 16-10-20244. Subsequently, only the best performing layouts are evaluated with the dataset of the whole week to verify if the found results also hold for a larger dataset. The best performing layouts for a whole week are given in Table 7.2, the full table can be found in Table E.4. This suggests that incorporating a midaisle, without considering other warehouse operations, does not enhance travel distance for the ambient zone. In Figure F.1 it can be seen that with 1 or 2 midaisles some shortcuts are possible, however due to the extra distance created by adding a midaisle, the total travel will still increase.

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
31	-	246214	+0.15%
29	33	248672	+1.15%

Table 7.2: Performance of different layouts for the ambient zone for a whole week (full in E.4)



(a) 1 midaisle

(b) 2 midaisles (full resolution in D.1)

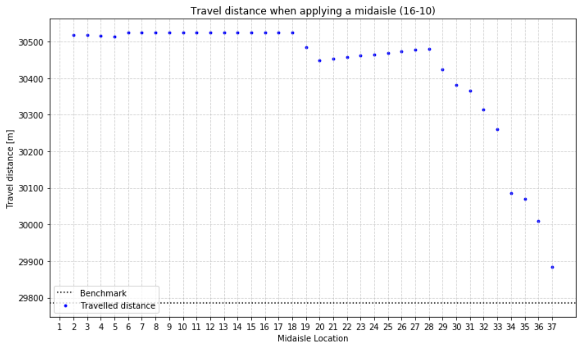
Figure 7.2: Travel distance for the ambient zone on 16-10 for different layouts

Chilled zone

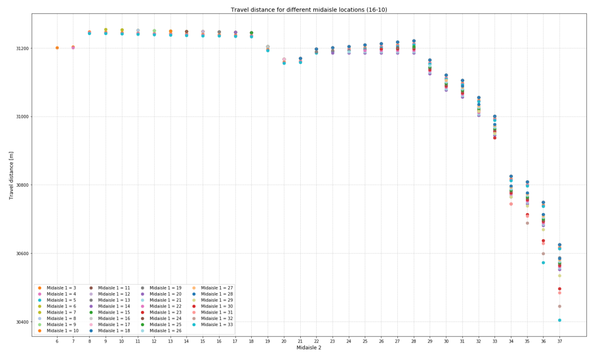
For the chilled zone the same strategy as for the ambient zone holds. The effect of adding a single and two midaisles are first evaluated on the single day 16-10, where after the most promising layouts are evaluated with the data of the whole week. The results for the addition of a single midaisle on 16-10 can be seen in Figure 7.3a and for a double midaisle in Figure 7.3b. For each configuration, the best performing midaisle locations are then evaluated on the data of the whole week. These best performing configurations for a week are given in Table 7.3, with the full table presented in Table E.5. It is evident that, as the same as for the ambient zone, adding a midaisle without taking other warehouse processes into account does not improve the travel distance. Out of the visualization, in Figure F.1, the same conclusion can be drawn. With 1 or 2 midaisles some shortcuts are possible, however due to the extra distance created by adding a midaisle, the total travel will still increase.

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
37	-	291518	+0.10%
33	37	297004	+1.99%

Table 7.3: Performance of different layouts for the chilled zone for a whole week (full in E.5)



(a) 1 midaisle



(b) 2 midaisles (full resolution in D.2)

Figure 7.3: Travel distance for the chilled zone on 16-10 for different layouts

Frozen zone

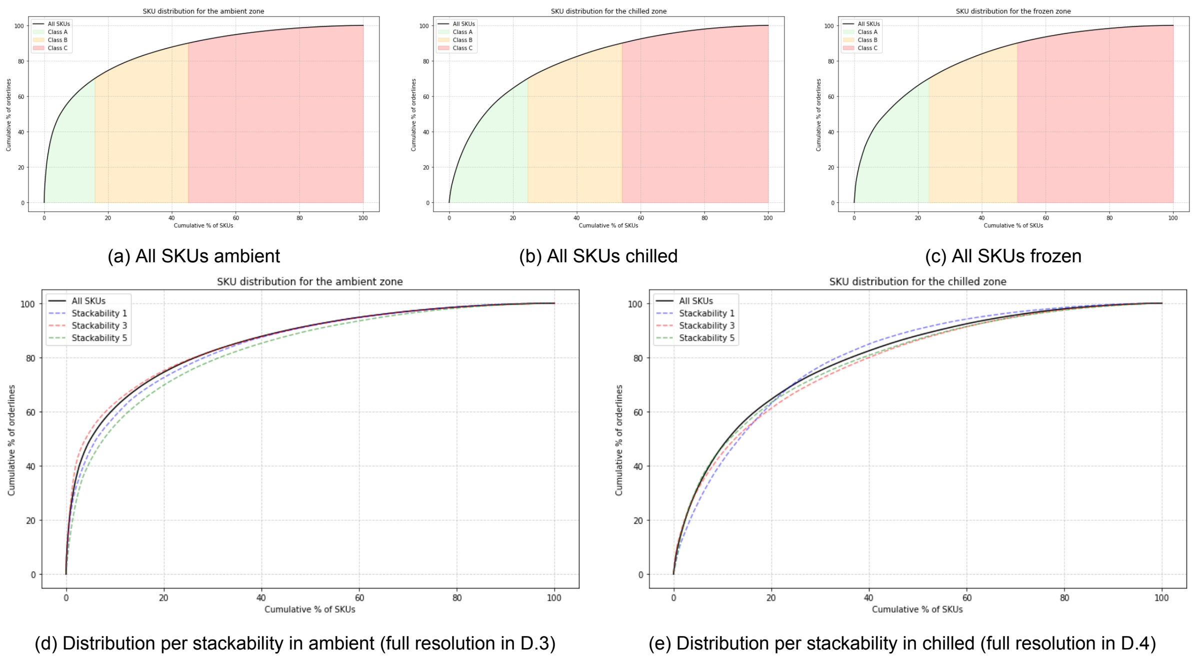
The layout of the frozen zone is quite different than the layouts in the ambient zone. The layout and its complications are described in section 6.3. Due to this layout only 3 possible midaisle locations are considered. This makes the step of evaluating for the scenario of 16-10 unnecessary as there are only 6 instances to evaluate the weekly travel distance on. Adding one or two midaisles to the frozen section will result in the travel distances depicted in Table 7.4. From this results it can be seen that adding a midaisle to the frozen zone, without considering other warehouse operations, will increase the travel distance. Due to the layout of the frozen zone, as depicted in Figure 6.5b, the first aisle is split into 2 aisles as can be seen in Figure F.1. From this visualization it can be seen that only 1 route uses the midaisle, which does not outweigh the extra travel distance caused by the midaisles.

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
2	-	93684	+4.95%
3	-	93776	+5.06%
4	-	93674	+4.97%
2	4	98220	+10.04%
2	4	98136	+9.94%
3	4	98244	+10.06%

Table 7.4: Performance of different layouts in the frozen zone for a whole week

7.2.2. Product allocation

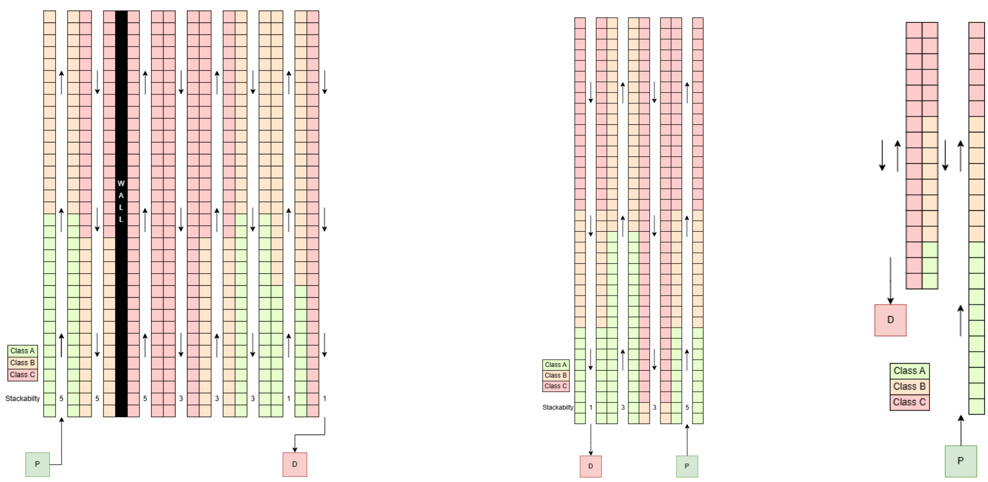
With respect to the product allocation, it is important to take the stackability of the SKU's into account.There are three stackability levels, and products must be picked in the correct sequence to avoid damaging fragile SKUs with heavier ones. This complicates the product allocation strategy since precedence constraints must be accounted for.Figure 3.4 illustrates four different allocation strategies. Among these, the across-aisle storage and within-aisle storage strategies will be assessed, as they are likely to align well with the stackability precedence constraints. Both strategies employ a class-based storage system. In the case of Crisp, SKUs are categorized by their popularity, i.e., their order frequency per week. The distribution is shown in Figure 7.4, where it's evident that each stackability almost follows the same distribution as the total distribution of the respective zone. The implementation to the Crisp warehouse of both the allocation policies are depicted in Figure 7.5 and Figure 7.6 for respectively the within- and across-aisle policy.



(a) All SKUs ambient (b) All SKUs chilled (c) All SKUs frozen

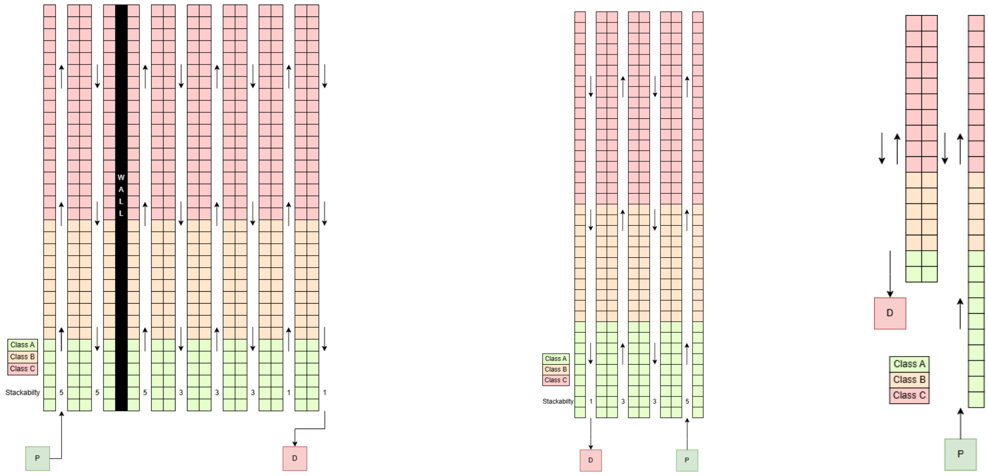
(d) Distribution per stackability in ambient (full resolution in D.3) (e) Distribution per stackability in chilled (full resolution in D.4)

Figure 7.4: Product distribution of SKU's for all zones



(a) Ambient (b) Chilled (c) Frozen

Figure 7.5: Visualization of the within-aisle policy for each zone (full resolution in Appendix G)



(a) Ambient (b) Chilled (c) Frozen

Figure 7.6: Visualization of the across-aisle policy for each zone (full resolution in Appendix G)

Ambient zone

In Figure 7.5a and Figure 7.6a, the allocation strategies implemented in the ambient zone are illustrated. As depicted in Figure 7.6a, the across-aisle policy is relatively straightforward, with the most popular items placed at the begin of the aisle. However, the within-aisle policy shown in Figure 7.5a may initially seem somewhat counterintuitive. It prioritizes the most popular SKUs by stackability at the first aisle and continues with the less popular SKUS. Per aisle, the most popular products are stacked at the beginning of the aisle, ensuring the most possible shortcuts. When going from stackability 5 to 3 the aisles with the least popular SKUs are placed next to each other to ensure the most possible shortcuts. The travel distances for the different allocation policies are presented in Table 7.5. The findings indicate that a within-aisle allocation policy can reduce travel distance by 1.93% in a single block warehouse layout, as some routes can take a shortcut and skip an aisle. In contrast, the across-aisle policy has negligible impact compared to the current random storage policy, with any differences in travel distance likely being due to accidental route advantages rather than the allocation strategy. From the visualization in Figure F.2 the difference between the zones is clearly depicted. Due to the within-aisle policy, the routes can skip the third and fourth aisle a few times, reducing the travel distance. The routes for an across-aisle policy are comparable to the benchmark.

Allocation policy	Travel distance [m]	Gap to benchmark
Within-aisle	241100	-1.93%
Across-aisle	245786	-0.03%

Table 7.5: Travel distance for different allocation polices for a whole week in the ambient zone

Chilled zone

In Figure 7.5b and Figure 7.6b, the allocation polices are visualized. The difference between the across-aisle and within-aisle policy in the chilled zone are less significant than in the ambient zone. This is due to the stackability and the number of aisles. Only the middle two aisles have the same stackability. The outside aisles of the chilled zone are allocated the same in both policies. The difference between the policies is located in the middle two aisles. The across-aisle policy is here again quite straightforward; the within-aisle policy needs a bit more explanation. The most popular SKU's with stackability 3 are placed in aisle 3 according to the route up. The least popular SKU's with stackability are placed at the top at aisle two and increasing by popularity when traversing the aisle down. This policy will return the most options for the picker to take a shortcut. The travel distances for the different allocation policies are presented in Table 7.6. The findings indicate that in a multi-block warehouse with a small number of aisles and high pick density, the storage policy has zero to none influence compared to a random storage policy. The visualization in Figure F.2 shows that for each allocation policy, the constructed routes are not able to take a shortcut.

Allocation policy	Travel distance [m]	Gap to benchmark
Within- aisle	291218	0.00%
Across-aisle	291366	+0.05%

Table 7.6: Travel distance for different allocation polices for a whole week in the chilled zone

Frozen zone

In the frozen zone, there is no difference in stackability for the SKU's. This makes the allocation plan somewhat simpler because stackability is not required to be taken into account. The implemented product allocation policies are visualized in Figure 7.5c and Figure 7.6c. The results of implementing an allocation policy to the frozen zone are given in Table 7.7. Implementing an within-aisle policy is the best performing policy and will reduce the travel distance with 26.76%. Implementing an allocation policy in the frozen zone leads to notable improvements compared to the other zones. This is because the frozen zone is more prone to potential shortcuts when applying only an allocation policy. From the visualization in Figure F.2 the difference between the two allocation policies is clearly visible. The within aisle concentrates the picking in the first aisle and thereby reducing the number of visits in the second aisle. The across-aisle policy concentrates the picking to the bottom of the layout and thus minimizes the number of visits in the farther away locations.

Allocation policy	Travel distance [m]	Gap to benchmark
Within-aisle	72882	-26.76%
Across-aisle	65372	-18.35%

Table 7.7: Travel distance for different allocation polices for a whole week in the frozen zone

7.2.3. Batching

The JOBPRP model outlined in section 4.6 is employed for order batching. According to section 4.4, the input data is processed by the model in chunks. These chunks correspond to the maximum number of parcels for a certain number of batches. Generally, while a greater number of batches can further decrease travel distance, it also demands more computational time.

Ambient zone

The results of applying the JOBPRP model for a specific day (16-10) are illustrated in Figure 7.7. Notably, with an input size of one complete batch, there is a notable improvement in travel distance over the benchmark results. This is caused by the current constructed batches not being fully loaded. Although efforts are made to maximize the number of parcels per batch, batches with fewer parcels than the maximum are still created in the current operation. Figure 7.7 also shows the correlation between the batch size, the travel distance, and the computation time. As in line with Figure 5.1; for a larger chunk size, the computation time will increase exponentially. To evaluate the effect of the JOBPRP model on the whole week, the maximum number of batches within reasonable computation time is 6 full batches. Electing a chunk size of 7 batches might yield slightly enhanced results, but solving these instances would require significantly more time. The results for a week are shown in Table 7.8, revealing not only the gap with the benchmark but also the gap relative to the solution for a full batch. This explicitly shows how increasing the chunk size affects the model. In general, solemnly implementing the JOBPRP model will reduce the travel distance. Larger chunk sizes provide better outcomes than smaller ones but also result in longer computation times. Determining the balance between results and computation time is based on the operational requirements. The visualization in Figure F.3 clearly shows the improvements on the constructed routes by increasing the chunk size of the JOBPRP model. The larger the number of parcels considered together, the more shortcuts the JOBPRP model is able to find.

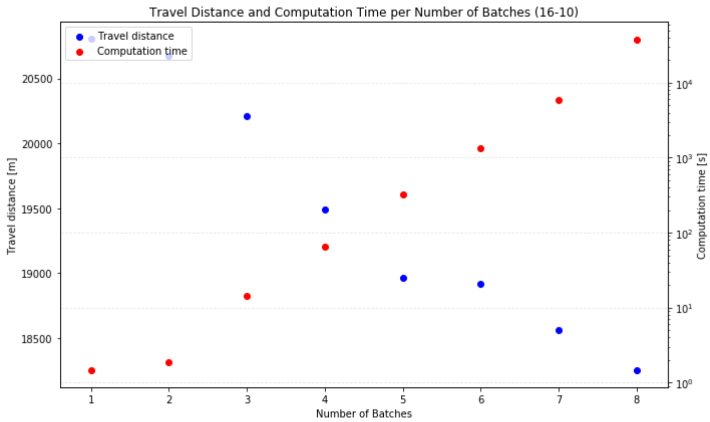


Figure 7.7: Travel distance with the JOBPRP on 16-10 in the ambient zone

Chunk size	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	209748	-14.69%	0%	7
2 full batches	208890	-15.03%	-0.41%	18
3 full batches	203808	-17.10%	-2.83%	290
4 full batches	195624	-20.43%	-6.73%	750
5 full batches	190871	-22.36%	-9.00%	2900
6 full batches	187415	-23.77%	-10.65%	12000

Table 7.8: Travel distance by integrating the JOBPRP model for a whole week in ambient

Chilled zone

The results of applying the JOBPRP model to the chilled zone are illustrated in Table 7.9. Due to the small batch size compared to the ambient zone (6 compared to 18), the model is able to use larger chunk sizes. By comparing the results of the chilled zone to the ambient zone, one things stand out. In the chilled zone the travel distance not necessary decreases by increasing the chunk size. Solving for larger chunk sizes will eventually return better results, but the differences are negligible. This is probably caused by the high pick density of the chilled section and the difficulty of finding a shortcut. Because the absence of cross aisle the route must skip 50% of the layout to find a single shortcut. Increasing the chunk size does give the model more possibilities regarding finding these shortcuts, however the chance of occurring is low. Due to this low occurrence of possible shortcuts, the chunk size can be enlarged and simultaneously keeping the computation time to a minimum. This is because the model has less possibilities and therefore reaches the final solution quicker. So solemnly implementing the JOBPRP model for a single block warehouse with a high pick density and only a few aisles does not effect the travel distance. From the visualization in Figure F.4 it can be clearly seen that for increasing chunk sizes, the routes are (almost) all the same.

Chunk size	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	286580	-1,59	0,00	30
2 full batches	286432	-1,64%	-0,05%	28
3 full batches	286432	-1,64%	-0,05%	48
4 full batches	286432	-1,64%	-0,05%	58
5 full batches	286432	-1,64%	-0,05%	88
6 full batches	286358	-1,67%	-0,08%	108
7 full batches	286519	-1,61%	-0,02%	166
8 full batches	286297	-1,69%	-0,10%	286
9 full batches	286210	-1,72%	-0,13%	402
10 full batches	286358	-1,67%	-0,08%	612
11 full batches	286519	-1,61%	-0,02%	820
12 full batches	286371	-1,66%	-0,07%	980
13 full batches	286297	-1,69%	-0,10%	1276
14 full batches	286297	-1,69%	-0,10%	2279
15 full batches	286075	-1,77%	-0,18%	3505

Table 7.9: Travel distance by integrating the JOBPRP model for a whole week in chilled

Frozen zone

The results of applying the JOBPRP model to the frozen zone are illustrated in Table 7.10. The frozen zone can be best compared to the chilled zone, due to the high pick density and the low number of aisles. For the frozen zone, the JOBPRP model will find better results for an increased chunk size. This is because the route in the frozen zone is not bound by a physical midaisle between aisle 1 and 2. Increasing the chunk size will thus provide the JOBPRP model with more possible solutions to skip parts of this aisle, which makes it able to provide better performing results. With a chunk size of 11 full batches, the JOBPRP model is able to reduce the travel distance with 8.48%. This percentage can even be enlarged by increasing the chunk size, however this will increase the computation time. The visualization in Figure F.5 clearly shows the improvements on the constructed routes by increasing the chunk size of the JOBPRP model. The larger the number of parcels considered together, the more shortcuts the JOBPRP model is able to find.

Chunk size	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	87544	-1.92%	0.00%	7
2 full batches	86064	-3.58%	-1.69%	9
3 full batches	84808	-4.99%	-3.13%	30
4 full batches	83944	-5.96%	-4.11%	48
5 full batches	83212	-6.78%	-4.95%	79
6 full batches	82920	-7.10%	-5.28%	154
7 full batches	82716	-7.33%	-5.51%	260
8 full batches	82572	-7.49%	-5.68%	738
9 full batches	82268	-7.84%	-6.03%	1412
10 full batches	81924	-8.22%	-6.42%	1666
11 full batches	81696	-8.48%	-6.68%	3475

Table 7.10: Travel distance by integrating the JOBPRP model for a whole week in frozen

7.2.4. Conclusion

The results of the best performing configurations for optimizing a single warehouse process are given in Table 7.11. From these results it can be concluded that in general improving the order picking process by concentrating on a single aspect is not very effective. There are some exceptions that actually do decrease the travel distance, however these are very depending on the other aspects of the warehouse. Only adding a cross aisle without taking other processes into account is proven to increase the travel distance for all zones. This holds for batches with multiple picks, for batches with only a few picks adding a cross aisle could still be advantageous. An suitable allocation policy will have a positive effect on the travel distance if the layout corresponds well with the chosen policy. Due to the different layout in the frozen zone, and thus the picker not being bound by physical cross aisles, the allocation policy returns enhanced results. The influence of the JOBPRP model depends on the pick density, possible shortcuts, and the number of parcels per batch. Because the ambient zone has a relatively low pick density, many parcels per batch, and sufficient possible shortcuts, the JOBPRP is able to find good performing batches and reduce the travel distance. For the chilled zone, the opposite hold; It has a high pick density, possible shortcuts are scarce, and the number of parcels per batch is low. Therefore, applying the JOBPRP model to the chilled zone does not improve the travel distance. In the frozen zone, the number of parcels per batch and the pick density limit the JOBPRP model. However, due to the ability to cross from aisle 1 to 2, the JOBPRP model is able to reduce the travel distance.

Process	Layout	Allocation	Batching[1]	Ambient	Chilled	Frozen
Layout	Single	X	X	+0.15%	+0.1%	+4.95%
	Double	X	X	+1.15%	+1.99%	+9.94%
Allocation	X	Within-aisle	X	-1.93%	0.00%	-26.76%
	X	Across-aisle	X	-0.03%	+0.05%	-18.35%
Batching	X	X	(6,15,11)	-23.77%	-1.77%	-8.48%

Table 7.11: Best performing configurations for a single process relative to the benchmark result

[1]The numbers represent the number of full chunks for the respective zones.

7.3. Combination between two warehouse processes

In contrast to section 7.2, where only a single warehouse process is optimized, this section evaluates combinations of two warehouse processes. For each combination, the correlation between these two processes is demonstrated, aligning with Step 3 of the experimental plan.

7.3.1. Layout & Product allocation

Compared to the outcomes presented in subsection 7.2.1 and subsection 7.2.2, adding a midaisle and combining this with an allocation policy is likely to enhance the travel distance. The presence of one or two midaisles, coupled with the allocation policies, grants the picker greater flexibility for taking shortcuts as opposed to a single block warehouse. To assess the impact of merging the layout with the allocation policy, four configurations are evaluated: a 2-block layout with an across-aisle policy, a 2-block layout with a within-aisle policy, a 3-block layout with an across-aisle policy, and a 3-block layout with a within-aisle policy. The allocation policies are the same as described in subsection 7.2.2

Ambient zone

The results for the 2-block warehouse and the two different allocation policies are shown in Figure 7.8, whereas the results for the 3 block warehouse with an across-aisle policy are shown in Figure 7.9a. For the 3-block warehouse utilizing a within-aisle policy, the results are shown in Figure 7.9b. These figures indicate that, contrary to the findings in subsection 7.2.1, the travel distance can be reduced by selecting a suitable allocation policy in combination with an improved layout. The results illustrated in Figure 7.8-7.9b contain only a single day (16-10-2024). The best performing combinations for each assessed situation are then evaluated with the dataset of the entire week to verify whether the found results also hold for larger datasets. The best performing configuration for each of the combinations are shown in Table 7.12, with the full table given in Table E.6. From this table, it can be concluded that introducing one or two midaisles while also adopting an allocation policy enhances travel distance. It is observable that an across-aisle strategy, combined with a multi block layout, reduces travel distance more effectively than a within-aisle strategy. Selecting more midaisle also has an positive effect on the travel distance, which is contrary to the results for a double midaisle without allocation policy. Adding an extra midaisle can thus be advantageous, however it depends on the allocation policy if, and how much, the travel distance decreases. The constructed routes for 16-10 are visualized in Figure F.6 and show the difference between each configuration. Due to the allocation policy and the presence of one or two midaisles, the picker is able to sometimes skip the top part of the aisle, reducing the travel distance.

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
26	-	Within	227584	-7.43%
26	-	Across	215552	-12.32%
20	30	Within	223790	-8.97%
23	29	Across	206448	-16.03%

Table 7.12: Performance of different layouts combined with an allocation policy for a whole week in the ambient zone (full in E.6)

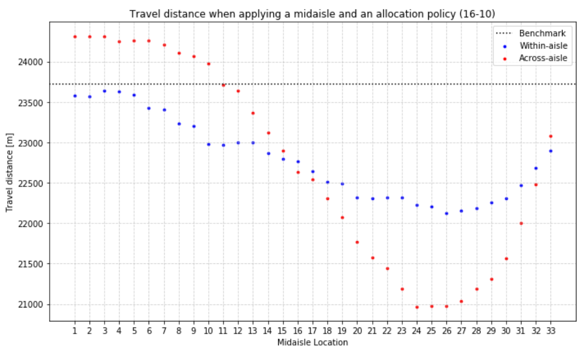
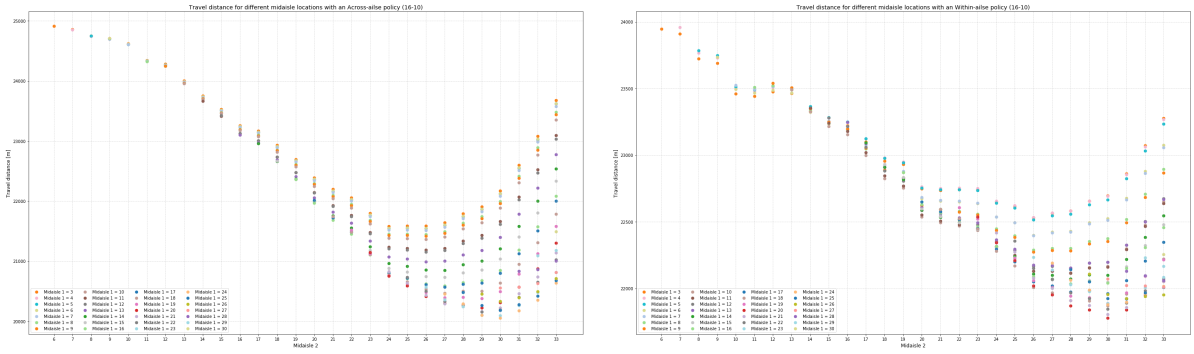


Figure 7.8: Travel distance for a layout with 1 midaisle and an allocation policy on 16-10 in the ambient zone



(a) Across-aisle policy (full resolution in D.5)

(b) Within-aisle policy (full resolution in D.6)

Figure 7.9: Travel distance for a layout with 2 midaisles and an allocation policy on 16-10 in the ambient zone

Chilled zone

For a layout with a single midaisle, the results for both allocation policies are shown in Figure 7.10. The results for a layout with 2 midaisle are shown in Figure 7.11 for both an across- and within-aisle policy. The results depicted in these figures are similar to the ambient zone, based on data from a single day (16-10). This approach highlights the most promising configurations, which are then evaluated on a weekly basis. For each configuration, the best performing instances for an entire week are presented in Table 7.13. while the full table of the evaluated instances can be found in Table E.7. Comparing the results for the chilled zone with the results for the ambient zone shows that the found results are comparable. The across-aisle policy yields the highest improvement and adding a second cross aisle will also benefit the travel distance. For a single mid aisle location it holds for both zones that the cross aisle is placed at roughly 75% of the picking aisle to return the best results. The constructed routes for 16-10 are visualized in Figure F.7 and show the difference between each configuration. The effect of the combination between changes in the layout and allocation policy for the chilled zone is comparable to the ambient zone. Due to the allocation policy and the presence of one or two midaisles, the picker is able to sometimes skip the top part of the aisle, reducing the travel distance. The across-aisle policy enhances this effect by placing the most popular SKUs at the beginning of each aisle, increasing the change to skip the top part.

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
29	-	Within	272150	-6.55%
30	-	Across	260978	-10.38%
27	34	Within	266382	-8.53%
27	33	Across	252671	-13.24%

Table 7.13: Performance of different layouts combined with an allocation policy for a whole week in the chilled zone

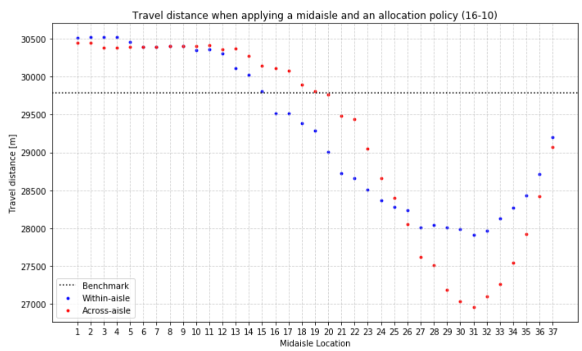
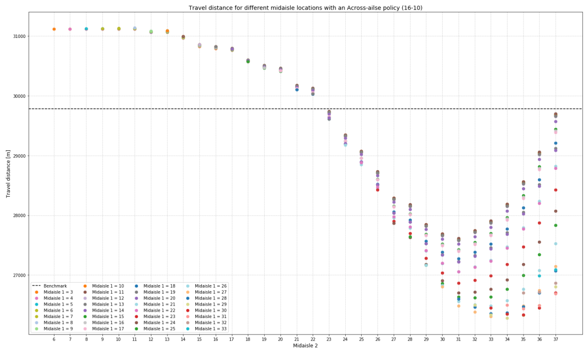
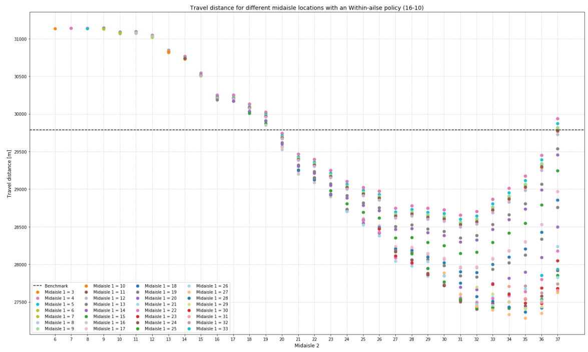


Figure 7.10: Travel distance for a layout with 1 midaisle and an allocation policy on 16-10 in the chilled zone



(a) Across-aisle policy (full resolution in D.7)



(b) Within-aisle policy (full resolution in D.8)

Figure 7.11: Travel distance for a layout with 2 midaisles and an allocation policy on 16-10 in the chilled zone

Frozen zone

Obtaining the results for the frozen zone for the combination between layout and allocation is somewhat simpler than the other zones. This is because the frozen zone only has 6 possible layouts that must be evaluated. The configurations can thus directly be evaluated with the dataset of a week and do not require to find the most promising layouts based on the data of a single day. The results for the frozen zone are depicted in Table 7.14. For the frozen zone, the within policy is the most favorable and adding an extra cross aisle will have a negative effect on the total travel distance. This is the opposite to the ambient and chilled zone, where the across-aisle policy is preferred and adding an extra cross aisle will reduce the travel distance. The difference between these zones is caused by the layout differences and the freedom to cross to the next aisle in the frozen zone. Comparing these results to the results in Table 7.7 concludes that adding a midaisle, when selecting an allocation policy, will only increase the travel distance for the frozen zone. This is also clearly visible in the visualization in Figure F.8. The midaisles are present, however are almost never used. This means that the addition of a midaisle will only increase the length of a full route and thus increases the total travel distance.

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
2	-	Within	68804	-22.92%
3	-	Within	68324	-23.46%
4	-	Within	67668	-24.19%
2	-	Across	77316	-13.38%
3	-	Across	76668	-14.11%
4	-	Across	74876	-16.12%
2	3	Within	71760	-19.61%
2	4	Within	71108	-20.34%
3	4	Within	70628	-20.88%
2	3	Across	81104	-9.14%
2	4	Across	79300	-11.16%
3	4	Across	78652	-11.89%

Table 7.14: Performance of different layouts combined with an allocation policy for a whole week in the frozen zone

7.3.2. Layout & Batching

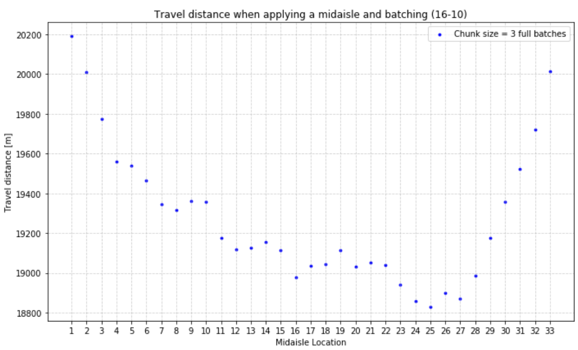
Incorporating one or two midaisles into the layout provides the JOBPRP model with greater flexibility in identifying batches that take advantage of shortcuts, consequently reducing travel distance. Nonetheless, introducing a cross aisle has drawbacks, particularly the impact it has on the computation time for the JOBPRP model. As discussed in subsection 4.4.1 and illustrated in section 6.3, the addition of a cross aisle leads to an enlarged distance matrix. Due to the presence of a midaisle, more locations are needed in the model, which has a negative effect on the computation time. The larger the chunk size used as input, the larger the computation time will be.

Ambient zone

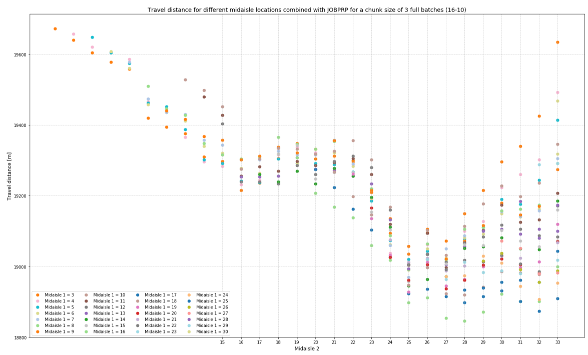
To minimize computation time, the correlation between the layout and the JOBPRP model is initially assessed using a chunk size of 3 full batches for the 16-10 scenario. The most promising solutions are subsequently evaluated with a larger chunk size. For a 2-block layout, the results are presented in Figure 7.12a, while those for a 3-block layout are depicted in Figure 7.12b. Each combination of a change in layout and the JOBPRP model lies below the benchmark result. Given that computation time grows exponentially by increasing the chunk size, the best performing layouts are first evaluated using one week's data for a small chunk size. The best performing configurations for both the 2-block and 3-block layouts are then solved by using a chunk size of up to 4 full batches. The results of the best performing layouts for different chunk sizes are detailed in Table 7.15. The complete table evaluating all promising layouts is shown in Table E.8. The results reveal that incorporating the JOBPRP model and selecting an appropriate layout can potentially reduce the travel distance by up to 25.32%. This reduction might be even greater by increasing the JOBPRP model's chunk size. Additionally, the table indicates that a 2-block warehouse layout yields marginally better results than a 3-block layout. The constructed routes for 16-10 are visualized in Figure F.9 and show the difference between each configuration for different chunk sizes of the JOBPRP model. It can be seen that for increasing chunk sizes the model is able to find routes that can take more shortcuts. Opting for one or two midaisles both return comparable results as most of the shortcuts are made by using the first midaisle.

Chunk size	Midaisle locations	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	25	214614	-12.71%	0%	17
2 full batches	25	198126	-19.41%	-7.68%	119
3 full batches	25	189830	-22.79%	-11.55%	1024
4 full batches	25	183594	-25.32%	-14.45%	10500
1 full batch	25 & 32	216378	-11.99%	0%	17
2 full batches	25 & 32	199034	-19.04%	-8.02%	233
3 full batches	25 & 32	190674	-22.24%	-11.88%	1762
4 full batches	25 & 32	184358	-25.01%	-14.80%	20764

Table 7.15: Travel distance by integrating the JOBPRP model for different layouts for a whole week for different chunk sizes in the ambient zone



(a) 1 midaisle



(b) 2 midaisles (full resolution in D.9)

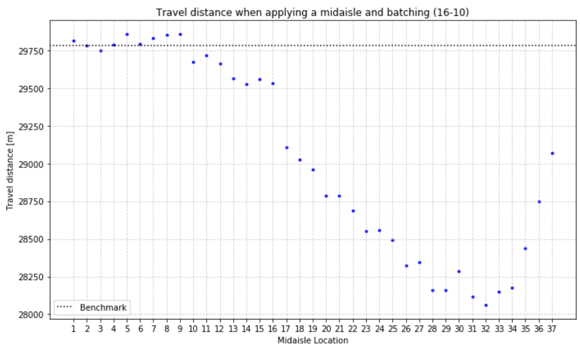
Figure 7.12: Travel distance for the ambient zone on 16-10 for different layouts and the JOBPRP model with a chunk size of 3 full batches

Chilled zone

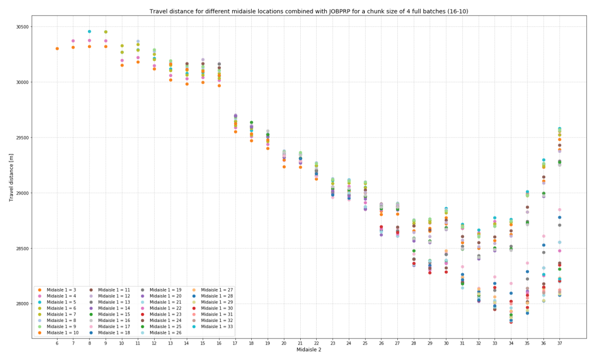
The chilled zone uses the same strategy as for the ambient: The combination between batching and layout is initially assessed on a single day, after which the most promising layouts are further explored. To keep the computation time to a minimum, a chunk size of 4 full batches is used. The results for a single midaisle are shown in Figure 7.13a and the results for two midaisles are shown in Figure 7.13b. To find the best performing layout in combination with the JOBPRP model, the most promising results for the single day are evaluated on a weekly basis. The full results for this analysis can be found in Table E.9. For the best configurations, the chunk size is also varied. These results can be seen in Table 7.16. For a low chunk size, the JOBPRP model applied to a single midaisle outperforms a double midaisle layout. For a chunk size of 4 full batches or more, a layout with two midaisles outperforms a single midaisle layout. This can be explained by the fact that with small chunk size, the possibility of using the second midaisle decreases and thus increasing the travel distance. The larger the chunk size, the more options are available, which improves the use of a second midaisle to reduce the travel distance. This is clearly illustrated in the visualization in Figure F.10, where the larger the chunk size is, the better the constructed routes are.

Chunk size	Midaisle locations	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	31	292788	+0.54%	0%	41
2 full batches	31	282572	-2.97%	-3.94%	42
3 full batches	31	277660	-4.66%	-5.17%	103
4 full batches	31	275212	-5.50%	-6.00%	216
5 full batches	31	273644	-6.03%	-6.54%	450
6 full batches	31	272672	-6.37%	-6.87%	812
7 full batches	31	272181	-6.54%	-7.04%	1825
8 full batches	31	271649	-6.72%	-7.22%	3550
1 full batch	27 & 34	298460	+2.49%	0%	40
2 full batches	27 & 34	284502	-2.31%	-4.68%	64
3 full batches	27 & 34	277960	-4.55%	-6.87%	207
4 full batches	27 & 34	273660	-6.03%	-8.31%	464
5 full batches	27 & 34	271136	-6.90%	-9.15%	1220
6 full batches	27 & 34	269450	-7.47%	-9.72%	2539
7 full batches	27 & 34	268513	-7.80%	-10.03%	15720
8 full batches	27 & 34	267395	-8.18%	-10.41%	34235

Table 7.16: Travel distance by integrating the JOBPRP model for different layouts for a whole week for different chunk sizes in the chilled zone



(a) 1 midaisle



(b) 2 midaisles (full resolution in D.10)

Figure 7.13: Travel distance for the ambient zone on 16-10 for different layouts and the JOBPRP model with a chunk size of 4 full batches

Frozen zone

To find the best performing layout in combination with the JOBPRP model a chunk size of 5 full batches is used to evaluate all layout possibilities. The results for this evaluating are shown in Table 7.17. For both a single- and double midaisle the best layouts are solved with an increasing chunk size, these results are shown in Table 7.18. Compared to the results depicted in Table 7.10, it can be concluded that adding a single or double midaisle to the frozen zone when including the JOBPRP model returns less favorable results than using the JOBPRP model on a layout without a midaisle. The visualization in Figure F.11 clearly shows the reason for this. The constructed midaisles are used, however only a very limited times. The extra travel distance created by this midaisle does not outweigh the formed shortcuts and thus will only increase the travel distance. The second midaisle is never used, so only increases the distance between locations and thus increase the travel distance. It also shows that for increasing chunk sizes, the constructed routes are performing better. Increasing the chunk size, which correlates to an increased computation time, will also in the frozen zone decrease the found travel distance.

