The impact of demand-based slotting decisions on order-picking efficiency in a distribution center using a Robotic Mobile Fulfilment System.

Including Case Study at Gall & Gall

E. S. Zandhuis

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The impact of demand-based slotting decisions on order-picking efficiency in a distribution center using a Robotic Mobile Fulfilment System.

Including Case Study at Gall & Gall

by

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Preface

Over the past nine months, I have worked on my master's thesis focused on demand-based slotting within a Robotic Mobile Fulfilment System. This research was conducted in collaboration with the Gall&Gall distribution center, which provided the essential data and context for the case study. The journey has been both rewarding and challenging, and I would like to take this opportunity to express my gratitude for the support I received along the way.

First and foremost, I would like to thank Mahnam Saeednia, my daily supervisor. The specific guidance, involvement and motivating words had a profound impact on me and the progress of this project. I also want to thank Gonçalo H.A. Correia, the chair of my committee, for the insightful and engaging discussions and for the critical and valuable feedback.

I am grateful for the opportunity Gall&Gall provided by allowing me to conduct my research within their distribution center. I want to thank my company coach, Tjeerd, for recognising the potential in my work from the outset, and for ensuring I had access to the necessary data for my research. I also want to thank Mark and Bas, the manager of the team where I conducted my research and the director of the distribution center, for their involvement throughout the process.

To all the colleagues at the Gall&Gall office, thank you for making this period so enjoyable. The walking breaks, positivity, encouragement, and warm atmosphere made each day at the office something to look forward to. Special thanks to Olivier for engaging in in-depth conversations about my topic, which were invaluable to my work, and for the mental support conversations, invaluable to my well-being.

Finally, I want to express my heartfelt thanks to my friends and family for giving me a free-pass on all my obligations over these months and never tiring of listening to the monologues about my research. For the endless offers of support, whether in the shape of a mental pep talk or practical help with a problem in my research and reading through this tome of a report (multiple times!).

E. S. Zandhuis
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Abstract

E-commerce is rapidly growing and is expected to encompass a quarter of all global sales by 2025. This growth pressures e-commerce warehouses to enhance efficiency. A promising innovation is the Robotic Mobile Fulfilment System (RMFS), which optimises warehouse operations by using robots to manage storage and retrieval tasks, thus significantly improving productivity, speed and accuracy. This research focuses on how inventory allocation (slotting) decisions with RMFS can optimise operational performance. In particular, how the slotting decision of Stock Keeping Unit (SKU) distribution across movable storage racks (pods) based on SKU turnover can maximise order throughput rates and optimise operational performance.

The research question guiding this study is: *What is the optimal demand-based slotting decision to maximise the order throughput rate in a Robotic Mobile Fulfilment System?* This question aims to provide insights into how different slotting configurations impact the efficiency and performance of e-commerce warehouses.

The research approach is twofold. A general analysis is conducted to understand the impact of turnover-based slotting decisions using synthesised demand profiles derived from literature. This is followed by a detailed case study for Gall&Gall using demand profiles derived from real-world data to find specific optimal slotting configurations and validate the synthesised demand results.

The methodology involves three main steps: determining demand configurations, generating slotting configurations with a mathematical model, and simulating these configurations to evaluate performance. Each demand configuration results in multiple slotting configurations, which are evaluated with the simulation to gain insights into the effect of slotting decisions on performance.
The different demand profiles consist of total SKU quantity, total item quantity, and SKU classification into three classes (A, B and C) based on their item turnover.
The different slotting configurations consist of different distributions of the three classes over the pods. These slotting configurations are obtained with a mathematical model that prioritises class distribution based on given weights.
The simulation tool RawSim-O assesses the slotting configurations on key performance indicators such as total order throughput rate and the number of items picked from a pod in one go (pile-on).

Key findings provide that pile-on and travel distance significantly affect the order throughput rate, with performance variations of up to 40 orders handled in 30 minutes.
High performance often arises with configurations aiming for an equal number of items per pod across classes and maximising the number of pods for SKUs in class A.
While synthetic demand profiles show high performance with class A distributed over the maximum number of pods or equal items per pod for all classes, the Gall&Gall demand profiles perform better with class B distributed over slightly more pods, indicating variability in optimal slotting approaches based on specific demand characteristics.
Overall, turnover-based slotting decisions significantly impact order throughput rates in RMFS, and tailoring slotting configurations to specific demand characteristics is crucial for optimal operational efficiency.

In addition to general slotting insights, this research developed a method that allows warehouses to input their specific demand characteristics and receive insights on optimal slotting approaches. Furthermore, the method enables the readjustment of warehouse-specific details, such as a warehouse's unique layout, for extra applicability and realism, and allows the integration of additional decision problems, such as order batching and routing, to broaden the method's scope. This supports warehouses with the design of a tailored, robust and effective slotting strategy for operational performance improvement.

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Glossary

Acronyms

EOQ	Economic Order Quantity	*An optimal ratio of inventory quantity according to the associated costs.*
RMFS	Robotic Mobile Fulfilment System	*Order-picking system for warehouses where orders are picked by robots with movable storage racks.*
SKU	Stock Keeping Unit	*Unique specific product with its own individual identifier such as a barcode.*

Terms

Assortment	The complete set of unique SKUs in the warehouse.
Class	Inventory classifications where the SKUs are categorised into classes, in this research three classes (A, B and C) based on turnover.
Demand	The orders and order contents over a specific time period.
Demand profile	A specific demand configuration regarding the number of SKUs and SKU turnover per class.
Inventory	The complete set of SKUs and items per SKU in the warehouse.
Item	An entity regardless of its respective SKU.
Order-batching	The combination of orders assigned to a picking station.
Order-picking	A warehouse activity involving the picking of items necessary for the orders.
Order throughput rate	The number of orders fulfilled in a certain time interval.
Order turnover time	The time it takes for an order to be fulfilled in a warehouse.
Pile-on	The number of items picked from a pod when it visits a workstation.
Pod	Movable storage rack in the Robotic Mobile Fulfilment System.
Replenishment	A warehouse activity involving the restocking of storage racks.
Robot	Entity that moves the pods between storage and workstations in the Robotic Mobile Fulfilment System.
Scenario	The specific slotting configuration of a specific demand profile.
Single-line orders	Orders that consist of an item quantity of a single SKU.
SKU turnover	The frequency with which a SKU is ordered.
Slotting	The inventory allocation of items in storage racks in the warehouse.
Split-orders	Fulfilling an order with more than one pod.
Workstation	Replenishment- or picking station in the Robotic Mobile Fulfilment System.

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1
Introduction

The introductory chapter of this research provides an overview of the research topic, describes the research purpose, outlines the objectives, and explains the approach used for the execution.

1.1. Research Context

E-commerce is the online commerce of goods and services, which has steadily been growing in the last years and is expected to keep growing, with a quarter of all global sales expected to be online by 2025 (McKinsey & Company, 2023). With this expected growth and simultaneously an increasing labour shortage (The Conference Board, 2022), there is pressure on e-commerce warehouse operations to increase efficiency and decrease manual labour requirements. The implementation of a Robotic Mobile Fulfilment System and optimisation of warehouse operations through inventory allocation (slotting) decisions address these challenges. This research focuses on the additional performance improvement gained from integrating warehouse-specific order demand in the inventory allocation decisions.

1.1.1. Warehouse Processes and Terminology

In e-commerce, warehouse operation involves the processing of customer orders and maintaining inventory control (Vazquez and Lago, 2022). The typical goods flow in a warehouse consists of multiple sub-processes: goods are received, stored, picked, packed and shipped to customers (da Costa Barros and Nascimento, 2021). One of the main performance indicators for an e-commerce warehouse is order turnover time (Lamballais et al., 2020). This is the time an order spends in the system from start to finish. Another general performance metric is order throughput rate, which is the number of orders processed in a certain time interval.
A simplification of the goods flow is visualised in Figure 1.1, where the storage area is divided into a reserve storage area and a picking storage area.

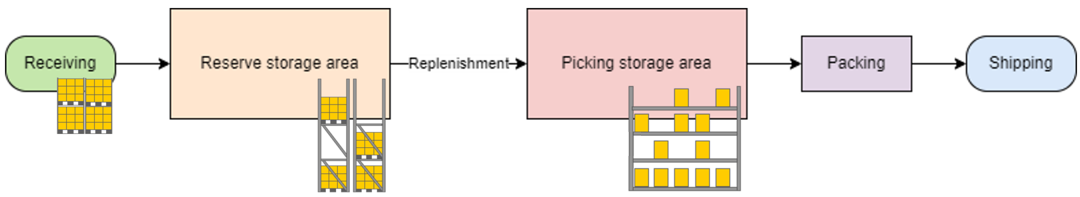


Figure 1.1: Goods Flow and Operations (Figures used from Warehouse-design (2020))

A reserve storage area is used as buffer storage where all the items are located after being received on pallets and in bulk. Replenishment is the reallocation of items from the reserve storage area to the picking storage area, where they are placed in storage racks to be picked. The replenishment decision of when and how many items are reallocated is part of the production strategy (Poon et al.,

2011). Possible approaches are daily replenishment based on expected order demand when this can be accurately estimated or real-time replenishment when a product is ordered.
Order-picking is the activity of accumulating the ordered items from the picking storage area, which accounts for 60% of the time spent on all labour activities in a warehouse (Drury, 1988). An order-pick assignment is a collection of orders picked in one task. When an order-picker is finished with the order-pick assignment, the orders are delivered to a packing station to be packed and shipped.

The terminology of items, orders and assignments is essential in understanding warehouse operations and is depicted in Figure 1.2. This also introduces the Stock Keeping Unit (SKU): A unique identifier for each specific product type that shows product details such as the size, price, brand and style, often represented with a barcode specific to that SKU to label and track inventory items.
A practical example of SKUs in liquor retail is the *25cl* Heineken bottle and the *30cl* Heineken bottle. Each unique product variation, such as different volumes in this example, is represented by a distinct SKU. The collective set of all SKUs in inventory constitutes the complete assortment of that warehouse.

In this study, the term *item* refers to an entity regardless of its associated SKU. For instance, when the emphasis is on quantity, such as the average number of items per order or the maximum number of items in a storage rack, where the specific SKUs, whether single or multiple, are irrelevant.

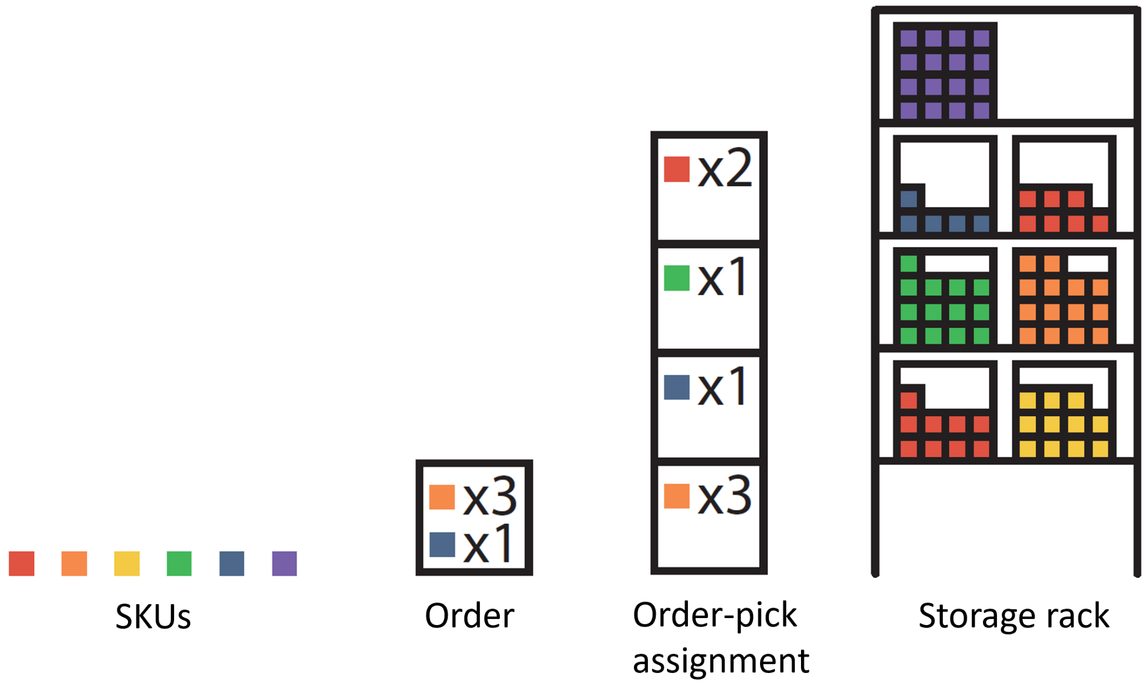


Figure 1.2: Terminology Visualisation (Figures used from Merschformann et al. (2017)).

The decisions on item placement in a storage area are referred to as slotting or slotting decisions. Examples of such decisions are the variety of SKUs present in one storage rack or the quantity of a certain SKU on a storage rack. Where the purpose of these decisions is to maximise operational efficiency.

Most traditional slotting approaches are based on order demand characteristics, such as SKU popularity, turnover and similarity (Petersen et al., 2005). SKU popularity refers to how often a given SKU is present in an order, turnover is the rate at which inventory is sold over a certain time interval, and SKU similarity indicates the relation between SKUs based on their likelihood of being ordered together. In this research, the focus is on the demand characteristic of SKU turnover to evaluate slotting approaches.

1.1.2. Robotic Mobile Fulfilment System

Automation options are an attractive solution for improving warehouse efficiency due to the low error rate, precision, speed and a reduction of manual labour demand. One of the developments in warehouse automation is a Robotic Mobile Fulfilment System (RMFS) (D'Andrea and Wurman, 2008). This system has many improvements over manual operations, such as increased productivity, speed, accuracy and flexibility (Wurman et al., 2008).

According to Azadeh et al. (2019), an RMF system consists of three major components (shown in Figure 1.3):

Inventory pods, are movable storage racks where the products are stored.

Workstations, used as either replenishment or picking stations.

Robots, that move the pods between storage and workstations.

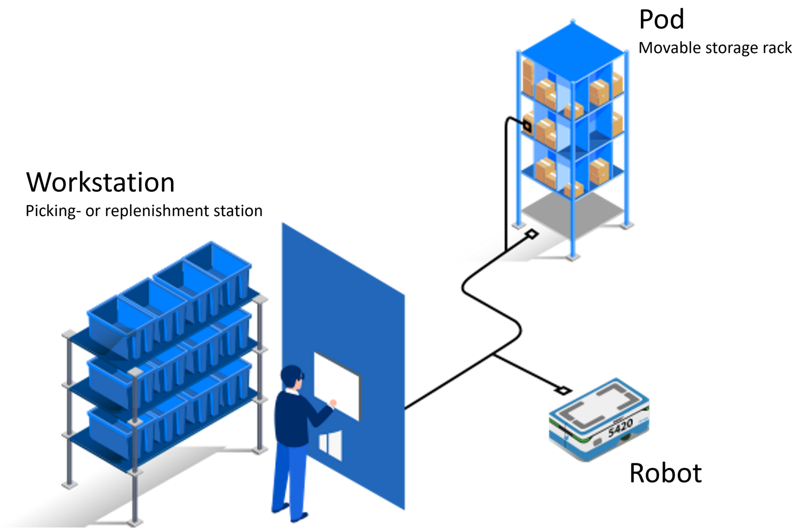
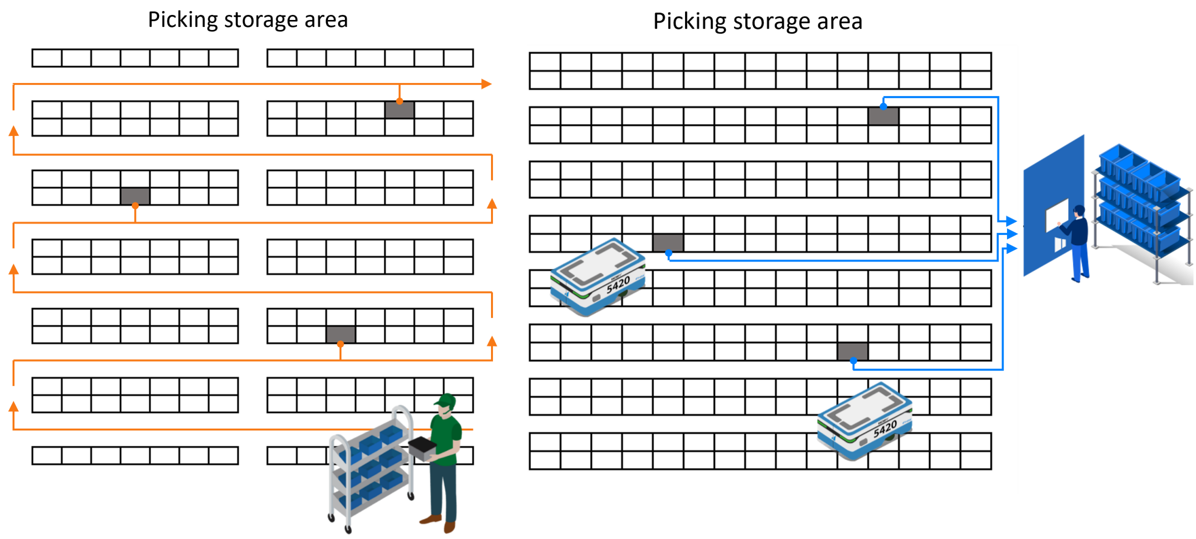


Figure 1.3: The Three Components of an RMFS (Figure from Scallog (2023)).

The robots lift the pods and drive them from the picking storage area to picking stations, where people manually pick items from the pods.

In the manual order-picking approach, depicted in Figure 1.4a, a human order-picker picks the products by walking past storage locations and collecting items from the necessary locations on a picking cart. In this activity, travel time accounts for 50% of the total order-pick time (Tompkins et al., 1996). When the order-picker is finished with the order-pick assignment, they place the orders at packing stations where they are packed and shipped.
With a Robotic Mobile Fulfilment System, the order-picking approach changes from a manual picker-to-parts approach to a robotic parts-to-picker approach by using robots that move the storage racks containing the necessary items to stations where the items are picked by a human order-picker (Figure 1.4b). Figure 1.4 visualises the different routes taken with an order-picking assignment for either picking approach.



(a) Picker-to-Parts Approach, with Human Order-Pickers Picking the Items Sequentially from the Storage Racks. (Figure used from Lucas Systems (2023)).

(b) Parts-to-Picker Approach, with Robots Retrieving the Storage Racks for Human Order-Pickers to Pick at Picking Stations.(Figure used from Scallog (2023)).

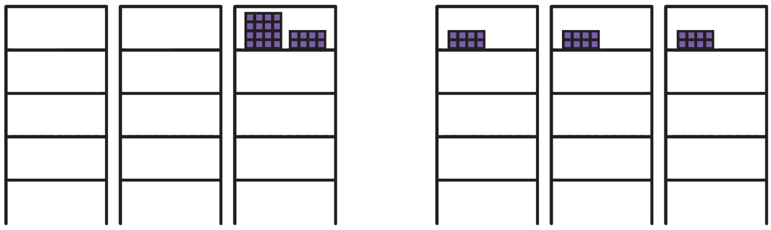
Figure 1.4: Order-Picking Approaches and Routes

The picking activity with the manual picker-to-parts approach occurs in the picking storage area while walking past all storage racks. In contrast, the picking activity with the robotic approach is split into two activities: retrieving the necessary storage racks, or pods, from the storage area and bringing them to the picking station, which is executed by one or multiple robots. Secondly, human order-pickers at the picking stations collect the necessary items from the pods. The retrieving and picking are not executed by the same entity, meaning they don't have to be executed consecutively, as with the picker-to-parts approach, but can occur simultaneously in parallel. This diminishes the time between picks by removing the travel time. This approach increases the order-pick speed up to three times and removes the walking tasks for the human order-pickers according to Guizzo (2008).

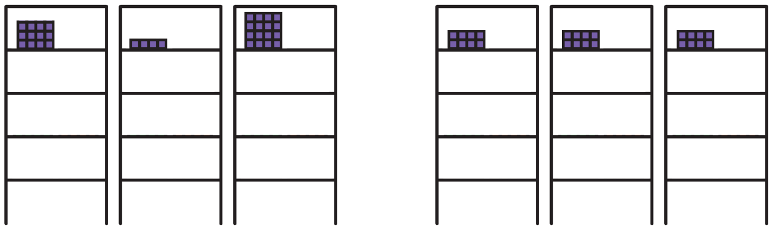
The replenishment activity occurs at replenishment stations, where items from the reserve storage area are placed in pods brought by robots to be allocated in the picking storage area.
The space necessary for the robots to drive through with a pod is significantly smaller than for human order-pickers, and up to 30% of space can be saved in the storage area (Scallog, 2020). This space can be replaced with additional pods to increase storage capacity.

With RMFS, the slotting dynamics are significantly altered compared to the traditional slotting approaches used with manual order-picking due to the continuous reallocation of storage racks. The study by Chou et al. (2019) identified that item slotting in an RMFS involves three main decisions, which are illustrated in Figure 1.5:

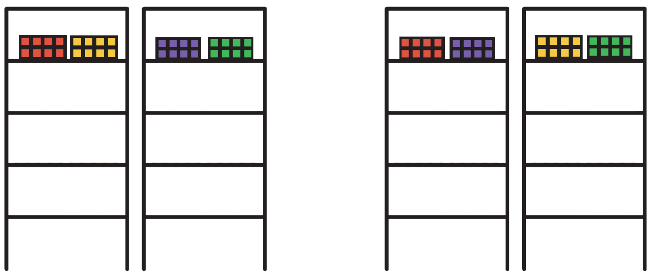
1. **The number of pods over which a SKU is distributed** (Figure 1.5a),
   Items of a SKU can be stored in a single pod, multiple pods, or spread across as many pods as possible.
2. **The quantity of each SKU within a single pod** (Figure 1.5b),
   This refers to setting a minimum and maximum quantity for items of a SKU within a pod and determining whether the quantities should vary across different pods or remain consistent.
3. **The combination of SKU types in one pod** (Figure 1.5c).
   Certain combinations of SKUs may be best stored together on a pod for optimal efficiency.



(a) An example of different options for the decision of *the number of pods over which a SKU is distributed*. On the left, all items of a SKU are stored in the same pod, whereas on the right, the items of a SKU are distributed over three different pods.



(b) An example of different options for the decision of *the quantity of each SKU within a single pod*. On the left, the quantities have a minimum of 4 items of that SKU and a maximum of 16 and the quantity is varied over all pods, whereas on the right, the quantity is similar on all pods.



(c) An example of different options for the decision of *the combination of SKU types in one pod*. On the left, two combinations of certain SKUs are made, whereas on the right, the SKUs are combined differently.

Figure 1.5: The three main slotting decisions in an RMFS

1.2. Problem Definition

The optimisation of the warehouse slotting approach is crucial for addressing the increased demand and labour shortages in e-commerce. A well-tailored slotting method can decrease the picking travel distance and improve the overall picking efficiency (Cai et al., 2021). This research mainly focuses on one of the three slotting decision problems: optimising SKU distribution over pods. The research gap this study focuses on is the limitations of current slotting decision models for optimal distribution of SKUs over pods. Existing research by Lamballais et al. (2020), has shown performance improvements when SKUs are distributed over multiple pods but all SKUs are treated uniformly without accounting for variation in turnover and demand. This research addresses the gap by exploring optimal decisions for SKU distribution over pods, focusing on how different slotting configurations of high and low-turnover SKUs affect performance for varying demand configurations.
Improving the slotting approach aims to increase order-picking efficiency, directly influencing the operational performance of e-commerce warehouses.

1.3. Research Questions

This research integrates the traditional focus on order demand by including item turnover. The impact of slotting decisions based on turnover is explored to improve the research regarding slotting and demand with an RMFS. This results in the following research question:

What is the optimal demand-based slotting decision to maximise the order throughput rate in a Robotic Mobile Fulfilment System?

The information used to address the main research question about slotting decisions and SKU distribution over pods is divided into two sub-questions. The first sub-question seeks to understand the general behaviour of slotting decisions for different order demand configurations. The second sub-question aims to validate these findings by evaluating the impact of demand-based slotting decisions in a specific use case.

1. *What is the impact of demand-based slotting decisions on the order throughput rate for different demand configurations with a Robotic Mobile Fulfilment System?*

2. *What is the impact of demand-based slotting decisions on the order throughput rate with a Robotic Mobile Fulfilment System for a Gall&Gall case study?*

1.4. Research Approach

This research is initially a general analysis of the impact of demand-based slotting decisions on the order throughput rate with synthesised order demand. The rationale behind synthesised and general demand profiles is to build insights beyond specific instances. This allows application of the drawn results and conclusions to various scenarios rather than being confined to a specific demand profile. Subsequently, a detailed case study is incorporated for the distribution center of Gall&Gall to validate and demonstrate the practical application.

An overview of the structure of this research and this report is depicted in Figure 1.6 below.

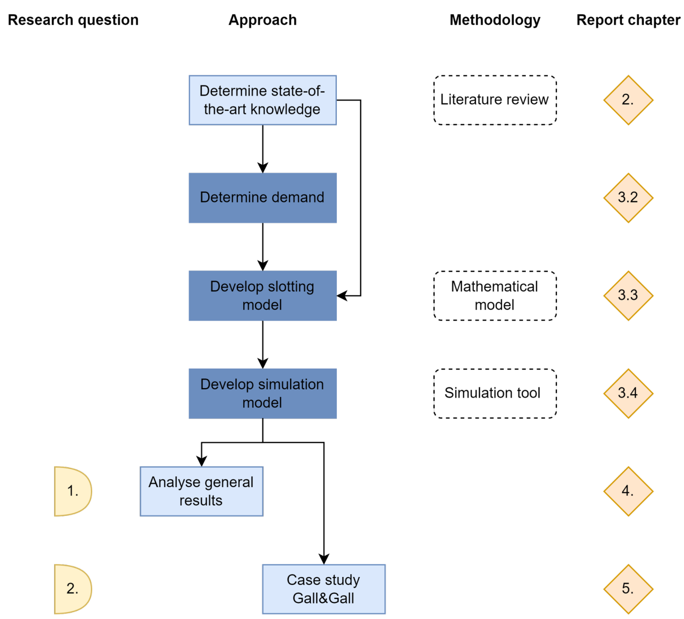


Figure 1.6: Flowchart of Research Structure.

First the existing literature is studied and reviewed in Chapter 2, on the general topic of slotting and RMFS. Traditional approaches for slotting are explained, and the new concepts introduced by RMFS are described. Demand characteristics are reviewed and the necessary information is gathered on how to include demand in slotting research. In Chapter 3 the methodology for the research is explained in detail. The core approach consists of three main components: demand determination, developing a slotting model for the demand and developing a simulation model for the demand. Each of these steps is built upon the previous step's output, generating input for the following one. A brief summary of these three main steps of the approach is explained below and illustrated in the flowchart in Figure 1.7.

Determine Demand Configurations
The demand profiles used in this study are a simplification of authentic order demand over a certain time interval. The demand configurations are derived from the literature review with varying SKU turnover, to evaluate the impact of demand-based slotting with different turnover configurations. An example is shown in Figure 1.7 as the output from the demand configuration and input of the slotting configuration: In a time interval, 124 items of 10 different SKUs are ordered; 2 of the SKUs are both ordered 40 times, 4 of the SKUs are ordered 9 times, and 4 of the SKUs are ordered 2 times.
Determine Slotting Configurations
A mathematical slotting model is developed that generates multiple different slotting configurations for each of the demand profiles. A slotting configuration specifies the exact contents of each pod. The fixed inventory of all pods is the output of the slotting model and input for the subsequent simulation step.
Simulate Scenarios
The RawSim-O simulation tool, developed by M. Merschformann et al. (2018), evaluates the modelled slotting configuration. This tool is designed to analyse various decisions and strategies, assessing their cumulative impact on performance indicators. Utilising this simulation model, the slotting process is tested, and key outcomes such as order throughput rate are measured and analysed for the set of all slotting configurations of all demand configurations.

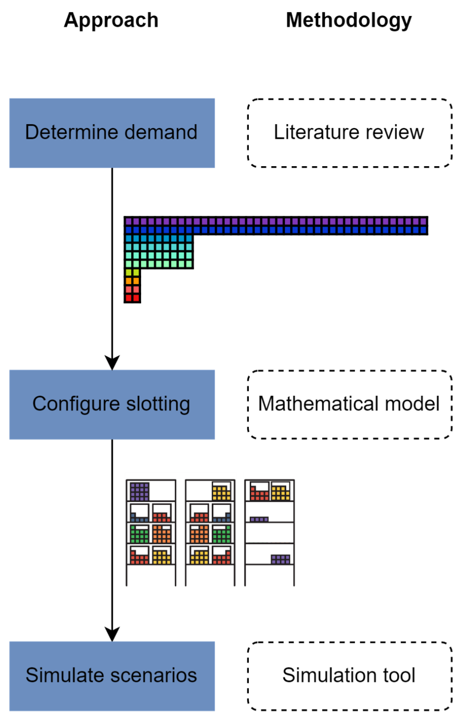


Figure 1.7: Flowchart of the Three Main Steps in Research Approach.

The demand-based slotting performance of the synthetic demand is analysed in Chapter 4 to find and evaluate general results on the performance metrics to address Research Question 1. Subsequently, the case study for Gall&Gall is executed in Chapter 5, by going through the same three main components from Figure 1.7. The demand is configured with order data from Gall&Gall, this demand is used to determine configurations, which are simulated and evaluated to answer Research Question 2.

1.5. Practical Value

The answers to the outlined research questions provide insights and practical guidance for optimising slotting decisions in warehouse operations concerning demand-based decisions within a Robotic Mobile Fulfilment System.
Efficient slotting decisions impact the operational efficiency of a warehouse. By determining the optimal demand-based slotting decisions, businesses can increase the order throughput rate, thereby streamlining the process, which reduces operational costs. By exploring the optimal distribution over pods for different demand scenarios, a balance can be struck between inventory spread and pod occupancy. This approach enables warehouses to utilise available storage space more effectively, mitigating the risk of under-utilisation or overcrowding.
Moreover, the research facilitates adaptive decision-making in response to dynamic market conditions. By understanding the relationship between item turnover and slotting priorities, businesses gain the

flexibility to adjust their decisions based on demand patterns.
Beyond the general insights into slotting optimisation with RMFS, the case study on Gall&Gall provides specific insights tailored to their order demand data. This research offers an understanding of the significance of this decision problem and provides insights into expected performance improvement.

1.6. Research Scope

The research scope only contains the storage allocation decisions relevant to a Robotic Mobile Fulfilment System. Other automation options may change processes and goods flows which changes the impact on the performance metrics due to different reasons than the ones studied in this research.

The research focuses on slotting. The strategic decision problems of warehouse layout, such as the amount and size of pods, and the number of order-picking stations, and tactical decision problems such as the replenishment approach, path planning, congestion prevention and pod zoning, are outside of the scope and are used as input parameters and variables.

This research assumes that demand is deterministic, which is particularly relevant in e-commerce environments with high-accuracy forecasts. The primary focus here is not on refining the accuracy of these demand forecasts. Given that the demand is assumed to be deterministic, the main objective is to optimise tactical-level slotting decisions.
Stochastic updates that occur throughout the day might derive some benefit from the findings of this research, however, they are not the central concern of this study.

2
Literature Analysis

The research question concerns the impact of demand-based slotting decisions on the order throughput rate in a Robotic Mobile Fulfilment System. This literature review provides further elaboration and explanation on the components of demand, decision problems with RMFS, slotting and the performance evaluation with the order throughput rate.

This chapter begins with literature on inventory classification in Section 2.1. Then the order demand traditionally used in research is reviewed in Section 2.2. After which follows a general review of the decision problems regarding a Robotic Mobile Fulfilment System and the relation of slotting to other decision problems in Section 2.3. Then slotting-specific literature is reviewed, where the research on SKU distribution over pods is covered in Section 2.4.1, and the research gap is clarified in Section 2.4.4. Finally, the performance evaluation of decision problems with an RMFS is discussed in Section 2.5, and the literature review is concluded in Section 2.6.

2.1. Inventory Classification

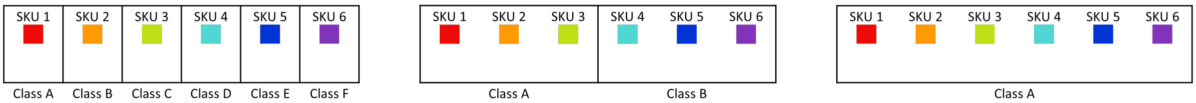
The inventory of a warehouse or distribution center refers to all the items from the complete set of Stock Keeping Units (SKUs) that are processed. The classification of the items in inventory provides information on possible integration of demand into this study.

When certain information on the items is available, SKUs can be organised into product classes based on distinct product characteristics, such as the height, weight and volume of a SKU, or on order demand characteristics, such as the turnover speed of a SKU. Inventory classification refers to the categorisation of the warehouse inventory. The slotting assignment then consists of allocating the classes to specific locations. The different classification policies are the following according to Gu et al. (2007), visualised in Figure 2.1:

Dedicated storage (Figure 2.1a):
The number of classes is equal to the number of SKUs. With dedicated storage, each SKU is assigned its class and, therefore, storage location.

Class-based storage (Figure 2.1b):
The number of classes is smaller than the total number of SKUs and larger than one.

Random storage (Figure 2.1c):
The number of classes is equal to one. When all SKUs are treated as the same class, the storage is randomly assigned.



(a) Dedicated storage classification. Each disjoint class contains exactly one SKU, and each SKU is assigned to exactly one class.

(b) Class-based storage classification. SKUs are categorised into disjoint classes, each assigned to exactly one class. However, classes may contain multiple SKUs.

(c) Random storage classification. Exactly one class exists to which all SKUs are assigned.

Figure 2.1: Three Storage Classification Policies

The results from the study of Hausman et al. (1976) state that increased storage performance is achieved with storage policies when inventory is classified into more classes. Random storage yields the poorest performance, followed by two-class storage, surpassed by three-class storage, and ultimately outperformed by dedicated storage. The research of Petersen et al. (2004) and Yuan, Graves, and Cezik (2019) confirm this result and conclude that storage policies with inventory separated into 4 and 3 classes, respectively, perform better than when separating inventory into 2 classes.

The study of Hausman et al. (1976), concluded that class-based turnover assignment policies generally outperform the closest-open-location policy, where they state that the closest-open-location policy is similar to the random policy. These findings are predicated on the availability of detailed product and order demand information. The research conducted by Petersen et al. (2005) on slotting in traditional warehouse systems employing human order-pickers demonstrates that SKU popularity, SKU turnover and an integrated metric of demand and volume lead to optimal slotting performance. Similarly, the study by Mirzaei et al. (2021) confirms the prevalence of a turnover-based storage policy in warehouse operations. Furthermore, Gu et al. (2007) finds that SKU popularity, SKU turnover and the integrated metric of demand and volume are commonly used bases for classifications in literature. Therefore, the frequently employed classification themes include the following:

Popularity
Defined as the number of orders containing a specific SKU within a given time interval.

Turnover speed
This is the rate at which inventory is sold over a certain time interval.

Maximum inventory
Refers to the total warehouse space allocated for a specific SKU, accounting for the combination of turnover and the geometrical characteristics of a SKU.

Cube-per-order-index
This metric combines two criteria, representing a ratio of the maximum inventory to the SKU popularity.

Research on slotting optimisation with RMFS is not as extensive as that of traditional storage location assignment. However, the existing research is often derived from traditional research where slotting primarily focuses on order demand characteristics (Cai et al., 2021). This is supported by the research of Mirzaei et al. (2021) and Yuan, Graves, and Cezik (2019), which conclude better performance with demand-based policies versus the random policy. Evaluating approaches by comparing performance with the random policy is common in reviewed studies. Research applying this evaluation practice include: Hausman et al. (1976), Yuan, Wang, and Li (2019), Mirzaei et al. (2021), Roy et al. (2019) and Weidinger and Boysen (2018).

When a class-based storage policy derives its classification from turnover speed into three classes, it is referred to as the ABC storage policy. The ABC method categorises inventory into three classes: A, B and C, with class A containing the inventory with the highest turnover and class C the lowest. This method is often complemented with the Pareto principle, which states that 80% of outcomes are caused by 20% of inputs (Pareto et al., 1906/2014). SKU turnover often approaches this principle (de Koster et al., 2007 and Weidinger et al., 2019), which translates to the guideline that approximately 20% of the set of all SKUs generate 80% of the sales or order demand, where the set of all SKUs in inventory is also referred to as assortment. A visualisation of normalised SKU turnover following a Pareto principle is shown in Figure 2.2. Where the normalised total sales consist of 100 items from 10 SKUs. 20% of the assortment (SKU 1 and SKU 2) is responsible for 80% of item turnover.

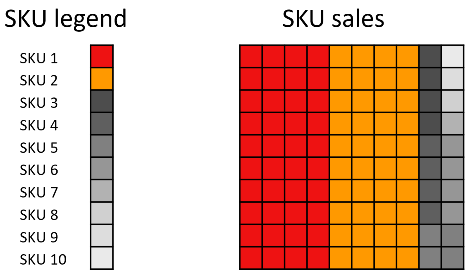


Figure 2.2: Assortment and Turnover Ratio According to the Pareto Principle.

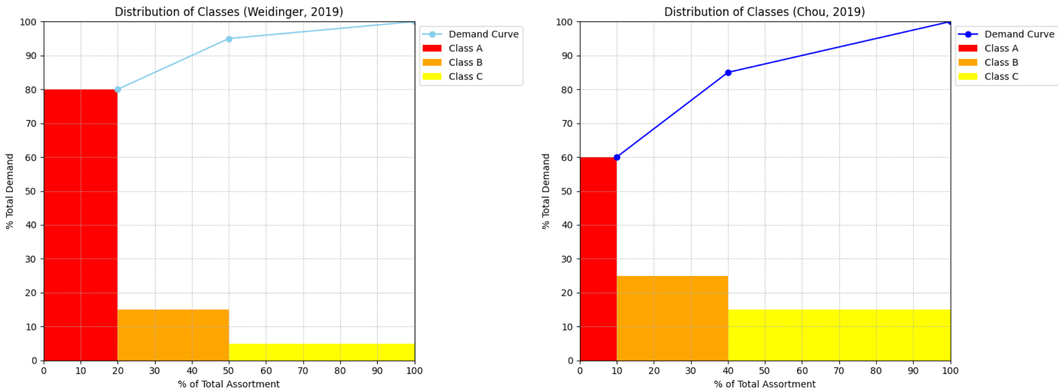
Inventory According to Order Demand

The complete inventory kept in storage by a warehouse typically reflects the order demand since having an abundance of items for a SKU takes up unnecessary space and increases costs, whereas insufficient items mean customer dissatisfaction and missed sales opportunities. Additionally, studies regarding storage policies and order-picking are often conducted with deterministic order demand (de Koster et al., 2007), which implies that the storage area can contain exactly the inventory to satisfy the order demand, guaranteeing that the proportion of storage dedicated per SKU reflects or equals the demand. When applied to the inventory in storage, the Pareto principle implies that 80% of the storage space is occupied by items from 20% of the assortment (Thieuleux, 2024). This extends the visualisation in Figure 2.2 to represent not only the assortment and turnover ratio, but also the assortment and storage area ratio. 20% of the assortment (SKU 1 and SKU 2) is responsible for 80% of item turnover and, therefore, 80% of the storage locations.

2.2. Order Demand Application in Research

The previous section states typical classification of order demand in research. The application of this order demand in existing research is elaborated on in this section, to provide insights into the possible integration of order demand in this study.

The study of Weidinger et al. (2019) performs their research with the ABC classification method where the demand strictly follows the Pareto principle. Class A consists of 20% of the SKUs with 80% of the total demand, B is 30% of SKUs and 15% of demand and C is 50% of SKUs and 5% of the total demand. This demand classification, including the corresponding demand curve, is plotted in Figure 2.3a. The demand curve is the cumulative percentage of demand (turnover) per unit of time versus the cumulative percentage of assortment, representing the ratio between the demand and assortment (Guo et al., 2016). A steep slope indicates that a relatively small assortment section is responsible for relatively high demand. The same distribution is used in the study of Winkelhaus et al. (2022).
The research from Chou et al. (2019) uses the ABC classification on demand with a slightly adjusted distribution. The class with the most significant portion of the turnover is A, with 10% of the total assortment, responsible for 60% of the demand. Class B is 30% of the SKUs and 25% of the demand, C is 60% of the assortment and 15% of the turnover, shown in Figure 2.3b. For this demand curve, 20% of total assortment corresponds to 68% of demand, which demonstrates the demand does not follow the Pareto principle.



(a) ABC Classification on Demand used in Weidinger et al. (2019).

(b) ABC Classification on Demand used in Chou et al. (2019).

Figure 2.3: Different Demand Proportions within the ABC Classification.

The study of Hausman et al. (1976) evaluates various storage policies by combining four classification policies with four order demand variations to find where improvements and optimisations have the largest effect. The classification policies are random storage, two-class-based, three-class-based and dedicated. The order demand variations are configured according to the ideal order quantity to minimise inventory cost, which is also referred to as the *Economic Order Quantity* (EOQ). The EOQ is an optimal ratio of inventory quantity according to the associated costs. This function was developed by Ford (1913) and later updated and reevaluated by many researchers as reviewed by Aro-Gordon (2016).

Based on the EOQ, Hausman et al. (1976) defined a function for a demand curve that represents the optimal ratio of order demand and assortment.

$$G(i) = i^s \tag{2.1}$$

Where function $G(i)$ represents the demand per (component of) assortment (i), with $0 < i \leq 1$, and s determines the slope of the curve. Hausman et al. (1976) determines four values for s, describing the curves where 20% of the assortment corresponds to 60%, 70%, 80% and 90% of the demand, visualised in Figure 2.4.

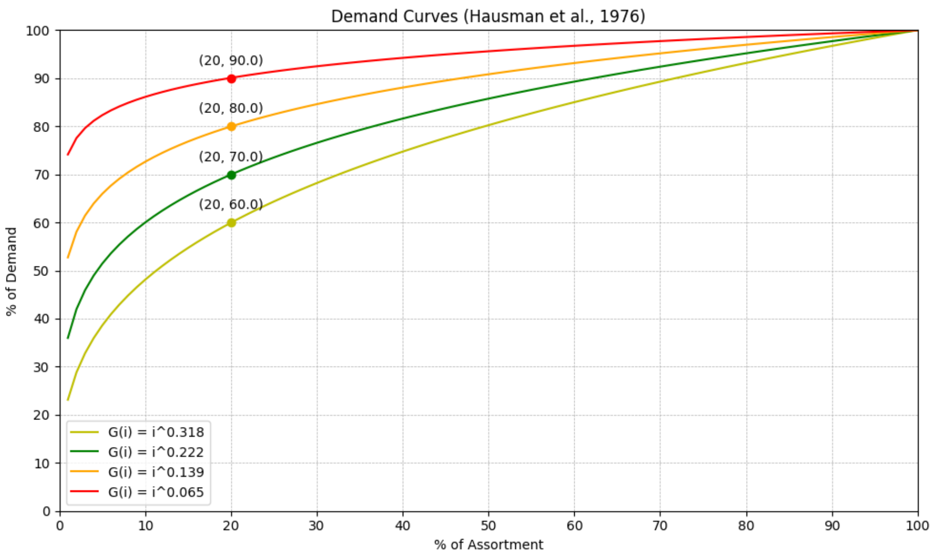
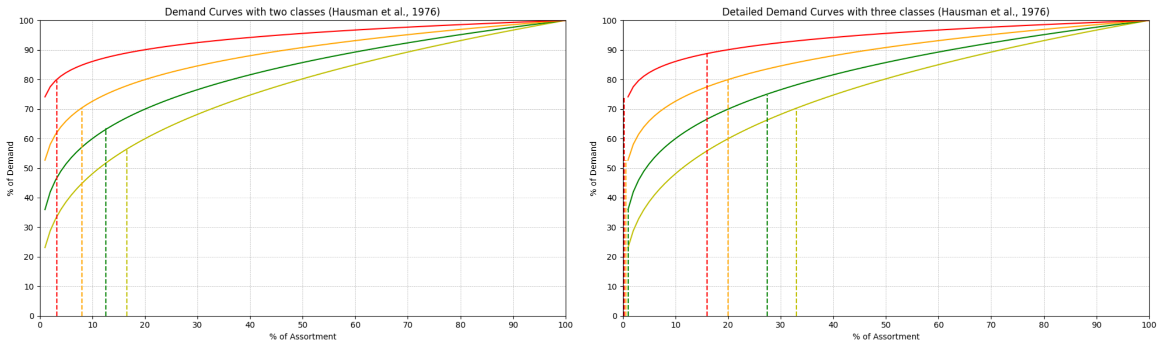


Figure 2.4: Demand Curves used by Hausman et al. (1976).

When using the demand from a demand curve for the evaluation of a dedicated storage policy, the demand strictly follows the curve. With the policies where the demand is classified into either two or three classes, the demand from the curve is divided.

The study of Hausman et al. (1976) separates the demand into two and three classes, depicted in Figure 2.5, where the optimal partitioning points between the classes are determined with an equation based on the assumed expected travel times. In Table 2.1, the resulting coordinates that belong to the class separations for each demand curve are reported.



(a) Four Demand Curves used by Hausman et al. (1976), Classified into Two Classes.

(b) Four Demand Curves used by Hausman et al. (1976), Classified into Three Classes.

Figure 2.5: Four Demand Curves used by Hausman et al. (1976), Classified into Two and Three Classes.

The demand curve for which 20% of the assortment is responsible for 90% of the demand (the red curve) in Figure 2.5a and Table 2.1 illustrates that the separation between class A and B in the two-class classification is where the demand curve where 3% of the assortment is responsible for 80% of demand. This means that the other 97% of the assortment is accountable for 20% of the demand.

Table 2.1: Coordinates of the Four Demand Curves and their Intersections with the Separation of Classes.

Demand curve (% assortment, % demand)	**Two-class separation** (% assortment, % demand)	**Three-class separation** (% assortment, % demand)	
(20, 60)	(17, 57)	(1, 23)	(33, 70)
(20, 70)	(13, 64)	(1, 36)	(28, 75)
(20, 80)	(8, 70)	(0.5, 53)	(20, 80)
(20, 90)	(3, 80)	(0.25, 74)	(16, 89)

The function for the demand curve is adopted by Guo et al. (2016) and Yu et al. (2015), with additional values for s. The corresponding demand curves are plotted in Figure 2.6.

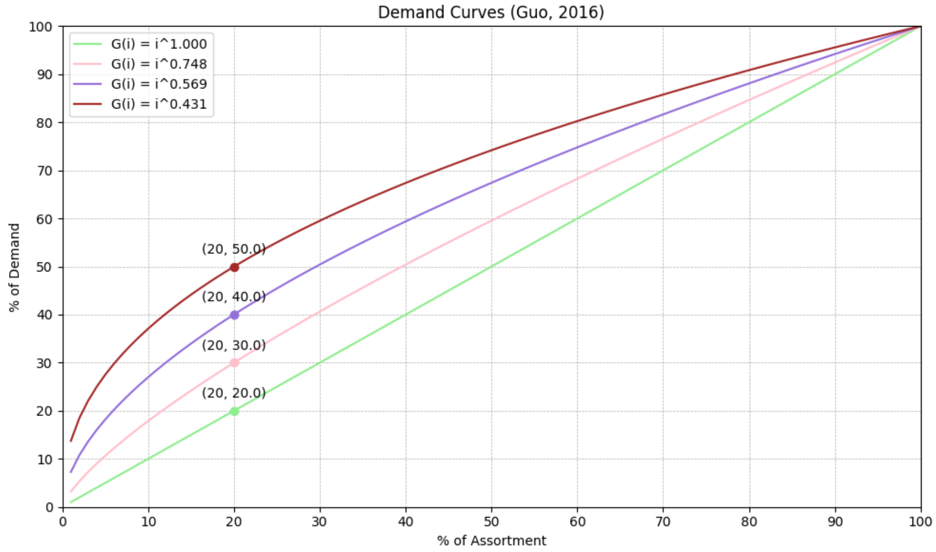


Figure 2.6: Demand Curves used by Guo et al. (2016).

The study of Mirzaei et al. (2021) uses the demand curves with a slope that indicate 20% of assortment corresponds to 40%, 60% and 80% of demand, which overlaps the demand in the research of Hausman et al. (1976), Guo et al. (2016) and Yu et al. (2015).

The order demand drawn from an exponential distribution emulates a typical ABC curve in e-commerce according to Lamballais (2019). This demand curve is constructed with the derivation of statistical distributions used for Lorenz curves, which is possibly due to their relation to demand curves according to Ultsch and Lötsch (2015) and Gastwirth (1971). The corresponding demand curve is plotted in Figure 2.7.

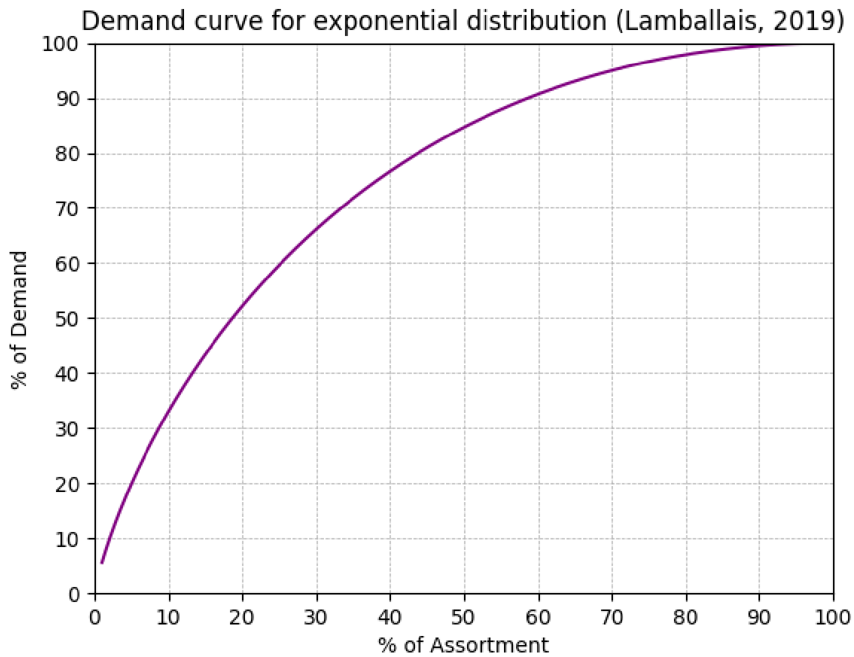


Figure 2.7: Demand Curve Derived from an Exponential Distribution, used by Lamballais (2019).

The combination of all demand curves used in the studies of Weidinger et al. (2019), Chou et al. (2019), Hausman et al. (1976), Guo et al. (2016) and Lamballais (2019) are visualised in a combined plot in Figure 2.8.

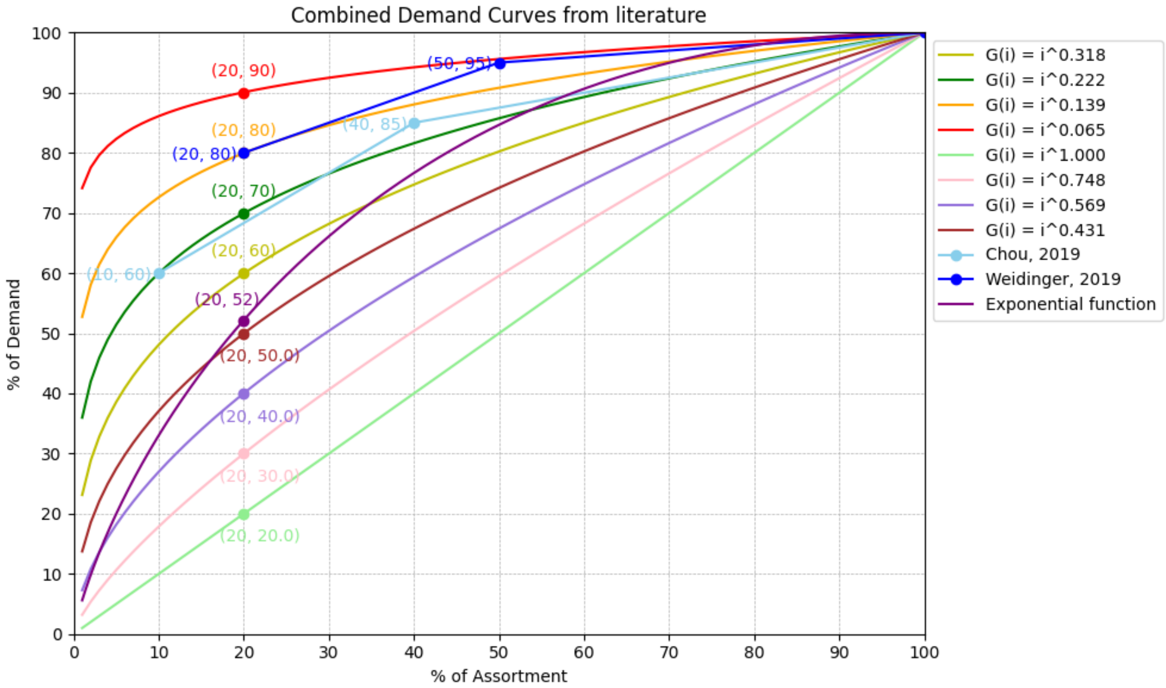


Figure 2.8: Comparison of Demand Curves used in Literature, where the Curves Referring to the Function $G(i) = i^s$, are from Hausman et al. (1976) and Guo et al. (2016).

