Eindhoven University of Technology

MASTER

Scheduling the container receiving operation in e-commerce logistics

van der Linden, G.A.L.

Award date:
2020

Link to publication

Scheduling the container receiving operation in e-commerce logistics

G. van der Linden

Master of Science in Operations Management and Logistics

Mierlo, April 12, 2020

Abstract

This research proposes a new algorithm to schedule the container receiving operations of a fast-growing e-commerce company with multiple warehouses in the same geographical area. The algorithm increases the efficiency of the warehouse operations receiving, put-away, picking and shipping simultaneously, by reducing the long-term cross docks while avoiding situations where containers are picked up after the demurrage date. Cross docks occur when the succeeding warehouse operation cannot be executed in the current warehouse, the total number of cross docks can be estimated on the pickup day and differ per receiving warehouse. The container receiving operation at VidaXL can be scheduled with the rolling horizon policy. The rolling horizon policy reschedules the receiving operation every day new information becomes available. First, an aggregate solution for the coming four days is provided with a binary decision model. The binary decision model selects a subset of containers out of the available containers and schedules each container to a warehouse. The binary decision model maximizes the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse while considering the demurrage date. Second, the FIFO dispatch rule is applied to gather a detailed solution for the first day. The detailed schedule of first day can immediately be implemented. The receiving operation can be rescheduled during succeeding days when new information becomes available. The potential of the scheduling algorithm is evaluated in a realistic simulation by comparing the results with scheduling the containers first in first out and minimizing the put-away cross docks first in first out every day. Moreover, the effect of including picking and shipping cross docks in the scheduling algorithm is investigated by running the model with and without considering cross docks based on the expected storage time.

Preface

After seventeen years of studying, the time has come to prove and develop myself further in industry. This thesis marks the final step towards my master's degree. My study career has been a wonderful journey with many grateful memories. I really appreciate the support of all educational institutions who made me a bit smarter, all companies who provided me with challenging assignments and all my friends and family members who supported me during the years.

First of all, completing my master's degree at the TUe was not possible without the support of my mentor Willem van Jaarsveld. He guided me through the past two years of my master's and I really appreciate your guidance. You challenged me to review the problem at VidaXL from different perspectives. But most important of all, you supported me to lead my own career path. Additionally, I would like to thank my second supervisor Rob Broekmeulen, the expert in consumer goods field, for the feedback during my project.

Secondly, I am really thankful towards Erik van der Hoofdt, the company supervisor of VidaXL. You really understand the logistical process at VidaXL and you are able to oversee almost all consequences of changes in the logistical process. Every week you challenged me to think one step ahead which saved me a lot of time. I am very grateful for having you as supervisor, and sometimes just a few words are enough to understand each other. I want to thank all colleagues at VidaXL who provided me with new insight during my project and helped me further develop my knowledge. Moreover, this project would not have been executed without the support of VidaXL. I am very grateful for this opportunity.

Furthermore, I would like to express my gratitude to my family and friends. I am blessed with having you in my life. You supported me during my study career and assured I had a lot of fun. A special thanks to my parents and girlfriend who supported me in realizing my ambitions during my entire study career. I'm very grateful to have you all in my life.

Giel van der Linden

Management summary

In 2002, management guru Peter Drucker forecasted that e-commerce would significantly impact how business is conducted. Seventeen years later, the Ecommerce Foundation expected that e-commerce would be a 621-billion-euro industry in 2019 in Europe. In 2007, only 30% of the European population bought items online, this percentage had almost doubled to 57% by 2017 (CBS, 2018). Logistics in e-commerce are highly complex since e-commerce typically regards small orders with low value from many different customers (Turban, King, Lee, Liang, & Turban, 2017). The flourishing E-commerce economy combined with new complex logistic challenges stresses the need for efficient warehouse operations. This research proposes a new scheduling algorithm to efficiently schedule the container receiving operations integrated with other warehouse operations at VidaXL.

Problem statement

E-commerce companies have a large product assortment to fulfill small orders from many different customers, and they typically have different warehouses to store the width assortment. Each warehouse is equipped for a special group of products. Decisions need to be made towards achieving an efficient flow of goods between the warehouses. The put-away, picking, checking, and packing strategy are already considered in the literature and in practice to increase warehouse efficiency (Davarzani & Norrman, 2014), and therefore this research focuses on scheduling the receiving operation integrated with the other warehouse operations at VidaXL. The company is opening two new warehouses in 2020 and lacks a scheduling tool to avoid unnecessary cross docks. Cross docks are inefficient flow of goods between warehouses and occur when the succeeding warehouse operation cannot be executed in the current warehouse. This research aims to define a scheduling algorithm which can be used daily to reduce inefficient cross docks between the warehouses integrated with the other warehouse operations. The main research question is formulated as follows:

"How can the container receiving operations be scheduled to increase efficiency during the warehouse operations put-away, picking, and shipping?"