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
2	-	86848	-2.70%
3	-	87420	-2.06%
4	-	86936	-2.61%
2	3	91128	+2.09%
2	4	90588	+1.49%
3	4	91180	+2.15%

Table 7.17: Travel distance by integrating the JOBPRP model for all possible layouts for a whole week with a chunk size of 5 full batches in the frozen zone

Chunk size	Midaisle locations	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	2	91952	+3.01%	0%	12
2 full batches	2	90204	+1.06%	-1.90%	18
3 full batches	2	88736	-0.59%	-3.50%	56
4 full batches	2	87756	-1.69%	-4.56%	100
5 full batches	2	86848	-2.70%	-5.55%	280
6 full batches	2	86400	-3.21%	-6.04%	741
7 full batches	2	86124	-3.52%	-6.34%	1858
8 full batches	2	85788	-3.89%	-6.70%	4099
9 full batches	2	85134	-4.62%	-7.41%	15494
1 full batch	2 & 4	96336	+7.92%	0%	12
2 full batches	2 & 4	94336	+5.68%	-2.08%	18
3 full batches	2 & 4	92676	+3.82%	-3.80%	60
4 full batches	2 & 4	91580	+2.60%	-4.94%	126
5 full batches	2 & 4	90588	+1.49%	-5.97%	345
6 full batches	2 & 4	90092	+0.93%	-6.48%	988
7 full batches	2 & 4	89752	+0.55%	-6.83%	2444
8 full batches	2 & 4	89444	+0.20%	-7.15%	3030
9 full batches	2 & 4	89180	-0.09%	-7.43%	19495

Table 7.18: Travel distance by integrating the JOBPRP model for different layouts for a whole week for different chunk sizes in the frozen zone

7.3.3. Product allocation & Batching

To assess the impact of the allocation policy combined with the JOBPRP model, the two different allocation policies, as defined in subsection 7.2.2, are applied to the single block warehouse and solved using the JOBPRP model. Because in the across-aisle policy the fast moving SKU's are spread out over all aisles, finding shortcuts by using the JOBPRP will most likely be challenging. With the within-aisle policy the JOBPRP should be better capable to find possible shortcuts with the batching strategy.

Ambient zone

For the ambient zone the allocation policies are depicted in Figure 7.5a and Figure 7.6a. The JOBPRP model is applied for both the allocation policies. The chunk size of the JOBPRP variates between 1 to 6 full batches. As subsection 7.2.3 showed this is the largest chunk size that has a computation time that is within reasonable time. The results can be found in Table 7.19. This table shows that combining the JOBPRP with an allocation policy will decrease the travel distance with up to 33.88%. It shows that integrating the JOBPRP model with an within-aisle policy will result in more reduced travel distances compared to an across-aisle policy. The across-aisle policy successfully decreases travel distance; however, its outcomes are similar to those of a random storage policy, as shown in Table 7.8. The difference between the two policies is due to the absence of midaisles. The across-aisle policy stored popular SKU's over all the aisle, where the within-aisle policy concentrates the most popular SKU's in a single aisle. This is clearly visible in the visualization in Figure F.12. Routes in the within-aisle policy mostly skip the third and fourth aisle, whereas in the across-aisle the shortcuts are more distributed over the other aisles.

Chunk size	Allocation policy	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	Within	207570	-15.57%	0%	4
2 full batches	Within	185328	-24.62%	-10.72%	26
3 full batches	Within	177511	-27.80%	-14.48%	80
4 full batches	Within	171798	-30.12%	-17.23%	360
5 full batches	Within	167376	-31.92%	-19.36%	1600
6 full batches	Within	162558	-33.88%	-21.69%	11600
1 full batch	Across	209682	-14.71%	0%	8
2 full batches	Across	208890	-15.03%	-0.38%	20
3 full batches	Across	204270	-16.91%	-2.58%	170
4 full batches	Across	195665	-20.41%	-6.68%	680
5 full batches	Across	191994	-21.91%	-8.44%	3200
6 full batches	Across	188232	-23.44%	-10.23%	20000

Table 7.19: Travel distance by integrating the JOBPRP model and an allocation policy for a whole week in the ambient zone

Chilled zone

The applied storage policies are visualized in Figure 7.5b and Figure 7.6b. These policies are combined with the JOBPRP model, for which the results are given in Table 7.20. It can be seen that the JOBPRP model applied to a single block layout with an across-aisle policy, has a minimal effect. By increasing the chunk size the improvement in the found solution is only 0.10%. This is comparable with the results of applying the JOBPRP model without an allocation policy, as can be seen in Table 7.9. This is because in both cases, the popular items are distributed over all the aisles, which gives the JOBPRP less opportunities to finding shorter routes. The within-aisle policy concentrates the high demanded SKU's in a single aisle, allowing the JOBPRP model to find some shortcuts. However due to the low number of aisles in the chilled zone and thus the possibilities of taking a shortcut, the improvement in travel distance is kept to a relative low percentage. This is visualized in Figure F.13, where it can be seen that for the within-aisle policy the routes slightly improve for increasing chunk sizes.

Chunk size	Allocation policy	Travel distance [m]	Gap to benchmark	Gap to Gap to 1 full batch [%]	Computation time [s]
1 full batch	Within	286580	-1.59%	0%	28
2 full batches	Within	286506	-1.62%	-0.03%	34
3 full batches	Within	285396	-2.00%	-0.41%	52
4 full batches	Within	284064	-2.46%	-0.88%	80
5 full batches	Within	281030	-3.50%	-1.94%	135
6 full batches	Within	278440	-4.39%	-2.84%	162
7 full batches	Within	277269	-4.79%	-3.25%	278
8 full batches	Within	275789	-5.30%	-3.77%	646
9 full batches	Within	275258	-5.48%	-3.95%	892
10 full batches	Within	274666	-5.68%	-4.16%	1025
11 full batches	Within	274235	-5.83%	-4.31%	1487
12 full batches	Within	273717	-6.01%	-4.49%	1577
1 full batch	Across	286580	-1.59%	0%	26
2 full batches	Across	286506	-1.62%	-0.03%	25
3 full batches	Across	286506	-1.62%	-0.03%	27
4 full batches	Across	286432	-1.64%	-0.05%	42
5 full batches	Across	286358	-1.67%	-0.08%	70
6 full batches	Across	286358	-1.67%	-0.08%	88
7 full batches	Across	286297	-1.69%	-0.10%	136
8 full batches	Across	286297	-1.69%	-0.10%	230
9 full batches	Across	286210	-1.72%	-0.13%	330
10 full batches	Across	286210	-1.72%	-0.13%	507
11 full batches	Across	286297	-1.69%	-0.10%	750
12 full batches	Across	286297	-1.69%	-0.10%	890

Table 7.20: Travel distance by integrating the JOBPRP model and an allocation policy for a whole week in the chilled zone

Frozen zone

The applied storage policies for the frozen zone are visualized in Figure 7.5c and Figure 7.6c. These policies are combined with the JOBPRP model, for which the results are given in Table 7.21. Applying the JOBPRP model to the frozen zone with an allocation policy is able to significantly reduce the travel distance. Compared to the results of the frozen zone without an allocation policy, which are shown in Table 7.10, the reduction in travel distance is almost five times higher when a suitable allocation policy is applied. The within-aisle policy outperforms the across-aisle policy in this zone. This is because this allocation policy is very well suited for the layout of the frozen zone. With this policy the changes of visiting the third aisle are reduced, which benefits the travel distance significantly. This is visualized in Figure F.14. The larger the chunk size of the JOBPRP model, the lower the number of routes that visit the third aisle.

Chunk size	Allocation policy	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	Within	64636	-27.59%	0.00%	13
2 full batches	Within	59080	-33.81%	-8.60%	14
3 full batches	Within	56192	-37.05%	-13.06%	21
4 full batches	Within	54812	-38.59%	-15.20%	48
5 full batches	Within	53772	-39.76%	-16.81%	87
6 full batches	Within	52992	-40.63%	-18.01%	196
7 full batches	Within	52388	-41.31%	-18.95%	494
8 full batches	Within	51968	-41.78%	-19.60%	1069
9 full batches	Within	51572	-42.22%	-20.21%	2105
10 full batches	Within	51276	-42.56%	-20.67%	3225
1 full batch	Across	72340	-18.96%	0.00%	12
2 full batches	Across	65140	-27.02%	-9.95%	13
3 full batches	Across	61712	-30.86%	-14.69%	34
4 full batches	Across	60004	-32.78%	-17.05%	59
5 full batches	Across	58316	-34.67%	-19.39%	107
6 full batches	Across	57464	-35.62%	-20.56%	299
7 full batches	Across	56832	-36.33%	-21.44%	906
8 full batches	Across	56056	-37.20%	-22.51%	2432
9 full batches	Across	55752	-37.54%	-22.93%	6649
10 full batches	Across	55220	-38.14%	-23.67%	22000

Table 7.21: Travel distance by integrating the JOBPRP model and an allocation policy for a whole week in the frozen zone

7.3.4. Conclusion

Improving the order picking process by combining 2 warehouse processes to find the best performing configuration is able to reduce the total travel distance for each combination. However depending on the zone, the effects can differ. The best performing instances for each combination of warehouse processes are given in Table 7.22. From this table some things can be concluded. First of all, the frozen zone is most affected by it's allocation policy. This is caused by the used routing and the freedom of crossing from the first to the second aisle. Also adding an extra cross aisle in the frozen zone, will only increase the travel distance. Selecting a suitable allocation policy for the frozen zone and using the JOBPRP model will return the highest percentage of improvement of 42.56%, which can be even larger for a larger chunk size. The results for changing the layout and selecting an allocation policy for the ambient and frozen zone are comparable. For both zones, the across-aisle policy returns the best results and for both zones adding two midaisles is preferred over adding a single midaisle. However, in the other combinations there are some differences between the ambient and chilled zone. By changing the layout and using the JOBPRP model, the travel distance in the ambient zone can be reduced with ±25%, where in the chilled zone this only ±7%. This is caused by the difference in pick density per parcel in the zone. In the chilled zone, parcels typically have more picks and thus must visit more locations. This has a negative influence on the JOBPRP model to formulate improved batches. Using the JOBPRP model and selecting an allocation policy also returns better results in the ambient zone than in the chilled zone. This is caused by the number of aisles per zone, whereas the ambient zone has 8 and the chilled zone only has 4. For the JOBPRP model being able to find a shortcut, in the ambient zone it should construct a batch that does not have to visit 25% of the aisles, where in the chilled zone this is 50%. The within-aisle policy returns in this case the best results because it concentrates high demanded SKU's in a single aisle, instead of spreading them over all the aisles. In general, focusing on the combination of 2 warehouse processes will return improved results compared to focusing on a single process. However this is depending on characteristics of the warehouse.

Process	Layout	Allocation	Batching[2]	Ambient	Chilled	Frozen
Layout & Allocation	Single	Within-aisle	X	-7.43%	-6.55%	-24.19%
	Single	Across-aisle	X	-12.32%	-10.38%	-16.12%
	Double	Within-aisle	X	-8.97%	-8.53%	-20.88%
	Double	Across-aisle	X	-16.03%	-13.24%	-11.89%
Layout & Batching	Single	X	(4,8,9)	-25.32%	-6.72%	-4.62%
	Double	X	(4,8,9)	-25.01%	-8.18%	-0.09%
Allocation & Batching	X	Within-aisle	(6,12,10)	-33.88%	-6.01%	-42.56%
	X	Across-aisle	(6,12,10)	-23.44%	-1.69%	-38.14%

Table 7.22: Best performing configurations for a combination between two processes relative to the benchmark result

7.4. Combination between all three warehouse processes

Where in section 7.2 and section 7.3 a single and two integrated warehouse processes are described, this section will evaluate the integration of all three warehouse processes. To assess the impact of combining the three warehouse processes, the JOBPRP model is applied to four different configurations: a 2-block layout with an across-aisle policy, a 2-block layout with a within-aisle policy, a 3-block layout with an across-aisle policy, and a 3-block layout with a within-aisle policy. This are the same configurations as in subsection 7.3.1. First the optimal layout is found, where after this layout is evaluated for different chunk sizes in the JOBPRP model.

Ambient zone

The results for the 2-block warehouse and the two different allocation policies are shown in Figure 7.14, whereas the results for the 3-block warehouse with an across- and within-aisle policy are shown in respectively Figure 7.15a and Figure 7.15b. The results illustrated in Figure 7.14-7.15 are again based on a single day (16-0). The best performing combinations for each assessed situation are then evaluated with the dataset of the entire week to verify whether the found results also hold for larger datasets. The complete evaluation of the best performing layouts can be found in Table E.10. The best performing configurations are then evaluated for different chunk sizes of the JOBPRP model and are shown in Table 7.23. From this table, it can be concluded that integrating all three warehouse processes can reduce the travel distance in the ambient zone with 48.19%. Increasing the chunk size of the JOBPRP will benefit the found solution, however has a rise of computation time as negative downside. For the ambient zone it is more favorable to add 2 midaisles compared to adding 1 or none. However, adding an extra midaisle adds more locations to the distance matrix and thereby increases the computation time of the JOBPPR model. From this table it can be seen that the across-aisle policy returns the best performing results, however it also need more time to find these solution. This can be caused because due to the across-aisle policy there are multiple solutions close to the optimal value, making it more challenging for the JOBPRP model to find the optimal solution. The visualization of the integration of all three warehouse processes can be found Figure F.15. This shows the differences in constructed routes for the different allocation policies. Shortcuts for the across-aisle policy are quite straightforward; they skip the upper part of the aisle. For the within-aisle policy the shortcuts also are able to skip whole aisles and are less focused on skipping the top part of the aisle. The final routes however return comparable travel distances.

[2] The numbers represent the number of full chunks for the respective zones.

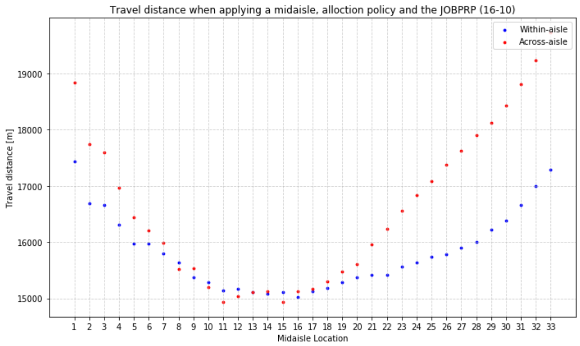
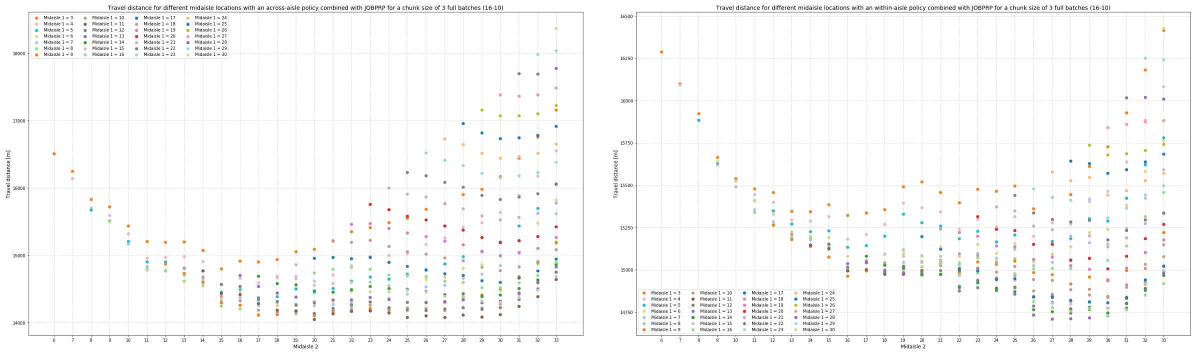


Figure 7.14: Travel distance for a layout with 1 midaisle, the JOBPRP with a chunk size of 3 full batches and an allocation policy on 16-10 in the ambient zone



(a) Across-aisle policy (full resolution in D.11)

(b) Within-aisle policy (full resolution in D.12)

Figure 7.15: Travel distance for a layout with 2 midaisles and an allocation policy and the JOBPRP model with a chunk size of 3 full batches on 16-10 in the ambient zone

Chunk size	Location midaisles	Allocation policy	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	15	Within	205118	-16.57%	0.00%	8
2 full batches	15	Within	167842	-31.73%	-18.17%	58
3 full batches	15	Within	150619	-38.74%	-26.57%	283
4 full batches	15	Within	143048	-41.82%	-30.26%	1855
5 full batches	15	Within	137846	-43.93%	-32.80%	6340
1 full batch	12	Across	211898	-13.81%	0.00%	6
2 full batches	12	Across	163030	-33.69%	-23.06%	51
3 full batches	12	Across	149593	-39.15%	-29.40%	387
4 full batches	12	Across	141517	-42.44%	-33.21%	3350
5 full batches	12	Across	135840	-44.75%	-35.89%	24950
1 full batch	13 & 17	Within	200030	-18.64%	0.00%	17
2 full batches	13 & 17	Within	163096	-33.66%	-18.46%	99
3 full batches	13 & 17	Within	147858	-39.86%	-26.08%	402
4 full batches	13 & 17	Within	139538	-43.24%	-30.24%	2201
5 full batches	13 & 17	Within	134358	-45.35%	-32.83%	13454
1 full batch	9 & 20	Across	203884	-17.07%	0.00%	21
2 full batches	9 & 20	Across	158064	-35.71%	-22.47%	106
3 full batches	9 & 20	Across	141048	-42.63%	-30.82%	494
4 full batches	9 & 20	Across	135216	-45.00%	-33.68%	10368
5 full batches	9 & 20	Across	127366	-48.19%	-37.53%	180423

Table 7.23: Travel distance by integrating all three warehouse processes for different chunk sizes for a whole week in the ambient zone

Chilled zone

To evaluate the chilled zone, the first step is done by using a chunk size of 4 full batches to keep the computation time to a minimum. The results of a single day for a single midaisle are shown in Figure 7.16 and for a double midaisle in Figure 7.17a and Figure 7.17b for respectively an across and within-aisle policy. The best performing layouts per allocation policy are then evaluated with the data for the whole week. The results of this can be found in Table E.11. The best performing layouts per allocation policy are then solved for different chunk sizes, to see the effect of the JOBPRP model. These results are shown in Table 7.24. From this table some things can be concluded. First of all, the across-aisle policy outperforms the within-aisle policy for both a single and a double midaisle. Opting for 2 midaisles instead of 1 also improves the travel distance, however results in a larger computation time. The computation time for the across-aisle policy is in general larger than the computation time for the within-aisle policy. Compared to a layout without a midaisle as shown in Table 7.20, adding a midaisle returns a significant improvement. This is caused because the chilled zone has only 4 aisles, adding a cross aisle gives the JOBPRP more possible solutions, which favor the outcome. The constructed routes for an within-aisle policy are shown in Figure F.16 and for the across-aisle policy in Figure F.17. From these visualizations it is clear the routes for an within-aisle policy must visit the third and fourth aisle more than the first and second aisle, which aligns with the allocation policy. The across-aisle policy finds the shortcuts at the end of each aisle. Concentrating the picking at the front of each aisle. The downside of this concentration of picking at the front of each aisle, is the sensitivity to congestion.

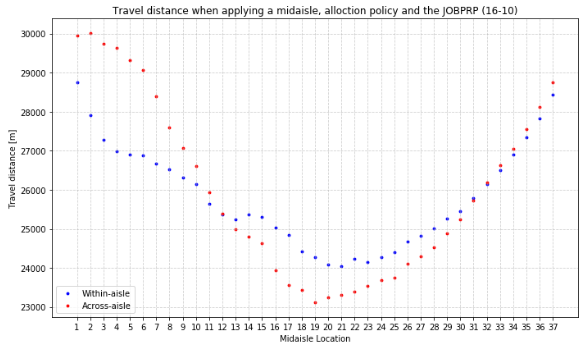
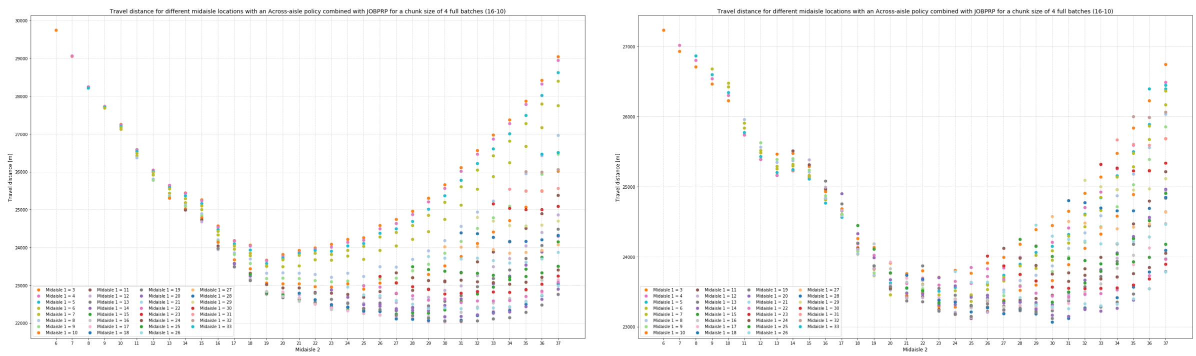


Figure 7.16: Travel distance for a layout with 1 midaisle, the JOBPRP with a chunk size of 4 full batches and an allocation policy on 16-10 in the chilled zone



(a) Across-aisle policy (full resolution in D.13)

(b) Within-aisle policy (full resolution in D.14)

Figure 7.17: Travel distance for a layout with 2 midaisles and an allocation policy and the JOBPRP model with a chunk size of 4 full batches on 16-10 in the chilled zone

Chunk size	Location midaisles	Allocation policy	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	21	Within	279696	-3.96%	0.00%	40
2 full batches	21	Within	254996	-12.44%	-8.83%	40
3 full batches	21	Within	241112	-17.21%	-13.79%	79
4 full batches	21	Within	235100	-19.27%	-15.94%	227
5 full batches	21	Within	230976	-20.69%	-17.42%	428
6 full batches	21	Within	228496	-21.54%	-18.31%	923
7 full batches	21	Within	225673	-22.51%	-19.31%	1950
8 full batches	21	Within	224441	-22.93%	-19.76%	3892
1 full batch	21	Across	281856	-3.21%	0.00%	40
2 full batches	21	Across	243764	-16.30%	-13.51%	40
3 full batches	21	Across	232964	-20.00%	-17.35%	107
4 full batches	21	Across	226196	-22.33%	-19.75%	200
5 full batches	21	Across	222124	-23.73%	-21.19%	398
6 full batches	21	Across	219856	-24.50%	-22.00%	640
7 full batches	21	Across	218649	-24.92%	-22.43%	1113
8 full batches	21	Across	217749	-25.23%	-22.74%	2528
1 full batch	18 & 30	Within	270936	-6.96%	0.00%	40
2 full batches	18 & 30	Within	243718	-16.31%	-10.05%	61
3 full batches	18 & 30	Within	232112	-20.30%	-14.33%	192
4 full batches	18 & 30	Within	224638	-22.86%	-17.09%	415
5 full batches	18 & 30	Within	219851	-24.51%	-18.86%	1238
6 full batches	18 & 30	Within	216787	-25.56%	-19.99%	3467
7 full batches	18 & 30	Within	214233	-26.44%	-20.93%	4986
8 full batches	18 & 30	Within	212071	-27.18%	24.76%	19500
1 full batch	18 & 29	Across	263580	-9.49%	0.00%	39
2 full batches	18 & 29	Across	233426	-19.84%	-11.44%	57
3 full batches	18 & 29	Across	200672	-31.09%	-23.87%	190
4 full batches	18 & 29	Across	213642	-26.64%	-18.95%	330
5 full batches	18 & 29	Across	209136	-28.19%	-20.66%	716
6 full batches	18 & 29	Across	206808	-28.99%	-21.54%	1170
7 full batches	18 & 29	Across	204335	-29.83%	-22.48%	2660
8 full batches	18 & 29	Across	202538	-30.45%	-28.14%	9124

Table 7.24: Travel distance by integrating all three warehouse processes for different chunk sizes for a whole week in the chilled zone

Frozen zone

For the frozen zone it is not necessary to find the best performing layout for a daily scenario due to the low number of possible layouts. All possible layouts are evaluated with a chunk size of 5 full batches with the data of a whole week. The results can be seen in Table 7.25. For both allocation policies with a single midaisle, the best performing location of this midaisle is location 2. For a layout with two midaisle, for both policies a midaisle at location 3 and 4 is the best performing. These layouts are evaluated with an increasing chunk size, which is depicted in Table 7.26. These results show that for the frozen zone, an within-aisle policy is preferred. Also adding extra midaisles to the frozen zone will only increase the travel distance. This is mainly caused by the characteristics of the zone and the routing policy. By implementing an within-aisle policy, the change of visiting the third aisle is reduced, which decreases the travel distance significantly. The constructed routes for an within-aisle policy are shown in Figure F.18 and for the across-aisle policy in Figure F.19. This shows that for both the allocation policies, zero routes use the midaisles. Adding midaisle is thus unnecessary and only increases the travel distance. Where the within-aisle policy tries to skip the third aisle in the routes, the across-aisle policy tries to skip the last part of each aisle. Both leading to the reduction in travel distance.

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
2	-	Within	56500	-36.70%
3	-	Within	56152	-37.09%
4	-	Within	55212	-38.15%
2	-	Across	61864	-30.69%
3	-	Across	60668	-32.03%
4	-	Across	59336	-35.53%
3	4	Within	58876	-34.04%
3	4	Within	57972	-35.05%
3	4	Within	57628	-35.44%
3	4	Across	64300	-27.96%
3	4	Across	62948	-29.48%
3	4	Across	61752	-30.82%

Table 7.25: Performance of different layouts combined with an allocation policy and the JOBPRP with a chunk size of 5 full batches for a whole week in the frozen zone

Chunk size	Location midaisles	Allocation policy	Travel distance [m]	Gap to benchmark	Gap to 1 full batch	Computation time [s]
1 full batch	2	Within	66930	-25.02%	0.00%	8
2 full batches	2	Within	60862	-31.82%	-9.07%	10
3 full batches	2	Within	57782	-35.27%	-13.67%	31
4 full batches	2	Within	56336	-36.89%	-15.83%	61
5 full batches	2	Within	55212	-38.15%	-17.51%	149
6 full batches	2	Within	54396	-39.06%	-18.73%	411
7 full batches	2	Within	53736	-39.80%	-19.71%	1363
8 full batches	2	Within	53290	-40.30%	-20.38%	3910
9 full batches	2	Within	52898	-40.74%	-20.97%	15563
1 full batch	2	Across	74394	-16.66%	0.00%	7
2 full batches	2	Across	66662	-25.32%	-10.39%	10
3 full batches	2	Across	62982	-29.44%	-15.34%	34
4 full batches	2	Across	61152	-31.49%	-17.80%	68
5 full batches	2	Across	59336	-33.53%	-20.24%	175
6 full batches	2	Across	58454	-34.51%	-21.43%	529
7 full batches	2	Across	57782	-35.27%	-22.33%	1855
8 full batches	2	Across	56978	-36.17%	-23.41%	6094
9 full batches	2	Across	56608	-36.58%	-23.91%	21833
1 full batch	3 & 4	Within	69872	-21.72%	0.00%	13
2 full batches	3 & 4	Within	63632	-28.71%	-8.93%	16
3 full batches	3 & 4	Within	60348	-32.39%	-13.63%	46
4 full batches	3 & 4	Within	58808	-34.12%	-15.83%	82
5 full batches	3 & 4	Within	57628	-35.44%	-17.52%	202
6 full batches	3 & 4	Within	56720	-36.46%	-18.82%	620
7 full batches	3 & 4	Within	56020	-37.24%	-19.82%	1866
8 full batches	3 & 4	Within	55512	-37.81%	-20.55%	5715
9 full batches	3 & 4	Within	55088	-38.29%	-21.16%	12452
1 full batch	3 & 4	Across	78224	-12.37%	0.00%	14
2 full batches	3 & 4	Across	69644	-21.98%	-10.97%	17
3 full batches	3 & 4	Across	65656	-26.45%	-16.07%	53
4 full batches	3 & 4	Across	63692	-28.65%	-18.58%	110
5 full batches	3 & 4	Across	61752	-30.82%	-21.06%	273
6 full batches	3 & 4	Across	60776	-31.91%	-22.31%	912
7 full batches	3 & 4	Across	60052	-32.72%	-23.23%	3269
8 full batches	3 & 4	Across	59180	-33.70%	-24.35%	7583
9 full batches	3 & 4	Across	58832	-34.09%	-24.79%	26717

Table 7.26: Travel distance by integrating all three warehouse processes for different chunk sizes for a whole week in the frozen zone

Conclusion

Table 7.27 shows for each zone the best performing configuration when integrating the three warehouse processes together. This table shows that, for selecting the optimal configuration, the layout and allocation policy can differ per zone. The characteristics of the warehouse play an important role in finding the optimal configuration. The results for the ambient and chilled zone are quite comparable, which is caused by the similarities between both zones. Both zones are a rectangular warehouse layout that follow the S shape heuristic. For those warehouses it can be concluded that two midaisles will return better results than none or one midaisle. Also the across-aisle policy is better suitable for these warehouse layouts and will outperform the within-aisle policy. For the frozen zone exactly the opposite holds. The within-aisle policy returns the best results and a layout without midaisle is the optimal configuration. The frozen zone is most effective by its allocation policy. Combining the allocation policy with the JOBPRP model will enhance this effect, as routes can optimally profit from the allocation policy.

Process	Layout	Allocation	Batching[3]	Ambient	Chilled	Frozen
All three processes	Single	Within-aisle	(5,8,8)	-43.93%	-22.93%	-40.74%
	Single	Across-aisle	(5,8,9)	-44.75%	-25.23%	-36.58%
	Double	Within-aisle	(5,8,9)	-45.35%	-27.18%	-38.29%
	Double	Across-aisle	(5,8,9)	-48.19%	-30.45%	-34.09%

Table 7.27: Best performing configurations for a combination between two processes relative to the benchmark result

[3]The numbers represent the number of full chunks for the respective zones.

7.5. Relation warehouse processes

This chapter's evaluation assesses the impact of various combinations of warehouse processes in relation to Crisp's benchmark results. However, some picking carts are not loaded with their maximum capacity, distorting the JOBPRP model's performance. With a chunk size of one full batch, there is an improvement over the benchmark. It is essential to account for this to make a fair comparison between each warehouse process. In the chilled and frozen zones, there's a discrepancy of 2 picking carts on 16-10, whereas in the ambient section, there is a 11-cart difference on 16-10. The weekly effect of this difference is even larger. To find the relative impact of warehouse processes, a new benchmark is established. The new standard uses the JOBPRP model with a chunk size of 1 full batch applied to the single-block warehouse without an allocation policy. The actual formed batches are thus replaced by this fully loaded batches, this new benchmark is shown in Table 7.28. For the chilled and frozen zones, this benchmark is quite similar compared to the real formed batched. However in the ambient zone, it differs significantly. By selecting the best performing configurations outlined in this chapter and then comparing their outcomes to this benchmark, the true impact of the warehouse processes can be evaluated. This comparison is illustrated in Table 7.29. As the number of batches formed remains consistent in each scenario, we can draw clear conclusions about the effect of each configuration.

Due to the uniform chunk size per zone, the effect of all warehouse processes can be compared to each other and we can identify the effect of the (combination of) processes on the order picking efficiency. The impact of the optimization of a single or multiple warehouse processes is depending on the characteristics of the warehouse. Each warehouse is unique, resulting in a different optimal configuration. However for a rectangular layout, the ambient and chilled zone, some general remarks can be made. First of all focusing on a single warehouse process does in most cases not improve the efficiency. Adding midaisles or opting for a different allocation policy does not improve the travel distance on its own. Batching the parcels by using the JOBPRP model can improve the travel distance, but the percentage is depending on the number of aisles and the pick density of the warehouse. When combining two warehouse processes the influence for a combination between layout and allocation is in both zones comparable. However when applying the JOBPRP model the two zones differ from each other. Due to the high pick density and low number of aisles in the chilled zone, finding optimal routes with the JOBPRP model is challenging. Therefore, these results are lower than the ambient zone, where there is more freedom in finding these optimal routes. Combining two processes proves beneficial over altering only one of those two processes. An integration of all three warehouse processes returns in both zones the best performing operation. For both zones, it holds that a layout with 2 midaisles outperforms none or 1 midaisle. The within-aisle or across-aisle preference depends on the layout, although for standard multi-block configurations, the across-aisle option is typically favored for minimizing travel distance. However, the order pikcig concentration at the aisle entrances can lead to potential congestion. Using the JOBPRP model will always improve the outcomes of an FCFS approach. Compared to the most common warehouse, a single-block warehouse with a FCFS batching- and random storage policy, integrating all three processes results in an improvement ranging from 30-40%, depending on the warehouse characteristics. These results are based on chunk sizes with reasonable computation times, however the actual percentage could be larger if the model is solved for larger chunk sizes. The frozen zone is due to its layout and routing self-contained. The allocation policy has the biggest influence on this zone. Where in the ambient and chilled zone it has been effective to incorporate an extra midaisle in the layout, in the frozen zone this only leads to an increased travel distance as the midaisles are almost never used. For the frozen zone integrating an within-aisle policy and the JOBPRP model on a layout without midaisle will return the best performing configuration and improve the operation with 41.09%.

Zone	14-Oct	15-Oct	16-Oct	17-Oct	18-Oct	19-Oct	20-Oct	Total
Ambient (actual)	48784	30668	23723	28545	38330	32129	43673	245852
Ambient (new)	41327	26010	20808	24276	32368	27166	37793	209748
Chilled (actual))	56376	34715	29785	36124	45354	39149	52586	294089
Chilled (new)	55706	34454	29463	32522	44114	38479	51842	286580
Frozen (actual)	15944	11222	10154	10532	14446	12208	14756	89262
Frozen (new)	15684	10980	9936	10412	14300	11916	14316	87544
Total (actual)	121104	76605	63662	72330	98130	83486	111015	626332
Total (new)	112717	71444	60207	67210	90782	77561	103951	583872

Table 7.28: Benchmark travel distance for a full week in meters

Process	Layout	Allocation	Batching[4]	Ambient	Chilled	Frozen
Layout	Single	X	X	+2.19%	+0.21%	+5.05%
	Double	X	X	+0.84%	+2.28%	+10.05%
Allocation	X	Within-aisle	X	-1.04%	0.00%	-26.17%
	X	Across-aisle	X	-0.03%	0.00%	-17.37%
Batching	X	X	(4,8,9)	-10.65%	-0.10%	-6.03%
Layout & Allocation	Single	Within-aisle	X	-5.23%	-5.86%	-22.24%
	Single	Across-aisle	X	-10.70%	-9.79%	-15.02%
	Double	Within-aisle	X	-6.28%	-7.68%	-20.19%
	Double	Across-aisle	X	-13.84%	-12.41%	-10.65%
Layout & Batching	Single	X	(4,8,9)	-12.47%	-5.21%	-2.75%
	Double	X	(4,8,9)	-12.11%	-6.69%	+1.87%
Allocation & Batching	X	Within-aisle	(4,8,9)	-18.09%	-3.95%	**-41.09%**
	X	Across-aisle	(4,8,9)	-6.71%	-0.13%	-36.32%
All three processes	Single	Within-aisle	(4,8,9)	-31.80%	-21.68%	-39.58%
	Single	Across-aisle	(4,8,9)	-32.53%	-24.02%	-35.34%
	Double	Within-aisle	(4,8,9)	-34.28%	-26.00%	-37.07%
	Double	Across-aisle	(4,8,9)	**-35.53%**	**-29.33%**	-32.80%

Table 7.29: Results for all possible combinations of warehouse processes relative to the new benchmark

7.6. Conclusion

This chapter presents the results of the conducted experiments and thereby provides an answer to subquestion 5 and 6. For all zones in the Crisp warehouse, the effect is evaluated of optimizing for a single or combination of the warehouse processes. The best performing results are shown in Table 7.11, Table 7.22 and Table 7.27 for respectively one, two and three combined warehouse processes and summarized in Table 7.30. This are the best performing results all using different chunk sizes in the JOBPRP model. Increasing this chunk size, is proven to enhance the results but increases the computation time.

All combinations of warehouse processes are evaluated for the Crisp warehouse. The optimal configuration for the ambient and chilled zone, both rectangular warehouse layouts, are a 3-block layout with an across-aisle policy and the JOBPRP model applied. For the ambient zone, the midaisle are located at location 9 and 20, dividing the aisle in almost 3 even large subaisles. For the chilled zone the midaisles are located at location 18 and 29, resulting in a subaisle of 50% and two subaisles of 25%. The optimal configuration for the ambient zone reduces the total travel distance with 48.19% and for the chilled zone with 30.45%. For the frozen zone it is clear that the allocation policy has the biggest influence on this zone. Where in the ambient and chilled zone it has been effective to incorporate an extra midaisle in the layout, in the frozen zone this midaisles is not used only leads to an increased travel distance. For the frozen zone integrating an within-aisle policy and the JOBPRP model on a layout without midaisle will return the best performing configuration and improve the operation for Crisp with 42.56%. If all zones are configured to their optimal configuration, this will reduce the weekly travel distance with 39.14%. The routes for the optimal configurations for each zone for 16 October are visualized in Figure 7.18, which clearly shows the made shortcuts and the improvement on the travel distance. This improvement in travel distances leads to an decrease in time required for order picking. As each working hour costs money, this reduction will favor the operational costs. The reduction of 39.14% on the travel distance will lead to a saving of €130.000,- on a yearly basis for the operational costs of the order picking process. The calculation of these savings is provided in Appendix H.

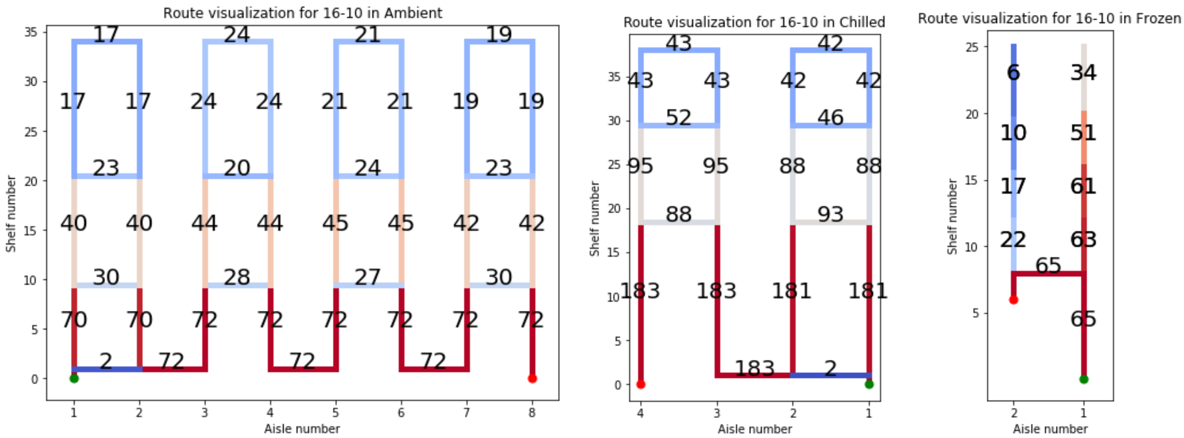
Due to the current batching process of Crisp not loading pick carts to their maximum capacity, evaluating the effect for different warehouse processes in based on a new benchmark that makes only full pick carts. This evaluating is provided in section 7.5. Improving the order picking process by altering one warehouse process has a limited effect on the travel distance. Incorporating two processes will enhance the results of a single process as the changes of possible shortcuts increase. The best performing warehouse configurations are however a combination between all three processes. The effect of each processes is always depending on the characteristics of the warehouse. When optimizing the warehouse, the first step is to find the best performing layout as this sets the boundaries for the other processes. Compared to the most common warehouse, a single-block warehouse with a FCFS batching- and random storage policy, integrating all three processes results in an improvement ranging

[4] The numbers represent the number of full chunks for the respective zones.

from 30-40%, depending on the warehouse characteristics.

Process	Layout	Allocation	Batching[5]	Ambient	Chilled	Frozen
Layout	Single	X	X	+0.15%	+0.1%	+4.95%
	Double	X	X	+1.15%	+1.99%	+9.94%
Allocation	X	Within-aisle	X	-1.93%	0.00%	-26.76%
	X	Across-aisle	X	-0.03%	+0.05%	-18.35%
Batching	X	X	(6,15,11)	-23.77%	-1.77%	-8.48%
Layout & Allocation	Single	Within-aisle	X	-7.43%	-6.55%	-24.19%
	Single	Across-aisle	X	-12.32%	-10.38%	-16.12%
	Double	Within-aisle	X	-8.97%	-8.53%	-20.88%
	Double	Across-aisle	X	-16.03%	-13.24%	-11.89%
Layout & Batching	Single	X	(4,8,9)	-25.32%	-6.72%	-4.62%
	Double	X	(4,8,9)	-25.01%	-8.18%	-0.09%
Allocation & Batching	X	Within-aisle	(6,12,10)	-33.88%	-6.01%	**-42.56%**
	X	Across-aisle	(6,12,10)	-23.44%	-1.69%	-38.14%
All three processes	Single	Within-aisle	(5,8,9)	-43.93%	-22.93%	-40.74%
	Single	Across-aisle	(5,8,9)	-44.75%	-25.23%	-36.58%
	Double	Within-aisle	(5,8,9)	-45.35%	-27.18%	-38.29%
	Double	Across-aisle	(5,8,9)	**-48.19%**	**-30.45%**	-34.09%

Table 7.30: Results for all possible combinations of warehouse processes relative to the benchmark of Crisp



(a) Ambient (b) Chilled (c) Frozen

Figure 7.18: Visualization of the routes on 16-10 for the best performing configuration for each zone

[5]The numbers represent the number of full chunks for the respective zones.

8
Conclusion

In this chapter, the final conclusion of this thesis is presented. It will provide an answer to the main research question: *"How can the order picking process in a large low-level picker-to-parts warehouse be optimized by incorporating different due times and multiple pickers, and what is the effect of the product allocation policy on the travel distance?"*. This research question was supported by several subquestions which will be answered separately before the conclusion of the main research question will be drawn.

Subquestion 1: *How is the current order picking process organized?*

Within the Crisp warehouse, multiple processes are employed between the receiving of product until the delivery. Products are received, occasionally pre-picked, stored, picked, and prepared for delivery. Orders are picked in three distinct zones, categorized by picking temperature. The picking process in each zone varies by parcel size, batch size and layout, yet all are picking following the S-shape heuristic. A blackbox- and CATWOE analysis were performed to find the key elements of the order picking system.