2.3. Decision Problems in a Robotic Mobile Fulfilment System

Lamballais et al. (2020), structures the decision problems regarding RMFS into three supply chain management levels: strategic, tactical and operational. Strategic-level decisions are long-term and high-level and are associated with, for instance, layout and process design. Tactical-level decisions are medium-term and usually involve production planning and inventory management. Tactical-level decisions considered in M. Merschformann et al. (2019) are, amongst others, SKU over pod distribution and the replenishment level of a pod. Operational-level decisions are short-term and real-time, consisting of resource- and order-assignment (Misni and Lee, 2017).

2.3.1. Order Demand Certainty

The decision problem of slotting is divided over the tactical level and the operational level, where the distinction lies in the type of demand being stochastic or deterministic:

Tactical level, *item allocation with deterministic demand.*
Orders are known in advance and remain constant, allowing for a single, optimal decision-making process without considering computational time constraints.

Operational level, *item allocation with stochastic demand.*
Typical in e-commerce environments driven by human consumer purchases, demand is uncertain until orders occur. Slotting at this level must address multiple decisions for intervals over time as orders are received.

Deterministic demand allows for straightforward slotting as the specifics of orders are predetermined. This suits operations where orders are forecasted with high accuracy or are placed well in advance, e.g., monthly orders in specific warehouses. Here, the demand is treated as fixed and can be planned for with certainty. Contrarily, stochastic demand introduces variability, as order specifics are unknown until the point of transaction. This requires a dynamic slotting approach to accommodate the unpredictability of orders typical in e-commerce settings. Slotting must be flexible and capable of adapting to real-time data.

A practical approach for the integration of deterministic demand and stochastic demand involves using forecasts to estimate deterministic demand while treating any deviations from these forecasts as stochastic, as is done in the research by Antic et al. (2022). This method allows for both predictive planning and adaptive responsiveness. Additionally, according to Azadeh et al. (2017), forecasting the item composition within orders is highly accurate. The research by Chou et al. (2019) and Dai et al. (2022) further complement this approach by exploring demand forecasting accuracy and its impact on inventory and replenishment strategies.

2.3.2. New Concepts with a Robotic Mobile Fulfilment System

Implementing RMFS reintroduces and enhances several interesting concepts that are related to slotting decisions or directly impact them, identified by Lamballais (2019):

Pile-on
Refers to the number of items that can be picked from one pod when it visits a picking station. A high pile-on means more orders are handled with fewer pods, reducing travel and waiting times.

Zoning with pod reallocation
Zoning is the decision problem that separates the available warehouse space into separate zones dedicated to specific criteria. The class-based storage approach in traditional warehouses is similar to the decision problem of zoning. The difference between class-based storage and zoning lies in the focus; with a class-based approach, the focus is on the classified products, whereas with zoning, the focus is on the physical warehouse layout. In traditional warehouses, the zoning decisions are integrated with the inventory allocation decision since the storage racks are stationary.
RMFS introduces moving storage racks that enable continuous reallocation of pods in the storage area. This innovation decouples zoning choices from the slotting decisions, leading to separate decision problems regarding zoning strategies in RMFS:

Well-sortedness
Each pod is assigned a popularity score, defined as a weighted total of all SKUs on a pod, based on a SKU's turnover multiplied by the quantity on that pod. The pods are positioned according to the scores, with those achieving the highest score nearest to the stations.

Priority zoning
Pods are assigned to zones based on the urgency of orders demanding SKUs present on that pod.

Dynamic resource assignment
Robots and workstations can be classified as either *dedicated*, which means they are assigned to exclusively picking or replenishment tasks, or *pooled*, indicating that they can process both tasks (Roy et al., 2019). The dynamic resource assignment refers to the reassignment option of robots and workstations between the picking and replenishment tasks throughout operations. Workstations can transition between designated picking or replenishment roles after each task. In addition to reassignment, robots may be relocated after each task to different areas.

The decision problem concerning zoning was studied by Roy et al. (2019) with a multi-class storage assignment and pooled robot assignment that reduced total order-turnover time. While the optimal slotting decision results could provide useful insights for zoning decisions, they are not an objective of this study and remain outside of the scope of this research.

The concept of pile-on, however, is directly impacted by tactical-level slotting decisions. Pile-on increases when multiple SKUs required for a single order-pick assignment are conveniently located on the same pod. This efficiency is directly affected by slotting decisions, such as the combination of SKUs in a pod and the distribution of SKUs over pods.

2.3.3. Decision Problem Correlations

The decision problem of slotting is correlated with several other decision problems on the strategic-, tactical- and operational levels. Understanding these correlations is crucial, as optimising one decision problem can often impact the efficiency of others due to inherent trade-offs. For effective warehouse management, it is essential to consider these interdependencies.

Decision problems correlated with slotting include (Lamballais, 2019):

Replenishment
This involves refilling (movable) storage racks with items. Decision problems include workstation and pod selection for the replenishment order.

Routing
The path planning decisions for the robots. This includes decisions on collision prevention and priority rules.

Order-batching
The assignment of orders to be picked at one station. This approach can, for instance, be based on SKU similarity by combining orders with similar SKUs or on pod-to-workstation distance by assigning orders requiring SKUs in nearby pods.

Pod-to-station assignment The selection of pods to fulfil the orders at a picking station. This approach can, for instance, be based on pod-to-workstation distance by assigning pods closest to the station or on quantity by assigning pods containing the most necessary SKUs.

Effective replenishment timing is critical to maintaining operational efficiency in warehouses. Inventory levels decrease as items are picked from storage pods, necessitating timely replenishment to prevent stock shortages of specific SKUs. Conversely, overly frequent replenishment can lead to inefficiencies, including increased robot travel and queuing at workstations due to limited storage space for incoming items.

The research of Lamballais (2019) studies the trade-off in determining the optimal inventory level for initiating replenishment activity. This study tests replenishment thresholds set at 0%, 50%, and 100% inventory levels, finding that a 50% threshold provides the best balance between maintaining stock availability and minimising replenishment frequency.

Additionally, Weidinger et al. (2019) compares replenishment strategies for different slotting approaches. Their findings suggest that the random slotting approach requires lower replenishment levels due to fewer location-specific requirements, enhancing flexibility. In contrast, with dedicated storage, a higher replenishment threshold of 85% is optimal.

This illustrates the interdependence of replenishment and slotting decisions and their impact on warehouse efficiency. The optimal slotting decision is a trade-off between order-picking efficiency and replenishment time. Therefore, the replenishment strategy and slotting strategy should complement each other. A slotting approach that integrates both replenishment and picking efficiency might involve replenishing only once a day if the demand is deterministic enough to allow that or replenishing based on expected daily demand to simulate deterministic demand while setting initial slotting decisions and relaxing them for subsequent replenishment tasks.

Additionally, an example of how slotting and routing decisions affect each other is separating SKUs that are rarely ordered together in different pods, which might ease the routing decisions and decrease the robot travel time due to less path-crossing occurrence. Pods could then have dedicated stations assigned that only have orders with those SKUs, including pod-to-station assignment decisions into the interdependent decisions.

2.4. Slotting Decision Problem in a Robotic Mobile Fulfilment System

The decision problem of slotting is divided into three main decisions regarding RMFS slotting, identified by Chou et al. (2019), introduced in Section 1.1.2 and visualised in Figure 1.5. The three decisions are:

1. The number of pods over which a SKU is distributed.
2. The item quantity of each SKU within a single pod.
3. The combination of SKU types in one pod.

The research questions in this study focus on the number of pods over which a SKU is distributed. Additionally, the literature on the two other slotting decisions is reviewed, providing insights that might be useful for potential future elaboration. The three slotting decisions are individually reviewed in the sections below.

2.4.1. Distribution of Stock Keeping Units over Pods

The research by Lamballais et al. (2020) shows that increasing the number of pods over which the items of a SKU are spread positively affects the total order throughput rate. Spreading the SKU over multiple pods increases the flexibility in pod choice, constituting an increased probability that an available pod is close to the designated picking station and, additionally, the likelihood that a pod contains more of the necessary items that can be picked at the picking station, increasing the pile-on. This is confirmed with the research from Guan and Li (2018), which shows a decrease in pod movement when the number of SKUs in a pod increases.
The research from Lamballais (2019) presents a strong relation between pile-on, robot travel distance and throughput rate. Where a high pile-on and shorter travel distance have a positive impact on the throughput rate. However, less items per SKU in a pod increases the number of replenishment actions and therefore decreases the total order throughput rate.

The number of pods to spread the SKU over is determined with a simulation (Lamballais et al., 2020), with different configurations for the number of pods a SKU is distributed over. The configurations range from 1 pod per SKU to 6 pods per SKU, where the best result was found with the maximum number of scenarios, 6 pods per SKU. The effect of spreading a SKU over more pods than 6, however, is not studied. The optimal result might be a distribution over even more pods.

By simulating multiple replenishment strategies, the research of Tsai et al. (2019) indicates that distributing SKUs with a high turnover rate over multiple pods positively affects the number of pod movements. This indicates that spreading SKUs over many pods might optimise results for both the order-picking efficiency and the replenishment efficiency.

The research of Tsai et al. (2019) is exclusively studied with the top 10% high turnover SKUs, yielding a positive result. The question of dependence on turnover remains, therefore, unanswered.

2.4.2. Item Quantity of a Stock Keeping Unit in a Pod

The research of Lamballais et al. (2020) suggests a large spread of SKUs across pods. However, the maximum distribution of SKUs leads to pods containing a small number of items per SKU. While factors like travel distance and pod availability contribute to the positive outcome of a maximum distribution (Lamballais et al., 2020), it is notable that these same factors might be the reason for the negative performance with low item quantities per SKU in a pod. Spreading the items of a SKU too thin decreases flexibility since orders might need more than the available item quantity of a SKU in that pod (Lamballais, 2019). This indicates a minimum item quantity per SKU within a pod. This minimum item quantity is likely influenced by order demand characteristics. Additionally, the demand characteristics of a SKU presumably impact the consequences of storing too few items on a pod, as demand indicates whether a SKU is frequently ordered as a single item or in multiples.

Additionally, this slotting decision correlates with the distribution of SKUs over pods. A constraint on the number of pods to spread a SKU over might depend on the minimum or optimal number of

SKUs on one pod, which has not been researched yet and might differ for SKUs with different demand characteristics, such as turnover, average number per order and SKU similarities to other SKUs.

2.4.3. Combinations of Stock Keeping Units in a Pod

When analysing order contents it is found that some SKUs are often ordered together and some SKUs are rarely ordered together. This is called SKU similarity or SKU correlation. In traditional order-picking systems, order-batching involves the decision of which orders to combine in the order-picking assignments. This is typically based on order similarity or SKU similarity, where orders are grouped based contained SKUs with the objective to minimise order-picking travel distance, for instance with the studies of Heskett (1963), Hwang et al. (1988), Chiang et al. (2011), Yang et al. (2015) and Zhang (2016).

With an RMFS, the concept of SKU similarity can be extended to consider not only the similarity of SKUs within orders, but also the similarity of SKUs in pods (Chou et al., 2023), since this significantly impacts pile-on.
The combination of SKUs on a pod is studied by Xiang et al. (2018), Yuan, Wang, and Li (2019) and Kim et al. (2020). Where Kim et al. (2020) advises to study the effects of assigning a SKU to more than one pod to increase potential SKU combinations. This correlates to the decision problem of distributing a SKU over pods, since both find increased performance due to pile-on. Moreover, the objectives in these studies regarding SKU similarity align with the SKU over pod distribution decision problem, with objectives of minimal pod travel distance and maximum pile-on.
The implementation of slotting approaches considering SKU combinations significantly impacts the number of pod movements necessary for replenishment according to the research of Tsai et al. (2019), where various pod replenishment strategies are compared with a simulation. This highlights the trade-off between the slotting and replenishment decision problem.

Notably, the concept of SKU similarity introduces a new aspect of order demand besides SKU turnover. While SKU similarity remains outside of the scope of this research, it is important to realise that incorporating SKU similarity in slotting decisions can further reduce travel time and increase pile-on, thereby amplifying the impact of the slotting decision.

2.4.4. General Slotting Research Gap

The SKU distribution researched by Lamballais et al. (2020) can be extended on several aspects concerning slotting. The slotting approach optimisation including demand, or more specifically, SKU turnover, is a research gap for all three components of the slotting decision problem: The SKU over pod distribution, the item quantity per SKU in a pod, and the SKU combinations in a pod.
The research gaps related to the scope of SKU distribution over pods are primarily concerned with pile-on and turnover. The main gaps include:

> The study by Lamballais et al. (2020) is conducted under the assumption of uniform demand, where all SKUs have the same turnover rate. The result is to distribute SKUs over as many pods as possible. However, warehouses operate within a defined inventory capacity limit, placing a constraint on how wide the SKUs can be distributed. Furthermore, the wider distribution of one SKU might limit the distribution of another. Therefore, it is essential to gain insights into the benefits of distributing a SKU with a certain turnover rate in order to determine the priority of distributing a certain SKU over more pods than another. For instance, a low-turnover SKU that is ordered only rarely might have a lower priority of maximum distribution than a high-turnover SKU that is ordered frequently.
>
> Distributing inventory across more pods reduces picking time through increased pod availability, decreased robot travel distance and increased pile-on. However, the impact of pile-on on performance is not fully captured in the simulation by Lamballais et al. (2020) due to three main simplifications:
>
> > *The pods contain one SKU exclusively.*
> > This limits the development of pile-on when an assigned pod circumstantially contains SKUs

that are also required by orders assigned to that station. Additionally, it prohibits the effect of assigning specific SKU combinations to a pod with the goal to increase pile-on.

Handling of split-orders is prohibited.
Split-orders is the use of more than one pod for one order. This decreases the set of pods to choose from, which decreases the pod availability.

The orders are single-line.
Single-line orders consist of one SKU exclusively. The quantity of that SKU is not restricted, so orders can still require multiple items; they will, however, all be the same SKU.
This limits the development of pile-on similar to the single SKU to pod assignment.

These simplifications limit the development of pile-on and reduce the impact of slotting specific SKU combinations in one pod, since the pile-on is only measured for orders requiring the same SKU.
Incorporating SKU turnover into slotting considerations, along with addressing the three simplifications, enhances applicability and realism of the slotting approach and its results.

2.5. Performance Evaluation

As introduced in Section 1.6, the RMFS decision problems can be structured in three management levels: Strategic, tactical and operational. Common objectives for strategic-level decisions are order throughput rate maximisation and storage capacity maximisation. The objectives for tactical- and operational-level decisions are often the minimisation of travel time, waiting time, or response time (Azadeh et al., 2019). Evidently, strategic objectives are generic and all-inclusive, whereas tactical-level objectives are scaled and more task-specific.
Additionally, the computational time for strategical and tactical level problems is of less importance, whereas for operational problems, this is relevant since they solve real-time problems (Xiang et al., 2018).

Azadeh et al. (2017) explains that there are two possible approaches for the performance evaluation of the slotting decision problem: Analytical models and simulation models. The benefit of using simulation is that it can accurately represent realistic scenarios with low error in the results. In contrast, the benefit of using an analytical model is that it is less time-intensive to design.
Both for tactical and strategical level decision problems, and therefore, both for throughput maximisation and travel time minimisation objectives, the modelling approach in the literature review by Azadeh et al. (2017) includes simulation and analytical models.
The study by Azadeh et al. (2017) concludes that research with integrated models where multiple decision problems are considered together remains a largely unexplored topic. That gap is addressed by M. Merschformann et al. (2018), who designed a detailed simulation framework to integrate the dynamic effects of decision problems (Lamballais et al., 2020). This framework is used by M. Merschformann et al. (2019) to evaluate multiple operational decision problems, among which the pick-order assignment and replenishment-order assignment, on the performance of measures such as unit throughput rate, order throughput rate, robot travel distance and pile-on.

The performance metric of order turnover time measures when an order is received to when it is completed. The order throughput rate refers to the number of orders processed within a certain time interval, reflecting overall system performance and particularly vital in e-commerce settings (Reid, 2024). Changes in performance regarding the order throughput rate are expected to be influenced by pod travel distance and item pile-on (M. Merschformann et al., 2019), as demonstrated by the findings of Xie et al. (2019) and Lamballais (2019).

2.6. Conclusion to Literature Review

The purpose of this literature review is to provide the essential information on the various components of the research question and to describe the research gap that this study addresses.

The research gap in slotting decisions with a Robotic Mobile Fulfilment System specifically lies in the consideration of demand, particularly SKU turnover.

While traditional slotting approaches often incorporate demand and consider turnover highly relevant, this has not been fully studied with slotting decisions in an RMFS. By incorporating demand through turnover-based classifications, such as the ABC classification, slotting decisions can be better aligned with the demand characteristics.
Furthermore, slotting decisions are rarely made in isolation and are often interconnected with other decisions within the system. While replenishment and other decision problems are crucial to overall warehouse efficiency and can not be neglected in real-world applications when deciding the slotting strategy, they remain outside the scope of this research. This study focuses solely on the impact of slotting decisions. However, by picking the approach of extending the existing simulation model of M. Merschformann et al. (2018) with slotting decisions, this study narrows the gap of integrating slotting and other decision problems.

The performance of slotting decisions is found in the order picking efficiency with metrics such as travel distance and pile-on, with order throughput rate as the overall performance metric.

This review provides the necessary information to address the research question regarding the impact of demand-based slotting decisions on the order throughput rate with a Robotic Mobile Fulfilment System. The elaborated methodology for answering this research question is further detailed in Section 3.1.

3

Methodology

With the relevant information for the research provided in the literature review in Chapter 2, this chapter of the report explains how the research is executed. Section 3.1, elaborates on the approach of the research itself, presenting a methodology flowchart and explaining all of the components. After this, the main processes of the research are explained: the different demand profiles are determined in Section 3.2, the slotting model is explained in section 3.3 and the simulation model in Section 3.4.

3.1. Research Approach

The methodology for finding the impact of demand-based slotting consists of processes, where the output of one process is the input for the next process. The process flowchart of the research methodology is depicted in Figure 3.1. Each of the processes is briefly summarised below, and elaborately explained in the corresponding section of this chapter.

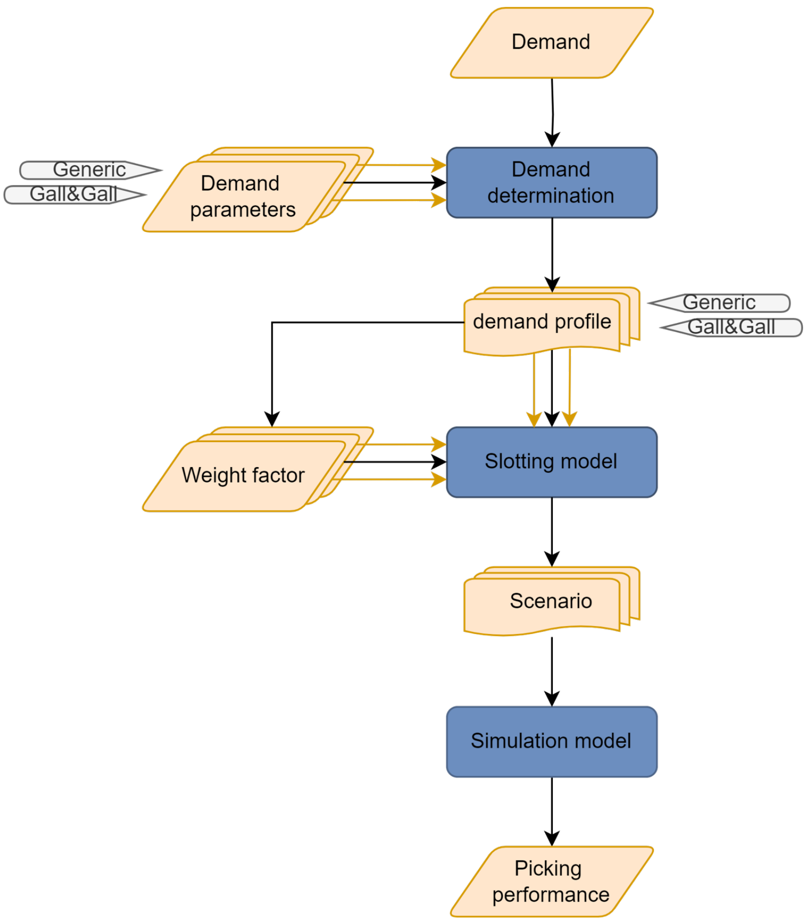


Figure 3.1: Flowchart of the Research Methodology.

Demand Determination Process

Firstly, the demand is determined in Section 3.2. This process is a preparation process where the demand is simplified into classes based on the frequency with which the SKUs are ordered (turnover): A, B and C, where all SKUs within a class share the same item turnover.

The process inputs and outputs for the demand determination are depicted in Figure 3.2. The two inputs for this process are the total demand and the demand parameters. Total demand refers to the total number of SKUs and the total number of items that are ordered. Where the demand parameters define the configurations regarding the SKU quantity and the item quantity in the classes for the different demand profiles. The output of the demand determination process is a variation of demand profiles.

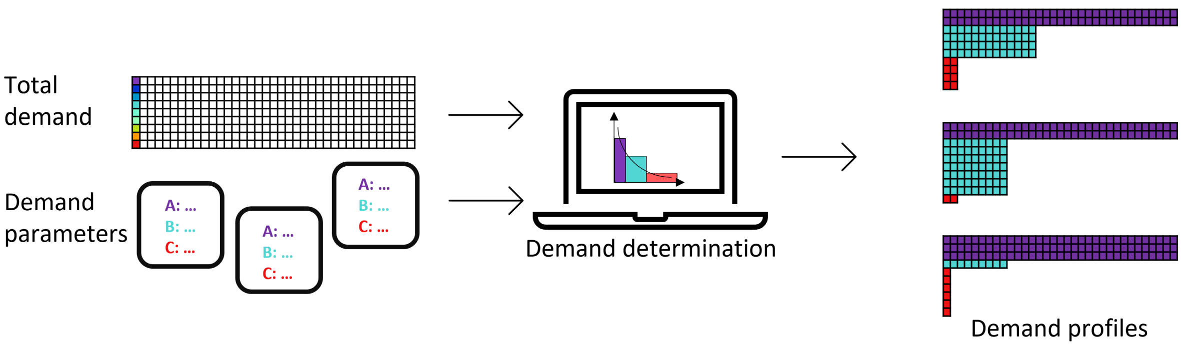


Figure 3.2: Demand Determination Process.

Initially, the steps in the flowchart are executed and explained in this chapter using synthetic demand parameters. Subsequently, the same methodology and process flowchart is applied to demand parameters from Gall&Gall, creating specific demand profiles for the Gall&Gall case study, detailed in Chapter 5.

Slotting Process

Secondly, a mathematical slotting model is developed and explained in Section 3.3. The process inputs and outputs for the slotting process are depicted in Figure 3.4. Each demand profile is used with multiple weight factors to generate multiple scenarios describing different distributions.

The distributions of the scenarios in Figure 3.4 are visualised with a ternary plot. To understand the figurative presentation of the slotting process, the basics of the ternary plot are explained with a supportive Figure 3.3. This triangular plot allows the plotting of three variables, in this plot the distribution of number of pods per SKU for the three classes. Each scenario is marked with an ***x***, and the axes in three directions present the distribution of the relative class.
Data representation with a ternary plot is further explained with the simulation analysis in Section 4.2.

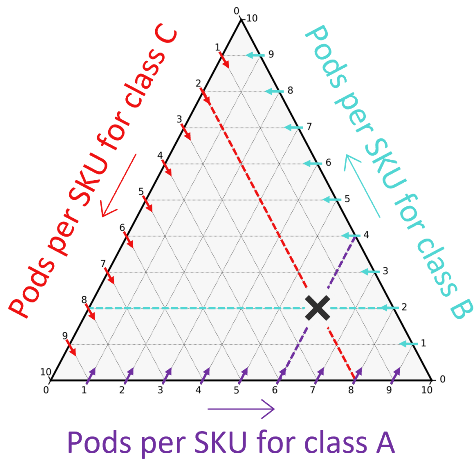


Figure 3.3: Explanation of a Ternary Plot.

The weight factors are used to vary the importance of the distribution of a class. The slotting model generates multiple different slotting configurations for each demand profile based on their specific weight factors. A slotting configuration is defined as a scenario, and specifies the exact distribution of SKUs over pods for the three classes.

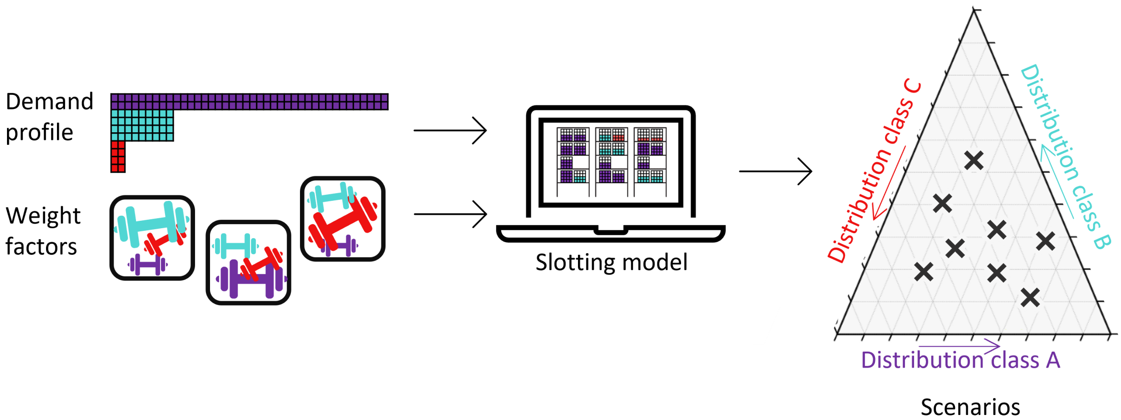


Figure 3.4: Slotting Process.

Simulation Process

Finally, the scenarios are evaluated with a simulation model in Section 3.4 and the process inputs and outputs for the simulation process are depicted in Figure 3.5. The RawSim-O simulation tool, developed by M. Merschformann et al. (2018), is extended to include slotting. This provides the performance for all scenarios per demand profile.

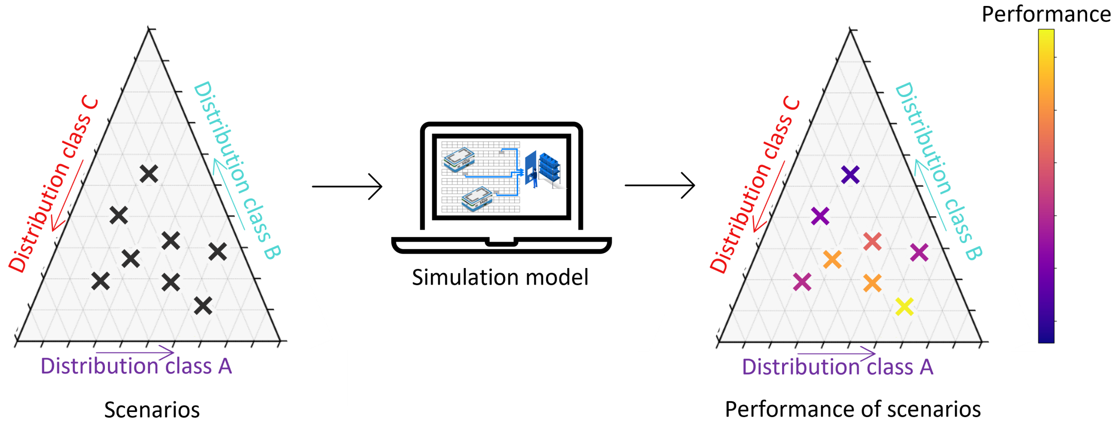


Figure 3.5: Simulation Process.

3.2. Demand Determination

As described in the research methodology in the previous section, the demand is configured into demand profiles based on demand parameters. The figure to depict this process is replicated in this section in Figure 3.6.

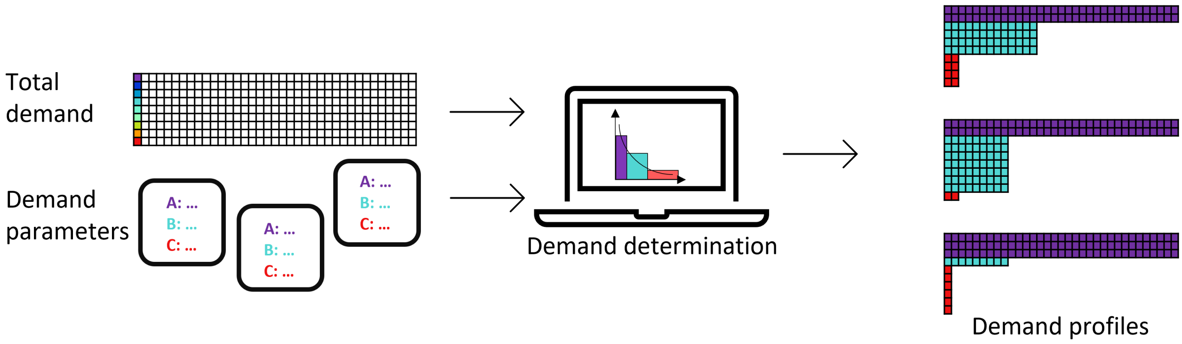


Figure 3.6: Figure Replication of the Demand Determination Process.

The demand profiles allow for evaluating the impact of demand-based slotting decisions under varying demand conditions. The significance of the demand profiles lies in the relative turnover rates of each class, which reflect differences in demand. Since the focus is on these relative differences rather than the specific time frame, whether daily or annually, the turnover period is often not specified.

First, the demand profiles are described, and the process of demand determination is explained in Section 3.2.1, after which the demand profiles for this study are configured in Section 3.2.2.

3.2.1. Demand Profile Description

The total demand with the same number of SKUs and the same number of items is configured into multiple demand profiles by categorising the SKUs into three classes based on demand parameters. The demand parameters consist of both the number of SKUs in each class and the turnover for the SKUs in each class. The demand parameters for the determination of the demand profiles are selected based on the demand curves drawn from previous research, as elaborated in Section 2.2. The demand curves are cumulative curves that describe the relation between the assortment and the demand, representing which portion of SKUs is responsible for specific portions of item turnover. The demand curve function, variables and parameters used in this section to describe and define the demand profiles are defined in Table 3.1.

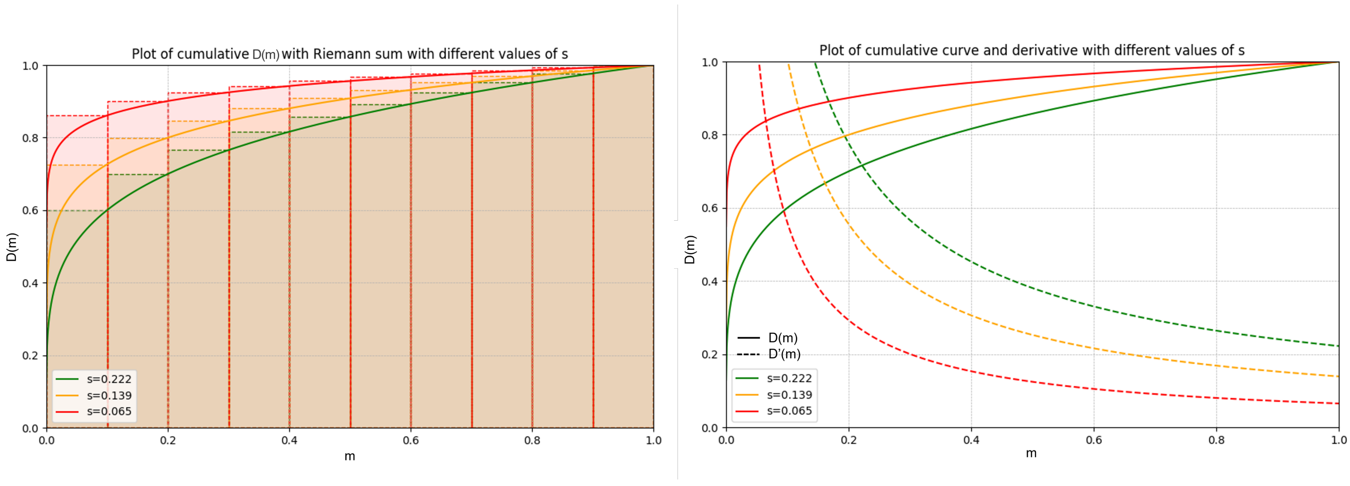
It is important to clarify that the parameters and variables used in Equation 2.1, $G(i) = i^s$, for the demand curve in Section 2.2, are named according to the respective literature. From this chapter on, they are referred to as $D(m) = m^s$ for clarity and to avoid confusion with other newly introduced variables in the rest of this research. The parameters and variables are defined in Table 3.1.

Parameter s (lowercase) determines the slope of the demand curve, and is distinct from S (uppercase), used to define the total number of SKUs. The two parameters are unrelated.
The proportion of SKUs is denoted by m, which ranges from $0 < m$ to 1, where $m * 100$ indicates percentage of the SKUs. The item demand proportion corresponding to this SKU proportion is represented by $D(m)$, following the function $D(m) = m^s$. Additionally, i represents the SKU index, and $D(i)$ denotes the demand for specific SKU i.

Table 3.1: Demand Profile Definitions. The Variables and Parameters from the Demand Curve Function are Changed from $G(i) = i^s$ to $D(m) = m^s$.

Definitions		
$D(m) = m^s$	Function of the demand curves	
m	Proportion of SKUs	$0 < m \leq 1$
$D(m)$	Item demand proportion for SKU proportion	$0 < D(m) \leq 1$
s	Parameter determining the slope of the demand curve	$s \in \{0.222, 0.139, 0.065\}$
i	SKU index	
$D(i)$	Item demand for SKU i	
S	Total number of SKUs	

The four demand curves from Hausman et al. (1976) are based on the optimal inventory management for a warehouse regarding the distribution of storage capacity over the total number of SKUs, as elaborated on in the literature review in Section 2.2. Therefore, it is assumed that these demand curves resemble realistic demand profiles. Additionally, the curve following the Pareto principle with a distribution where 80% of the demand is caused by 20% is widely used in research (de Koster et al., 2007 and Weidinger et al., 2019). This curve, along with its two adjacent curves where 20% of the SKUs is responsible for 70% and 90% of the demand, are used in this research for the demand parameters. The three curves are presented in Figure 3.7, and referred to in the legend of the plots with the parameter value of the respective curve used for s. The curve with the Pareto distribution is the yellow curve with $s = 0.139$, the red curve with $s = 0.065$, has a distribution where 20% of the SKUs are responsible for 90% of order demand, and 20% of SKUs are 70% of the demand for the green curve with $s = 0.222$.



(a) Three Cumulative Demand Curves with Riemann-sums.

(b) Three Cumulative Demand Curves and the Derivatives.

Figure 3.7: Three Cumulative Demand Curves (m^s) for the Demand Profiles, where Parameter s Defines the Slope of the Curve.

The demand curves are cumulative functions. Therefore, they are used to determine the demand of an interval with the right Riemann-sums of the top-right vertex of each bin within the interval to guarantee the final bin one has a demand proportion value of 1. The height of the bins reflects the cumulative proportion of demand in items, $D(m)$, and the bins' width indicates the assortment proportion, m, see Figure 3.7a.

The item demand per interval is determined by taking the demand value of the function increments and subtracting the value of the previous increment. However, with an increasing steepness for m approaches 0, the limit of the function's derivative goes to infinity, as depicted in Figure 3.7b. Consequently, the domain of function $D(m) = m^s$ is $\{0 < m \leq 1\}$, which excludes 0. This function behaviour explains that the first increment always contains the extremity of an infinite value when separating the curves into increments. This extremity becomes more pronounced when the number of increments increases. Therefore, the demand curve is only employed to divide the demand into classes rather than serve as a dedicated SKU demand curve for individual SKUs. With the item demand separated into classes, the width of each increment corresponds to that class's assortment proportion.

An example of demand profiles with a class distribution according to a demand curve with 10 SKUs in total and a total demand of 100 items is depicted in Figure 3.8. The classes are separated at 20% and 60% of the assortment, creating intervals of 20%, 40% and 40%. Distributing the item demand proportions amongst these SKU proportions yields the quantities per SKU shown in Figure 3.9 and detailed with the associated demand per SKU in Table 3.2.

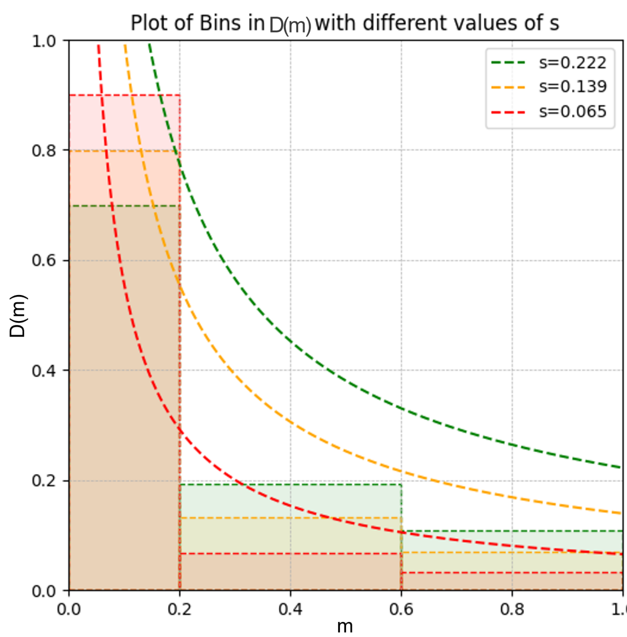


Figure 3.8: Classification with Demand Proportion $D(m)$, of Assortment Proportion m , from the Demand Curves (m^s) with 100 Items and 10 SKUs.

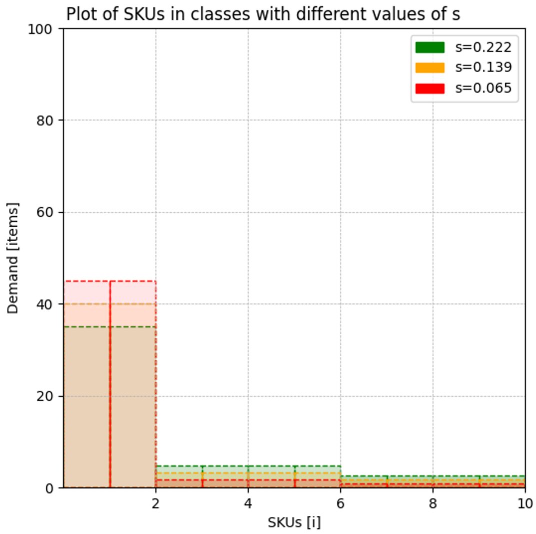


Figure 3.9: Classification with Item Demand $D(i)$, per SKU i, from the Demand Curves (m^s) with 100 Items and 10 SKUs.

Table 3.2: Classification of Item Demand $D(i)$, per SKU i, for Different Demand Curves (m^s) with 100 Items and 10 SKUs.

Demand curve (m^s) [s]	**SKU index [i]**	**Item demand [$D(i)$]**	**Cumulative Demand ($D(m)$) [%]**
	0	35	35%
	1	35	70%
	2	5	75%
	3	5	80%
0,222	4	5	84%
	5	5	89%
	6	3	92%
	7	3	95%
	8	3	97%
	9	3	100%
	0	40	40%
	1	40	80%
	2	3	83%
	3	3	87%
0,139	4	3	90%
	5	3	93%
	6	2	95%
	7	2	97%
	8	2	98%
	9	2	100%
	0	45	45%
	1	45	90%
	2	2	92%
	3	2	93%
0,065	4	2	95%
	5	2	97%
	6	1	98%
	7	1	98%
	8	1	99%
	9	1	100%

In this example of distributed demand into demand profiles, the demand curve with $s = 0.139$ (yellow) follows the Pareto principle: the item demand of the first two SKUs together are 80% of the total demand. In the plot for $s = 0.222$ (green), the demand of the first class is lower than for the other curves, and the demand of the SKUs in the other classes is slightly higher than for the other curves due to the low skewness of the curve. A high skewness implies a bigger difference between classes. The demand of the first two SKUs for the curve with $s = 0.065$ (red), add up to 90% of the total item demand, while the last four SKUs contribute only 1% to the total demand.

3.2.2. Demand Profile Configuration

The demand profiles are classified according to an ABC classification since the simplification of demand into three classes focuses the result insights towards turnover impact. Additionally, this is what demand curves are typically used for, and they are less suitable for dedicated demand, resulting in extreme demand values.

The demand is separated into classes according to two classifications: one with separation at 20% and 60% of the assortment and another at 10% and 20%. The class intervals are determined to ensure the difference in quantity between classes A and B does not render class B insignificant. In contrast, the difference between classes B and C remains substantial. Additionally, the research by Weidinger et al. (2019) and Chou et al. (2019) used 10% and 20% separations for class A.

In the simulation conducted by Lamballais (2019), 1000 SKUs with over 8000 items are used. This configuration assumes roughly an average demand of 8 items per SKU. This demand is scaled to 10 items per SKU for simplification. Because adjusting the total number of items per SKU affects the overall volume without changing the proportion of SKUs, it is assumed that scaling will not significantly impact the results. The demand configuration used in this research operates with an assortment of 100 SKUs with a demand of 1000 items.

Table 3.3: Demand Profile Configurations

	Configuration	
s	Parameter determining the slope of the demand curve	$0.222 \quad \vee \quad 0.139 \quad \vee \quad 0.065$
	Class separations	$[20\%, 60\%] \quad \vee \quad [10\%, 20\%]$
S	Total number of SKUs	100
$\sum_i D_i$	Sum of demand for all SKUs i	1000

The two options for class separation are combined with the three options for the demand curve to create six demand profiles. The demand profiles are referred to as DP_A through DP_E, representing demand profiles A to E. The three demand profiles with class separation $[10\%, 20\%]$ are plotted in Figure 3.10a, and the three with $[20\%, 60\%]$ are plotted in Figure 3.10b.

(a) Three Demand Profiles, DP_A, DP_C and DP_E, with Class Separation on (10%, 20%) from the Three Demand Curves.

(b) Three Demand Profiles, DP_B, DP_D and DP_F, with Class Separation on (20%, 60%) from the Three Demand Curves.

Figure 3.10: The Six Demand Profiles.

The demand from these plots results in decimal values for the items in some of the classes. Since the item count can not be decimal values but are integers, the demand is manually rearranged to create integer values where the sum of all demand satisfies the total demand of 1000. The result is the demand profiles presented in Table 3.4.

Table 3.4: Demand Configuration with Item Count and SKU Count per Class

Demand profile	Class	Item count $[D_i]$	SKU count
DP_A	A	58	10
	B	10	10
	C	4	80
DP_B	A	34	20
	B	5	40
	C	3	40
DP_C	A	69	10
	B	7	10
	C	3	80
DP_D	A	40	20
	B	3	40
	C	2	40
DP_E	A	86	10
	B	6	10
	C	1	80
DP_F	A	44	20
	B	2	40
	C	1	40

For the demand in Table 3.4, it is important to note that both demand profile DP_E and DP_F have a demand of 1 item for the SKUs in class C. This will simplify the distribution of these demand profiles since there is one less category to consider, as one item can only be distributed over exactly one pod. For DP_F, the SKUs in class B are also very limited, with only two items, which makes this the most simple demand profile to consider. Class C for profile DP_E, while only consisting of 1 item, consists of 80 SKUs. The difference in the number of SKUs between classes A and C is most significant for this demand profile. The difference between class A and C is the smallest for demand profile DP_B, which is also the profile with the lowest item count for class A and a SKU count of 20 as opposed to 10. This demand profile is most balanced for the three classes, both regarding SKU count and item count.

3.3. Slotting Model

To determine the impact of slotting SKUs into varying numbers of pods based on turnover, each demand profile from Section 3.2, is slotted with various slotting configurations and referred to as a scenario. The figure to depict the slotting process is replicated from the methodology approach in Section 3.1, in this section in Figure 3.11.

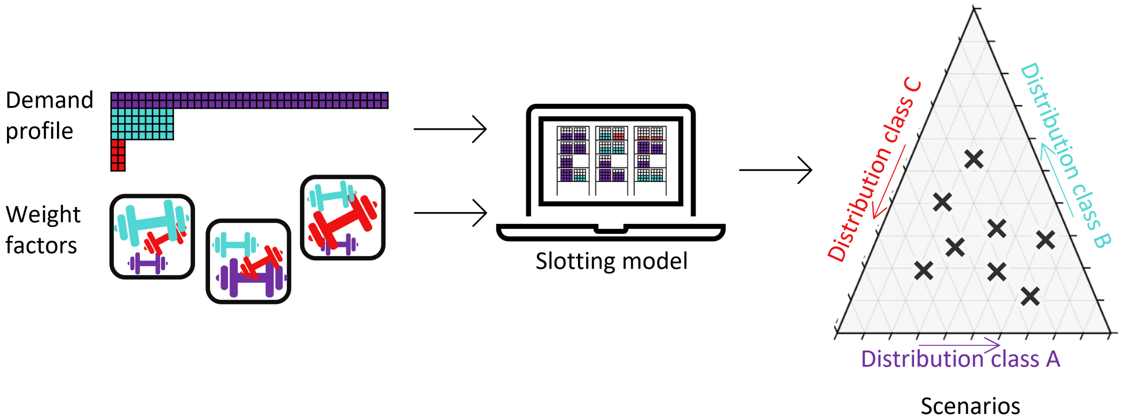


Figure 3.11: Figure Replication of the Slotting Process.

The input for the slotting model consists of the demand profile and the weight factors, which are defined from the demand profile as seen in the flowchart in Figure 3.1. The weight configurations are the origin of the different slotting configurations. The mathematical slotting model is described and explained in Section 3.3.1, and the parameters are configured in Section 3.3.2. The weight factors are configured in Section 3.3.2.1.

3.3.1. Slotting Model Description

The mathematical model is a slotting algorithm that generates exact inventory allocations according to the slotting approach and the demand. The model is based on a three-dimensional bin packing problem formulated by Paquay et al. (2016). This model is translated to a two-dimensional model, and the geometrical constraints are neglected. The model is extended by configuring slotting-specific variables and parameters, including turnover classes and adjusting the objective function to generate a configuration that approaches the distribution determined by weighted importance for each class.

Brief Model Overview

The following is a summary of the model intended to convey its purpose and components. A detailed description follows in subsequent sections.

The demand profile separates the SKU demand (D_i) into three classes (t). A distribution indicator (z_t) represents the distribution per class as the average number of pods per item for all SKUs in a class (I_t). Weight factors (w_t) indicate the relative importance of each class's distribution. The distribution indicators (z_t) and weight factors (w_t) for all classes are used in an equilibrium equation, referred to as the distribution equation.

The model consists of two objective functions. One objective is to maximise distribution (x_{ij}), maximising different SKUs on each pod. The second objective is to distribute the classes to best match the distribution equation.

3.3.1.1. Sets, Parameters and Decision Variables

The mathematical model's set, parameters and decision variables are defined in table 3.5.

Table 3.5: Sets, Parameters and Decision Variables

Sets		
I	Set of all SKUs	$i \in I$
J	Set of all pods	$j \in J$
T	Set of turnover categories, consisting of unique values in D_i	$t \in T$
I_t	Subset of I, for which each SKU i in I_t has turnover category t	
Parameters		
S	Total number of SKUs	
P	Total number of pods	
B	Maximum number of items that can be stored in a pod	
V	Maximum number of different SKUs in a pod	
D_i	Demand number of items per SKU to be assigned	$\forall i \in I$
Q_t	Number of SKUs per turnover category	$\forall t \in T$
w_t	The weight reflecting the importance per turnover category	$\forall t \in T$
Decision variables		
x_{ij}	$= \begin{cases} 1, & \text{if SKU } i \text{ is on pod } j, \\ 0, & \text{otherwise.} \end{cases}$	
y_{ij}	= Integer variable. Number of items of SKU i that occupy pod j.	
z_t	= Continuous variable. Average number of pods per item for SKUs in turnover category t.	

3.3.1.2. Objective Functions

Distributing a SKU over more pods increases the order throughput rate according to Lamballais et al. (2020), since it improves the availability of pods containing the necessary items, which decreases the travel time and increases the potential that multiple items can be picked from the same pod, which is called pile-on. This distribution is formulated in the model with two objectives. The first objective regards the general distribution of SKUs over pods, whereas the second objective specifies the relative importance of the different turnover classes with weight factors.

First Objective

The first objective is to maximise the presence of SKUs on different pods.

$$Max\ G = \left(\sum_i \sum_j x_{ij} \right) \tag{3.1}$$

General objective function 3.1: Maximise the number of different SKUs per pod. This entails the distribution of all SKUs in the inventory across as many pods as feasible within the constraints.
Due to parameters concerning the maximum number of SKUs and items per pod, this objective is bounded, and there are multiple solutions. This objective could similarly have been formulated as constraint: $x_{ij} = P * V$, which is the upper bound of the objective.

Second Objective

The second objective function determines the relative importance of the distribution of a class by integrating the distribution of a class with decision variable z_t with a weight factor for each class (w_t).

The demand is separated into turnover-based classes (t), described in Section 3.2. The distribution of SKUs in class t is described with z_t.

The objective is to approach the equality for all turnover classes (t) with the following equilibrium equation:

$$z_t * w_t = z_{t'} * w_{t'} \qquad \forall\, t, t' \in T \quad and \quad t' \neq t \tag{3.2}$$

In this equation, the weight serves as compensation in the equation for that class. A large weight indicates a low distribution of that class relative to the other classes.
This very strict equation causes infeasability in many cases as a constraint to the model. Therefore, this equality is approached with an objective function that minimises the difference between the sides of the equation.

The weighted objective function is formulated as follows:

$$Min\ diff_t = (z_t * w_t) - (z_{t'} * w_{t'}) \qquad \forall\, t, t' \in T \quad and \quad t' \neq t \tag{3.3}$$

Weighted objective function 3.3: The difference between the weighted distribution for class t and t' is minimised, for all $t \in T$.

3.3.1.3. Constraints

The objective functions are subject to multiple constraints that define the solution space. An explanation for all constraints is provided underneath that constraint.

$$\sum_i y_{ij} \leq B, \qquad \forall j \in J \tag{3.4}$$

Constraint 3.4: Guarantees that the maximum number of items per pod is not exceeded.

$$\sum_i x_{ij} \leq V, \qquad \forall j \in J \tag{3.5}$$

Constraint 3.5: The number of different SKUs on one pod is smaller than or equal to the maximum allowed number of different SKUs on a pod.

$$\sum_j y_{ij} = D_i, \qquad \forall i \in I \tag{3.6}$$

Constraint 3.6: All the demand per SKU must be distributed amongst the pods.

$$y_{ij} \geq x_{ij}, \qquad \forall i \in I, j \in J \tag{3.7}$$

Constraint 3.7: One or more items from SKU i can only be assigned to pod j if selected to contain that SKU.

$$y_{ij} \leq B * x_{ij}, \qquad \forall i \in I, j \in J \tag{3.8}$$

Constraint 3.8: A pod is selected to contain a SKU when items are assigned to the pod.

Distribution Constraints

The following mathematical constraints distinguish the SKUs in different turnover categories t and define that all SKUs are assigned to exactly one category.

$$z_t = \frac{\sum_{i \in I_t} \sum_j x_{ij}}{Q_t * D_i} \qquad \forall t \in T \tag{3.9}$$

Constraint 3.9: The decision variable of z_t is the average number of pods per item for all SKUs i in I_t, where D_i is equal for all $i \in I_t$.

$$\bigcup_t I_t = I \tag{3.10}$$

Constraint 3.10: The union of all I_t covers the entire set I. All SKUs $i \in I$ are assigned to subset I_t with turnover category t.

$$I_t \cap I_{t'} = \emptyset, \qquad \forall\, t, t' \in T \quad and \quad t' \neq t \tag{3.11}$$

Constraint 3.11: The subsets I_t are disjoint. All SKUs i are assigned to exactly one subset I_t.

Domain Constraints
These are domain constraints to ensure that the decision variables exclusively assume the intended values.

$$x_{ij} \in \{0, 1\}, \qquad \forall i \in I, j \in J \tag{3.12}$$

$$y_{ij} \geq 0, \qquad \forall i \in I, j \in J \tag{3.13}$$

Constraints 3.12 and 3.13: Variable x_{ij} is a binary variable that is either 0 or 1. Variable y_{ij} can not be negative.

3.3.1.4. Parameter Boundaries

The parameters used as input for the model are subjected to boundaries to guarantee the feasibility of the model.

$$\sum_i D_i \leq P * B, \qquad \forall i \in I \tag{3.14}$$

Boundary 3.14: The total number of items should fit the total number of storage locations on all pods.

$$S \leq V * P \tag{3.15}$$

Boundary 3.15: The SKU diversity is not larger than the number of locations for different SKUs.

$$P \geq \sum_{i=1}^{S} \left(\left\lfloor \frac{D_i}{B} \right\rfloor + \min\left(\left\lceil \frac{\mathbb{I}(D_i \mod B \neq 0)}{V} \right\rceil, \sum_{i=1}^{S} (D_i \mod B) \right) \right), \qquad \forall i \in I, j \in J \tag{3.16}$$

Boundary 3.16: There is at least the number of pods to satisfy the SKU diversity when a SKU occupies more than one pod without violating the maximum number of different SKUs per pod. Each SKU's demand is divided by the pod capacity; the integer quotient signifies the required pods for full SKU quantities. Additional pods are needed to accommodate remainders. This is the minimum of either the number of different SKUs with a remainder over the maximum limit v, or the total sum of remainders.