Subquestion 2: *Which warehouse processes influence the order picking performance and which approaches can be used to enhance the order picking performance?*

There are four main aspects found that have a significant influence of the warehouse operations; The layout, the product allocation, order batching and the routing. The configuration of the racks will set the physical outline for the rest of the warehouse processes and therefore influences the warehouse efficiency. How and where products are placed can influence the efficiency by placing specific products in the most easily accessible locations allowing for shortcuts in the routing. SKU's can be allocated with a random, dedicated and class-based policy. While random storage is the most space-efficient, dedicated and class-based storage policies generally improve picker efficiency and travel distances. Dedicated storage returns the highest picker efficiency, but suffers from low space utilization. Class-based storage strikes a balance between the two, offering a compromise in both space efficiency and travel distance reduction. With order batching, a given set of customer orders is batched into a feasible batch such that the objective function is minimized. Which orders are batched together depends on the the storage allocation and the routing method. When solving the JOBPRP, reducing the total travel distance is often the objective. Solving the batching and routing is found to be an effective combination to optimize the travel distance. All warehouse processes are connected and finding the best performing configuration will be a combination between all processes. This thesis applies an exact algorithm to solve the JOBPRP and uses the layout and allocation as input. To overcome computational challenges, the problem is divided into smaller parts, enabling an exact approximation approach. This method ensures solutions that closely approximate the optimal value while maintaining feasibility within the constraints of computational resources.

Subquestion 3: *How can a model be designed to minimize travel distance while simultaneously meeting the due times of orders?*

To create the model, the initial step involves defining the goal, key performance indicators, and model requirements. A constrained optimization model is then constructed to simulate the order picking process. This model's aim is to reduce the total travel distance, bound by the operational constraints. To ensure orders meet their due times, the data is sorted by delivery time. The data is structured so that orders processed together by the JOBPRP model are allowed to be batched together considered time limitations. The orders are processed in a first comes, first served principle.

Subquestion 4: *How can the developed model be applied to the Crisp warehouse using real-world data?*

The developed model can be adapted for any warehouse with appropriate modifications. The key aspect is the layout and how it's integrated into the model. This layout is depicted through a distance matrix, which details the distances between nodes within the warehouse. Each aisle's shelves are consolidated into a single node. Modifying the distance matrix values allows for adjustments to changes in the warehouse layout. In order to convert the data of Crisp into a format suitable for the JOBPRP model, certain data processing steps are necessary. Parameters, like the maximum batching capacity, can be conveniently modified to align with the real situation.

Subquestion 5: *How do different warehouse processes affect the performance of order picking operations in a picker-to-parts warehouse?*

The impact of the optimization of a single or multiple warehouse processes is depending on the characteristics of the warehouse. Each warehouse is unique, resulting in a different effect of each process. However for a rectangular layout, some general conclusions can be made. First of all focusing on a single warehouse process does in most cases not improve the efficiency. Adding midaisles or opting for a different allocation policy does not improve the travel distance on its own. Batching the parcels by using the JOBPRP model can improve the travel distance, but the percentage is depending on the number of aisles and the pick density of the warehouse. An combination between the warehouse processes will return a lower travel distance, however which combination is preferable is depending on the characteristics of the warehouse. The allocation policy can improve the travel distance by grouping high demanded SKUs together. This means most of the picks are concentrated to a smaller area of the warehouse, allowing to reduce the travel distance. This is only effective if possible shortcuts can be found. Adding midaisles can enhance the travel distance by allowing the picker to skip parts of an aisle. However adding a cross aisle has the downside that it uses space that was normally used as shelf. So the improvements obtained by adding a cross aisle is depending on the warehouse. The JOBPRP model improves the efficiency by batching similar parcels together, such that some batches can take shortcuts. This calculates the optimal batch strategy and will most likely improve the travel distance. The percentage of improvement is however depending on the other warehouse processes. Combining all three processes will affect the travel distance the most. The first step is finding the best suitable layout, as this demarcates the allocation and batching. Compared to the most common warehouse, a single-block warehouse with a FCFS batching- and random storage policy, integrating all three processes results in an improvement ranging from 30-40%, depending on the warehouse characteristics.

Subquestion 6: *For the low-level picker-to-part warehouse of Crisp, what are the optimal configurations for the different operational characteristics?*

To find the optimal configuration for the different zones with each their own characteristics all possible combinations of warehouse processes are evaluated. First the best performing layout for a single day are found, where after the most promising layouts are explored with larger datasets. For the ambient and chilled zone, both a rectangular warehouse layout, the optimal configuration is a 3-block layout with an across-aisle policy and the JOBPRP model applied. This optimal configuration is able to reduce the travel distance in the ambient zone with 48.19% for a chunk size of 5 full batches and in the chilled zone a reduction of 30.45% is made by a chunk size of 8 full batches. The frozen zone has quite different characteristics, which results in a different optimal configuration. The optimal frozen zone consists of a layout without added midaisles, an within-aisle policy and the JOBPRP model applied. This combination leads to a improvement of 42.56% for a chunk size of 10 full batches. With all three zones performing in their optimal configuration, the total weekly travel distance can be reduced with 39.14% for the warehouse of Crisp, reducing the order picking costs with €130.000.

Research question: *How can the order picking process in a large scale low-level picker-to-parts warehouse be optimized by incorporating different due times, and what is the effect of the integration of multiple warehouse processes on the travel distance?*

The research question is supported by the previous answered subquestions, which provide an general conclusion to the main research question: The order picking process in a large low-level picker-to-parts warehouse can be optimized through a holistic approach. The four defined warehouse processes, routing, layout, allocation and batching are all interconnected. Finding the optimal configuration is thus depending on all four processes. The effectiveness of these optimizations depends on warehouse-specific characteristics, requiring a detailed evaluation of the layout, pick density, and operational constraints. This thesis provides a framework for such evaluations, ensuring optimal configurations for diverse warehouse environments. The applied JOBPRP model uses an exact approximation approach. This method ensures solutions that closely approximate the optimal value while maintaining feasibility within the constraints of computational resources. This thesis evaluates a large order picking warehouse with a high pick density per batch. Compared to the most common warehouse, a single-block warehouse with a FCFS batching and random storage policy, integrating all three processes results in an improvement ranging from 30-40%, depending on the warehouse characteristics. The presence of a suitable allocation policy is proven to improve the outcomes of the order picking process as the locations of the SKUs are an important parameter for the JOBPRP model. However the effectiveness of the allocation policy is depending on the other warehouse processes and the possibilities to make short cuts in the routing. For the single-block warehouse zones of Crisp, solely adding a allocation policy has a negligible effect on the travel distance. Combing the allocation policy with other warehouse processes, such as the layout or batching, can improve the travel distance compared to a random allocation policy with respectively 7-16% and 2-34%. For the frozen zone, with total different characteristics, the allocation alone already yields an improvement of 26.75%. The allocation policy is thus of importance when optimizing the order picking process, however the percentage of improvement is depending on the warehouse and its characteristics.

9
Discussion and recommendations

The previous chapter has drawn the final conclusions to this thesis, however it is important to mention the gaps and limitations of this research and what could be the follow up steps in further research. This is described in this chapter.

9.1. Discussion

The developed model aims to be a good as possible representation of the reality, however the are some limititions and gaps compared to the reality that needs to be explained. This will be explained below point by point.

- **Product sizes**
  The model assumes each product has an uniform size. However in reality the SKUs all come in different sizes and need different storage sizes. Due to the uniformity that is assumed, this research places products at the same location that in reality exceed the available storage space. In the real case scenario the needed space to store all SKUs assigned to a single warehouse node by be larger or smaller. This will influence the found results as the travel distances of subaisles may increase or decrease.
- **Data processing**
  The data is processed in such a way that it is sorted per delivery route an in an ascending order of the delivery due time. This data is then solved by the model in specified chunk sizes. However which parcel is assigned to which batch affects the found travel distance reduction. Also due to the constraint that no parcels with an exceeding delivery time of 2 hours can be batched together, some chunks are cut off if this threshold is met. How many parcels are in the chunk that is cut off, has an effect on the found value. If this are only 3 parcels, a new route must be constructed for only 3 parcels. However if this is the 15th parcel, the effect is much less drastic.

9.2. Recommendations

The recommendations following from this thesis are divided into two categories; recommendations for further research and recommendations for Crisp.

9.2.1. Scientific recommendations

This thesis suggest an approach to solve the JOBPRP for large warehouse layouts with an high pick density. It is able to solve a large number of orders in a reasonable computation time. However there are always recommendations for further research. Which are described below:

- **Different routing policy**
  The proposed model uses the S-shape heuristic for the routing policy. However further research could evaluate the effect of different routing policies and investigate how these interact with the other warehouse processes. This can be incorporated into the model by changes to the distance matrix and applying minor changes to the constraints of the mathematical model.

- **The nearest-subaisle policy**
  The proposed allocation policies are independent of the layout. By this independency, changes to the layout do not require a new allocation policy. It would be interesting to see if dedicated allocation policies for each layout, such as the nearest-subaisle policy, return improved results compared to the across-aisle and within-aisle policy.

- **Asses the effect of congestion**
  Applying an allocation policy can decrease the travel distance, however has the downside of concentrating the picking process. It could be interesting to investigate the effect of the congestion on the picking time and to see if incorporating this in the objective value returns different results.

- **Dynamic picking times**
  The objective of this thesis is to reduce the total travel distance, however it could be interesting to evaluate the picking process based on the total picking time. By optimizing for the total picking time, a dynamic picking time can be implemented. With this is meant that picking multiple of the same SKUs generally takes less time than picking different time. Further research could focus on implementing this different picking time in the model.

9.2.2. Recommendations for Crisp

This thesis is performed in cooperation with Crisp, so this subsection will describe the recommendations concluded from this thesis for Crisp. The thesis concludes that the order picking process in the Crisp warehouse can be improved. This subsection will discuss the recommendations per zone and evaluates their possible improvements but also discussed the challenges with implementing these new configurations.

- **The ambient zone**
  Implementing a combination of all three processes in the ambient zone has shown to be able to reduce the travel distance with 43.35% and 48.19% for respectively a single and double midaisle layout. This uses and across-aisle policy which mean the SKU's should be divided into 2 or 3 classes (depending on the number of midaisles). This distinction can be made on weekly sales and be an variable parameter for each product. This configuration is proven to reduce the travel distance the most, however there is one downside of this configuration. Due to the chunk size of 4 full batches, 72 parcels are handled simultaneously by the JOBPRP model. In the current situation, the batches are consists of parcels that mostly are assigned to the same route. Selecting the a configuration that uses the JOBPRP model will distribute the order per route over different picking carts. This distribution of parcels will increase the complexity of the sorting process, as the parcels for a route are now distributed over more picking carts. The other possible option is to only optimize the order picking process by selecting a suitable layout with an allocation policy. The picking carts do now consist of parcels assigned to the same route, however this returns only an improvement of 16.03% compared to the 48.19% which is possible by integrating the JOBPRP model into the equation. The downside is with the across aisle policy the aisles become more sensitive for possible congestion, however the products are distributed over 10 shelves and if the pickers start as they do now, not all at once, this should be within the limitations.

- **The chilled zone**
  Integrating all warehouse processes can return an improvement of 30.45% of the travel distance. For the chilled zone, the recommendation is to integrate all three processes together. Where in the ambient zone it could be beneficial to exclude the JOBPRP model to reduce the sorting complexity, the chilled zone solves for 8 full batches with correspond to 48 parcels. In general 48 chilled parcels will be assigned to ±2 delivery route, making the complexity of the sorting less drastic than for the ambient zone. If the distribution between of 2 routes over 8 picking carts is considered to be undesired, the chunk size can also be reduced. With a chunk size of 4 full batches, the model found travel distance will be 4% higher, but has the positive effect that parcels of the same route are most likely to be placed in the same batch.

- **The frozen zone**
  The frozen zone is most sensitive to optimization by applying a suitable allocation policy. The recommendation is thus to relocate the SKUs in the frozen zone according to the within aisle

policy. Only implementing the allocation policy in the frozen zone will already improve the travel distance with 26.76%. Integrating the JOBPRP model returns an improvement of 42.56% for a chunk size of 10 full batches, which correspond to 40 parcels. A delivery route consists of ±4 parcels, meaning the parcels per chunk represents ±10 delivery routes. Applying the JOBPRP model will thus distribute the parcels of a delivery route over multiple picking carts. However due the relative low number of parcels, the extra sorting step should be able to be handled.

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Optimization of the order picking process for large scale FMCG picker-to-part warehouses - a Crisp casy study

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***Abstract*— Over the past decade, consumer shopping habits have increasingly shifted toward online grocery purchases, driving the need for efficient warehouse operations. This study addresses the Joint Order Batching Picker Routing Problem (JOBPRP) by developing an exact optimization approach and examining the interdependencies among key warehouse processes. Using a case study of Crisp B.V., an online grocery retailer, the proposed algorithm was implemented to optimize configurations across multiple temperature-controlled zones with varying operational characteristics. The approach yielded a 33.32% reduction in weekly travel distance compared to the benchmark. These findings highlight the significant impact of integrating order batching and picker routing on warehouse efficiency. The study not only demonstrates the critical correlation between warehouse processes but also provides actionable insights for optimizing order picking in high-density, large-scale warehouses.**

I. INTRODUCTION

In recent years, consumer shopping habits have undergone a significant transformation, shifting from in-store purchases to online shopping. This trend has been driven by advancements in internet technology, which have made online shopping more accessible and convenient. Although the rise of e-Commerce initially focused on traditional parcels such as clothing and electronics, it has now expanded to include fast-moving consumer goods (FMCG). Supermarkets increasingly offer online platforms with next-day grocery delivery, reflecting this shift in consumer behavior.

This surge in online shopping has put greater demands on warehouse operations, which serve as a crucial component of the supply chain. Warehousing processes, including receiving, storing, order picking, and shipping, must be executed with maximum efficiency to meet growing consumer expectations and remain competitive. Among these, order picking is the most resource-intensive operation, accounting for approximately 55% of total warehouse operating costs (Karásek, 2013). This makes it a critical focus for optimization, particularly in FMCG warehouses, where large and diverse orders must be processed efficiently to meet daily demand.

The complexity of optimizing order picking stems from its dependency on several interrelated factors, including warehouse layout design, routing policies, product allocation strategies, and order batching. Each of these processes influences performance, but their interdependencies make it challenging to identify an optimal configuration. For example, layout decisions determine the foundation for all subsequent processes, while routing policies, product allocation, and batching must be carefully coordinated to minimize travel distances and operational costs. These problems are often modeled as Mixed-Integer Programming (MIP) problems, which are computationally complex (NP-hard). Consequently, there is growing interest in integrated approaches that address these challenges holistically to improve warehouse efficiency.

This research investigates the optimization of the order picking process in collaboration with Crisp, a Dutch online supermarket specializing in fresh, sustainable, and locally sourced products. Unlike larger supermarkets, Crisp maintains a curated product assortment, typically avoiding duplicate brands for similar items. This allows for a streamlined logistics approach while meeting high standards of sustainability and quality.

Crisp operates two warehouses, located in Amsterdam and Breda, along with three cross-docking hubs. These facilities handle a daily order volume of 1,500 to 3,500 orders, with approximately 70% processed in Amsterdam and the remaining 30% in Breda. The warehouses employ a low-level picker-to-parts system, where pickers retrieve products directly from accessible racks without mechanical assistance. The facilities are divided into three temperature-specific zones —ambient, chilled, and frozen— to accommodate different storage requirements. Each zone has unique operational characteristics, such as varying order sizes, cart capacities, and layouts. Because its relatively simple current setup, Crisp's order picking process offers significant opportunities for improvement. By addressing key challenges such as layout design, routing, and batching, this research aims to optimize the process by reducing the travel distance.

With the increasing reliance on warehouses, research dedicated to warehouse optimization has grown significantly. Most studies focus on either routing or batching optimization, with limited efforts to integrate these processes into a joint approach. Furthermore, existing research often examines scenarios with low pick density per batch and small batch sizes, making their applicability to large-scale operations limited. This study contributes to the field by adapting the Joint Order Batching and Picker Routing Problem (JOBPRP) to a large-scale warehouse environment characterized by high pick density per batch. It seeks to address the following research question:

How can the order picking process in a large scale low-level picker-to-parts warehouse be optimized by incorporating different due times, and what is the effect of the integration of multiple warehouse processes on the travel distance?

The rest of the paper is organized as follows: Section II will review the related literature. Section III will formulate the problem and formulate a mixed-integer programming model. Section IV will provide a case study based on the warehouse of Crisp. After which Section V will provide the conclusion and recommendations.

II. LITERATURE REVIEW

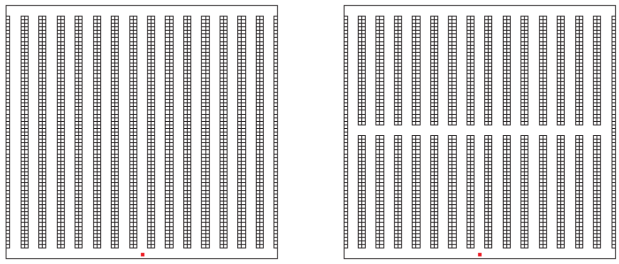
The literature review chapter examines the key concepts regarding optimizing a picker to part warehouse. This aims to provide a comprehensive understanding on all the relevant aspects of warehouse optimization. The decisions regarding the order picking process can be categorized on a strategic, tactical and operational level (Rouwenhorst et al., 2000; van Gils et al., 2018).

A. Strategic level

Strategic-level decisions in warehouse design encompass long-term considerations with significant investment implications, such as the level of automation, equipment selection, and picking policies (Rouwenhorst et al., 2000; van Gils et al., 2018). The level of automation reflects the extent to which manual processes are replaced by automated systems, ranging from fully manual to fully automated operations. Equipment requirements vary based on automation levels. In low-level picker-to-parts systems, critical equipment includes picking carts, which can be customized for size, weight capacity, and drivetrain, as well as devices for guiding pickers, such as scanners. Additionally, low-level or high-level shelves impact equipment needs and overall efficiency (Rouwenhorst et al., 2000). The picking policy defines how orders are retrieved and is closely linked to automation and equipment choices. Dallari et al. (2009) identified five picking strategies; Picker-to-parts, pick-to-box, pick-and-sort, parts-to-picker and automated picking, which influence operational efficiency and equipment requirements.

B. Tactical level

At the tactical level, decisions are made that impact the medium term (van Gils et al., 2018), based on the outcomes of the strategic decisions (Rouwenhorst et al., 2000). Tactical decisions typically concern the dimensions of resources (e.g. storage size, storage capacity, number of employees), the determination of the layout and storage assignment (Rouwenhorst et al., 2000). The dimensions of a warehouse are constrained by its physical structure, which dictates its total size. Within these bounds, the warehouse is segmented into zones dedicated to specific functions, such as picking, inbound, outbound, and backstock operations. Determining the size of each zone is a critical tactical decision. Warehouse layout is a key component of operational performance, directly affecting order picking and travel distances (Karásek, 2013; Mohamud et al., 2023). It demarcates the dimensions for the other warehouse operations. The aisle configuration can have a significant effect on order picking and the travel distances (Karásek, 2013). A conventional layout is shown in Figure 1a. Adding cross aisles in a warehouse layout has been researched in various studies. Roodbergen et al. (2008) concluded that, apart from special cases with a very high picking density, it is always favorable to have a multiple block layout. The research done by Ertek et al. (2007) presented a detailed discussion of the impact of cross aisles on a rectangular warehouse. They defined the optimal amount of cross aisles with respect to the amount of aisles and the length of the aisles. hey concluded that establishing cross aisles can bring significant travel-time savings and that it is more desirable to establish only equally spaced cross blocks than unequally spaced cross blocks. This is in contrary to the research by Küçük (2003), which concluded that a lower number of unequally spaced cross aisles provide the same travel distance reductions due to a higher number of equally spaced cross aisles.Berglund and Batta (2012) presented a method for calculating the maximal efficient cross aisle positions for a picker-to-parts warehouse. The proposed method is suitable for multiple warehouse sizes, different storing policies and can vary the amount of cross aisles. Besides the conventional rectangular warehouse designs, the studies of Gue and Meller (2008), Gue et al. (2012), Pohl et al. (2010),Dukic and Opetuk (2012), Çelik et al. (2012) study the effects of non-conventional layouts. Çelik et al. (2012) compared the fishbone layout with a conventional layout with two middle cross aisles. Their study finds that the conventional layout will outperform the fishbone layout for all orders with 3 or more picks.

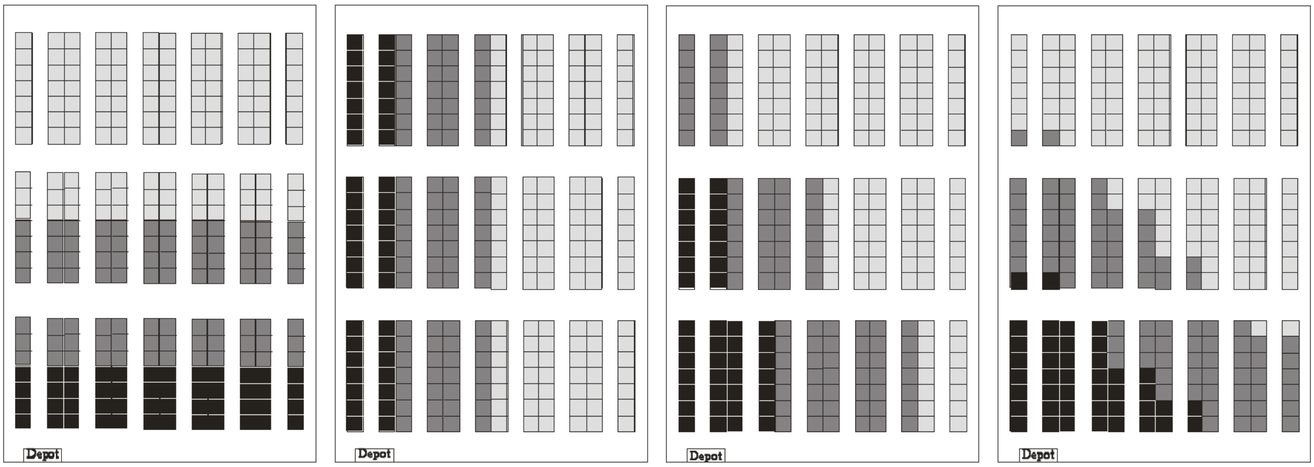


(a) Conventional warehouse layout, single block

(b) Warehouse layout with middle cross aisle, multi-block

Fig. 1: Conventional layouts with a single P&D point (adapted from: (Gue & Meller, 2008))

There are numerous ways to store products within the warehouse. The effect of the product allocation policy is related to the routing policy. The simplest storage method is the *random storage policy*. In this policy the Storage Keeping Units (SKU's) are assigned to a randomly selected location in the warehouse (De Koster et al., 2007). The *closest open location policy* is in most aspects similar to the random storage policy, however the SKU's will be stocked in the first encountered empty location, concentrating the SKU's



(a) Across-aisle storage (b) Within-aisle storage (c) Nearest-subaisle storage (d) Nearest-location storage

Fig. 2: class-based storage assignment configurations; *Black boxes are class A, Dark grey boxes are class B, Light boxes are class C* (taken from: (Roodbergen, 2012))

around the P&D point. Unlike the *random- and closest open location policy*, dedicated storage policies store SKU's at their dedicated place. The disadvantage of this is that a location is also reserved for products that are out of stock, which leads to the lowest space utilization among all policies (De Koster et al., 2007). The *class-based storage policy* combines the random and dedicated storage policies. It first divides all SKU's in several classes. Each class is dedicated to a specific area of the warehouse where the storage of SKU's is done randomly. In assigning the classes to an area in the warehouse multiple configurations are possible as shown in Figure 2.

C. Operational level

At the operational level, processes have to be carried out within the boundaries set at the strategic and technical level. The decisions typically concern daily operations such as job assignment, batch formation and the routing. In every picker-to-part warehouse, an order picker must follow a route to visit all pick up locations. Routing will impact the order picking efficiency as it directly impacts the travel distance. The routing plays a role in almost every study related to warehouse optimization as most of the objectives are directly linked with the travel distance. The algorithm used to solve the routing problem can be classified in three general types; an exact algorithm, heuristics, and meta-heuristics (Masae et al., 2020). For a single-block warehouse with narrow aisles there are 5 *basic* heuristics defined in literature. The *traversal (S-shape)*, the *midpoint*, the *largest gap* heuristic, the *return* and the *composite* heuristic. The S-shape heuristic is the most common heuristic and also used in this research. The heuristic is visualized in Figure 3

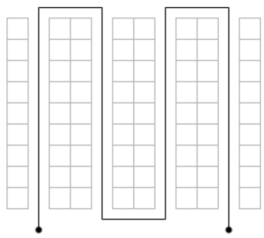


Fig. 3: S-shape heuristic

The *basic* heuristics were originally developed for a single block layout, nevertheless the studies of Roodbergen and De Koster (2001a), Vaughan and Petersen (1999) and Shouman et al. (2007) extended these heuristics to a multiple block layout and defined new heuristics. Exact algorithms tend to find an optimal solution to the PRP. The work of Ratliff and Rosenthal (1983) is seen as a seminar work. Ratliff and Rosenthal (1983) is specified to a single block warehouse, so multiple authors extended the algorithm to a multiple block warehouse. Roodbergen and De Koster (2001b) were the first to extend the research to a conventional warehouse with a middle cross aisle. Chabot et al. (2017) used a branch-and-cut algorithm to solve the order picking problem with precedence constraints. They concluded that both the exact algorithms are performing better than heuristics, but have longer computational times. The study of Theys et al. (2010) is in essence quite similar. The study applied an exact algorithm and compared the results to heuristics. The exact results are obtained by using the exact Concorde TSP algorithm, which uses a branch-and-cut algorithm to find the shortest route. Matusiak et al. (2014) used the A* algorithm, which is based on dynamic programming, to solve the combined precedence-constrained order picker routing and order batching problem. Su et al. (2023) proposed two mathematical optimization formulations for the multi-block layout with Mixed Integer Linear Programming (MILP). Meta-heuristics are mostly used to solve a combination of multiple order picking problems at once. The most commonly used meta-heuristics are (Masae et al., 2020): *Genetic Algorithms (GA), Simulated Annealing (SA), a Tabu Search*

(TS), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and *Adaptive Large Neighborhood Search (ALNS)*. Meta-heuristics typically return results comparable to results provided by exact algorithms, but in general use less computation time and find near optimal solutions instead of the optimal solution. The studies of Tsai et al. (2008), Kordos et al. (2020), Lin et al. (2016) and Chen et al. (2016) all solve the PRP by using one of the mentioned meta-heuristics. The different meta-heuristics are all capable of solving the PRP and all approach the optimal solution.

The Order Batching Problem (OBP) is the grouping of a given set of customer orders into feasible picking orders such that the objective function is minimized. When solving the order batching problem exact, it can be considered as a NP-hard problem and many studies focus on developing algorithms or (meta-)heuristics for solving it. It is most effective when combined with the PRP, solving the Joint Order Batching Picker Routing Problem (JOBPRP). Ene and Öztürk (2012) represent the JOBPRP with an integer programming formulation. Due to the need for short computation time, they solve this problem by using a genetic algorithm to approximate the results. Won and Olafsson (2005) proposed two different heuristics to solve the JOBPRP. Their solution is based on combining a Bin-Packing Problem (BPP) with a TSP. The first heuristic is the Sequential Order Batching and Picking (SBP) algorithm. It is sequential in the sense that it first solves the batching problem and then solves the picking problem for these batches. The second heuristic, the Joint Order Batching and Picking (JBP) algorithm, simultaneously constructs batches and tours. Tsai et al. (2008) proposed a multi-GA method to solve the JOBPRP. It consists of two genetic algorithms, one for the batching and one for the routing. Solving the JOBPRP can be divided in two main solution approaches; integrating both problems in one optimization problem, or iterative solving both problems sequentially.

III. MODEL DEVELOPMENT

A. Modeled situation

The goal of this research is to define an optimal order picking operation in the Crisp warehouse. The literature review outlined four main aspects of warehouse optimization; the layout, the product allocation, the batching method and the routing. The layout and the product allocation are considered as input for the JOBPRP model, which combines the other two aspects. The objective of the model is to minimize the total travel distance of the picking carts. Figure 4 gives a black box representation of the JOBPRP model.

The model should be a valid representation of reality, giving it a few requirements is should meet. The requirements are the following:

- A parcel should be picked entirely in a single batch, it can not be splitsed.
- Each picking zone has an unique maximum capacity of parcels per batch.
- Each order should be picked before their pick deadline.

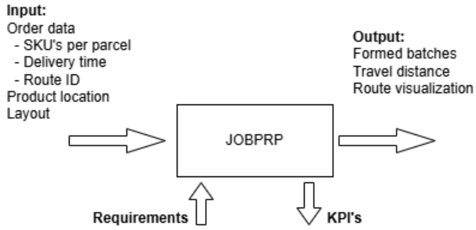


Fig. 4: Blackbox representation of the JOBPRP model

- The route visits the locations only one time, so no detours are allowed.
- The aisles have directional traffic and follow the S-shape heuristic.
- In a batch, the maximum time difference between the pick deadline of 2 parcels is 2 hours.
- To reduce the complexity in the rest of the supply chain, parcels on the same delivery route are batched as much as possible together

These requirements are either addressed by the constraints within the mathematical model or managed through the relevant input data. The requirements set the boundaries for the model. The model should be as close to reality as possible, however to model a real situation some assumptions are made. This is because modeling the actual situation is too complex and can be simplified with a few assumptions. The made assumptions and simplification are the following:

- The routing considered is the S-shape (traversal) heuristic
- Product locations are considered per shelf instead of single locations
- Travel distances between the picking cart and the shelves are neglected
- For the reallocation of SKU's, the SKU's are assumed to be uniform
- Parcels can consist of multiple containers, however containers are not interchanged to other parcels
- The chunks of input data do not contain parcels with a delivery time with a difference of more than 2 hours.
- The current batches are loaded to their maximum capacity

These simplifications and assumptions help to model the warehouse in a manageable way, reducing its complexity. Due to the one-directional aisles, if an aisle is entered, the entire aisle is traversed. This allows for the consolidation of all the locations within a given aisle into a single node, while still capturing the fact that all locations within the aisle are visited. By modeling entire aisles as single nodes, the size of the distance matrix is reduced, leading to fewer locations to consider in the optimization process. Through these simplifications, the JOBPRP model remains computationally feasible, while still being a close approximation to real-world conditions.

The distance matrix, denoted as $d_{i,j}$, represents the travel distance between nodes i and j. Each node corresponds to a (sub)aisle in the warehouse. This matrix encapsulates the layout of the warehouse and serves as a crucial input. In a rectangular warehouse layout, this node-based representation is visualized in Figure 7a, where m represents the number of aisles, and n represents the number of locations per aisle. The general form of the distance matrix is given in Figure 5 and the matrix for a S-shape in Figure 6, with M being a very large number.

$$d_{ij} = \begin{bmatrix} d_{PD,PD} & d_{PD,1} & d_{PD,2} & d_{PD,3} & \cdots & d_{PD,nm} \\ d_{1,PD} & d_{1,1} & d_{1,2} & d_{1,3} & \cdots & d_{1,nm} \\ d_{2,PD} & d_{2,1} & d_{2,2} & d_{2,3} & \cdots & d_{2,nm} \\ d_{3,PD} & d_{3,1} & d_{3,2} & d_{3,3} & \cdots & d_{3,nm} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{nm,PD} & d_{nm,1} & d_{nm,2} & d_{nm,3} & \cdots & d_{nm,nm} \end{bmatrix}$$

Fig. 5: Distance matrix

$$d_{ij} = \begin{bmatrix} 0 & d_{PD,1} & d_{PD,2} & d_{PD,3} & \cdots & d_{PD,nm} \\ d_{1,PD} & 0 & d_{1,2} & d_{1,3} & \cdots & d_{1,nm} \\ d_{2,PD} & M & 0 & d_{2,2} & \cdots & d_{2,nm} \\ d_{3,PD} & M & M & 0 & \cdots & d_{3,nm} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{1,PD} & M & M & M & \cdots & 0 \end{bmatrix}$$

Fig. 6: Distance matrix S-shape

B. Mathematical model

The mathematical model is based on the works of Kulak et al. (2012) and Cano et al. (2021). Which provide the basis of this mathematical model and provided the first 5 constraints. The last two constraints are designed to fit the configuration for Crisp.

Sets and Indices

- $b \in B$: Set of Batches
- $p \in P$: Set of Parcels
- $i, j \in L$: Set of storage locations
- $I_p \subset L$: Set of storage locations per parcel $\forall p \in P$

Parameters

- Q : Max batch capacity
- W_p : Weight per parcel $\forall p \in P$
- $d_{i,j}$: Distance matrix between i and j

Binary decision variables

$$x_{i,j,b} = \begin{cases} 1 & \text{If the route for batch } b \text{ goes from the, location to perform pick operation } i \text{ to the location to perform pick operation } j \\ 0 & \text{otherwise.} \end{cases}$$

$$y_{p,b} = \begin{cases} 1 & \text{if parcel } p \text{ is performed by batch } b \\ 0 & \text{otherwise} \end{cases}$$

The objective function is:

$$\text{Min} \sum_{b \in B} \sum_{(i,j) \in L} d_{ij} x_{i,j,b} \tag{1}$$

s.t.

1) Each parcel is assigned to one batch only

$$\sum_{b \in B} y_{p,b} = 1 \quad \forall p \in P \tag{2}$$

2) Each route starts in the P&D point

$$\sum_{j \in L} x_{0,j,b} = 1 \quad \forall b \in B \tag{3}$$

3) Each route ends in the P&D point

$$\sum_{i \in L} x_{i,0,b} = 1 \quad \forall b \in B \tag{4}$$

4) A visited pick location in batch b should also be left by batch b

$$\sum_{j \in L} x_{i,j,b} = \sum_{j \in L} x_{j,i,b} \quad \forall i \in I, \forall b \in B \tag{5}$$

5) Each batch has a maximum capacity

$$\sum_{p \in P} W_o \cdot y_{p,b} \leq Q \quad \forall b \in B \tag{6}$$

6) Subtour elimination

$$x_{i,j,b} = 0 \quad \forall b \in B, \forall i \in L, \forall j \in L \setminus \{0\} \text{ and } j \leq i \tag{7}$$

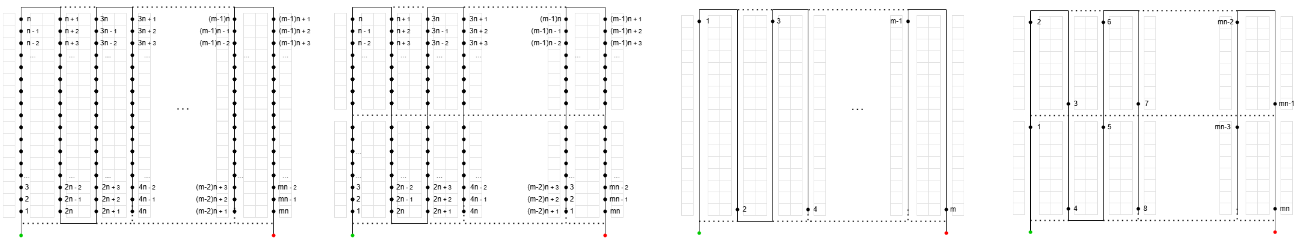
7) If parcel p is assigned to batch b, all pick locations of parcel p are visited by batch b

$$y_{p,b} \leq \sum_{j \in L} x_{i,j,b} \quad \forall p \in P, \forall i \in I_p, \forall b \in B \tag{8}$$

The objective function in 1 minimizes the total travel distance. The constraint in 2 ensures that all parcels are only assigned to one batch only. The constraints in 3 and 4 ensure that the picker starts and finishes their route in the P&D point. Constraint 5 ensures that a visited location by a batch is also left by the same batch. The constraint in 6 ensure that the constructed batches not do exceed the maximum capacity of the pick carts. 7 ensures the one directional flow, the picker is due to this constraint not allowed to move back to previous locations. Constraint 8 ensures that if a parcel is assigned to a batch, that batch visits all locations of the parcel. The JOBPRP model is solved for chunks of the full problem. Each chunk has a maximum parcel capapcity, proposing an exact approximation of the full problem. The JOBPRP model is solved with the solver Gurobi, version 9.1.2. on a computer with a 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHZ with 4 cores CPU and 16 GB of RAM.

IV. CASE STUDY AND RESULTS

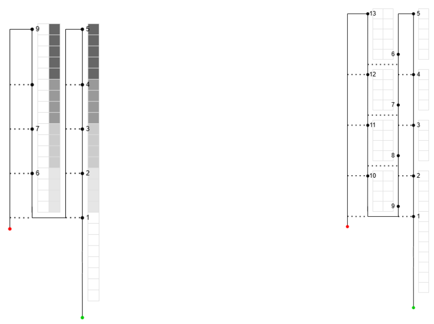
The JOBPRP model is applied to the different order picking zones of Crisp. For the model to reflect each zone, some slight adjustments to the model are made. The research evaluates the influence of two distinct allocation policies, which are elaborated as well. Each zone has their own characteristics, which can be found in Table I. The ambient and chilled zone can both be approached as an rectangular



(a) no midaisle (b) with midaisle (c) no midaisle simplified (d) with midaisle simplified

Fig. 7: Simplified node representation of the locations in the warehouse

warehouse. The simplified node representation presented in Figure 7 is therefore applicable. The frozen zone is in terms of layout quite different than the ambient and chilled zone. This is because the frozen zone is not a standard rectangular warehouse. It is built using the available space and therefore differs with respect to the other two zones. The picking strategy is also quite different, where in the ambient and chilled zone the picker picks on both sides of the aisle, the picker in the frozen zone only picks at the right hand side. This means that when moving from the first to the second aisle, the picker will not be bound by midaisles, they can just cross anywhere they like. Moving from the second to the third aisle however, is again bound by the physical midaisle. The simplified representations are shown in Figure 8. If there are no midaisle, the locations in the first and second aisle are modeled at one node. This can be seen with the hatching in Figure 8a.

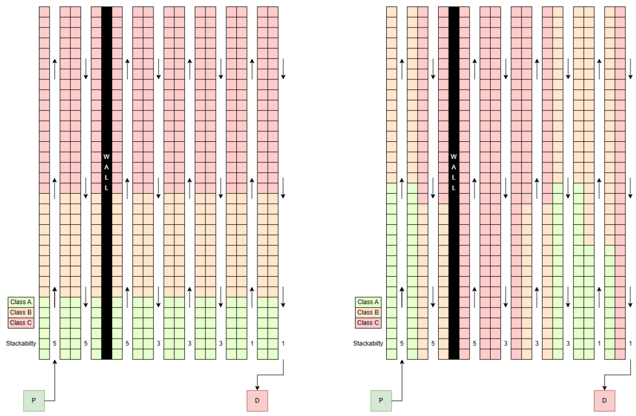


(a) no midaisle (b) with midaisle at any location

Fig. 8: Simplified node representation of the locations in the frozen zone

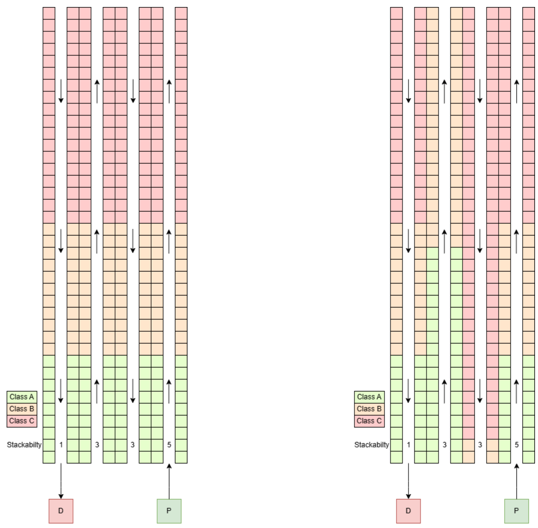
A. Allocation policies

This research evaluates the benchmark (random allocation policy) to the across-aisle and within-aisle policy. These policies are class-based storage policies. Meaning the SKUs are assinged to a class based on popularity. Each class has assigned locations in the warehouse. The visualization of these policies are depcited per zone are depicted in Figure 9-11



(a) Across-aisle policy (b) Within-aisle policy

Fig. 9: Product allocation policies for the ambient zone



(a) Across-aisle policy (b) Within-aisle policy

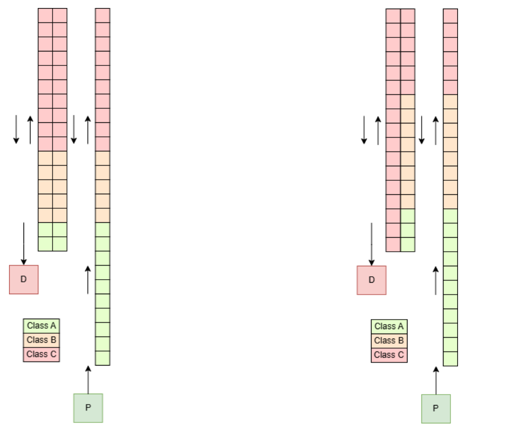
Fig. 10: Product allocation policies for the chilled zone

B. Benchmark results

The benchmark results represent the travel distance for full batches in the actual configuration. The warehouse of Crisp and their order picking process can be compared to a single block low-level picker-to-parts warehouse with a First-Come-First-Served (FCFS) batching policy, S-shape routing

TABLE I: Specifications per picking zone

Zone	Storage locations	# SKU's	Parcels per batch	Range picks/parcel	Average parel size	average picks/batch
Ambient	4800	3500	18	[1-25]	12	180
Chilled	3500	2000	6	[1-20]	15	90
Frozen	800	500	4	[1-35]	20	75



(a) Across-aisle policy (b) Within-aisle policy

Fig. 11: Product allocation policies for the frozen zone

heuristic, and random product allocation policy. In daily operations, Crisp encounters what is called 'missings', which occur when a SKU is out of stock at the time a batch reaches the SKU's location. The parcel with a missing SKU is then placed on a new special "missing pick cart', which solely retrieves the missing SKU once it is restocked. This leads to additional travel distance. However, when computing benchmark results, these 'missings' are not considered. The benchmark assumes a scenario in which there are no missing SKUs, as this aspect is also excluded from the JOBPRP model.

Zone	Travel distance [m]
Ambient	209748
Chilled	286580
Frozen	87544
Total	583872

TABLE II: Benchmark travel distance for a full week in meters

C. Results

Table III shows the results for optimizing by adjusting each (combination of) warehouse processes. For all the combinations that optimize by changes to the layout, first the best performing layout is found with the data of a single day. This reduces the computation time as for the ambient and chilled zone respectively 406 and 527 distinct layouts are evaluated. The best performing instances are then evaluated on the weekly data. The performance of the JOBPRP model depends on the selected chunk size. Due to computational limits, the model solves the problem in small chunks. Increasing the number of parcels that are solved per chunk, the model returns improved solutions, however with a larger computation time as the result. The results in Table III display the best performing configurations for each of the combinations. The best performing combination all integrate the JOBPRP model, with an allocation policy and a suiting layout. Applying the JOBPRP model performs thus the best if combined with the other processes incorporated. This combination of processes makes the JOBPRP able to construct more favorable batches and enhances its result. The performance of altering warehouse processes is depending on the possibility to find shortcuts in the routing. The results depict the interplay between different processes and which combinations are preferable for different warehouse charestericties.

V. CONCLUSION

This research investigated how the order picking process in a large low-level picker-to-parts warehouse can be optimized by assessing the impact of all different warehouse processes on the travel distance. By examining the interplay between key warehouse processes —layout, product allocation, order batching, and routing— a comprehensive optimization framework was developed and tested using real-world data.

The study revealed that warehouse efficiency is influenced by the integration of these processes rather than by optimizing them in isolation. The warehouse layout sets the physical boundaries for operations, with the configuration of aisles and cross-aisles impacting picker movement. Product allocation policies, such as class-based storage, play a significant role in reducing travel distances by strategically grouping frequently picked items. Order batching and routing further enhance efficiency by minimizing redundant travel through careful grouping and sequencing of customer orders.

A constrained optimization model was developed to address the Joint Order Batching and Picker Routing Problem (JOBPRP), aiming to minimize travel distances. The model employed an exact approximation approach to balance computational feasibility and solution quality, enabling the application of optimization techniques to large-scale instances.

For the Crisp warehouse, custom configurations were identified for each picking zone. The ambient and chilled zones benefited from a 3-block layout with across-aisle policies, achieving travel distance reductions of 35.53% and 29.33%, respectively. The frozen zone required a different approach, using a within-aisle policy without mid-aisles, which reduced

[1]The numbers represent the number of full chunks for the respective zones.

TABLE III: Results for all possible combinations of warehouse processes relative to the benchmark result

Process	Layout	Allocation	Batching[1]	Ambient	Chilled	Frozen
Layout	Single	X	X	+2.19%	+0.21%	+5.05%
	Double	X	X	+0.84%	+2.28%	+10.05%
Allocation	X	Within-aisle	X	-1.04%	0.00%	-26.17%
	X	Across-aisle	X	-0.03%	0.00%	-17.37%
Batching	X	X	(4,8,9)	-10.65%	-0.10%	-6.03%
Layout & Allocation	Single	Within-aisle	X	-5.23%	-5.86%	-22.24%
	Single	Across-aisle	X	-10.70%	-9.79%	-15.02%
	Double	Within-aisle	X	-6.28%	-7.68%	-20.19%
	Double	Across-aisle	X	-13.84%	-12.41%	-10.65%
Layout & Batching	Single	X	(4,8,9)	-12.47%	-5.21%	-2.75%
	Double	X	(4,8,9)	-12.11%	-6.69%	+1.87%
Allocation & Batching	X	Within-aisle	(4,8,9)	-18.09%	-3.95%	**-41.09%**
	X	Across-aisle	(4,8,8)	-6.71%	-0.13%	-36.32%
All three processes	Single	Within-aisle	(4,8,9)	-31.80%	-21.68%	-39.58%
	Single	Across-aisle	(4,8,9)	-32.53%	-24.02%	-35.34%
	Double	Within-aisle	(4,8,9)	-34.28%	-26.00%	-37.07%
	Double	Across-aisle	(4,8,9)	**-35.53%**	**-29.33%**	-32.80%

travel distance by 41.09%. Collectively, these optimizations reduced total weekly travel distance by 33.32%.

This research underscores the importance of a holistic approach to warehouse optimization. The interplay between layout, allocation, batching, and routing processes must be carefully tailored to the specific characteristics of the warehouse. The developed framework provides a scalable and adaptable solution for optimizing large-scale order picking systems, offering practical insights to improve efficiency in diverse warehouse environments.

This study highlights several gaps and limitations that could be interesting for further research. This research assumes uniform product sizes, which does not reflect the reality of diverse SKU dimensions. Further research could adjust the product allocation policies to incorporate the non-uniformity. This research is limited to the S-shape heuristics for the routing, further research could evaluate the effect of different routing policies and investigate how these interact with the other warehouse processes. The objective of this thesis is to reduce the total travel distance, however it could be interesting to evaluate the picking process based on the total picking time. By optimizing for the total picking time, a dynamic picking time can be implemented. With this is meant that picking multiple of the same SKUs generally takes less time than picking different time. Further research could focus on implementing this different picking time in the model. This could also be combined with research on the effect of congestion, as this is also neglected in this study.

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B Data processing

The picking data of Crisp can not be used as input for the JOBPRP model without any processing steps. The data of Crisp is namely per scan hit. This means each scanned product will generate a data row. A small part of the full data set can be found in Table B.1. This is transformed to a suitable data format, shown in Table B.2, by the following steps:

1. Read data file
2. Process data
    - Remove unnecessary data columns
    - Convert 'stock_product_id' to string
    - Group data by parcel and concatenate 'stock_location' as a string
3. Assign unique location numbers
    - Split stock locations, assign numbers, remove duplicates, and sort
4. Sort by 'Delivery_Time' and 'Delivery_route'
5. Add Unique order number and order weight
6. Save results
    - Filter data by 'product_delivery_temp' for 3 different data files (ambient, chilled, frozen)
    - Pass orders and location data to batching model

hit_id	hit_time	container_id	parcel_id	type	order_id	location_id	product_id	location	delivery_on	count	zone	warehouse_deadline	route_id
17271543	10:20:09	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-120079	nl-18311	T-821-1	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271649	10:32:10	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-114298	nl-9201	W-538-1	16-10-2024	3	ambient	10-16-2024 16:45:00	nl-201286
17271657	10:33:05	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-177622	nl-6406	W-826-1	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271682	10:35:47	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-115576	nl-2797	Y-300-1	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271633	10:30:08	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-113881	nl-1477	W-315-4	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271667	10:34:14	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-115366	nl-8602	X-700-1	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271511	10:16:51	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-116952	nl-17813	S-385-1	16-10-2024	2	ambient	10-16-2024 16:45:00	nl-201286
17271729	10:41:09	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-115854	nl-14172	Y-511-3	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271664	10:33:47	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-151562	nl-3242	X-310-2	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17271726	10:40:45	nl-34095243	nl-33839089	bigBox	nl-2111..	nl-115786	nl-7532	Y-500-1	16-10-2024	1	ambient	10-16-2024 16:45:00	nl-201286
17264634	17:44:35	nl-34081467	nl-33823883	smallBag	nl-2125..	nl-146991	nl-5586	H-524-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17264414	17:32:46	nl-34081459	nl-33823883	smallBag	nl-2121..	nl-146986	nl-14535	G-588-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17264566	17:40:50	nl-34081459	nl-33823883	smallBag	nl-2121..	nl-144065	nl-10603	H-384-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17264431	17:33:38	nl-34081459	nl-33823883	smallBag	nl-2121..	nl-143969	nl-3469	G-648-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17264281	17:24:50	nl-34081459	nl-33823883	smallBag	nl-2121..	nl-177510	nl-15511	G-336-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17264349	17:29:00	nl-34081525	nl-33823883	smallBag	nl-2127..	nl-178289	nl-3258	G-401-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17264722	17:49:29	nl-34081525	nl-33823883	smallBag	nl-2127..	nl-144090	nl-7769	L-376-1	16-10-2024	1	frozen	10-15-2024 22:00:00	nl-201261
17261245	15:39:06	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-147075	nl-7438	D-224-3	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261045	15:36:42	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-24029	nl-4605	C-754-3	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261194	15:38:19	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-142829	nl-2730	C-885-3	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261220	15:38:50	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-147064	nl-1760	D-210-4	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261000	15:35:19	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-142239	nl-15457	C-310-1	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261591	15:41:55	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-143482	nl-19819	D-741-1	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17260965	15:32:58	nl-34081903	nl-33824442	paperBag	nl-2126..	nl-141620	nl-2627	B-536-4	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261341	15:39:52	nl-34081932	nl-33824416	smallBox	nl-2127..	nl-152969	nl-904	D-360-2	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17261008	15:35:56	nl-34081932	nl-33824416	smallBox	nl-2127..	nl-23302	nl-15553	C-511-1	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268
17260929	15:30:38	nl-34081932	nl-33824416	smallBox	nl-2127..	nl-152434	nl-908	B-240-2	16-10-2024	1	chilled	10-15-2024 22:00:00	nl-201268

Table B.1: Pickdata from Crisp on 16-10-2024

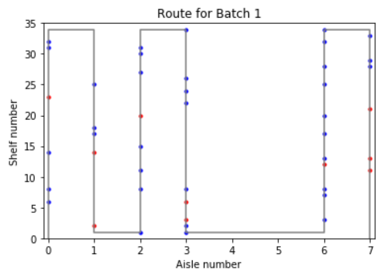
Order_id	Parcel_ID	Zone	Delivery_Time	route_id	Stock_Locations	Location_Numbers	Order_number	W_o
nl-212473086	nl-33824995	chilled	10-15-2024 22:00:00	nl-201273	A-936-1, D-360-2, B-711-1, D-531-1, B-420-1, C...	1, 2, 3, 4	1	4
nl-212473086	nl-33825071	ambient	10-15-2024 22:00:00	nl-201273	Y-711-2, S-379-1, V-815-1, Z-822-2, X-795-1, V...	1, 4, 5, 6, 7, 8	2	4
nl-212473086	nl-33825083	frozen	10-15-2024 22:00:00	nl-201273	G-464-1, L-386-1, L-512-2	1, 3	3	4
nl-212492445	nl-33825074	ambient	10-15-2024 22:00:00	nl-201273	W-760-2, U-740-4, V-287-4, U-707-2	3, 4, 5	4	4
nl-212492445	nl-33825081	chilled	10-15-2024 22:00:00	nl-201273	A-350-1	1	5	4
nl-212492445	nl-33825084	frozen	10-15-2024 22:00:00	nl-201273	G-480-1, G-310-1, G-368-4	1	6	4
nl-212500356	nl-33825001	chilled	10-15-2024 22:00:00	nl-201273	D-236-2, D-240-2, B-406-2, B-745-1, C-885-3, D...	1, 2, 3, 4	7	4
nl-212500356	nl-33825057	ambient	10-15-2024 22:00:00	nl-201273	V-207-1, Y-736-4, Y-400-1, V-236-4, S-355-1, X...	1, 3, 4, 6, 7	8	4
nl-212500356	nl-33825082	frozen	10-15-2024 22:00:00	nl-201273	H-444-2, L-512-2	2, 3	9	4
nl-212549874	nl-33825004	chilled	10-15-2024 22:00:00	nl-201273	C-866-2, C-291-1, B-420-1, C-340-1, D-781-1, C...	2, 3, 4	10	4
…	…	…	…	…	…	…	…	…
nl-212749269	nl-33834484	frozen	10-16-2024 18:20:00	nl-201288	G-310-1, H-436-2, H-278-1	1, 2	3529	4
nl-212750376	nl-33834444	chilled	10-16-2024 18:20:00	nl-201288	C-846-2, D-305-3, A-915-3, D-737-4, C-737-3, D...	1, 2, 3, 4	3530	4
nl-212750376	nl-33834474	ambient	10-16-2024 18:20:00	nl-201288	Y-750-4, V-205-3, W-754-3, S-539-1, W-309-1, V...	1, 4, 5, 7	3531	4
nl-212750376	nl-33834484	frozen	10-16-2024 18:20:00	nl-201288	G-416-1, H-334-1	1, 2	3532	4
nl-212763309	nl-33834450	chilled	10-16-2024 18:20:00	nl-201288	C-260-1, A-906-4, C-500-1, B-730-1	1, 2, 3	3533	4
nl-212763309	nl-33834461	ambient	10-16-2024 18:20:00	nl-201288	W-389-1, S-439-1, W-323-4, W-439-4, U-745-3, Z...	1, 3, 5, 7, 8	3534	4
nl-212763309	nl-33834479	frozen	10-16-2024 18:20:00	nl-201288	L-366-1, L-478-1	3	3535	4
nl-212770896	nl-33834453	chilled	10-16-2024 18:20:00	nl-201288	D-325-3, C-790-1, C-707-4, C-820-4, C-711-1	3, 4	3536	4
nl-212770896	nl-33834466	ambient	10-16-2024 18:20:00	nl-201288	Y-710-2, W-309-1	5, 7	3537	4
nl-212770896	nl-33834482	frozen	10-16-2024 18:20:00	nl-201288	L-368-1, L-270-1	3	3538	4

Table B.2: Input data for the JOBPRP model on 16-10-2024

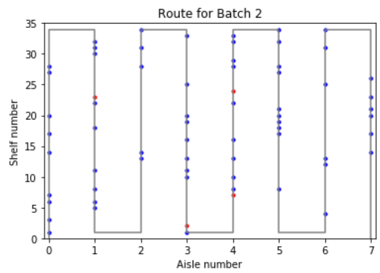
C

Routes for verification

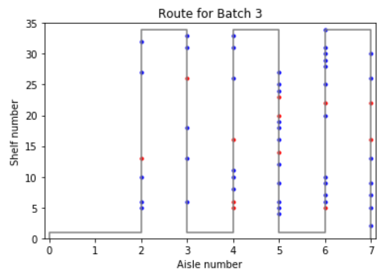
C.1. Verification distance matrix



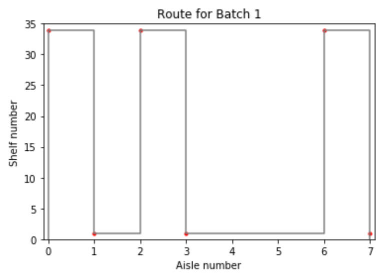
(a) non-simplified



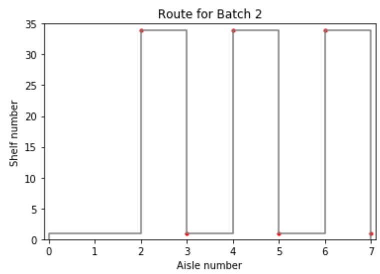
(b) non-simplified



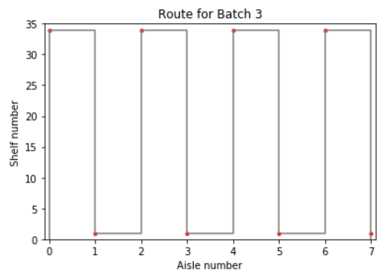
(c) non-simplified



(d) simplified

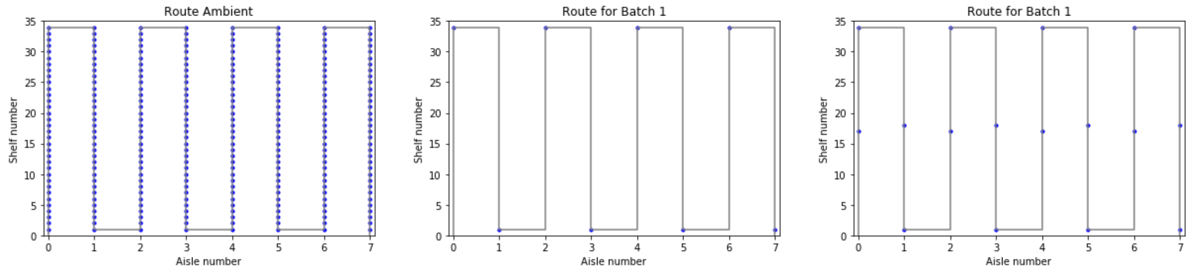


(e) simplified



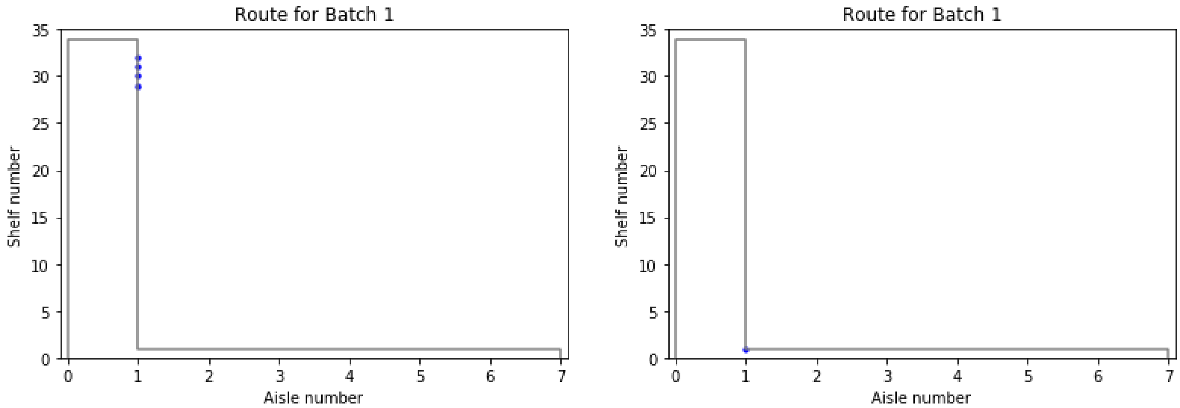
(f) simplified

Figure C.1: Routing ambient section 50 orders with 4 SKU/parcel



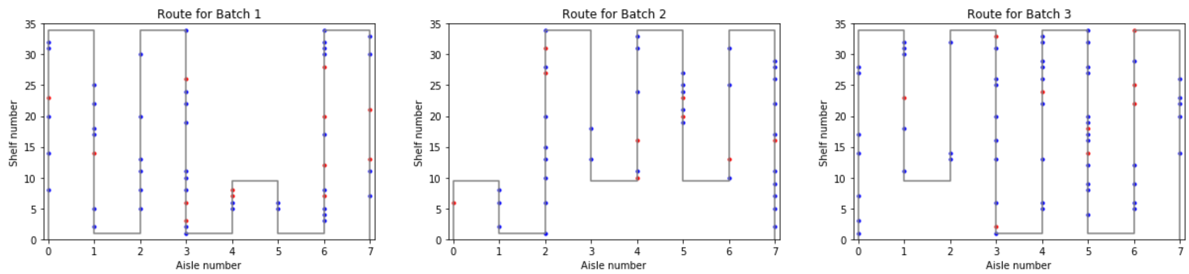
(a) non-simplified (b) simplified (c) simplified + midaisle

Figure C.2: full routes in ambient

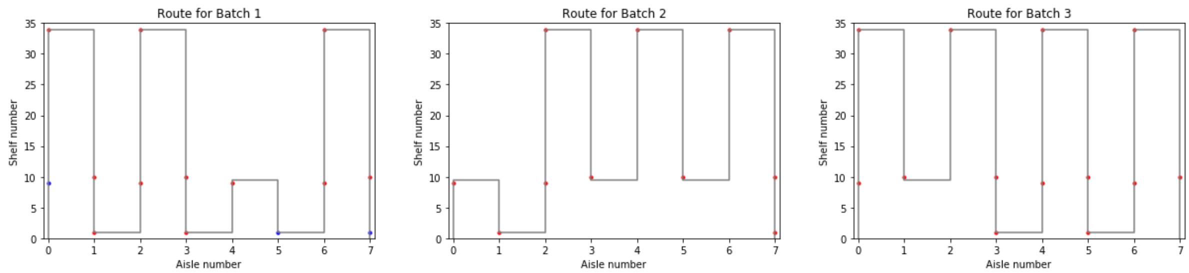


(a) non-simplified (b) simplified

Figure C.3: ambient routes with only picks in one aisle

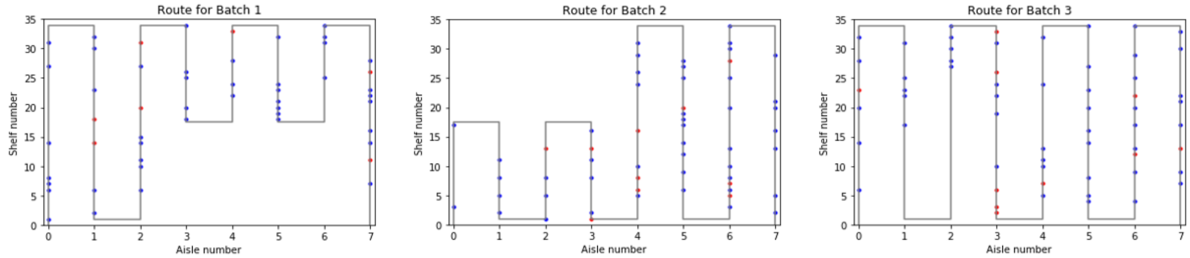


(a) non-simplified (b) non-simplified (c) non-simplified

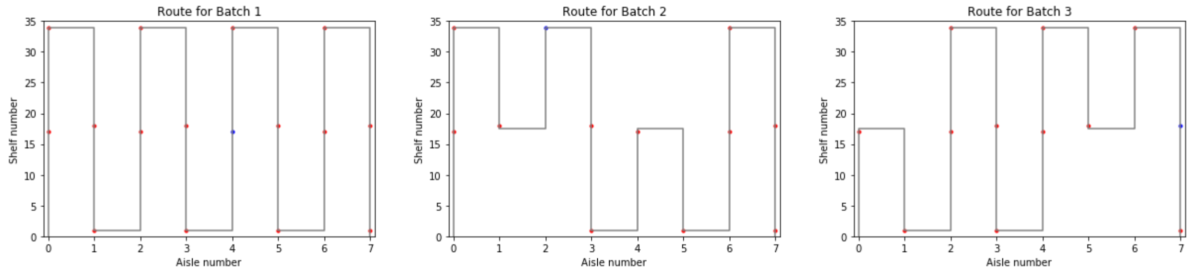


(d) simplified (e) simplified (f) simplified

Figure C.4: Routing ambient section 50 orders with 4 SKU/order and a midaisle between 9 and 10

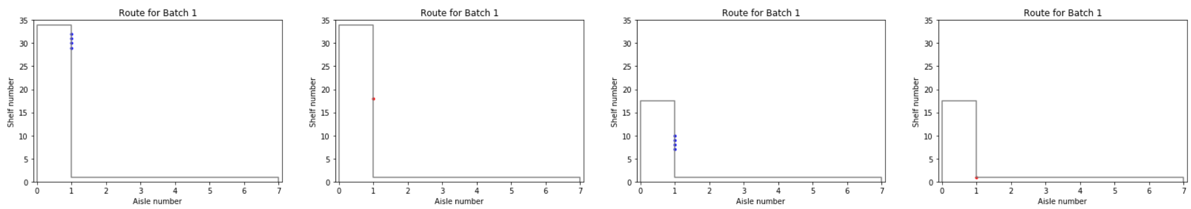


(a) non-simplified (b) non-simplified (c) non-simplified



(d) simplified (e) simplified (f) simplified

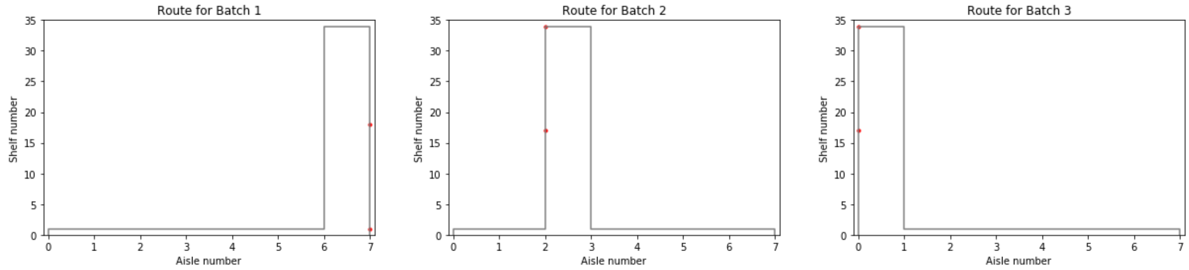
Figure C.5: Routing ambient section 50 orders with 4 SKU/order and a midaisle between 17 and 18



(a) non-simplified (b) simplified (c) non-simplified (d) simplified

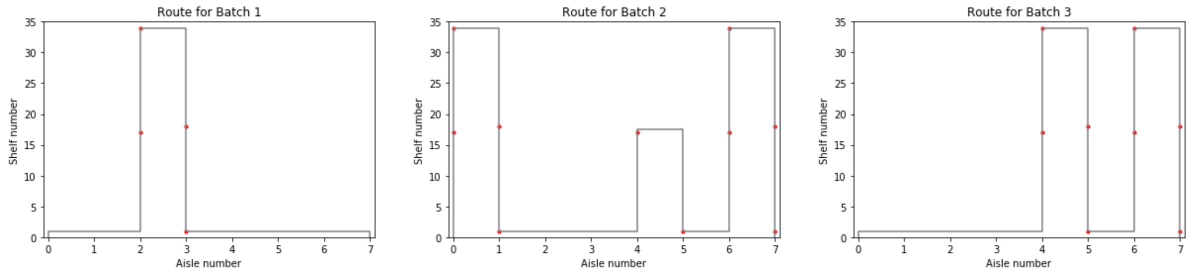
Figure C.6: ambient routes with a midaisle with only picks in one aisle

C.2. Verification scenario testing



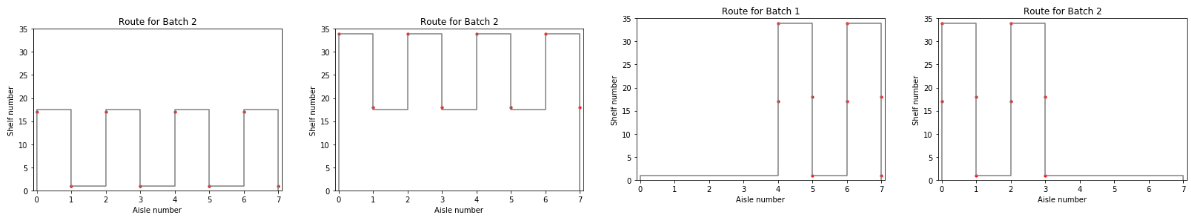
(a) (b) (c)

Figure C.7: Routes for 3*18 the same parcel, located in different aisles



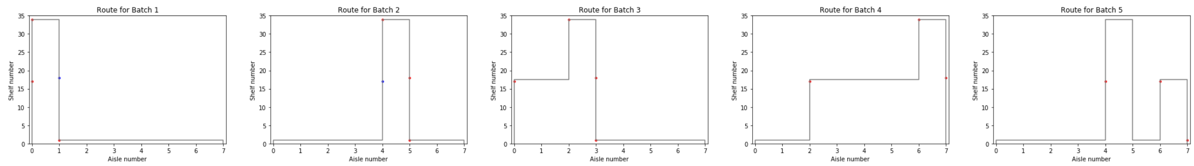
(a) (b) (c)

Figure C.8: Routes for 18 of the same parcel, the other parcels have only picks in different aisles



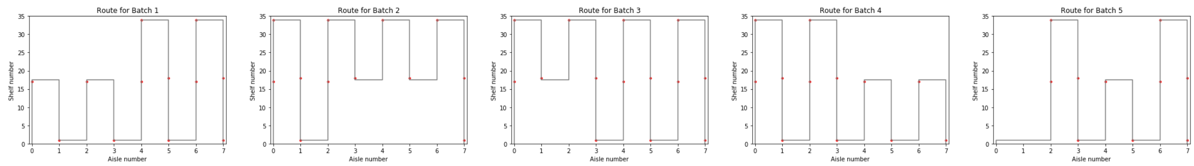
(a) Picks only in the bottom part (b) Picks only in the top part (c) Combined data of C.9a and C.9b batch 1 (d) Combined data of C.9a and C.9b batch 2

Figure C.9: Routes for datasets with only picks at the top or the bottom and the combination



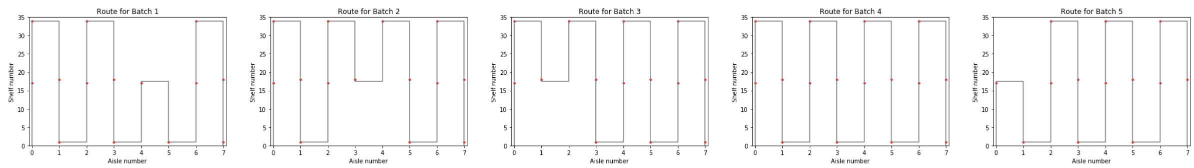
(a) (b) (c) (d) (e)

Figure C.10: Routes for parcels with 1 pick/parcel



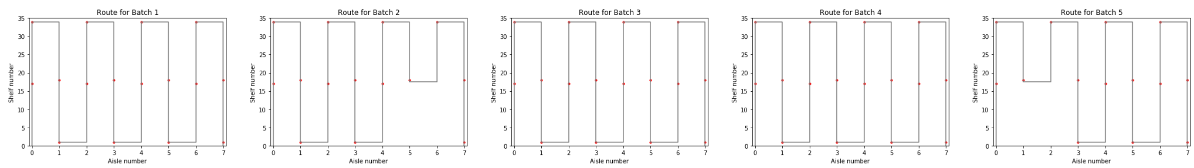
(a) (b) (c) (d) (e)

Figure C.11: Routes for parcels with 4 picks/parcel



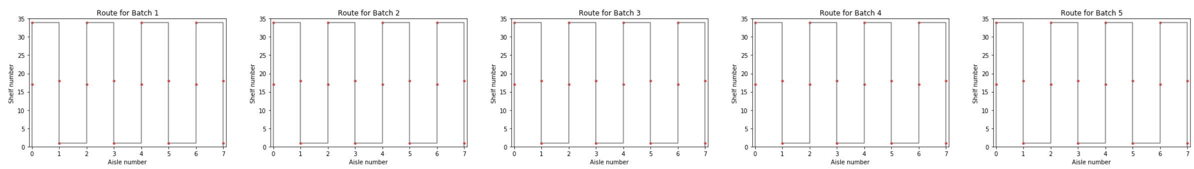
(a) (b) (c) (d) (e)

Figure C.12: Routes for parcels with 8 picks/parcel



(a) (b) (c) (d) (e)

Figure C.13: Routes for parcels with 12 picks/parcel



(a) (b) (c) (d) (e)

Figure C.14: Routes for parcels with 16 picks/parcel

D

Figures

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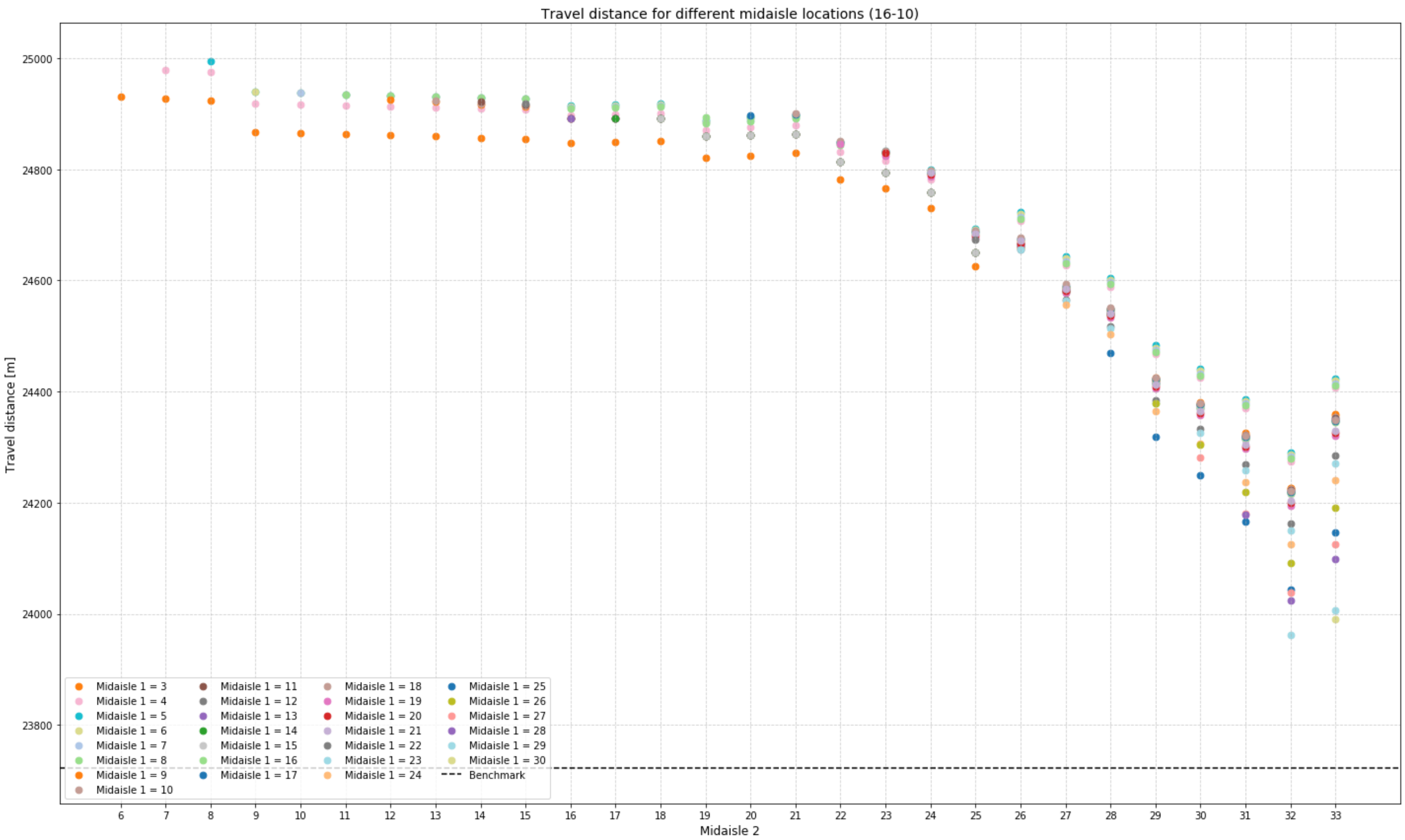