3.3.2. Parameter Configuration

The parameters for the slotting configuration are configured in such a way that they resemble realistic situations. Since realistic situations are often on a larger scale, the parameters are downscaled while keeping the mutual relationships similar.
The number of pods from the research of Lamballais (2019) follows the scale of around 60 items per pod (parameter B) for 170 pods (parameter P), which is a ratio of around $B = 0.3 * P$. Satisfying the parameter boundary 3.14, this translates to $P = 60$ pods, with a pod capacity of $B = 20$ items.
The maximum number of different SKUs in one pod, parameter V, impacts the pile-on possibilities, which has a large expected effect on the order throughput rate. With a small V, fewer SKUs can be combined onto a single pod, which decreases pile-on chances, however parameter V also acts as constraint for maximum distribution of SKUs that allow trade-off with the weight factors. Since with V too large, all SKUs can be distributed maximally according to their respective demand. Additionally,

parameter v is determined to satisfy the parameter boundaries 3.15 and 3.16.
Table 3.6 states the parameter configurations for the slotting approaches.

Table 3.6: Slotting Approach Configurations

Parameter configuration		
P	Total number of pods	60
B	Maximum number of items that can be stored in a pod	20
V	Maximum number of different SKUs in a pod	4

3.3.2.1. Weight Factor Configuration

The weight factors in Objective function 3.3, are used to determine the importance of the distribution of a class relative to the other classes by approaching Equilibrium equation 3.2. In this section, the weight factors (w_t) for the classes (t), used in Objective function 3.3, are further specified by determining the range of their potential values in the slotting configurations.

In Section 3.2, it was determined that there are three different demand classes for t (A, B and C). This means that there are three weight factors (w_A, w_B and w_C). Since the weights convey the importance of the distribution of a class relative to the other classes, the weight of one class is set to 1, and the others relative to that. With $w_A = 1$, the following equation is derived from Equilibrium equation 3.2.

$$z_A = z_B * w_B = z_C * w_C \tag{3.17}$$

With this equation, the values for the weights are the following:

$$w_B = \frac{z_A}{z_B} \tag{3.18}$$

$$w_C = \frac{z_A}{z_C} \tag{3.19}$$

The range for the weights follows from the ranges of z_A, z_B and z_C:

$$range(w_B) = \left(\frac{min(z_A)}{max(z_B)}, \frac{max(z_A)}{min(z_B)}\right) \tag{3.20}$$

$$range(w_C) = \left(\frac{min(z_A)}{max(z_C)}, \frac{max(z_A)}{min(z_C)}\right) \tag{3.21}$$

The minimum and maximum of $z_t \forall t$ is determined with the following equation:

$$range(z_t) = \left(\frac{max_{i\in I_t}(x_{ij})}{D_i}, \frac{min_{i\in I_t}(x_{ij})}{D_i}\right), \quad \forall t \quad where\ D_i = D_{i'} \quad \forall i \in I_t \tag{3.22}$$

Where D_i is equal for all i in I_t.

The values for $min(x_{ij})$ and $max(x_{ij})$ are determined with the following equations:

$$min_{i\in I_t}(x_{ij}) = max_{i\in I_t}\left(1, \frac{D_i}{B}\right), \qquad \forall t \tag{3.23}$$

$$max_{i \in I_t}(x_{ij}) = min_{i \in I_t}(D_i, P), \qquad \forall t \tag{3.24}$$

The minimum distribution of pods per SKU for each t is the maximum of 1 or the demand for SKU i divided by B.
The maximum distribution of pods per SKU for each t, is the minimum of either the demand for SKU i, or the total number of pods P.

Combining Equations 3.20, 3.21 and 3.22 gives the following range for the weight factors:

$$range(w_B) = \left(\frac{max_{i \in I_A}(x_{ij})/D_{i \in I_A}}{min_{i \in I_B}(x_{ij})/D_{i \in I_B}}, \frac{min_{i \in I_A}(x_{ij})/D_{i \in I_A}}{max_{i \in I_B}(x_{ij})/D_{i \in I_B}} \right) \tag{3.25}$$

$$range(w_C) = \left(\frac{max_{i \in I_A}(x_{ij})/D_{i \in I_A}}{min_{i \in I_C}(x_{ij})/D_{i \in I_C}}, \frac{min_{i \in I_A}(x_{ij})/D_{i \in I_A}}{max_{i \in I_C}(x_{ij})/D_{i \in I_C}} \right) \tag{3.26}$$

With the demand configuration from Section 3.2 and the slotting configuration from Table 3.6, the initial ranges for the weight factors for each demand configuration are stated in Table 3.7.

Table 3.7: Weight Parameter Configuration

Demand profile	**Range w_B**	**Range w_C**
DP_A	(0.052, 10)	(0.052, 4)
DP_B	(0.059, 5)	(0.059, 3)
DP_C	(0.058, 6.087)	(0.058, 2.609)
DP_D	(0.05, 3)	(0.05, 2)
DP_E	(0.058, 4.186)	(0.058, 0.0698)
DP_F	(0.068, 2)	(0.068, 1)

To find the optimal distribution of the classes, variations of weight factor configurations are used as slotting approaches. The weight values are varied in n increments of the range. The number of increments in a weight range is determined per class (n_B and n_C). The values for w_B and w_C are composed of:

$$w_B = w_{B,1}, w_{B,2}, ..., w_{B,n_B} \tag{3.27}$$

$$w_C = w_{C,1}, w_{C,2}, ..., w_{C,n_C} \tag{3.28}$$

All resulting weight values for class B are combined with all resulting weight values for class C, to comprise all slotting configurations.

3.3.2.2. Weight Configuration Refinement

The goal of the weights is to determine the importance of the distribution of the three different classes, and with that, generate different slotting configurations. However, some weight configurations result in the same slotting configuration. Because variable x_{ij} is binary, its sum always results in an integer variable. Some different values for the continuous variables of the weights (w_t) and the pods per item distribution (z_t), will not be enough to cause an integer change in x_{ij}.
Consider the following example:

Example Class Distribution

The Distribution equation 3.9 used with the weight configurations in Objective 3.3 is was the following:

$$\frac{\sum_{i\in I_A}\sum_j x_{ij}}{D_{i\in I_A}} = w_B * \frac{\sum_{i\in I_B}\sum_j x_{ij}}{D_{i\in I_B}} = w_C * \frac{\sum_{i\in I_C}\sum_j x_{ij}}{D_{i\in I_C}} \tag{3.29}$$

The order demand of the example has the following configuration:
The set of SKUs in class A (I_A) consists of 1 SKU ($i = 1$) with 9 items ($D_1 = 9$), class B (I_B) is 1 SKU ($i = 2$) with 6 items ($D_2 = 6$) and class C (I_C) has 1 SKU ($i = 3$) with 3 items ($D_3 = 3$), and with pods $J = 6$. This is depicted in Figure 3.12.

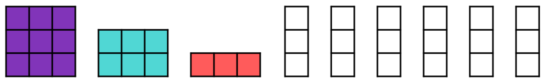


Figure 3.12: Example Demand with $D_1 = 9$, $D_2 = 6$ and $D_3 = 3$, and Number of Pods $J = 6$.

With weight factors: $w_B = 1$ and $w_C = 1$, all classes should approach equal distribution. The equations are given in 3.30, and a visualisation in Figure 3.13.

$$\frac{\sum_j x_{1j}}{9} = \frac{\sum_j x_{2j}}{6} = \frac{\sum_j x_{3j}}{3} \quad \Rightarrow \quad \frac{3}{9} = \frac{2}{6} = \frac{1}{3} \tag{3.30}$$

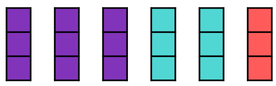


Figure 3.13: The Distribution of SKUs over Pods with Weights $w_B = 1$ and $w_B = 1$.

Now, with weights $w_B = 24/27$ and $w_C = 4/3$, the equation is shown in 3.31 and the distribution is visualised in Figure 3.14.

$$\frac{\sum_j x_{1j}}{9} = \frac{24}{27} * \frac{\sum_j x_{2j}}{6} = \frac{4}{3} * \frac{\sum_j x_{3j}}{3} \quad \Rightarrow \quad \frac{4}{9} = \frac{24}{27} * \frac{3}{6} = \frac{2}{3} * \frac{1}{3} \tag{3.31}$$

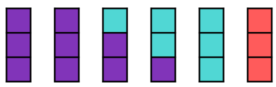


Figure 3.14: The Distribution of SKUs over Pods with Weights $w_B = 24/27$ and $w_C = 4/3$.

With the weights from equation 3.31 ($w_B = 24/27$ and $w_C = 4/3$) both SKU $i = 1$ and SKU $i = 2$ are distributed over 1 more pod than with the weights from equation 3.30 ($w_B = 1$ and $w_C = 1$). There are more possible configurations for weight values between $24/27$ and 1 for w_B, between $4/3$ and 1 for w_C and possible combinations of the two. However, for all these weight factor combinations, the result in the distribution will remain either one of these distributions since there is no possible distribution in between; the distribution of SKU $i = 1$ is the integer value of either 3 or 4, and nothing in between, and similarly, the distribution for SKU $i = 2$ is either 2 or 3, and nothing in between.

In addition to the example, the information is gathered from observations that the resulting distribution from the mathematical slotting model with the analytically configured weights from Table 3.7 is similar or equal for some weight configurations. The reason why the analytically determined ranges are still too broad is likely due to them being calculated based on the maximum and minimum distribution of one SKU, which is bounded by the number of items for that SKU, the number of pods and their storage capacity, as opposed to the maximum and minimum distribution of that SKU when there are more SKUs, since then the bounds are also determined by the number of items of the other SKUs.

For example, there are 6 pods with a capacity of 3 items per pod and a SKU with 10 items. That SKU can be distributed over a minimum of 4 pods and a maximum of 6 pods. However, with more SKUs that are to be distributed over the same pods and a parameter that states the maximum of different SKUs in one pod, the range between the minimum and maximum decreases.

The research aims to analyse the impact of different slotting configurations, and the weights are a tool to gain these different configurations. Therefore, the weights are empirically evaluated on the slotting they impose and filtered on whether they result in unique slotting configurations.

The refined weight ranges and number of steps are presented in Table 3.8 and visualised with a plot in Figure 3.15. Since the weight range for most classes is between 0 and 1, the scale of the y-axis, representing the weight, is transformed with a rooted function. This creates larger intervals in the plot for a low weight and smaller intervals for a high weight.

Table 3.8: Weight Parameter Reconfiguration with Weight Range and Number of Steps for each Demand Profile.

Demand profile	**Range w_B**	**Range w_C**	**Steps w_B**	**Steps w_C**
DP_A	(0.052, 10)	(0.052, 1.039)	6	4
DP_B	(0.059, 1.295)	(0.059, 0.794)	6	4
DP_C	(0.058, 6.087)	(0.058, 0.7)	6	4
DP_D	(0.05, 0.79)	(0.05, 0.54)	6	4
DP_E	(0.058, 1)	(0.058)	5	1
DP_F	(0.1, 0.38)	(0.068)	7	1

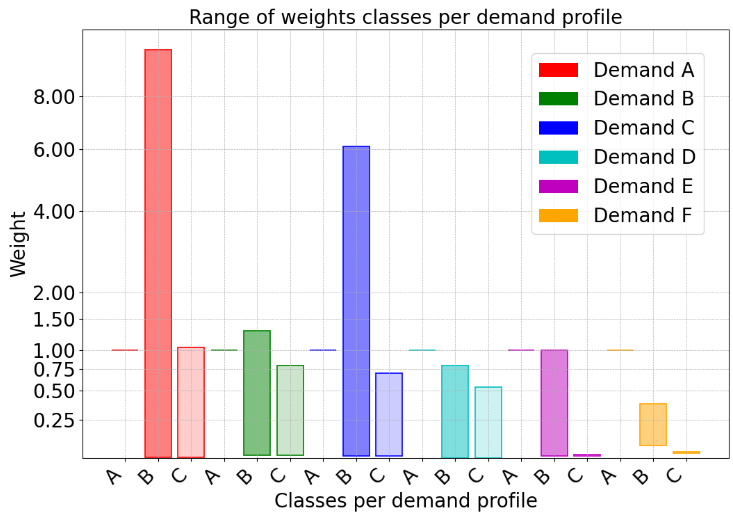


Figure 3.15: Plot of the Weight Ranges per Class [w_A, w_B, w_C] for all Demand Profiles.

The weight of class A is 1 for all demand profiles. In the figure, this is represented by a bar of insignificant height. The range of w_C for demand profile DP_E and DP_F only contains one value, and correspondingly, the number of steps for w_C is 1 since the item demand (D_i) for that class is 1. With only 1 item to distribute, the class's weight will not influence that class's distribution. Varying a class's weight without possibly impacting the distribution of that class could only have undesirable side effects for the distribution of other classes due to the distribution being decided by minimising the difference between the distribution equation and the weights. By varying the weight without possibly varying the distribution equation for that class, that side of the equilibrium equation will change, affecting the optimal distribution of the other classes. Completely isolating the impact of class B and C on each other is difficult since they are related through class A, however this is approximated by for instance removing the weight of class C when no variation is possible.

Noteworthy is the maximum value for the ranges of w_B and w_C closely resembles the item count (D_i) of the related class. This is due to the weight being configured based on the maximum distributions of that relative class and class A. However, with reconfiguration, the range is slightly adjusted and does not match perfectly.
Additionally, the minimum value in the range for both w_B and w_C is nearly equal. This value is the minimum distribution for class A, divided by the maximum distribution value for class B and C, respectively. This maximum distribution is often equal to 1, which indicates the maximum distribution of 1 item per pod. With a denominator equal to 1, the minimum value in the weight range is the same as the maximum distribution of class A.

3.3.3. Model Execution

For reproduction purposes, the slotting model and additional files for the generation of plots and figures are shared in this GitHub repository: https://github.com/EvaZandhuis/Slotting_public.git.

3.3.3.1. Solver Algorithm

The mathematical model is solved with Gurobi Optimizer (Gurobi Optimization, LLC, 2024), as python optimisation package Gurobipy and uses a branch-and-bound based algorithm for multi-integer programming problems (Gurobi-Optimizer, 2024).

The solver offers an integrated approach for both a blended and hierarchical configuration of multilevel objective problems. This approach implies that objectives are solved hierarchically in order of priority, with objectives of the same priority being blended and optimised based on weight.
The priority and weight of both objectives are defined, with the hierarchical configuration prioritising the optimisation of Objective 3.1 before optimising Objective 3.3. The blended approach involves setting weights for the objective functions, which is not utilised. Instead, to account for the classes, weights are used within the formulation of Objective 3.3.

3.3.3.2. Random Seeds

The mathematical slotting model can yield multiple solutions that satisfy the constraints and the objective functions. This is particularly true since the order demand only varies between three classes, rather than being unique for each SKU. Consequently, the optimal solutions allow interchanging SKUs in the same class. Furthermore, the algorithm used to find the solution may influence the results when optimal alternatives exist. For example, suppose the algorithm distributes items based on the order in which SKU demand is supplied to establish an initial state. In that case, this input order will be reflected in the results. Multiple random seeds are generated for each scenario to negate the unintentional presence of biases and trends in the slotting solutions that might affect the simulation outcomes. The demand configuration used as input for the slotting configuration is shuffled before each optimisation run. This process produces slightly different slotting results while satisfying the same demand and slotting configurations.

3.4. Simulation Model

The scenarios for all demand profiles configured in Section 3.3, are evaluated with a simulation model. The simulation process is depicted in Figure 3.16 with a replicated figure from the methodology approach in Section 3.1.

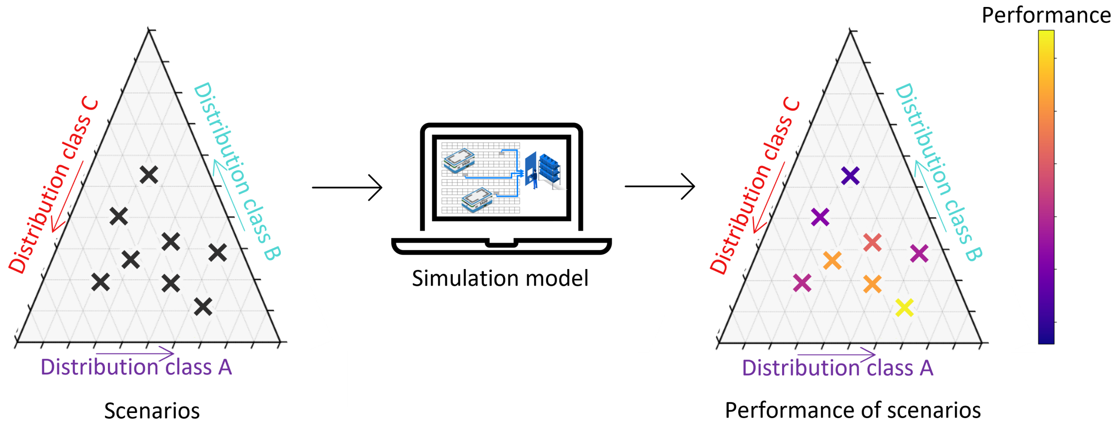


Figure 3.16: Figure Replication of the Simulation Process.

The performance evaluation is achieved by integrating the scenarios into the RawSim-O simulation tool, developed by M. Merschformann et al. (2018). The simulation model is described in Section 3.4.1 and configured in Section 3.4.2. The integration of the scenarios into the model is described in Section 3.4.3.

3.4.1. Simulation Model Description

The simulation tool RawSim-O is an agent-based and discrete-event-driven simulation system designed to analyse and evaluate the impact of different decision problems within a robotic mobile fulfilment system (M. Merschformann et al., 2018).

Agent-based simulations revolve around a collection of autonomous entities, which in the case of RawSim-O are the stations, the robots driving the pods towards and from the stations, and the controllers that manage the order processes. These agents interact with each other according to the programmed behaviour of the system, where that behaviour is tracked and analysed to learn about the system.

Event-driven simulation indicates that the system's behaviour is determined by the occurrence of events, which trigger the controller agents to act. Examples of events are items picked from a pod or a task assigned to a robot. These events are generated and queued to be processed sequentially according to a specified order. Discrete events indicate that the events occur instantaneously, as a response to a sequence of events, and not only continuously over time. These events update the state of system components, such as the availability of an item, the location of a pod, or the status of an order.

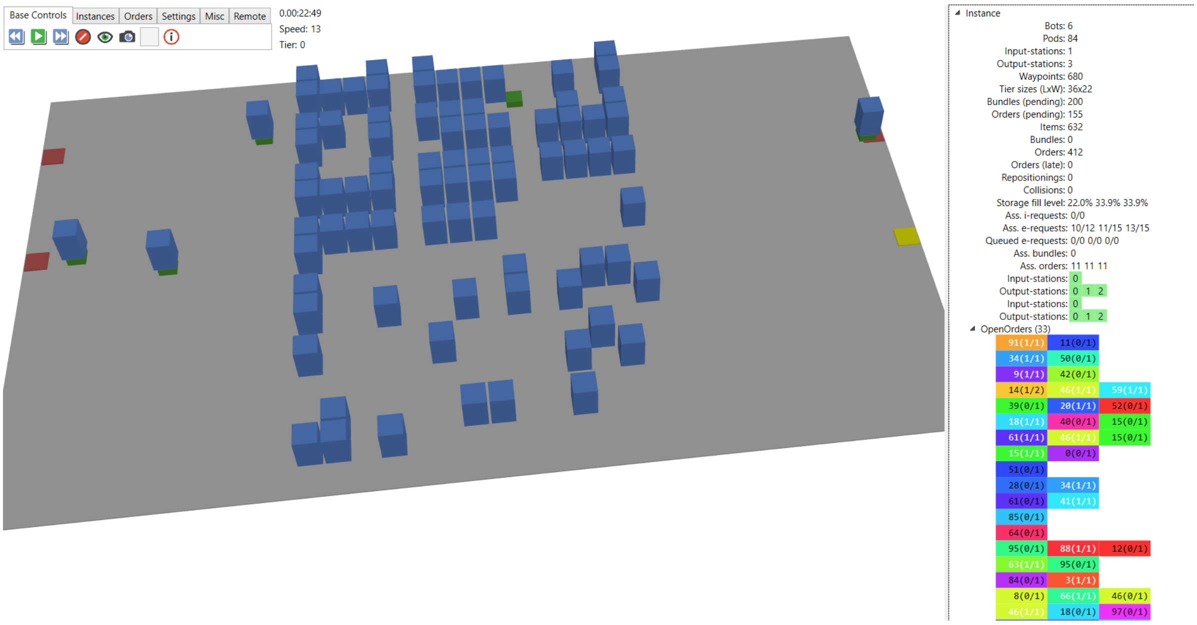


Figure 3.17: Visualisation of Simulation with the RawSim-O Application.

Multiple decision problems can be configured and evaluated together, as described in Section 2.5, allowing analysis of the combined impact on many performance metrics. The settings to configure are distributed into three input levels (M. Merschformann et al., 2018):

Layout configuration, where the dimensions and characteristics of the system are specified.

Setting configuration, where the order generation and simulation characteristics are chosen.

Controller configuration, where the controlling mechanisms and methods are specified.

The tool has various built-in evaluation options for the behaviour of the system. Heat-mapping the results to analyse robot and pod movements, plots generated on time-logged information to analyse the behaviour of the system for the whole simulation duration, and finally, the performance metrics of the simulation execution to compare multiple runs with each other, such as travel distance, queueing time and the order throughput rate. Where the last option enables the comparison of the execution runs of the different scenarios developed with the mathematical model.

3.4.2. Simulation Model Configuration

The simulation tool contains options for configuring many decision problems on strategic, tactical and operational levels. The configuration of these controllers and parameters is explained per input level.

3.4.2.1. Layout Configuration

The layout configurations consist of the warehouse design and dimensions. A visualisation of the layout configuration used in the simulations is presented in Figure 3.18.

The number of pods can not be directly configured, but it results from the number of aisles and the pod amount, which is the number of pods generated relative to the number of available spaces.
The number of robots is determined so that it is less than optimal to increase the impact of slotting configurations. All layout configurations are presented in Table 3.9.

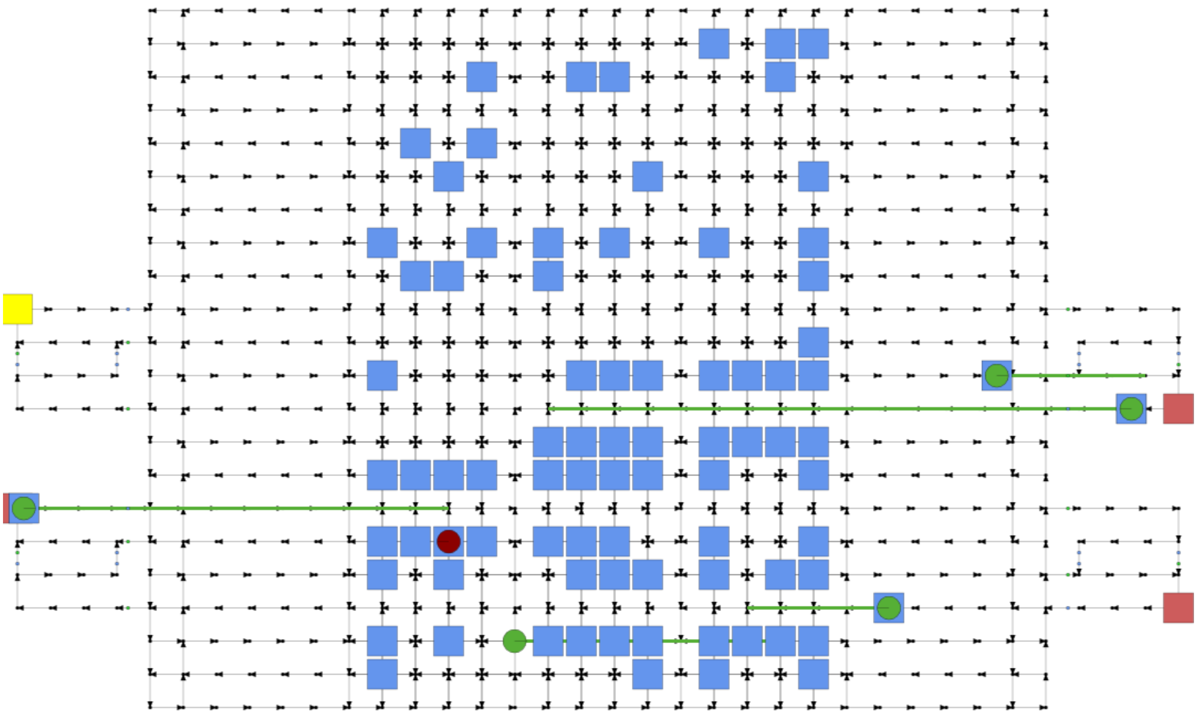


Figure 3.18: Top View of the Layout Configuration in RawSim-O.

Table 3.9: Simulation Layout Configuration.

	Simulation layout configuration	
P	Total number of pods	60
B	Maximum number of items that can be stored in a pod	20
V	Maximum number of different SKUs in a pod	4
	Total number of robots	6
	Pod amount	0.5%
	Number of horizontal isles	2
	Number of vertical isles	6
	Horizontal block length	4
	Width hall (in pod widths)	6
	Pick stations west	1
	Pick stations east	2
	Pick stations capacity	12
	Replenishment stations west	1

The replenishment station is deactivated since this will diminish the fixed slotting configurations by replenishing random items into pods. However, the system does not allow a configuration without a replenishment station. Therefore, it is placed but deactivated.
The width of the warehouse area is 6 pod widths, which is slightly larger than the minimum in order to increase the impact of travel distance.
The pick-station capacity is the maximum number of orders to be assigned to one station. Increasing this number will allow for more efficient pod to station assignment, however, to simulate a situation where order input is stochastic, the number is set to 12.

3.4.2.2. Setting Configuration

Simulation Duration

To accurately assess the effects of slotting decisions on warehouse operations, it is essential to establish an appropriate duration for the simulation. The effects of replenishment on the fixed slotting are neglected by deactivating the replenishment station, limiting the simulation to run until pod depletion. Without replenishment, the inventory of the pods in the storage area will decrease throughout the simulation until a stock-out situation occurs. The main objective of the research is the distribution of SKUs over pods; however, with continuously declining inventory levels, this distribution will be affected shortly after starting the simulation. Weidinger and Boysen (2018) studied the optimal inventory level for initiating replenishment with the dedicated storage approach, finding the most efficient point to start replenishment is when pod inventory reaches 85%. This suggests that under normal operations, the process should continue without replenishing until the inventory level drops to 85%. Therefore, applying this threshold to the current research is reasonable, reflected in the simulation duration.

Order Generation

For this research, the item turnover is fixed. This is represented by the assumption that the total stored items are equivalent to a full day of demand. By fixing the item demand quantities in the mathematical slotting model, the order generation can be set to a demand-based generation. This method creates orders according to the available stock. A similar approach is used in the research of Boysen et al., 2017 to guard against stock-out situations and ensure the feasibility of the problem instances.
Additional configurations for order generation consist of the probability distribution of specific quantities occurring, which is set to a uniform distribution for the item probability of the items in storage. The setting configurations are presented in Table 3.10.

Table 3.10: Simulation Setting Configuration.

Simulation setting configuration	
Simulation duration (in seconds)	1800
Item count minimum	1
Item count maximum	2
SKU count minimum	1
SKU count maximum	3
SKU count mean	1
SKU count standard deviation	1

The item count refers to the number of items of one SKU in one order, and the SKU count refers to the number of different SKUs in one order. An example of orders resulting from these order generation configurations is depicted in Figure 3.19. Each coloured block represents a SKU, the index inside represents the specific SKU index, and the numbers between brackets indicate how many items are in that order and how many have already been fulfilled.

Figure 3.19: Example of Generated Orders in RawSim-O.

Seeds

The random seeds for the simulation vary in order of generation. The sequence and specific configuration of orders are different for each simulation, which is how the random seeds differ.

As explained in Section 3.3.3.2, three random seeds are generated of each slotting configuration to decrease the influence of randomness on the results. Furthermore, each of these configurations is simulated with three additional random seeds. This means that for each weight configuration, there are a total of nine seed runs.

3.4.2.3. Controller Configuration

All controller configurations remain set to their default settings. This precaution ensures compatibility among configurations, thereby ensuring proper functionality as intended.

Routing

The storage assignment and performance are highly correlated with the routing decision problem. However, the focus is on the storage assignment. For the simulation, the *Far path planning configuration* is used. Which is a fast and memory-efficient pathfinding algorithm developed by Wang and Botea (2008).
The tunnelling option for robots is activated, meaning that the robots can drive underneath the pods when not carrying a pod. This simplifies routing and increases total system efficiency.
The evading strategy used in the controller is called *evade by rerouting*, where the alternative is *evade to next node*.

Robot Assignment

Robots can be configured as either dedicated or pooled, which indicates whether they are assigned to exclusively picking or replenishment tasks, or they can process both tasks (Roy et al., 2019). Dedicating robots to specific tasks involves several decisions related to the specifics of the warehouse processes, including the number of robots allocated to each task at any given time. An implementation of zoning introduces even additional layers of decision-making for robot assignment. However, as the impact of robot assignment and zoning is beyond the scope of this research, the robots in this study are configured as pooled.

Order Batching

Order batching combines orders in one station assignment or pod assignment for optimal efficiency. For instance, assigning a pod with SKUs that can be used for many orders at a certain workstation increases efficiency. The configuration used is the *Pod matching order batching configuration*. This is an approach that selects an order for a station, depending on which station has the best match for items for an incoming pod.

3.4.2.4. Performance Metrics

A simulation approach, as opposed to an analytical approach, is used to evaluate performance and consider the impact of multiple decision problems.
This is due to the dependency of order pick time on various decision problems such as replenishment, collision avoidance, routing algorithms, and order batching, as is explained in Section 2.3.3. It is challenging to exclude the other decision problems from the slotting decision problem completely, so they are present in the model with assumptions.

Additionally, as explained in Section 2.5, the performance of slotting can be measured with multiple metrics, such as the combination of pile-on and travel distance, making it complex to assess purely through a mathematical model. Therefore, the simulation model is used for evaluation. The generic objective for overall performance is indicated by the total number of orders handled in the simulation duration, which is similar to the order throughput rate, as both metrics count the number of orders completed within a certain time interval. The goal of the study is to evaluate performance in terms of order-picking efficiency. As elaborated in Section 2.3.2, slotting impacts the efficiency of both the order-picking and replenishment activity. However, with slotting as the only variation in the simulations and the replenishment activity excluded, order-picking is the sole warehouse activity impacting performance. Therefore, the number of orders handled reflects the order-picking efficiency.

Although simulation is often avoided due to the extensive computational time required to build such models, this issue is mitigated since the model foundation already exists and is extended. Furthermore, using a simulation is advantageous as the case study is included, allowing for a more accurate representation of a realistic situation. Incorporating a simulation model ensures that results are consistent and comparable with those of preceding studies. Additionally, choices for decision problems like routing and batching can be aligned with the configurations used in the case study.

The potential downside of longer run times is not particularly relevant, as the simulation's run time does not directly affect operational processes. The insights yielded by the research inform tactical decision-making. The goal of this research is to assess the impact of specific decisions, not to develop a real-time decision-making model.

3.4.3. Simulation Model Extension

For reproduction purposes, the repository with the simulation model is shared in this GitHub repository: https://github.com/EvaZandhuis/Simulation_RAWSimO-thesis.git.

Slotting is not currently included in the various options and configurations of decision problems in RawSim-O. The model is adjusted to incorporate slotting so that outputs from the mathematical slotting model can serve as inputs in the simulation.

The initial pod content generator is modified to enable the integration of fixed slotting. Originally, the system employs a random pod content generator, which randomly generates and places items within the pods during the simulation setup. Instead of this random approach, a new method is developed where the initial pod content is predetermined to match the fixed slotting configurations.
This method represents a limited integration of slotting since the slotting decisions can not be maintained during the replenishment task, as the replenishment method remains unchanged. As explained in Section 2.3.3, replenishment remains outside the scope of this research. Hence, the current slotting integration method is sufficient for this research objective.

3.5. Methodology Conclusion

The previous sections in this chapter explain and describe the approach for the demand profile configurations, the slotting model and the simulation model, as visualised in the methodology flowchart in Figure 3.1.

The input for the demand determination is the total demand of 100 SKUs and 1000 items. The input for the demand parameters for the synthetic demand profiles are the demand curves of $i^{0.222}$, $i^{0.139}$ and $i^{0.065}$, and the class separations on 10% and 20% of the SKUs and on 20% and 60% of the SKUs. The resulting synthetic demand profiles are presented in Table 3.11.

The demand profile and respective weight factors are inputs in the slotting model. The weight factors are expressed as the range of potential values and number of steps within the range used to determine the weight factors for the scenarios, where the steps indicate how many evenly spaced values from the weight range are used as weight factors. The weight range and steps are presented for all demand profiles in Table 3.11.

Table 3.11: Demand and Weight Configurations Overview.

Demand profile	**Class**	**Item count** $[D_i]$	**SKU count** $[Q_t]$	**Weight range** $[w_t]$	**Steps** $[n_t]$
DP_A	A	58	10	(1)	1
	B	10	10	(0.052, 10)	6
	C	4	80	(0.052, 1.039)	4
DP_B	A	34	20	(1)	1
	B	5	40	(0.059, 1.295)	6
	C	3	40	(0.059, 0.794)	4
DP_C	A	69	10	(1)	1
	B	7	10	(0.058, 6.087)	6
	C	3	80	(0.058, 0.7)	4
DP_D	A	40	20	(1)	1
	B	3	40	(0.05, 0.79)	6
	C	2	40	(0.05, 0.54)	4
DP_E	A	86	10	(1)	1
	B	6	10	(0.058, 1)	5
	C	1	80	(0.058)	1
DP_F	A	44	20	(1)	1
	B	2	40	(0.1, 0.38)	7
	C	1	40	(0.068)	1

The configurations in this table are used in the slotting model to create the scenarios which are evaluated with the simulation model. The slotting and simulation model are shared for reproduction purposes in the following GitHub repositories: https://github.com/EvaZandhuis/Slotting_public.git and https://github.com/EvaZandhuis/Simulation_RAWSimO-thesis.git.
The analysis of the resulting scenarios and the performance is detailed in Chapter 4.

4

Analysis

This chapter presents and analyses the demand-based slotting configurations and the simulations using the synthetic demand profiles to provide general insights into the impact of demand-based slotting. Specific case study demands and results are addressed in subsequent Chapter 5.
The analysis of the variation in slotting distributions for the different demand profiles is presented in Section 4.1. This is relevant for explaining and interpreting results from the simulation analysis, discussed in Section 4.2 since performance behaviour observed from the simulation might be attributed to both slotting and demand characteristics. Consequently, the conditions under which optimal performance is achieved may vary depending on the demand profile.

The demand profiles are referred to as DP_A as in the previous chapters and the classes or turnover categories are referred to either as classes A, B and C, or as w_A, w_B and w_C. Where class A has the highest turnover and class C has the lowest turnover, as in Section 2.2, and where w_A refers to the class with the highest turnover and w_C to the class with the lowest turnover, as in Section 3.3.

4.1. Scenario Slotting Analysis

For each demand profile, the slotting is determined using the mathematical slotting model. This results in a slotting configuration described with three distribution indicators: pods per item, items per pod and pods per SKU. Pods per item (z) and items per pod (y_{ij}) represent the same distribution: The number of items of SKUs i, distributed over the number of pods j. For pods per item, 1 is the maximum obtainable since then, each item from a SKU is placed on a different pod. The value for the pods per item is the reciprocal of items per pod, where the results for all classes obtain a value between 0 and 1. The reason for two indicators to represent the same distribution is that with the distribution indicator for pods per item (z), the equal range of the three classes is convenient for the weighted equilibrium equations, Equation 3.9. Whereas the distribution indicator of items per pod (y_{ij}) is a more intuitive and understandable distribution for interpretation.
The distribution indicator of pods per SKU ($\sum_j x_{ij}$) indicates how many pods a SKU is distributed on average for that class.
The numerous results for these three distribution indicators obtained from the slotting model are presented as a range in Table 4.1. The detailed information for each slotting can be found in Appendix A.

Table 4.1: The Distribution Results from the Mathematical Slotting Model per Demand per Class t.

Demand profile	Class [t]	Distribution ranges		
		Pods/item [z_t]	Items/pod [y_{ij}]	Pods/SKU [$\sum_j x_{ij}$]
DP_A	A	[0.086, 0.259]	[3.867, 11.6]	[5, 15]
	B	[0.1, 1]	[1, 10]	[1, 10]
	C	[0.25, 0.553]	[1.808, 4]	[1, 2.213]
DP_B	A	[0.0897, 0.2353]	[4.25, 11.1475]	[3.05, 8.0]
	B	[0.2, 0.625]	[1.6, 5.0]	[1.0, 3.125]
	C	[0.3333, 1.0]	[1.0, 3.0]	[1.0, 3.0]
DP_C	A	[0.0739, 0.2174]	[4.6, 13.5294]	[5.1, 15.0]
	B	[0.1429, 1.0]	[1.0, 7.0]	[1.0, 7.0]
	C	[0.3333, 0.7375]	[1.3559, 3.0]	[1.0, 2.2125]
DP_D	A	[0.1, 0.2]	[5.0, 10.0]	[4.0, 8.0]
	B	[0.3333, 1.0]	[1.0, 3.0]	[1.0, 3.0]
	C	[0.5, 1.0]	[1.0, 2.0]	[1.0, 2.0]
DP_E	A	[0.1163, 0.1744]	[5.7333, 8.6]	[10.0, 15.0]
	B	[0.1667, 1.0]	[1.0, 6.0]	[1.0, 6.0]
	C	[1.0, 1.0]	[1.0, 1.0]	[1.0, 1.0]
DP_F	A	[0.1364, 0.1818]	[5.5, 7.3333]	[6.0, 8.0]
	B	[0.5, 1.0]	[1.0, 2.0]	[1.0, 2.0]
	C	[1.0, 1.0]	[1.0, 1.0]	[1.0, 1.0]

The range of the result values from Table 4.1 for pods/item, items/pod and pods/SKU is visualised for each class for all demand profiles in Figures 4.1, 4.2 and 4.3 respectively.

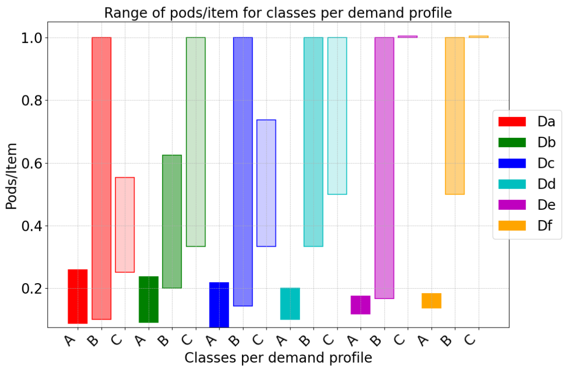


Figure 4.1: The Value Range for Pods per Item for each Class for all Demand Profiles.

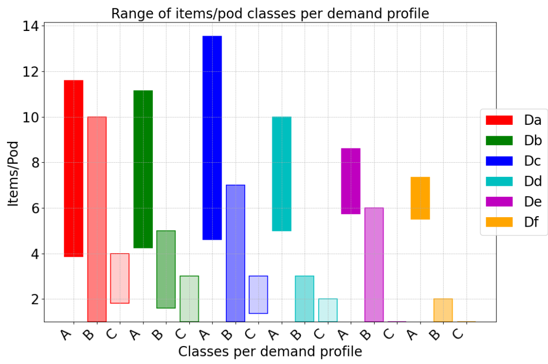


Figure 4.2: The Value Range for Items per Pod for each Class for all Demand Profiles.

The range for the values in Figure 4.1 is larger than 0 and maximally 1. The figure shows that a maximum distribution of $z = 1$ is not possible for all classes from all demand profiles; however, it is possible for at least one class of each demand profile. A distribution of 1 pod/item translates to 1 item/pod in Figure 4.2, which means that $y_{ij} \leq 1$, since the pod then either contains an item, or it does not. Indeed, only the classes of the demand where the range of pods/item (Figure 4.1) include 1, also include 1 in the range of items/pod (Figure 4.2).
The minimum results for items/pod of class A are higher than the minimum results of class B for all

demands. Where class A never reaches the minimum distribution of 1 pod/item. For demand DP_C and DP_E, this is evident from D_i of class A (Figure 3.11), which is larger than the total number of pods. However, for the other demand profiles, this would be possible within the constraints.
The maximum value for items/pods decreases from class A to class C, which is explained by the decreasing value for D_i (Figure 4.1). The maximum number of items/pod for class A does not approach the total number of items D_i for SKUs in that class, however the range of class B does include the value for D_i, as does the range for class C. This shows that there are slotting results where class B and C are distributed with all the items of a SKU in one pod, which is never the result for class A.

Figure 4.3 shows the range of results for the pods/SKU distribution. This distribution indicator shows how many pods one SKU i occupies, $\sum_j y_{ij}$.

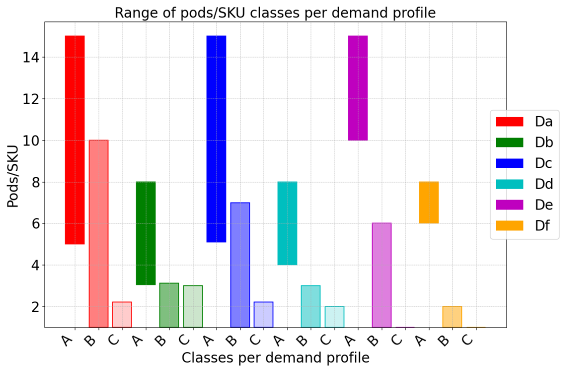


Figure 4.3: The Value Range for Pods per SKU for each Class for all Demand Profiles.

The number of pods/SKU for the C classes of all demand profiles except for DP_A ranges from 1 to the number of items of a SKU in that class D_i (Figure 4.1). Class C of demand profile DP_A ranges from 1 to 2, where $D_i = 4$, which means that the class of this demand profile is never distributed with only 1 item on a pod.
The difference between the range of the result for the pods/SKU distribution indicator for classes A and B is larger for demand DP_D, DP_E and DP_F, with a gap between the minimum value in the range of class A and the maximum value in the range of class B. These SKUs are never distributed over the same number of pods.

4.1.1. Data Statistics from the Mathematical Slotting Model

The results from the mathematical slotting model are presented in Tables 4.2, 4.3 and 4.4. Visualised with box plots and violin plots to indicate the data distribution. The mean statistic in the tables is calculated with all data points, including the ones considered outliers in the box plots. The median, quartiles and whiskers statistics are computed using the data excluding the outliers from the box plots. With box plots, data points are considered outliers when not within 1.5 * inter-quartile range. From the box plots showing the range of the pods/item results in Figure 4.4 and pods/SKU distribution in Figure 4.8, it can be seen that for class B from demand profile DP_A there are many outliers, where the thicker circles at point pods/item= 1 indicate more than 1 data point. Therefore, the data is also shown with a violin plot introducing a density trace for the data range.

Data Statistics of the Pods per Item Range

The statistical information of the pods per item results are presented in Table 4.2, where Figures 4.4 and 4.5 visualise the data with a box plot and a violin plot respectively.

Table 4.2: Statistics of Data Range of Pods per Item for each Class for all Demand Profiles.

Demand	**Class**	**Mean**	**Median**	**Lower quartile**	**Upper quartile**	**Lower whisker**	**Upper whisker**
DP_A	A	0.175	0.162	0.103	0.224	0.086	0.259
	B	0.266	0.1	0.1	0.17	0.1	0.23
	C	0.35	0.312	0.25	0.425	0.25	0.553
DP_B	A	0.168	0.181	0.118	0.212	0.09	0.235
	B	0.294	0.24	0.2	0.345	0.2	0.535
	C	0.555	0.408	0.333	0.667	0.333	1.0
DP_C	A	0.156	0.146	0.11	0.194	0.074	0.217
	B	0.272	0.143	0.143	0.186	0.143	0.229
	C	0.472	0.4	0.333	0.538	0.333	0.738
DP_D	A	0.16	0.169	0.142	0.191	0.1	0.2
	B	0.496	0.383	0.333	0.575	0.333	0.717
	C	0.659	0.525	0.5	0.8	0.5	1.0
DP_E	A	0.158	0.167	0.15	0.174	0.116	0.174
	B	0.397	0.267	0.167	0.517	0.167	1.0
	C	1.0	1.0	1.0	1.0	1.0	1.0
DP_F	A	0.164	0.169	0.151	0.179	0.136	0.182
	B	0.698	0.644	0.528	0.841	0.5	1.0
	C	1.0	1.0	1.0	1.0	1.0	1.0

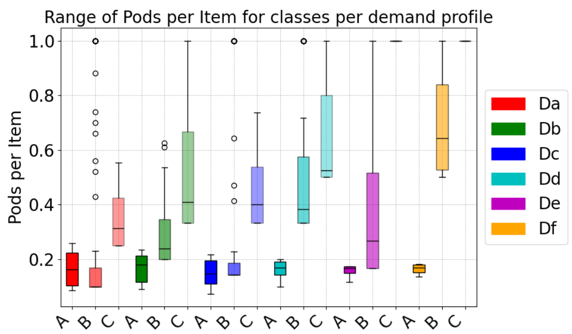


Figure 4.4: The Data Distribution of Pods per Item Represented with a Box Plot for each Class for all Demand Profiles.

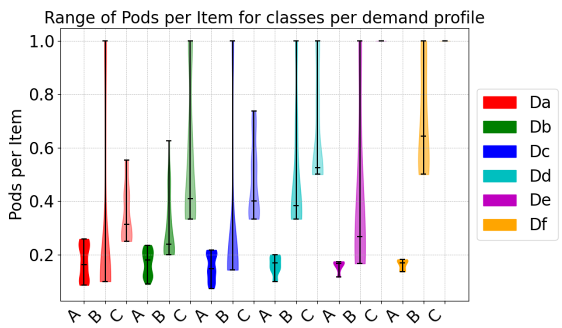


Figure 4.5: The Data Distribution of Pods per Item Represented with a Violin Plot for each Class for all Demand Profiles.

With the box plot of the results from the pods/item distribution class B of demand profile DP_A, 21% of the result data points are considered outliers and 56% of the outliers, equal to 12% of all data points, constituted from point pods/item$= 1$. A data point is considered an outlier when it is above the upper quartile with 1.5 * the inter-quartile range or below the lower quartile with 1.5 * the inter-quartile range. These data points considered as outliers is why the mean for class B from DP_A is lower than, for instance class B from DP_B, even though the range presented in Figure 4.1 shows that the results for DP_A include higher values than for DP_B. Notably, the mean for class B of demand DP_A is 0.266, which is higher than the value for the upper quantile, 0.17. Additionally, the violin plot in Figure 4.5 shows that the outliers, even with being 12% of total results, are nearly unnoticeable in the density trace. The skewness of this data is due to multiple weight configurations resulting in similar or equal distributions for class B, where the distributions of class A and C are still varying.
The same argumentation causes the skewness of classes B from demand profile DP_C and DP_D. For demand profile DP_D, an additional explanation for the weight configuration often resulting in the same distribution is the item count $D_i = 3$. With limited distribution possibilities, the impact of unequal weight distribution is focused only on those options.

The result for the C classes of all demand profiles is skewed, with the median closer to the lower quartile, a large whisker showing the distance between the upper quartile and the maximum value, and an equal value for the lower quartile and the minimum value.
All B and C classes for all demand profiles show an equal value for the lower quartile and the minimum value, except for class B of demand profile DP_F. Additionally, the boxes of these classes are asymmetrical, with a larger upper quartile and smaller lower quartile, which means that the median gravitates downward. This behaviour is the opposite for class A of all demand profiles, where the upper quartile range is smaller, and the median is higher. This indicates that for many results the distribution for class A is more towards the maximum of the range, wherass the distribution for class B and C is more towards the minimum of the range.

Data Statistics of the Items per Pod Range
The statistical information of the items per pod results is presented in Table 4.3, where Figures 4.6 and 4.7 visualise the data with a box plot and a violin plot respectively.

Table 4.3: Statistics of Data Range of Items per Pod for each Class for all Demand Profiles.

Demand	Class	Mean	Median	Lower quartile	Upper quartile	Lower whisker	Upper whisker
DP_A	A	6.677	6.17	4.462	9.667	3.867	11.6
	B	7.618	10.0	6.087	10.0	1.0	10.0
	C	3.078	3.2	2.353	4.0	1.808	4.0
DP_B	A	6.445	5.528	4.706	8.5	4.25	11.148
	B	3.815	4.167	2.899	5.0	1.6	5.0
	C	2.142	2.449	1.5	3.0	1.0	3.0
DP_C	A	7.203	6.832	5.149	9.085	4.6	13.529
	B	5.662	7.0	5.385	7.0	4.375	7.0
	C	2.292	2.5	1.86	3.0	1.356	3.0
DP_D	A	6.566	5.926	5.229	7.018	5.0	8.791
	B	2.333	2.609	1.739	3.0	1.0	3.0
	C	1.641	1.905	1.25	2.0	1.0	2.0
DP_E	A	6.447	5.975	5.733	6.667	5.733	6.667
	B	3.785	3.887	1.936	6.0	1.0	6.0
	C	1.0	1.0	1.0	1.0	1.0	1.0
DP_F	A	6.178	5.929	5.579	6.642	5.5	7.333
	B	1.534	1.561	1.197	1.895	1.0	2.0
	C	1.0	1.0	1.0	1.0	1.0	1.0

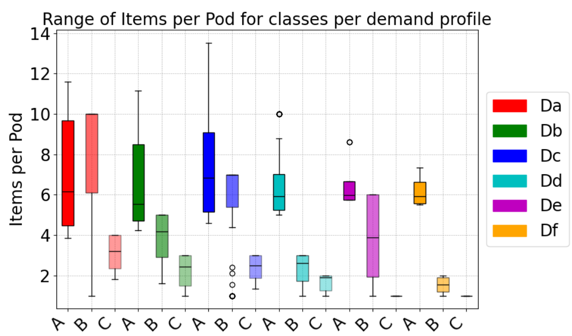


Figure 4.6: The Data Distribution of Items per Pod Represented with a Box Plot for each Class for all Demand Profiles.

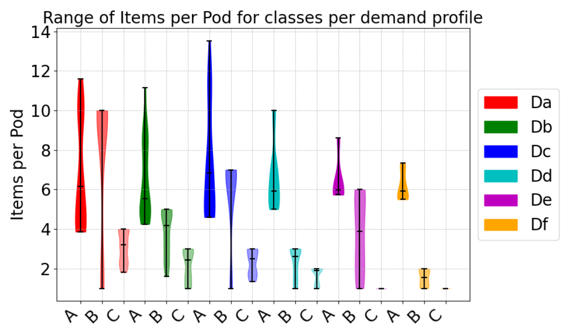


Figure 4.7: The Data Distribution of Items per Pod Represented with a Violin Plot for each Class for all Demand Profiles.

The data statistics of pods per item are reflected in the results for the statistics of the items per pod data since these distribution indicators are reciprocal. Consequently, the trend in the data from items per pod is mirrored in the results from items per pod. The A classes for all demand profiles have a smaller lower quartile than the upper quartile, with a downwards skewed median, whereas classes B and C have a larger lower quartile and an upwards skewed median.
Where 21% of the data points for class B of demand profile DP_A is considered an outlier in the box plots with the pods per item distribution (Figure 4.4), in the items per pod box plot none of the data points is considered as an outlier. The same applies to class B of DP_B. This means that expressing the distribution of class B of DP_A and DP_B as pods per item results in a larger deviation from the upper quartile than when expressing it as items per pod.
The view of this distribution as items per pods reveals new outliers in class A of demand profile DP_E. These outliers result from a relatively small number of configurations for DP_F, which results from varying only one weight factor while keeping the other two consistent throughout the configurations. With the addition of a configuration where all the weights are equal $(w_t, w_{t'}, w_{t''}) = (1, 1, 1)$, the distribution of the data points is minimally disrupted, resulting in the exclusion of data points as outliers. For reference, an overview of this data is presented in Appendix Table A.5.
Classes A and B from the demand profiles varying the configurations for all three classes, DP_A, DP_B, DP_C and DP_D, show a density trace in the violin plot that varies from either widening towards the top or towards the bottom, where class A is more dense towards the bottom and class B towards the top. However, class C shows a relatively symmetrical density trace for these demand profiles. In addition to symmetry, to density trace of class C from demand profile DP_A, DP_B and DP_C, and class B for demand DP_E and DP_F, the density is also relatively constant. These are all the lowest classes that still allow a varying configuration, except for DP_D. This indicates that the different distribution results of items per pod for the lowest class with varying configurations are evenly represented in the configurations. The results for the largest class (A) are more often present with distributions towards the minimum, and for class B, distributions towards the maximum are present.

Data Statistics of the Pods per SKU Range

The statistical information of the pods per SKU results is presented in Table 4.4, where Figures 4.8 and 4.9 visualise the data with a box plot and a violin plot respectively.

Table 4.4: Statistics of Data Range of Pods per SKU for each Class for all Demand Profiles.