Figure D.1: Travel distance for the ambient zone with 2 midaisles on 16-10

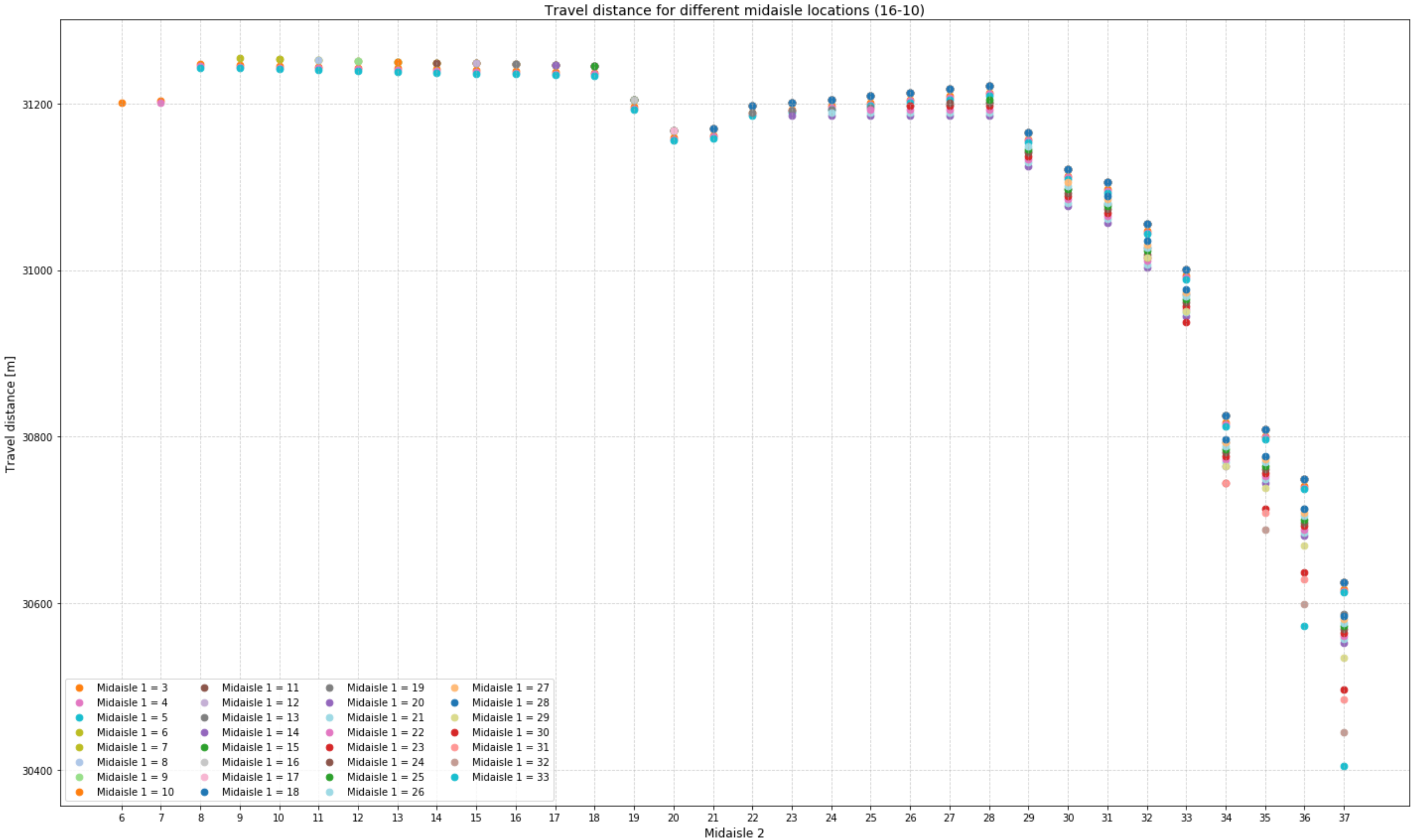

Figure D.2: Travel distance for the chilled zone with 2 midaisles on 16-10

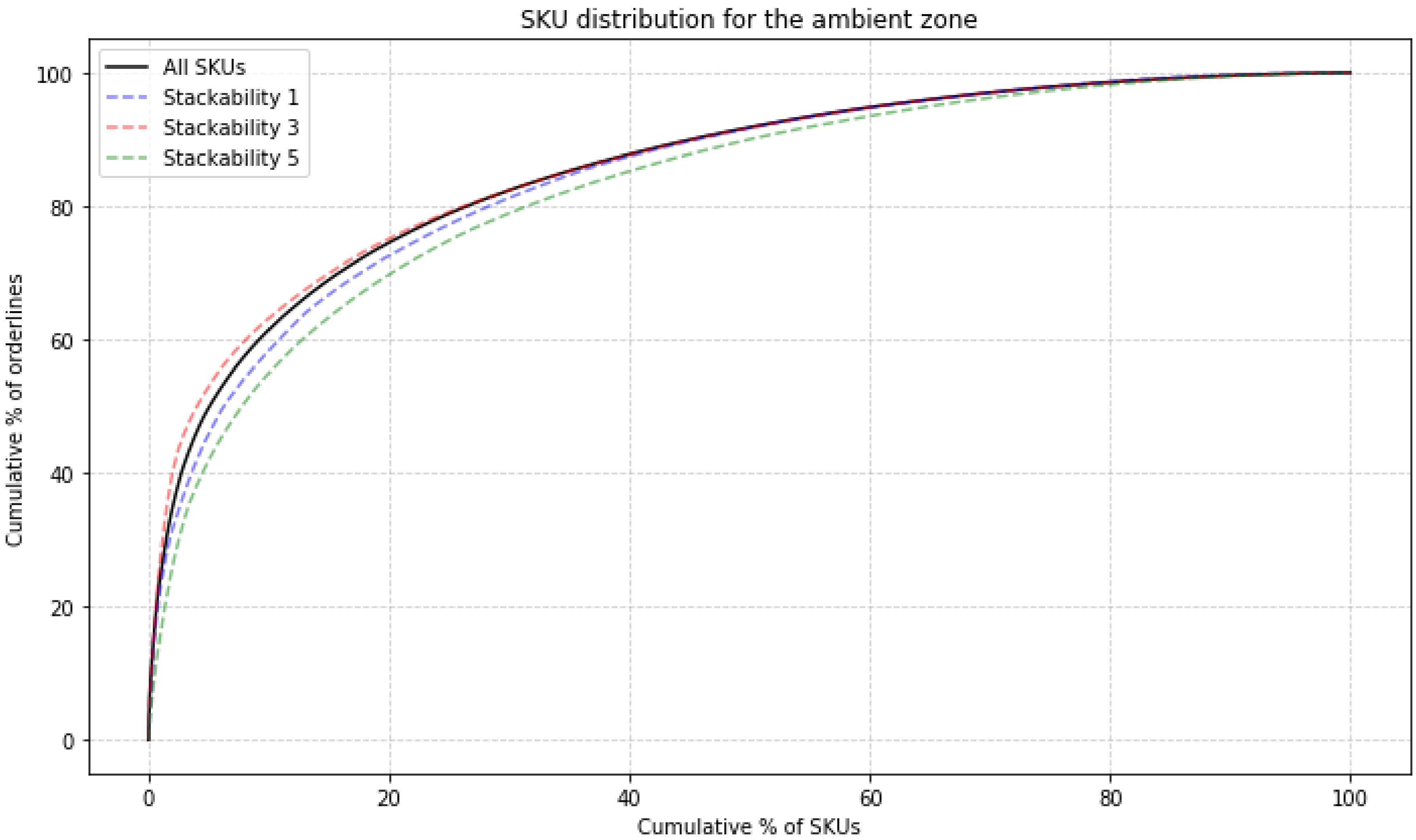

Figure D.3: Distribution per stackability in the ambient zone

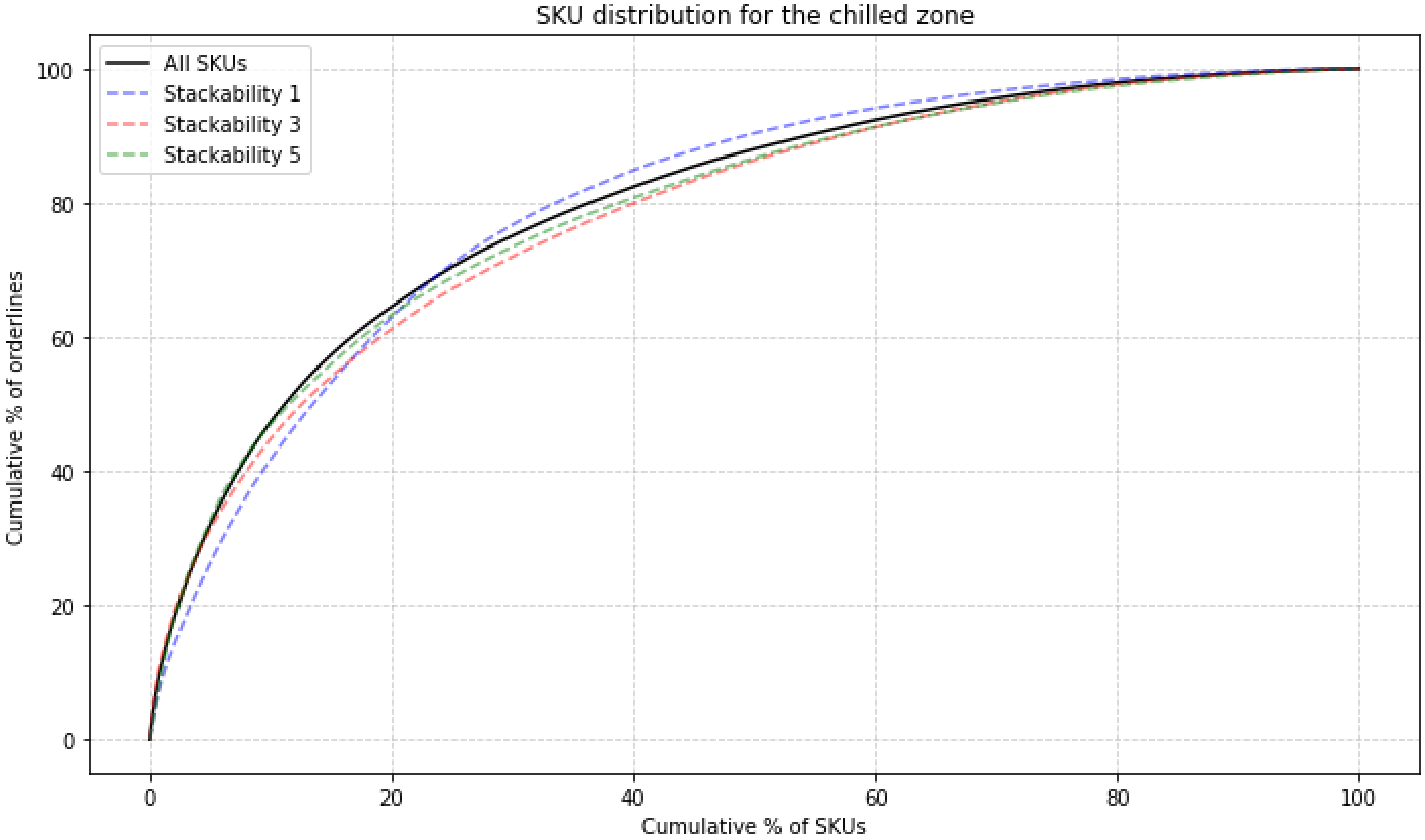

Figure D.4: Distribution per stackability in the chilled zone

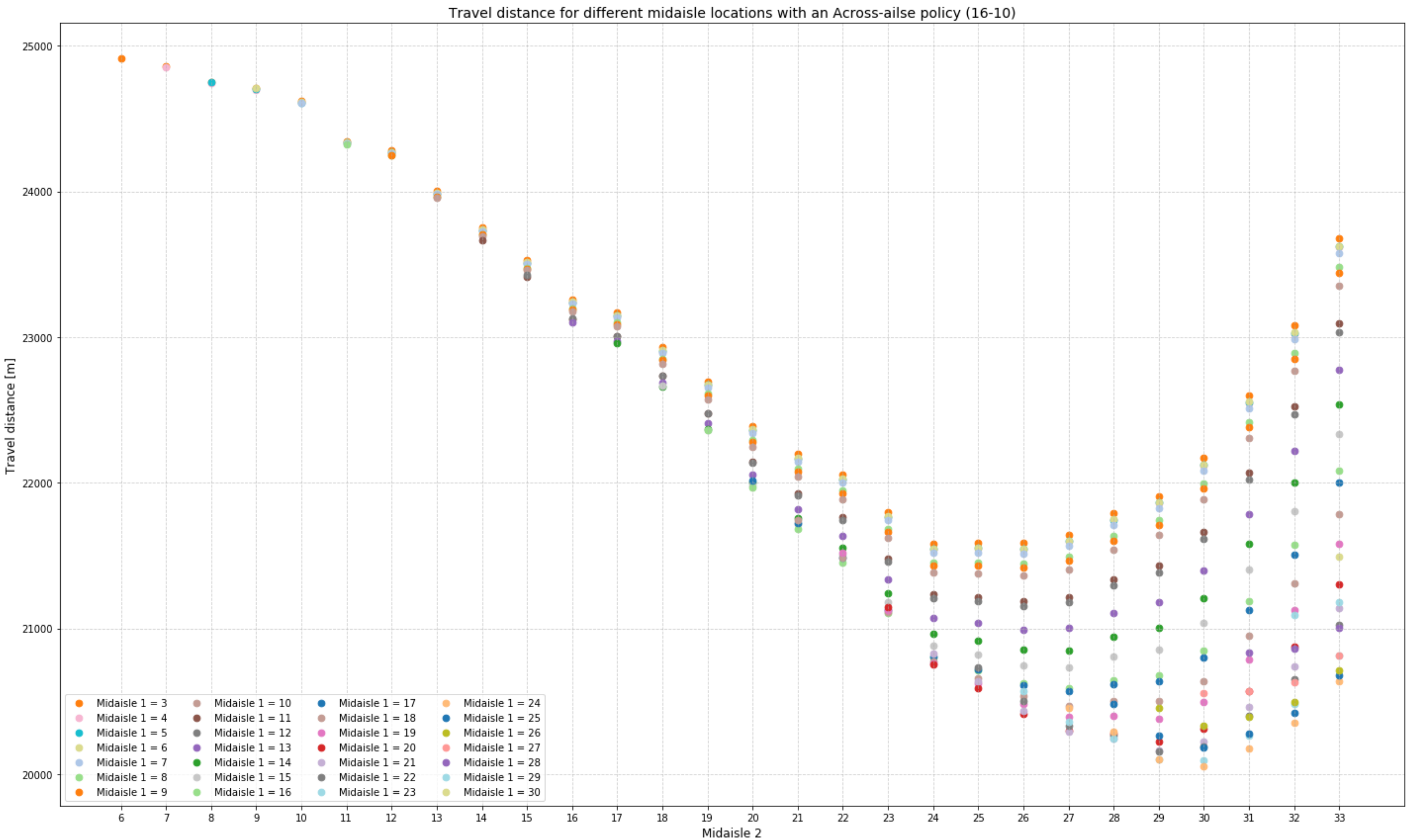

Figure D.5: Travel distance for a layout with 2 midaisles and an Across-aisle policy on 16-10 in the ambient zone

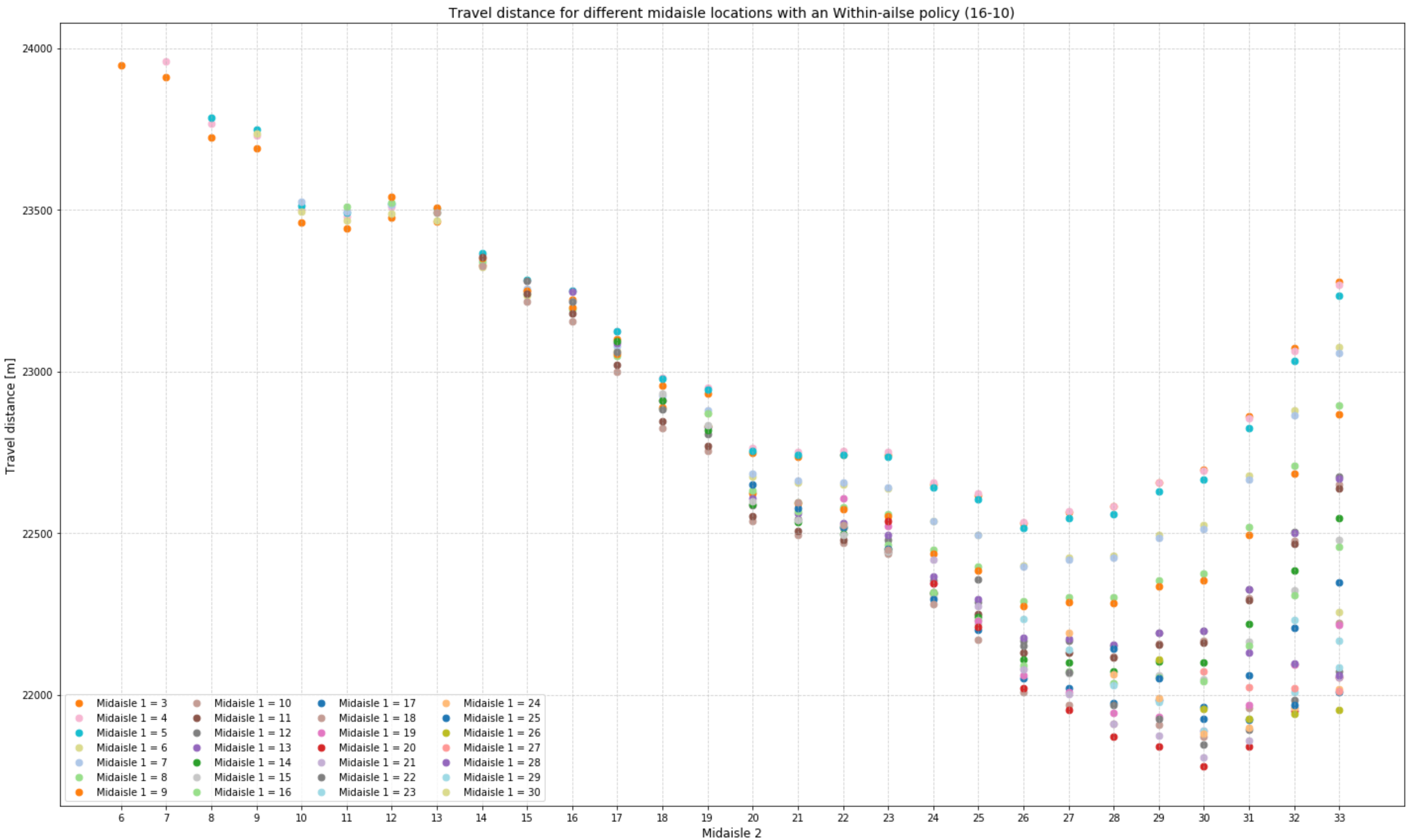

Figure D.6: Travel distance for a layout with 2 midaisles and an Within-aisle policy on 16-10 in the ambient zone

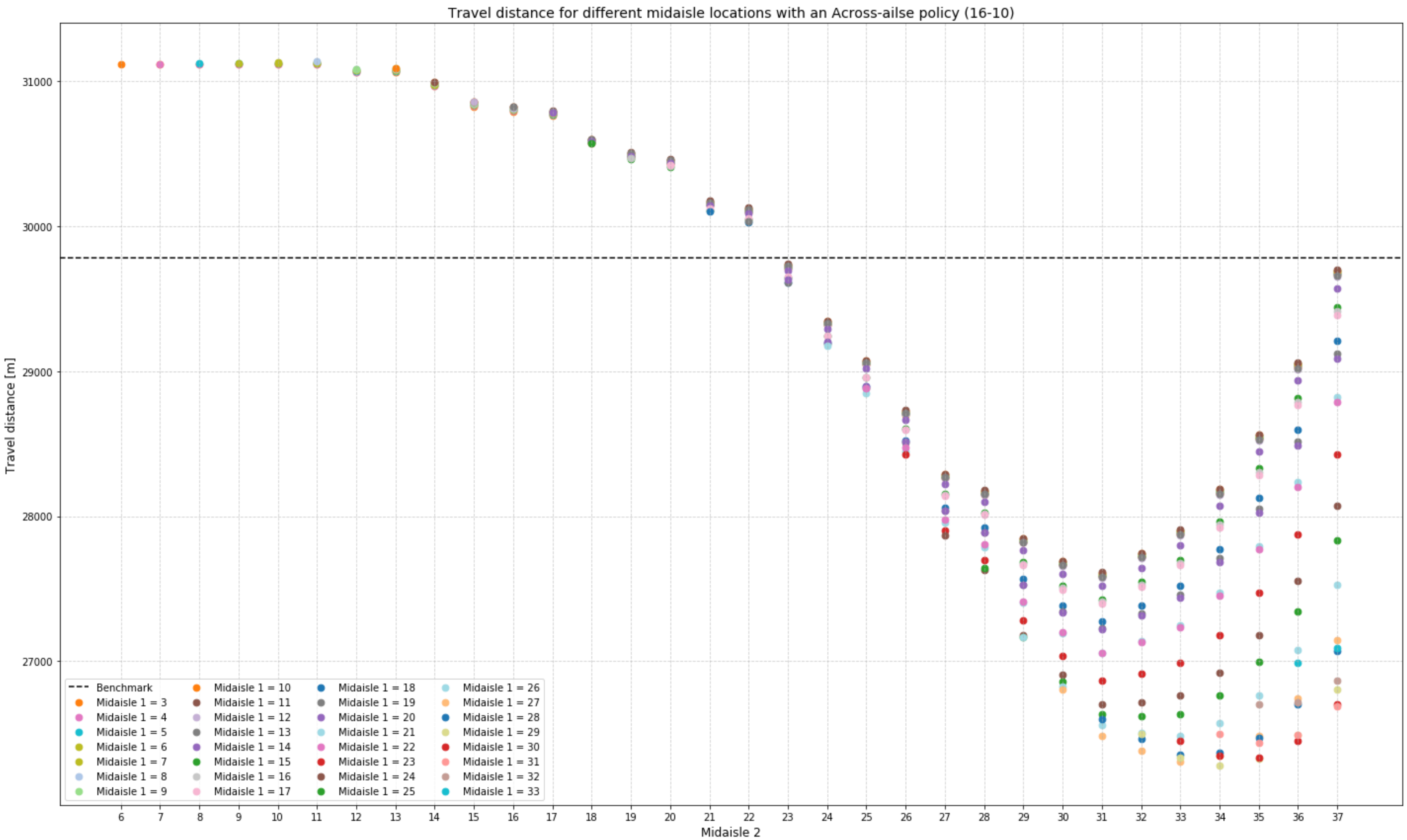

Figure D.7: Travel distance for a layout with 2 midaisles and an Across-aisle policy on 16-10 in the chilled zone

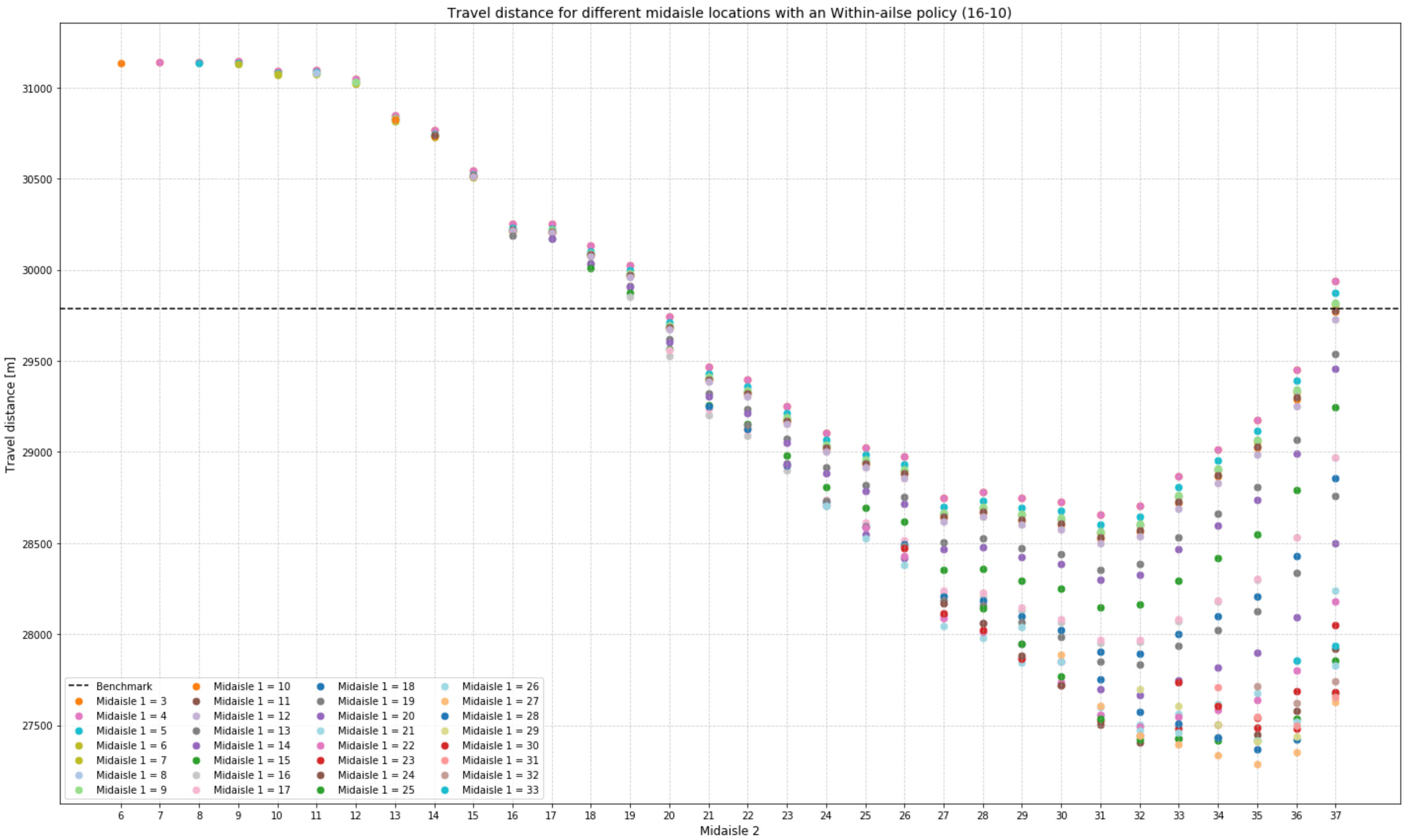

Figure D.8: Travel distance for a layout with 2 midaisles and an Within-aisle policy on 16-10 in the chilled zone

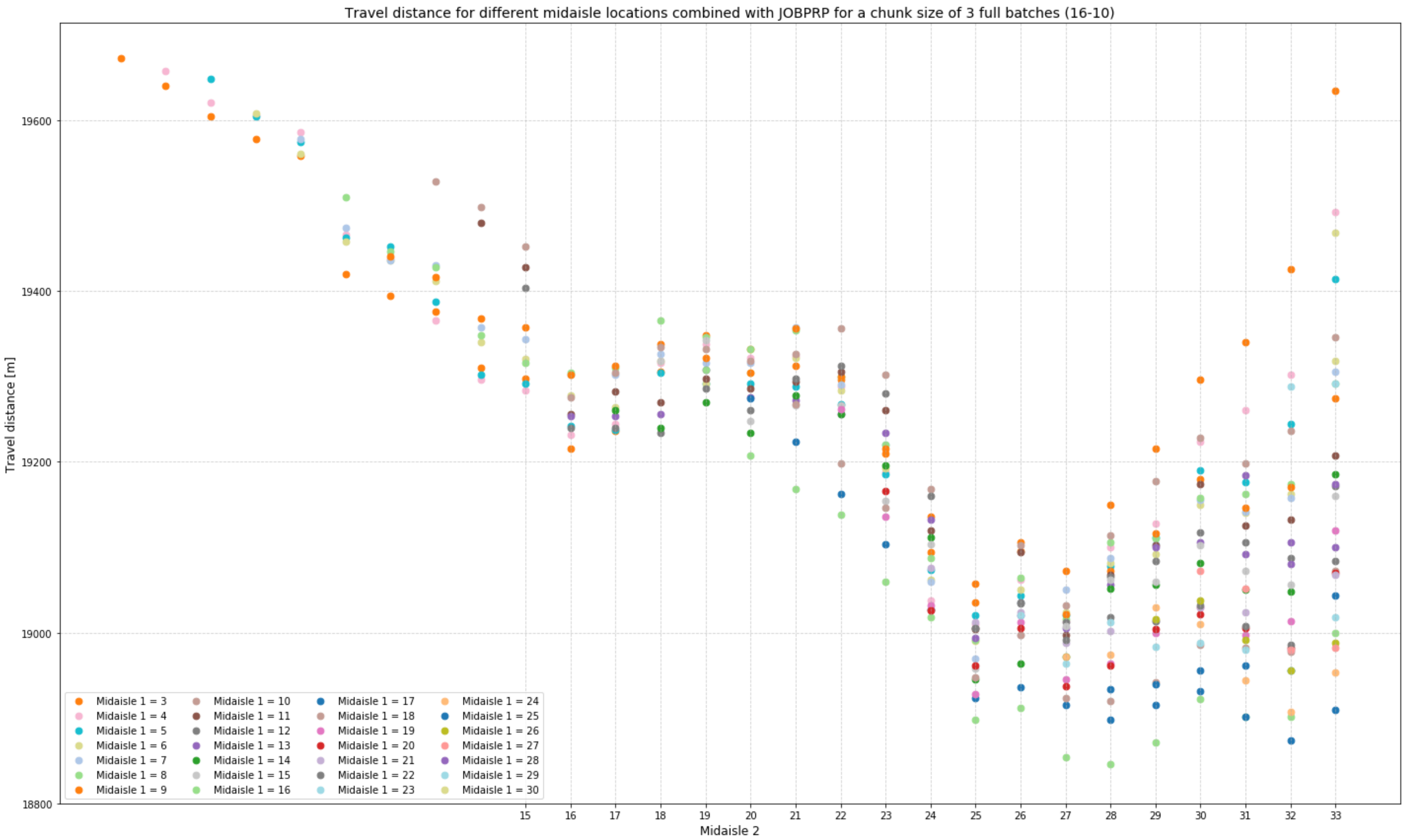

Figure D.9: Travel distance for a layout with 2 midaisles and the JOBPRP with a chunk size of 4 full batches on 16-10 in the ambient zone

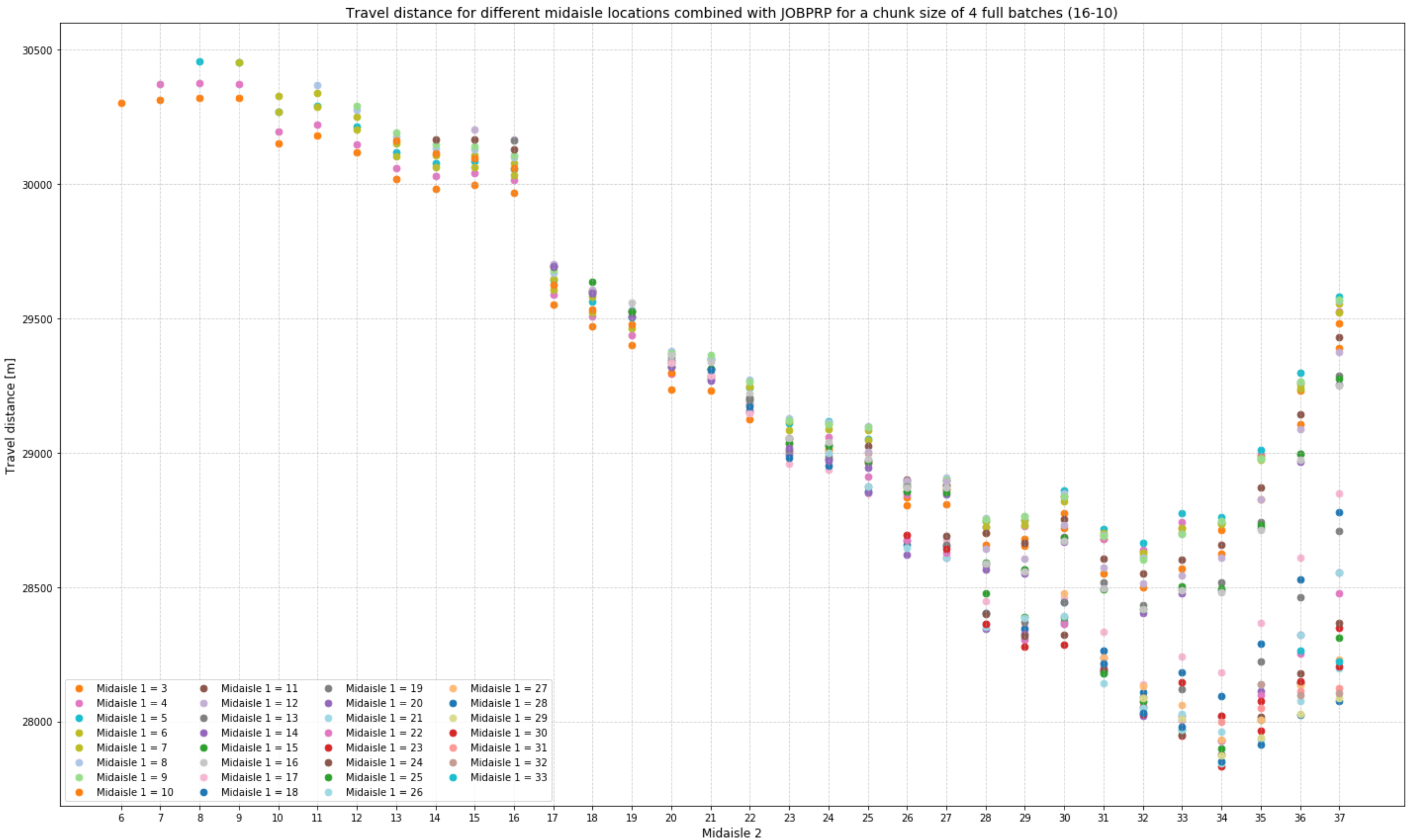

Figure D.10: Travel distance for a layout with 2 midaisles and the JOBPRP with a chunk size of 4 full batches on 16-10 in the chilled zone

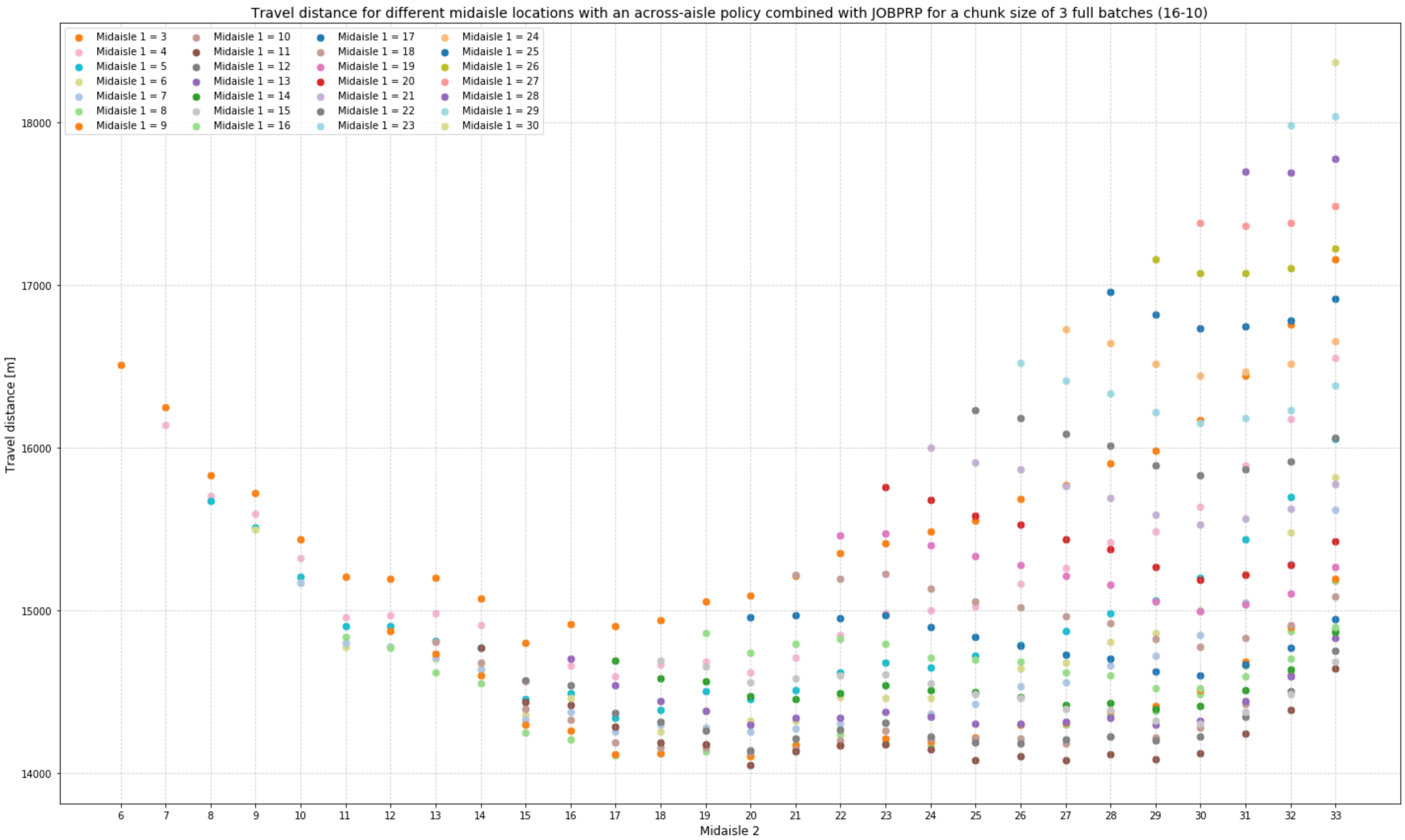

Figure D.11: Travel distance for a layout with 2 midaisles with an across-aisle policy combined with the JOBPRP for a chunk size of 3 full batches on 16-10 in the ambient zone

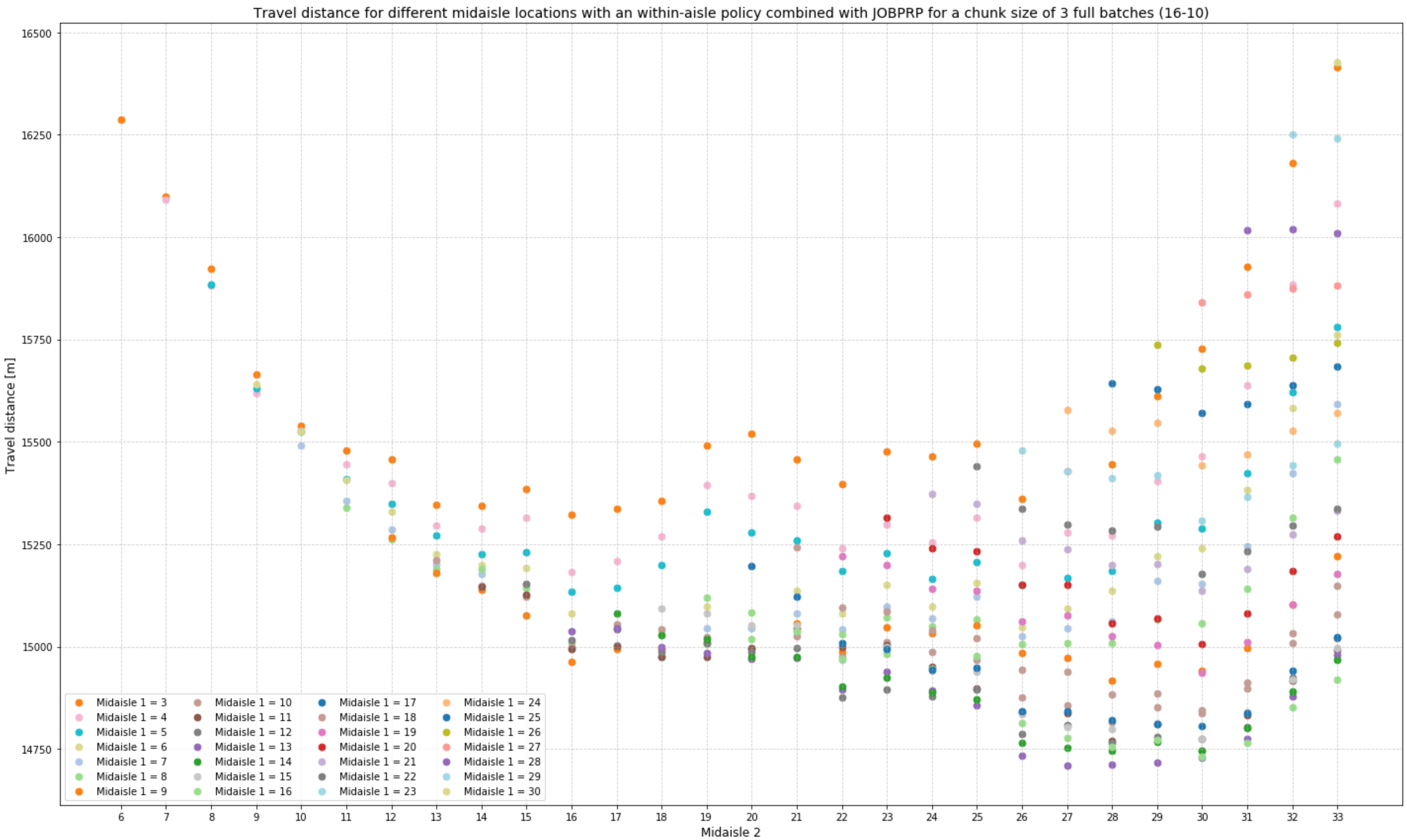

Figure D.12: Travel distance for a layout with 2 midaisles with an within-aisle policy combined with the JOBPRP for a chunk size of 3 full batches on 16-10 in the ambient zone

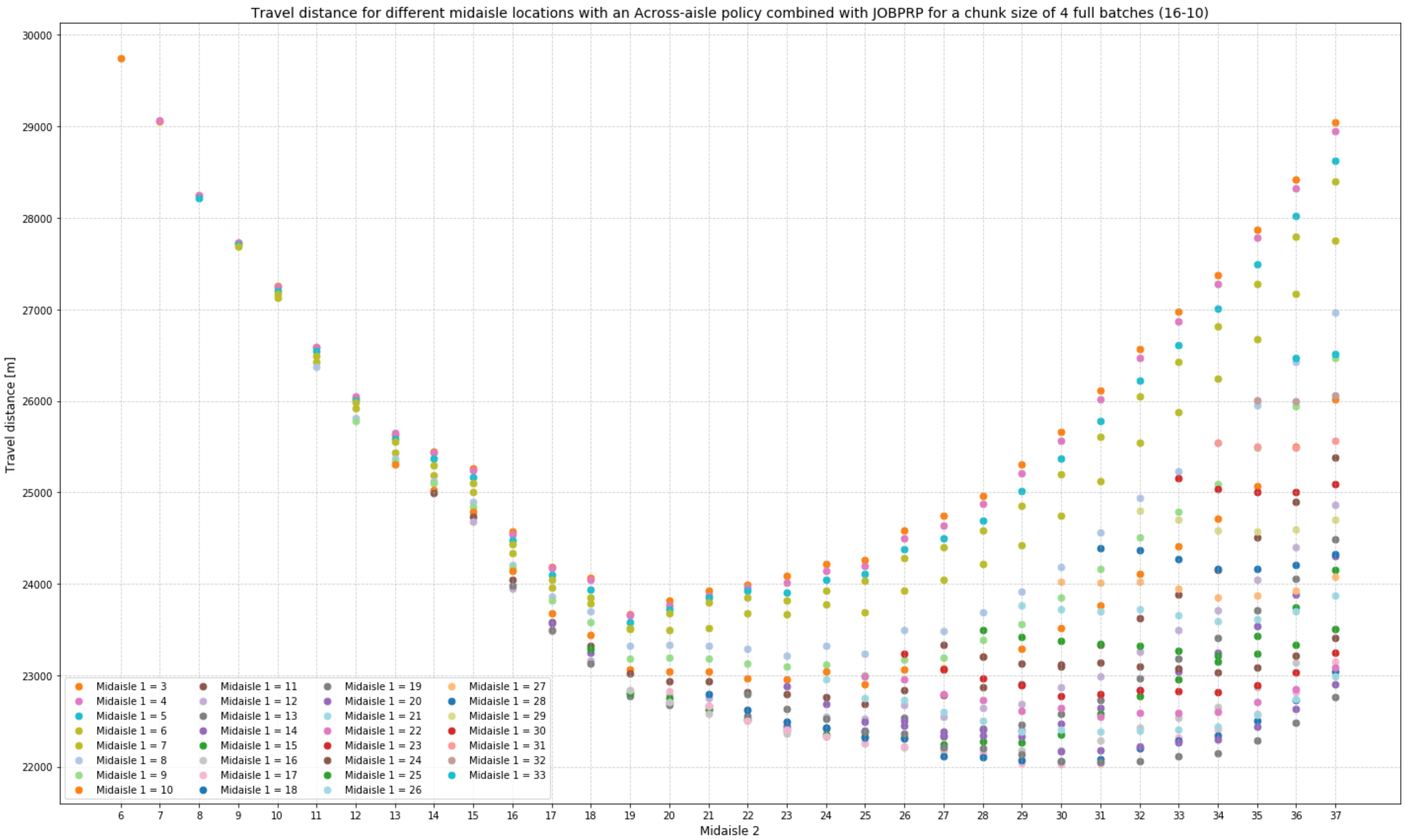

Figure D.13: Travel distance for a layout with 2 midaisles with an across-aisle policy combined with the JOBPRP for a chunk size of 4 full batches on 16-10 in the chilled zone

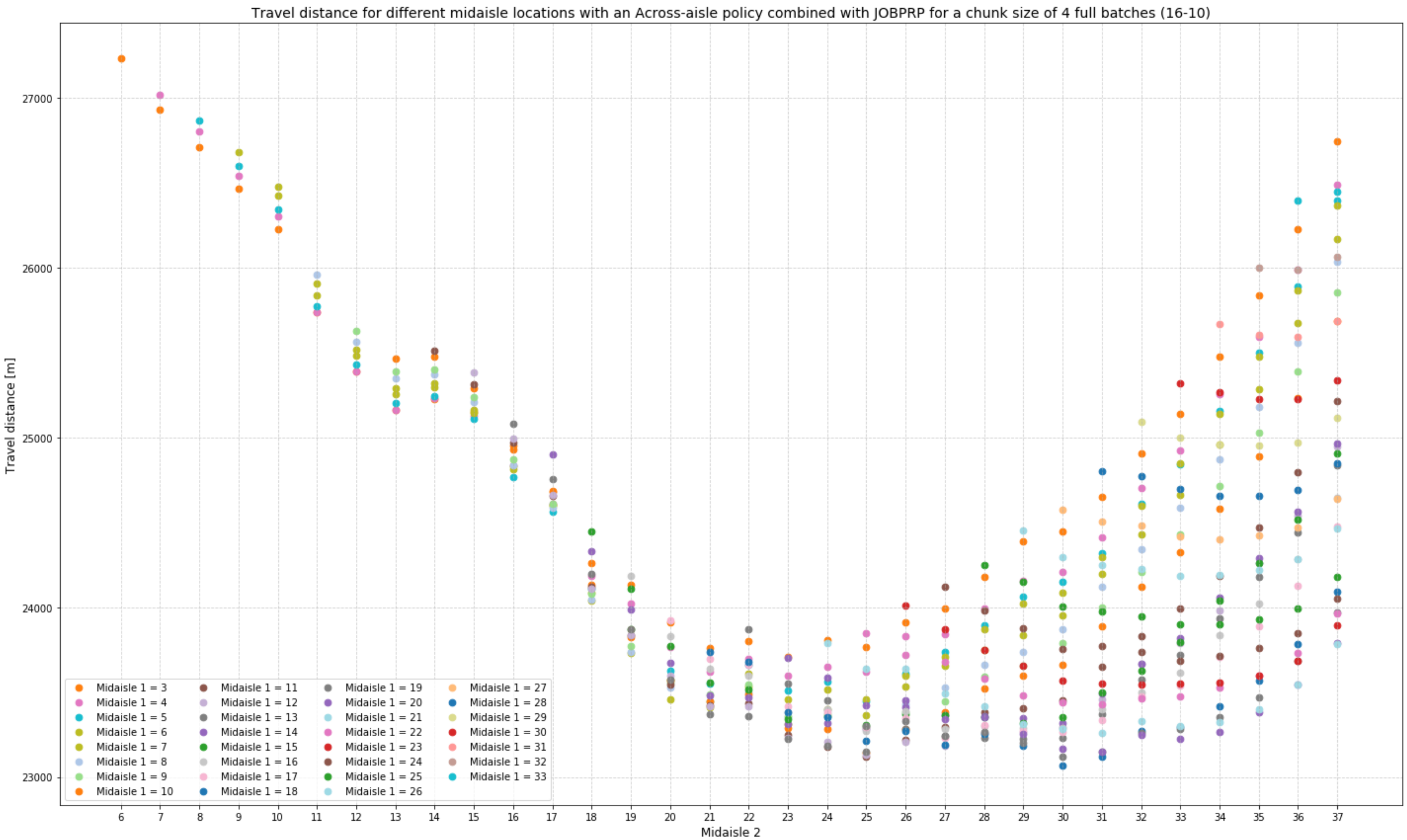

Figure D.14: Travel distance for a layout with 2 midaisles with an within-aisle policy combined with the JOBPRP for a chunk size of 4 full batches on 16-10 in the chilled zone

E

Tables

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Layout	Aisle width	Space utilization	Congestion	Routing	Allocation impact	Notes
Single Block	Narrow	**+ +** A narrow single block warehouse is the most space efficient configuration possible	**- -** Because of the narrow aisles, pickers are not able to (easily) surpass each other	**-** A single block warehouse provides worse solutions to the routing problem in comparison with multi-block warehouses	**- -** Applying a storage location policy will locate high demanded SKU's on the easy accessible locations. This will lead to extra congestion as picks are concentrated in these small areas	A narrow single block warehouse is the most 'easy' warehouse configuration. It is the most space efficient layout but is also the least efficient. It is very sensitive for congestion and the routing policy is bound to the simple layout
	Wide	**-** By increasing the aisle width, the needed warehouse space will drastically increase as all aisles will use more space	**+** With wide aisles the pickers can surpass each other	**-** The effect of the aisle width on the routing is the possibility to turn, by having a wide enough aisle the picker is able to turn	**-** This is the same for a narrow single block warehouse. Nevertheless because of the wide aisles, pickers can surpass each other, which could reduce the congestion	Changing the aisle width to a wide aisle will mostly affect the congestion. Pickers are now able to surpass each other more easily. The biggest downside is that the space utilization will decrease
Multi-Block	Narrow	**+** Adding a cross aisle to a warehouse will reduce the storing space, as a storage rack is replaced for a cross aisle	**-** Adding a cross aisle will give the picker more options for the routing and could avoid occurring congestion	**+** Adding cross aisles will have a positive effect on the routing problem, as there are more possible routes and picker could take shortcuts	**+** The storage policy for a multi-block warehouse has more possible advantages than a single block as parts of the warehouse could be cut off. Nevertheless congestion is still a downside	A multi-block warehouse will outperform a single block warehouse on the routing solution. Because of the multi blocks, the are more product allocation options available that could increase efficiency even more. The cross aisles also reduce the congestion by giving possible shortcuts to the routing

	Wide	**- -** A wide multi block warehouse is the worst space configuration, as both the wide aisle as the addition of cross-aisle has a negative effect on the space utilization	**+** A wide multi-block warehouse is the best solution for minimizing the congestion	**+** The effect of the aisle width on the routing is the possibility to turn, by having a wide enough aisle the picker is able to turn	**+ +** This is the same for a narrow multi-block warehouse. Nevertheless because of the wide aisles, pickers can surpass each other, which could minimize the congestion	Here the same goes for a wide single block warehouse, the difference by changing the aisle width will decrease the congestion. Nevertheless this will have a negative effect on the space utilization
Fishbone[1]	N/A	**- -** A fishbone warehouse has a higher space utilization then conventional warehouses with cross aisles due to the configuration of the racks	**+** research on the congestion in a fishbone warehouse is lacking in literature so the score is based on reasoning. The configuration is best comparable with a multi block warehouse, it is assumed that the perpendicular aisles slightly reduce congestion	**-** literature shows that the fishbone layout is outperformed by a conventional multi-block warehouse	Literature shows that the product allocation in a fishbone layout is crucial for the performance. Different policies yield very different results	A fishbone layout is proven to be effective for unit-load warehouses but for multiple picks it will be outperformed by a multi-block layout. The product allocation has a significant effect on the performance of a fishbone layout

Table E.1: Reasoning for Table 3.1

[1]The fishbone layout is the only non conventional layout that is evaluated as the flying-V and inverted-V layouts are comparable with a multi-block layout

	Space utilization	Picker familiarity	Routing	Difficulty to implement	Congestion	Precedence constraints
Single	+ A single storage will only store a SKU in one location	+ A SKU is only located in one location, pickers are not confused by a second location	- In comparison with a scattered storage, the single storage limits the routing	+ Single storage is the most common and easy method to apply	- The warehouse is more concentrated then a scattered storage	+ Adaptability to the precedence constraints is more depended on random or dedicated storage. Both single as scattered storage could handle the constraints
Scattered	- A scattered storage will store SKU's in multiple location, increasing the needed warehouse size	- Scattering the SKU's can cause confusion by the pickers	+ storing SKU's in multiple location could improve the routing as there are more possibilities	- Storing SKU's in multiple places increases the complexity	+ Scattering the SKU's could be able to ease the congestion	
Random	+ + A random storage policy uses the least space as SKU's are not bound to a location	- - Due to the random policy, the location of the SKU's constantly changes	- - A random policy will result in the highest travel distance	+ implementing a random storage is the most easy policy to implement, for a full random policy a computer controlled environment is needed	+ + A random policy distributes the SKU's evenly throughout the warehouse, minimizing congestion	- - Not possible to account for precedence constraints
Closest open location	+ + The same as for a random policy, the used space will convert more to the P%D point	- - The same as for a random policy, the location of the SKU's constantly changes	- A closest open location is performing slightly better than a random policy, but still result in high travel distances	+ + this is the most simple policy, the picker will simply select the nearest feasible location	+ The same as for a random policy, the only difference is that the SKU's will be more clustered to the P%D point	- - Not possible to account for precedence constraints

Dedicated	- - Each SKU has a fixed place and therefore the space utilization is the highest	+ + Each SKU has their own fixed location, pickers will get familiar with the layout	+ + A dedicated storage results in the lowest travel distances	- - Dedicated storage is the hardest to implement. Every SKU needs a defined location. Using a algorithm to determine these location is the hardest option	- - The most demanded products are placed on the most easy accessible location resulting in congestion	+ + Product can be placed at specific places and thereby take the precedence constraints in account
Class-based	+ Class-based is in between the random and dedicated policies	+ In the classes, the SKU's are distributed random. The pickers will have an idea where to find the SKU, but know not for sure	+ The class-based policy gives comparable results with the dedicated policy but gets slightly outperformed	- to determine which SKU belongs to which class, (historical) data should be known to do the classification	- the congestion is comparable with a dedicated storage, but due to the random distribution in each class it perform slightly better on congestion	+ Product with precedence constraints can be placed in a specific class and then located in suitable locations

Table E.2: Reasoning for Table 3.2

Parcel	Number of picks per parcel															
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1	14	252	14	55	73	94	136	259	262	240	163	4	216	198	164	50
2	160	187	1	112	90	174	142	6	61	91	241	80	255	16	120	72
3	27	173	39	250	193	1	261	220	159	145	177	205	228	17	215	113
4	184	235	99	63	138	100	219	128	103	167	239	67	138	40	122	215
5	136	58	160	238	184	252	207	170	171	96	104	123	60	268	209	154
6	199	211	232	260	225	78	153	119	272	185	137	193	215	182	91	213
7	146	81	152	271	226	97	255	105	181	202	41	140	180	141	235	116
8	160	6	217	102	183	58	151	150	14	47	135	245	99	173	240	58
9	142	185	209	81	258	248	200	197	47	265	20	4	210	272	200	60
10	260	134	115	98	237	150	184	169	209	216	155	6	33	213	127	156
11	64	81	126	144	36	251	236	220	166	96	234	16	106	32	129	138
12	88	229	99	83	174	145	101	68	11	211	204	172	37	192	93	119
13	259	37	158	7	14	263	223	241	79	271	185	191	26	251	262	181
14	266	251	185	181	61	215	178	243	147	208	151	265	148	39	221	176
15	224	260	131	23	252	255	176	76	261	182	250	12	111	44	255	107
16	208	143	127	118	20	99	269	150	78	68	109	74	251	9	135	199
17	247	117	164	46	117	159	20	221	194	231	205	55	215	132	7	238
18	185	214	167	257	225	244	60	136	90	174	228	247	51	177	147	17
19	234	235	209	142	10	89	190	39	2	33	138	145	63	262	95	158
20	111	262	236	51	120	201	203	81	116	158	107	21	203	203	229	146
21	74	78	169	169	92	91	166	209	40	28	199	60	256	68	11	164
22	104	171	135	28	123	143	3	45	228	186	122	151	44	12	251	136
23	216	134	113	32	159	86	224	156	64	187	108	22	10	181	75	269
24	119	247	182	257	101	125	147	171	269	68	219	14	36	58	213	115
25	144	73	141	224	83	263	116	43	210	252	50	45	55	112	114	23
26	31	79	88	67	86	185	239	7	231	141	56	11	96	70	95	229
27	129	252	212	76	151	19	133	86	69	256	30	110	171	245	118	105
28	201	104	189	251	9	240	225	29	124	83	92	4	213	106	49	139
29	210	187	229	193	2	148	104	120	83	75	184	117	183	119	218	62
30	188	253	121	17	158	136	181	23	88	267	35	201	255	49	118	203
31	229	216	46	149	171	181	165	243	269	235	98	50	177	174	161	184
32	226	111	131	191	66	228	94	241	232	151	203	122	48	51	30	270
33	233	100	178	213	9	46	103	152	6	243	11	173	231	58	144	65
34	191	124	196	162	100	28	55	3	126	76	110	126	239	203	97	166
35	165	177	3	135	194	233	217	108	157	164	5	268	193	9	160	172
36	180	268	152	186	105	6	99	218	36	113	246	122	22	175	118	72
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40	256	146	96	185	82	189	156	136	182	71	223	174	271	95	223	16
41	20	143	252	47	123	33	248	260	131	245	159	240	182	27	248	201
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44	266	111	200	243	147	42	160	70	105	210	42	271	90	143	7	101
45	197	14	38	168	196	127	166	219	213	97	133	153	221	10	241	208
46	8	55	103	238	76	140	189	106	133	74	2	47	105	197	172	205
47	211	207	136	232	185	163	227	132	59	1	98	153	223	196	212	13
48	238	141	226	106	235	46	55	132	117	218	266	89	118	62	17	262
49	240	216	44	135	144	248	24	188	269	65	198	231	180	243	202	227
50	221	23	131	52	153	214	73	218	60	83	175	87	187	58	106	109
51	132	223	161	236	144	203	49	146	173	195	104	182	96	218	68	81
52	118	134	117	127	4	51	202	195	107	229	96	200	36	265	33	198
53	206	16	199	232	7	160	93	167	263	143	52	201	268	57	256	53
54	210	70	55	170	80	128	178	231	91	160	248	68	101	13	22	214
55	34	104	63	194	163	237	136	137	59	15	250	175	247	142	82	180
56	251	74	223	210	85	85	188	234	148	250	260	87	185	164	63	33
57	161	108	142	11	65	156	165	217	94	96	159	253	238	52	272	241
58	112	160	180	121	122	35	3	18	249	101	201	123	266	218	116	52
59	81	90	36	224	80	189	62	97	213	59	112	59	194	207	69	20
60	265	180	35	4	248	226	165	153	107	162	270	125	216	268	122	193
61	163	160	109	68	22	150	216	38	64	140	61	262	183	198	179	174
62	63	56	103	270	178	153	13	183	243	265	141	79	95	181	142	139
63	185	69	144	68	139	49	228	90	207	74	75	112	9	267	188	5
64	207	54	24	109	206	100	198	53	77	109	247	190	51	27	50	24
65	52	263	20	204	106	226	146	54	6	207	167	21	2	115	212	211
66	252	255	222	70	17	247	1	163	122	203	262	49	102	136	7	212
67	84	61	112	92	101	228	166	179	245	156	20	8	233	107	229	38

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
68	123	136	218	99	197	72	26	166	4	235	66	13	190	152	51	103
69	130	125	36	107	118	51	91	248	250	49	163	73	187	45	249	31
70	59	171	240	98	240	27	229	179	79	101	232	24	56	56	98	163
71	90	204	105	216	36	238	43	167	118	68	10	103	101	191	236	140
72	8	191	173	251	226	202	125	138	9	180	156	56	241	125	69	32
73	133	197	77	56	122	129	257	207	181	232	204	271	261	262	233	258
74	53	66	254	9	96	253	51	236	89	254	101	170	120	7	72	191
75	64	117	145	41	261	106	98	107	223	268	103	12	193	19	101	178
76	230	204	230	197	66	158	106	72	186	145	127	41	25	112	32	44
77	90	13	51	193	81	13	107	127	250	125	184	7	181	249	243	102
78	23	226	178	88	110	235	261	117	3	8	108	190	19	242	131	166
79	54	151	50	132	82	50	80	96	62	179	1	157	162	63	3	222
80	57	230	98	35	100	146	53	241	6	131	53	139	102	107	55	66
81	30	38	220	255	198	205	208	221	42	145	64	167	251	220	107	168
82	162	174	164	123	53	53	13	210	197	127	14	35	239	89	201	221
83	113	172	78	106	66	160	258	65	188	79	207	218	178	4	160	153
84	194	7	74	21	228	201	196	266	63	63	207	52	231	272	229	5
85	73	86	23	120	92	104	229	254	168	57	19	242	213	101	76	231
86	270	89	147	87	75	163	40	108	81	91	179	219	166	58	71	247
87	36	70	31	246	235	73	255	75	89	158	63	184	188	262	123	139
88	84	236	48	236	48	218	69	170	145	22	190	207	205	224	173	255
89	235	237	148	61	49	54	215	199	219	141	238	261	14	83	132	260
90	87	178	257	237	20	200	243	110	120	224	66	172	96	56	200	193
91	134	226	138	33	123	150	70	75	220	173	144	111	20	19	23	97
92	223	101	25	38	103	86	68	175	91	221	231	261	110	262	58	154
93	20	70	83	256	170	186	146	108	206	57	62	229	104	227	95	156
94	215	138	108	56	235	124	159	13	70	271	268	67	154	197	115	15
95	201	209	107	110	27	111	53	36	59	1	246	114	113	66	97	216
96	3	235	235	38	126	264	88	111	14	156	212	155	108	119	213	39
97	137	102	230	233	41	34	98	192	250	228	80	224	64	51	153	176
98	83	214	8	40	8	47	234	228	93	41	216	153	88	215	238	141
99	70	78	96	115	124	10	200	77	175	241	37	124	131	184	172	26
100	74	186	25	254	272	208	44	232	207	13	255	110	143	57	220	177
101	39	80	160	3	180	84	113	24	272	168	215	6	195	133	96	32
102	256	124	37	137	89	233	240	184	140	226	13	235	188	5	208	142
103	227	61	168	177	180	68	45	58	240	20	155	4	118	228	17	153
104	201	122	44	152	85	84	187	240	16	267	55	235	4	272	245	25
105	220	24	56	27	70	135	219	104	69	119	18	252	187	245	119	179
106	49	185	184	116	117	206	146	23	198	23	53	92	198	2	34	193
107	213	57	263	107	106	257	11	29	108	142	194	179	121	148	173	232
108	164	208	98	112	109	99	47	177	191	264	20	32	23	259	220	169
109	107	197	262	129	30	85	218	184	26	187	108	249	271	188	245	23
110	38	208	233	215	254	181	32	134	188	182	188	44	41	217	22	176
111	34	180	223	68	224	271	255	148	21	104	184	79	213	227	146	49
112	130	89	268	34	112	134	181	88	82	47	10	12	270	73	206	253
113	34	90	182	168	170	169	49	127	267	228	27	188	3	211	140	65
114	127	235	107	221	133	160	26	19	139	234	95	84	27	206	188	97
115	106	158	59	7	75	165	112	131	77	112	219	220	98	66	173	245
116	219	201	230	17	238	160	54	109	255	51	28	93	94	140	85	17
117	194	45	175	12	181	242	112	151	98	163	198	17	243	67	214	84
118	226	37	19	218	125	157	118	232	68	18	90	268	48	37	187	53
119	255	73	97	59	146	251	68	81	64	60	162	170	217	128	251	263
120	227	216	56	247	106	98	28	94	213	266	150	198	61	152	77	262

Table E.3: Dataset containing locations per parcel for the ambient zone.

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
30	-	246826	+0.40%
31	-	246214	+0.15%
32	-	246220	+0.15%
33	-	246618	+0.31%
22	32	252116	+2.55%
23	32	251586	+2.33%
24	32	251338	+2.23%
25	31	250944	+2.07%
25	32	250662	+1.96%
25	33	250772	+2.00%
26	32	250410	+1.85%
27	32	249654	+1.55%
27	33	249492	+1.48%
28	31	250304	+1.81%
28	32	249634	+1.54%
28	33	249356	+1.43%
29	32	249222	+1.37%
29	33	248672	+1.15%
30	33	248756	+1.18%

Table E.4: Performance of different layouts for the ambient zone for a whole week

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
34	-	295500	+1.47%
35	-	294810	+1.23%
36	-	293248	+0.70%
37	-	291518	+0.10%
20	37	298036	+2.34%
21	37	298151	+2.38%
22	37	298086	+2.36%
23	37	298093	+2.36%
24	37	298098	+2.36%
25	37	298145	+2.38%
26	37	298024	+2.34%
27	37	297975	+2.32%
28	37	297966	+2.32%
29	37	297703	+2.23%
30	37	297596	+2.19%
31	37	297489	+2.15%
32	37	297202	+2.05%
33	36	299086	+2.70%
33	37	297004	+1.99%

Table E.5: Performance of different layouts for the chilled zone for a whole week

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
24	-	Within	228136	-7.21%
25	-	Within	227834	-7.33%
26	-	Within	227584	-7.43%
27	-	Within	228136	-7.21%
24	-	Across	216694	-11.86%
25	-	Across	216010	-12.14%
26	-	Across	215552	-12.32%
27	-	Across	216162	-12.08%
18	29	Within	224400	-8.73%
18	30	Within	224488	-8.69%
19	30	Within	224136	-8.83%
20	28	Within	224564	-8.66%
20	29	Within	223948	-8.91%
20	30	Within	223790	-8.97%
20	31	Within	223976	-8.90%
21	29	Within	224126	-8.84%
21	30	Within	223852	-8.95%
21	31	Within	223922	-8.92%
22	30	Within	223970	-8.90%
22	31	Within	223904	-8.93%
23	30	Within	224204	-8.81%
24	30	Within	224570	-8.66%
24	31	Within	224180	-8.82%
20	29	Across	207828	-15.47%
21	28	Across	207184	-15.73%
21	29	Across	207370	-15.65%
21	30	Across	208760	-15.09%
22	28	Across	206870	-15.86%
22	29	Across	206708	-15.92%
22	30	Across	207750	-15.50%
23	28	Across	207000	-15.80%
23	29	Across	206448	-16.03%
23	30	Across	207100	-15.76%
24	29	Across	206932	-15.83%
24	30	Across	207188	-15.73%
24	31	Across	208468	-15.21%
25	29	Across	208218	-15.31%
25	30	Across	208080	-15.36%

Table E.6: Performance of different layouts combined with an allocation policy for a whole week in the ambient zone

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
25	-	Within	275798	-5.30%
26	-	Within	274400	-5.78%
27	-	Within	273250	-6.17%
28	-	Within	272688	-6.36%
29	-	Within	272150	-6.55%
30	-	Within	272170	-6.54%
31	-	Within	272386	-6.47%
32	-	Within	273012	-6.25%
33	-	Within	274282	-5.82%
34	-	Within	275950	-5.24%
26	-	Across	267378	-8.19%
27	-	Across	265262	-8.91%
28	-	Across	263436	-9.54%
29	-	Across	261806	-10.10
30	-	Across	260978	-10.38
31	-	Across	261086	-10.35
32	-	Across	262378	-9.90%
33	-	Across	264842	-9.06%
34	-	Across	268226	-7.90%
35	-	Across	272678	-6.37%
24	32	Within	267590	-8.11%
25	34	Within	267002	-8.32%
25	35	Within	267588	-8.11%
26	35	Within	266886	-8.36%
27	33	Within	266814	-8.38%
27	34	Within	266382	-8.53%
27	35	Within	266486	-8.49%
27	36	Within	267540	-8.13%
28	35	Within	266650	-8.44%
29	35	Within	266976	-8.32%
27	32	Across	252981	-13.13%
27	33	Across	252671	-13.24%
27	34	Across	253281	-13.03%
28	33	Across	252936	-13.15%
28	34	Across	253128	-13.08%
29	33	Across	253717	-12.88%
29	34	Across	253427	-12.98%
29	35	Across	254205	-12.71%
30	34	Across	254600	-12.57%
30	35	Across	254880	-12.48%

Table E.7: Performance of different layouts combined with an allocation policy for a whole week in the chilled zone

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
16	-	193460	-21.31%
17	-	193654	-21.23%
20	-	192782	-21.59%
22	-	191644	-22.05%
23	-	190742	-22.42%
24	-	190444	-22.54%
25	-	189830	-22.79%
26	-	190620	-22.47%
27	-	190958	-22.33%
28	-	191894	-21.95%
16	25	191836	-21.97%
16	26	191868	-21.96%
16	27	191390	-22.15%
16	28	191498	-22.11%
16	29	191456	-22.13%
16	31	192208	-21.82%
16	32	192706	-21.62%
17	27	191544	-22.09%
17	28	191704	-22.02%
17	29	191652	-22.05%
18	28	191776	-22.00%
24	32	190944	-22.33%
25	31	190720	-22.42%
25	32	190674	-22.44%
25	33	190738	-22.42%

Table E.8: Performance of different layouts combined with the JOBPRP model with a chunk size of 3 full batches for a whole week in the ambient zone

Location midaisle 1	Location midaisle 2	Travel distance [m]	Gap to benchmark
25	–	278260	-4.45%
26	-	277012	-4.88%
27	-	276148	-5.17%
28	-	275684	-5.33%
29	-	275348	-5.45%
30	-	275242	-5.49%
31	-	275212	-5.50%
32	-	275320	-5.46%
33	-	276280	-5.13%
34	-	276318	-5.12%
20	34	276432	-5.08%
21	34	275974	-5.23%
22	34	274926	-5.59%
23	33	275474	-5.41%
23	34	274396	-5.78%
24	33	275356	-5.45%
24	34	274324	-5.80%
25	34	274344	-5.79%
26	34	273834	-5.97%
26	35	274008	-5.91%
27	34	273660	-6.03%
28	34	273720	-6.01%
28	35	273744	-6.00%
29	34	273906	-5.94%
29	35	273844	-5.97%

Table E.9: Performance of different layouts combined with the JOBPRP model with a chunk size of 4 full batches for a whole week in the chilled zone

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
13	-	Within	151343	-38.44%
14	-	Within	150661	-38.72%
15	-	Within	150619	-38.74%
16	-	Within	150689	-38.71%
17	-	Within	151007	-38.58%
11	-	Across	150387	-38.83%
12	-	Across	149593	-39.15%
13	-	Across	149631	-39.14%
14	-	Across	150377	-38.83%
15	-	Across	150899	-38.62%
12	28	Within	148174	-39.73%
12	30	Within	148440	-39.62%
13	26	Within	147926	-39.83%
13	27	Within	147858	-39.86%
13	28	Within	147938	-39.83%
13	29	Within	148140	-39.74%
13	30	Within	148358	-39.66%
14	26	Within	148066	-39.77%
14	27	Within	147966	-39.82%
14	28	Within	147924	-39.83%
14	29	Within	148046	-39.78%
14	30	Within	148292	-39.68%
16	28	Within	148280	-39.69%
16	30	Within	148400	-39.64%
16	31	Within	148728	-39.51%
8	17	Across	142116	-42.19%
8	18	Across	141710	-42.36%
8	19	Across	141264	-42.54%
8	20	Across	141358	-42.50%
9	17	Across	142056	-42.22%
9	18	Across	141560	-42.42%
9	20	Across	141048	-42.63%
10	20	Across	141088	-42.61%
11	20	Across	141526	-42.43%
11	25	Across	141440	-42.47%
11	26	Across	141402	-42.48%
11	27	Across	141640	-42.39%
11	28	Across	141646	-42.39%
11	29	Across	141952	-42.26%
11	30	Across	142570	-42.01%

Table E.10: Performance of different layouts with an within-aisle policy combined with the JOBPRP for a chunk size of 3 full batches for a whole week in the ambient zone

Location midaisle 1	Location midaisle 2	Allocation policy	Travel distance [m]	Gap to benchmark
18	-	Within	237738	-18.36%
19	-	Within	236288	-18.86%
20	-	Within	235408	-19.16%
21	-	Within	235100	-19.27%
22	-	Within	235764	-19.04%
23	-	Within	236268	-18.87%
24	-	Within	237326	-18.51%
25	-	Within	238280	-18.18%
26	-	Within	240130	-17.54%
27	-	Within	242036	-16.89%
16	-	Across	234162	-19.59%
17	-	Across	231724	-20.43%
18	-	Across	229532	-21.18%
19	-	Across	227464	-21.89%
20	-	Across	226478	-22.23%
21	-	Across	226196	-22.33%
22	-	Across	226202	-22.33%
23	-	Across	227032	-22.04%
24	-	Across	228554	-21.52%
25	-	Across	229756	-21.11%
10	25	Within	226118	-22.35%
11	24	Within	226288	-22.30%
11	25	Within	225876	-22.44%
12	25	Within	225908	-22.43%
12	27	Within	226402	-22.26%
13	24	Within	225892	-22.43%
13	25	Within	225664	-22.51%
18	27	Within	225488	-22.57%
18	29	Within	225008	-22.74%
18	30	Within	224638	-22.86%
18	31	Within	225028	-22.73%
19	30	Within	225088	-22.71%
19	31	Within	225202	-22.67%
20	30	Within	225674	-22.51%
20	31	Within	225496	-22.57%
16	28	Across	213834	-26.57%
17	28	Across	213774	-26.59%
17	29	Across	213674	-26.63%
17	30	Across	214052	-26.50%
17	31	Across	214828	-26.23%
18	27	Across	213966	-26.53%
18	28	Across	213754	-26.60%
18	29	Across	213642	-26.64%
18	30	Across	213754	-26.60%
18	31	Across	214366	-26.39%
19	29	Across	214500	-26.34%
19	30	Across	214402	-26.38%
19	31	Across	214612	-26.31%
19	32	Across	215076	-26.15%
19	33	Across	216010	-25.83%

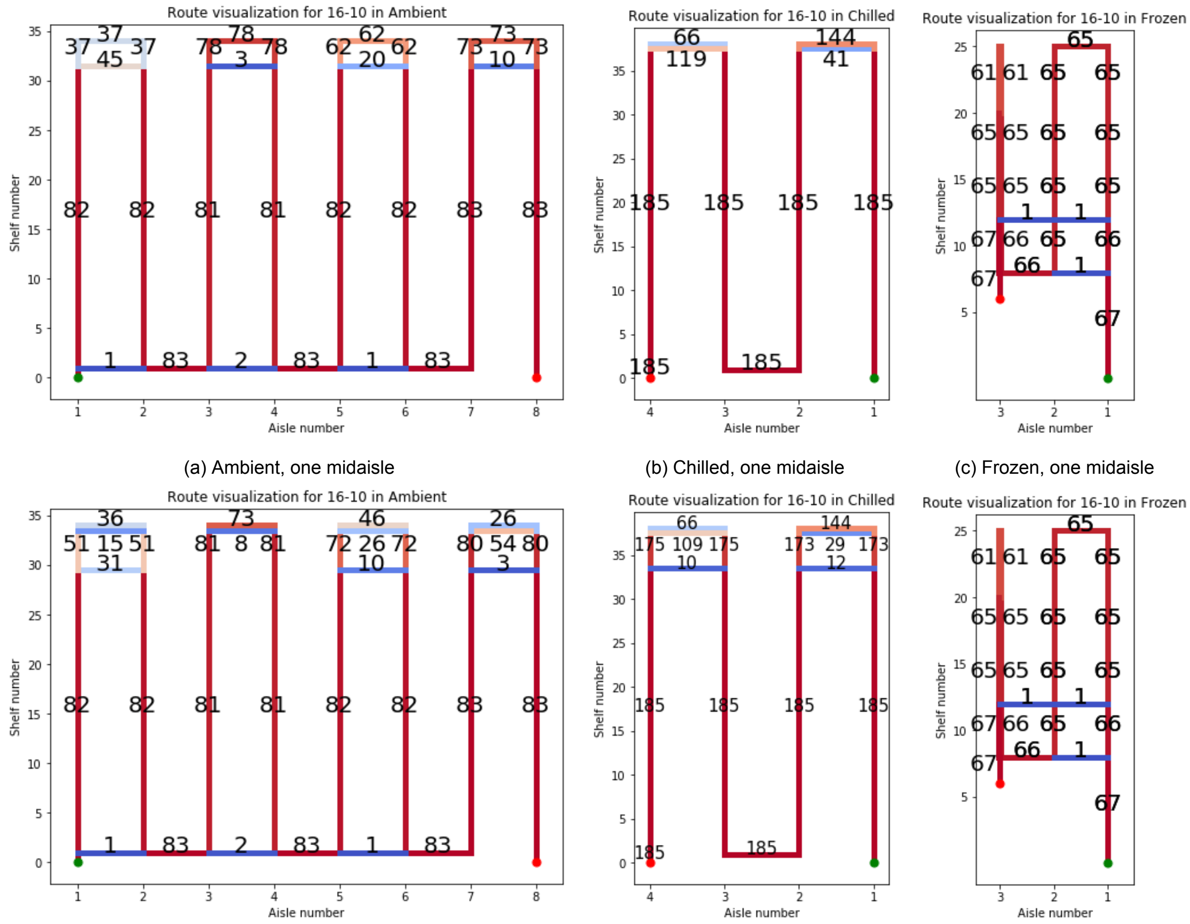
Table E.11: Performance of different layouts with an within-aisle policy combined with the JOBPRP for a chunk size of 3 full batches for a whole week in the chilled zone

F

Visualization constructed batches

This appendix depicts the constructed routes for each possible configuration. The routes are all visualizations of the 16-10 scenario. For each different configuration, all conducted experiments are here visualized. The results are sorted for each combination of warehouse processes

Layout

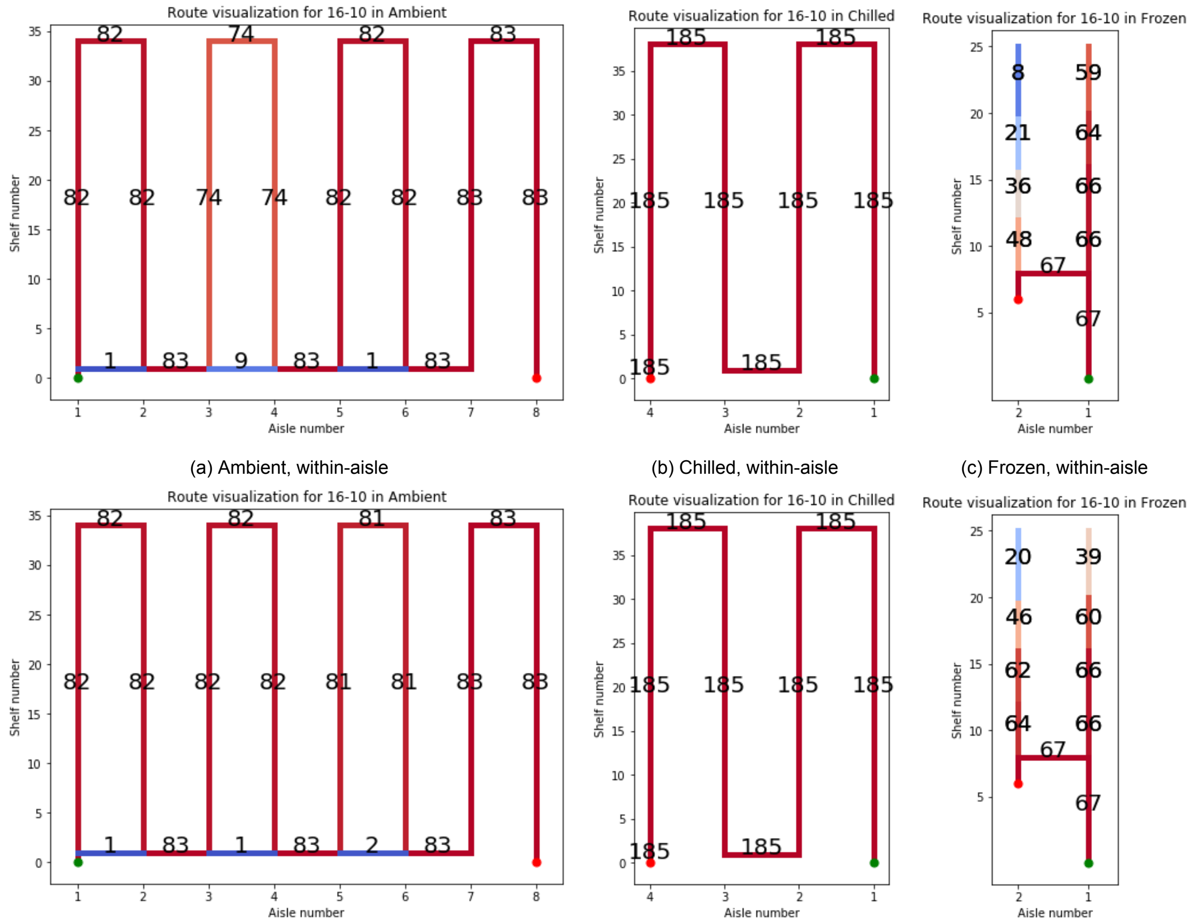


(a) Ambient, one midaisle (b) Chilled, one midaisle (c) Frozen, one midaisle

(d) Ambient, two midaisles (e) Chilled, two midaisles (f) Frozen, two midaisles

Figure F.1: Visualization of the routes on 16-10 with changes to the layout for each zone

Allocation

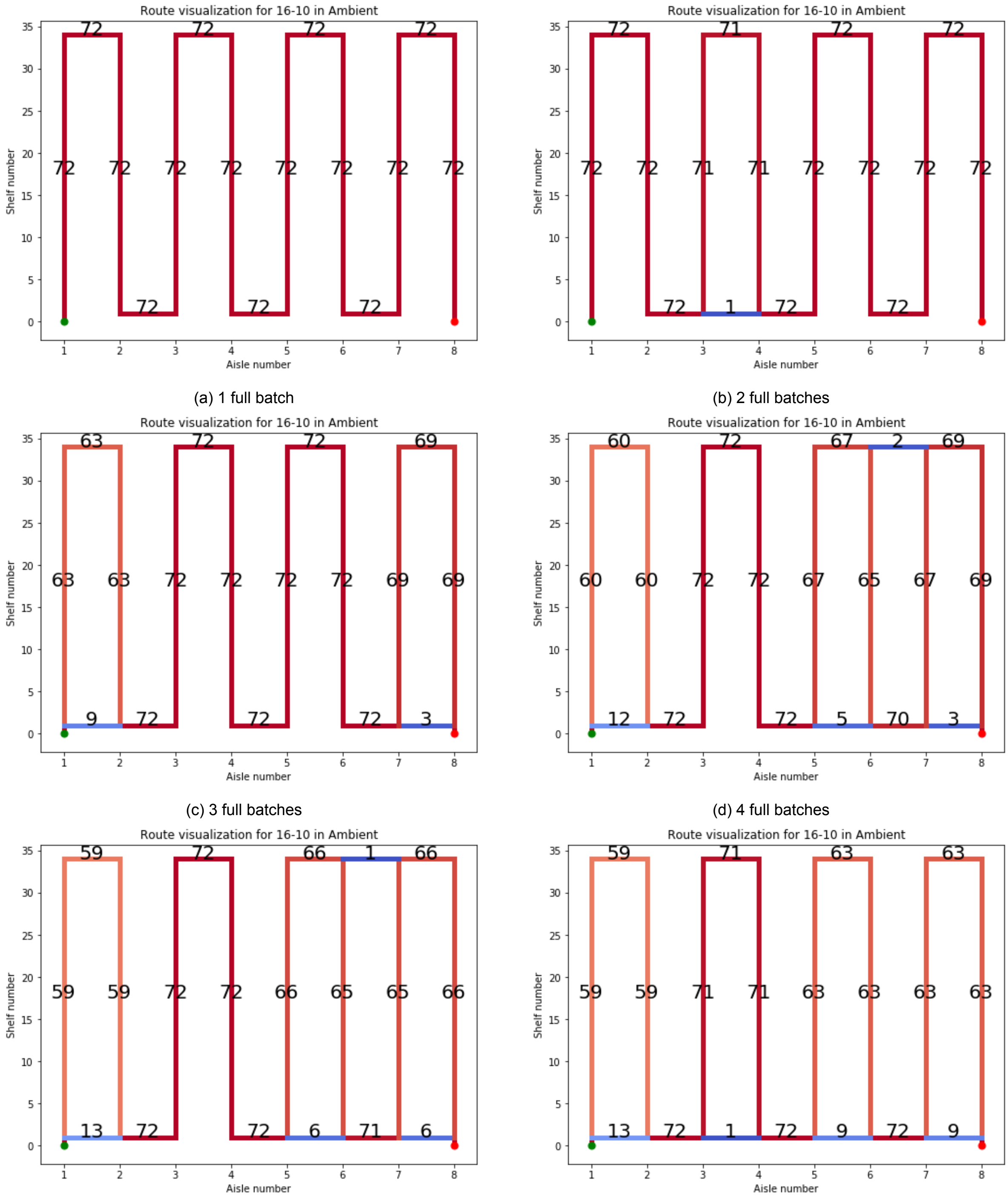


(a) Ambient, within-aisle (b) Chilled, within-aisle (c) Frozen, within-aisle

(d) Ambient, across-aisle (e) Chilled, across-aisle (f) Frozen, across-aisle

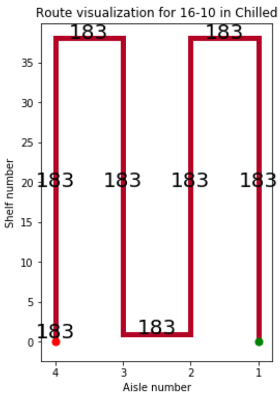
Figure F.2: Visualization of the routes on 16-10 with an allocation policy for each zone

Batching

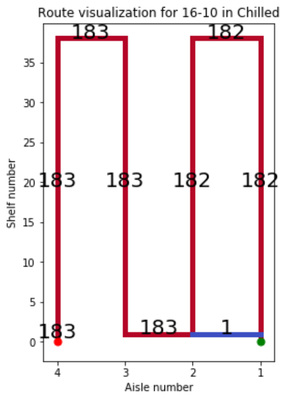


(a) 1 full batch
(b) 2 full batches
(c) 3 full batches
(d) 4 full batches
(e) 5 full batches
(f) 6 full batches

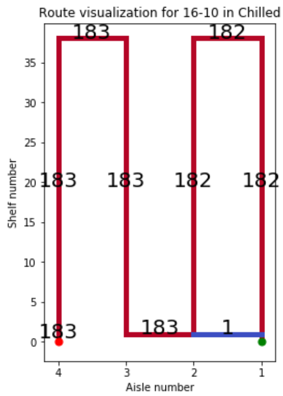
Figure F.3: Visualization of the routes on 16-10 with the JOBPRP model with different chunk sizes for the ambient zone



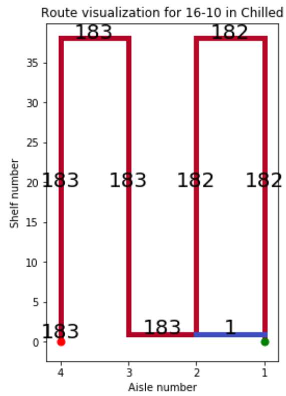
(a) 1 full batch



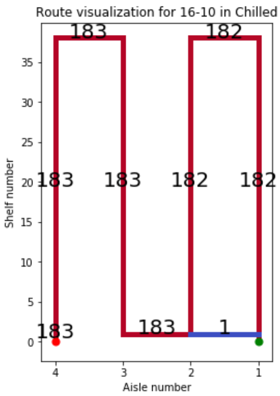
(b) 2 full batches



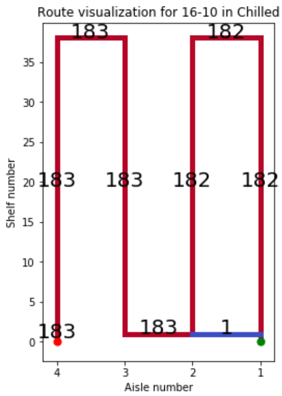
(c) 3 full batches



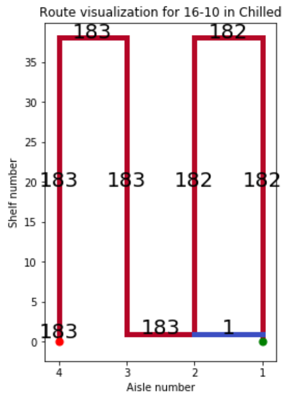
(d) 4 full batches



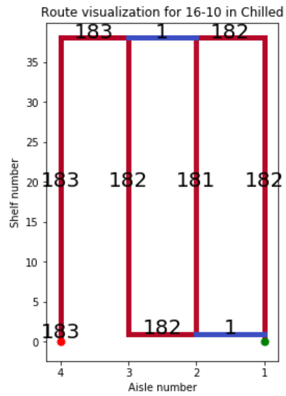
(e) 5 full batches



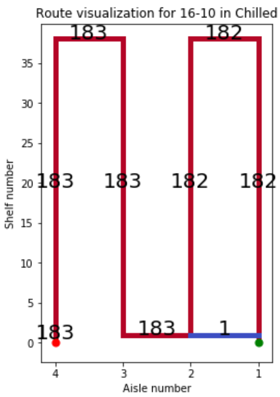
(f) 6 full batches



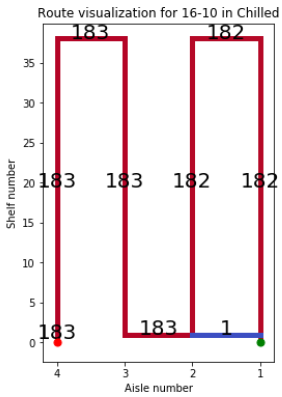
(g) 7 full batches



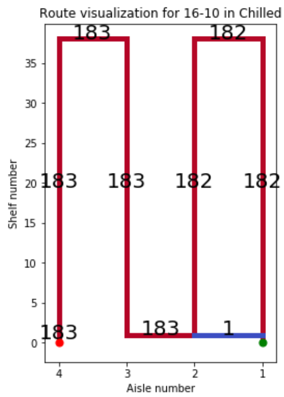
(h) 8 full batches



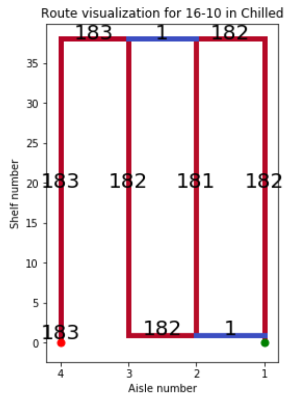
(i) 9 full batches



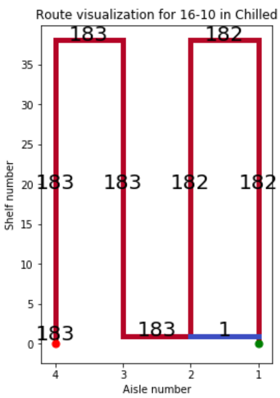
(j) 10 full batches



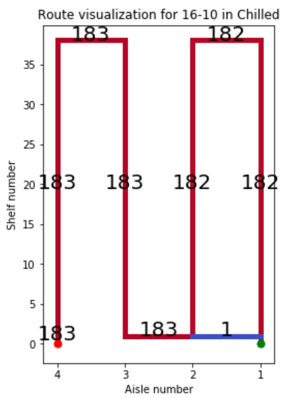
(k) 11 full batches



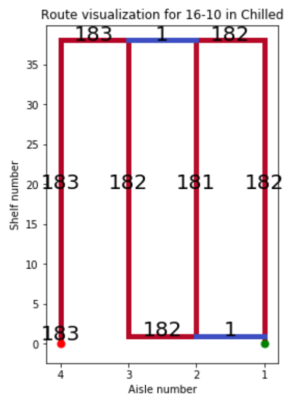
(l) 12 full batches



(m) 13 full batches

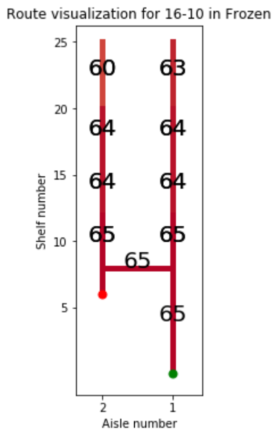


(n) 14 full batches

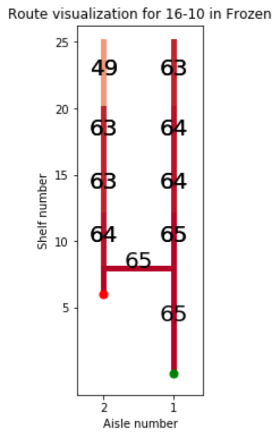


(o) 15 full batches

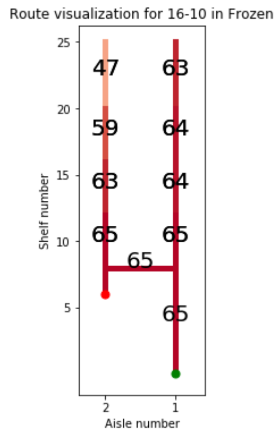
Figure F.4: Visualization of the routes on 16-10 with the JOBPRP model with different chunk sizes for the chilled zone