Demand	Class	Mean	Median	Lower quartile	Upper quartile	Lower whisker	Upper whisker
DP_A	A	10.133	9.4	6.0	13.0	5.0	15.0
	B	2.657	1.0	1.0	1.7	1.0	2.3
	C	1.401	1.25	1.0	1.7	1.0	2.212
DP_B	A	5.729	6.15	4.0	7.225	3.05	8.0
	B	1.47	1.2	1.0	1.725	1.0	2.675
	C	1.666	1.225	1.0	2.0	1.0	3.0
DP_C	A	10.773	10.1	7.6	13.4	5.1	15.0
	B	1.901	1.0	1.0	1.3	1.0	1.6
	C	1.416	1.2	1.0	1.612	1.0	2.212
DP_D	A	6.39	6.75	5.7	7.65	4.0	8.0
	B	1.487	1.15	1.0	1.725	1.0	2.15
	C	1.318	1.05	1.0	1.6	1.0	2.0
DP_E	A	13.617	14.4	12.9	15.0	10.0	15.0
	B	2.383	1.6	1.0	3.1	1.0	6.0
	C	1.0	1.0	1.0	1.0	1.0	1.0
DP_F	A	7.206	7.425	6.638	7.887	6.0	8.0
	B	1.397	1.288	1.056	1.681	1.0	2.0
	C	1.0	1.0	1.0	1.0	1.0	1.0

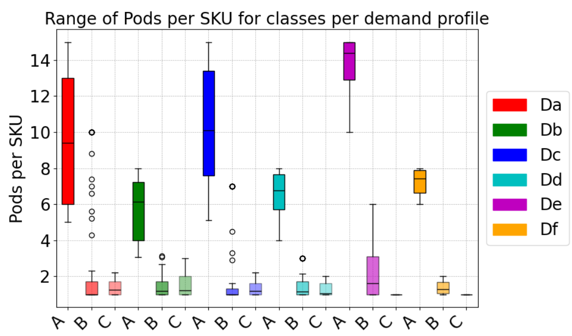


Figure 4.8: The Data Distribution of Pods per SKU Represented with a Box Plot for each Class for all Demand Profiles.

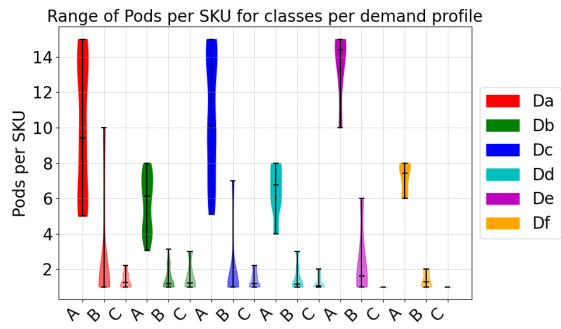


Figure 4.9: The Data Distribution of Pods per SKU Represented with a Violin Plot for each Class for all Demand Profiles.

In the box plot for the range of the pods per SKU results in Figure 4.8, classes B and C for the demand profiles varying all three class configurations, and class B for the demand profiles varying only two configurations have a small range and a median approaching the minimum value. However, This small range is due to the many data points considered outliers for all B classes. When comparing the data with the violin plot in Figure 4.9, the density of the outliers is visualised. This confirms that the results are predominantly a low value for pods per SKU, even with the outliers included. This demonstrates that class B exclusively results with many pods per SKU when both the weights for class B and C are their most extreme, with the maximum weight for B and the minimum weight for class C.
The density trace in the violin plot for the pods per SKU distribution in Figure 4.9 indicates a solid distribution of results throughout the whole range for class A of demand profile DP_A and DP_C. Class A for demand DP_B is less constant but remains symmetrical. All other classes of all other demands show an apparent skewness towards either the maximum or the minimum value. When comparing this with the violin plot for items per pod in Figure 4.7, the density trace is neither constant nor symmetrical for class A of demand profile DP_A and DP_C. While the results of these classes dominate the lower values for the number of items per pod, the number of pods per SKU is relatively constant. However, the values for these two distributions are directly related since, for instance, 6 pods per SKU with demand profile DP_A with $D_i = 58$ can only be distributed as 10 items per pod, this apparent difference in density trace means that the range for pods per SKU larger, which stretches the density trace and decreases the visibility of the density trace inconsistency.

4.1.2. Algorithmic Results of the Slotting Configurations

The model's runtime varies depending on the demand profile and the weight configurations. The shortest runtime observed across all scenarios was 14 seconds, while the longest reached the cutoff time of 120 seconds.

The collection of all scenarios consists of the different weight configurations for class B multiplied by the different weight configurations for class C, and an additional equal-weight configuration. This results in 25 scenarios for demand profiles DP_A, DP_B, DP_C and DP_D, 6 for demand profile DP_E, and 8 for demand profile DP_F, with each scenario being run with 3 different seeds. Consequently, the model was run 342 times in total. A cutoff time of 2 minutes was set to limit the runtime, amounting to a total maximum runtime of 11 hours and 24 minutes.

Out of all slotting configurations, 15% reaches the 2-minute cutoff, while 85% has a runtime between 14 and 40 seconds. When the model finishes before the cutoff, both objectives are solved with a 0% optimality gap, meaning the obtained values match the best possible values.
The first objective of the model consistently achieves a 0% optimality gap with an average runtime of 3 seconds. The longer runtimes are attributed to the second objective, which involves weight factors. In the 85% of cases where the runtime is below 40 seconds, the second objective also reaches a 0% optimality gap. However, for the remaining 15% that hits the cutoff, the optimality gap varies between 0% and 80%.

The impact of a large optimality gap with the second objective is that the slotting result is not always aligned with the weight factors as expected. The objective function with the weight factors aims to achieve a distribution that satisfies the equilibrium equation, so any optimality gap indicates a deviation from this equilibrium distribution.

The goal of the slotting model is to generate various distributions. The weight factor objective is a means to this end, but achieving distributions that strictly conform to the weights is not the objective outside of the slotting model. Evaluation of the slotting configurations is performed through simulation rather than within the mathematical model. Thus, a gap between the model result and the optimal result is acceptable, as it still produces a specific distribution for evaluation.

However, it is important to note that larger gaps, where the results do not fully meet the objective function, diminish the relevance and significance of the weight factors in the outcome and performance of the scenarios.

4.1.3. Conclusion to Slotting Configurations

The results reveal significant variability in slotting configurations across different classes (A, B, C) within each demand profile (DP_A, DP_B, DP_C, DP_D, DP_E, DP_F). Class A consistently exhibits higher pods per SKU and items per pod than classes B and C across all demand profiles, reflecting its higher item demand per SKU. The exception is demand profile DP_A, where class B occupies more pods per SKU than class A.
Classes B and C show varying levels of pods per SKU and items per pod depending on the demand profile.

The demand profiles DP_B, DP_D and DP_F have class separation on 20% and 60%, resulting in SKU quantities of 20, 40 and 40 for class A, B and C, respectively, which results in slight difference in item demand between class A and B. For these demand profiles, class B exhibits lower pods per SKU and items per pod compared to demand profiles, where this difference is more significant, even though the total item demand for class B is higher than for the demand profiles with class separation on 10% and 20%. The range for these class distributions remains closer to the distributions of class C.

The impact of weight configurations on the slotting outcomes varies among the demand profiles. Demand profiles DP_A and DP_C have a wide weight range for class B, producing unique distributions at the minimum and maximum values while resulting in similar distributions for many intermediate weight configurations. Consequently, these profiles exhibit low sensitivity to weight variations.
Class C generally shows high sensitivity to the weight factors due to its higher SKU count, with the apparent exception for demand profiles DP_E and DP_F, where there is only one possible configuration for class C.

Demand profiles DP_B, DP_D, and DP_F, where the difference between classes B and C is minimal in both SKU and item quantity, show similar sensitivity to weight configurations. The small weight ranges and similar item quantities for classes B and C result in comparable sensitivity, where no single class weight disproportionately impacts the resulting distribution.

In demand profiles showing low sensitivity to weights (DP_A and DP_C), distributions remain confined to a small range across different slotting configurations, indicating that observed performance differences are due to minor distribution changes. With high sensitivity to weights (DP_B, DP_D and DP_F), exhibit more significant distribution variations with different weight configurations, leading to observed performance differences from the simulation likely being due to bigger distribution differences.

This highlights the significant impact of demand profiles on slotting configurations. Including these insights is crucial for interpreting the simulation results and the performance of demand-based slotting decisions across different demand profiles.

4.2. Scenario Simulation Analysis

The scenarios resulting from the mathematical slotting model are evaluated with a simulation to determine the impact of slotting decisions on the performance measures for different demand profiles. First, the performance is evaluated independent of the demand profile in Section 4.2.1, after which the results are evaluated specifically for each demand profile in Section 4.2.2.

4.2.1. Performance of Simulation Results

Item pile-on is one of the performance measures for the simulation. It measures the number of items taken from a pod when it visits a picking-station. The measure reported in the tables and figures is the average pile-on for all pod-to-station visits within the simulation duration. Travel distance is the total distance travelled by all robots throughout the simulation duration. Orders handled are the total number of orders finished before the simulation ends.

Multiple generic performance metrics evaluate the system, including the number of orders processed, order turnover time, item throughput rate, and order throughput rate.

All metrics show similar results except order turnover time. This disparity arises from how orders are handled in the simulation: incoming orders generate a backlog that can be processed. Initially, picking orders based on their arrival time might seem logical, but it often leads to sub-optimal outcomes by preventing order batching. Therefore, orders are picked in a sequence unrelated to their arrival time, affecting the turnover time metric differently than the others.

The plots with the metrics' results are presented in Appendix B for reference. The generic performance metric used in the continuation of this chapter is the numbers of orders handled, since this metric is self-explanatory and effectively illustrated the meaning.

The intermediate performance metrics of pile-on and travel distance are expected to affect the number of orders handled as detailed in Section 2.4.1. This is validated with the plot in Figure 4.10, which shows the impact of travel distance and pile-on on the total number of orders handled for the simulation of all slotting configurations for all demand profiles.

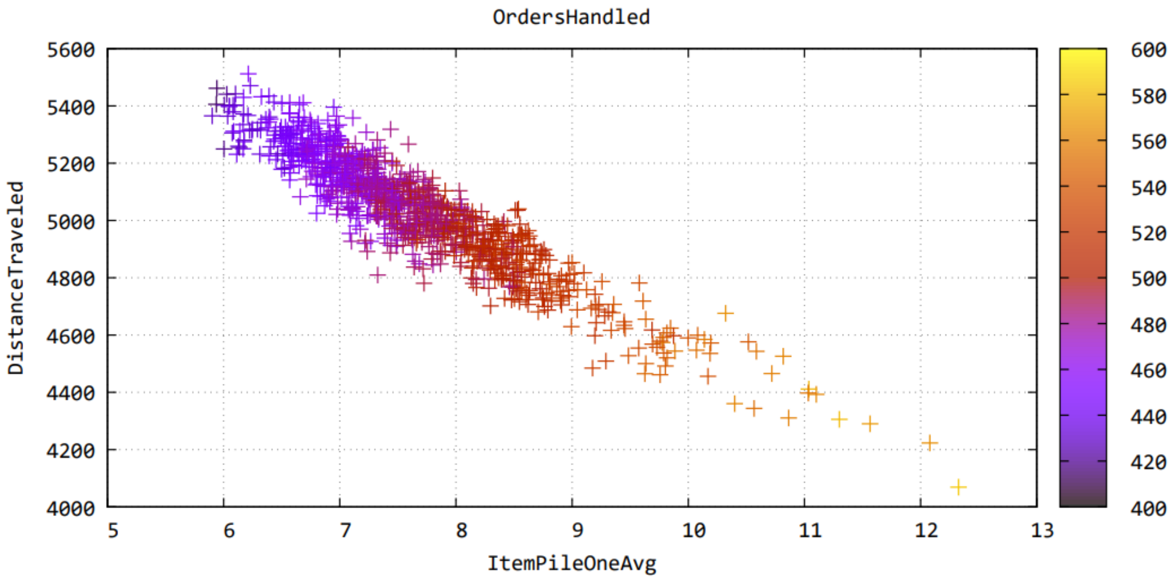


Figure 4.10: Plot the Number of Orders Handled for Travel Distance and Pile-on from all Slotting Configurations for all Demand Profiles.

The first conclusion from the plot is that travel distance and pile-on indeed positively affect the total number of orders handled. The second is that the results in these plots are all with the same layout and controller configuration, and only the demand profiles and the slotting in the setting configurations are varied. This shows that, depending on the demand profile, the slotting configuration can impact the total number of orders handled with a difference of 200 orders for the simulation duration, which was

30 minutes.

An explanation for the diagonal shape of the plot is that pile-on and travel distance are related, whereas a decreasing pile-on correlates to an increasing travel distance, which makes sense since a lower pile-on means that less items are picked from one pod on one visit, so a new pod must travel there to provide the necessary items.

4.2.2. Simulation Results per Demand Profile

The simulation results of the distribution configurations are evaluated per demand profile to provide insights on the impact of slotting decisions. The results of all simulation runs are printed in Appendix C for reference, summaries of the results are presented in tables per demand profile in the relative sections.
As described in Section 3.3.2.1, the weight for class A is fixed as 1 for all configurations and the weights for class B (referred to as w_B in text or $W2$ in figures) and C (referred to as w_C in text or $W3$ in figures) are configured according to the range presented in Table 3.8.

Ternary Plot Interpretation

The distribution of the classes of a scenario is visualised with a ternary plot, as introduced in Section 3.1. The interpretation of a ternary plot is supported with Figure 4.11.

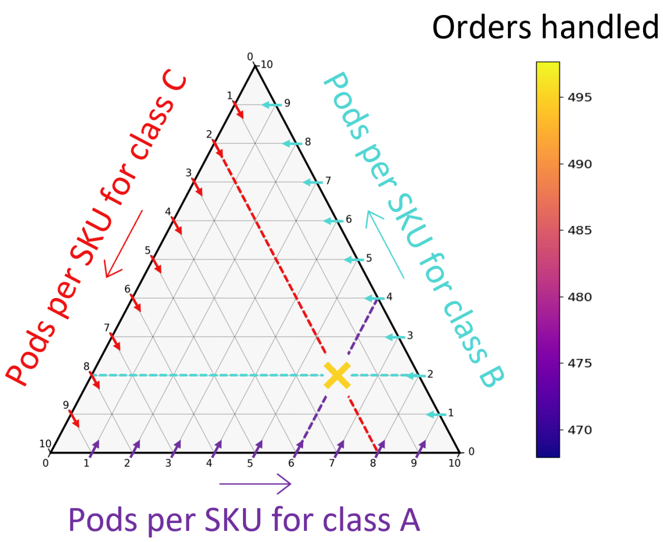


Figure 4.11: Explanation of the interpretation of a ternary plot.

Each scenario is marked with an ***x***, and the axes in three directions present the distribution of the relative class. This triangular plot allows the plotting of three variables under the condition that the sum of the three variables remains constant. This applies to the distribution of pods per SKU (per class), since there is a constraint on the total number of pods ($P = 60$) and on the number of SKUs allowed in a pod ($V = 4$). The sum of pods across all classes is always 240, since that is the product of the maximum number of SKUs per pod and the number of pods ($\sum_i \sum_j x_{ij} = P * V$). The three variables maintain an equilibrium, where increasing the distribution of one requires reducing another. The label on the axis is divided by the number of SKUs in a class to create the label of the average number of pods per SKU for a class.

The performance of a scenario is represented with the colour of the ***x*** marking. A colour scale, displayed on the right-hand side of the ternary plot, represents the number of orders handled during the simulation time. Blue indicates a relatively poor performance with a low number of orders handled, and yellow indicates a relatively high performance.

4.2.2.1. Simulation Results with Demand Profile DP_A

The results for all the slotting configurations with demand profile DP_A are presented in Table 4.5. The mean value and standard deviation for all simulation seeds with the same weight configurations w_B and w_C are shown, in addition to the mean and standard deviation of all simulation seeds for this demand profile.

Table 4.5: The Performance Measures for all Weight Configurations of Demand Profile DP_A.

w_B	w_C	**Pile-on**		**Travel distance**		**Orders handled**		**Count**
		Mean	SD	Mean	SD	Mean	SD	
Total		*7.2*	*0.42*	*5149.29*	*106.37*	*469.48*	*16.38*	*225*
0.052	0.052	7.11	0.36	5127.59	129.5	461.44	12.2	9
0.052	0.381	6.96	0.41	5143.05	68.03	463.0	15.25	9
0.052	0.71	6.94	0.43	5173.16	80.66	467.0	17.23	9
0.052	1.039	7.07	0.41	5198.47	135.97	466.78	16.35	9
1.0	1.0	7.67	0.37	5058.17	51.75	483.22	15.75	9
10.0	0.052	7.05	0.37	5150.43	125.72	471.56	11.25	9
10.0	0.381	7.05	0.35	5144.45	80.25	467.33	15.8	9
10.0	0.71	6.93	0.24	5243.67	88.67	458.89	8.72	9
10.0	1.039	7.35	0.17	5124.29	73.1	470.22	10.65	9
2.042	0.052	7.43	0.4	5089.2	77.97	479.33	13.47	9
2.042	0.381	7.19	0.31	5146.63	105.07	471.44	14.68	9
2.042	0.71	7.11	0.34	5200.72	65.52	466.0	16.95	9
2.042	1.039	7.6	0.53	5088.64	52.46	482.44	17.41	9
4.031	0.052	7.16	0.61	5159.56	145.72	468.11	26.49	9
4.031	0.381	7.21	0.29	5146.22	60.11	470.67	17.41	9
4.031	0.71	7.0	0.43	5201.54	108.11	461.89	16.71	9
4.031	1.039	7.27	0.26	5141.06	91.04	464.89	12.8	9
6.021	0.052	7.15	0.34	5139.67	111.0	469.0	15.8	9
6.021	0.381	7.27	0.4	5125.66	121.29	470.56	19.03	9
6.021	0.71	7.08	0.37	5195.15	85.79	470.56	16.89	9
6.021	1.039	7.53	0.24	5077.23	85.52	475.89	10.66	9
8.01	0.052	7.33	0.56	5098.36	131.18	476.89	21.72	9
8.01	0.381	6.92	0.39	5212.45	164.43	460.22	12.55	9
8.01	0.71	7.06	0.29	5217.18	97.28	462.89	12.0	9
8.01	1.039	7.45	0.36	5129.75	86.42	476.78	17.9	9

The mean results from the table have a range in number of orders handled from 459 to 483, this range is slightly more significant when looking at the plot in Figure 4.12, which has a range from 419 to 510. This complies with the standard deviation shown in the table, with values ranging between 10 and 20 orders. This corresponds to the lower performing half of the results from the number of orders handled overall demand profiles in Figure 4.10.

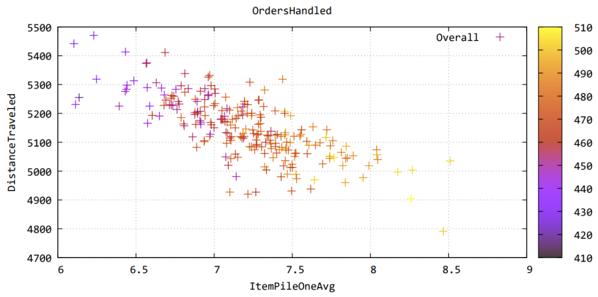


Figure 4.12: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_A, Plotted over the Pile-on and Travel Distance.

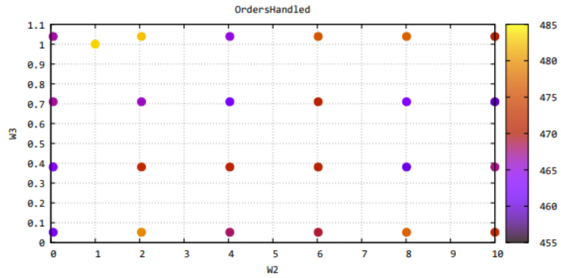


Figure 4.13: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_A, Plotted over the Weights.

Figure 4.13 depicts the number of orders handled plotted for the different weight configurations. There is one node where the weight configuration varies from the step sizes used for the other weight configurations, which is where all the weights are configured equal to 1 $(w_A, w_B, w_C) = (1, 1, 1)$. The result for this configuration is the maximum obtained mean performance for all the means from the different weight configurations (Table 4.5), closely followed by the result with weights $(2.042, 1.039)$. However, the maximum obtained number of orders handled for a single seed, as opposed to the mean value of all seeds from the same weight configuration, is found in a seed from the simulation results of weight $(2.042, 0.052)$.

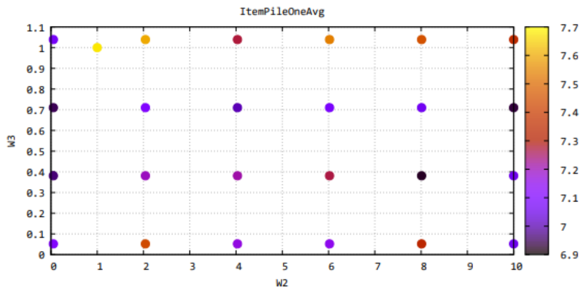


Figure 4.14: The Average Pile-on for all Weight Configurations of Demand Profile DP_A.

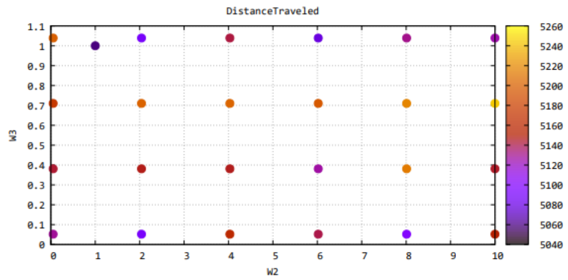


Figure 4.15: The Total Distance Travelled by the Robots for all Weight Configurations of Demand Profile DP_A.

Figure 4.14 and 4.15, present the result with the performance indicators of item pile-on and total distance travelled, respectively. It can be seen that the results are very similar to the number of orders handled. Travel distance shows an opposite result since this measure is minimised for optimal performance. Therefore, only the number of orders handled is plotted for the remainder of the demand profiles.

The weights in the slotting configuration are mainly used as a tool to gain different distributions for the three classes. These distributions are shown with the average number of pods/SKU ($\sum_j x_{ij}$) for each class in a ternary plot in Figure 4.16. Similar to the weight configurations plots, the average of the performance metric is shown for all simulations with the same values for the axis.

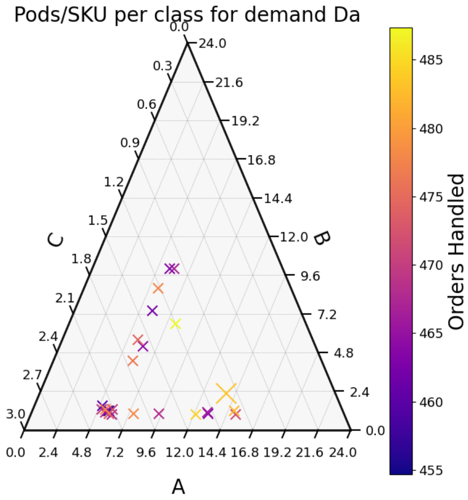


Figure 4.16: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of Demand Profile DP_A, with the Configurations as Pods per SKU Distribution per Class.

The ternary plot for demand profile DP_A shows that the configurations are varied mostly with the same distribution of minimum pods for SKUs in class A, and a varying number of pods for B and C, and minimum pods for class B while varying pods for class A and C. The variations with the distribution of minimum pods for C are few, whereas the simulations with maximum pods for C are the most frequent. This creates a triangle of simulations within the triangular plot axis, where the boundaries are narrower than the plot boundaries; this is due to the axis being based on a percentage of distribution, whereas a distribution of 100% is not possible for one class since the other classes have minimum distributions larger than 0%.
The configurations where the distribution of class C is minimal show relatively high performance for the number of orders handled. With a minimal class C distribution, the maximum class B distribution shows the lowest performance. The best performance is found with a high distribution of class A and a low distribution of classes B and C.

In the plot of the performance for different weight configurations (Figure 4.13), the configuration with equal weights (1, 1, 1) performed best. This configuration is plotted in the ternary plot with node *X*, more significant than the other nodes. It now is not the best performing configurations because a specific weight configuration is not the same as a specific slotting configuration. Multiple weight configurations might result in the same slotting, and one weight configuration may result in different slotting configurations.

4.2.2.2. Simulation Results with Demand Profile DP_B

The results for all the slotting configurations with demand profile DP_B are presented in Table 4.6. The mean value and standard deviation for all simulations with the same weight configurations w_B and w_C are shown, in addition to the mean and standard deviation of all simulations for this demand profile.

Table 4.6: The Performance Measures for all Weight Configurations of Demand Profile DP_B.

w_B	w_C	**Pile-on** Mean	**Pile-on** SD	**Travel distance** Mean	**Travel distance** SD	**Orders handled** Mean	**Orders handled** SD	**Count**
Total		*6.84*	*0.46*	*5223.9*	*113.57*	*458.45*	*18.47*	*225*
0.059	0.059	6.84	0.36	5193.37	89.96	454.11	16.33	9
0.059	0.304	7.01	0.41	5196.12	99.93	464.11	12.92	9
0.059	0.549	6.85	0.34	5189.81	107.4	462.11	18.16	9
0.059	0.794	7.02	0.44	5204.9	115.44	466.44	20.36	9
0.306	0.059	6.18	0.22	5368.94	60.47	433.78	13.8	9
0.306	0.304	6.76	0.33	5220.82	110.28	453.89	11.62	9
0.306	0.549	6.95	0.43	5165.39	86.25	465.22	17.31	9
0.306	0.794	6.76	0.31	5215.73	100.9	459.33	15.65	9
0.553	0.059	6.33	0.34	5305.7	79.36	442.22	16.44	9
0.553	0.304	6.69	0.5	5260.65	123.09	452.67	25.93	9
0.553	0.549	6.82	0.24	5232.49	69.33	456.33	12.32	9
0.553	0.794	6.83	0.23	5211.17	100.23	456.67	10.51	9
0.801	0.059	6.55	0.36	5311.87	110.14	453.11	15.91	9
0.801	0.304	6.64	0.23	5288.5	71.33	448.89	13.05	9
0.801	0.549	6.87	0.39	5195.52	66.54	459.11	16.77	9
0.801	0.794	7.02	0.41	5153.75	91.73	468.11	16.02	9
1.0	1.0	7.57	0.32	5063.5	104.69	483.33	9.99	9
1.048	0.059	6.64	0.49	5247.32	89.86	447.67	17.3	9
1.048	0.304	6.91	0.45	5226.84	100.43	461.44	18.22	9
1.048	0.549	6.82	0.3	5281.65	71.67	459.67	13.65	9
1.048	0.794	7.43	0.39	5111.18	150.74	478.56	17.44	9
1.295	0.059	6.67	0.52	5253.3	109.72	458.44	14.95	9
1.295	0.304	6.65	0.23	5255.93	89.6	449.89	16.5	9
1.295	0.549	6.8	0.2	5310.24	67.8	452.89	12.69	9
1.295	0.794	7.33	0.39	5132.92	94.62	473.33	17.63	9

The mean value for number of orders handled is 458 for demand profile DP_B. The range for the number of orders handled for this demand is similar to DP_A, with the range in the plot in Figure 4.17 from 410 to 510 orders. However, the maximum pile-on for this demand is 8 items, as opposed to the 8,5 from DP_A. This maximum value for pile-on is found with weights (1.0478, 0.794), with a mean orders handled of 479. Only the weigh configuration with (1, 1) has a higher mean of 483.

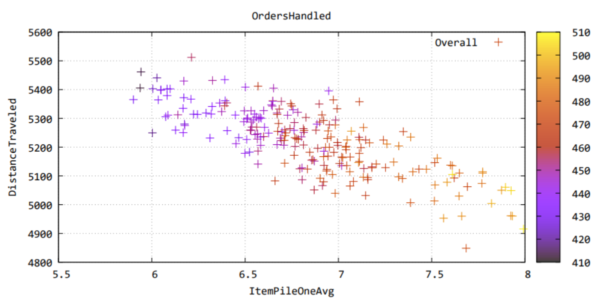


Figure 4.17: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_B, Plotted over the Pile-on and Travel Distance.

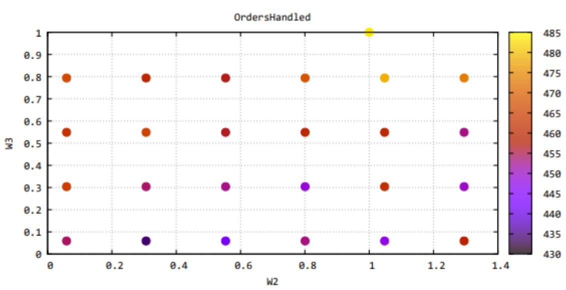


Figure 4.18: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_B, Plotted over the Weights.

In the plot in Figure 4.18, the number of orders handled seems to increase where the value for w_C

increases. This indicates that a lower distribution for this class (C) increases the performance.

The translation of weight configurations to distribution configurations is plotted in a ternary plot in Figure 4.19.

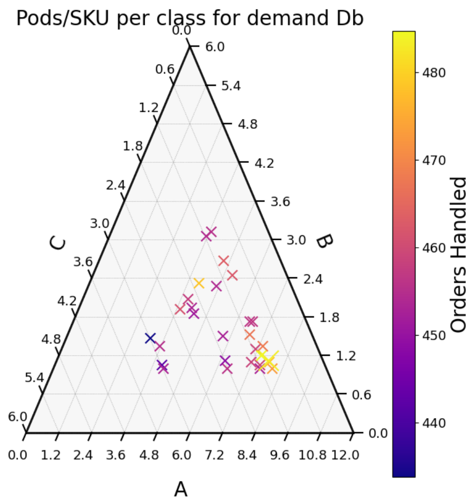


Figure 4.19: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of Demand Profile DP_B, with the Configurations as Pods per SKU Distribution per Class.

It can be seen that the range of the results is triangular inside the triangular plot, as it was with demand profile DP_A, but the triangle is shifted upward and to the right. This is due to the demand configuration of the profile. The number of SKUs in classes A and B is higher, reflected in the increased minimum and maximum distribution range of these classes. The number of SKUs in class C is lower, so the distribution range is also lower.

The worst-performing distribution configurations are found where A and B are distributed minimally, and class C is distributed maximally. The best-performing distributions are where class A is distributed maximally and B and C minimally. This is also the slotting result from weight configuration $(1, 1, 1)$. Along the line where class C is distributed minimally, the different configurations for A and B are performing better than with a larger C.

4.2.2.3. Simulation Results with Demand Profile DP_C

The results for all the slotting configurations with demand profile DP_C are presented in Table 4.7. The mean value and standard deviation for all simulations with the same weight configurations w_B and w_C are shown, in addition to the mean and standard deviation of all simulations for this demand profile.

Table 4.7: The Performance Measures for all Weight Configurations of Demand Profile DP_C.

w_B	w_C	Pile-on Mean	Pile-on SD	Travel distance Mean	Travel distance SD	Orders handled Mean	Orders handled SD	Count
Total		*8.11*	*0.52*	*4927.64*	*112.45*	*498.79*	*16.17*	*225*
0.058	0.058	7.72	0.32	5002.28	101.01	494.67	6.28	9
0.058	0.272	7.96	0.42	4989.32	81.0	499.67	12.9	9
0.058	0.486	7.85	0.39	4999.82	90.98	493.44	18.32	9
0.058	0.7	8.05	0.42	4922.15	54.84	497.44	14.84	9
1.0	1.0	8.7	0.31	4804.26	94.44	511.56	10.68	9
1.264	0.058	8.09	0.6	4924.38	111.15	501.89	20.84	9
1.264	0.272	7.66	0.4	5007.41	63.0	483.56	13.15	9
1.264	0.486	8.04	0.47	4902.78	94.53	497.89	15.01	9
1.264	0.7	8.84	0.4	4797.45	113.95	517.56	17.11	9
2.47	0.058	8.11	0.26	4952.61	70.21	502.22	8.38	9
2.47	0.272	7.64	0.4	4968.65	114.7	487.89	18.76	9
2.47	0.486	8.37	0.41	4890.66	93.23	507.0	11.52	9
2.47	0.7	8.26	0.27	4936.74	77.97	498.33	7.26	9
3.675	0.058	7.9	0.42	4995.1	88.34	490.22	12.81	9
3.675	0.272	7.95	0.6	5019.24	142.04	487.89	18.2	9
3.675	0.486	8.47	0.44	4865.9	138.68	510.78	14.53	9
3.675	0.7	8.52	0.31	4851.6	88.8	508.89	14.39	9
4.881	0.058	7.89	0.48	4894.14	79.36	490.33	15.86	9
4.881	0.272	7.69	0.26	4996.57	100.25	487.11	10.97	9
4.881	0.486	8.58	0.48	4838.09	127.98	505.44	19.03	9
4.881	0.7	8.29	0.42	4907.04	74.82	502.89	14.53	9
6.087	0.058	7.96	0.44	4953.23	72.74	495.67	9.77	9
6.087	0.272	7.57	0.18	4997.39	92.27	488.67	8.99	9
6.087	0.486	8.13	0.49	4919.86	111.83	500.33	17.54	9
6.087	0.7	8.55	0.34	4854.33	87.96	508.44	14.61	9

With a mean value of 499 orders handled for demand profile DP_C and a range in the plot in Figure 4.20 from 450 to 550, the performance is better than for DP_A and DP_B. Confirming the results from Figure 4.10, the mean pile-on is higher, and the mean travel distance is lower for the demand profile of DP_A and DP_B.

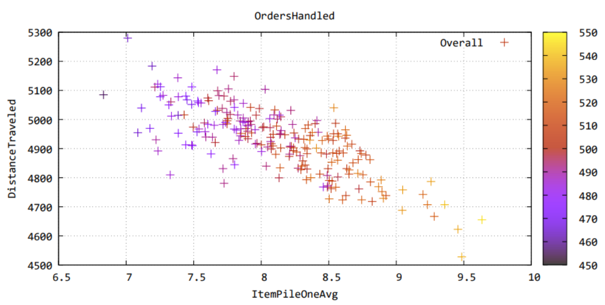


Figure 4.20: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_C, Plotted over the Pile-on and Travel Distance.

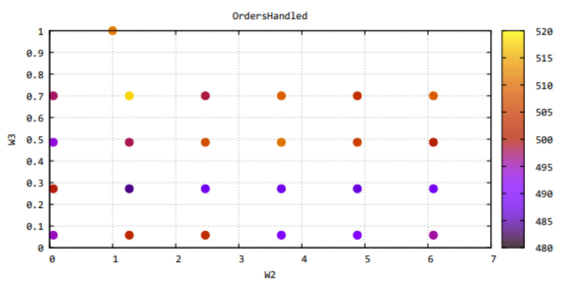


Figure 4.21: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_C, Plotted over the Weights.

In Figure 4.21, it can be seen that the weight configuration with $w_C = 0.272$ performs worse for almost all configurations of w_B except for $w_B = 0.058$. Weight configuration $(0.058, 0.272)$ has distribution $z_B = 1$ for all simulations, which might cause the increased performance (see Appendix A.3 for reference). The performance increases for $w_C \geq 0.486$ and is optimal for $(1.2638, 0.7)$.

The distribution of pods per SKU for demand profile DP_C is shown in a ternary plot in Figure 4.22.

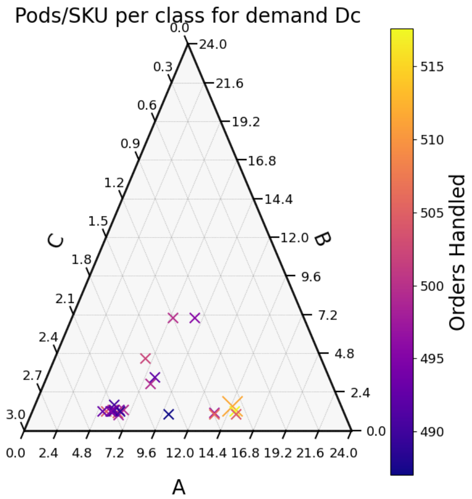


Figure 4.22: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of Demand Profile DP_C, with the Configurations as Pods per SKU Distribution per Class.

Similar to the performance from demand profile DP_A and DP_B, the best results are where the distribution of class A is maximum, and the distributions of class B and C are minimum. The configuration with equal weights in this configuration has the distribution where the SKUs in class A are distributed over $14, 5$ pods, class B over 1.5 pods and class C over 1 pod.

4.2.2.4. Simulation Results with Demand Profile DP_D

The results for all the slotting configurations with demand profile DP_D are presented in Table 4.8. The mean value and standard deviation for all simulations with the same weight configurations w_B and w_C are shown, in addition to the mean and standard deviation of all simulations for this demand profile.

Table 4.8: The Performance Measures for all Weight Configurations of Demand Profile DP_D.

w_B	w_C	**Pile-on** Mean	**Pile-on** SD	**Travel distance** Mean	**Travel distance** SD	**Orders handled** Mean	**Orders handled** SD	**Count**
Total		*7.71*	*0.56*	*5011.12*	*123.88*	*487.15*	*17.98*	*225*
0.05	0.05	8.27	0.26	4950.58	87.62	502.67	17.89	9
0.05	0.213	7.3	0.46	5080.81	86.58	479.11	14.89	9
0.05	0.377	7.54	0.27	4999.93	107.54	485.56	10.3	9
0.05	0.54	7.29	0.24	5057.49	159.19	475.22	10.69	9
0.198	0.05	7.15	0.19	5107.06	60.54	473.0	10.98	9
0.198	0.213	7.27	0.43	5070.58	128.95	473.67	17.86	9
0.198	0.377	7.43	0.37	5025.76	80.94	478.11	14.44	9
0.198	0.54	7.62	0.42	5020.38	112.79	482.33	12.88	9
0.346	0.05	7.38	0.32	5066.42	88.3	477.67	10.89	9
0.346	0.213	7.43	0.28	5046.68	66.98	476.44	12.5	9
0.346	0.377	7.6	0.32	5058.69	79.71	484.78	12.54	9
0.346	0.54	7.69	0.39	5056.05	70.0	488.56	16.69	9
0.494	0.05	7.65	0.19	5014.07	97.9	484.22	8.21	9
0.494	0.213	7.54	0.38	5054.28	133.88	484.0	12.29	9
0.494	0.377	7.75	0.43	5041.59	109.2	490.78	17.89	9
0.494	0.54	7.89	0.62	4980.14	119.21	492.67	17.43	9
0.642	0.05	7.54	0.41	5068.11	87.28	479.33	17.03	9
0.642	0.213	7.42	0.29	5036.01	81.4	474.78	8.48	9
0.642	0.377	8.12	0.39	4923.8	84.69	498.78	12.74	9
0.642	0.54	8.29	0.54	4866.77	110.69	506.89	15.85	9
0.79	0.05	7.33	0.34	5090.87	88.75	475.78	10.95	9
0.79	0.213	7.58	0.27	5102.43	91.51	487.56	9.95	9
0.79	0.377	8.48	0.37	4905.68	88.69	508.0	14.47	9
0.79	0.54	8.22	0.51	4873.3	77.05	500.22	17.39	9
1.0	1.0	8.88	0.5	4780.56	99.01	518.67	16.72	9

The mean number of orders handled for demand profile DP_D is 487 orders, which is lower than DP_C but better than DP_A and DP_B. The maximum mean number of orders handled is 518 orders for the configuration with weights $(1, 1)$. The maximum number of orders handled for all simulations is 538 orders and is also with this weight configuration.

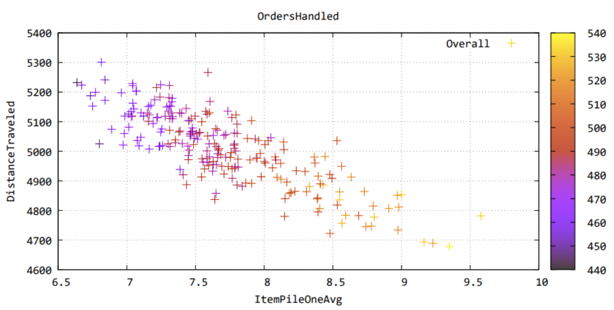


Figure 4.23: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_D, Plotted over the Pile-on and Travel Distance.

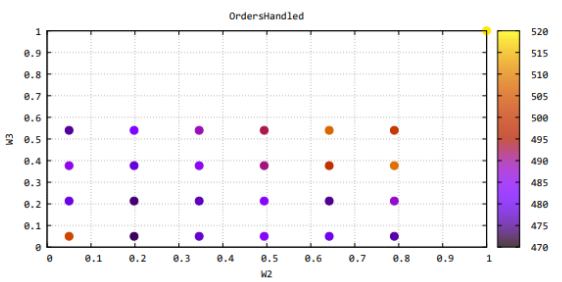


Figure 4.24: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_D, Plotted over the Weights.

The best performance is simulated with w_B and w_C increasing, which indicates the distribution class B and C decreasing. One weight configuration where w_B and w_C are the minimum values shows an improved performance from the surrounding configurations. This might be due to the similarity of the weights resulting in a distribution similar to the distributions with maximum w_B and w_C. From the weight plot it seems that the distribution with $w_B = 1$ and $w_C = 1$ performs best, however, this weight configuration has the same distribution as with $(0.642, 0.54)$ and $(0.79, 0.54)$. These distributions are where class A is distributed maximally, in the ternary plot in Figure 4.25, this configuration has the distribution of 8 pods for SKUs in class A, and 1 pod for SKUs in classes B and C. The best-performing configurations are found in a diagonal line perpendicular to the axis of class A with a sharp cutoff for A ≤ 6.8 where the configurations near this line show better performance on the side where A and C decrease and B increase.

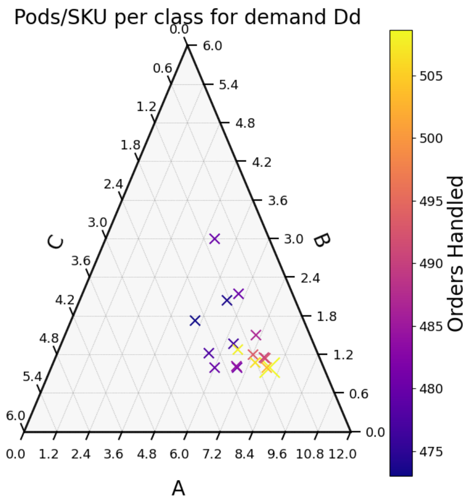


Figure 4.25: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of Demand Profile DP_D, with the Configurations as Pods per SKU Distribution per Class.

4.2.2.5. Simulation Results with Demand Profile DP_E

The results for all the slotting configurations with demand profile DP_E are presented in Table 4.9. The mean value and standard deviation for all simulations with the same weight configurations w_B and w_C are shown, in addition to the mean and standard deviation of all simulations for this demand profile. For this demand profile, the distribution of class C is limited since all SKUs in class C only consist of 1 item. Therefore, only one weight configuration for this class is included, except configuration $(1, 1)$.

Table 4.9: The Performance Measures for all Weight Configurations of Demand Profile DP_E.

w_B	w_C	**Pile-on**		**Travel distance**		**Orders handled**		**Count**
		Mean	SD	Mean	SD	Mean	SD	
Total		*9.97*	*0.82*	*4544.39*	*146.44*	*541.31*	*19.34*	*54*
0.058	0.058	9.35	0.54	4609.38	155.49	531.33	19.44	9
0.293	0.058	9.85	0.5	4609.95	48.78	537.0	17.04	9
0.529	0.058	9.63	0.65	4541.33	131.76	529.78	21.29	9
0.764	0.058	9.6	0.39	4626.59	90.41	539.56	11.1	9
1.0	1.0	10.29	0.64	4511.31	102.43	547.78	15.48	9
1.0	0.058	11.11	0.77	4367.78	161.15	562.44	12.53	9

The results of the configurations for demand profile DP_E show significantly better performance with a mean number of orders handled of 541 orders, which is 42 orders more than the performance of demand profile DP_C.

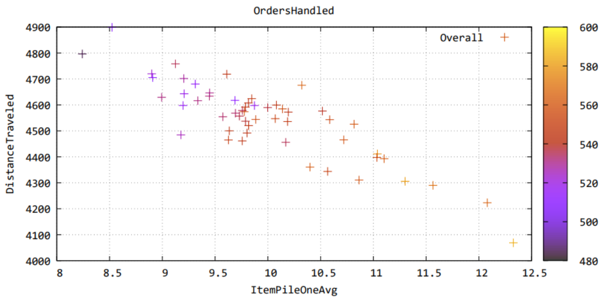


Figure 4.26: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_E, Plotted over the Pile-on and Travel Distance.

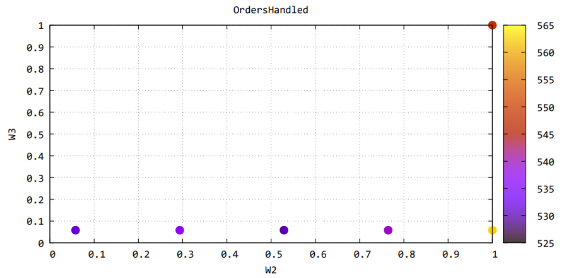


Figure 4.27: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_E, Plotted over the Weights.

The plot in Figure 4.27 shows the best result with $w_B = 1$. However, the second best performing configuration is the configuration with the weight configuration $(1, 1)$. The performance for number of orders handled is not gradually decreasing together with w_B. The configuration with weight w_B in the middle of the range, $w_B = 0.529$, is the worst-performing configuration for this demand.
There is only one possible configuration for class C, which makes the results easier to read. The best performance is reached where the distributions for class A and B are similar, which is most often with weight configurations $(1, 0.058)$ and $(1, 1)$, the configurations where the weight for class B decreases perform better than with a larger weights for class B. This is mainly confirmed by the ternary plot in Figure 4.28.

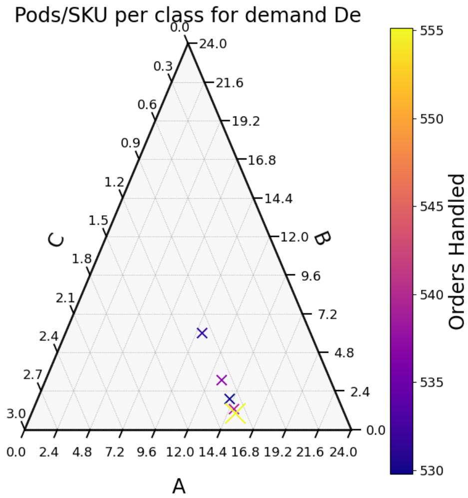


Figure 4.28: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of Demand Profile DP_E, with the Configurations as Pods per SKU Distribution per Class.

Interestingly, the plot for the weight configurations shows 6 weight configurations, but the ternary plot shows 5 distribution configurations, which means that two of the weight configurations result in the same distribution. These are the weight configurations for $(1, 1)$ and $(1, 0.058)$. Since both configurations showed far better performance than the other configurations in the weight configuration plot in Figure 4.27, it is unsurprising that this is similar to the performance shown in the ternary distribution plot.

4.2.2.6. Simulation Results with Demand Profile DP_F

The results for all the slotting configurations with demand profile DP_F are presented in Table 4.10. The mean value and standard deviation for all simulations with the same weight configurations are shown, in addition to the mean and standard deviation of all simulations for this demand profile.

Table 4.10: The Performance Measures for all Weight Configurations of Demand Profile DP_F.

w_B	w_C	Pile-on		Travel distance		Orders handled		Count
		Mean	SD	Mean	SD	Mean	SD	
Total		*8.36*	*0.39*	*4863.82*	*110.7*	*504.03*	*12.64*	*72*
0.1	0.068	8.29	0.46	4888.32	175.99	500.67	14.84	9
0.147	0.068	8.07	0.28	4953.41	79.57	497.67	17.04	9
0.193	0.068	8.51	0.17	4853.38	78.31	505.0	7.68	9
0.24	0.068	8.45	0.41	4782.72	83.57	508.78	11.21	9
0.287	0.068	8.43	0.45	4839.83	81.94	505.67	13.8	9
0.333	0.068	8.47	0.36	4805.19	61.51	506.33	10.97	9
0.38	0.068	8.56	0.36	4833.36	103.3	506.67	11.79	9
1.0	1.0	8.07	0.32	4954.33	71.89	501.44	12.78	9

The performance of the number of orders handled for this demand profile is 504 orders, which is better than for all demand profiles except for DP_E. The standard deviation is also the smallest compared to all other demand profiles. The minimum number of orders handled is 461 and results from a simulation with weight configuration $(0.147, 0.068)$, which is also where the mean for number of orders handled is lowest. However, the standard deviation for this weight configuration is more significant than most others in this demand profile. The maximum mean for number of orders handled is 525 orders, which surfaces in two configurations. Among which the configuration with the highest mean, $(0.24, 0.068)$.

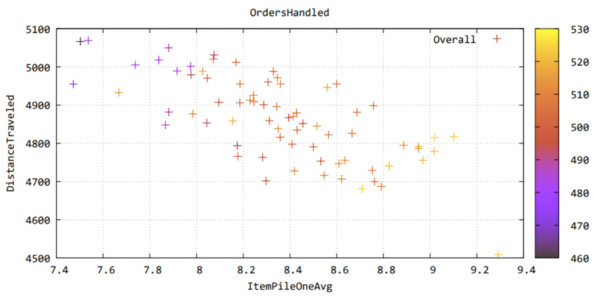


Figure 4.29: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_F, Plotted over the Pile-on and Travel Distance.

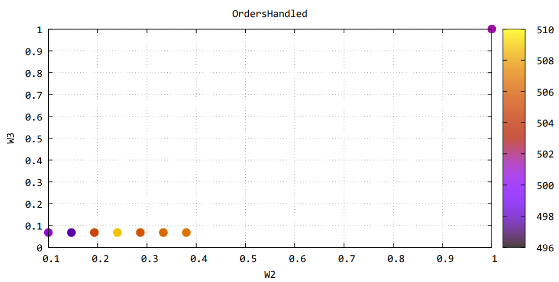


Figure 4.30: The Total Number of Orders Handled for all Weight Configurations of Demand Profile DP_F, Plotted over the Weights.

From the plot in Figure 4.30 and Figure 4.29, it can be seen that a larger portion of all simulations performs towards the maximum value when comparing to the other demand profiles.
Similar to demand profile DP_E, class C has only one possible configuration. The distributions for this demand profile, however, are less clear. A slight correlation exists where configurations with larger values for z_C have lower performance. This would indicate that the performance increases with class B less distributed and class A more distributed.

The distribution configurations associated with these weight configurations are plotted in a ternary plot in Figure 4.31.

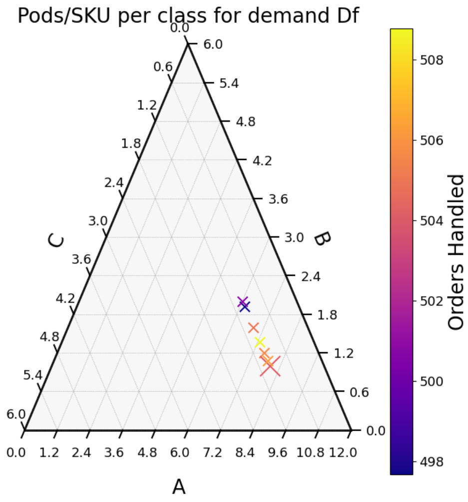


Figure 4.31: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of Demand Profile DP_F, with the Configurations as Pods per SKU Distribution per Class.

Since there is only one possibility for the distribution of SKUs in class C, the configurations result in one line for $C = 1$. The worst performance is where B is distributed maximally and A minimally. The best result, however, is not found with A distributed maximally and B minimally, but the performance seems to increase towards the configuration in the middle. The configuration where class A is distributed maximally performs better than where A is distributed minimally, but the optimal performance seems more towards the middle.

4.2.3. Conclusion to Scenario Simulation

The simulation results highlight the significant impact of pile-on and travel distance on the order throughput rate, independent of the demand profile. Across the 30-minute simulation period, the slotting configuration decisions lead to variations of up to 200 orders handled.

The vast weight range for demand profiles DP_A and DP_C results in slotting configurations concentrated in one area due to similar distributions resulting from multiple weight configurations. The distribution with classes A and B is frequently distributed minimally and C maximally since the configuration concentrations are in the lower left corner. However, the wide range has not decreased because a few configurations lead to new distributions. These concentrations are not a problem. However, they impose less diversity in the distributions for these demand profiles.

In contrast, demand profiles DP_B, DP_D, and DP_F exhibited more evenly scattered slotting configurations due to similar weight ranges and similar item demand in classes B and C. This spread provides better insight into performance for different slotting configurations.

The objective of this section is to answer Sub-Question 1: *What is the impact of demand-based slotting decisions on the order throughput rate for different demand configurations in an RMFS?*

Among the various demand profiles, DP_E and DP_F emerge as top performers regarding the total number of orders handled during the simulation. These two demand profiles share that class C consists of only 1 item. Demand profile DP_E particularly excels. This might be due to having only 1 item in class C, DP_E has the largest number of SKUs in that class with $Q_t = 80$ as opposed to $Q_t = 40$ of DP_F. The demand in profile DP_E and DP_F follow the same demand curve, where 20% of SKUs are 90% of the item demand, where the difference between both demand profiles is the classification. For demand profile DP_E, the classes are separated on 10% and 20% of SKUs, resulting in class A and B consisting of 10 SKUs and class C of 80 SKUs, while demand profile DP_F has class separation on 20% and 60%, which is 20 SKUs in class A and 40 in B and C.

This indicates that the classification of the demand profiles, in addition to the turnover, impacts the performance. Supporting this, both other demand profiles with class separation of 10% and 20% (DP_A and

DP_C) show better performance than the demand profile with the same curve but different classification (DP_B and DP_D).
Demand profiles with a classification containing fewer SKUs in class A and more SKUs in class C show better performance.

The ternary plots reveal that high performance is typically achieved in the lower right corner, associated with configurations with more pods for SKUs in class A and fewer for classes B and C. However, deviations from this pattern are observed with, for instance, demand profile DP_F showing optimal performance when class B is distributed around the middle of its range. Similarly, demand profile DP_B has one high-performing configuration towards the middle of the plot. Demand profile DP_D demonstrates high performance in configurations where class A distribution is not the maximum. In contrast, demand profile DP_A presents inconclusive results except for low performance with minimal pods for class A and C and maximum pods for class B.

The number of pods over which class C can be distributed affects the readability of the results in the ternary plots and the clarity of the trends. For demand profiles DP_E and DP_F, class C can be distributed over a maximum of one pod, resulting in a single line of results. For demand profile DP_D, class C can be distributed over two pods, showing an evident trend where the lower right performs best and the other areas perform poorly. Demand profiles DP_B and DP_C, where class C can be distributed over three pods, are somewhat unclear. The lower left performs poorly, and the lower right performs well, while the top performs less distinctly.

It is evident that with fewer pods over which class C might be distributed, it becomes clearer that maximising pods for class C and minimising pods for class A is not desirable. This is because as the possible number of pods for class C decreases, the closer a distribution gets towards maximising class C, thereby highlighting negative performance.

The lowest performance across all profiles is found in the lower left corner, which is the slotting with minimal pods for class A and B, and maximal pods for class C. Additionally, low performance is also seen at the top of the ternary plot for most profiles, which is the distribution with minimal pods for class A and C, and maximal pods for class B. These two corners are the extreme configurations with minimal pods for class A.
This suggests that the distribution of class A is critical for the order throughput performance, with large distributions generally showing the best performance. However, configurations with slightly fewer pods for class A and more pods for class B also perform well.

The equal weights configuration of $w_B = 1$ and $w_C = 1$ consistently achieves high performance across all demand profiles. This suggests that maintaining a similar number of items per pod for the three classes is beneficial. This equal items per pod configuration often aligns with the high-performing lower right corner of the ternary plots, corresponding to maximum pods for class A and minimum pods for classes B and C distributions. For demand profiles DP_D, DP_E, and DP_F, this configuration is the same. For demand profile DP_D and DP_F, it is not possible to distribute classes A and B with the same number of items per pod (Table 4.1), making the lower right corner the closest to an equal distribution. The other high-performing configurations for demand profile DP_D are further from the equal distribution, and the best-performing configuration for demand profile DP_F involves more pods for class B and fewer for A, suggesting that both equal items per pod and maximising pods for class A are not always the optimal slotting decision.
For demand profiles DP_A, DP_B and DP_C, the equal configuration is located in the lower right corner of the ternary plot but is not the most extreme configuration in regards to pods for class A. However, it shows better performance than the most extreme configuration in these cases, which could indicate that maximum A is not always the best.

In conclusion, while it is challenging to determine whether maximising pods for class A or achieving equal items per pod distribution for all classes is the best single strategy, both approaches generally result in a good performance.

5
Case Study

The model from Chapter 3 and the results from Chapter 4 are validated with a case study for the Gall&Gall distribution center.
This chapter begins with an introduction to the distribution center of Gall&Gall, after which the methodology described in Section 3.1 is repeated to create demand profiles based on real-life order demand from Gall&Gall. This demand is slotted with the mathematical model with multiple slotting approaches through weight configurations. Finally, the slotting configurations are simulated to evaluate the impact of different slotting approaches on the performance of total number of orders handled.

5.1. Introduction to Case Study of Gall&Gall

This research is executed in collaboration with the distribution center of Gall&Gall, which is the largest liquor retailer in the Netherlands. Gall&Gall offers an extensive assortment of approximately 4000 Stock Keeping Units (SKUs) through 600 physical stores (Gall&Gall, 2024) and a webshop, supplied from one distribution center. The e-commerce channel was launched in 2014, and has undergone constant improvement since then, including a physical expansion to increase capacity and the implementation of a Warehouse Management System for improved inventory management. The next steps for Gall&Gall involve the exploration of process automation.
The primary benefit of this research for Gall&Gall is to investigate the potential advantages of slotting optimisation in combination with automation. Gall&Gall currently does not operate with a Robotic Mobile Fulfilment System (RMFS), and implementing such a system is beyond the scope of this research. This exploration provides insights into the significance of this decision problem and the level of effort required to address it. Additionally, these insights help Gall&Gall anticipate key considerations for development proposals or implementation designs for such a system. Specifically, understanding the potential of the benefits of slotting optimisation is crucial for deciding the design, configuration, and features to include. For example, when defining system requirements, it is important to recognise which RMFS systems or algorithms include slotting optimisation, as some may not offer this feature.

Demand Type

The orders from Gall&Gall are next-day delivery until 22:00 every day. This indicates that customers can place orders until 22:00 and receive them the next day. For the process, this means that demand is uncertain and continuously received throughout the day, and only after 22:00 is the demand certain. So, the operational demand type is mostly stochastic, with the last two hours being deterministic.
The forecasting occurs on two levels: quantitative order forecasting, which happens on the total number of orders and the total number of items produced daily to accommodate the necessary resources like labour hours and transport capacity towards the delivery centers. The other is item-specific forecasting, which happens on a daily to weekly basis. This facilitates the execution of replenishment tasks from the reserve storage area to the picking storage area (Figure 1.1) at the beginning of a production day for the estimated items as if the demand is deterministic. This replenishment task of the items from

the forecasted demand can be slotted according to slotting approaches where deterministic demand is necessary.

5.2. Order Demand Profiles of Gall&Gall

The order demand from Gall&Gall recognises two different recurring order profiles: The order demand from a relatively regular month and the demand for December. This is the year's peak for Gall&Gall, where demand is higher, and the demand profile differs from the rest of the year.

The original demand data spans a month, however, as with the demand profiles in Chapter 3.2, the significance of the demand profiles lies in their relative turnover rates. This makes the specific temporal unit irrelevant. The impact of turnover-based slotting is assessed, regardless of whether the turnover is measured daily or monthly.

The data is classified into A, B and C classes. The classes are configured with class separation of 20%, 30% and 50%, which shows the closest resemblance to the order demand of Gall&Gall.
The regular order demand with respective class configuration is visualised in Figure 5.1, and the peak order demand with classifications is shown in Figure 5.2.

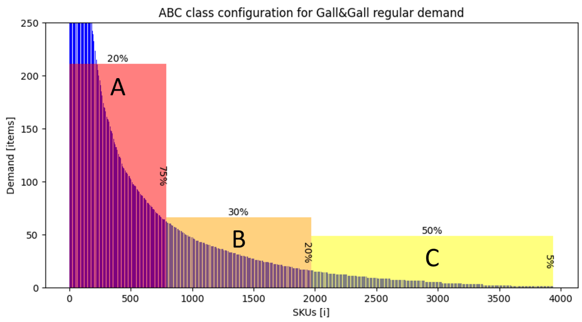


Figure 5.1: Regular Demand from Gall&Gall in ABC Classification.

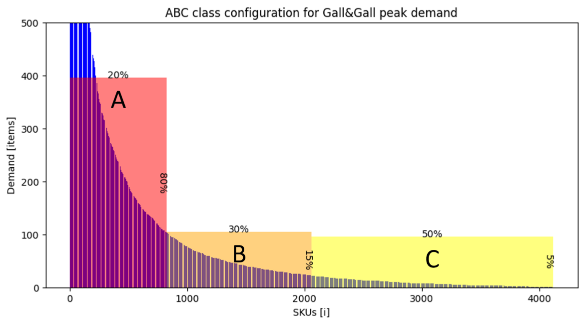


Figure 5.2: Peak Demand from Gall&Gall in ABC Classification.

The tail of the histograms in both figures that comprises class C is determined at 5% of the total demand and accounts for 50% of the total number of SKUs. The difference between the regular and peak demand profile is a 5% demand shift from class B to A. This indicates that with peak demand, the popularity of popular SKUs increases.

The classification of the regular and peak demand data is used to scale the data to 100 SKUs and 1000 items in total, according to the configurations in Chapter 4. This results in the demand profiles presented in Table 5.1.

Table 5.1: Demand Configuration for Gall&Gall with Item Count and SKU Count per Class

Demand profile	**Class**	**Item count** $[D_i]$	**SKU count** $[Q_t]$
Regular	A	37	20
	B	7	30
	C	1	50
Peak	A	40	20
	B	5	30
	C	1	50

The long tail of SKUs with low demand in class C is configured with a demand of 1 item for both demand profiles. The popularity shift between regular demand and peak demand is configured with a demand difference of 3 items for class A and 2 items for class B.

5.3. Slotting Configuration

A slotting configuration is generated with the slotting model described in Section 3.3. The configurations and constraints regarding the number of pods, pod capacity and number of SKUs allowed in a pod are identical to the configurations used for the synthetic demand profiles, to enable comparison.

Each demand profile is slotted in multiple configurations according to different weight combinations used to determine the relative importance of the distribution of the demand classes A, B and C. The weight ranges for the Gall&Gall scenarios are initially configured with Equations 3.20 and 3.21 and adjusted empirically based on the results found with those weights. The weights are used as compensation in the distribution equation with the distribution indicator of pods per item. This means that a low weight indicates a high distribution and vice versa. The weight for class A is fixed as 1 for all configurations so that the weights of class B and C indicate their relative magnitude to class A. The weight for class C, w_C, knows only one configuration for both demand profiles since the SKUs in this class consist of 1 item and can, therefore, only be distributed in a single configuration. Therefore, class A and C weights are fixed at 1.
The resulting weight ranges are presented in Table 5.2.

Table 5.2: Weight Range Configuration for Gall&Gall Scenarios.

Demand profile	**Range w_B**	**Range w_C**	**Steps w_B**	**Steps w_C**
Regular	(0.01, 1.6)	(1)	12	1
Peak	(0.01, 1)	(1)	12	1

The weights are varied from the minimum to the maximum in 12 steps, with an additional configuration where all the weights are equal to 1 when that is not one of the existing configurations. Each configuration is slotted with 3 random seeds, resulting in 36 or 39 slotting configurations.

5.3.1. Slotting Analysis

The demand is distributed into different slotting configurations based on the specific weight parameters. Each configuration results in a distribution described by three key indicators: pods per item, items per pod and pods per SKU. The results of all slotting configurations is printed in Appendix A, for reference. Figures 5.3, 5.4 and 5.5 respectively, illustrate the data distribution of the indicators in all slotting configurations, showing how often each distribution configuration occurs with a density trace. The data from the figures is presented in Table 5.3.

Table 5.3: Statistics of Data Range of Distribution Indicators for each Class for Gall&Gall Demand Profiles.

Demand	Label	Mean	Median	Lower quartile	Upper quartile	Lower whisker	Upper whisker
				Pods per item			
Regular	A	0.176	0.19	0.154	0.208	0.09	0.216
	B	0.284	0.236	0.173	0.363	0.143	0.586
	C	1.0	1.0	1.0	1.0	1.0	1.0
Peak	A	0.16	0.173	0.137	0.19	0.082	0.2
	B	0.412	0.343	0.253	0.537	0.2	0.827
	C	1.0	1.0	1.0	1.0	1.0	1.0
				Items per pod			
Regular	A	6.069	5.27	4.813	6.513	4.625	8.506
	B	4.313	4.264	2.761	5.801	1.707	7.0
	C	1.0	1.0	1.0	1.0	1.0	1.0
Peak	A	6.685	5.78	5.264	7.346	5.0	10.256
	B	2.98	2.926	1.879	3.956	1.21	5.0
	C	1.0	1.0	1.0	1.0	1.0	1.0
				Pods per SKU			
Regular	A	6.515	7.025	5.688	7.688	3.35	8.0
	B	1.99	1.65	1.208	2.542	1.0	4.1
	C	1.0	1.0	1.0	1.0	1.0	1.0
Peak	A	6.412	6.925	5.475	7.6	3.3	8.0
	B	2.058	1.717	1.267	2.683	1.0	4.133
	C	1.0	1.0	1.0	1.0	1.0	1.0

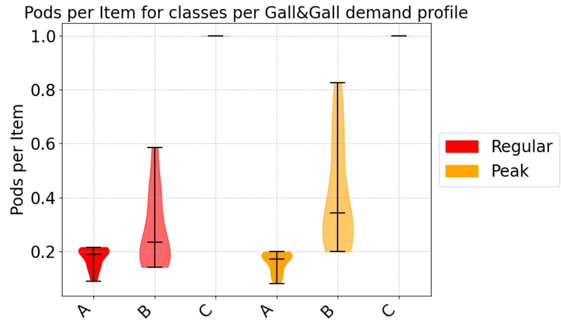


Figure 5.3: The Data Distribution of Pods per Item Represented with a Violin Plot for each Class for the Demand Profiles.

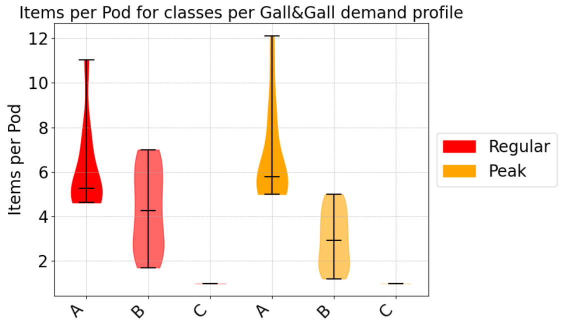


Figure 5.4: The Data Distribution of Items per Pod Represented with a Violin Plot for each Class for the Demand Profiles.

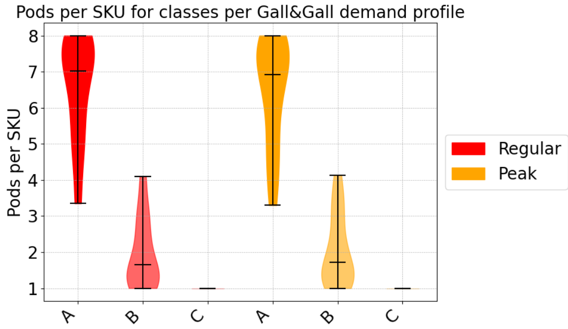


Figure 5.5: The Data Distribution of Pods per SKU Represented with a Violin Plot for each Class for the Demand Profiles.

The pods per item (Figure 5.3) and items per pod (Figure 5.4) distributions for both demand profiles have overlapping values for class A and B. This indicates configurations where the items are distributed *equally* in both classes. Where equal means that items are distributed with the same quantity per pod, independent of the total number of items for that SKU. Whereas Figure 5.5 visualises the distribution of pods per SKU. For the regular demand, this can not be distributed *equally* due to the difference in class A and B demand. The overlap in Figure 5.3 for the general demand profile explains why the configurations for this weight range below and above 1 (Table 5.2), whereas the weight for the peak demand can maximally be 1 since the items in class B can not be distributed with more pods per items than class A.

With the peak demand, the distribution of pods per item (Figure 5.4) of class B shifts upwards with a higher minimum and maximum number of pods per item than for the regular demand. The maximum of class B for the peak demand reaches further towards 0, where approaching 0 means that all the items are slotted on one pod (which is not possible for both classes A, see Figure 5.5), and the maximum pods per item for class B of the peak demand is higher than for the regular demand, where reaching 1 means that each item for a SKU in that class is slotted with one item per pod.

5.4. Simulation Analysis

The simulation configuration remains similar to the configurations used in Section 3.4 to compare the results of the different configurations. The number of seeds used with these configurations is 6. The scatter plots in Figures 5.6 and 5.7 show the impact of slotting decisions on travel distance and pile-on, and with that, the impact of slotting on the total number of orders handled, for the simulations of all slotting configurations for the regular demand profile and the peak demand profile for Gall&Gall respectively.

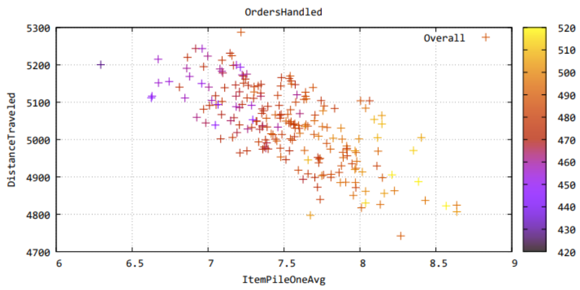


Figure 5.6: The Total Number of Orders Handled for all Weight Configurations of the Regular Gall&Gall Demand Profile, Plotted over the Pile-on and Travel Distance.

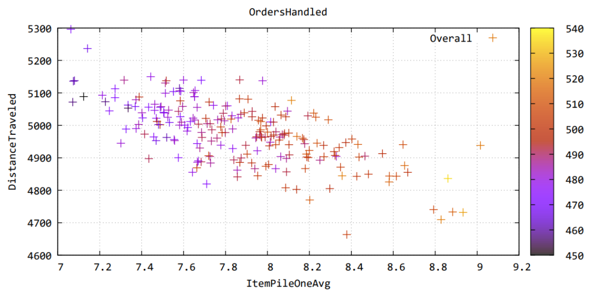


Figure 5.7: The Total Number of Orders Handled for all Weight Configurations of the Peak Gall&Gall Demand Profile, Plotted over the Pile-on and Travel distance.

From the plot in Figures 5.6 and 5.7, it can be seen that the range of obtained performances is similar for both demand profiles, with a difference of 30 orders handled. For both demand profiles, a minority of all the simulations perform near the maximum and minimum number of orders handled, this indicates that many configurations lead to moderate performance, but only a few configurations perform significantly better or worse. However, even within the group of most simulations' results, the performance difference can still be 100 orders handled.
The majority of the results for the regular demand profile seem to be performing around the average. In contrast, the peak demand has more simulations performing towards the minimum of the range. Notably, the minimum of the range for the peak demand is similar to the middle of the range for the regular demand.

When comparing the performance of the demand profiles from Gall&Gall with the performance of other demand profiles in Figure 4.10, it can be seen that the performance of the Gall&Gall demand profiles is similar to the lesser performing half of the synthetic demand profiles in Chapter 4. The performance of the synthetic demand profiles varies between 400 orders handled in 30 minutes of simulation and 600 orders handled (Figure 4.10), whereas the performance of the demand profiles from Gall&Gall varies between 420 orders handled and 540 orders handled.

The performance of the different weight configurations is shown in the plot in Figure 5.8 for the regular demand profile of Gall&Gall, and in Figure 5.9 for the peak demand profile. The performance measures per weight configuration are presented in Table 5.4. The results of all simulation runs are printed in Appendix C, for reference.

Table 5.4: The Performance Measures for all Weight Configurations for the Gall&Gall Demand Profiles.

W2	**W3**	**Pile-on**		**Travel distance**		**Orders handled**	
		Mean	SD	Mean	SD	Mean	SD
Regular demand profile							
0.01	1.0	7.92	0.35	4970.01	91.21	492.33	15.24
0.155	1.0	7.22	0.33	5084.44	86.17	474.11	12.74
0.299	1.0	7.67	0.29	5003.34	100.25	485.67	12.71
0.444	1.0	7.57	0.3	4991.71	106.43	482.89	13.27
0.588	1.0	7.72	0.31	4980.98	79.24	483.0	10.26
0.733	1.0	7.63	0.5	5040.16	125.86	481.11	13.07
0.877	1.0	7.59	0.5	5009.0	103.52	477.83	17.66
1.022	1.0	7.37	0.32	5099.57	71.18	473.67	12.31
1.166	1.0	7.46	0.38	5084.38	99.02	479.44	15.17
1.311	1.0	7.25	0.41	5074.7	92.03	467.89	15.63
1.455	1.0	7.46	0.31	5058.91	92.91	476.78	14.1
1.6	1.0	7.42	0.29	5064.16	104.68	476.72	14.93
Total		*7.52*	*0.41*	*5038.45*	*104.02*	*479.29*	*14.98*
Peak demand profile							
0.01	1.0	7.94	0.36	4969.16	69.68	493.67	10.71
0.1	1.0	7.55	0.24	5026.01	72.53	483.56	14.86
0.19	1.0	7.83	0.35	4970.98	98.78	490.28	14.05
0.28	1.0	7.71	0.36	5017.23	73.09	483.22	10.88
0.37	1.0	7.84	0.38	4976.0	92.3	491.61	15.55
0.46	1.0	8.15	0.39	4906.51	113.25	497.28	15.95
0.55	1.0	7.78	0.29	4992.64	92.56	487.22	10.11
0.64	1.0	8.11	0.38	4947.91	85.57	496.22	14.68
0.73	1.0	7.79	0.25	5020.97	74.48	489.11	12.19
0.82	1.0	7.69	0.35	5036.83	116.8	484.33	15.48
0.91	1.0	7.9	0.32	4957.12	62.9	490.67	11.83
1.0	1.0	8.04	0.52	4911.32	79.79	491.61	16.48
Total		*7.86*	*0.39*	*4977.72*	*94.76*	*489.9*	*14.11*

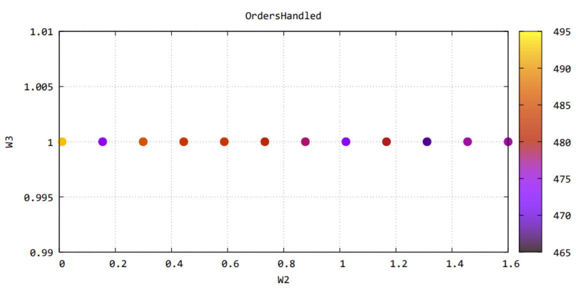


Figure 5.8: The Total Number of Orders Handled for all Weight Configurations of the Regular Gall&Gall Demand Profile, Plotted over the Weights.

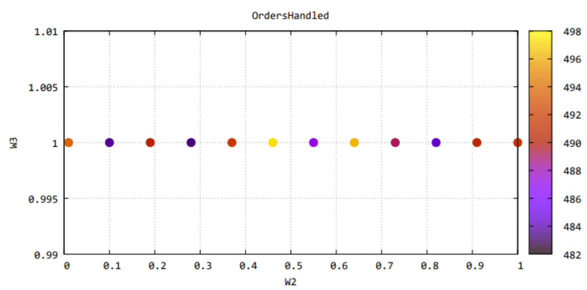


Figure 5.9: The Total Number of Orders Handled for all Weight Configurations of the Peak Gall&Gall Demand Profile, Plotted over the Weights.

The weight configuration where all weights are 1 showed good performance for many demand profiles in Chapter 4. However, for both demand profiles from Gall&Gall, the performance is not among the highest-performing configurations.
With the regular demand profile, the best performing configuration is where $W2$ is minimal. The perfor-

mance decreases significantly for $W2 \geq 1$, which indicates that class A is distributed over more pods per item than class B. This might explain why such a clear trend is difficult to find with the peak demand since the weight for class B can not be larger than 1.

The distribution configurations associated with these weight configurations are plotted in ternary plots in Figure 5.10 for the regular demand profile of Gall&Gall and in Figure 5.11 for the peak demand.

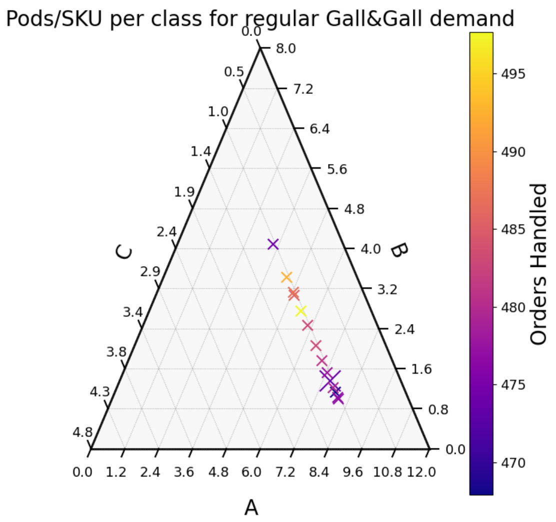


Figure 5.10: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of the Regular Gall&Gall Demand Profile, with the Configurations as Pods per SKU Distribution per Class.

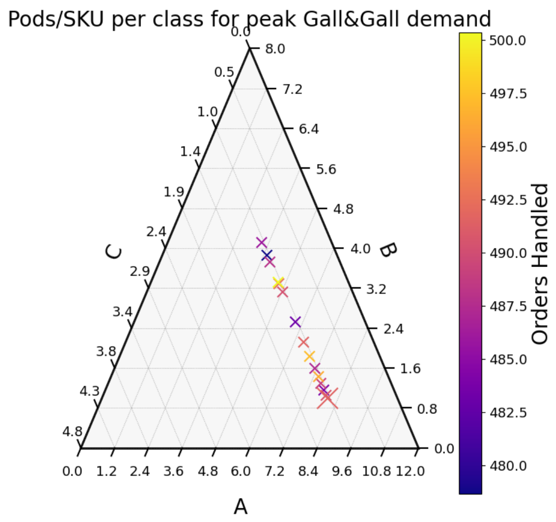


Figure 5.11: Ternary Plot of the Number of Orders Handled for all Slotting Configurations of the Peak Gall&Gall Demand Profile, with the Configurations as Pods per SKU Distribution per Class.

The distributions for the regular demand profile, where the SKUs in class B are distributed either towards their minimum or their maximum, perform relatively low. On the other hand, the configurations where classes A and B are distributed somewhere in the middle of their range perform best.
The configuration with equal weights performs relatively low when compared to the other configurations.
The configurations where class B is distributed maximally show low performance for the peak demand profile. The same range as for the regular demand also seems to perform well for this demand. However, the distributions where class A is distributed more and class B less also show better performance or the peak demand.

5.5. Conclusion to Gall&Gall Case Study

The objective of this conclusion is to answer Sub-Question 2: *What is the impact of demand-based slotting decisions on the order throughput rate with a Robotic Mobile Fulfilment System for a Gall&Gall case study?*

The demand for both Gall&Gall demand profiles is very similar, with a limited number of items shifted from class B to class A during peak demand. Overall, the peak demand performs better, with a mean difference of 10 orders handled in the simulation duration of 30 minutes. The difference for the lowest performing configurations from both demand profiles is 16 orders handled and for the best performing configuration 5 orders handled.

The case study results indicate the highest performance when class A is not maximally distributed for both demand profiles. Optimal performance is also not achieved with the configuration where items per pod are equal across all classes. This is notable, as most demand profiles analysed in Chapter 4 show high performance for both maximising pods for class A and distributing items per pod equally.

The top in the ternary plot has configurations where class A and C are distributed over the minimum number of pods and class B maximally. This configuration shows low performance, aligning with the results from Chapter 4.

The Gall&Gall demand profiles show performance similar to the demand profiles from Chapter 4, with better performance compared to demand profile DP_A and DP_B, but lower performance than for demand profile DP_E and DP_F. The performance difference between demand profiles DP_E, DP_F, and the Gall&Gall demand profiles might be attributed to the differences in the classification of classes A, B, and C. For demand profile DP_E, class A and B consist of 10 SKUs and class C of 80 SKUs, while demand profile DP_F has 20 SKUs in class A and 40 in B and C, which is more similar to the classification for Gall&Gall of 20 SKUs in class A, 30 in class B and 50 in class C.
The significantly higher performance with demand profile DP_E compared to DP_F and the demand from Gall&Gall supports that the classification impacts the performance. Where demand profiles with fewer SKUs in class A and more SKUs in class C perform better.

The class separation on 30% and 50% of SKUs for the Gall&Gall demand is new compared to the 10%, 20% and 20%, 60% classification from Chapter 4. This might also be the underlying reason why optimal performance is not in the lower right corner where class A is maximally distributed but more towards the maximum distribution of class B.

In conclusion, while the maximum distribution of class B shows low performance for both Gall&Gall demand profiles, the slotting configuration with the best performance depends on the specific demand profile.

The optimal order-picking efficiency is demand profile specific, and can be read from the ternary plots in Figures 5.10 for the regular order demand and in Figure 5.11 for the peak order demand.

When the order demand shifts towards more SKUs in class A and fewer in class B with the peak demand, slotting configurations where class A is distributed over more pods and class B over fewer pods (towards the lower right of the plot) perform better compared to the regular demand. Therefore, as the order demand increases for SKUs in class A, slotting configurations that allocate more pods to class A show improved performance.

The results of the ternary plots are interpreted as slotting advice for Gall&Gall. The optimal picking efficiency for the regular order demand is reached with a slotting configuration where the SKUs in class A are distributed over 5.4 pods on average, the SKUs in class B are distributed over 2.8 pods on average, and the SKUs in class C are distributed over 1 pod.
When the regular order demand transforms to peak order demand, the optimal slotting changes accordingly. The scenario with the best performance is where class A shifts towards a distribution over 4.6 pods on average and a distribution of 3.3 pods on average for class B.

However, the performance of the scenarios where class A is distributed over more pods also increases. Two interesting slotting approaches emerge when the demand shifts to peak demand.

The first approach focuses on achieving the best possible performance, but only a relatively small number of scenarios meet this optimal performance. This approach is beneficial when slottings are configured with high accuracy.

The second approach aims for a wider range of scenarios where performance is not as high as the optimal slotting scenario but still improved compared to regular demand. Distributing class A over more than 6 pods on average yields a broad range of scenarios, all of which show increased performance when compared to the regular demand profile and relatively good performance when compared to the other scenarios for the peak demand profile. When achieving a single specific optimal scenario is challenging, this broader approach might be more practical, as it provides more flexibility and a higher likelihood of improved performance.

Additionally, the results show that the scenarios where class A is distributed over approximately 4.8 pods and class B over 3.2 pods result in a relatively high performance for both demand profiles. This information is valuable when evaluating the benefits and the costs of adjusting the slotting approach.

When adjusting the slotting approach proves costly, it might be beneficial to maintain the same slotting approach for both demand profiles. The results for both demand profiles present this as a viable option and provide necessary and valuable insights to make this trade-off.

The results indicate that slotting configurations can lead to a performance increase of approximately 5% for the regular Gall&Gall demand, increasing from 470 to 495 orders handled in 30 minutes. If the number of robots, pods, and workstations are scaled up appropriately and do not become limiting factors, for instance, handling 470 orders with 1,000 items could potentially scale to approximately 11,750 orders with 25,000 items, provided the system scales linearly, and other operational constraints are managed. The projected 5% performance increase is a performance difference of 590 orders per 30 minutes. This underscores the potential impact of optimising slotting configurations.

5.6. Limitations Specific to Gall&Gall Case Study

This case study is executed with models, which, by definition, are a simplification of reality and rely on assumptions regarding the data input. Recognising these limitations on realism and applicability is important for proper result interpretation.

The total item demand and total number of SKUs are configured similarly to the configurations in Chapter 4. This means the demand per SKU ratio for Gall&Gall is adjusted. The original ratio for Gall&Gall is 55 items per SKU, averaged over a day or over a month. For the regular demand, this means that 100 SKUs, as used in Section 3.2, are associated with a demand of 5500 items. This ratio was adjusted for configurations with equal demand to fit the configuration of the ratio of 10 items per SKU. The percentage of SKUs accounting for the percentage of demand is according to the order demand of Gall&Gall.

For the Gall&Gall demand, popularity changes are considered using demand data over a single month for both peak and regular demand. However, demand characteristics may vary on different days or months, simplifying the regular demand profile of a specific month. The peak demand data is generalised for the entire month, while specific days exhibit even more extreme peaks. Consequently, specific daily demand profiles could reveal different optimal slotting decisions.

The performance difference between regular-demand slotting configurations is 24 orders handled, with an average standard deviation of 15 orders handled for all weight configurations. The difference for peak demand is 14 orders handled, with an average standard deviation of 14. The observed trends might be less reliable and conclusive because the standard deviation is relatively high and of similar size to the difference between maximum and minimum results.

6 Conclusions and Recommendations

This chapter explains the results of the previous chapter regarding the main research question. Additionally, the assumptions and limitations of these conclusions and results are discussed, after which possible and interesting topics for further research are discussed, both to decrease the limitations and broaden the research scope.

6.1. Conclusion

The analysis of various demand profiles and slotting configurations shows the impact of demand-based slotting decisions on the order throughput rate in a Robotic Mobile Fulfilment System (RMFS). The key findings from both the synthetic demand profiles and the demand profiles from Gall&Gall converge to answer the main research question: *What is the impact of demand-based slotting decisions on the order throughput rate for different demand configurations in an RMFS?*

The results from the synthetic demand and Gall&Gall demand consistently show that both pile-on and travel distance significantly affect the order throughput rate, independent of the specific demand profile. Where the specific slotting configuration leads to substantial variations in the number of orders handled, with differences of up to 200 orders observed over 30 minutes.

The performance from the synthetic demand and the Gall&Gall demand consistently show that class A, B and C demand classification affects the order throughput. Classifications with less SKUs in class A and more SKUs in class C, such as demand profiles *De* and *Df*, consistently perform better than the same demand with different classifications.

The analysis reveals that configurations aiming for an equal number of items per pod across classes perform well. This balance often aligns closely with high-performing configurations, which typically cluster around the lower right corner of ternary plots for the synthetic demand profiles, which represents slotting with maximum pods for class A and minimal pods for classes B and C. This makes it challenging to determine whether the origin of the high performance is due to maximum pods for class A or equal items per pod for all classes.
In the lower-left corner of ternary plots, poor performance is observed when class C is maximally distributed, and class A is minimally distributed. Generally, low performance is also seen at the top of the ternary plot, where class B is configured with maximum pods and class A and C minimum. However, this is not true for all demand profiles.
These observations indicate that the distribution of class A is crucial for the performance.

The Gall&Gall demand profiles did not achieve optimal performance with maximum pods for class A or equal items per pod, differing from the synthetic demand profiles. Instead, configurations with slightly increased pods for class B performed better, suggesting that optimal slotting decisions vary depending on the specific demand characteristics.

Both the synthetic demand profiles and the Gall&Gall demand profiles highlight that demand-based slotting decisions significantly impact order throughput rates in RMFS. Demand profiles with less high-turnover SKUs (class A) and more lower-turnover SKUs (class C) tend to perform best. However, the optimal slotting strategy varies depending on the specific demand characteristics.

Achieving a balance in items per pod for the three classes and maximising the pods per SKU for class A often leads to high performance. However, these strategies do not hold for all demand profiles, as they did not for the demand of Gall&Gall.
This study underscores the importance of tailored slotting configurations to optimise throughput based on specific demand characteristics, ultimately enhancing operational efficiency.

6.1.1. Practical Value and Implementation

Based on the results of the demand profiles evaluated in this research, working with the right slotting configuration can facilitate an efficiency difference of up to 40 orders handled in 30 minutes, representing a 10% efficiency increase compared to the worst-performing slotting configuration for that demand profile.

This efficiency improvement is implemented by adjusting the number of pods per SKU per class according to the performance results of a specific demand profile.

In addition to providing Gall&Gall with specific demand-based slotting insights, this research provides a method that can be used by warehouses in general, to gain specific insights into the impact of various demand-based slotting configurations by using demand profiles specific to their order demand. These insights are crucial for making informed decisions about slotting approaches.

Warehouses can use these findings to determine an appropriate slotting strategy, whether dealing with a consistent demand profile throughout the year or varying demand profiles. The results of different demand profiles enable evaluation of the correlation of the results. This can be used to determine an approach to best accommodate all demand profiles, whether that is switching between slotting approaches based on circumstances or designing a single approach based on the gained insights that best accommodates the different demand profiles. It provides insights valuable for weighing the benefits against the costs of an approach, weighing multiple approaches against each other, or designing a combination of certain approaches.

The developed method easily extends beyond the focus on a tailored slotting approach based on demand specifics. Modification of the simulation configurations allows elaboration on the specificity and scope of this research.

By enabling the integration of warehouse-specific details in addition to order demand specifics, such as a warehouse's unique layout, the method enhances applicability and realism, ensuring that the slotting strategy is finely tuned to the specific warehouse conditions. Moreover, ability to integrate additional decision problems, such as order-batching and routing, expands the scope of the method, offering more comprehensive and complete decision-making insights. By considering slotting decisions in combination with various decision problem approaches, warehouses can develop more robust and effective strategies. Increasing the system's adaptability, the ability to accurately estimate performance under different conditions, and increase overall operations coordination and strategy.

This dual enhancement, increasing specificity and broadening the scope, enables the slotting approach to be more accurate and more versatile in addressing more complex operational scenarios.

6.2. Considerations, Limitations and Assumptions

This research operates under several assumptions and simplifications may affect the realism and applicability of the results. Recognising these limitations is essential to interpret and implement the findings correctly. This section describes the study's limits and necessary considerations and explains their effect on the results.

6.2.1. Demand Profile Considerations

The demand configurations used in this study significantly simplify real-world demand by categorising it into three classes. This reduction in demand variability might affect the performance since the results indicate that differences between demand classes impact the optimal slotting decisions and overall demand performance. Classification deviations from the configurations used in this research will influence performance outcomes.

Additionally, the study uses a fixed demand profile with 100 SKUs and 1000 items, which is not representative of all real-world situations, as demand is highly dependent on the retail sector and specific warehouse characteristics. Adjusting the number of items per SKU alters optimal slotting results.

The synthetic demand is modelled using three typical demand curves from the literature, representing specific demand configurations. These may not be relevant for warehouses where the demand highly deviates from these demand profiles and these demand parameters.

6.2.2. Slotting Considerations

The parameters for slotting items in pods are simplified in terms of variety and size. A maximum of four different SKUs per pod is set to analyse the impact of slotting decisions on pile-on. Additionally, a fixed pod capacity of 60 items is used, while realistic pod capacity varies depending on item and pod sizes. These parameter configurations may affect performance and alter conclusions. For example, allowing only two different SKUs per pod might affect optimal prioritisation decisions and their impact.

The slotting configuration model utilises weight factors to drive specific configurations. However, in some cases, these weight factor configurations do not result in the desired slotting configuration and may produce identical slotting configurations for different weight configurations. Additionally, the step size of the weights may not align with the steps in resulting slotting configurations, limiting the distribution consistency and variety of slotting configurations. Restricting the variety in slotting configurations limits the range of simulated and observed configurations and their performance.

6.2.3. Simulation Considerations

Simulation approaches can accurately mimic reality and minimise errors, while analytical approaches are less time-consuming and useful in the early design phases when exploring solution and configuration spaces (Azadeh et al., 2017). Using a simulation tool for performance evaluation requires many decisions about configurations beyond the study's scope, potentially affecting the generality of the results.

One significant limitation is the exclusion of replenishment in the simulation. Slotting decisions are closely related to replenishment since the benefits of slotting are often measured in terms of picking efficiency and replenishment costs. For example, placing one SKU on multiple pods might improve order-picking time but worsen replenishment time. The slotting decision impacts both aspects, often requiring a trade-off. Replenishment considerations are not included in the scope of this research. Including replenishment would provide a more accurate assessment of whether the overall costs and benefits of slotting decisions result in a positive outcome or if adjustments are needed.
However, the impact of neglecting replenishment depends on the demand type. With stochastic demand, replenishment tasks are executed multiple times a day. In contrast, with deterministic demand, replenishment might be reduced to a daily task. Since this study assumes deterministic demand, the impact of neglecting replenishment decreases.

Assuming deterministic demand implies frequent replenishment is unnecessary, making continuous simulation towards stock-out situations realistic. The current simulation duration is 30 minutes to avoid stock-out situations, as frequent replenishment in a stochastic order demand scenario prevents stock-out.

As the simulation progresses towards stock-out, the pods will contain less different SKUs, and the number of available pods for assignment to orders diminishes, decreasing pile-on and increasing travel distance. When assuming deterministic demand, the simulation shows only the best-performing interval, where realistic performance is expected to decrease towards the low-performing configurations.

Simulation configurations, such as warehouse layout, number of robots, distances, item picking times, and order generation, are set uniformly. Orders are generated with a uniform distribution of 1 to 3 SKUs per order, each containing 1 or 2 items. The primary performance metric is the number of orders handled, though order content varies. Differences in the number of orders handled could be due to variations in order content. However, using multiple random simulation seeds where order generation differs for each reduces the likelihood of this variation affecting the results.
Additionally, the generation of orders with 1 to 3 SKUs might influence performance, as order characteristics impact pile-on quantity. For example, orders containing more items benefit more from pile-on enhancing slotting methods. Therefore, results depend on the assumed order generation. Since orders with more items are expected to increase pile-on, the results found in this study will likely have increased performance on orders with more than 1 to 3 SKUs.

The difference in performance between the best and worst-performing slotting configurations for certain demand profiles is similar to the standard deviation found in simulations for those distributions. For example, in demand profile *Df*, the performance difference between the best and worst configurations is 10 orders. In comparison, the mean standard deviation across all configurations is 12.6 orders, exceeding the maximum performance difference. This suggests that some results and trends may not be conclusive.

6.3. Recommendations for Further Research

This section's recommendations for further research pursue two objectives: refining result specification and extending the research scope.

6.3.1. Recommendations for Result Specification

To refine result specificity, it is crucial to delve deeper into several aspects. Firstly, evaluating demand profiles with minimal differences will help isolate the factors responsible for performance changes. The specific impacts of altering individual variables can be discerned by analysing turnover and classification variations separately across three classes.

Additionally, studying the isolated impact of classification methods presents an interesting opportunity. Comparing results between dedicated storage for each SKU and simplified classification into three classes will provide insights into optimising storage strategies. Exploration of intermediary strategies, such as the effect of deciding the slotting configuration of the demand with class-based simplification and simulating the original demand without classification, will further provide insights into the practical implications of classification methods.

Another critical area for exploration is assessing the performance implications of selecting the wrong slotting configuration. Understanding how inaccuracies between the demand used to find the optimal slotting configuration and the actual demand affect performance is essential when working with demand forecasts. By comparing outcomes between dedicated storage and class-based storage policies under varying levels of forecast certainty, robust approaches can minimise performance disruptions due to forecasting errors. For instance, dedicated storage may perform better with highly accurate forecasts but could under-perform compared to class-based storage with even slight deviations in forecast accuracy.

6.3.2. Recommendations for Scope Extension

A possible expansion of the research scope involves transitioning from deterministic to stochastic demand environments. This shift moves the research focus towards operational levels where demand is stochastic, aligning with the supply chain challenge of limited research regarding stochastic demand (de Koster et al., 2007).

Furthermore, researching the slotting decision problem on an operational level allows the integration of replenishment, which represents a significant extension of the research. Exploring the trade-off between replenishment and picking time in the slotting decision problem provides valuable insights.

In Chapter 1 and 2, it was stated that the slotting decision problem consists of three main decisions: How to distribute SKUs over pods, what the quantity of a SKU on a pod should be, and which SKUs to combine on a pod.
Completing the slotting decision problem by extending this research towards insights on optimal SKU quantities per pod and optimising SKU combinations on pods provides a comprehensive understanding of the slotting decision problem with RMFS. Analysing the impact of individual decision components and exploring synergies between them will support maximising overall operational performance.

Enhancing the RawSim-O simulation tool with an integrated slotting module rather than the sequential use of a separate slotting model and a simulation model is pivotal for both result specification and scope extension. This allows comprehensible integration of slotting and other decision problems regarding layout, settings, and controller configuration variations.

A

Slotting Results per Demand Profile

A.1. Slotting Results DP_A

Table A.1: Slotting Results with Demand Profile DP_A

Weights $[w_A, w_B, w_C]$	Distribution (pods/item) $[z_A, z_B, z_C]$	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 0.052, 0.052]	[0.0983, 0.7, 0.3531]	[10.1754, 1.4286, 2.8319]	[5.7, 7.0, 1.4125]	1
[1.0, 0.052, 0.052]	[0.1, 0.13, 0.5281]	[10.0, 7.6923, 1.8935]	[5.8, 1.3, 2.1125]	1
[1.0, 0.052, 0.052]	[0.0862, 0.15, 0.5469]	[11.6, 6.6667, 1.8286]	[5.0, 1.5, 2.1875]	2
[1.0, 0.052, 0.052]	[0.0966, 0.12, 0.5375]	[10.3571, 8.3333, 1.8605]	[5.6, 1.2, 2.15]	3
[1.0, 0.052, 0.381]	[0.0983, 1.0, 0.2594]	[10.1754, 1.0, 3.8554]	[5.7, 10.0, 1.0375]	1
[1.0, 0.052, 0.381]	[0.0983, 1.0, 0.2594]	[10.1754, 1.0, 3.8554]	[5.7, 10.0, 1.0375]	2
[1.0, 0.052, 0.381]	[0.0983, 1.0, 0.2594]	[10.1754, 1.0, 3.8554]	[5.7, 10.0, 1.0375]	3
[1.0, 0.052, 0.71]	[0.1034, 1.0, 0.25]	[9.6667, 1.0, 4.0]	[6.0, 10.0, 1.0]	1
[1.0, 0.052, 0.71]	[0.1034, 1.0, 0.25]	[9.6667, 1.0, 4.0]	[6.0, 10.0, 1.0]	2
[1.0, 0.052, 0.71]	[0.1034, 1.0, 0.25]	[9.6667, 1.0, 4.0]	[6.0, 10.0, 1.0]	3
[1.0, 0.052, 1.039]	[0.1034, 1.0, 0.25]	[9.6667, 1.0, 4.0]	[6.0, 10.0, 1.0]	1
[1.0, 0.052, 1.039]	[0.1034, 1.0, 0.25]	[9.6667, 1.0, 4.0]	[6.0, 10.0, 1.0]	2
[1.0, 0.052, 1.039]	[0.1034, 1.0, 0.25]	[9.6667, 1.0, 4.0]	[6.0, 10.0, 1.0]	3
[1.0, 1.0, 1.0]	[0.2362, 0.23, 0.25]	[4.2336, 4.3478, 4.0]	[13.7, 2.3, 1.0]	1
[1.0, 1.0, 1.0]	[0.2362, 0.23, 0.25]	[4.2336, 4.3478, 4.0]	[13.7, 2.3, 1.0]	2
[1.0, 1.0, 1.0]	[0.2362, 0.23, 0.25]	[4.2336, 4.3478, 4.0]	[13.7, 2.3, 1.0]	3
[1.0, 10.0, 0.052]	[0.0862, 0.13, 0.5531]	[11.6, 7.6923, 1.8079]	[5.0, 1.3, 2.2125]	1
[1.0, 10.0, 0.052]	[0.0948, 0.12, 0.5406]	[10.5455, 8.3333, 1.8497]	[5.5, 1.2, 2.1625]	2
[1.0, 10.0, 0.052]	[0.0983, 0.1, 0.5406]	[10.1754, 10.0, 1.8497]	[5.7, 1.0, 2.1625]	3
[1.0, 10.0, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	1
[1.0, 10.0, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	2
[1.0, 10.0, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	3
[1.0, 10.0, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	1
[1.0, 10.0, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	2
[1.0, 10.0, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	3
[1.0, 10.0, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	1
[1.0, 10.0, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	2
[1.0, 10.0, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	3
[1.0, 2.0416, 0.052]	[0.1, 0.43, 0.4344]	[10.0, 2.3256, 2.3022]	[5.8, 4.3, 1.7375]	1
[1.0, 2.0416, 0.052]	[0.1345, 0.66, 0.3]	[7.4359, 1.5152, 3.3333]	[7.8, 6.6, 1.2]	2
[1.0, 2.0416, 0.052]	[0.0948, 0.56, 0.4031]	[10.5455, 1.7857, 2.4806]	[5.5, 5.6, 1.6125]	3
[1.0, 2.0416, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	1
[1.0, 2.0416, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	2

Table A.1 continued from previous page

Weights $[w_A, w_B, w_C]$	Distribution (pods/item) $[z_A, z_B, z_C]$	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 2.0416, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	3
[1.0, 2.0416, 0.71]	[0.2224, 0.11, 0.3125]	[4.4961, 9.0909, 3.2]	[12.9, 1.1, 1.25]	1
[1.0, 2.0416, 0.71]	[0.2224, 0.11, 0.3125]	[4.4961, 9.0909, 3.2]	[12.9, 1.1, 1.25]	2
[1.0, 2.0416, 0.71]	[0.2224, 0.11, 0.3125]	[4.4961, 9.0909, 3.2]	[12.9, 1.1, 1.25]	3
[1.0, 2.0416, 1.039]	[0.2552, 0.12, 0.25]	[3.9189, 8.3333, 4.0]	[14.8, 1.2, 1.0]	1
[1.0, 2.0416, 1.039]	[0.2552, 0.12, 0.25]	[3.9189, 8.3333, 4.0]	[14.8, 1.2, 1.0]	2
[1.0, 2.0416, 1.039]	[0.2552, 0.12, 0.25]	[3.9189, 8.3333, 4.0]	[14.8, 1.2, 1.0]	3
[1.0, 4.0312, 0.052]	[0.0983, 0.74, 0.3406]	[10.1754, 1.3514, 2.9358]	[5.7, 7.4, 1.3625]	1
[1.0, 4.0312, 0.052]	[0.0931, 0.88, 0.3063]	[10.7407, 1.1364, 3.2653]	[5.4, 8.8, 1.225]	2
[1.0, 4.0312, 0.052]	[0.1052, 0.52, 0.3969]	[9.5082, 1.9231, 2.5197]	[6.1, 5.2, 1.5875]	3
[1.0, 4.0312, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	1
[1.0, 4.0312, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	2
[1.0, 4.0312, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	3
[1.0, 4.0312, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	1
[1.0, 4.0312, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	2
[1.0, 4.0312, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	3
[1.0, 4.0312, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	1
[1.0, 4.0312, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	2
[1.0, 4.0312, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	3
[1.0, 6.0208, 0.052]	[0.1017, 0.1, 0.5344]	[9.8305, 10.0, 1.8713]	[5.9, 1.0, 2.1375]	1
[1.0, 6.0208, 0.052]	[0.0862, 0.13, 0.5531]	[11.6, 7.6923, 1.8079]	[5.0, 1.3, 2.2125]	2
[1.0, 6.0208, 0.052]	[0.0914, 0.13, 0.5437]	[10.9434, 7.6923, 1.8391]	[5.3, 1.3, 2.175]	3
[1.0, 6.0208, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	1
[1.0, 6.0208, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	2
[1.0, 6.0208, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	3
[1.0, 6.0208, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	1
[1.0, 6.0208, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	2
[1.0, 6.0208, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	3
[1.0, 6.0208, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	1
[1.0, 6.0208, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	2
[1.0, 6.0208, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	3
[1.0, 8.0104, 0.052]	[0.2086, 0.1, 0.3406]	[4.7934, 10.0, 2.9358]	[12.1, 1.0, 1.3625]	1
[1.0, 8.0104, 0.052]	[0.0931, 0.11, 0.5469]	[10.7407, 9.0909, 1.8286]	[5.4, 1.1, 2.1875]	2
[1.0, 8.0104, 0.052]	[0.1293, 0.1, 0.4844]	[7.7333, 10.0, 2.0645]	[7.5, 1.0, 1.9375]	3
[1.0, 8.0104, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	1
[1.0, 8.0104, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	2
[1.0, 8.0104, 0.381]	[0.1621, 0.1, 0.425]	[6.1702, 10.0, 2.3529]	[9.4, 1.0, 1.7]	3
[1.0, 8.0104, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	1
[1.0, 8.0104, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	2
[1.0, 8.0104, 0.71]	[0.2241, 0.1, 0.3125]	[4.4615, 10.0, 3.2]	[13.0, 1.0, 1.25]	3
[1.0, 8.0104, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	1
[1.0, 8.0104, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	2
[1.0, 8.0104, 1.039]	[0.2586, 0.1, 0.25]	[3.8667, 10.0, 4.0]	[15.0, 1.0, 1.0]	3