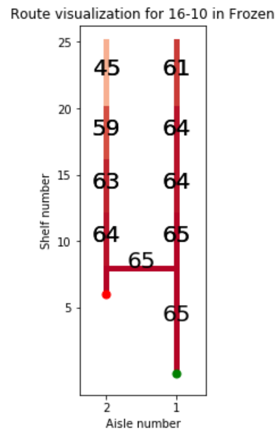
(a) 1 full batch



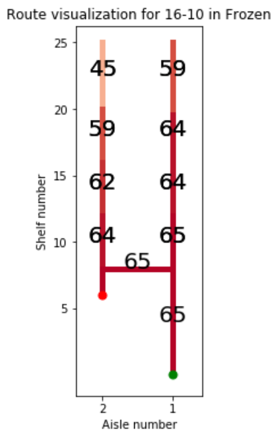
(b) 2 full batches



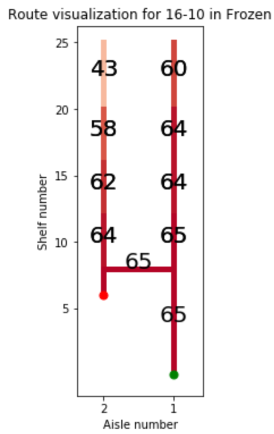
(c) 3 full batches



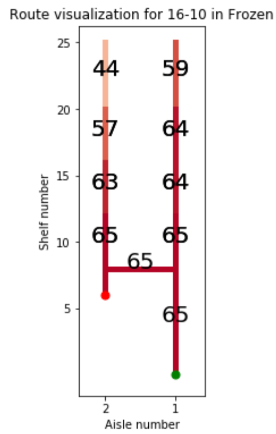
(d) 4 full batches



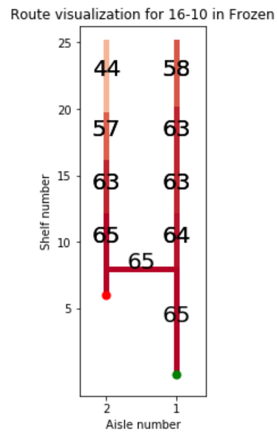
(e) 5 full batches



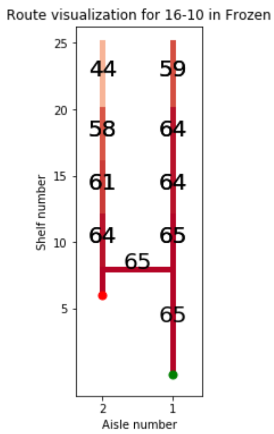
(f) 6 full batches



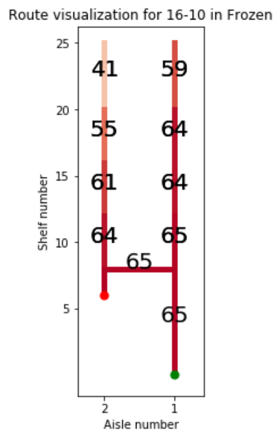
(g) 7 full batches



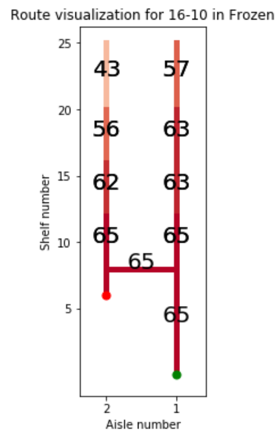
(h) 8 full batches



(i) 9 full batches



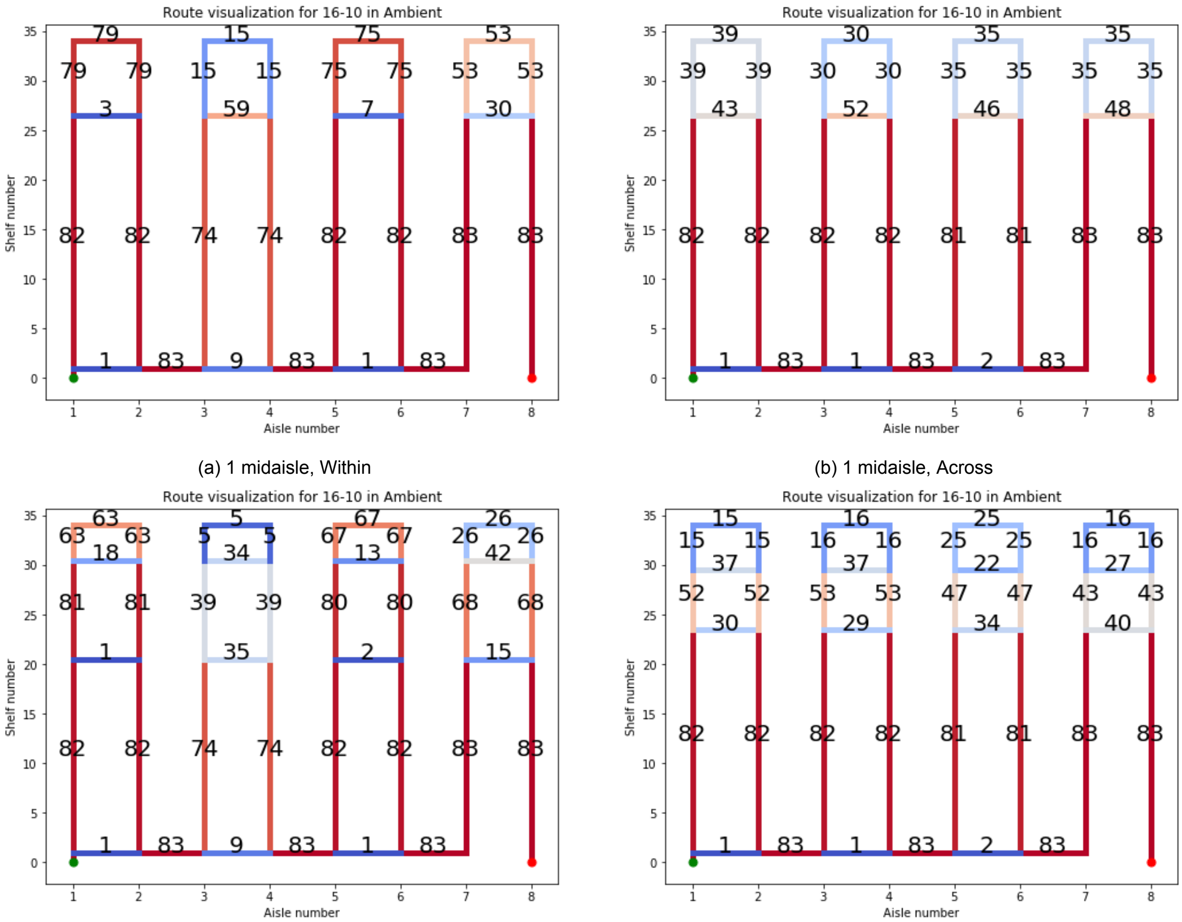
(j) 10 full batches



(k) 11 full batches

Figure F.5: Visualization of the routes on 16-10 with the JOBPRP model with different chunk sizes for the frozen zone

Layout & Product allocation



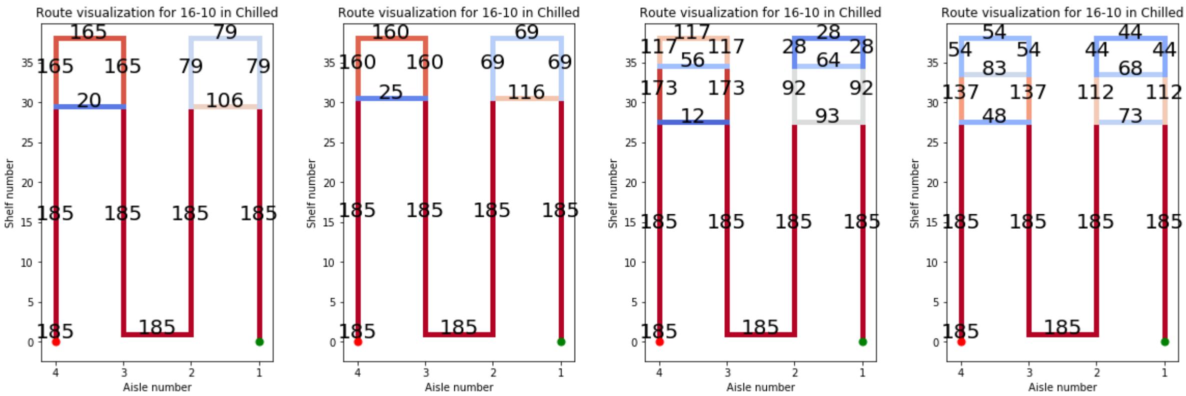
(a) 1 midaisle, Within

(b) 1 midaisle, Across

(c) 2 midaisles, Within

(d) 2 midaisles, Across

Figure F.6: Visualization of the routes on 16-10 with an allocation policy for different layouts for the ambient zone



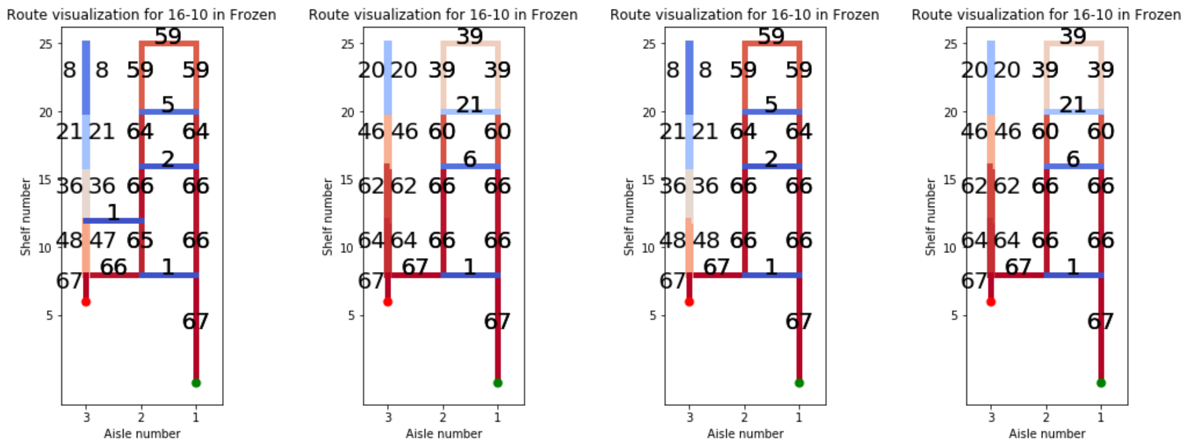
(a) 1 midaisle, Within

(b) 1 midaisle, Across

(c) 2 midaisles, Within

(d) 2 midaisle, Across

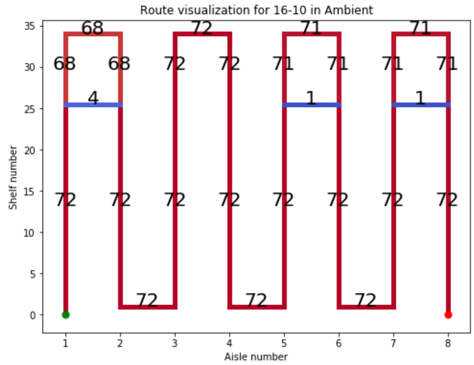
Figure F.7: Visualization of the routes on 16-10 with an allocation policy for different layouts for the chilled zone



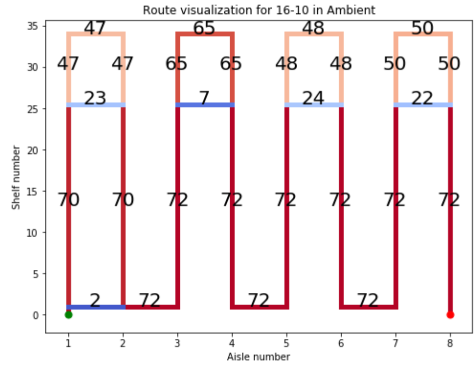
(a) Within, 1 midaisle (b) Across, 1 midaisle (c) Within, 2 midaisle (d) Across, 2 midaisle

Figure F.8: Visualization of the routes on 16-10 with an allocation policy for different layouts for the frozen zone

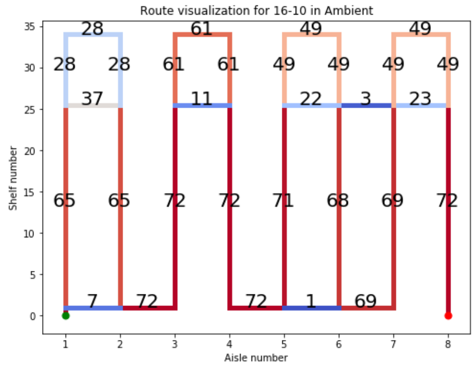
Layout & Batching



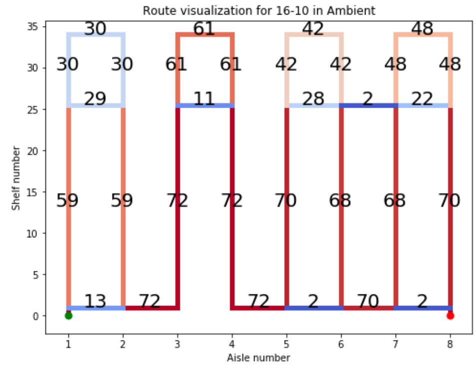
(a) 1 midaisle, 1 full batch



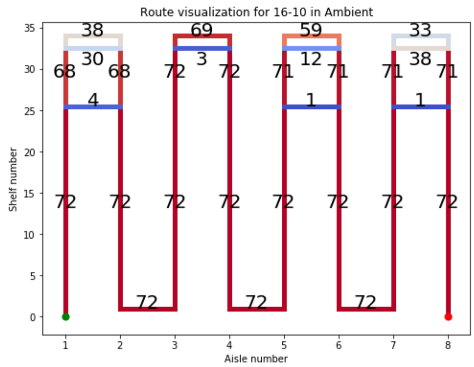
(b) 1 midaisle, 2 full batches



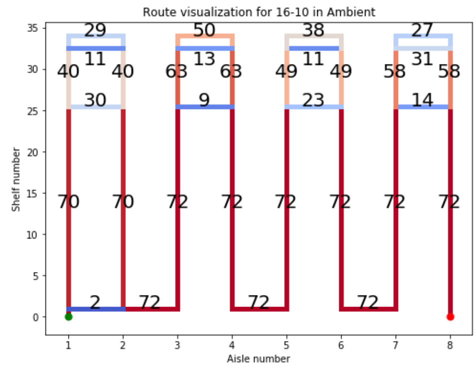
(c) 1 midaisle, 3 full batches



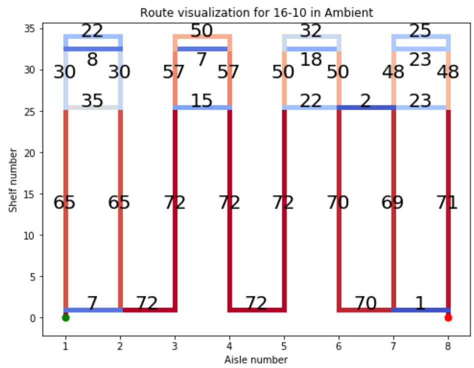
(d) 1 midaisle, 4 full batches



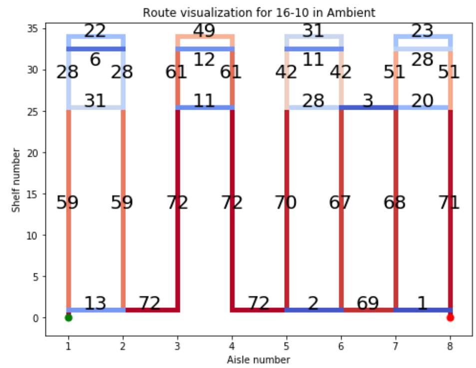
(e) 2 midaisles, 1 full batch



(f) 2 midaisles, 2 full batches

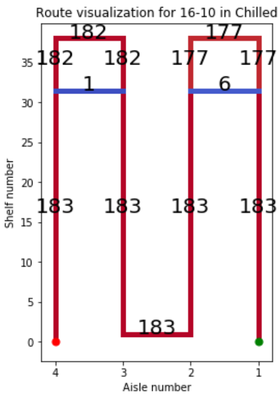


(g) 2 midaisles, 3 full batches

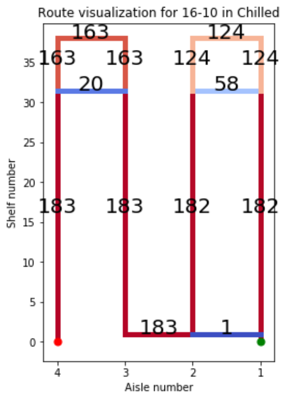


(h) 2 midaisles, 4 full batches

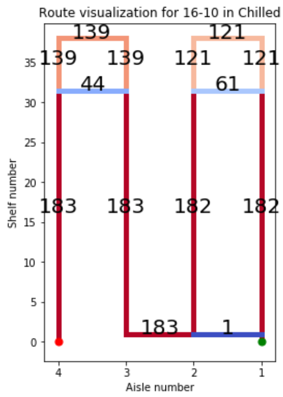
Figure F.9: Visualization of the routes on 16-10 with the JOBPRP model for different layouts for the ambient zone



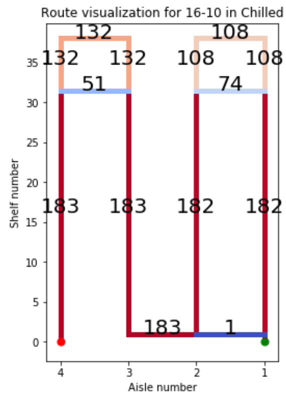
(a) 1 midaisle, 1 full batch



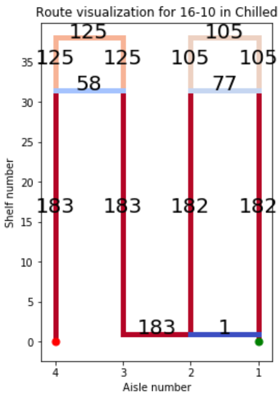
(b) 1 midaisle, 2 full batches



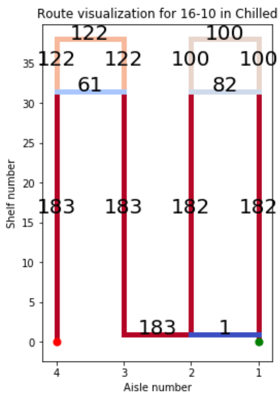
(c) 1 midaisle, 3 full batches



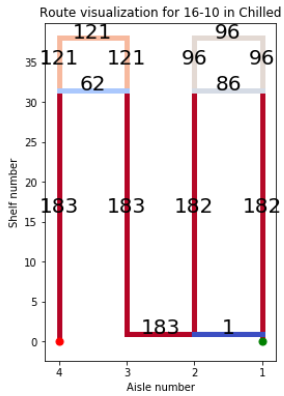
(d) 1 midaisle, 4 full batches



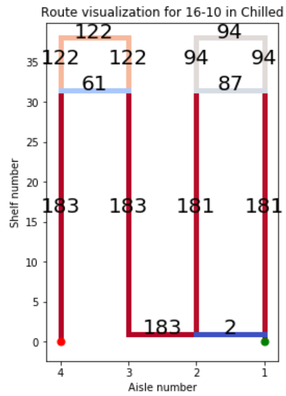
(e) 1 midaisle, 5 full batches



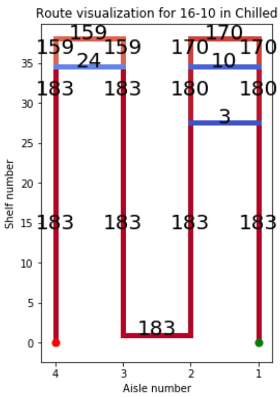
(f) 1 midaisle, 6 full batches



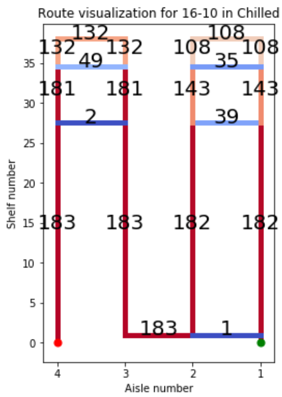
(g) 1 midaisle, 7 full batches



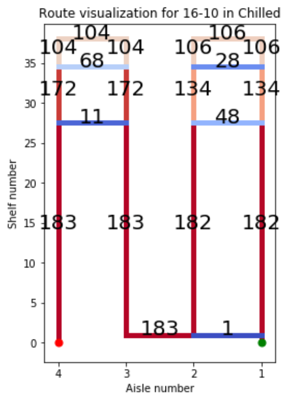
(h) 1 midaisle, 8 full batches



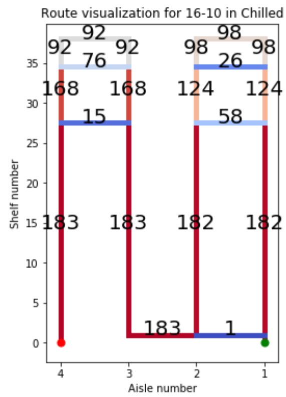
(i) 2 midaisles, 1 full batch



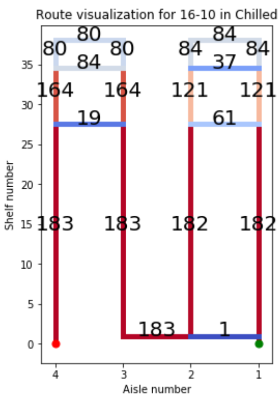
(j) 2 midaisles, 2 full batches



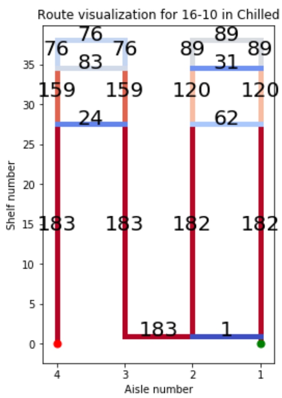
(k) 2 midaisles, 3 full batches



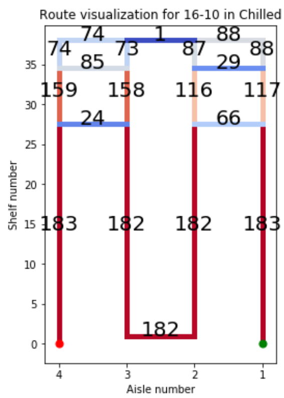
(l) 2 midaisles, 4 full batches



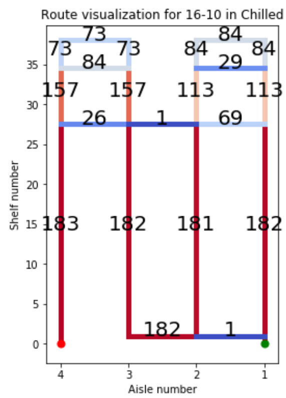
(m) 2 midaisles, 5 full batches



(n) 2 midaisles, 6 full batches

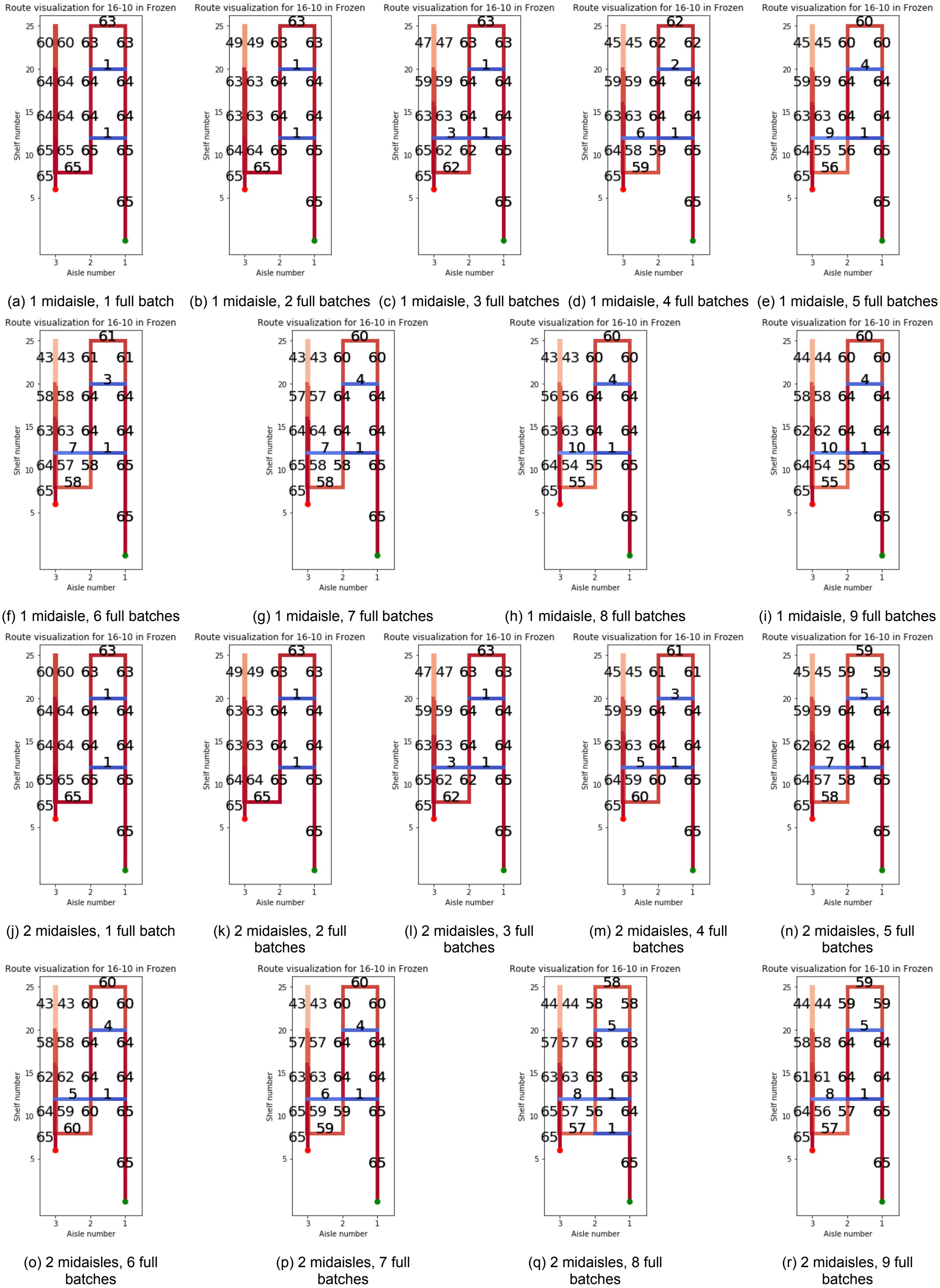


(o) 2 midaisles, 7 full batches



(p) 2 midaisles, 8 full batches

Figure F.10: Visualization of the routes on 16-10 with the JOBPRP model for different layouts for the chilled zone



(a) 1 midaisle, 1 full batch (b) 1 midaisle, 2 full batches (c) 1 midaisle, 3 full batches (d) 1 midaisle, 4 full batches (e) 1 midaisle, 5 full batches

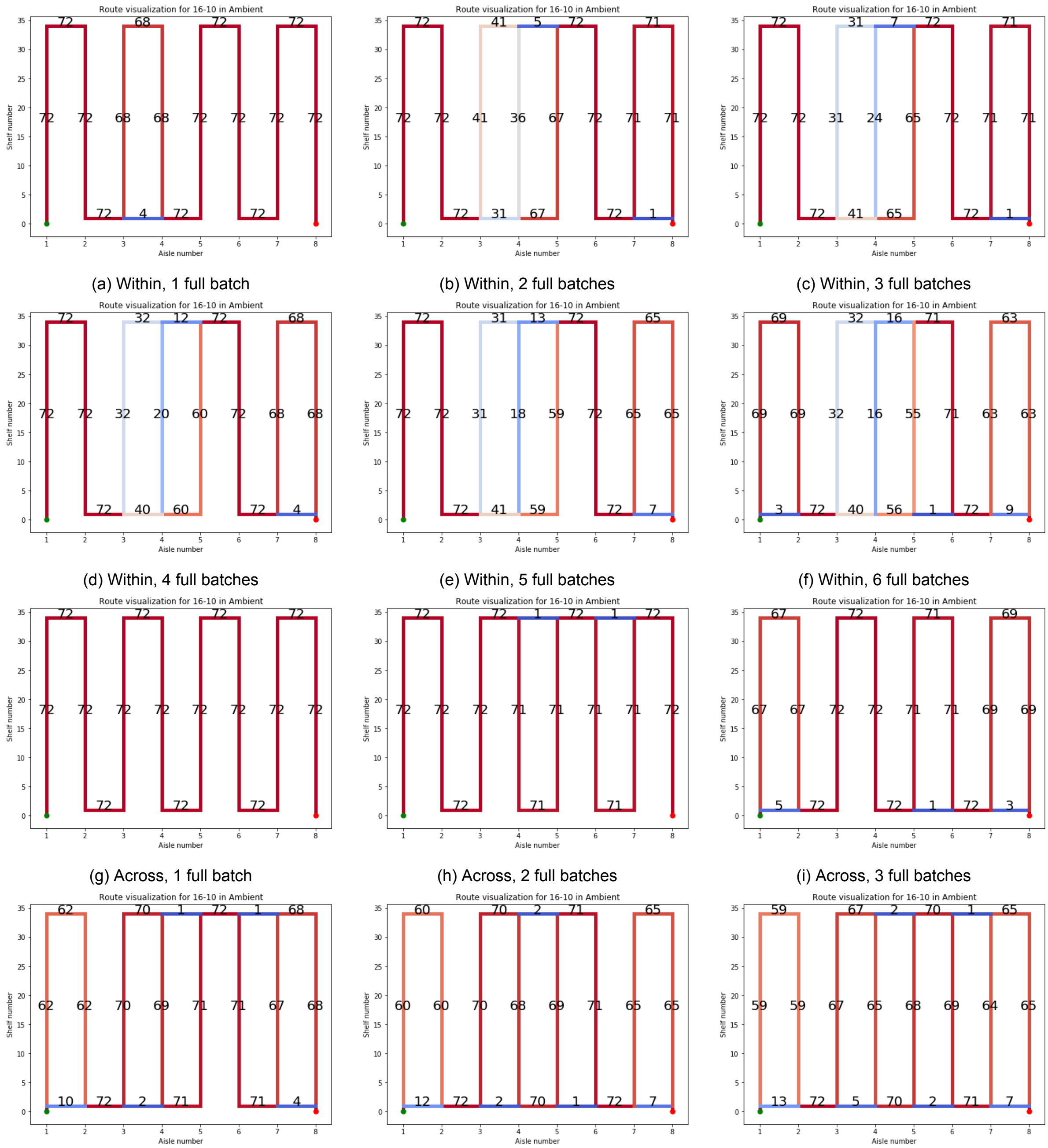
(f) 1 midaisle, 6 full batches (g) 1 midaisle, 7 full batches (h) 1 midaisle, 8 full batches (i) 1 midaisle, 9 full batches

(j) 2 midaisles, 1 full batch (k) 2 midaisles, 2 full batches (l) 2 midaisles, 3 full batches (m) 2 midaisles, 4 full batches (n) 2 midaisles, 5 full batches

(o) 2 midaisles, 6 full batches (p) 2 midaisles, 7 full batches (q) 2 midaisles, 8 full batches (r) 2 midaisles, 9 full batches

Figure F.11: Visualization of the routes on 16-10 with the JOBPRP model for different layouts for the frozen zone

Product allocation & batching



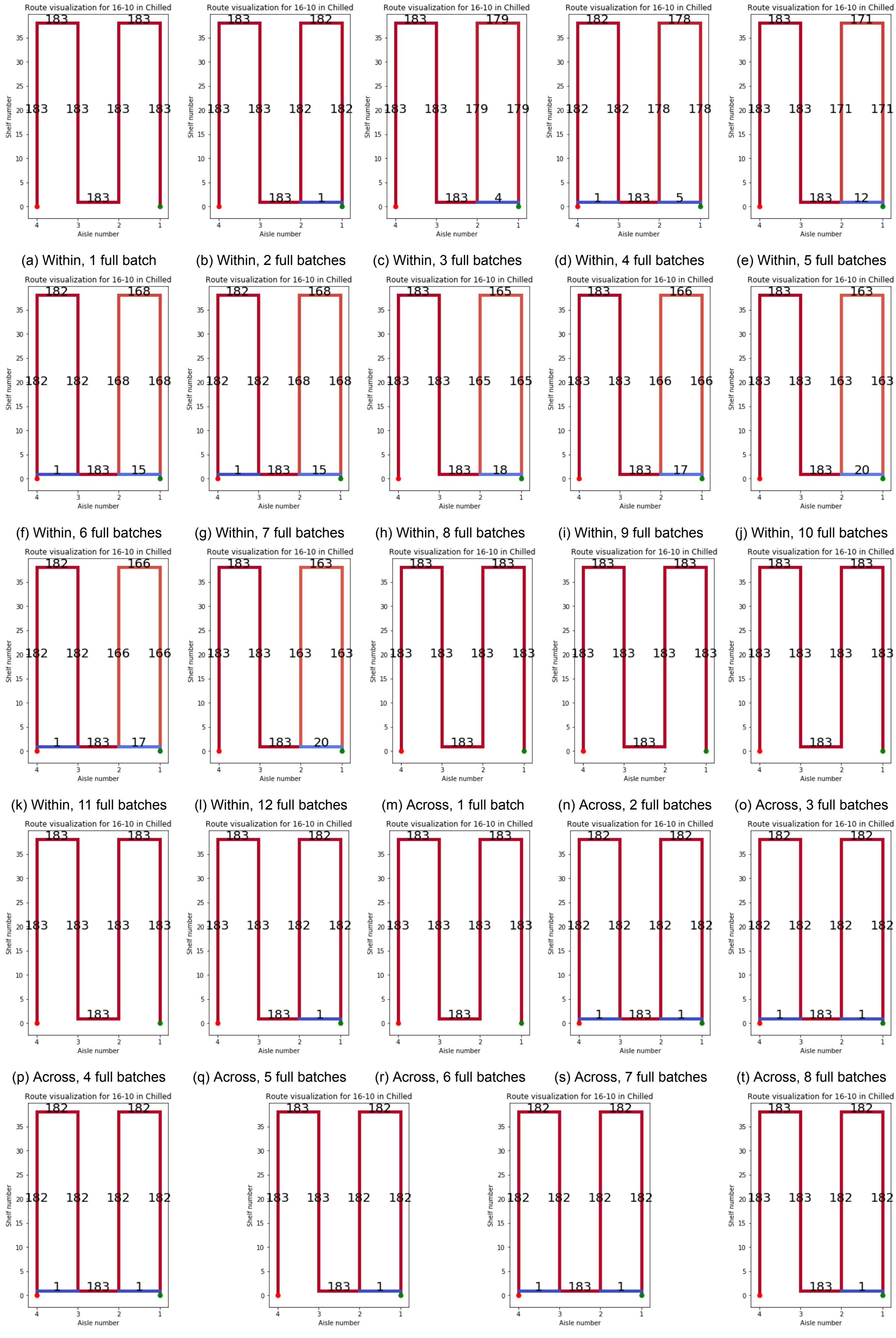
(a) Within, 1 full batch (b) Within, 2 full batches (c) Within, 3 full batches

(d) Within, 4 full batches (e) Within, 5 full batches (f) Within, 6 full batches

(g) Across, 1 full batch (h) Across, 2 full batches (i) Across, 3 full batches

(j) Across, 4 full batches (k) Across, 5 full batches (l) Across, 6 full batches

Figure F.12: Visualization of the routes on 16-10 with the JOBPRP model with different chunk sizes and an allocation policy for the ambient zone



(a) Within, 1 full batch (b) Within, 2 full batches (c) Within, 3 full batches (d) Within, 4 full batches (e) Within, 5 full batches

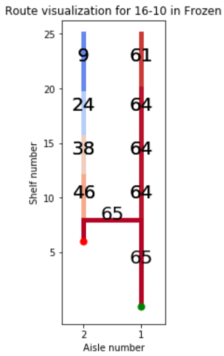
(f) Within, 6 full batches (g) Within, 7 full batches (h) Within, 8 full batches (i) Within, 9 full batches (j) Within, 10 full batches

(k) Within, 11 full batches (l) Within, 12 full batches (m) Across, 1 full batch (n) Across, 2 full batches (o) Across, 3 full batches

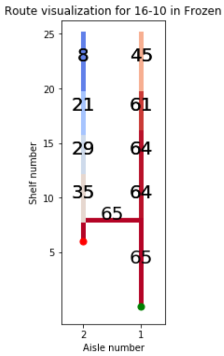
(p) Across, 4 full batches (q) Across, 5 full batches (r) Across, 6 full batches (s) Across, 7 full batches (t) Across, 8 full batches

(u) Across, 9 full batches (v) Across, 10 full batches (w) Across, 11 full batches (x) Across, 12 full batches

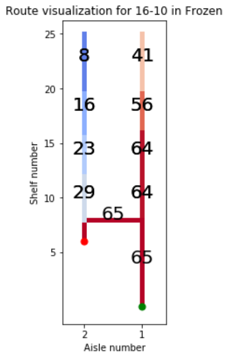
Figure F.13: Visualization of the routes on 16-10 with the JOBPRP model with different chunk sizes and an allocation policy for the chilled zone



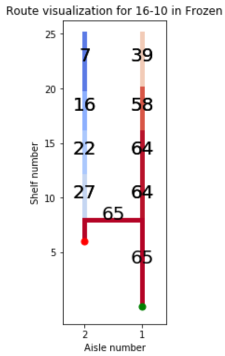
(a) Within, 1 full batch



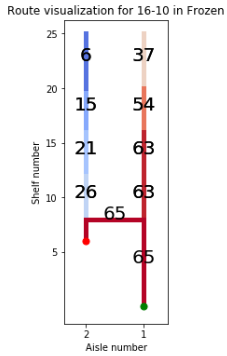
(b) Within, 2 full batches



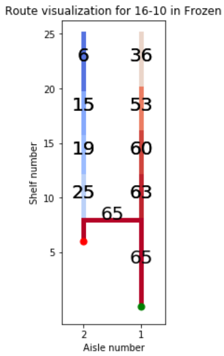
(c) Within, 3 full batches



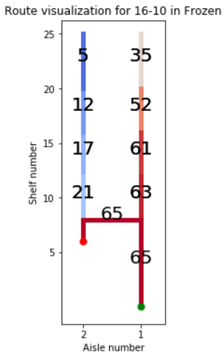
(d) Within, 4 full batches



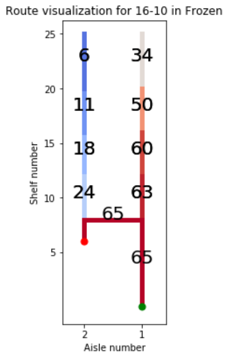
(e) Within, 5 full batches



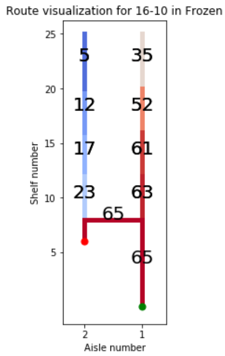
(f) Within, 6 full batches



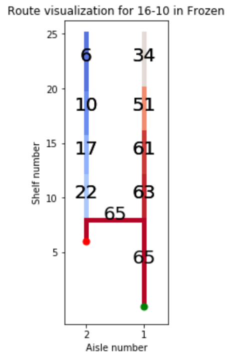
(g) Within, 7 full batches



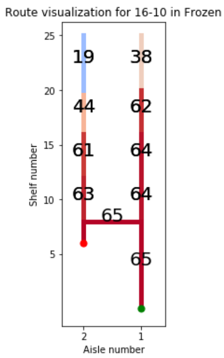
(h) Within, 8 full batches



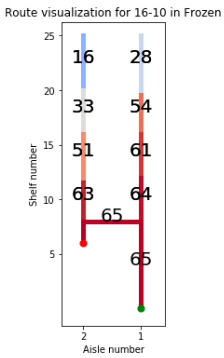
(i) Within, 9 full batches



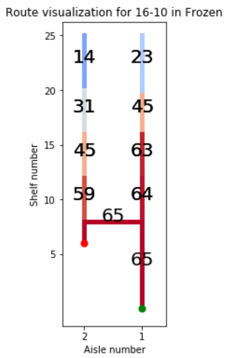
(j) Within, 10 full batches



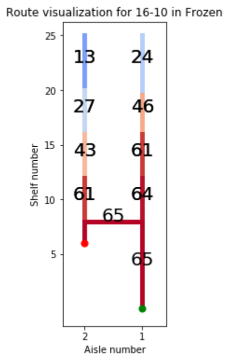
(k) Across, 1 full batch



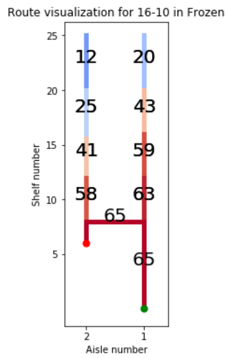
(l) Across, 2 full batches



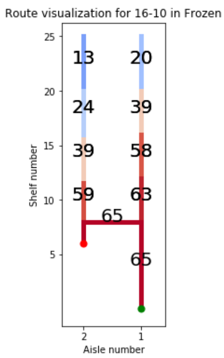
(m) Across, 3 full batches



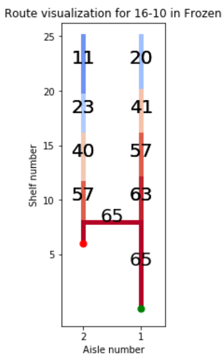
(n) Across, 4 full batches



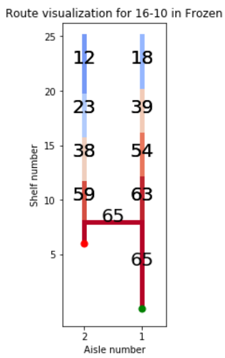
(o) Across, 5 full batches



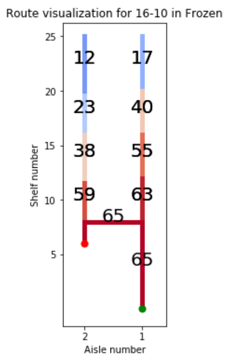
(p) Across, 6 full batches



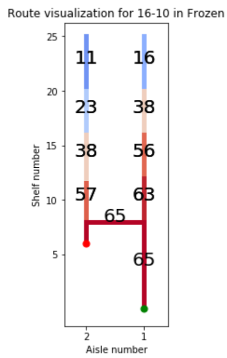
(q) Across, 7 full batches



(r) Across, 8 full batches



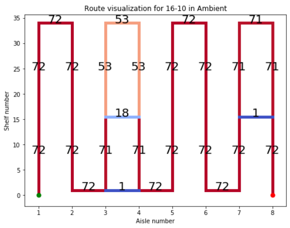
(s) Across, 9 full batches



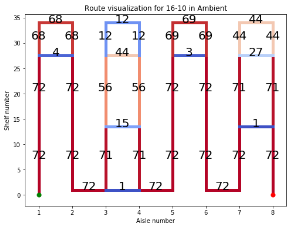
(t) Across, 10 full batches

Figure F.14: Visualization of the routes on 16-10 with the JOBPRP model with different chunk sizes and an allocation policy for the frozen zone