A.2. Slotting Results DP_B

Table A.2: Slotting Results with Demand Profile DP_B

Weights $[w_A, w_B, w_C]$	Distribution (pods/item) $[z_A, z_B, z_C]$	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 0.059, 0.059]	[0.1044, 0.27, 0.9583]	[9.5775, 3.7037, 1.0435]	[3.55, 1.35, 2.875]	1
[1.0, 0.059, 0.059]	[0.1044, 0.61, 0.3917]	[9.5775, 1.6393, 2.5532]	[3.55, 3.05, 1.175]	2
[1.0, 0.059, 0.059]	[0.1206, 0.39, 0.6667]	[8.2927, 2.5641, 1.5]	[4.1, 1.95, 2.0]	3
[1.0, 0.059, 0.304]	[0.1074, 0.625, 0.35]	[9.3151, 1.6, 2.8571]	[3.65, 3.125, 1.05]	1
[1.0, 0.059, 0.304]	[0.1176, 0.465, 0.5583]	[8.5, 2.1505, 1.791]	[4.0, 2.325, 1.675]	2
[1.0, 0.059, 0.304]	[0.2103, 0.22, 0.4417]	[4.7552, 4.5455, 2.2642]	[7.15, 1.1, 1.325]	3
[1.0, 0.059, 0.549]	[0.1088, 0.385, 0.7417]	[9.1892, 2.5974, 1.3483]	[3.7, 1.925, 2.225]	1
[1.0, 0.059, 0.549]	[0.1132, 0.415, 0.6667]	[8.8312, 2.4096, 1.5]	[3.85, 2.075, 2.0]	2
[1.0, 0.059, 0.549]	[0.1956, 0.305, 0.3833]	[5.1128, 3.2787, 2.6087]	[6.65, 1.525, 1.15]	3
[1.0, 0.059, 0.794]	[0.2176, 0.24, 0.3667]	[4.5946, 4.1667, 2.7273]	[7.4, 1.2, 1.1]	1
[1.0, 0.059, 0.794]	[0.1338, 0.535, 0.35]	[7.4725, 1.8692, 2.8571]	[4.55, 2.675, 1.05]	2
[1.0, 0.059, 0.794]	[0.1265, 0.37, 0.6667]	[7.907, 2.7027, 1.5]	[4.3, 1.85, 2.0]	3
[1.0, 0.3062, 0.059]	[0.0897, 0.295, 1.0]	[11.1475, 3.3898, 1.0]	[3.05, 1.475, 3.0]	1
[1.0, 0.3062, 0.059]	[0.0897, 0.295, 1.0]	[11.1475, 3.3898, 1.0]	[3.05, 1.475, 3.0]	2
[1.0, 0.3062, 0.059]	[0.0897, 0.295, 1.0]	[11.1475, 3.3898, 1.0]	[3.05, 1.475, 3.0]	3
[1.0, 0.3062, 0.304]	[0.1382, 0.455, 0.4583]	[7.234, 2.1978, 2.1818]	[4.7, 2.275, 1.375]	1
[1.0, 0.3062, 0.304]	[0.1382, 0.455, 0.4583]	[7.234, 2.1978, 2.1818]	[4.7, 2.275, 1.375]	2
[1.0, 0.3062, 0.304]	[0.1382, 0.455, 0.4583]	[7.234, 2.1978, 2.1818]	[4.7, 2.275, 1.375]	3
[1.0, 0.3062, 0.549]	[0.15, 0.49, 0.3333]	[6.6667, 2.0408, 3.0]	[5.1, 2.45, 1.0]	1
[1.0, 0.3062, 0.549]	[0.15, 0.49, 0.3333]	[6.6667, 2.0408, 3.0]	[5.1, 2.45, 1.0]	2
[1.0, 0.3062, 0.549]	[0.15, 0.49, 0.3333]	[6.6667, 2.0408, 3.0]	[5.1, 2.45, 1.0]	3
[1.0, 0.3062, 0.794]	[0.15, 0.49, 0.3333]	[6.6667, 2.0408, 3.0]	[5.1, 2.45, 1.0]	1
[1.0, 0.3062, 0.794]	[0.15, 0.49, 0.3333]	[6.6667, 2.0408, 3.0]	[5.1, 2.45, 1.0]	2
[1.0, 0.3062, 0.794]	[0.15, 0.49, 0.3333]	[6.6667, 2.0408, 3.0]	[5.1, 2.45, 1.0]	3
[1.0, 0.5534, 0.059]	[0.1147, 0.21, 1.0]	[8.7179, 4.7619, 1.0]	[3.9, 1.05, 3.0]	1
[1.0, 0.5534, 0.059]	[0.1147, 0.21, 1.0]	[8.7179, 4.7619, 1.0]	[3.9, 1.05, 3.0]	2
[1.0, 0.5534, 0.059]	[0.1147, 0.21, 1.0]	[8.7179, 4.7619, 1.0]	[3.9, 1.05, 3.0]	3
[1.0, 0.5534, 0.304]	[0.1676, 0.3, 0.55]	[5.9649, 3.3333, 1.8182]	[5.7, 1.5, 1.65]	1
[1.0, 0.5534, 0.304]	[0.1676, 0.3, 0.55]	[5.9649, 3.3333, 1.8182]	[5.7, 1.5, 1.65]	2
[1.0, 0.5534, 0.304]	[0.1676, 0.3, 0.55]	[5.9649, 3.3333, 1.8182]	[5.7, 1.5, 1.65]	3
[1.0, 0.5534, 0.549]	[0.1897, 0.345, 0.35]	[5.2713, 2.8986, 2.8571]	[6.45, 1.725, 1.05]	1
[1.0, 0.5534, 0.549]	[0.1897, 0.345, 0.35]	[5.2713, 2.8986, 2.8571]	[6.45, 1.725, 1.05]	2
[1.0, 0.5534, 0.549]	[0.1897, 0.345, 0.35]	[5.2713, 2.8986, 2.8571]	[6.45, 1.725, 1.05]	3
[1.0, 0.5534, 0.794]	[0.1926, 0.345, 0.3333]	[5.1908, 2.8986, 3.0]	[6.55, 1.725, 1.0]	1
[1.0, 0.5534, 0.794]	[0.1926, 0.345, 0.3333]	[5.1908, 2.8986, 3.0]	[6.55, 1.725, 1.0]	2
[1.0, 0.5534, 0.794]	[0.1926, 0.345, 0.3333]	[5.1908, 2.8986, 3.0]	[6.55, 1.725, 1.0]	3
[1.0, 0.8006, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	1
[1.0, 0.8006, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	2
[1.0, 0.8006, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	3
[1.0, 0.8006, 0.304]	[0.1809, 0.225, 0.6]	[5.5285, 4.4444, 1.6667]	[6.15, 1.125, 1.8]	1
[1.0, 0.8006, 0.304]	[0.1809, 0.225, 0.6]	[5.5285, 4.4444, 1.6667]	[6.15, 1.125, 1.8]	2
[1.0, 0.8006, 0.304]	[0.1809, 0.225, 0.6]	[5.5285, 4.4444, 1.6667]	[6.15, 1.125, 1.8]	3
[1.0, 0.8006, 0.549]	[0.2088, 0.26, 0.3833]	[4.7887, 3.8462, 2.6087]	[7.1, 1.3, 1.15]	1
[1.0, 0.8006, 0.549]	[0.2088, 0.26, 0.3833]	[4.7887, 3.8462, 2.6087]	[7.1, 1.3, 1.15]	2
[1.0, 0.8006, 0.549]	[0.2088, 0.26, 0.3833]	[4.7887, 3.8462, 2.6087]	[7.1, 1.3, 1.15]	3
[1.0, 0.8006, 0.794]	[0.2147, 0.27, 0.3333]	[4.6575, 3.7037, 3.0]	[7.3, 1.35, 1.0]	1
[1.0, 0.8006, 0.794]	[0.2147, 0.27, 0.3333]	[4.6575, 3.7037, 3.0]	[7.3, 1.35, 1.0]	2
[1.0, 0.8006, 0.794]	[0.2147, 0.27, 0.3333]	[4.6575, 3.7037, 3.0]	[7.3, 1.35, 1.0]	3
[1.0, 1.0, 1.0]	[0.2279, 0.225, 0.3333]	[4.3871, 4.4444, 3.0]	[7.75, 1.125, 1.0]	1
[1.0, 1.0, 1.0]	[0.2279, 0.225, 0.3333]	[4.3871, 4.4444, 3.0]	[7.75, 1.125, 1.0]	2

Table A.2 continued from previous page

Weights $[w_A, w_B, w_C]$	**Distribution (pods/item)** $[z_A, z_B, z_C]$	**Distribution (items/pod) [A, B, C]**	**Distribution (pods/SKU) [A, B, C]**	**Seed**
[1.0, 1.0, 1.0]	[0.2279, 0.225, 0.3333]	[4.3871, 4.4444, 3.0]	[7.75, 1.125, 1.0]	3
[1.0, 1.0478, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	1
[1.0, 1.0478, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	2
[1.0, 1.0478, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	3
[1.0, 1.0478, 0.304]	[0.1868, 0.2, 0.6083]	[5.3543, 5.0, 1.6438]	[6.35, 1.0, 1.825]	1
[1.0, 1.0478, 0.304]	[0.1868, 0.2, 0.6083]	[5.3543, 5.0, 1.6438]	[6.35, 1.0, 1.825]	2
[1.0, 1.0478, 0.304]	[0.1868, 0.2, 0.6083]	[5.3543, 5.0, 1.6438]	[6.35, 1.0, 1.825]	3
[1.0, 1.0478, 0.549]	[0.2206, 0.21, 0.4]	[4.5333, 4.7619, 2.5]	[7.5, 1.05, 1.2]	1
[1.0, 1.0478, 0.549]	[0.2206, 0.21, 0.4]	[4.5333, 4.7619, 2.5]	[7.5, 1.05, 1.2]	2
[1.0, 1.0478, 0.549]	[0.2206, 0.21, 0.4]	[4.5333, 4.7619, 2.5]	[7.5, 1.05, 1.2]	3
[1.0, 1.0478, 0.794]	[0.2294, 0.22, 0.3333]	[4.359, 4.5455, 3.0]	[7.8, 1.1, 1.0]	1
[1.0, 1.0478, 0.794]	[0.2294, 0.22, 0.3333]	[4.359, 4.5455, 3.0]	[7.8, 1.1, 1.0]	2
[1.0, 1.0478, 0.794]	[0.2294, 0.22, 0.3333]	[4.359, 4.5455, 3.0]	[7.8, 1.1, 1.0]	3
[1.0, 1.295, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	1
[1.0, 1.295, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	2
[1.0, 1.295, 0.059]	[0.1176, 0.2, 1.0]	[8.5, 5.0, 1.0]	[4.0, 1.0, 3.0]	3
[1.0, 1.295, 0.304]	[0.1868, 0.2, 0.6083]	[5.3543, 5.0, 1.6438]	[6.35, 1.0, 1.825]	1
[1.0, 1.295, 0.304]	[0.1868, 0.2, 0.6083]	[5.3543, 5.0, 1.6438]	[6.35, 1.0, 1.825]	2
[1.0, 1.295, 0.304]	[0.1868, 0.2, 0.6083]	[5.3543, 5.0, 1.6438]	[6.35, 1.0, 1.825]	3
[1.0, 1.295, 0.549]	[0.2221, 0.2, 0.4083]	[4.5033, 5.0, 2.449]	[7.55, 1.0, 1.225]	1
[1.0, 1.295, 0.549]	[0.2221, 0.2, 0.4083]	[4.5033, 5.0, 2.449]	[7.55, 1.0, 1.225]	2
[1.0, 1.295, 0.549]	[0.2221, 0.2, 0.4083]	[4.5033, 5.0, 2.449]	[7.55, 1.0, 1.225]	3
[1.0, 1.295, 0.794]	[0.2353, 0.2, 0.3333]	[4.25, 5.0, 3.0]	[8.0, 1.0, 1.0]	1
[1.0, 1.295, 0.794]	[0.2353, 0.2, 0.3333]	[4.25, 5.0, 3.0]	[8.0, 1.0, 1.0]	2
[1.0, 1.295, 0.794]	[0.2353, 0.2, 0.3333]	[4.25, 5.0, 3.0]	[8.0, 1.0, 1.0]	3

A.3. Slotting Results DP_C

Table A.3: Slotting Results with Demand Profile DP_C

Weights [w_A, w_B, w_C]	Distribution (pods/item) [z_A, z_B, z_C]	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 0.058, 0.058]	[0.0913, 0.1857, 0.6833]	[10.9524, 5.3846, 1.4634]	[6.3, 1.3, 2.05]	1
[1.0, 0.058, 0.058]	[0.0957, 0.1857, 0.6708]	[10.4545, 5.3846, 1.4907]	[6.6, 1.3, 2.0125]	2
[1.0, 0.058, 0.058]	[0.0841, 0.2286, 0.6917]	[11.8966, 4.375, 1.4458]	[5.8, 1.6, 2.075]	3
[1.0, 0.058, 0.272]	[0.1072, 1.0, 0.4]	[9.3243, 1.0, 2.5]	[7.4, 7.0, 1.2]	1
[1.0, 0.058, 0.272]	[0.1072, 1.0, 0.4]	[9.3243, 1.0, 2.5]	[7.4, 7.0, 1.2]	2
[1.0, 0.058, 0.272]	[0.1072, 1.0, 0.4]	[9.3243, 1.0, 2.5]	[7.4, 7.0, 1.2]	3
[1.0, 0.058, 0.486]	[0.1304, 1.0, 0.3333]	[7.6667, 1.0, 3.0]	[9.0, 7.0, 1.0]	1
[1.0, 0.058, 0.486]	[0.1304, 1.0, 0.3333]	[7.6667, 1.0, 3.0]	[9.0, 7.0, 1.0]	2
[1.0, 0.058, 0.486]	[0.1304, 1.0, 0.3333]	[7.6667, 1.0, 3.0]	[9.0, 7.0, 1.0]	3
[1.0, 0.058, 0.7]	[0.1304, 1.0, 0.3333]	[7.6667, 1.0, 3.0]	[9.0, 7.0, 1.0]	1
[1.0, 0.058, 0.7]	[0.1304, 1.0, 0.3333]	[7.6667, 1.0, 3.0]	[9.0, 7.0, 1.0]	2
[1.0, 0.058, 0.7]	[0.1304, 1.0, 0.3333]	[7.6667, 1.0, 3.0]	[9.0, 7.0, 1.0]	3
[1.0, 1.0, 1.0]	[0.2101, 0.2143, 0.3333]	[4.7586, 4.6667, 3.0]	[14.5, 1.5, 1.0]	1
[1.0, 1.0, 1.0]	[0.2101, 0.2143, 0.3333]	[4.7586, 4.6667, 3.0]	[14.5, 1.5, 1.0]	2
[1.0, 1.0, 1.0]	[0.2101, 0.2143, 0.3333]	[4.7586, 4.6667, 3.0]	[14.5, 1.5, 1.0]	3
[1.0, 1.2638, 0.058]	[0.0841, 0.1857, 0.7042]	[11.8966, 5.3846, 1.4201]	[5.8, 1.3, 2.1125]	1
[1.0, 1.2638, 0.058]	[0.113, 0.4143, 0.5542]	[8.8462, 2.4138, 1.8045]	[7.8, 2.9, 1.6625]	2
[1.0, 1.2638, 0.058]	[0.0841, 0.1714, 0.7083]	[11.8966, 5.8333, 1.4118]	[5.8, 1.2, 2.125]	3
[1.0, 1.2638, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	1
[1.0, 1.2638, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	2
[1.0, 1.2638, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	3
[1.0, 1.2638, 0.486]	[0.1942, 0.1571, 0.3958]	[5.1493, 6.3636, 2.5263]	[13.4, 1.1, 1.1875]	1
[1.0, 1.2638, 0.486]	[0.1942, 0.1571, 0.3958]	[5.1493, 6.3636, 2.5263]	[13.4, 1.1, 1.1875]	2
[1.0, 1.2638, 0.486]	[0.1942, 0.1571, 0.3958]	[5.1493, 6.3636, 2.5263]	[13.4, 1.1, 1.1875]	3
[1.0, 1.2638, 0.7]	[0.2145, 0.1714, 0.3333]	[4.6622, 5.8333, 3.0]	[14.8, 1.2, 1.0]	1
[1.0, 1.2638, 0.7]	[0.2145, 0.1714, 0.3333]	[4.6622, 5.8333, 3.0]	[14.8, 1.2, 1.0]	2
[1.0, 1.2638, 0.7]	[0.2145, 0.1714, 0.3333]	[4.6622, 5.8333, 3.0]	[14.8, 1.2, 1.0]	3
[1.0, 2.4696, 0.058]	[0.0913, 0.1571, 0.6917]	[10.9524, 6.3636, 1.4458]	[6.3, 1.1, 2.075]	1
[1.0, 2.4696, 0.058]	[0.0928, 0.1429, 0.6917]	[10.7812, 7.0, 1.4458]	[6.4, 1.0, 2.075]	2
[1.0, 2.4696, 0.058]	[0.0783, 0.1714, 0.725]	[12.7778, 5.8333, 1.3793]	[5.4, 1.2, 2.175]	3
[1.0, 2.4696, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	1
[1.0, 2.4696, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	2
[1.0, 2.4696, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	3
[1.0, 2.4696, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	1
[1.0, 2.4696, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	2
[1.0, 2.4696, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	3
[1.0, 2.4696, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	1
[1.0, 2.4696, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	2
[1.0, 2.4696, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	3
[1.0, 3.6754, 0.058]	[0.0855, 0.1714, 0.7042]	[11.6949, 5.8333, 1.4201]	[5.9, 1.2, 2.1125]	1
[1.0, 3.6754, 0.058]	[0.0928, 0.1714, 0.6833]	[10.7812, 5.8333, 1.4634]	[6.4, 1.2, 2.05]	2
[1.0, 3.6754, 0.058]	[0.0855, 0.1857, 0.7]	[11.6949, 5.3846, 1.4286]	[5.9, 1.3, 2.1]	3
[1.0, 3.6754, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	1
[1.0, 3.6754, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	2
[1.0, 3.6754, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	3
[1.0, 3.6754, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	1
[1.0, 3.6754, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	2
[1.0, 3.6754, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	3
[1.0, 3.6754, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	1
[1.0, 3.6754, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	2

Table A.3 continued from previous page

Weights $[w_A, w_B, w_C]$	**Distribution (pods/item)** $[z_A, z_B, z_C]$	**Distribution (items/pod) [A, B, C]**	**Distribution (pods/SKU) [A, B, C]**	**Seed**
[1.0, 3.6754, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	3
[1.0, 4.8812, 0.058]	[0.1145, 0.4714, 0.5333]	[8.7342, 2.1212, 1.875]	[7.9, 3.3, 1.6]	1
[1.0, 4.8812, 0.058]	[0.0841, 0.1714, 0.7083]	[11.8966, 5.8333, 1.4118]	[5.8, 1.2, 2.125]	2
[1.0, 4.8812, 0.058]	[0.0826, 0.1714, 0.7125]	[12.1053, 5.8333, 1.4035]	[5.7, 1.2, 2.1375]	3
[1.0, 4.8812, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	1
[1.0, 4.8812, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	2
[1.0, 4.8812, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	3
[1.0, 4.8812, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	1
[1.0, 4.8812, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	2
[1.0, 4.8812, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	3
[1.0, 4.8812, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	1
[1.0, 4.8812, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	2
[1.0, 4.8812, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	3
[1.0, 6.087, 0.058]	[0.0957, 0.6429, 0.5375]	[10.4545, 1.5556, 1.8605]	[6.6, 4.5, 1.6125]	1
[1.0, 6.087, 0.058]	[0.0739, 0.1714, 0.7375]	[13.5294, 5.8333, 1.3559]	[5.1, 1.2, 2.2125]	2
[1.0, 6.087, 0.058]	[0.0855, 0.1714, 0.7042]	[11.6949, 5.8333, 1.4201]	[5.9, 1.2, 2.1125]	3
[1.0, 6.087, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	1
[1.0, 6.087, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	2
[1.0, 6.087, 0.272]	[0.1464, 0.1429, 0.5375]	[6.8317, 7.0, 1.8605]	[10.1, 1.0, 1.6125]	3
[1.0, 6.087, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	1
[1.0, 6.087, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	2
[1.0, 6.087, 0.486]	[0.1942, 0.1429, 0.4]	[5.1493, 7.0, 2.5]	[13.4, 1.0, 1.2]	3
[1.0, 6.087, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	1
[1.0, 6.087, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	2
[1.0, 6.087, 0.7]	[0.2174, 0.1429, 0.3333]	[4.6, 7.0, 3.0]	[15.0, 1.0, 1.0]	3

A.4. Slotting Results DP_D

Table A.4: Slotting Results with Demand Profile DP_D

Weights $[w_A, w_B, w_C]$	Distribution (pods/item) $[z_A, z_B, z_C]$	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 0.05, 0.05]	[0.1638, 0.425, 0.725]	[6.1069, 2.3529, 1.3793]	[6.55, 1.275, 1.45]	1
[1.0, 0.05, 0.05]	[0.185, 0.3583, 0.6125]	[5.4054, 2.7907, 1.6327]	[7.4, 1.075, 1.225]	2
[1.0, 0.05, 0.05]	[0.18, 0.4, 0.6]	[5.5556, 2.5, 1.6667]	[7.2, 1.2, 1.2]	3
[1.0, 0.05, 0.2133]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	1
[1.0, 0.05, 0.2133]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	2
[1.0, 0.05, 0.2133]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	3
[1.0, 0.05, 0.3767]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	1
[1.0, 0.05, 0.3767]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	2
[1.0, 0.05, 0.3767]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	3
[1.0, 0.05, 0.54]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	1
[1.0, 0.05, 0.54]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	2
[1.0, 0.05, 0.54]	[0.1, 1.0, 0.5]	[10.0, 1.0, 2.0]	[4.0, 3.0, 1.0]	3
[1.0, 0.198, 0.05]	[0.1137, 0.575, 1.0]	[8.7912, 1.7391, 1.0]	[4.55, 1.725, 2.0]	1
[1.0, 0.198, 0.05]	[0.1137, 0.575, 1.0]	[8.7912, 1.7391, 1.0]	[4.55, 1.725, 2.0]	2
[1.0, 0.198, 0.05]	[0.1137, 0.575, 1.0]	[8.7912, 1.7391, 1.0]	[4.55, 1.725, 2.0]	3
[1.0, 0.198, 0.2133]	[0.135, 0.6833, 0.625]	[7.4074, 1.4634, 1.6]	[5.4, 2.05, 1.25]	1
[1.0, 0.198, 0.2133]	[0.135, 0.6833, 0.625]	[7.4074, 1.4634, 1.6]	[5.4, 2.05, 1.25]	2
[1.0, 0.198, 0.2133]	[0.135, 0.6833, 0.625]	[7.4074, 1.4634, 1.6]	[5.4, 2.05, 1.25]	3
[1.0, 0.198, 0.3767]	[0.1425, 0.7167, 0.5]	[7.0175, 1.3953, 2.0]	[5.7, 2.15, 1.0]	1
[1.0, 0.198, 0.3767]	[0.1425, 0.7167, 0.5]	[7.0175, 1.3953, 2.0]	[5.7, 2.15, 1.0]	2
[1.0, 0.198, 0.3767]	[0.1425, 0.7167, 0.5]	[7.0175, 1.3953, 2.0]	[5.7, 2.15, 1.0]	3
[1.0, 0.198, 0.54]	[0.1425, 0.7167, 0.5]	[7.0175, 1.3953, 2.0]	[5.7, 2.15, 1.0]	1
[1.0, 0.198, 0.54]	[0.1425, 0.7167, 0.5]	[7.0175, 1.3953, 2.0]	[5.7, 2.15, 1.0]	2
[1.0, 0.198, 0.54]	[0.1425, 0.7167, 0.5]	[7.0175, 1.3953, 2.0]	[5.7, 2.15, 1.0]	3
[1.0, 0.346, 0.05]	[0.1387, 0.4083, 1.0]	[7.2072, 2.449, 1.0]	[5.55, 1.225, 2.0]	1
[1.0, 0.346, 0.05]	[0.1387, 0.4083, 1.0]	[7.2072, 2.449, 1.0]	[5.55, 1.225, 2.0]	2
[1.0, 0.346, 0.05]	[0.1387, 0.4083, 1.0]	[7.2072, 2.449, 1.0]	[5.55, 1.225, 2.0]	3
[1.0, 0.346, 0.2133]	[0.1575, 0.4583, 0.7375]	[6.3492, 2.1818, 1.3559]	[6.3, 1.375, 1.475]	1
[1.0, 0.346, 0.2133]	[0.1575, 0.4583, 0.7375]	[6.3492, 2.1818, 1.3559]	[6.3, 1.375, 1.475]	2
[1.0, 0.346, 0.2133]	[0.1575, 0.4583, 0.7375]	[6.3492, 2.1818, 1.3559]	[6.3, 1.375, 1.475]	3
[1.0, 0.346, 0.3767]	[0.175, 0.5, 0.5]	[5.7143, 2.0, 2.0]	[7.0, 1.5, 1.0]	1
[1.0, 0.346, 0.3767]	[0.175, 0.5, 0.5]	[5.7143, 2.0, 2.0]	[7.0, 1.5, 1.0]	2
[1.0, 0.346, 0.3767]	[0.175, 0.5, 0.5]	[5.7143, 2.0, 2.0]	[7.0, 1.5, 1.0]	3
[1.0, 0.346, 0.54]	[0.175, 0.5, 0.5]	[5.7143, 2.0, 2.0]	[7.0, 1.5, 1.0]	1
[1.0, 0.346, 0.54]	[0.175, 0.5, 0.5]	[5.7143, 2.0, 2.0]	[7.0, 1.5, 1.0]	2
[1.0, 0.346, 0.54]	[0.175, 0.5, 0.5]	[5.7143, 2.0, 2.0]	[7.0, 1.5, 1.0]	3
[1.0, 0.494, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	1
[1.0, 0.494, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	2
[1.0, 0.494, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	3
[1.0, 0.494, 0.2133]	[0.1688, 0.3417, 0.8]	[5.9259, 2.9268, 1.25]	[6.75, 1.025, 1.6]	1
[1.0, 0.494, 0.2133]	[0.1688, 0.3417, 0.8]	[5.9259, 2.9268, 1.25]	[6.75, 1.025, 1.6]	2
[1.0, 0.494, 0.2133]	[0.1688, 0.3417, 0.8]	[5.9259, 2.9268, 1.25]	[6.75, 1.025, 1.6]	3
[1.0, 0.494, 0.3767]	[0.1913, 0.3833, 0.5125]	[5.2288, 2.6087, 1.9512]	[7.65, 1.15, 1.025]	1
[1.0, 0.494, 0.3767]	[0.1913, 0.3833, 0.5125]	[5.2288, 2.6087, 1.9512]	[7.65, 1.15, 1.025]	2
[1.0, 0.494, 0.3767]	[0.1913, 0.3833, 0.5125]	[5.2288, 2.6087, 1.9512]	[7.65, 1.15, 1.025]	3
[1.0, 0.494, 0.54]	[0.1925, 0.3833, 0.5]	[5.1948, 2.6087, 2.0]	[7.7, 1.15, 1.0]	1
[1.0, 0.494, 0.54]	[0.1925, 0.3833, 0.5]	[5.1948, 2.6087, 2.0]	[7.7, 1.15, 1.0]	2
[1.0, 0.494, 0.54]	[0.1925, 0.3833, 0.5]	[5.1948, 2.6087, 2.0]	[7.7, 1.15, 1.0]	3
[1.0, 0.642, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	1
[1.0, 0.642, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	2

Table A.4 continued from previous page

Weights $[w_A, w_B, w_C]$	**Distribution (pods/item)** $[z_A, z_B, z_C]$	**Distribution (items/pod) [A, B, C]**	**Distribution (pods/SKU) [A, B, C]**	**Seed**
[1.0, 0.642, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	3
[1.0, 0.642, 0.2133]	[0.17, 0.3333, 0.8]	[5.8824, 3.0, 1.25]	[6.8, 1.0, 1.6]	1
[1.0, 0.642, 0.2133]	[0.17, 0.3333, 0.8]	[5.8824, 3.0, 1.25]	[6.8, 1.0, 1.6]	2
[1.0, 0.642, 0.2133]	[0.17, 0.3333, 0.8]	[5.8824, 3.0, 1.25]	[6.8, 1.0, 1.6]	3
[1.0, 0.642, 0.3767]	[0.1975, 0.3333, 0.525]	[5.0633, 3.0, 1.9048]	[7.9, 1.0, 1.05]	1
[1.0, 0.642, 0.3767]	[0.1975, 0.3333, 0.525]	[5.0633, 3.0, 1.9048]	[7.9, 1.0, 1.05]	2
[1.0, 0.642, 0.3767]	[0.1975, 0.3333, 0.525]	[5.0633, 3.0, 1.9048]	[7.9, 1.0, 1.05]	3
[1.0, 0.642, 0.54]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	1
[1.0, 0.642, 0.54]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	2
[1.0, 0.642, 0.54]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	3
[1.0, 0.79, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	1
[1.0, 0.79, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	2
[1.0, 0.79, 0.05]	[0.15, 0.3333, 1.0]	[6.6667, 3.0, 1.0]	[6.0, 1.0, 2.0]	3
[1.0, 0.79, 0.2133]	[0.17, 0.3333, 0.8]	[5.8824, 3.0, 1.25]	[6.8, 1.0, 1.6]	1
[1.0, 0.79, 0.2133]	[0.17, 0.3333, 0.8]	[5.8824, 3.0, 1.25]	[6.8, 1.0, 1.6]	2
[1.0, 0.79, 0.2133]	[0.17, 0.3333, 0.8]	[5.8824, 3.0, 1.25]	[6.8, 1.0, 1.6]	3
[1.0, 0.79, 0.3767]	[0.1975, 0.3333, 0.525]	[5.0633, 3.0, 1.9048]	[7.9, 1.0, 1.05]	1
[1.0, 0.79, 0.3767]	[0.1975, 0.3333, 0.525]	[5.0633, 3.0, 1.9048]	[7.9, 1.0, 1.05]	2
[1.0, 0.79, 0.3767]	[0.1975, 0.3333, 0.525]	[5.0633, 3.0, 1.9048]	[7.9, 1.0, 1.05]	3
[1.0, 0.79, 0.54]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	1
[1.0, 0.79, 0.54]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	2
[1.0, 0.79, 0.54]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	3
[1.0, 1.0, 1.0]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	1
[1.0, 1.0, 1.0]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	2
[1.0, 1.0, 1.0]	[0.2, 0.3333, 0.5]	[5.0, 3.0, 2.0]	[8.0, 1.0, 1.0]	3

A.5. Slotting Results DP_E

Table A.5: Slotting Results with Demand Profile DP_E

Weights $[w_A, w_B, w_C]$	**Distribution (pods/item)** $[z_A, z_B, z_C]$	**Distribution (items/pod) [A, B, C]**	**Distribution (pods/SKU) [A, B, C]**	**Seed**
[1.0, 0.058, 0.058]	[0.1163, 1.0, 1.0]	[8.6, 1.0, 1.0]	[10.0, 6.0, 1.0]	1
[1.0, 0.058, 0.058]	[0.1163, 1.0, 1.0]	[8.6, 1.0, 1.0]	[10.0, 6.0, 1.0]	2
[1.0, 0.058, 0.058]	[0.1163, 1.0, 1.0]	[8.6, 1.0, 1.0]	[10.0, 6.0, 1.0]	3
[1.0, 0.2935, 0.058]	[0.15, 0.5167, 1.0]	[6.6667, 1.9355, 1.0]	[12.9, 3.1, 1.0]	1
[1.0, 0.2935, 0.058]	[0.15, 0.5167, 1.0]	[6.6667, 1.9355, 1.0]	[12.9, 3.1, 1.0]	2
[1.0, 0.2935, 0.058]	[0.15, 0.5167, 1.0]	[6.6667, 1.9355, 1.0]	[12.9, 3.1, 1.0]	3
[1.0, 0.529, 0.058]	[0.164, 0.3167, 1.0]	[6.0993, 3.1579, 1.0]	[14.1, 1.9, 1.0]	1
[1.0, 0.529, 0.058]	[0.164, 0.3167, 1.0]	[6.0993, 3.1579, 1.0]	[14.1, 1.9, 1.0]	2
[1.0, 0.529, 0.058]	[0.164, 0.3167, 1.0]	[6.0993, 3.1579, 1.0]	[14.1, 1.9, 1.0]	3
[1.0, 0.7645, 0.058]	[0.1709, 0.2167, 1.0]	[5.8503, 4.6154, 1.0]	[14.7, 1.3, 1.0]	1
[1.0, 0.7645, 0.058]	[0.1709, 0.2167, 1.0]	[5.8503, 4.6154, 1.0]	[14.7, 1.3, 1.0]	2
[1.0, 0.7645, 0.058]	[0.1709, 0.2167, 1.0]	[5.8503, 4.6154, 1.0]	[14.7, 1.3, 1.0]	3
[1.0, 1.0, 1.0]	[0.1744, 0.1667, 1.0]	[5.7333, 6.0, 1.0]	[15.0, 1.0, 1.0]	1
[1.0, 1.0, 1.0]	[0.1744, 0.1667, 1.0]	[5.7333, 6.0, 1.0]	[15.0, 1.0, 1.0]	2
[1.0, 1.0, 1.0]	[0.1744, 0.1667, 1.0]	[5.7333, 6.0, 1.0]	[15.0, 1.0, 1.0]	3
[1.0, 1.0, 0.058]	[0.1744, 0.1667, 1.0]	[5.7333, 6.0, 1.0]	[15.0, 1.0, 1.0]	1
[1.0, 1.0, 0.058]	[0.1744, 0.1667, 1.0]	[5.7333, 6.0, 1.0]	[15.0, 1.0, 1.0]	2
[1.0, 1.0, 0.058]	[0.1744, 0.1667, 1.0]	[5.7333, 6.0, 1.0]	[15.0, 1.0, 1.0]	3

A.6. Slotting Results DP_F

Table A.6: Slotting Results with Demand Profile DP_F

Weights $[w_A, w_B, w_C]$	Distribution (pods/item) $[z_A, z_B, z_C]$	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 0.1, 0.068]	[0.1364, 1.0, 1.0]	[7.3333, 1.0, 1.0]	[6.0, 2.0, 1.0]	1
[1.0, 0.1, 0.068]	[0.1364, 1.0, 1.0]	[7.3333, 1.0, 1.0]	[6.0, 2.0, 1.0]	2
[1.0, 0.1, 0.068]	[0.1364, 1.0, 1.0]	[7.3333, 1.0, 1.0]	[6.0, 2.0, 1.0]	3
[1.0, 0.1467, 0.068]	[0.1398, 0.9625, 1.0]	[7.1545, 1.039, 1.0]	[6.15, 1.925, 1.0]	1
[1.0, 0.1467, 0.068]	[0.1398, 0.9625, 1.0]	[7.1545, 1.039, 1.0]	[6.15, 1.925, 1.0]	2
[1.0, 0.1467, 0.068]	[0.1398, 0.9625, 1.0]	[7.1545, 1.039, 1.0]	[6.15, 1.925, 1.0]	3
[1.0, 0.1933, 0.068]	[0.1545, 0.8, 1.0]	[6.4706, 1.25, 1.0]	[6.8, 1.6, 1.0]	1
[1.0, 0.1933, 0.068]	[0.1545, 0.8, 1.0]	[6.4706, 1.25, 1.0]	[6.8, 1.6, 1.0]	2
[1.0, 0.1933, 0.068]	[0.1545, 0.8, 1.0]	[6.4706, 1.25, 1.0]	[6.8, 1.6, 1.0]	3
[1.0, 0.24, 0.068]	[0.1648, 0.6875, 1.0]	[6.069, 1.4545, 1.0]	[7.25, 1.375, 1.0]	1
[1.0, 0.24, 0.068]	[0.1648, 0.6875, 1.0]	[6.069, 1.4545, 1.0]	[7.25, 1.375, 1.0]	2
[1.0, 0.24, 0.068]	[0.1648, 0.6875, 1.0]	[6.069, 1.4545, 1.0]	[7.25, 1.375, 1.0]	3
[1.0, 0.2867, 0.068]	[0.1727, 0.6, 1.0]	[5.7895, 1.6667, 1.0]	[7.6, 1.2, 1.0]	1
[1.0, 0.2867, 0.068]	[0.1727, 0.6, 1.0]	[5.7895, 1.6667, 1.0]	[7.6, 1.2, 1.0]	2
[1.0, 0.2867, 0.068]	[0.1727, 0.6, 1.0]	[5.7895, 1.6667, 1.0]	[7.6, 1.2, 1.0]	3
[1.0, 0.3333, 0.068]	[0.1784, 0.5375, 1.0]	[5.6051, 1.8605, 1.0]	[7.85, 1.075, 1.0]	1
[1.0, 0.3333, 0.068]	[0.1784, 0.5375, 1.0]	[5.6051, 1.8605, 1.0]	[7.85, 1.075, 1.0]	2
[1.0, 0.3333, 0.068]	[0.1784, 0.5375, 1.0]	[5.6051, 1.8605, 1.0]	[7.85, 1.075, 1.0]	3
[1.0, 0.38, 0.068]	[0.1818, 0.5, 1.0]	[5.5, 2.0, 1.0]	[8.0, 1.0, 1.0]	1
[1.0, 0.38, 0.068]	[0.1818, 0.5, 1.0]	[5.5, 2.0, 1.0]	[8.0, 1.0, 1.0]	2
[1.0, 0.38, 0.068]	[0.1818, 0.5, 1.0]	[5.5, 2.0, 1.0]	[8.0, 1.0, 1.0]	3
[1.0, 1.0, 1.0]	[0.1818, 0.5, 1.0]	[5.5, 2.0, 1.0]	[8.0, 1.0, 1.0]	1
[1.0, 1.0, 1.0]	[0.1818, 0.5, 1.0]	[5.5, 2.0, 1.0]	[8.0, 1.0, 1.0]	2
[1.0, 1.0, 1.0]	[0.1818, 0.5, 1.0]	[5.5, 2.0, 1.0]	[8.0, 1.0, 1.0]	3

A.7. Slotting Results Regular Gall&Gall Demand Profile

Table A.7: Slotting Results with Regular Gall&Gall Demand Profile.

Weights $[w_A, w_B, w_C]$	Distribution (pods/item) $[z_A, z_B, z_C]$	Distribution (items/pod) [A, B, C]	Distribution (pods/SKU) [A, B, C]	Seed
[1.0, 0.01, 1.0]	[0.1446, 0.3952, 1.0]	[6.9159, 2.5301, 1.0]	[5.35, 2.7667, 1.0]	1
[1.0, 0.01, 1.0]	[0.1297, 0.4476, 1.0]	[7.7083, 2.234, 1.0]	[4.8, 3.1333, 1.0]	2
[1.0, 0.01, 1.0]	[0.1176, 0.4905, 1.0]	[8.5057, 2.0388, 1.0]	[4.35, 3.4333, 1.0]	3
[1.0, 0.1545, 1.0]	[0.0905, 0.5857, 1.0]	[11.0448, 1.7073, 1.0]	[3.35, 4.1, 1.0]	1
[1.0, 0.1545, 1.0]	[0.0905, 0.5857, 1.0]	[11.0448, 1.7073, 1.0]	[3.35, 4.1, 1.0]	2
[1.0, 0.1545, 1.0]	[0.0905, 0.5857, 1.0]	[11.0448, 1.7073, 1.0]	[3.35, 4.1, 1.0]	3
[1.0, 0.2991, 1.0]	[0.1324, 0.4381, 1.0]	[7.551, 2.2826, 1.0]	[4.9, 3.0667, 1.0]	1
[1.0, 0.2991, 1.0]	[0.1324, 0.4381, 1.0]	[7.551, 2.2826, 1.0]	[4.9, 3.0667, 1.0]	2
[1.0, 0.2991, 1.0]	[0.1324, 0.4381, 1.0]	[7.551, 2.2826, 1.0]	[4.9, 3.0667, 1.0]	3
[1.0, 0.4436, 1.0]	[0.1568, 0.3524, 1.0]	[6.3793, 2.8378, 1.0]	[5.8, 2.4667, 1.0]	1
[1.0, 0.4436, 1.0]	[0.1568, 0.3524, 1.0]	[6.3793, 2.8378, 1.0]	[5.8, 2.4667, 1.0]	2
[1.0, 0.4436, 1.0]	[0.1568, 0.3524, 1.0]	[6.3793, 2.8378, 1.0]	[5.8, 2.4667, 1.0]	3
[1.0, 0.5882, 1.0]	[0.173, 0.2952, 1.0]	[5.7812, 3.3871, 1.0]	[6.4, 2.0667, 1.0]	1
[1.0, 0.5882, 1.0]	[0.173, 0.2952, 1.0]	[5.7812, 3.3871, 1.0]	[6.4, 2.0667, 1.0]	2
[1.0, 0.5882, 1.0]	[0.173, 0.2952, 1.0]	[5.7812, 3.3871, 1.0]	[6.4, 2.0667, 1.0]	3
[1.0, 0.7327, 1.0]	[0.1851, 0.2524, 1.0]	[5.4015, 3.9623, 1.0]	[6.85, 1.7667, 1.0]	1
[1.0, 0.7327, 1.0]	[0.1851, 0.2524, 1.0]	[5.4015, 3.9623, 1.0]	[6.85, 1.7667, 1.0]	2
[1.0, 0.7327, 1.0]	[0.1851, 0.2524, 1.0]	[5.4015, 3.9623, 1.0]	[6.85, 1.7667, 1.0]	3
[1.0, 0.8773, 1.0]	[0.1946, 0.219, 1.0]	[5.1389, 4.5652, 1.0]	[7.2, 1.5333, 1.0]	1
[1.0, 0.8773, 1.0]	[0.1946, 0.219, 1.0]	[5.1389, 4.5652, 1.0]	[7.2, 1.5333, 1.0]	2
[1.0, 0.8773, 1.0]	[0.1946, 0.219, 1.0]	[5.1389, 4.5652, 1.0]	[7.2, 1.5333, 1.0]	3
[1.0, 1.0218, 1.0]	[0.2014, 0.1952, 1.0]	[4.9664, 5.122, 1.0]	[7.45, 1.3667, 1.0]	1
[1.0, 1.0218, 1.0]	[0.2014, 0.1952, 1.0]	[4.9664, 5.122, 1.0]	[7.45, 1.3667, 1.0]	2
[1.0, 1.0218, 1.0]	[0.2014, 0.1952, 1.0]	[4.9664, 5.122, 1.0]	[7.45, 1.3667, 1.0]	3
[1.0, 1.1664, 1.0]	[0.2068, 0.1762, 1.0]	[4.8366, 5.6757, 1.0]	[7.65, 1.2333, 1.0]	1
[1.0, 1.1664, 1.0]	[0.2068, 0.1762, 1.0]	[4.8366, 5.6757, 1.0]	[7.65, 1.2333, 1.0]	2
[1.0, 1.1664, 1.0]	[0.2068, 0.1762, 1.0]	[4.8366, 5.6757, 1.0]	[7.65, 1.2333, 1.0]	3
[1.0, 1.3109, 1.0]	[0.2108, 0.1619, 1.0]	[4.7436, 6.1765, 1.0]	[7.8, 1.1333, 1.0]	1
[1.0, 1.3109, 1.0]	[0.2108, 0.1619, 1.0]	[4.7436, 6.1765, 1.0]	[7.8, 1.1333, 1.0]	2
[1.0, 1.3109, 1.0]	[0.2108, 0.1619, 1.0]	[4.7436, 6.1765, 1.0]	[7.8, 1.1333, 1.0]	3
[1.0, 1.4555, 1.0]	[0.2149, 0.1476, 1.0]	[4.6541, 6.7742, 1.0]	[7.95, 1.0333, 1.0]	1
[1.0, 1.4555, 1.0]	[0.2149, 0.1476, 1.0]	[4.6541, 6.7742, 1.0]	[7.95, 1.0333, 1.0]	2
[1.0, 1.4555, 1.0]	[0.2149, 0.1476, 1.0]	[4.6541, 6.7742, 1.0]	[7.95, 1.0333, 1.0]	3
[1.0, 1.6, 1.0]	[0.2162, 0.1429, 1.0]	[4.625, 7.0, 1.0]	[8.0, 1.0, 1.0]	1
[1.0, 1.6, 1.0]	[0.2162, 0.1429, 1.0]	[4.625, 7.0, 1.0]	[8.0, 1.0, 1.0]	2
[1.0, 1.6, 1.0]	[0.2162, 0.1429, 1.0]	[4.625, 7.0, 1.0]	[8.0, 1.0, 1.0]	3

A.8. Slotting Results Peak Gall&Gall Demand Profile

Table A.8: Slotting Results with Peak Gall&Gall Demand Profile.

Weights $[w_A, w_B, w_C]$	**Distribution (pods/item)** $[z_A, z_B, z_C]$	**Distribution (items/pod) [A, B, C]**	**Distribution (pods/SKU) [A, B, C]**	**Seed**
[1.0, 0.01, 1.0]	[0.0975, 0.7467, 1.0]	[10.2564, 1.3393, 1.0]	[3.9, 3.7333, 1.0]	1
[1.0, 0.01, 1.0]	[0.1125, 0.6667, 1.0]	[8.8889, 1.5, 1.0]	[4.5, 3.3333, 1.0]	2
[1.0, 0.01, 1.0]	[0.1137, 0.66, 1.0]	[8.7912, 1.5152, 1.0]	[4.55, 3.3, 1.0]	3
[1.0, 0.1, 1.0]	[0.0925, 0.7733, 1.0]	[10.8108, 1.2931, 1.0]	[3.7, 3.8667, 1.0]	1
[1.0, 0.1, 1.0]	[0.0825, 0.8267, 1.0]	[12.1212, 1.2097, 1.0]	[3.3, 4.1333, 1.0]	2
[1.0, 0.1, 1.0]	[0.0825, 0.8267, 1.0]	[12.1212, 1.2097, 1.0]	[3.3, 4.1333, 1.0]	3
[1.0, 0.19, 1.0]	[0.12, 0.6267, 1.0]	[8.3333, 1.5957, 1.0]	[4.8, 3.1333, 1.0]	1
[1.0, 0.19, 1.0]	[0.12, 0.6267, 1.0]	[8.3333, 1.5957, 1.0]	[4.8, 3.1333, 1.0]	2
[1.0, 0.19, 1.0]	[0.12, 0.6267, 1.0]	[8.3333, 1.5957, 1.0]	[4.8, 3.1333, 1.0]	3
[1.0, 0.28, 1.0]	[0.1425, 0.5067, 1.0]	[7.0175, 1.9737, 1.0]	[5.7, 2.5333, 1.0]	1
[1.0, 0.28, 1.0]	[0.1425, 0.5067, 1.0]	[7.0175, 1.9737, 1.0]	[5.7, 2.5333, 1.0]	2
[1.0, 0.28, 1.0]	[0.1425, 0.5067, 1.0]	[7.0175, 1.9737, 1.0]	[5.7, 2.5333, 1.0]	3
[1.0, 0.37, 1.0]	[0.1575, 0.4267, 1.0]	[6.3492, 2.3438, 1.0]	[6.3, 2.1333, 1.0]	1
[1.0, 0.37, 1.0]	[0.1575, 0.4267, 1.0]	[6.3492, 2.3438, 1.0]	[6.3, 2.1333, 1.0]	2
[1.0, 0.37, 1.0]	[0.1575, 0.4267, 1.0]	[6.3492, 2.3438, 1.0]	[6.3, 2.1333, 1.0]	3
[1.0, 0.46, 1.0]	[0.1688, 0.3667, 1.0]	[5.9259, 2.7273, 1.0]	[6.75, 1.8333, 1.0]	1
[1.0, 0.46, 1.0]	[0.1688, 0.3667, 1.0]	[5.9259, 2.7273, 1.0]	[6.75, 1.8333, 1.0]	2
[1.0, 0.46, 1.0]	[0.1688, 0.3667, 1.0]	[5.9259, 2.7273, 1.0]	[6.75, 1.8333, 1.0]	3
[1.0, 0.55, 1.0]	[0.1775, 0.32, 1.0]	[5.6338, 3.125, 1.0]	[7.1, 1.6, 1.0]	1
[1.0, 0.55, 1.0]	[0.1775, 0.32, 1.0]	[5.6338, 3.125, 1.0]	[7.1, 1.6, 1.0]	2
[1.0, 0.55, 1.0]	[0.1775, 0.32, 1.0]	[5.6338, 3.125, 1.0]	[7.1, 1.6, 1.0]	3
[1.0, 0.64, 1.0]	[0.1837, 0.2867, 1.0]	[5.4422, 3.4884, 1.0]	[7.35, 1.4333, 1.0]	1
[1.0, 0.64, 1.0]	[0.1837, 0.2867, 1.0]	[5.4422, 3.4884, 1.0]	[7.35, 1.4333, 1.0]	2
[1.0, 0.64, 1.0]	[0.1837, 0.2867, 1.0]	[5.4422, 3.4884, 1.0]	[7.35, 1.4333, 1.0]	3
[1.0, 0.73, 1.0]	[0.1888, 0.26, 1.0]	[5.298, 3.8462, 1.0]	[7.55, 1.3, 1.0]	1
[1.0, 0.73, 1.0]	[0.1888, 0.26, 1.0]	[5.298, 3.8462, 1.0]	[7.55, 1.3, 1.0]	2
[1.0, 0.73, 1.0]	[0.1888, 0.26, 1.0]	[5.298, 3.8462, 1.0]	[7.55, 1.3, 1.0]	3
[1.0, 0.82, 1.0]	[0.1938, 0.2333, 1.0]	[5.1613, 4.2857, 1.0]	[7.75, 1.1667, 1.0]	1
[1.0, 0.82, 1.0]	[0.1938, 0.2333, 1.0]	[5.1613, 4.2857, 1.0]	[7.75, 1.1667, 1.0]	2
[1.0, 0.82, 1.0]	[0.1938, 0.2333, 1.0]	[5.1613, 4.2857, 1.0]	[7.75, 1.1667, 1.0]	3
[1.0, 0.91, 1.0]	[0.1975, 0.2133, 1.0]	[5.0633, 4.6875, 1.0]	[7.9, 1.0667, 1.0]	1
[1.0, 0.91, 1.0]	[0.1975, 0.2133, 1.0]	[5.0633, 4.6875, 1.0]	[7.9, 1.0667, 1.0]	2
[1.0, 0.91, 1.0]	[0.1975, 0.2133, 1.0]	[5.0633, 4.6875, 1.0]	[7.9, 1.0667, 1.0]	3
[1.0, 1.0, 1.0]	[0.2, 0.2, 1.0]	[5.0, 5.0, 1.0]	[8.0, 1.0, 1.0]	1
[1.0, 1.0, 1.0]	[0.2, 0.2, 1.0]	[5.0, 5.0, 1.0]	[8.0, 1.0, 1.0]	2
[1.0, 1.0, 1.0]	[0.2, 0.2, 1.0]	[5.0, 5.0, 1.0]	[8.0, 1.0, 1.0]	3

B

Performance Metric Plots

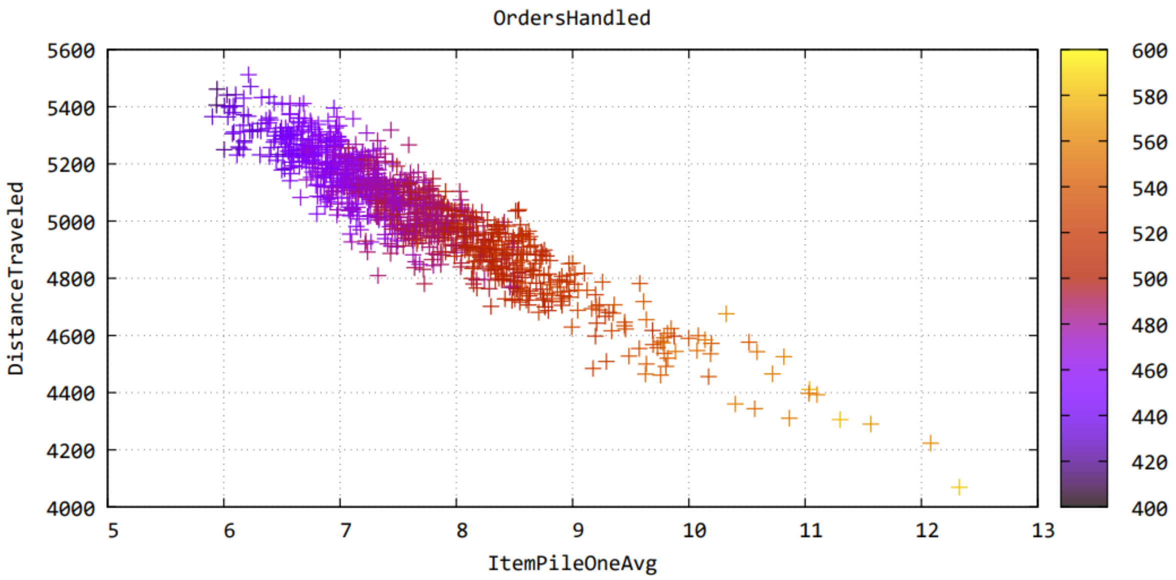


Figure B.1: Plot of Performance Metric 'orders handled' for Travel Distance and Pile-on from all Slotting Configurations for all Demand Profiles.

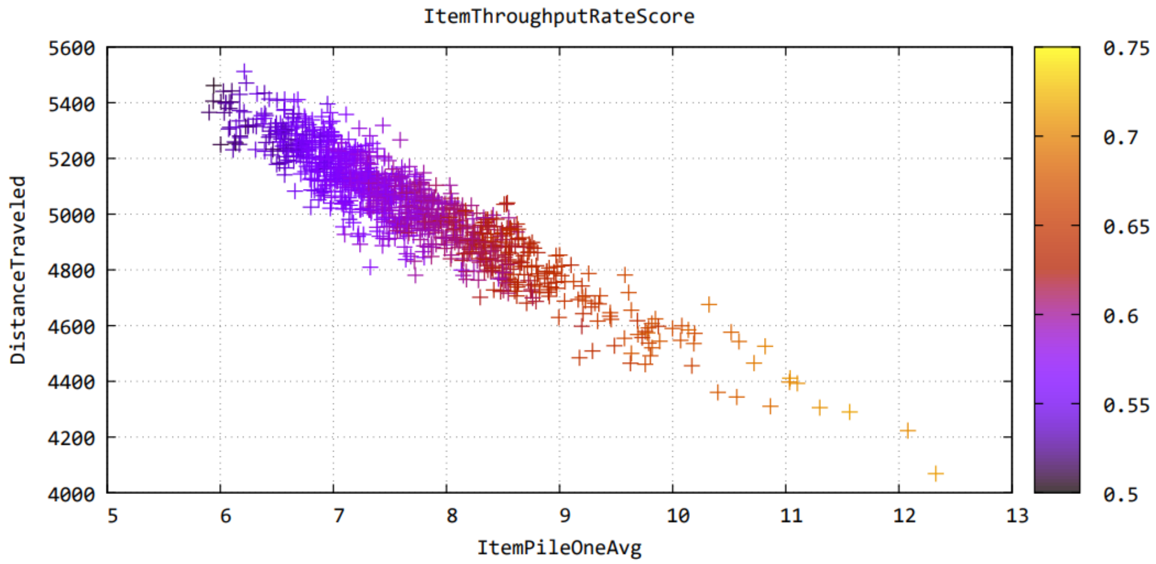


Figure B.2: Plot of Performance Metric 'item throughput rate' for Travel Distance and Pile-on from all Slotting Configurations for all Demand Profiles.

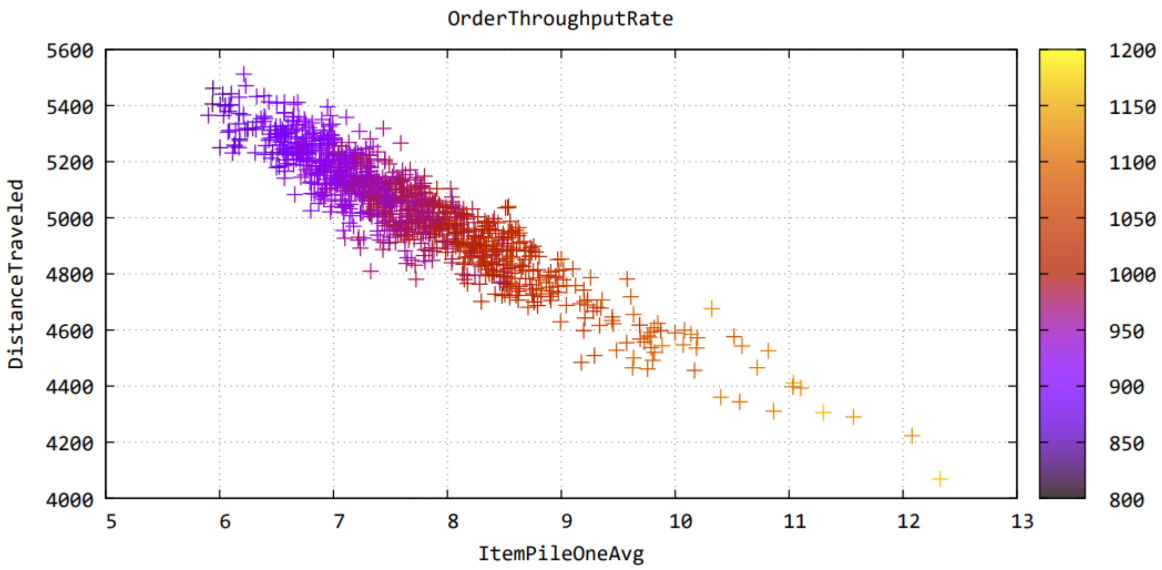


Figure B.3: Plot of Performance Metric 'order throughput rate' for Travel Distance and Pile-on from all Slotting Configurations for all Demand Profiles.

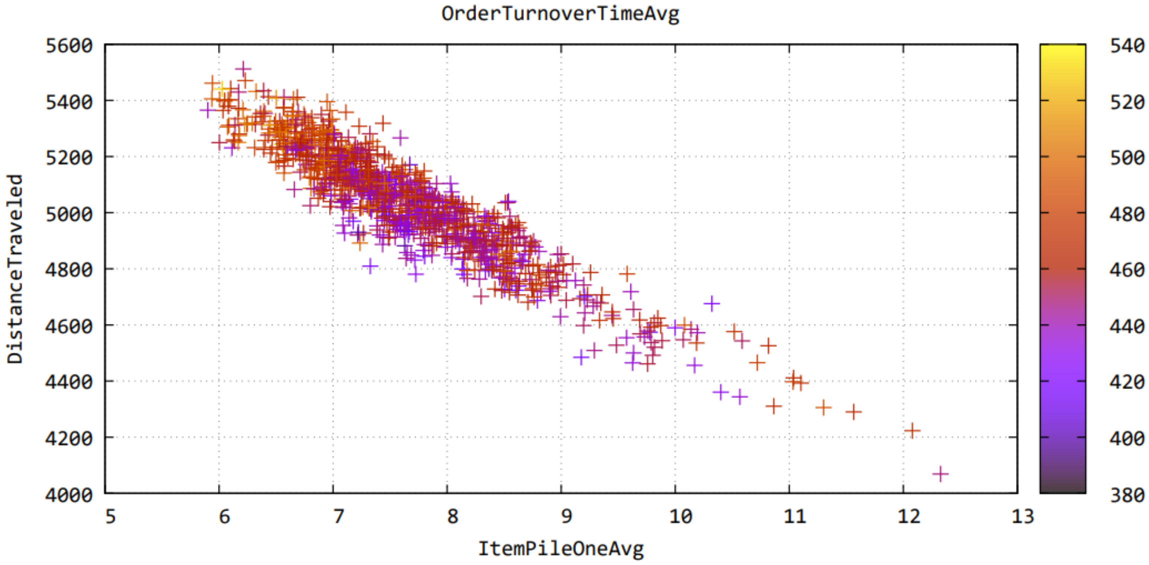


Figure B.4: Plot of Performance Metric 'order turnover time [seconds]' for Travel Distance and Pile-on from all Slotting Configurations for all Demand Profiles.

C

Simulation Results per Demand Profile

C.1. Simulation Results DP_A

Table C.1: Simulation Results with Demand Profile DP_A.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.050	0.050	0.10	0.13	0.53	7.62	4937.87	472
0.050	0.050	0.10	0.13	0.53	7.11	5043.22	475
0.050	0.050	0.10	0.13	0.53	7.56	5143.09	463
0.050	0.050	0.09	0.15	0.55	7.01	5269.59	455
0.050	0.050	0.09	0.15	0.55	7.28	5128.75	474
0.050	0.050	0.09	0.15	0.55	7.14	4981.24	450
0.050	0.050	0.10	0.12	0.54	6.43	5276.27	443
0.050	0.050	0.10	0.12	0.54	6.89	5082.38	471
0.050	0.050	0.10	0.12	0.54	6.94	5285.92	450
0.050	0.380	0.10	1.00	0.26	6.57	5165.91	441
0.050	0.380	0.10	1.00	0.26	6.60	5193.42	463
0.050	0.380	0.10	1.00	0.26	6.88	5196.20	449
0.050	0.380	0.10	1.00	0.26	7.14	5058.97	461
0.050	0.380	0.10	1.00	0.26	6.39	5225.40	449
0.050	0.380	0.10	1.00	0.26	7.14	5183.05	462
0.050	0.380	0.10	1.00	0.26	7.69	5024.92	478
0.050	0.380	0.10	1.00	0.26	6.94	5101.65	486
0.050	0.380	0.10	1.00	0.26	7.30	5137.92	478
0.050	0.710	0.10	1.00	0.25	7.23	5084.84	475
0.050	0.710	0.10	1.00	0.25	7.46	5072.75	489
0.050	0.710	0.10	1.00	0.25	7.10	5114.59	461
0.050	0.710	0.10	1.00	0.25	6.94	5192.21	473
0.050	0.710	0.10	1.00	0.25	7.49	5098.86	489
0.050	0.710	0.10	1.00	0.25	6.76	5283.58	443
0.050	0.710	0.10	1.00	0.25	6.72	5252.61	469
0.050	0.710	0.10	1.00	0.25	6.11	5231.05	441
0.050	0.710	0.10	1.00	0.25	6.68	5227.90	463
0.050	1.040	0.10	1.00	0.25	6.10	5442.06	429
0.050	1.040	0.10	1.00	0.25	7.25	5142.69	476
0.050	1.040	0.10	1.00	0.25	7.28	5162.24	472
0.050	1.040	0.10	1.00	0.25	6.88	5249.05	471
0.050	1.040	0.10	1.00	0.25	7.10	5159.99	480
0.050	1.040	0.10	1.00	0.25	7.23	5308.12	470
0.050	1.040	0.10	1.00	0.25	6.96	5264.60	454
0.050	1.040	0.10	1.00	0.25	7.53	4973.56	482
0.050	1.040	0.10	1.00	0.25	7.30	5083.92	467
1.000	1.000	0.24	0.23	0.25	7.39	5084.97	474
1.000	1.000	0.24	0.23	0.25	7.84	5086.03	496
1.000	1.000	0.24	0.23	0.25	8.04	5074.04	482
1.000	1.000	0.24	0.23	0.25	7.27	5125.41	470
1.000	1.000	0.24	0.23	0.25	8.17	4996.14	505
1.000	1.000	0.24	0.23	0.25	7.38	5046.55	484
1.000	1.000	0.24	0.23	0.25	7.95	4977.44	492
1.000	1.000	0.24	0.23	0.25	7.82	5018.93	493
1.000	1.000	0.24	0.23	0.25	7.19	5114.04	453
10.000	0.050	0.09	0.13	0.55	7.81	5065.12	486
10.000	0.050	0.09	0.13	0.55	6.97	5119.94	481
10.000	0.050	0.09	0.13	0.55	6.94	5105.20	465
10.000	0.050	0.10	0.12	0.54	7.10	4927.17	479
10.000	0.050	0.10	0.12	0.54	6.74	5259.48	461
10.000	0.050	0.10	0.12	0.54	6.57	5375.26	451
10.000	0.050	0.10	0.10	0.54	7.39	5208.72	476
10.000	0.050	0.10	0.10	0.54	6.88	5162.01	467
10.000	0.050	0.10	0.10	0.54	7.09	5131.00	478
10.000	0.380	0.16	0.10	0.43	6.86	5118.73	454
10.000	0.380	0.16	0.10	0.43	7.20	5146.04	488
10.000	0.380	0.16	0.10	0.43	7.19	5120.48	470
10.000	0.380	0.16	0.10	0.43	7.44	5018.29	473
10.000	0.380	0.16	0.10	0.43	7.18	5129.88	487
10.000	0.380	0.16	0.10	0.43	6.98	5168.87	463
10.000	0.380	0.16	0.10	0.43	7.33	5099.95	460
10.000	0.380	0.16	0.10	0.43	7.04	5179.13	473
10.000	0.380	0.16	0.10	0.43	6.25	5318.72	438
10.000	0.710	0.22	0.10	0.31	6.89	5200.21	465
10.000	0.710	0.22	0.10	0.31	6.91	5162.69	448
10.000	0.710	0.22	0.10	0.31	7.24	5200.55	466
10.000	0.710	0.22	0.10	0.31	6.98	5296.17	459
10.000	0.710	0.22	0.10	0.31	6.56	5373.30	456
10.000	0.710	0.22	0.10	0.31	6.77	5241.19	454

Table C.1 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
10.000	0.710	0.22	0.10	0.31	6.83	5286.24	451
10.000	0.710	0.22	0.10	0.31	7.36	5094.46	476
10.000	0.710	0.22	0.10	0.31	6.81	5338.25	455
10.000	1.040	0.26	0.10	0.25	7.52	5060.92	479
10.000	1.040	0.26	0.10	0.25	7.11	5119.84	463
10.000	1.040	0.26	0.10	0.25	7.18	5194.47	456
10.000	1.040	0.26	0.10	0.25	7.28	5245.86	458
10.000	1.040	0.26	0.10	0.25	7.46	5078.75	490
10.000	1.040	0.26	0.10	0.25	7.30	5186.64	467
10.000	1.040	0.26	0.10	0.25	7.49	5012.31	472
10.000	1.040	0.26	0.10	0.25	7.59	5103.07	473
10.000	1.040	0.26	0.10	0.25	7.18	5116.77	474
2.040	0.050	0.10	0.43	0.43	7.35	5122.10	465
2.040	0.050	0.10	0.43	0.43	7.55	5127.34	488
2.040	0.050	0.10	0.43	0.43	7.47	5073.02	476
2.040	0.050	0.13	0.66	0.30	7.55	5121.86	479
2.040	0.050	0.13	0.66	0.30	8.26	4904.19	510
2.040	0.050	0.13	0.66	0.30	7.11	5106.53	473
2.040	0.050	0.10	0.56	0.40	7.46	5100.61	479
2.040	0.050	0.10	0.56	0.40	6.79	5185.80	478
2.040	0.050	0.10	0.56	0.40	7.32	5061.36	466
2.040	0.380	0.16	0.10	0.43	6.78	5232.65	458
2.040	0.380	0.16	0.10	0.43	7.15	5191.24	472
2.040	0.380	0.16	0.10	0.43	7.40	5062.72	473
2.040	0.380	0.16	0.10	0.43	7.15	5048.00	474
2.040	0.380	0.16	0.10	0.43	7.64	4969.62	502
2.040	0.380	0.16	0.10	0.43	7.65	5089.99	477
2.040	0.380	0.16	0.10	0.43	6.89	5241.80	451
2.040	0.380	0.16	0.10	0.43	7.07	5256.52	476
2.040	0.380	0.16	0.10	0.43	7.00	5227.15	460
2.040	0.710	0.22	0.11	0.31	6.91	5175.27	457
2.040	0.710	0.22	0.11	0.31	6.68	5264.13	445
2.040	0.710	0.22	0.11	0.31	7.21	5230.55	466
2.040	0.710	0.22	0.11	0.31	7.44	5318.46	482
2.040	0.710	0.22	0.11	0.31	7.72	5116.41	500
2.040	0.710	0.22	0.11	0.31	7.04	5180.83	449
2.040	0.710	0.22	0.11	0.31	6.98	5160.70	465
2.040	0.710	0.22	0.11	0.31	6.71	5229.87	459
2.040	0.710	0.22	0.11	0.31	7.25	5130.23	471
2.040	1.040	0.26	0.12	0.25	7.13	5150.02	471
2.040	1.040	0.26	0.12	0.25	7.46	5133.21	492
2.040	1.040	0.26	0.12	0.25	7.34	5124.82	471
2.040	1.040	0.26	0.12	0.25	7.07	5049.07	451
2.040	1.040	0.26	0.12	0.25	7.39	5124.88	479
2.040	1.040	0.26	0.12	0.25	8.04	5056.85	496
2.040	1.040	0.26	0.12	0.25	7.17	5120.00	476
2.040	1.040	0.26	0.12	0.25	8.27	5003.50	504
2.040	1.040	0.26	0.12	0.25	8.51	5035.42	502
4.030	0.050	0.10	0.74	0.34	8.05	5039.89	484
4.030	0.050	0.10	0.74	0.34	6.23	5470.66	435
4.030	0.050	0.10	0.74	0.34	7.10	5211.31	468
4.030	0.050	0.09	0.88	0.31	7.27	5088.18	469
4.030	0.050	0.09	0.88	0.31	7.45	5207.01	501
4.030	0.050	0.09	0.88	0.31	7.27	5092.64	463
4.030	0.050	0.11	0.52	0.40	6.14	5255.12	419
4.030	0.050	0.11	0.52	0.40	7.52	4988.57	491
4.030	0.050	0.11	0.52	0.40	7.43	5082.70	483
4.030	0.380	0.16	0.10	0.43	7.08	5096.66	472
4.030	0.380	0.16	0.10	0.43	7.15	5219.87	485
4.030	0.380	0.16	0.10	0.43	6.98	5127.76	445
4.030	0.380	0.16	0.10	0.43	7.51	5120.77	478
4.030	0.380	0.16	0.10	0.43	7.24	5192.57	485
4.030	0.380	0.16	0.10	0.43	7.52	5062.47	471
4.030	0.380	0.16	0.10	0.43	7.06	5178.74	466
4.030	0.380	0.16	0.10	0.43	7.61	5089.59	492
4.030	0.380	0.16	0.10	0.43	6.74	5227.51	442
4.030	0.710	0.22	0.10	0.31	7.84	5044.09	478
4.030	0.710	0.22	0.10	0.31	6.81	5163.82	472
4.030	0.710	0.22	0.10	0.31	6.49	5313.33	433
4.030	0.710	0.22	0.10	0.31	6.63	5306.61	453
4.030	0.710	0.22	0.10	0.31	7.01	5234.21	474
4.030	0.710	0.22	0.10	0.31	7.09	5020.30	458
4.030	0.710	0.22	0.10	0.31	7.29	5195.11	475
4.030	0.710	0.22	0.10	0.31	7.29	5246.83	474
4.030	0.710	0.22	0.10	0.31	6.57	5289.54	440
4.030	1.040	0.26	0.10	0.25	7.08	5133.92	453
4.030	1.040	0.26	0.10	0.25	7.43	4980.34	469
4.030	1.040	0.26	0.10	0.25	6.91	5207.30	456
4.030	1.040	0.26	0.10	0.25	7.74	5087.64	481
4.030	1.040	0.26	0.10	0.25	7.32	5223.65	474
4.030	1.040	0.26	0.10	0.25	7.21	5200.07	470
4.030	1.040	0.26	0.10	0.25	7.07	5190.09	451
4.030	1.040	0.26	0.10	0.25	7.50	5023.67	481
4.030	1.040	0.26	0.10	0.25	7.18	5222.89	449
6.020	0.050	0.10	0.10	0.53	7.72	5143.31	484
6.020	0.050	0.10	0.10	0.53	6.79	5295.91	457
6.020	0.050	0.10	0.10	0.53	7.33	5004.00	461
6.020	0.050	0.09	0.13	0.55	6.73	5228.91	455
6.020	0.050	0.09	0.13	0.55	7.32	5014.70	487
6.020	0.050	0.09	0.13	0.55	6.91	5169.62	444
6.020	0.050	0.09	0.13	0.54	6.88	5203.20	471
6.020	0.050	0.09	0.13	0.54	7.47	4989.43	489
6.020	0.050	0.09	0.13	0.54	7.17	5207.91	473
6.020	0.380	0.16	0.10	0.43	7.45	5126.02	487
6.020	0.380	0.16	0.10	0.43	7.84	4960.15	493
6.020	0.380	0.16	0.10	0.43	7.27	4927.02	460
6.020	0.380	0.16	0.10	0.43	7.76	5105.54	485
6.020	0.380	0.16	0.10	0.43	7.42	5074.42	486
6.020	0.380	0.16	0.10	0.43	6.94	5247.85	455
6.020	0.380	0.16	0.10	0.43	7.19	5241.97	463
6.020	0.380	0.16	0.10	0.43	6.94	5222.60	471
6.020	0.380	0.16	0.10	0.43	6.59	5225.37	435
6.020	0.710	0.22	0.10	0.31	7.29	5164.91	479
6.020	0.710	0.22	0.10	0.31	7.74	5050.94	498
6.020	0.710	0.22	0.10	0.31	6.89	5205.91	453
6.020	0.710	0.22	0.10	0.31	7.37	5078.10	479
6.020	0.710	0.22	0.10	0.31	7.05	5179.20	473
6.020	0.710	0.22	0.10	0.31	6.66	5288.01	443
6.020	0.710	0.22	0.10	0.31	6.69	5246.02	460

Table C.1 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
6.020	0.710	0.22	0.10	0.31	6.73	5262.09	466
6.020	0.710	0.22	0.10	0.31	7.32	5281.18	484
6.020	1.040	0.26	0.10	0.25	7.45	5036.04	478
6.020	1.040	0.26	0.10	0.25	7.12	5179.32	477
6.020	1.040	0.26	0.10	0.25	7.36	5138.30	455
6.020	1.040	0.26	0.10	0.25	7.68	5098.25	483
6.020	1.040	0.26	0.10	0.25	7.89	5053.15	488
6.020	1.040	0.26	0.10	0.25	7.45	5200.17	467
6.020	1.040	0.26	0.10	0.25	7.85	5046.08	489
6.020	1.040	0.26	0.10	0.25	7.50	4930.95	472
6.020	1.040	0.26	0.10	0.25	7.50	5012.79	474
8.010	0.050	0.21	0.10	0.34	8.47	4791.57	501
8.010	0.050	0.21	0.10	0.34	7.49	5192.17	495
8.010	0.050	0.21	0.10	0.34	7.00	5150.35	457
8.010	0.050	0.09	0.11	0.55	7.51	5050.59	482
8.010	0.050	0.09	0.11	0.55	6.65	5190.88	444
8.010	0.050	0.09	0.11	0.55	7.26	5073.76	479
8.010	0.050	0.13	0.10	0.48	7.08	5169.98	478
8.010	0.050	0.13	0.10	0.48	7.74	5052.17	504
8.010	0.050	0.13	0.10	0.48	6.76	5213.79	452
8.010	0.380	0.16	0.10	0.43	7.60	5060.25	469
8.010	0.380	0.16	0.10	0.43	7.27	5108.06	470
8.010	0.380	0.16	0.10	0.43	6.43	5413.10	437
8.010	0.380	0.16	0.10	0.43	6.69	5411.21	459
8.010	0.380	0.16	0.10	0.43	7.22	4920.28	472
8.010	0.380	0.16	0.10	0.43	7.00	5284.81	464
8.010	0.380	0.16	0.10	0.43	6.81	5157.13	453
8.010	0.380	0.16	0.10	0.43	6.81	5273.64	472
8.010	0.380	0.16	0.10	0.43	6.44	5283.54	446
8.010	0.710	0.22	0.10	0.31	6.91	5277.04	460
8.010	0.710	0.22	0.10	0.31	6.44	5298.00	438
8.010	0.710	0.22	0.10	0.31	7.36	5106.89	474
8.010	0.710	0.22	0.10	0.31	6.97	5332.02	467
8.010	0.710	0.22	0.10	0.31	7.19	5232.61	471
8.010	0.710	0.22	0.10	0.31	7.40	5126.91	461
8.010	0.710	0.22	0.10	0.31	6.96	5326.14	460
8.010	0.710	0.22	0.10	0.31	7.24	5083.41	479
8.010	0.710	0.22	0.10	0.31	7.07	5171.58	456
8.010	1.040	0.26	0.10	0.25	7.74	5043.97	487
8.010	1.040	0.26	0.10	0.25	7.77	5046.78	505
8.010	1.040	0.26	0.10	0.25	7.99	5018.71	492
8.010	1.040	0.26	0.10	0.25	7.39	5096.21	475
8.010	1.040	0.26	0.10	0.25	7.63	5153.51	484
8.010	1.040	0.26	0.10	0.25	6.96	5261.67	451
8.010	1.040	0.26	0.10	0.25	7.05	5210.00	470
8.010	1.040	0.26	0.10	0.25	7.43	5120.23	476
8.010	1.040	0.26	0.10	0.25	7.08	5216.69	451

C.2. Simulation Results DP_B

Table C.2: Simulation Results with Demand Profile DP_B.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.060	0.060	0.10	0.27	0.96	7.65	5109.86	480
0.060	0.060	0.10	0.27	0.96	6.87	5151.51	450
0.060	0.060	0.10	0.27	0.96	6.70	5252.88	435
0.060	0.060	0.10	0.61	0.39	6.32	5341.34	435
0.060	0.060	0.10	0.61	0.39	6.97	5104.79	478
0.060	0.060	0.10	0.61	0.39	6.57	5227.91	449
0.060	0.060	0.12	0.39	0.67	6.79	5227.17	460
0.060	0.060	0.12	0.39	0.67	6.91	5066.29	455
0.060	0.060	0.12	0.39	0.67	6.76	5258.56	445
0.060	0.300	0.11	0.63	0.35	6.37	5323.54	448
0.060	0.300	0.11	0.63	0.35	6.67	5254.98	464
0.060	0.300	0.11	0.63	0.35	6.69	5359.05	454
0.060	0.300	0.12	0.47	0.56	7.16	5094.51	470
0.060	0.300	0.12	0.47	0.56	7.30	5148.25	482
0.060	0.300	0.12	0.47	0.56	7.47	5123.32	483
0.060	0.300	0.21	0.22	0.44	7.62	5092.71	465
0.060	0.300	0.21	0.22	0.44	6.77	5233.15	463
0.060	0.300	0.21	0.22	0.44	7.02	5135.59	448
0.060	0.550	0.11	0.39	0.74	6.91	5312.00	464
0.060	0.550	0.11	0.39	0.74	7.11	5146.42	486
0.060	0.550	0.11	0.39	0.74	6.31	5231.68	434
0.060	0.550	0.11	0.42	0.67	6.45	5212.13	443
0.060	0.550	0.11	0.42	0.67	6.98	5039.61	476
0.060	0.550	0.11	0.42	0.67	6.69	5222.53	454
0.060	0.550	0.20	0.31	0.38	6.73	5311.04	448
0.060	0.550	0.20	0.31	0.38	7.11	5226.22	479
0.060	0.550	0.20	0.31	0.38	7.39	5006.63	475
0.060	0.790	0.22	0.24	0.37	7.52	5068.52	485
0.060	0.790	0.22	0.24	0.37	7.82	5004.30	497
0.060	0.790	0.22	0.24	0.37	6.96	5235.59	472
0.060	0.790	0.13	0.54	0.35	7.04	5135.84	471
0.060	0.790	0.13	0.54	0.35	6.98	5277.17	476
0.060	0.790	0.13	0.54	0.35	6.57	5298.40	443
0.060	0.790	0.13	0.37	0.67	7.12	5198.34	466
0.060	0.790	0.13	0.37	0.67	6.74	5264.52	457
0.060	0.790	0.13	0.37	0.67	6.39	5361.42	431
0.310	0.060	0.09	0.30	1.00	6.54	5294.15	443
0.310	0.060	0.09	0.30	1.00	6.10	5402.48	434
0.310	0.060	0.09	0.30	1.00	6.17	5371.92	431
0.310	0.060	0.09	0.30	1.00	6.03	5364.22	431
0.310	0.060	0.09	0.30	1.00	6.17	5250.35	438
0.310	0.060	0.09	0.30	1.00	5.94	5405.56	412
0.310	0.060	0.09	0.30	1.00	6.57	5411.80	461
0.310	0.060	0.09	0.30	1.00	6.08	5379.20	434
0.310	0.060	0.09	0.30	1.00	6.03	5440.75	420
0.310	0.300	0.14	0.46	0.46	6.32	5315.01	437
0.310	0.300	0.14	0.46	0.46	6.92	5079.57	465
0.310	0.300	0.14	0.46	0.46	7.14	5125.78	457
0.310	0.300	0.14	0.46	0.46	6.76	5171.76	462
0.310	0.300	0.14	0.46	0.46	6.33	5431.88	450
0.310	0.300	0.14	0.46	0.46	6.88	5258.96	458
0.310	0.300	0.14	0.46	0.46	6.40	5257.25	433
0.310	0.300	0.14	0.46	0.46	6.94	5122.42	464
0.310	0.300	0.14	0.46	0.46	7.15	5224.78	459
0.310	0.550	0.15	0.49	0.33	7.08	5080.80	469
0.310	0.550	0.15	0.49	0.33	7.01	5143.23	461
0.310	0.550	0.15	0.49	0.33	6.55	5243.55	447
0.310	0.550	0.15	0.49	0.33	6.94	5117.01	471
0.310	0.550	0.15	0.49	0.33	6.90	5091.75	474
0.310	0.550	0.15	0.49	0.33	6.54	5269.70	451
0.310	0.550	0.15	0.49	0.33	6.53	5259.06	453
0.310	0.550	0.15	0.49	0.33	7.93	5048.92	504
0.310	0.550	0.15	0.49	0.33	7.11	5234.45	457
0.310	0.790	0.15	0.49	0.33	6.81	5207.51	457
0.310	0.790	0.15	0.49	0.33	6.95	5256.43	475
0.310	0.790	0.15	0.49	0.33	7.06	5064.93	470
0.310	0.790	0.15	0.49	0.33	6.92	5136.64	458
0.310	0.790	0.15	0.49	0.33	7.05	5224.89	484
0.310	0.790	0.15	0.49	0.33	6.53	5326.41	447
0.310	0.790	0.15	0.49	0.33	6.68	5332.47	458
0.310	0.790	0.15	0.49	0.33	6.81	5086.64	454
0.310	0.790	0.15	0.49	0.33	6.07	5305.69	431
0.550	0.060	0.12	0.21	1.00	6.08	5402.39	430
0.550	0.060	0.12	0.21	1.00	6.86	5156.54	468
0.550	0.060	0.12	0.21	1.00	6.60	5236.53	456
0.550	0.060	0.12	0.21	1.00	6.17	5334.84	434
0.550	0.060	0.12	0.21	1.00	5.90	5365.23	430
0.550	0.060	0.12	0.21	1.00	6.76	5285.47	454
0.550	0.060	0.12	0.21	1.00	6.21	5366.83	435
0.550	0.060	0.12	0.21	1.00	6.40	5353.88	455
0.550	0.060	0.12	0.21	1.00	6.00	5249.61	418
0.550	0.300	0.17	0.30	0.55	5.94	5461.52	413
0.550	0.300	0.17	0.30	0.55	7.02	5165.77	461
0.550	0.300	0.17	0.30	0.55	6.95	5199.70	465
0.550	0.300	0.17	0.30	0.55	6.71	5259.90	457
0.550	0.300	0.17	0.30	0.55	7.61	5104.91	505
0.550	0.300	0.17	0.30	0.55	6.79	5124.60	456
0.550	0.300	0.17	0.30	0.55	6.05	5399.02	426
0.550	0.300	0.17	0.30	0.55	6.58	5303.48	445
0.550	0.300	0.17	0.30	0.55	6.60	5326.91	446
0.550	0.550	0.19	0.35	0.35	6.59	5300.18	440
0.550	0.550	0.19	0.35	0.35	6.93	5199.40	474
0.550	0.550	0.19	0.35	0.35	7.25	5128.76	467
0.550	0.550	0.19	0.35	0.35	6.99	5216.10	460
0.550	0.550	0.19	0.35	0.35	6.56	5269.55	456
0.550	0.550	0.19	0.35	0.35	6.51	5297.83	440
0.550	0.550	0.19	0.35	0.35	6.76	5329.88	444
0.550	0.550	0.19	0.35	0.35	6.94	5168.56	463
0.550	0.550	0.19	0.35	0.35	6.85	5182.17	463
0.550	0.790	0.19	0.35	0.33	6.67	5318.75	450
0.550	0.790	0.19	0.35	0.33	6.98	5181.87	461
0.550	0.790	0.19	0.35	0.33	7.11	5150.53	470

Table C.2 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.550	0.790	0.19	0.35	0.33	6.87	5051.26	457
0.550	0.790	0.19	0.35	0.33	6.83	5303.18	457
0.550	0.790	0.19	0.35	0.33	7.18	5131.55	456
0.550	0.790	0.19	0.35	0.33	6.55	5314.74	442
0.550	0.790	0.19	0.35	0.33	6.71	5144.29	473
0.550	0.790	0.19	0.35	0.33	6.56	5304.38	444
0.800	0.060	0.12	0.20	1.00	6.99	5333.47	461
0.800	0.060	0.12	0.20	1.00	7.06	5114.50	477
0.800	0.060	0.12	0.20	1.00	6.36	5353.37	442
0.800	0.060	0.12	0.20	1.00	6.21	5512.00	455
0.800	0.060	0.12	0.20	1.00	6.09	5311.26	441
0.800	0.060	0.12	0.20	1.00	6.45	5311.53	436
0.800	0.060	0.12	0.20	1.00	6.24	5313.81	434
0.800	0.060	0.12	0.20	1.00	6.65	5360.94	474
0.800	0.060	0.12	0.20	1.00	6.89	5195.94	458
0.800	0.300	0.18	0.23	0.60	6.39	5434.54	438
0.800	0.300	0.18	0.23	0.60	6.74	5350.72	462
0.800	0.300	0.18	0.23	0.60	6.60	5269.01	442
0.800	0.300	0.18	0.23	0.60	6.95	5277.57	458
0.800	0.300	0.18	0.23	0.60	6.69	5231.09	450
0.800	0.300	0.18	0.23	0.60	6.17	5280.22	425
0.800	0.300	0.18	0.23	0.60	6.78	5321.10	450
0.800	0.300	0.18	0.23	0.60	6.71	5223.51	468
0.800	0.300	0.18	0.23	0.60	6.67	5208.75	447
0.800	0.550	0.21	0.26	0.38	6.58	5235.36	439
0.800	0.550	0.21	0.26	0.38	7.32	5096.66	480
0.800	0.550	0.21	0.26	0.38	7.00	5206.06	458
0.800	0.550	0.21	0.26	0.38	7.35	5254.03	467
0.800	0.550	0.21	0.26	0.38	6.92	5167.00	474
0.800	0.550	0.21	0.26	0.38	6.50	5178.68	441
0.800	0.550	0.21	0.26	0.38	6.18	5275.15	442
0.800	0.550	0.21	0.26	0.38	7.13	5095.60	480
0.800	0.550	0.21	0.26	0.38	6.81	5251.16	451
0.800	0.790	0.22	0.27	0.33	6.53	5258.82	451
0.800	0.790	0.22	0.27	0.33	6.83	5123.72	465
0.800	0.790	0.22	0.27	0.33	6.86	5154.76	456
0.800	0.790	0.22	0.27	0.33	6.57	5141.18	449
0.800	0.790	0.22	0.27	0.33	7.66	4960.02	490
0.800	0.790	0.22	0.27	0.33	7.40	5114.39	481
0.800	0.790	0.22	0.27	0.33	7.52	5146.00	470
0.800	0.790	0.22	0.27	0.33	7.07	5255.59	491
0.800	0.790	0.22	0.27	0.33	6.78	5229.24	460
1.000	1.000	0.23	0.23	0.33	7.17	5215.02	475
1.000	1.000	0.23	0.23	0.33	7.56	4952.92	491
1.000	1.000	0.23	0.23	0.33	7.34	5090.90	476
1.000	1.000	0.23	0.23	0.33	7.87	5050.11	493
1.000	1.000	0.23	0.23	0.33	7.15	5031.93	464
1.000	1.000	0.23	0.23	0.33	7.77	5073.92	483
1.000	1.000	0.23	0.23	0.33	7.93	4960.38	494
1.000	1.000	0.23	0.23	0.33	7.39	5234.96	485
1.000	1.000	0.23	0.23	0.33	7.92	4961.38	489
1.050	0.060	0.12	0.20	1.00	7.77	5109.68	488
1.050	0.060	0.12	0.20	1.00	6.63	5248.77	443
1.050	0.060	0.12	0.20	1.00	6.52	5182.70	428
1.050	0.060	0.12	0.20	1.00	6.51	5226.71	440
1.050	0.060	0.12	0.20	1.00	6.49	5288.40	444
1.050	0.060	0.12	0.20	1.00	6.98	5294.19	454
1.050	0.060	0.12	0.20	1.00	6.17	5429.84	446
1.050	0.060	0.12	0.20	1.00	6.57	5186.38	453
1.050	0.060	0.12	0.20	1.00	6.13	5259.18	433
1.050	0.300	0.19	0.20	0.61	6.01	5402.91	424
1.050	0.300	0.19	0.20	0.61	6.92	5292.84	462
1.050	0.300	0.19	0.20	0.61	6.51	5301.08	445
1.050	0.300	0.19	0.20	0.61	7.61	5135.29	480
1.050	0.300	0.19	0.20	0.61	7.04	5199.86	483
1.050	0.300	0.19	0.20	0.61	6.94	5230.05	468
1.050	0.300	0.19	0.20	0.61	6.81	5264.41	457
1.050	0.300	0.19	0.20	0.61	7.16	5087.06	462
1.050	0.300	0.19	0.20	0.61	7.18	5128.11	472
1.050	0.550	0.22	0.21	0.40	7.06	5165.59	470
1.050	0.550	0.22	0.21	0.40	6.71	5240.13	472
1.050	0.550	0.22	0.21	0.40	6.82	5258.13	462
1.050	0.550	0.22	0.21	0.40	6.65	5404.93	448
1.050	0.550	0.22	0.21	0.40	6.22	5314.39	429
1.050	0.550	0.22	0.21	0.40	7.24	5224.72	470
1.050	0.550	0.22	0.21	0.40	6.68	5282.16	461
1.050	0.550	0.22	0.21	0.40	6.90	5287.01	459
1.050	0.550	0.22	0.21	0.40	7.11	5357.82	466
1.050	0.790	0.23	0.22	0.33	6.64	5347.02	445
1.050	0.790	0.23	0.22	0.33	7.58	5078.00	492
1.050	0.790	0.23	0.22	0.33	7.53	5161.57	485
1.050	0.790	0.23	0.22	0.33	7.60	5137.41	479
1.050	0.790	0.23	0.22	0.33	7.99	4915.50	508
1.050	0.790	0.23	0.22	0.33	7.68	4848.56	473
1.050	0.790	0.23	0.22	0.33	7.43	5123.63	470
1.050	0.790	0.23	0.22	0.33	7.26	5210.69	485
1.050	0.790	0.23	0.22	0.33	7.11	5178.27	470
1.300	0.060	0.12	0.20	1.00	7.77	5114.44	489
1.300	0.060	0.12	0.20	1.00	6.66	5082.68	465
1.300	0.060	0.12	0.20	1.00	6.71	5206.81	448
1.300	0.060	0.12	0.20	1.00	6.75	5343.09	462
1.300	0.060	0.12	0.20	1.00	6.05	5398.39	438
1.300	0.060	0.12	0.20	1.00	6.39	5343.56	458
1.300	0.060	0.12	0.20	1.00	7.04	5191.15	468
1.300	0.060	0.12	0.20	1.00	6.14	5312.40	450
1.300	0.060	0.12	0.20	1.00	6.53	5287.16	448
1.300	0.300	0.19	0.20	0.61	6.29	5318.76	430
1.300	0.300	0.19	0.20	0.61	6.57	5246.47	449
1.300	0.300	0.19	0.20	0.61	6.80	5127.92	448
1.300	0.300	0.19	0.20	0.61	6.58	5206.28	446
1.300	0.300	0.19	0.20	0.61	6.72	5249.42	469
1.300	0.300	0.19	0.20	0.61	6.47	5232.82	429
1.300	0.300	0.19	0.20	0.61	6.50	5408.64	442
1.300	0.300	0.19	0.20	0.61	7.02	5163.15	479
1.300	0.300	0.19	0.20	0.61	6.90	5349.93	457
1.300	0.550	0.22	0.20	0.41	6.67	5313.68	460
1.300	0.550	0.22	0.20	0.41	6.50	5326.26	446
1.300	0.550	0.22	0.20	0.41	6.92	5185.85	444
1.300	0.550	0.22	0.20	0.41	6.65	5359.79	442

Table C.2 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
1.300	0.550	0.22	0.20	0.41	7.13	5268.30	479
1.300	0.550	0.22	0.20	0.41	6.95	5395.62	441
1.300	0.550	0.22	0.20	0.41	6.97	5364.27	465
1.300	0.550	0.22	0.20	0.41	6.65	5342.70	449
1.300	0.550	0.22	0.20	0.41	6.80	5235.72	450
1.300	0.790	0.24	0.20	0.33	7.20	5141.26	473
1.300	0.790	0.24	0.20	0.33	7.32	5203.95	484
1.300	0.790	0.24	0.20	0.33	7.65	5029.89	486
1.300	0.790	0.24	0.20	0.33	7.51	5013.02	481
1.300	0.790	0.24	0.20	0.33	7.04	5202.67	465
1.300	0.790	0.24	0.20	0.33	6.77	5202.50	455
1.300	0.790	0.24	0.20	0.33	6.89	5279.94	443
1.300	0.790	0.24	0.20	0.33	7.90	5060.65	502
1.300	0.790	0.24	0.20	0.33	7.69	5062.45	471

C.3. Simulation Results DP_C

Table C.3: Simulation Results with Demand Profile DP_C.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.060	0.060	0.09	0.19	0.68	7.38	5143.28	486
0.060	0.060	0.09	0.19	0.68	7.61	5064.55	499
0.060	0.060	0.09	0.19	0.68	8.07	4898.80	498
0.060	0.060	0.10	0.19	0.67	8.08	4916.79	503
0.060	0.060	0.10	0.19	0.67	7.68	5098.72	494
0.060	0.060	0.10	0.19	0.67	7.89	4969.17	501
0.060	0.060	0.08	0.23	0.69	7.21	5111.62	494
0.060	0.060	0.08	0.23	0.69	7.49	4912.17	485
0.060	0.060	0.08	0.23	0.69	8.05	4905.41	492
0.060	0.270	0.11	1.00	0.40	7.75	5024.00	491
0.060	0.270	0.11	1.00	0.40	8.24	4902.79	505
0.060	0.270	0.11	1.00	0.40	7.58	4958.16	484
0.060	0.270	0.11	1.00	0.40	7.92	4983.01	493
0.060	0.270	0.11	1.00	0.40	7.43	5016.00	504
0.060	0.270	0.11	1.00	0.40	7.72	5080.61	496
0.060	0.270	0.11	1.00	0.40	7.80	5067.74	491
0.060	0.270	0.11	1.00	0.40	8.54	5040.34	528
0.060	0.270	0.11	1.00	0.40	8.63	4831.23	505
0.060	0.490	0.13	1.00	0.33	8.53	4885.30	513
0.060	0.490	0.13	1.00	0.33	7.77	5062.79	495
0.060	0.490	0.13	1.00	0.33	8.32	4932.15	512
0.060	0.490	0.13	1.00	0.33	7.74	4990.16	479
0.060	0.490	0.13	1.00	0.33	7.53	5063.37	475
0.060	0.490	0.13	1.00	0.33	7.19	5183.62	463
0.060	0.490	0.13	1.00	0.33	7.90	4933.88	497
0.060	0.490	0.13	1.00	0.33	7.85	4952.08	515
0.060	0.490	0.13	1.00	0.33	7.84	4995.05	492
0.060	0.700	0.13	1.00	0.33	7.09	4954.66	465
0.060	0.700	0.13	1.00	0.33	8.14	4833.93	515
0.060	0.700	0.13	1.00	0.33	8.35	4981.24	508
0.060	0.700	0.13	1.00	0.33	8.18	4947.64	503
0.060	0.700	0.13	1.00	0.33	8.44	4885.20	510
0.060	0.700	0.13	1.00	0.33	8.04	4839.77	493
0.060	0.700	0.13	1.00	0.33	7.90	4959.72	493
0.060	0.700	0.13	1.00	0.33	7.88	4941.14	500
0.060	0.700	0.13	1.00	0.33	8.42	4956.06	490
1.000	1.000	0.21	0.21	0.33	8.21	4873.26	501
1.000	1.000	0.21	0.21	0.33	8.81	4785.37	513
1.000	1.000	0.21	0.21	0.33	8.57	4802.62	497
1.000	1.000	0.21	0.21	0.33	8.52	4762.08	506
1.000	1.000	0.21	0.21	0.33	8.62	4964.56	521
1.000	1.000	0.21	0.21	0.33	8.65	4812.38	509
1.000	1.000	0.21	0.21	0.33	8.56	4883.39	508
1.000	1.000	0.21	0.21	0.33	9.04	4687.91	532
1.000	1.000	0.21	0.21	0.33	9.28	4666.80	517
1.260	0.060	0.08	0.19	0.70	9.23	4707.07	522
1.260	0.060	0.08	0.19	0.70	8.11	4977.44	509
1.260	0.060	0.08	0.19	0.70	7.39	4952.85	474
1.260	0.060	0.11	0.41	0.55	7.25	5078.16	472
1.260	0.060	0.11	0.41	0.55	8.41	4901.67	530
1.260	0.060	0.11	0.41	0.55	8.14	5009.23	496
1.260	0.060	0.08	0.17	0.71	8.24	4953.87	501
1.260	0.060	0.08	0.17	0.71	8.37	4799.75	522
1.260	0.060	0.08	0.17	0.71	7.64	4939.37	491
1.260	0.270	0.15	0.14	0.54	7.59	4939.92	491
1.260	0.270	0.15	0.14	0.54	8.01	4972.42	496
1.260	0.270	0.15	0.14	0.54	7.90	4992.33	491
1.260	0.270	0.15	0.14	0.54	7.80	5041.62	479
1.260	0.270	0.15	0.14	0.54	8.07	4938.63	499
1.260	0.270	0.15	0.14	0.54	7.87	4991.60	478
1.260	0.270	0.15	0.14	0.54	7.60	4983.69	480
1.260	0.270	0.15	0.14	0.54	7.23	5121.49	483
1.260	0.270	0.15	0.14	0.54	6.83	5084.97	455
1.260	0.490	0.19	0.16	0.40	7.11	5039.62	469
1.260	0.490	0.19	0.16	0.40	8.14	4902.33	509
1.260	0.490	0.19	0.16	0.40	8.43	4812.27	510
1.260	0.490	0.19	0.16	0.40	8.24	4892.74	504
1.260	0.490	0.19	0.16	0.40	7.66	4920.89	498
1.260	0.490	0.19	0.16	0.40	7.80	4967.25	483
1.260	0.490	0.19	0.16	0.40	7.96	5014.97	498
1.260	0.490	0.19	0.16	0.40	8.55	4767.28	518
1.260	0.490	0.19	0.16	0.40	8.49	4807.70	492
1.260	0.700	0.21	0.17	0.33	8.49	4767.35	504
1.260	0.700	0.21	0.17	0.33	9.46	4622.56	535
1.260	0.700	0.21	0.17	0.33	9.26	4786.86	534
1.260	0.700	0.21	0.17	0.33	8.92	4738.48	512
1.260	0.700	0.21	0.17	0.33	9.05	4758.18	533
1.260	0.700	0.21	0.17	0.33	8.68	4850.95	512
1.260	0.700	0.21	0.17	0.33	8.90	4729.01	527
1.260	0.700	0.21	0.17	0.33	8.64	4908.53	518
1.260	0.700	0.21	0.17	0.33	8.13	5015.08	483
2.470	0.060	0.09	0.16	0.69	8.14	4951.35	494
2.470	0.060	0.09	0.16	0.69	8.38	4955.23	521
2.470	0.060	0.09	0.16	0.69	8.40	4985.89	499
2.470	0.060	0.09	0.14	0.69	7.75	5003.63	501
2.470	0.060	0.09	0.14	0.69	8.27	4832.66	494
2.470	0.060	0.09	0.14	0.69	8.02	4974.81	499
2.470	0.060	0.08	0.17	0.73	8.33	4843.58	508
2.470	0.060	0.08	0.17	0.73	7.92	5041.56	505
2.470	0.060	0.08	0.17	0.73	7.75	4984.82	499
2.470	0.270	0.15	0.14	0.54	7.33	5060.69	494
2.470	0.270	0.15	0.14	0.54	7.58	4988.38	495
2.470	0.270	0.15	0.14	0.54	7.38	5014.36	463
2.470	0.270	0.15	0.14	0.54	7.18	4969.58	470
2.470	0.270	0.15	0.14	0.54	8.00	4912.99	504
2.470	0.270	0.15	0.14	0.54	7.44	5080.35	473
2.470	0.270	0.15	0.14	0.54	7.69	5082.34	493
2.470	0.270	0.15	0.14	0.54	8.50	4727.25	522
2.470	0.270	0.15	0.14	0.54	7.63	4881.90	477
2.470	0.490	0.19	0.14	0.40	7.73	4780.70	492
2.470	0.490	0.19	0.14	0.40	8.45	4927.69	518
2.470	0.490	0.19	0.14	0.40	8.22	5031.35	493

Table C.3 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
2.470	0.490	0.19	0.14	0.40	8.29	4827.34	507
2.470	0.490	0.19	0.14	0.40	8.61	4884.95	510
2.470	0.490	0.19	0.14	0.40	8.72	4862.31	512
2.470	0.490	0.19	0.14	0.40	7.77	5017.33	496
2.470	0.490	0.19	0.14	0.40	8.87	4769.07	526
2.470	0.490	0.19	0.14	0.40	8.67	4915.19	509
2.470	0.700	0.22	0.14	0.33	8.10	5033.06	507
2.470	0.700	0.22	0.14	0.33	8.55	4986.99	501
2.470	0.700	0.22	0.14	0.33	8.22	4907.70	502
2.470	0.700	0.22	0.14	0.33	8.62	4936.06	502
2.470	0.700	0.22	0.14	0.33	8.53	4788.39	506
2.470	0.700	0.22	0.14	0.33	8.25	4936.91	488
2.470	0.700	0.22	0.14	0.33	7.84	4928.19	487
2.470	0.700	0.22	0.14	0.33	7.99	5037.66	498
2.470	0.700	0.22	0.14	0.33	8.29	4875.71	494
3.680	0.060	0.09	0.17	0.70	8.36	4944.91	500
3.680	0.060	0.09	0.17	0.70	7.67	5031.71	498
3.680	0.060	0.09	0.17	0.70	7.66	5027.61	472
3.680	0.060	0.09	0.17	0.68	7.90	4978.49	488
3.680	0.060	0.09	0.17	0.68	7.71	5038.24	494
3.680	0.060	0.09	0.17	0.68	7.67	5170.72	484
3.680	0.060	0.09	0.19	0.70	8.81	4861.88	514
3.680	0.060	0.09	0.19	0.70	7.88	4989.43	485
3.680	0.060	0.09	0.19	0.70	7.44	4912.93	477
3.680	0.270	0.15	0.14	0.54	8.23	4983.13	491
3.680	0.270	0.15	0.14	0.54	7.25	5112.52	471
3.680	0.270	0.15	0.14	0.54	8.06	5003.06	484
3.680	0.270	0.15	0.14	0.54	7.01	5279.87	464
3.680	0.270	0.15	0.14	0.54	8.13	4799.31	497
3.680	0.270	0.15	0.14	0.54	8.03	5103.74	490
3.680	0.270	0.15	0.14	0.54	7.45	5067.70	469
3.680	0.270	0.15	0.14	0.54	8.63	4945.86	520
3.680	0.270	0.15	0.14	0.54	8.77	4877.93	505
3.680	0.490	0.19	0.14	0.40	8.07	4972.24	496
3.680	0.490	0.19	0.14	0.40	8.36	4929.07	528
3.680	0.490	0.19	0.14	0.40	8.14	4948.45	494
3.680	0.490	0.19	0.14	0.40	8.49	4830.99	502
3.680	0.490	0.19	0.14	0.40	8.49	4942.83	516
3.680	0.490	0.19	0.14	0.40	8.34	4882.73	506
3.680	0.490	0.19	0.14	0.40	8.09	4948.94	503
3.680	0.490	0.19	0.14	0.40	9.48	4527.82	537
3.680	0.490	0.19	0.14	0.40	8.75	4809.99	515
3.680	0.700	0.22	0.14	0.33	8.89	4752.11	521
3.680	0.700	0.22	0.14	0.33	8.57	4942.28	525
3.680	0.700	0.22	0.14	0.33	8.73	4892.25	499
3.680	0.700	0.22	0.14	0.33	8.58	4891.62	508
3.680	0.700	0.22	0.14	0.33	8.71	4814.68	526
3.680	0.700	0.22	0.14	0.33	8.50	4790.51	510
3.680	0.700	0.22	0.14	0.33	7.83	5015.59	488
3.680	0.700	0.22	0.14	0.33	8.34	4793.14	514
3.680	0.700	0.22	0.14	0.33	8.49	4772.25	489
4.880	0.060	0.11	0.47	0.53	8.74	4883.14	515
4.880	0.060	0.11	0.47	0.53	7.79	4865.44	492
4.880	0.060	0.11	0.47	0.53	7.52	4957.35	470
4.880	0.060	0.08	0.17	0.71	7.97	4918.15	496
4.880	0.060	0.08	0.17	0.71	7.24	4891.82	486
4.880	0.060	0.08	0.17	0.71	7.49	5051.70	469
4.880	0.060	0.08	0.17	0.71	7.72	4831.13	491
4.880	0.060	0.08	0.17	0.71	8.11	4880.39	511
4.880	0.060	0.08	0.17	0.71	8.46	4768.13	483
4.880	0.270	0.15	0.14	0.54	7.80	5148.36	494
4.880	0.270	0.15	0.14	0.54	7.27	5083.05	485
4.880	0.270	0.15	0.14	0.54	7.49	4910.14	474
4.880	0.270	0.15	0.14	0.54	7.80	4844.65	478
4.880	0.270	0.15	0.14	0.54	7.60	5073.85	498
4.880	0.270	0.15	0.14	0.54	7.82	4963.33	483
4.880	0.270	0.15	0.14	0.54	7.72	4982.83	486
4.880	0.270	0.15	0.14	0.54	8.21	4905.27	508
4.880	0.270	0.15	0.14	0.54	7.54	5057.64	478
4.880	0.490	0.19	0.14	0.40	8.07	4924.36	489
4.880	0.490	0.19	0.14	0.40	8.52	4853.30	519
4.880	0.490	0.19	0.14	0.40	8.12	5001.52	494
4.880	0.490	0.19	0.14	0.40	8.21	4907.96	489
4.880	0.490	0.19	0.14	0.40	8.74	4723.91	519
4.880	0.490	0.19	0.14	0.40	8.72	4761.61	498
4.880	0.490	0.19	0.14	0.40	8.41	4996.55	490
4.880	0.490	0.19	0.14	0.40	9.63	4655.33	545
4.880	0.490	0.19	0.14	0.40	8.82	4718.25	506
4.880	0.700	0.22	0.14	0.33	9.20	4742.39	520
4.880	0.700	0.22	0.14	0.33	8.09	4909.23	508
4.880	0.700	0.22	0.14	0.33	8.50	4933.08	511
4.880	0.700	0.22	0.14	0.33	8.15	4961.96	490
4.880	0.700	0.22	0.14	0.33	8.32	4903.53	513
4.880	0.700	0.22	0.14	0.33	8.00	4890.00	483
4.880	0.700	0.22	0.14	0.33	7.92	4994.91	495
4.880	0.700	0.22	0.14	0.33	8.57	4860.05	520
4.880	0.700	0.22	0.14	0.33	7.85	4968.21	486
6.090	0.060	0.10	0.64	0.54	8.54	4951.00	509
6.090	0.060	0.10	0.64	0.54	8.34	4898.89	509
6.090	0.060	0.10	0.64	0.54	7.96	4915.55	488
6.090	0.060	0.07	0.17	0.74	8.09	5015.90	490
6.090	0.060	0.07	0.17	0.74	7.22	4930.38	490
6.090	0.060	0.07	0.17	0.74	8.34	4829.94	499
6.090	0.060	0.09	0.17	0.70	7.39	5078.12	483
6.090	0.060	0.09	0.17	0.70	7.93	4954.09	504
6.090	0.060	0.09	0.17	0.70	7.87	5005.24	489
6.090	0.270	0.15	0.14	0.54	7.49	5112.13	475
6.090	0.270	0.15	0.14	0.54	7.33	4809.58	485
6.090	0.270	0.15	0.14	0.54	7.54	4967.57	487
6.090	0.270	0.15	0.14	0.54	7.34	5011.66	482
6.090	0.270	0.15	0.14	0.54	7.75	4995.83	505
6.090	0.270	0.15	0.14	0.54	7.85	4943.92	488
6.090	0.270	0.15	0.14	0.54	7.55	5056.64	485
6.090	0.270	0.15	0.14	0.54	7.50	4973.88	499
6.090	0.270	0.15	0.14	0.54	7.76	5105.32	492
6.090	0.490	0.19	0.14	0.40	7.87	5055.53	486
6.090	0.490	0.19	0.14	0.40	8.30	4839.93	515
6.090	0.490	0.19	0.14	0.40	8.63	4738.52	506
6.090	0.490	0.19	0.14	0.40	8.26	4888.15	511

Table C.3 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
6.090	0.490	0.19	0.14	0.40	7.32	5050.08	477
6.090	0.490	0.19	0.14	0.40	7.65	4980.23	484
6.090	0.490	0.19	0.14	0.40	7.95	4965.04	485
6.090	0.490	0.19	0.14	0.40	8.89	4792.19	527
6.090	0.490	0.19	0.14	0.40	8.33	4969.04	512
6.090	0.700	0.22	0.14	0.33	8.60	4723.53	515
6.090	0.700	0.22	0.14	0.33	8.57	4950.77	506
6.090	0.700	0.22	0.14	0.33	8.31	4857.76	502
6.090	0.700	0.22	0.14	0.33	8.21	4880.87	492
6.090	0.700	0.22	0.14	0.33	9.36	4707.12	540
6.090	0.700	0.22	0.14	0.33	8.48	4881.32	498
6.090	0.700	0.22	0.14	0.33	8.28	4932.91	499
6.090	0.700	0.22	0.14	0.33	8.65	4826.73	520
6.090	0.700	0.22	0.14	0.33	8.53	4928.00	504