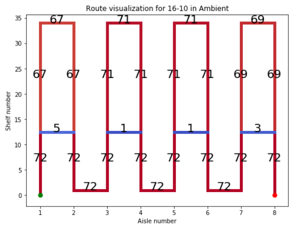
All three warehouse processes



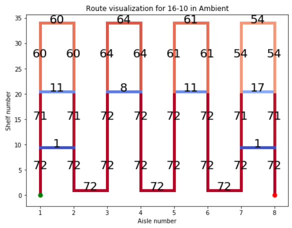
(a) 1 midaisle, Within, 1 full batch



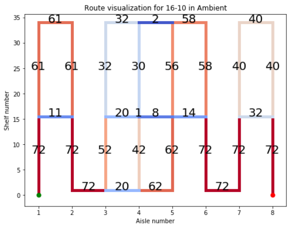
(b) 2 midaisles, Within, 1 full batch



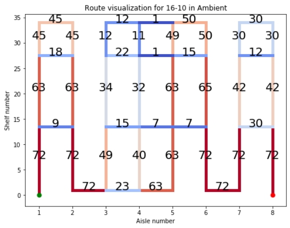
(c) 1 midaisle, Across, 1 full batch



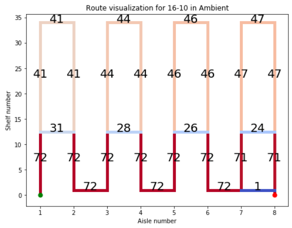
(d) 2 midaisles, Across, 1 full batch



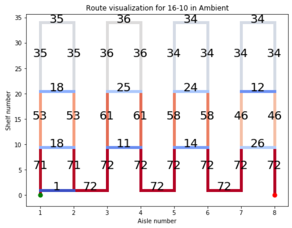
(e) 1 midaisle, Within, 2 full batches



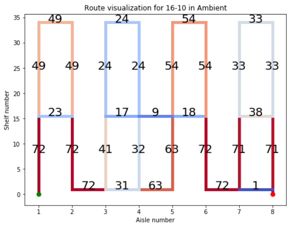
(f) 2 midaisles, Within, 2 full batches



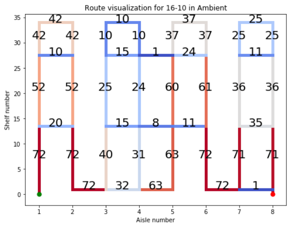
(g) 1 midaisle, Across, 2 full batches



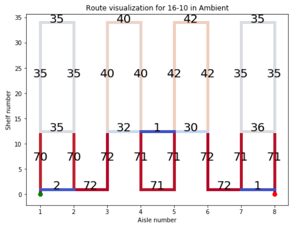
(h) 2 midaisles, Across, 2 full batch



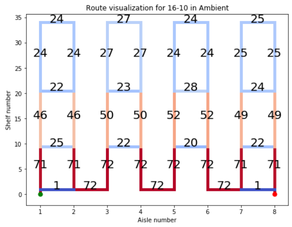
(i) 1 midaisle, Within, 3 full batches



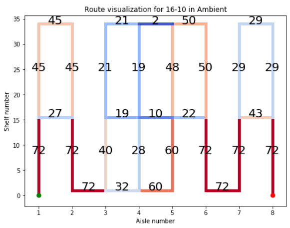
(j) 2 midaisles, Within, 3 full batches



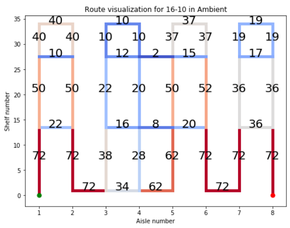
(k) 1 midaisle, Across, 3 full batches



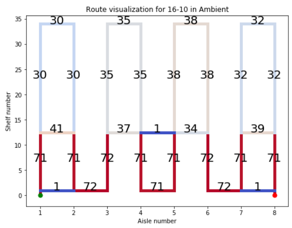
(l) 2 midaisles, Across, 3 full batches



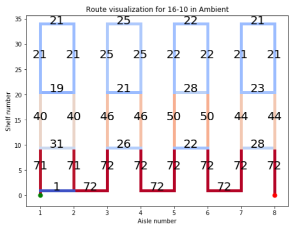
(m) 1 midaisle, Within, 4 full batches



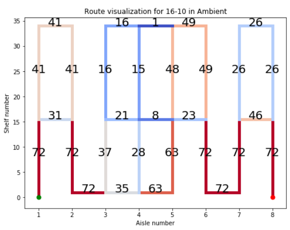
(n) 2 midaisles, Within, 4 full batches



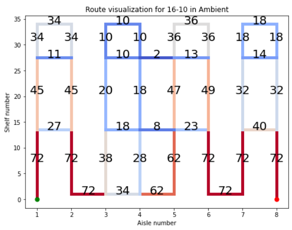
(o) 1 midaisle, Across, 4 full batches



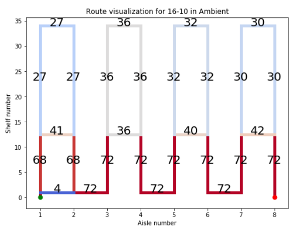
(p) 2 midaisles, Across, 4 full batch



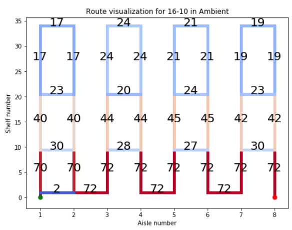
(q) 1 midaisle, Within, 5 full batches



(r) 2 midaisles, Within, 5 full batches

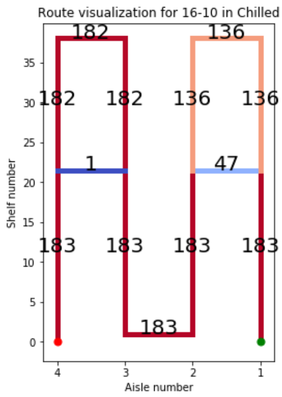


(s) 1 midaisle, Across, 5 full batches

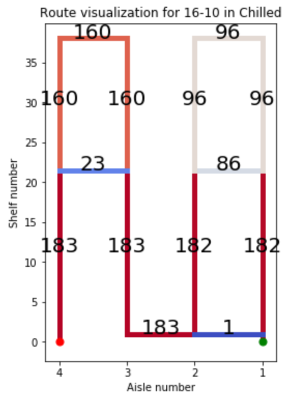


(t) 2 midaisles, Across, 5 full batch

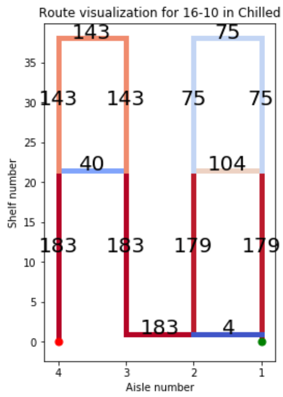
Figure F.15: Visualization of the routes on 16-10 by integrating all three warehouse processes for the ambient zone



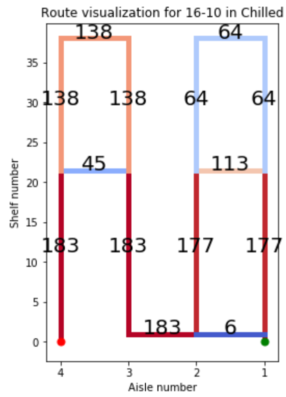
(a) 1 midaisle, 1 full batch



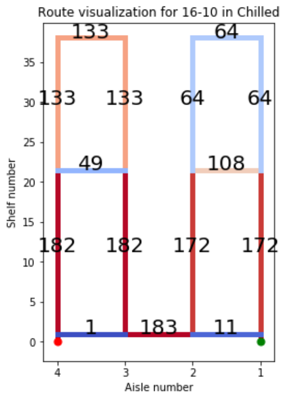
(b) 1 midaisle, 2 full batches



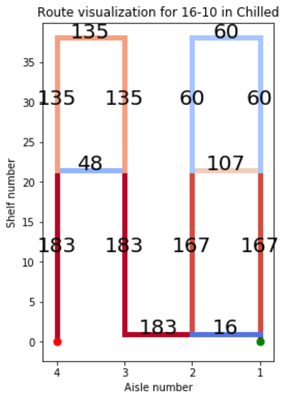
(c) 1 midaisle, 3 full batches



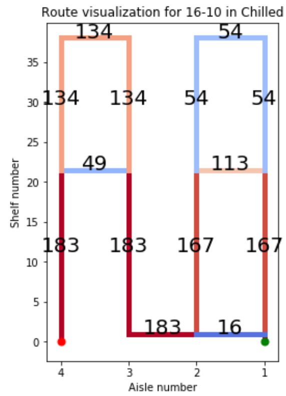
(d) 1 midaisle, 4 full batches



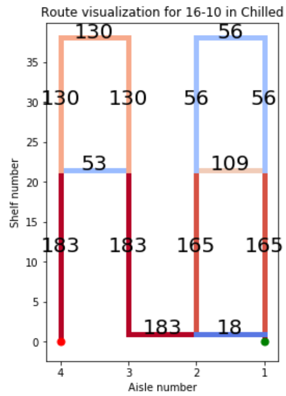
(e) 1 midaisle, 5 full batches



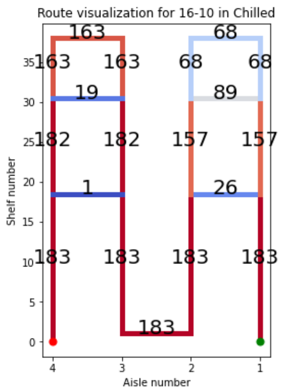
(f) 1 midaisle, 6 full batches



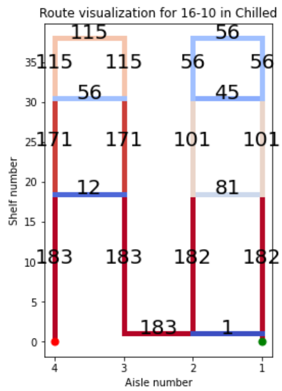
(g) 1 midaisle, 7 full batches



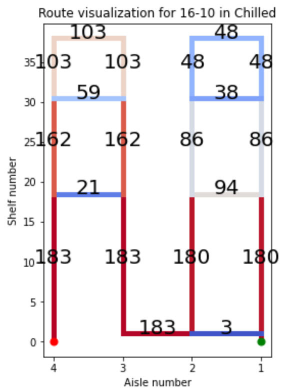
(h) 1 midaisle, 8 full batches



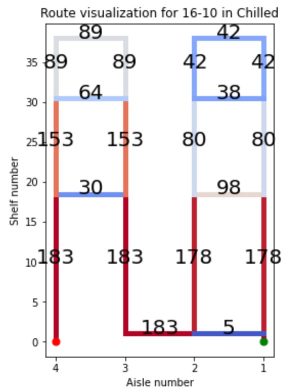
(i) 2 midaisles, 1 full batch



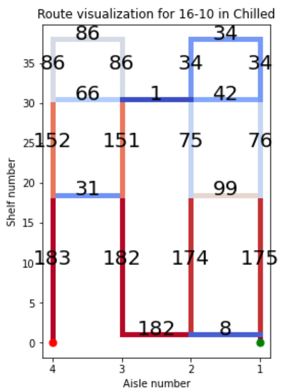
(j) 2 midaisles, 2 full batches



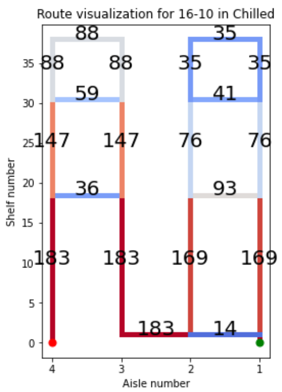
(k) 2 midaisles, 3 full batches



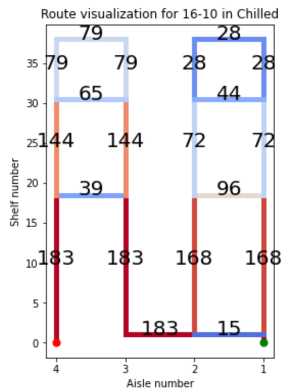
(l) 2 midaisles, 4 full batches



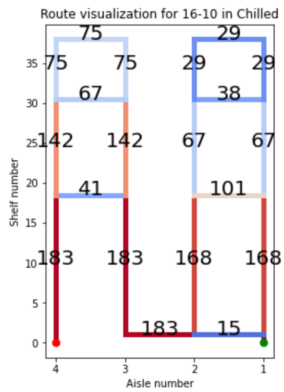
(m) 2 midaisles, 5 full batches



(n) 2 midaisles, 6 full batches

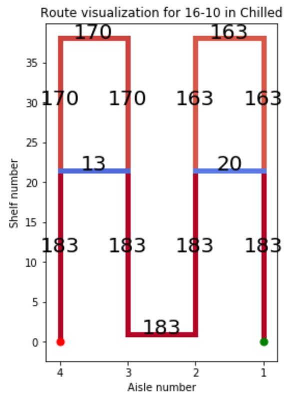


(o) 2 midaisles, 7 full batches

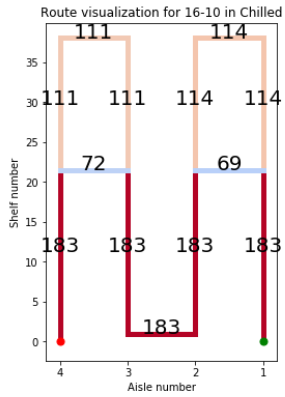


(p) 2 midaisles, 8 full batches

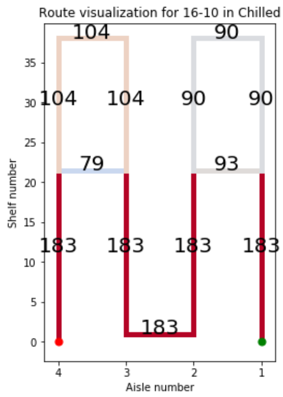
Figure F.16: Visualization of the routes on 16-10 by integrating all three warehouse processes with an within-aisle policy for the chilled zone



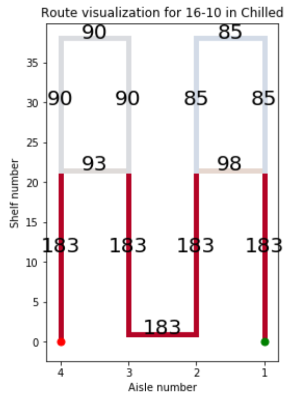
(a) 1 midaisle, 1 full batch



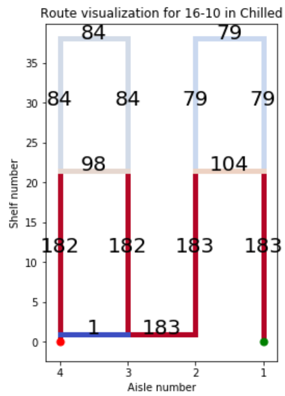
(b) 1 midaisle, 2 full batches



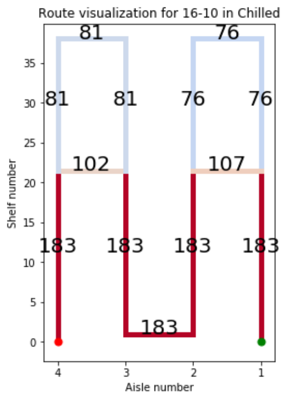
(c) 1 midaisle, 3 full batches



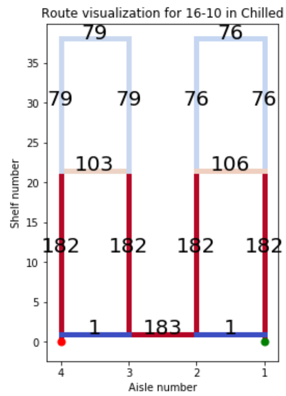
(d) 1 midaisle, 4 full batches



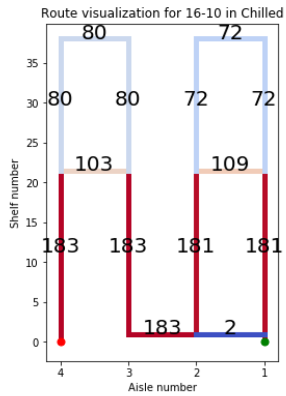
(e) 1 midaisle, 5 full batches



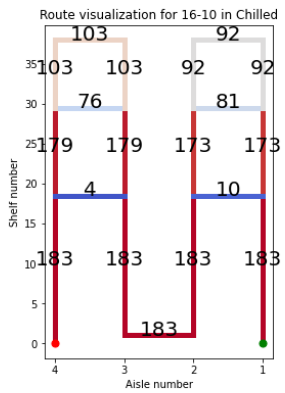
(f) 1 midaisle, 6 full batches



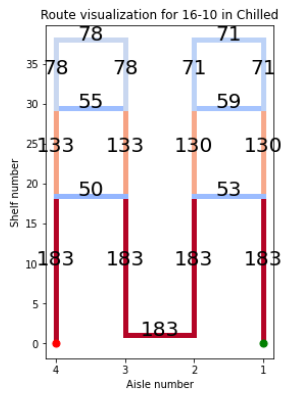
(g) 1 midaisle, 7 full batches



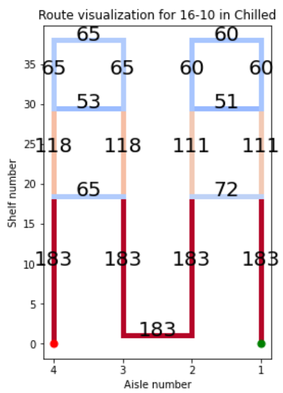
(h) 1 midaisle, 8 full batches



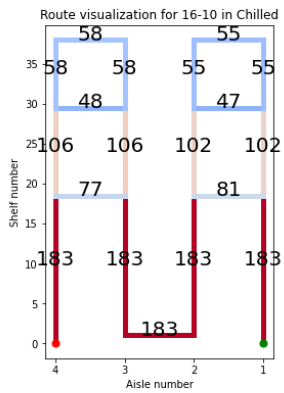
(i) 2 midaisles, 1 full batch



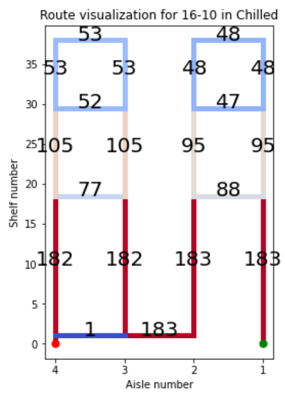
(j) 2 midaisles, 2 full batches



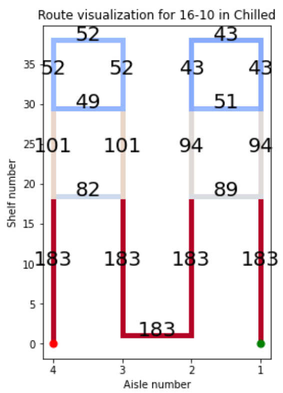
(k) 2 midaisles, 3 full batches



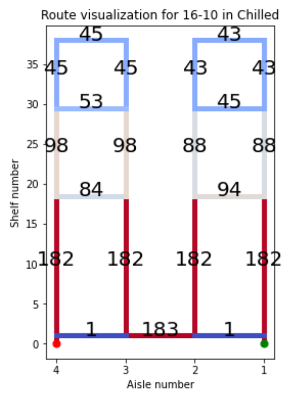
(l) 2 midaisles, 4 full batches



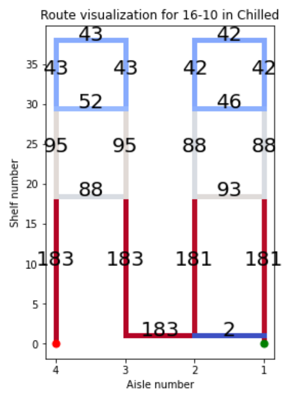
(m) 2 midaisles, 5 full batches



(n) 2 midaisles, 6 full batches

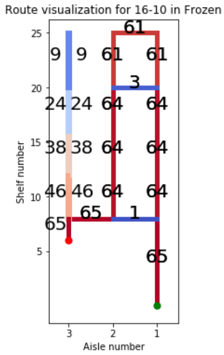


(o) 2 midaisles, 7 full batches

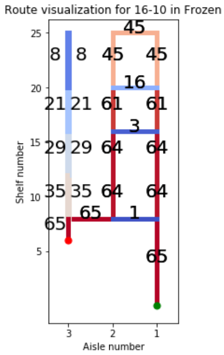


(p) 2 midaisles, 8 full batches

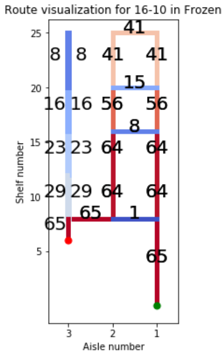
Figure F.17: Visualization of the routes on 16-10 by integrating all three warehouse processes with an across-aisle policy for the chilled zone



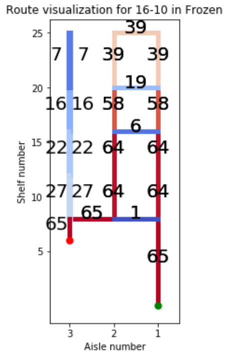
(a) 1 midaisle, 1 full batch



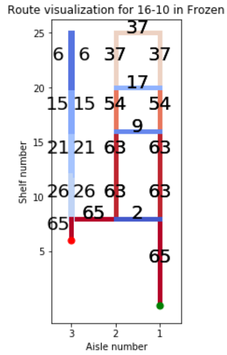
(b) 1 midaisle, 2 full batches



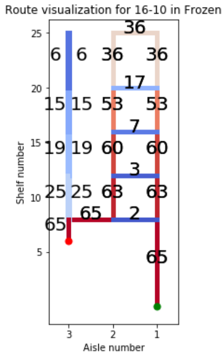
(c) 1 midaisle, 3 full batches



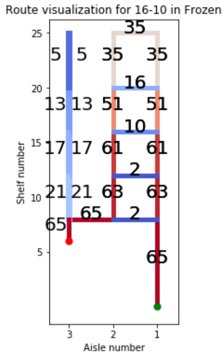
(d) 1 midaisle, 4 full batches



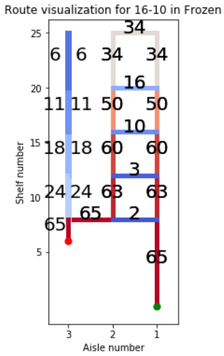
(e) 1 midaisle, 5 full batches



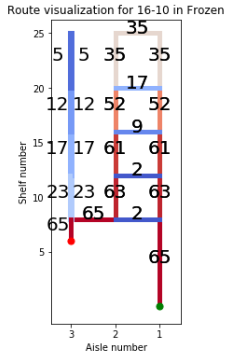
(f) 1 midaisle, 6 full batches



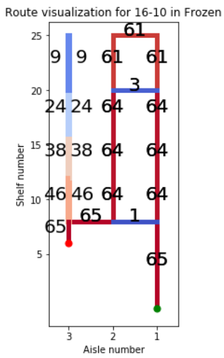
(g) 1 midaisle, 7 full batches



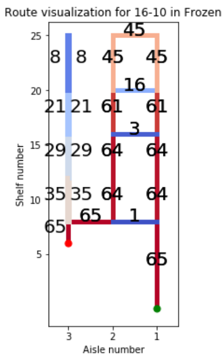
(h) 1 midaisle, 8 full batches



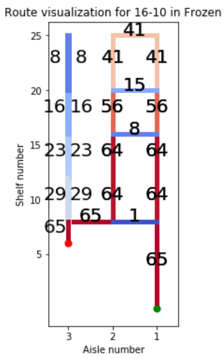
(i) 1 midaisle, 9 full batches



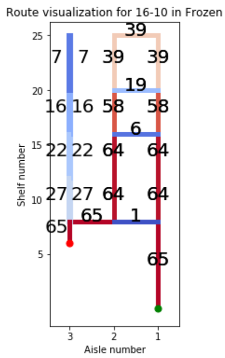
(j) 2 midaisles, 1 full batch



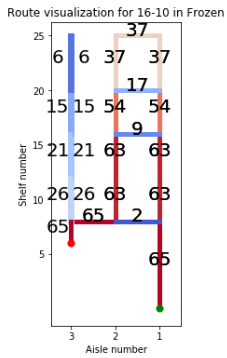
(k) 2 midaisles, 2 full batches



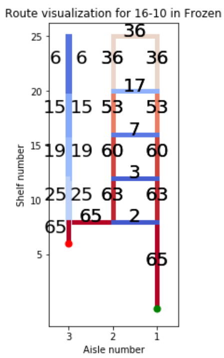
(l) 2 midaisles, 3 full batches



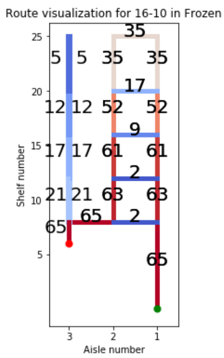
(m) 2 midaisles, 4 full batches



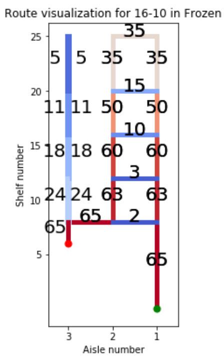
(n) 2 midaisles, 5 full batches



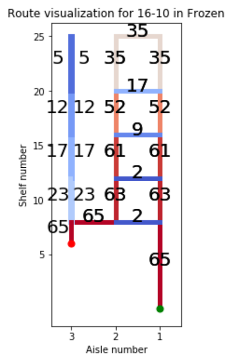
(o) 2 midaisles, 6 full batches



(p) 2 midaisles, 7 full batches

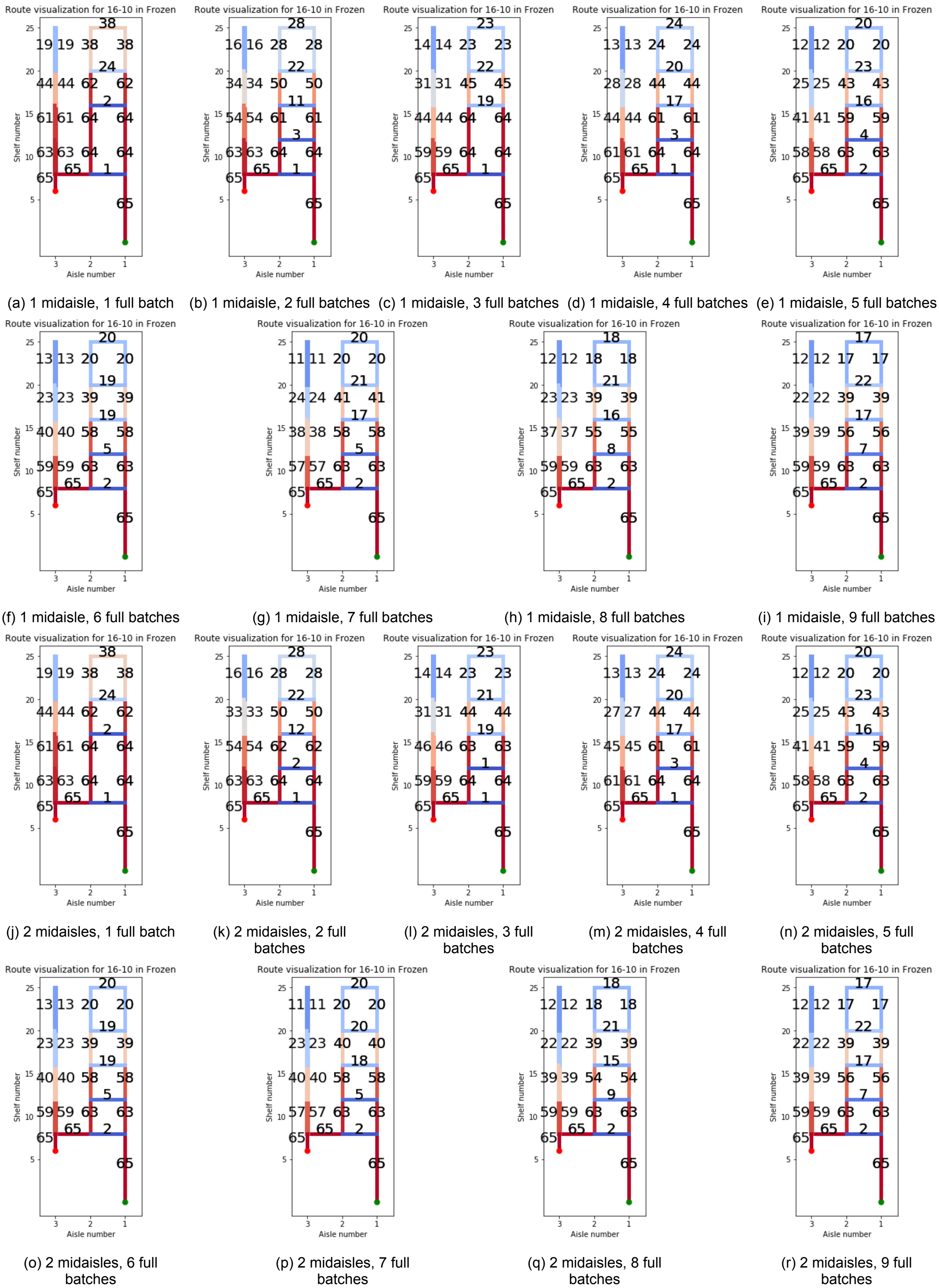


(q) 2 midaisles, 8 full batches



(r) 2 midaisles, 9 full batches

Figure F.18: Visualization of the routes on 16-10 by integrating all three warehouse processes with an within-aisle policy for the frozen zone



(a) 1 midaisle, 1 full batch (b) 1 midaisle, 2 full batches (c) 1 midaisle, 3 full batches (d) 1 midaisle, 4 full batches (e) 1 midaisle, 5 full batches

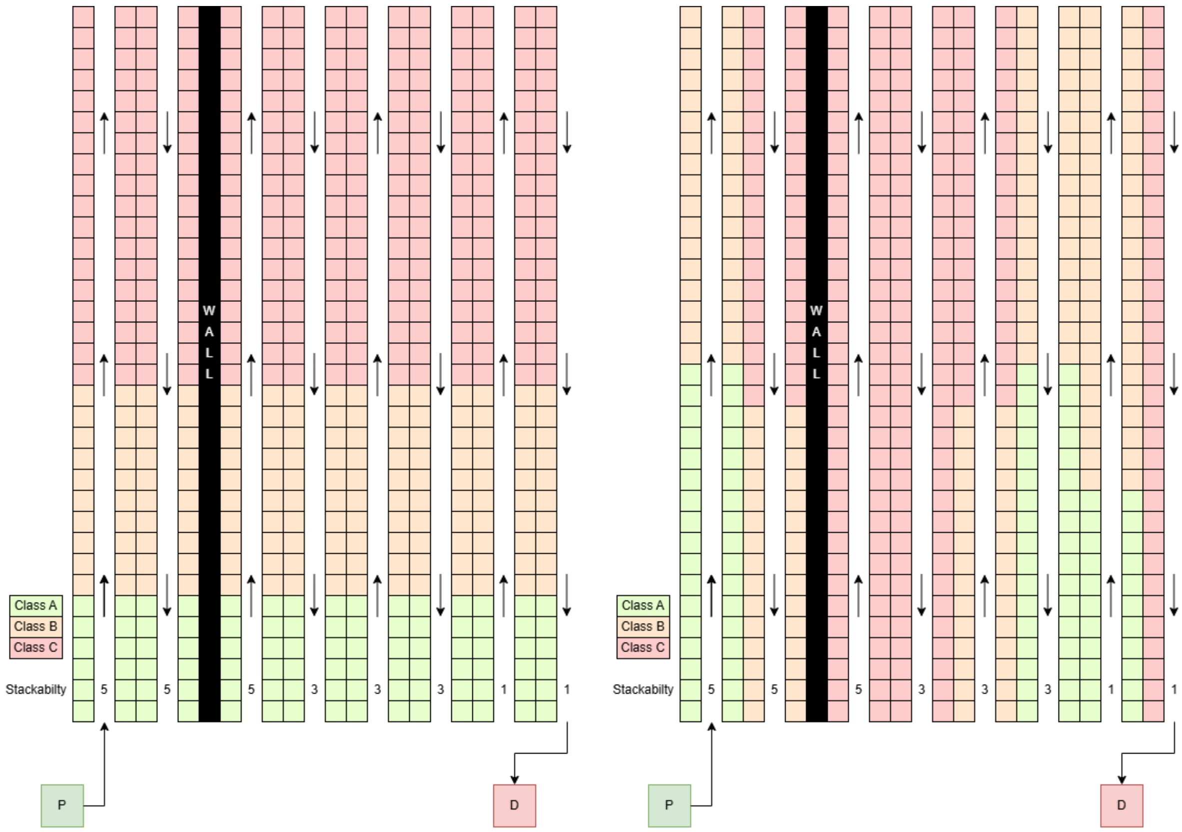
(f) 1 midaisle, 6 full batches (g) 1 midaisle, 7 full batches (h) 1 midaisle, 8 full batches (i) 1 midaisle, 9 full batches

(j) 2 midaisles, 1 full batch (k) 2 midaisles, 2 full batches (l) 2 midaisles, 3 full batches (m) 2 midaisles, 4 full batches (n) 2 midaisles, 5 full batches

(o) 2 midaisles, 6 full batches (p) 2 midaisles, 7 full batches (q) 2 midaisles, 8 full batches (r) 2 midaisles, 9 full batches

Figure F.19: Visualization of the routes on 16-10 by integrating all three warehouse processes with an across-aisle policy for the frozen zone

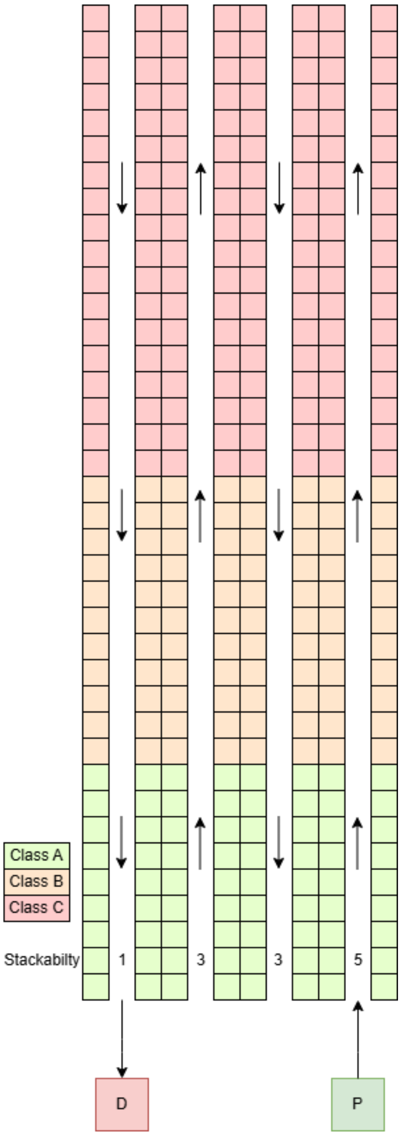
G Visualization allocation policies



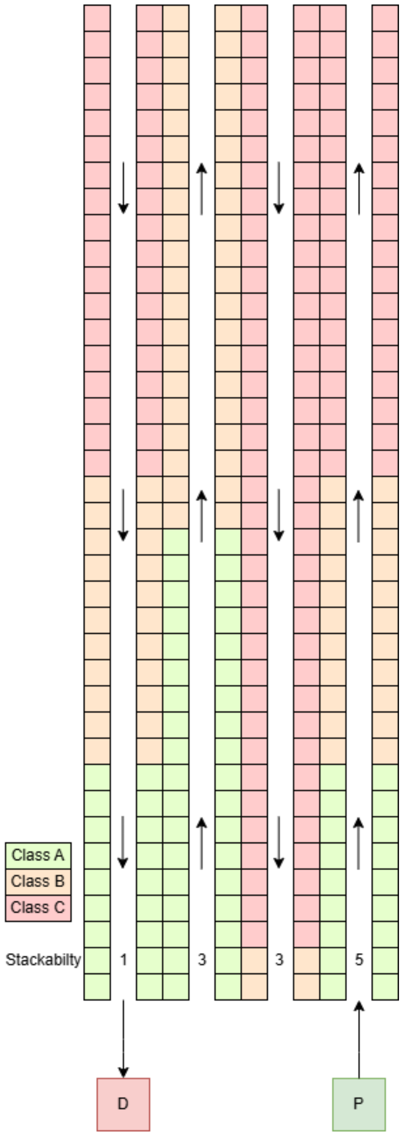
(a) Across-aisle policy

(b) Within-aisle policy

Figure G.1: Product allocation policies for the ambient zone

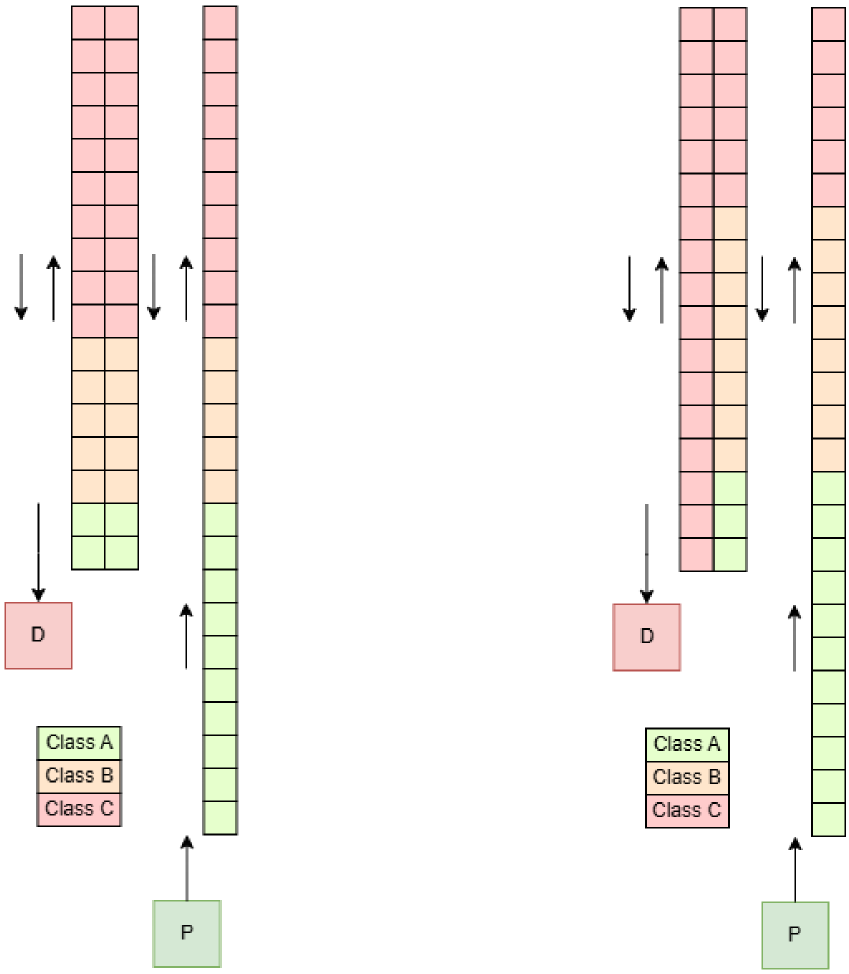


(a) Across-aisle policy



(b) Within-aisle policy

Figure G.2: Product allocation policies for the chilled zone



(a) Across-aisle policy

(b) Within-aisle policy

Figure G.3: Product allocation policies for the frozen zone

H
Cost calculation

Constants

- $t_{pick} = 12.5s$: Average pick time per SKU
- $t_{travel} = 3.125s$: Average travel time per SKU
- $N_{sku} = 320752$: Number of picked SKUs per week
- $N_{order} = 17214$: Number of orders per week
- $C_{hour} = €23/h$: Cost per hour
- $\%_{impr} = 39.14\%$: Improvement on travel distance

When assuming the reduction in travel distance, returns the same reduction in travel time the following equation are used to calculate the cost reduction:

$$\text{Time reduction per week } (t_{red,week}) = \%_{impr} * t_{travel} * N_{sku}/3600 = 108.98 \text{ hour} \quad \text{(H.1)}$$

$$\text{Cost reduction per year} = t_{red,week} * C_{hour} * 52 = €130337 \quad \text{(H.2)}$$