C.4. Simulation Results DP_D

Table C.4: Simulation Results with Demand Profile DP_D.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.050	0.050	0.16	0.43	0.73	8.48	4921.74	495
0.050	0.050	0.16	0.43	0.73	8.43	4886.05	526
0.050	0.050	0.16	0.43	0.73	8.22	4864.70	503
0.050	0.050	0.19	0.36	0.61	8.00	4965.60	496
0.050	0.050	0.19	0.36	0.61	8.33	4881.01	525
0.050	0.050	0.19	0.36	0.61	8.53	5035.83	499
0.050	0.050	0.18	0.40	0.60	7.80	5091.72	486
0.050	0.050	0.18	0.40	0.60	8.55	4862.74	520
0.050	0.050	0.18	0.40	0.60	8.05	5045.83	474
0.050	0.210	0.10	1.00	0.50	7.72	4979.95	480
0.050	0.210	0.10	1.00	0.50	7.79	4942.59	500
0.050	0.210	0.10	1.00	0.50	6.67	5223.48	457
0.050	0.210	0.10	1.00	0.50	6.98	5059.96	473
0.050	0.210	0.10	1.00	0.50	6.75	5152.62	465
0.050	0.210	0.10	1.00	0.50	7.33	5109.89	480
0.050	0.210	0.10	1.00	0.50	7.08	5036.63	470
0.050	0.210	0.10	1.00	0.50	7.50	5118.65	486
0.050	0.210	0.10	1.00	0.50	7.91	5103.56	501
0.050	0.380	0.10	1.00	0.50	7.62	4933.01	479
0.050	0.380	0.10	1.00	0.50	7.75	4978.87	493
0.050	0.380	0.10	1.00	0.50	7.35	5029.07	483
0.050	0.380	0.10	1.00	0.50	7.07	5203.22	468
0.050	0.380	0.10	1.00	0.50	7.58	4975.18	499
0.050	0.380	0.10	1.00	0.50	7.91	4891.54	498
0.050	0.380	0.10	1.00	0.50	7.30	5135.13	477
0.050	0.380	0.10	1.00	0.50	7.45	4971.67	490
0.050	0.380	0.10	1.00	0.50	7.84	4881.65	483
0.050	0.540	0.10	1.00	0.50	7.25	5224.23	467
0.050	0.540	0.10	1.00	0.50	7.64	4837.26	490
0.050	0.540	0.10	1.00	0.50	6.81	5300.80	463
0.050	0.540	0.10	1.00	0.50	7.20	5174.03	477
0.050	0.540	0.10	1.00	0.50	7.43	4886.95	488
0.050	0.540	0.10	1.00	0.50	7.22	5114.63	468
0.050	0.540	0.10	1.00	0.50	7.46	5051.54	478
0.050	0.540	0.10	1.00	0.50	7.41	4920.57	484
0.050	0.540	0.10	1.00	0.50	7.16	5007.38	462
0.200	0.050	0.11	0.58	1.00	7.23	5016.36	474
0.200	0.050	0.11	0.58	1.00	6.97	5021.15	469
0.200	0.050	0.11	0.58	1.00	6.84	5171.95	463
0.200	0.050	0.11	0.58	1.00	7.10	5129.75	470
0.200	0.050	0.11	0.58	1.00	7.04	5119.14	485
0.200	0.050	0.11	0.58	1.00	7.16	5151.06	463
0.200	0.050	0.11	0.58	1.00	7.25	5065.21	465
0.200	0.050	0.11	0.58	1.00	7.47	5110.15	496
0.200	0.050	0.11	0.58	1.00	7.33	5178.78	472
0.200	0.210	0.14	0.68	0.63	7.60	5025.01	476
0.200	0.210	0.14	0.68	0.63	7.87	4892.83	495
0.200	0.210	0.14	0.68	0.63	7.04	5228.65	472
0.200	0.210	0.14	0.68	0.63	6.98	5118.79	467
0.200	0.210	0.14	0.68	0.63	7.54	4913.13	492
0.200	0.210	0.14	0.68	0.63	6.74	5187.44	451
0.200	0.210	0.14	0.68	0.63	7.45	4985.70	478
0.200	0.210	0.14	0.68	0.63	7.59	5051.73	489
0.200	0.210	0.14	0.68	0.63	6.64	5231.95	443
0.200	0.380	0.14	0.72	0.50	7.43	5144.59	480
0.200	0.380	0.14	0.72	0.50	7.30	5024.92	489
0.200	0.380	0.14	0.72	0.50	7.80	4886.02	488
0.200	0.380	0.14	0.72	0.50	7.98	4913.95	491
0.200	0.380	0.14	0.72	0.50	7.66	5070.99	480
0.200	0.380	0.14	0.72	0.50	7.01	5081.49	461
0.200	0.380	0.14	0.72	0.50	7.40	5025.89	479
0.200	0.380	0.14	0.72	0.50	7.51	5059.00	487
0.200	0.380	0.14	0.72	0.50	6.80	5024.99	448
0.200	0.540	0.14	0.72	0.50	7.65	5016.20	481
0.200	0.540	0.14	0.72	0.50	8.15	4839.96	497
0.200	0.540	0.14	0.72	0.50	7.94	4977.35	478
0.200	0.540	0.14	0.72	0.50	8.16	4895.93	503
0.200	0.540	0.14	0.72	0.50	7.76	4995.09	492
0.200	0.540	0.14	0.72	0.50	7.39	5068.31	483
0.200	0.540	0.14	0.72	0.50	7.19	5093.62	466
0.200	0.540	0.14	0.72	0.50	7.04	5221.78	474
0.200	0.540	0.14	0.72	0.50	7.25	5075.14	467
0.350	0.050	0.14	0.41	1.00	7.58	5001.31	482
0.350	0.050	0.14	0.41	1.00	7.38	5065.25	490
0.350	0.050	0.14	0.41	1.00	7.31	5222.23	482
0.350	0.050	0.14	0.41	1.00	7.66	4978.89	482
0.350	0.050	0.14	0.41	1.00	7.67	5009.15	488
0.350	0.050	0.14	0.41	1.00	7.07	5203.61	464
0.350	0.050	0.14	0.41	1.00	6.89	5074.18	462
0.350	0.050	0.14	0.41	1.00	7.78	5024.78	484
0.350	0.050	0.14	0.41	1.00	7.09	5018.39	465
0.350	0.210	0.16	0.46	0.74	7.60	4981.28	480
0.350	0.210	0.16	0.46	0.74	7.55	4974.69	487
0.350	0.210	0.16	0.46	0.74	7.46	5058.71	462
0.350	0.210	0.16	0.46	0.74	7.78	5061.44	478
0.350	0.210	0.16	0.46	0.74	7.35	5038.34	495
0.350	0.210	0.16	0.46	0.74	7.81	4946.70	479
0.350	0.210	0.16	0.46	0.74	7.03	5117.16	471
0.350	0.210	0.16	0.46	0.74	7.16	5123.15	482
0.350	0.210	0.16	0.46	0.74	7.12	5118.70	454
0.350	0.380	0.18	0.50	0.50	6.96	5197.67	465
0.350	0.380	0.18	0.50	0.50	8.03	5035.69	498
0.350	0.380	0.18	0.50	0.50	7.71	5053.43	479
0.350	0.380	0.18	0.50	0.50	7.67	5004.29	488
0.350	0.380	0.18	0.50	0.50	7.90	4970.97	501
0.350	0.380	0.18	0.50	0.50	7.31	5181.24	484
0.350	0.380	0.18	0.50	0.50	7.63	5053.42	472
0.350	0.380	0.18	0.50	0.50	7.68	4987.77	498
0.350	0.380	0.18	0.50	0.50	7.49	5043.77	478
0.350	0.540	0.18	0.50	0.50	7.65	5076.11	493
0.350	0.540	0.18	0.50	0.50	7.77	4941.07	493
0.350	0.540	0.18	0.50	0.50	7.44	5017.25	474

Table C.4 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.350	0.540	0.18	0.50	0.50	7.29	5149.56	467
0.350	0.540	0.18	0.50	0.50	8.44	4982.06	519
0.350	0.540	0.18	0.50	0.50	7.38	5130.05	483
0.350	0.540	0.18	0.50	0.50	7.33	5117.20	474
0.350	0.540	0.18	0.50	0.50	8.14	5031.20	507
0.350	0.540	0.18	0.50	0.50	7.80	5059.98	487
0.490	0.050	0.15	0.33	1.00	7.53	5063.81	487
0.490	0.050	0.15	0.33	1.00	7.71	4923.29	489
0.490	0.050	0.15	0.33	1.00	7.65	4857.80	478
0.490	0.050	0.15	0.33	1.00	7.76	5114.06	486
0.490	0.050	0.15	0.33	1.00	7.97	4992.80	499
0.490	0.050	0.15	0.33	1.00	7.66	4991.63	478
0.490	0.050	0.15	0.33	1.00	7.33	5167.02	472
0.490	0.050	0.15	0.33	1.00	7.74	4948.46	490
0.490	0.050	0.15	0.33	1.00	7.48	5067.73	479
0.490	0.210	0.17	0.34	0.80	7.17	5155.69	466
0.490	0.210	0.17	0.34	0.80	8.15	4780.15	495
0.490	0.210	0.17	0.34	0.80	7.32	5152.24	473
0.490	0.210	0.17	0.34	0.80	7.28	5118.16	478
0.490	0.210	0.17	0.34	0.80	8.08	4980.68	508
0.490	0.210	0.17	0.34	0.80	7.57	5134.48	488
0.490	0.210	0.17	0.34	0.80	7.15	5129.02	481
0.490	0.210	0.17	0.34	0.80	7.32	5129.46	482
0.490	0.210	0.17	0.34	0.80	7.77	4908.69	485
0.490	0.380	0.19	0.38	0.51	7.72	5056.97	480
0.490	0.380	0.19	0.38	0.51	8.55	4836.29	531
0.490	0.380	0.19	0.38	0.51	7.48	5065.90	481
0.490	0.380	0.19	0.38	0.51	7.95	4976.10	506
0.490	0.380	0.19	0.38	0.51	7.74	5135.37	477
0.490	0.380	0.19	0.38	0.51	8.23	4934.22	497
0.490	0.380	0.19	0.38	0.51	7.40	5128.19	478
0.490	0.380	0.19	0.38	0.51	7.24	5183.13	484
0.490	0.380	0.19	0.38	0.51	7.46	5058.11	483
0.490	0.540	0.19	0.38	0.50	7.63	4955.89	479
0.490	0.540	0.19	0.38	0.50	8.63	4912.79	520
0.490	0.540	0.19	0.38	0.50	8.39	4795.05	498
0.490	0.540	0.19	0.38	0.50	8.98	4811.19	519
0.490	0.540	0.19	0.38	0.50	7.31	5071.02	490
0.490	0.540	0.19	0.38	0.50	7.78	5020.57	486
0.490	0.540	0.19	0.38	0.50	7.52	5040.95	468
0.490	0.540	0.19	0.38	0.50	7.45	5102.95	492
0.490	0.540	0.19	0.38	0.50	7.31	5110.89	482
0.640	0.050	0.15	0.33	1.00	7.78	5009.90	484
0.640	0.050	0.15	0.33	1.00	7.48	5022.66	497
0.640	0.050	0.15	0.33	1.00	8.01	5022.43	496
0.640	0.050	0.15	0.33	1.00	8.01	4960.17	489
0.640	0.050	0.15	0.33	1.00	7.79	5122.83	492
0.640	0.050	0.15	0.33	1.00	7.45	5104.16	462
0.640	0.050	0.15	0.33	1.00	6.84	5241.23	454
0.640	0.050	0.15	0.33	1.00	7.45	5003.71	483
0.640	0.050	0.15	0.33	1.00	7.01	5125.92	457
0.640	0.210	0.17	0.33	0.80	7.31	5153.66	473
0.640	0.210	0.17	0.33	0.80	7.16	5101.46	486
0.640	0.210	0.17	0.33	0.80	7.39	4938.44	464
0.640	0.210	0.17	0.33	0.80	7.59	4962.63	475
0.640	0.210	0.17	0.33	0.80	7.26	5019.44	469
0.640	0.210	0.17	0.33	0.80	7.79	4947.68	482
0.640	0.210	0.17	0.33	0.80	7.05	5143.06	463
0.640	0.210	0.17	0.33	0.80	7.31	5015.83	476
0.640	0.210	0.17	0.33	0.80	7.93	5041.84	485
0.640	0.380	0.20	0.33	0.53	7.56	4963.65	479
0.640	0.380	0.20	0.33	0.53	8.74	4745.39	515
0.640	0.380	0.20	0.33	0.53	8.37	4960.34	502
0.640	0.380	0.20	0.33	0.53	7.64	5025.54	490
0.640	0.380	0.20	0.33	0.53	8.12	4905.53	514
0.640	0.380	0.20	0.33	0.53	8.41	4890.16	501
0.640	0.380	0.20	0.33	0.53	8.12	4959.04	502
0.640	0.380	0.20	0.33	0.53	8.31	4863.63	504
0.640	0.380	0.20	0.33	0.53	7.79	5000.90	482
0.640	0.540	0.20	0.33	0.50	8.39	4842.49	497
0.640	0.540	0.20	0.33	0.50	8.59	4783.65	523
0.640	0.540	0.20	0.33	0.50	8.69	4782.70	505
0.640	0.540	0.20	0.33	0.50	7.55	5099.69	491
0.640	0.540	0.20	0.33	0.50	8.80	4777.61	529
0.640	0.540	0.20	0.33	0.50	8.91	4807.03	521
0.640	0.540	0.20	0.33	0.50	7.69	4949.22	489
0.640	0.540	0.20	0.33	0.50	8.40	4806.58	517
0.640	0.540	0.20	0.33	0.50	7.60	4952.00	490
0.790	0.050	0.15	0.33	1.00	7.63	4964.62	492
0.790	0.050	0.15	0.33	1.00	6.77	5199.09	467
0.790	0.050	0.15	0.33	1.00	7.04	5162.57	458
0.790	0.050	0.15	0.33	1.00	7.03	5134.14	468
0.790	0.050	0.15	0.33	1.00	7.58	5125.27	485
0.790	0.050	0.15	0.33	1.00	7.65	4955.04	480
0.790	0.050	0.15	0.33	1.00	7.53	5061.79	483
0.790	0.050	0.15	0.33	1.00	7.61	5168.12	481
0.790	0.050	0.15	0.33	1.00	7.10	5047.17	468
0.790	0.210	0.17	0.33	0.80	7.48	5078.78	474
0.790	0.210	0.17	0.33	0.80	7.88	5043.16	498
0.790	0.210	0.17	0.33	0.80	7.22	5113.18	475
0.790	0.210	0.17	0.33	0.80	7.22	5215.40	489
0.790	0.210	0.17	0.33	0.80	7.60	5129.98	496
0.790	0.210	0.17	0.33	0.80	7.59	5266.38	486
0.790	0.210	0.17	0.33	0.80	7.47	5065.32	478
0.790	0.210	0.17	0.33	0.80	7.96	5036.27	500
0.790	0.210	0.17	0.33	0.80	7.81	4973.37	492
0.790	0.380	0.20	0.33	0.53	8.08	4970.74	486
0.790	0.380	0.20	0.33	0.53	8.09	4912.00	505
0.790	0.380	0.20	0.33	0.53	8.56	4949.14	510
0.790	0.380	0.20	0.33	0.53	8.14	5005.53	491
0.790	0.380	0.20	0.33	0.53	8.79	4814.84	515
0.790	0.380	0.20	0.33	0.53	8.30	4931.59	501
0.790	0.380	0.20	0.33	0.53	8.36	4980.39	512
0.790	0.380	0.20	0.33	0.53	9.00	4853.05	534
0.790	0.380	0.20	0.33	0.53	8.97	4733.85	518
0.790	0.540	0.20	0.33	0.50	8.19	4860.31	493
0.790	0.540	0.20	0.33	0.50	8.78	4747.41	519
0.790	0.540	0.20	0.33	0.50	8.53	4818.54	492
0.790	0.540	0.20	0.33	0.50	8.73	4863.88	517

Table C.4 continued from previous page

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.790	0.540	0.20	0.33	0.50	8.39	4839.00	506
0.790	0.540	0.20	0.33	0.50	7.57	4940.50	490
0.790	0.540	0.20	0.33	0.50	7.24	5016.85	464
0.790	0.540	0.20	0.33	0.50	8.18	4857.18	509
0.790	0.540	0.20	0.33	0.50	8.39	4916.04	512
1.000	1.000	0.20	0.33	0.50	8.06	4944.02	499
1.000	1.000	0.20	0.33	0.50	9.16	4693.50	532
1.000	1.000	0.20	0.33	0.50	9.23	4689.21	523
1.000	1.000	0.20	0.33	0.50	8.48	4722.50	505
1.000	1.000	0.20	0.33	0.50	8.57	4756.82	526
1.000	1.000	0.20	0.33	0.50	8.49	4908.43	490
1.000	1.000	0.20	0.33	0.50	8.97	4850.96	522
1.000	1.000	0.20	0.33	0.50	9.35	4677.92	538
1.000	1.000	0.20	0.33	0.50	9.58	4781.70	533

C.5. Simulation Results DP_E

Table C.5: Simulation Results with Demand Profile DP_E.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.060	0.060	0.12	1.00	1.00	8.52	4898.88	508
0.060	0.060	0.12	1.00	1.00	9.78	4573.95	558
0.060	0.060	0.12	1.00	1.00	9.20	4701.61	528
0.060	0.060	0.12	1.00	1.00	9.63	4500.26	544
0.060	0.060	0.12	1.00	1.00	10.40	4360.42	561
0.060	0.060	0.12	1.00	1.00	9.18	4484.59	525
0.060	0.060	0.12	1.00	1.00	9.21	4643.04	518
0.060	0.060	0.12	1.00	1.00	9.34	4616.30	531
0.060	0.060	0.12	1.00	1.00	8.91	4705.34	509
0.290	0.060	0.15	0.52	1.00	8.99	4629.29	531
0.290	0.060	0.15	0.52	1.00	10.32	4675.81	564
0.290	0.060	0.15	0.52	1.00	10.00	4589.77	537
0.290	0.060	0.15	0.52	1.00	10.59	4543.17	553
0.290	0.060	0.15	0.52	1.00	9.85	4624.19	546
0.290	0.060	0.15	0.52	1.00	9.69	4617.50	511
0.290	0.060	0.15	0.52	1.00	10.19	4572.29	541
0.290	0.060	0.15	0.52	1.00	9.73	4557.06	536
0.290	0.060	0.15	0.52	1.00	9.31	4680.52	514
0.530	0.060	0.16	0.32	1.00	9.76	4461.36	543
0.530	0.060	0.16	0.32	1.00	9.45	4633.80	532
0.530	0.060	0.16	0.32	1.00	8.24	4796.31	484
0.530	0.060	0.16	0.32	1.00	9.20	4597.73	515
0.530	0.060	0.16	0.32	1.00	9.63	4465.00	548
0.530	0.060	0.16	0.32	1.00	10.57	4343.78	550
0.530	0.060	0.16	0.32	1.00	9.82	4520.37	544
0.530	0.060	0.16	0.32	1.00	10.17	4455.95	535
0.530	0.060	0.16	0.32	1.00	9.87	4597.64	517
0.760	0.060	0.17	0.22	1.00	9.61	4718.51	542
0.760	0.060	0.17	0.22	1.00	8.90	4719.94	522
0.760	0.060	0.17	0.22	1.00	9.45	4646.37	530
0.760	0.060	0.17	0.22	1.00	9.12	4758.22	535
0.760	0.060	0.17	0.22	1.00	10.14	4584.67	556
0.760	0.060	0.17	0.22	1.00	9.69	4568.23	533
0.760	0.060	0.17	0.22	1.00	9.82	4607.58	541
0.760	0.060	0.17	0.22	1.00	9.88	4544.00	555
0.760	0.060	0.17	0.22	1.00	9.80	4491.81	542
1.000	1.000	0.17	0.17	1.00	9.76	4578.51	535
1.000	1.000	0.17	0.17	1.00	9.79	4591.73	543
1.000	1.000	0.17	0.17	1.00	9.57	4554.42	533
1.000	1.000	0.17	0.17	1.00	10.08	4599.43	543
1.000	1.000	0.17	0.17	1.00	11.30	4305.63	580
1.000	1.000	0.17	0.17	1.00	11.10	4392.88	561
1.000	1.000	0.17	0.17	1.00	10.72	4465.53	558
1.000	1.000	0.17	0.17	1.00	9.79	4537.26	538
1.000	1.000	0.17	0.17	1.00	10.52	4576.39	539
1.000	0.060	0.17	0.17	1.00	10.19	4535.81	546
1.000	0.060	0.17	0.17	1.00	11.04	4411.31	578
1.000	0.060	0.17	0.17	1.00	11.03	4397.48	553
1.000	0.060	0.17	0.17	1.00	10.86	4310.50	558
1.000	0.060	0.17	0.17	1.00	12.33	4068.81	584
1.000	0.060	0.17	0.17	1.00	11.57	4290.12	568
1.000	0.060	0.17	0.17	1.00	12.08	4223.13	564
1.000	0.060	0.17	0.17	1.00	10.07	4547.11	551
1.000	0.060	0.17	0.17	1.00	10.82	4525.79	560

C.6. Simulation Results DP_F

Table C.6: Simulation Results with Demand Profile DP_F.

w_B	w_C	z_A	z_B	z_C	**Pile-on**	**Travel distance**	**Orders handled**
0.100	0.070	0.14	1.00	1.00	9.29	4509.04	523
0.100	0.070	0.14	1.00	1.00	8.52	4845.07	515
0.100	0.070	0.14	1.00	1.00	8.17	5012.06	503
0.100	0.070	0.14	1.00	1.00	8.29	4900.74	497
0.100	0.070	0.14	1.00	1.00	8.19	4955.37	507
0.100	0.070	0.14	1.00	1.00	7.97	5001.44	482
0.100	0.070	0.14	1.00	1.00	7.88	5049.86	489
0.100	0.070	0.14	1.00	1.00	8.55	4716.34	510
0.100	0.070	0.14	1.00	1.00	7.74	5005.01	480
0.150	0.070	0.14	0.96	1.00	7.50	5066.41	461
0.150	0.070	0.14	0.96	1.00	8.16	4858.72	519
0.150	0.070	0.14	0.96	1.00	8.43	4879.36	500
0.150	0.070	0.14	0.96	1.00	7.98	4979.27	497
0.150	0.070	0.14	0.96	1.00	8.07	5020.41	507
0.150	0.070	0.14	0.96	1.00	7.87	4848.00	487
0.150	0.070	0.14	0.96	1.00	8.35	4971.56	509
0.150	0.070	0.14	0.96	1.00	8.24	4925.67	509
0.150	0.070	0.14	0.96	1.00	8.08	5031.28	490
0.190	0.070	0.16	0.80	1.00	8.60	4955.54	506
0.190	0.070	0.16	0.80	1.00	8.41	4870.59	514
0.190	0.070	0.16	0.80	1.00	8.76	4898.53	504
0.190	0.070	0.16	0.80	1.00	8.31	4858.97	503
0.190	0.070	0.16	0.80	1.00	8.75	4729.18	509
0.190	0.070	0.16	0.80	1.00	8.39	4867.15	494
0.190	0.070	0.16	0.80	1.00	8.56	4946.27	517
0.190	0.070	0.16	0.80	1.00	8.50	4790.87	503
0.190	0.070	0.16	0.80	1.00	8.28	4763.34	495
0.240	0.070	0.17	0.69	1.00	8.04	4853.26	493
0.240	0.070	0.17	0.69	1.00	8.18	4765.87	504
0.240	0.070	0.17	0.69	1.00	8.30	4701.68	500
0.240	0.070	0.17	0.69	1.00	8.10	4907.28	498
0.240	0.070	0.17	0.69	1.00	7.98	4877.13	510
0.240	0.070	0.17	0.69	1.00	8.95	4791.99	520
0.240	0.070	0.17	0.69	1.00	8.79	4687.03	508
0.240	0.070	0.17	0.69	1.00	8.71	4680.96	525
0.240	0.070	0.17	0.69	1.00	9.02	4779.32	521
0.290	0.070	0.17	0.60	1.00	8.19	4906.00	506
0.290	0.070	0.17	0.60	1.00	8.34	4896.11	509
0.290	0.070	0.17	0.60	1.00	8.62	4706.67	509
0.290	0.070	0.17	0.60	1.00	9.02	4815.06	525
0.290	0.070	0.17	0.60	1.00	8.53	4753.42	499
0.290	0.070	0.17	0.60	1.00	8.89	4795.00	514
0.290	0.070	0.17	0.60	1.00	8.56	4822.22	506
0.290	0.070	0.17	0.60	1.00	8.25	4909.07	509
0.290	0.070	0.17	0.60	1.00	7.47	4954.90	474
0.330	0.070	0.18	0.54	1.00	7.88	4881.74	489
0.330	0.070	0.18	0.54	1.00	8.23	4912.58	510
0.330	0.070	0.18	0.54	1.00	8.36	4815.95	500
0.330	0.070	0.18	0.54	1.00	8.61	4746.97	512
0.330	0.070	0.18	0.54	1.00	8.97	4755.47	521
0.330	0.070	0.18	0.54	1.00	8.67	4826.06	506
0.330	0.070	0.18	0.54	1.00	8.95	4786.22	516
0.330	0.070	0.18	0.54	1.00	8.42	4727.86	512
0.330	0.070	0.18	0.54	1.00	8.17	4793.86	491
0.380	0.070	0.18	0.50	1.00	7.84	5018.11	483
0.380	0.070	0.18	0.50	1.00	9.10	4817.36	522
0.380	0.070	0.18	0.50	1.00	8.69	4881.32	506
0.380	0.070	0.18	0.50	1.00	8.43	4834.58	501
0.380	0.070	0.18	0.50	1.00	8.36	4955.37	510
0.380	0.070	0.18	0.50	1.00	8.82	4740.67	521
0.380	0.070	0.18	0.50	1.00	8.41	4797.71	501
0.380	0.070	0.18	0.50	1.00	8.76	4699.78	504
0.380	0.070	0.18	0.50	1.00	8.64	4755.35	512
1.000	1.000	0.18	0.50	1.00	8.05	4970.77	499
1.000	1.000	0.18	0.50	1.00	7.67	4932.96	515
1.000	1.000	0.18	0.50	1.00	7.92	4989.23	484
1.000	1.000	0.18	0.50	1.00	7.54	5068.97	482
1.000	1.000	0.18	0.50	1.00	8.03	4988.47	517
1.000	1.000	0.18	0.50	1.00	8.31	4960.43	503
1.000	1.000	0.18	0.50	1.00	8.35	4838.54	514
1.000	1.000	0.18	0.50	1.00	8.33	4987.88	503
1.000	1.000	0.18	0.50	1.00	8.46	4851.77	496

C.7. Simulation Results Regular Gall&Gall Demand Profile

Table C.7: Simulation Results with Regular Gall&Gall Demand Profile.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.010	1.000	0.12	0.50	1.00	7.19	5074.53	474
0.010	1.000	0.12	0.50	1.00	7.79	5005.83	507
0.010	1.000	0.12	0.50	1.00	7.40	5050.00	467
0.010	1.000	0.15	0.40	1.00	7.32	5145.08	478
0.010	1.000	0.15	0.40	1.00	8.41	5004.56	517
0.010	1.000	0.15	0.40	1.00	8.06	5023.32	492
0.010	1.000	0.12	0.49	1.00	7.47	5098.84	484
0.010	1.000	0.12	0.49	1.00	7.50	5126.95	491
0.010	1.000	0.12	0.49	1.00	7.02	5159.03	474
0.240	1.000	0.12	0.49	1.00	7.36	5036.81	476
0.240	1.000	0.12	0.49	1.00	7.40	4982.70	479
0.240	1.000	0.12	0.49	1.00	7.14	5189.72	467
0.240	1.000	0.12	0.49	1.00	7.77	5006.00	496
0.240	1.000	0.12	0.49	1.00	7.76	5096.96	491
0.240	1.000	0.12	0.49	1.00	7.56	5120.89	482
0.240	1.000	0.12	0.49	1.00	7.56	4962.30	483
0.240	1.000	0.12	0.49	1.00	8.04	4983.30	513
0.240	1.000	0.12	0.49	1.00	7.60	4975.06	474
0.460	1.000	0.16	0.34	1.00	7.41	4990.29	480
0.460	1.000	0.16	0.34	1.00	7.77	4982.58	490
0.460	1.000	0.16	0.34	1.00	7.61	4973.08	480
0.460	1.000	0.16	0.34	1.00	7.44	4940.79	483
0.460	1.000	0.16	0.34	1.00	7.02	5203.53	457
0.460	1.000	0.16	0.34	1.00	6.83	5186.77	453
0.460	1.000	0.16	0.34	1.00	6.72	5271.46	455
0.460	1.000	0.16	0.34	1.00	8.30	5036.74	508
0.460	1.000	0.16	0.34	1.00	7.79	4991.03	471
0.690	1.000	0.18	0.26	1.00	7.61	4947.94	473
0.690	1.000	0.18	0.26	1.00	7.68	5120.57	503
0.690	1.000	0.18	0.26	1.00	7.79	4987.08	495
0.690	1.000	0.18	0.26	1.00	7.66	5026.02	485
0.690	1.000	0.18	0.26	1.00	7.76	4978.32	488
0.690	1.000	0.18	0.26	1.00	7.52	5030.43	469
0.690	1.000	0.18	0.26	1.00	7.72	4910.47	481
0.690	1.000	0.18	0.26	1.00	7.37	5004.01	487
0.690	1.000	0.18	0.26	1.00	7.85	5167.35	487
0.920	1.000	0.20	0.21	1.00	7.23	5176.04	473
0.920	1.000	0.20	0.21	1.00	7.94	4950.34	495
0.920	1.000	0.20	0.21	1.00	6.58	5263.98	441
0.920	1.000	0.20	0.21	1.00	7.21	5232.67	477
0.920	1.000	0.20	0.21	1.00	7.32	5044.24	477
0.920	1.000	0.20	0.21	1.00	7.68	4958.04	481
0.920	1.000	0.20	0.21	1.00	7.87	4851.19	490
0.920	1.000	0.20	0.21	1.00	7.24	5113.40	483
0.920	1.000	0.20	0.21	1.00	7.74	5110.15	481
1.000	1.000	0.20	0.20	1.00	7.45	5050.91	477
1.000	1.000	0.20	0.20	1.00	6.78	5262.75	456
1.000	1.000	0.20	0.20	1.00	7.83	4909.88	483
1.000	1.000	0.20	0.20	1.00	7.51	5096.73	477
1.000	1.000	0.20	0.20	1.00	7.98	4991.55	507
1.000	1.000	0.20	0.20	1.00	7.97	5017.08	484
1.000	1.000	0.20	0.20	1.00	7.86	5103.46	493
1.000	1.000	0.20	0.20	1.00	7.20	5133.44	472
1.000	1.000	0.20	0.20	1.00	6.88	5219.71	448
1.150	1.000	0.21	0.18	1.00	6.48	5334.32	442
1.150	1.000	0.21	0.18	1.00	7.34	5212.37	479
1.150	1.000	0.21	0.18	1.00	7.12	5185.58	453
1.150	1.000	0.21	0.18	1.00	7.31	5222.99	463
1.150	1.000	0.21	0.18	1.00	7.52	5060.57	483
1.150	1.000	0.21	0.18	1.00	7.07	5049.46	450
1.150	1.000	0.21	0.18	1.00	7.03	5206.91	460
1.150	1.000	0.21	0.18	1.00	7.13	5134.90	459
1.150	1.000	0.21	0.18	1.00	7.58	5236.87	472
1.370	1.000	0.21	0.15	1.00	7.27	5169.82	467
1.370	1.000	0.21	0.15	1.00	7.65	4954.73	490
1.370	1.000	0.21	0.15	1.00	7.27	5231.51	469
1.370	1.000	0.21	0.15	1.00	7.54	5012.12	476
1.370	1.000	0.21	0.15	1.00	8.32	4825.80	513
1.370	1.000	0.21	0.15	1.00	7.83	5032.47	490
1.370	1.000	0.21	0.15	1.00	7.72	4886.54	473
1.370	1.000	0.21	0.15	1.00	7.56	5021.93	480
1.370	1.000	0.21	0.15	1.00	7.86	5152.33	480
1.600	1.000	0.22	0.14	1.00	7.72	5002.12	489
1.600	1.000	0.22	0.14	1.00	7.60	4945.28	474
1.600	1.000	0.22	0.14	1.00	7.32	5036.98	461
1.600	1.000	0.22	0.14	1.00	7.68	5017.24	478
1.600	1.000	0.22	0.14	1.00	7.61	4912.31	488
1.600	1.000	0.22	0.14	1.00	6.98	5138.85	465
1.600	1.000	0.22	0.14	1.00	8.10	5032.53	492
1.600	1.000	0.22	0.14	1.00	7.91	4990.44	506
1.600	1.000	0.22	0.14	1.00	7.54	5009.30	489

C.8. Simulation Results Peak Gall&Gall Demand Profile

Table C.8: Simulation Results with Peak Gall&Gall Demand Profile.

w_B	w_C	z_A	z_B	z_C	Pile-on	Travel distance	Orders handled
0.010	1.000	0.08	0.85	1.00	7.52	5079.60	485
0.010	1.000	0.08	0.85	1.00	7.62	4970.13	504
0.010	1.000	0.08	0.85	1.00	7.84	5144.18	486
0.010	1.000	0.10	0.72	1.00	7.52	5079.60	485
0.010	1.000	0.10	0.72	1.00	7.60	5063.97	503
0.010	1.000	0.10	0.72	1.00	8.13	4895.72	491
0.010	1.000	0.08	0.85	1.00	8.24	4891.15	512
0.010	1.000	0.08	0.85	1.00	7.79	4899.53	491
0.010	1.000	0.08	0.85	1.00	7.52	5087.67	465
0.150	1.000	0.11	0.70	1.00	7.93	5009.26	496
0.150	1.000	0.11	0.70	1.00	8.09	4914.17	495
0.150	1.000	0.11	0.70	1.00	7.77	5059.50	481
0.150	1.000	0.11	0.70	1.00	7.77	4956.17	498
0.150	1.000	0.11	0.70	1.00	6.86	5180.32	475
0.150	1.000	0.11	0.70	1.00	7.04	5150.30	456
0.150	1.000	0.11	0.70	1.00	7.74	4928.27	484
0.150	1.000	0.11	0.70	1.00	7.83	4945.20	501
0.150	1.000	0.11	0.70	1.00	7.25	5128.72	465
0.290	1.000	0.15	0.49	1.00	7.54	5011.69	489
0.290	1.000	0.15	0.49	1.00	7.90	4937.35	495
0.290	1.000	0.15	0.49	1.00	7.36	5138.10	476
0.290	1.000	0.15	0.49	1.00	7.63	4960.80	476
0.290	1.000	0.15	0.49	1.00	8.18	4916.36	509
0.290	1.000	0.15	0.49	1.00	8.65	4834.12	504
0.290	1.000	0.15	0.49	1.00	7.59	5008.21	485
0.290	1.000	0.15	0.49	1.00	8.22	4887.30	505
0.290	1.000	0.15	0.49	1.00	8.01	4956.80	497
0.430	1.000	0.17	0.38	1.00	7.69	5041.48	489
0.430	1.000	0.17	0.38	1.00	8.35	4927.51	510
0.430	1.000	0.17	0.38	1.00	7.95	4963.14	490
0.430	1.000	0.17	0.38	1.00	7.95	5040.54	493
0.430	1.000	0.17	0.38	1.00	7.74	4911.12	502
0.430	1.000	0.17	0.38	1.00	7.78	4966.40	478
0.430	1.000	0.17	0.38	1.00	7.97	4828.31	502
0.430	1.000	0.17	0.38	1.00	7.89	4865.27	494
0.430	1.000	0.17	0.38	1.00	7.53	5057.87	480
0.580	1.000	0.18	0.31	1.00	7.79	4988.57	476
0.580	1.000	0.18	0.31	1.00	7.42	4906.04	494
0.580	1.000	0.18	0.31	1.00	7.65	4937.33	487
0.580	1.000	0.18	0.31	1.00	8.03	5036.11	503
0.580	1.000	0.18	0.31	1.00	7.43	5015.00	473
0.580	1.000	0.18	0.31	1.00	7.53	4911.00	474
0.580	1.000	0.18	0.31	1.00	7.66	5060.00	484
0.580	1.000	0.18	0.31	1.00	8.23	4856.99	523
0.580	1.000	0.18	0.31	1.00	7.90	5051.52	492
0.720	1.000	0.19	0.26	1.00	7.49	4989.75	486
0.720	1.000	0.19	0.26	1.00	7.94	4986.46	499
0.720	1.000	0.19	0.26	1.00	8.30	4808.98	499
0.720	1.000	0.19	0.26	1.00	7.89	4986.27	493
0.720	1.000	0.19	0.26	1.00	8.57	4881.70	511
0.720	1.000	0.19	0.26	1.00	7.18	5081.20	463
0.720	1.000	0.19	0.26	1.00	8.51	4916.33	512
0.720	1.000	0.19	0.26	1.00	7.81	4996.00	472
0.720	1.000	0.19	0.26	1.00	7.48	5086.92	470
0.860	1.000	0.20	0.23	1.00	7.80	5084.09	489
0.860	1.000	0.20	0.23	1.00	8.44	4789.04	500
0.860	1.000	0.20	0.23	1.00	7.96	4907.05	500
0.860	1.000	0.20	0.23	1.00	7.94	4887.25	495
0.860	1.000	0.20	0.23	1.00	7.81	4885.00	494
0.860	1.000	0.20	0.23	1.00	7.93	4826.81	486
0.860	1.000	0.20	0.23	1.00	7.83	4988.41	500
0.860	1.000	0.20	0.23	1.00	8.60	4786.39	517
0.860	1.000	0.20	0.23	1.00	8.19	4996.99	502
1.000	1.000	0.20	0.20	1.00	7.92	4886.25	496
1.000	1.000	0.20	0.20	1.00	7.97	4807.41	500
1.000	1.000	0.20	0.20	1.00	8.24	4897.13	497
1.000	1.000	0.20	0.20	1.00	7.21	5105.74	472
1.000	1.000	0.20	0.20	1.00	7.99	4935.84	514
1.000	1.000	0.20	0.20	1.00	7.86	4946.52	488
1.000	1.000	0.20	0.20	1.00	7.02	5116.15	463
1.000	1.000	0.20	0.20	1.00	7.47	5031.64	491
1.000	1.000	0.20	0.20	1.00	7.36	4929.55	467

Bibliography

Antic, S., Milutinovic, L. D., & Lisec, A. (2022). Dynamic Discrete Inventory Control Model with Deterministic and Stochastic Demand in Pharmaceutical Distribution. *Applied Sciences 2022, Vol. 12, Page 1536*, *12*(3), 1536. https://doi.org/10.3390/APP12031536

Aro-Gordon, S. (2016). OVERVIEW OF THE CLASSIC ECONOMIC ORDER QUANTITY APPROACH TO INVENTORY MANAGEMENT. *The Business Age*.

Azadeh, K., De Koster, R., & Roy, D. (2017). *Robotized and Automated Warehouse Systems: Review and Recent Developments* (tech. rep.). https://ssrn.com/abstract=2977779

Azadeh, K., De Koster, R., & Roy, D. (2019). *Robotized and Automated Warehouse Systems: Review and Recent Developments* (tech. rep.). https://ssrn.com/abstract=2977779

Boysen, N., Briskorn, D., & Emde, S. (2017). Parts-to-picker based order processing in a rack-moving mobile robots environment. *European Journal of Operational Research*, *262*(2), 550–562. https://doi.org/10.1016/J.EJOR.2017.03.053

Cai, J., Li, X., Liang, Y., & Ouyang, S. (2021). Collaborative optimization of storage location assignment and path planning in robotic mobile fulfillment systems. *Sustainability (Switzerland)*, *13*(10). https://doi.org/10.3390/SU13105644

Chiang, D. M.-H., Lin, C.-C., & Chen, M.-C. (2011). The adaptive approach for storage assignment by mining data of warehouse management system for distribution centres. *Enterprise Information Systems*, *5*(2), 219–234. https://doi.org/10.1080/17517575.2010.537784

Chou, S.-Y., Hendrawan, E., Dewabharata, A., & Zulvia, F. E. (2019, November). Replenishment Policy and SKU Classification to Pod Assignment Design for Robotic Mobile Fulfillment System Performances. https://doi.org/10.3233/atde230633

Chou, S.-Y., Mauliddina, A. N., Dewabharata, A., & Zulvia, F. E. (2023). Pick Order Assignment and Order Batching Strategy for Robotic Mobile Fulfilment System Warehouse. *2023 Winter Simulation Conference (WSC)*, 1700–1711. https://doi.org/10.1109/WSC60868.2023.10408409

da Costa Barros, Í. R., & Nascimento, T. P. (2021, March). Robotic Mobile Fulfillment Systems: A survey on recent developments and research opportunities. https://doi.org/10.1016/j.robot.2021.103729

Dai, H., Xiao, Q., Yan, N., Xu, X., & Tong, T. (2022). Item-level Forecasting for E-commerce Demand with High-dimensional Data Using a Two-stage Feature Selection Algorithm. *Journal of Systems Science and Systems Engineering*, *31*(2), 247–264. https://doi.org/10.1007/S11518-022-5520-1/METRICS

D'Andrea, R., & Wurman, P. (2008). Future challenges of coordinating hundreds of autonomous vehicles in distribution facilities. *IEEE International Conference on Technologies for Practical Applications.* https://www-semanticscholar-org.tudelft.idm.oclc.org/paper/Future-challenges-of-coordinating-hundreds-of-in-D%E2%80%99Andrea-Wurman/c4791ee92af28af2325fbe8c23ed44061387c8

de Koster, R., Le-Duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, *182*(2), 481–501. https://doi.org/10.1016/j.ejor.2006.07.009

Drury, J. (1988). *Towards more efficient order picking*. The Institute of Materials Management.

Ford, H. W. (1913). The Magazine of Management. *10*(2), 152.

Gall&Gall. (2024). Gall & Gall. https://www.gall.nl/over/

Gastwirth, J. L. (1971). A General Definition of the Lorenz Curve. *Econometrica*, *39*(6), 1037. https://doi.org/10.2307/1909675

Gu, J., Goetschalckx, M., & McGinnis, L. F. (2007). Research on warehouse operation: A comprehensive review. *European Journal of Operational Research*, *177*(1), 1–21. https://doi.org/10.1016/J.EJOR.2006.02.025

Guan, M., & Li, Z. (2018). Genetic Algorithm for Scattered Storage Assignment in Kiva Mobile Fulfillment System. *American Journal of Operations Research*, *08*(06), 474–485. https://doi.org/10.4236/ajor.2018.86027

Guizzo, E. (2008). Three engineers, hundreds of robots, one warehouse. *IEEE Spectrum*, *45*(7), 26–34. https://doi.org/10.1109/MSPEC.2008.4547508

Guo, X., Yu, Y., & De Koster, R. B. (2016). Impact of required storage space on storage policy performance in a unit-load warehouse. *International Journal of Production Research*, *54*(8), 2405–2418. https://doi.org/10.1080/00207543.2015.1083624

Gurobi Optimization, LLC. (2024). Gurobi Optimizer Reference Manual. https://www.gurobi.com

Gurobi-Optimizer. (2024). Mixed-Integer Programming (MIP) – A primer on the basics - Gurobi Optimization. https://www.gurobi.com/resources/mixed-integer-programming-mip-a-primer-on-the-basics/

Hausman, W. H., Schwarz, L. B., & Graves, S. C. (1976). OPTIMAL STORAGE ASSIGNMENT IN AUTOMATIC WAREHOUSING SYSTEMS. *Management Science*, *22*(6), 629–638. https://doi.org/10.1287/MNSC.22.6.629

Heskett, J. L. (1963). Cube-per-order Index – A Key to Warehouse Stock Location. *Transportation and Distribution Management*, *3*, 27–31.

Hwang, H., Baek, W. J., & Lee, M. K. (1988). Clustering algorithms for order picking in an automated storage and retrieval system. *International Journal of Production Research*, *26*(2), 189–201. https://doi.org/10.1080/00207548808947853

Kim, H. J., Pais, C., & Shen, Z. J. M. (2020). Item assignment problem in a robotic mobile fulfillment system. *IEEE Transactions on Automation Science and Engineering*, *17*(4), 1854–1867. https://doi.org/10.1109/TASE.2020.2979897

Lamballais, T. T. (2019). *Optimizing the Performance of Robotic Mobile Full llment Systems TIM LAMBALLAIS TESSENSOHN ERIM PhD Series Research in Management* (tech. rep.). www.erim.eur.nl

Lamballais, T. T., Roy, D., & De Koster, R. B. (2020). Inventory allocation in robotic mobile fulfillment systems. *IISE Transactions*, *52*(1), 1–17. https://doi.org/10.1080/24725854.2018.1560517

Lucas Systems. (2023, July). How to Double DC Productivity With AI-Based Batch Picking. https://www.lucasware.com/warehouse-order-picking-introduction/what-is-batch-picking/

McKinsey & Company. (2023, June 29). *What is e-commerce?* https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-e-commerce

Merschformann, M., Lamballais, T., de Koster, M. B., & Suhl, L. (2019). Decision rules for robotic mobile fulfillment systems. *Operations Research Perspectives*, *6*. https://doi.org/10.1016/j.orp.2019.100128

Merschformann, M., Xie, ·. L., Li, ·. H., Merschformann, M. S. M., De, M., Xie, L., & Li, H. (2018). *RAWSim-O: A Simulation Framework for Robotic Mobile Fulfillment Systems* (tech. rep.). http://www.dsor.dehttp://www.leuphana.de/iis

Merschformann, Xie, L., Li, H., Tessensohn, T. L., Erdmann, D., Knickmeier, L., König, J., Herbort, M., & Grawe, M. (2017). GitHub - Merschformann/RAWSim-O: a simulation framework for robotic mobile fulfillment systems. https://github.com/merschformann/RAWSim-O

Mirzaei, M., Zaerpour, N., & de Koster, R. (2021). The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance. *Transportation Research Part E: Logistics and Transportation Review*, *146*. https://doi.org/10.1016/j.tre.2020.102207

Misni, F., & Lee, L. S. (2017). A Review on Strategic, Tactical and Operational Decision Planning in Reverse Logistics of Green Supply Chain Network Design. *Journal of Computer and Communications*, *05*(08), 83–104. https://doi.org/10.4236/jcc.2017.58007

Paquay, C., Schyns, M., & Limbourg, S. (2016). A mixed integer programming formulation for the three-dimensional bin packing problem deriving from an air cargo application. *International Transactions in Operational Research*, *23*(1-2), 187–213. https://doi.org/10.1111/itor.12111

Pareto, V., Montesano, A., Zanni, A., Bruni, L., Chipman, J. S., & McLure, M. (2014). *Manual of political economy: A critical and variorum translation*. Oxford University Press. https://global.oup.com/academic/product/manual-of-political-economy-9780199607952 (Original work published 1906)

Petersen, C. G., Aase, G. R., & Heiser, D. R. (2004). Improving order-picking performance through the implementation of class-based storage. *International Journal of Physical Distribution & Logistics Management*, *34*(7), 534–544. https://doi.org/10.1108/09600030410552230

Petersen, C. G., Siu, C., & Heiser, D. R. (2005). Improving order picking performance utilizing slotting and golden zone storage. *International Journal of Operations and Production Management*, *25*(10), 997–1012. https://doi.org/10.1108/01443570510619491/FULL/PDF

Poon, T. C., Choy, K. L., Chan, F. T. S., Ho, G. T. S., Gunasekaran, A., Lau, H. C. W., & Chow, H. K. H. (2011). A real-time warehouse operations planning system for small batch replenishment problems in production environment. *Elsevier, Expert Systems with Application*, (38). https://doi.org/10.1016/j.eswa.2011.01.053

Reid, H. (2024, January). 9 ecommerce fulfillment metrics you should be tracking. https://dclcorp.com/blog/fulfillment/ecommerce-fulfillment-metrics/

Roy, D., Nigam, S., de Koster, R., Adan, I., & Resing, J. (2019). Robot-storage zone assignment strategies in mobile fulfillment systems. *Transportation Research Part E: Logistics and Transportation Review*, *122*, 119–142. https://doi.org/10.1016/J.TRE.2018.11.005

Scallog. (2020). Scallog | Robotic solution for order picking in warehouse. PresentationSlides

Scallog. (2023). *Ergonomic workstation for warehouses*. https://www.scallog.com/en/workstation/

The Conference Board. (2022). Future occupational labor shortages risk index. https://www.conference-board.org/pdfdownload.cfm?masterProductID=38938

Thieuleux, E. (2024, April). ABC Analysis Examples - a Step-by-Step tutorial in Excel. https://abcsupplychain.com/abc-analysis/

Tompkins, J. A., White, J. A., Bozer, Y. A., & Tanchoco, J. M. A. (1996). *Facilities Planning FOURTH EDITION* (tech. rep.). Wiley, facility planning. https://www.academia.edu/44877867/Facilities_Planning_John_A_White_Yavuz_A_Bozer_J_M_A_Tanchoco_by_James_A_Tompkins_z_lib_org_

Tsai, K.-M., Chen, M.-H., Bremer, P., & Chen, T.-Y. (2019). *IMPLEMENTING ASSOCIATION RULES FOR RACK REPLENISHMENT IN KIVA SYSTEMS* (tech. rep.). https://www.researchgate.net/profile/Santi-Setyaningsih/publication/339401715_THE_EFFECT_OF_SUPPLY_CHAIN_COOPERATION_ON_THE_STRATEGY_OF_SMES_IN_HUNGARY/links/5e4fb82792851c7f7f49bff6/THE-EFFECT-OF-SUPPLY-CHAIN-COOPERATION-ON-THE-STRATEGY-OF-SMES-IN-HUNGARY.pdf#page=571

Ultsch, A., & Lötsch, J. (2015). Computed ABC analysis for rational selection of most informative variables in multivariate data. *PLoS ONE*, *10*(6). https://doi.org/10.1371/JOURNAL.PONE.0129767

Vazquez, H. C., & Lago, V. D. (2022). Rethinking Inventory Forecasting Problems in E-commerce: Exploring the effect of integrating forecasting and inventory decisions. *The International FLAIRS Conference Proceedings*, *35*. https://doi.org/10.32473/FLAIRS.V35I.130572

Wang, K.-H. C., & Botea, A. (2008). *Fast and Memory-Efficient Multi-Agent Pathfinding* (tech. rep.). www.aaai.org%20https://www.researchgate.net/publication/220936230_Fast_and_Memory-Efficient_Multi-Agent_Pathfinding#fullTextFileContent

Warehouse-design. (2020, April). https://warehouse-design.com/key-warehouse-process/outbound/picking/

Weidinger, F., & Boysen, N. (2018). Scattered Storage: How to Distribute Stock Keeping Units All Around a Mixed-Shelves Warehouse. *https://doi-org.tudelft.idm.oclc.org/10.1287/trsc.2017.0779*, *52*(6), 1412–1427. https://doi.org/10.1287/TRSC.2017.0779

Weidinger, F., Boysen, N., & Schneider, M. (2019). Picker routing in the mixed-shelves warehouses of e-commerce retailers. *European Journal of Operational Research*, *274*(2), 501–515. https://doi.org/10.1016/J.EJOR.2018.10.021

Winkelhaus, S., Zhang, M., Grosse, E. H., & Glock, C. H. (2022). NC-ND license Hybrid order picking: A simulation model of a joint manual and autonomous order picking system. https://doi.org/10.1016/j.cie.2022.107981

Wurman, P. R., DAndrea, R., & Mountz, M. (2008). *Coordinating Hundreds of Cooperative, Autonomous Vehicles in Warehouses* (tech. rep.).

Xiang, X., Liu, C., & Miao, L. (2018). Storage assignment and order batching problem in Kiva mobile fulfilment system. *Engineering Optimization*, *50*(11), 1941–1962. https://doi.org/10.1080/0305215X.2017.1419346

Xie, L., Thieme, N., Krenzler, R., & Li, H. (2019). Efficient order picking methods in robotic mobile fulfillment systems. http://www.leuphana.de/or/

Yang, P., Miao, L., Xue, Z., & Ye, B. (2015). Variable neighborhood search heuristic for storage location assignment and storage/retrieval scheduling under shared storage in multi-shuttle automated storage/retrieval systems. *Transportation Research Part E: Logistics and Transportation Review*, *79*, 164–177. https://doi.org/10.1016/j.tre.2015.04.009

Yu, Y., De Koster, R. B., & Guo, X. (2015). Class-Based Storage with a Finite Number of Items: Using More Classes is not Always Better. *Production and Operations Management*, *24*(8), 1235–1247. https://doi.org/10.1111/POMS.12334

Yuan, R., Graves, S. C., & Cezik, T. (2019). Velocity-Based Storage Assignment in Semi-Automated Storage Systems. *Production and Operations Management*, *28*(2), 354–373. https://doi.org/10.1111/poms.12925

Yuan, R., Wang, H., & Li, J. (2019). *The Pod Assignment Model and Algorithm in Robotic Mobile Fulfillment Systems*. IEEE.

Zhang, Y. (2016). Correlated Storage Assignment Strategy to reduce Travel Distance in Order Picking. *IFAC-PapersOnLine*, *49*(2), 30–35. https://doi.org/10.1016/j.ifacol.2016.03.006