Research topic

Warehousing regards the intermediate storage of goods between successive stages of a supply chain and can be implemented to reduce transportation costs and provide customer service. Warehouses fulfill customer demand through reorganization, which involves the operations: receiving, put-away, order picking, checking and packing, and shipping. Each warehouse tries to increase the efficiency of its warehousing operations by reducing double handling (Bartholdi & Hackman, 2019). The objective of this research is to schedule the receiving operations in e-commerce logistics to increase the efficiency of the warehouse operations put-away, picking and shipping simultaneously, by reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date.

Framework

The framework to schedule the receiving operation integrated with other warehouse operations consists of three layers: input data, scheduling algorithm and output data. Each layer subsequentially fulfill certain tasks and provide the subsequent layer with information to complete the scheduling process.

Input data

Containers can be classified as critical and noncritical containers. Critical containers must be received as soon as possible at a specific warehouse, while noncritical containers are preferred to be processed within ten days. However, these containers lack any other scheduling restrictions and it is therefore possible to efficiently schedule the receiving operation. Arriving containers can contain one stock keeping unit or over hundred different stock keeping units. Not every warehouse operation can be executed in each warehouse for each stock keeping unit. Items must be cross docked between the warehouses when the subsequent operation cannot be executed in the current warehouse. The inherent expected number of cross docks during each warehouse operation when the container is received in one of the warehouses can be estimated on the pickup day.

The number of put-away cross docks per container are based on the available storage types in each warehouse. The picking and shipping cross docks are estimated by calculating the equivalent number of cross docks if a container is received in a less preferred warehouse based on the expected storage time. For many stock keeping units, most of the warehouse operations can be executed in the ship warehouses. The total number of picking and shipping cross docks can therefore be reduced through receiving containers with a short storing time in the ship warehouses, containers with an average storage time in the pick warehouse and containers with a long storage time in the overflow warehouses. Consequently, more containers are received in the preferred ship warehouse resulting in less cross docks and the efficiency during put-away, picking and shipping operations increases.

Each warehouse is constraint by the inbound capacity per container type and the total inbound capacity per warehouse per day. The receiving operations must be scheduled such that all inbound capacity constraints are met.

Scheduling algorithm

In an ideal situation, the container and warehouse data are known far in advance. When there is enough inbound capacity, it would then be possible to schedule the receiving operation of each container before the demurrage date while minimizing the total long-term cross docks. A binary decision must be made, containers must be picked up by a warehouse on a specific date. A triple sum objective function can minimize the total long-term cross docks by assigning the containers to warehouses on specific periods.

The container receiving operation at VidaXL is not ideal, the exact inbound capacity per warehouse is only known a few days in advance, the actual arriving date of each container almost always differs from the estimated arrival date and it is almost impossible to estimate the number of cross docks of each receiving container far in advance. Containers received during previous days, increases the current stock level in each warehouse and therefore affect the estimated number of cross docks of the new receiving containers. It would be possible to resolve the triple sum objective function each day when new information becomes available. However, solving a triple sum objective function is complex and requires computational effort while there is only limited time available to revise the receiving schedule. This paper therefore proposes an alternative rolling horizon scheduling algorithm to deal with uncertain container arrivals and new information availability while reducing the computation time and complexity of the problem.

First, an aggregate solution for the coming four days is provided with a binary decision model. The binary decision model selects a subset of containers out of the available containers and schedules them to a warehouse while considering the four days inbound capacity. The binary decision model

maximizes the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse while considering the demurrage date. Second, the FIFO dispatch rule is applied to gather a detailed solution for the first day. The dispatch rule schedules the container FIFO to each day such that the throughput time decreases, and the containers are picked up before its demurrage date. The detailed schedule of first day can immediately be implemented. The receiving operation can be rescheduled during succeeding days when new information becomes available.

Output data

The scheduling algorithm is able to provide the aggregate schedule for the upcoming four days through selecting and scheduling as many containers as all warehouses can receive from the available set of containers. However, VidaXL must only confirm the pickup date of the detailed schedule for next day in order to retain flexible to new information. New containers can arrive at the container yard and the number of cross docks associated with receiving the container at one of the warehouses can differ over time. The receiving schedule can therefore be revised on next day.

Results

The potential of the algorithm is evaluated in a realistic simulation by comparing the performance with the theoretical upper bound, scheduling containers first in first out and minimizing the total put-away cross docks first in first out every day. Moreover, the effect of including picking and shipping cross docks in the algorithm is investigated by running the model with and without additional cross docks based on the storage time. The results are evaluated in two situations: 1) ramp-up, after opening a new warehouse and 2) steady-state, when each warehouse has the same start utilization.

The theoretical upper bound quantifies the optimal solution when everything is known beforehand, resulting in 5.7% and 10.4% less cross docks in ramp-up and steady state situations respectively as the solution provided by the scheduling algorithm. However, there does not exist a scheduling algorithm that provides an optimal solution without prior knowledge (Dertouzos & Mok, 1989).

After opening a new ship warehouse, the number of cross docks can be reduced with 26.3%, 28.7% and 45.6% compared with the scheduling algorithm without considering picking an shipping cross docks, minimizing the put-away cross docks first in first out every day and first in first out procedure respectively. Moreover, 99.7% of the containers are picked up before the demurrage date. The number of cross docks decreases when the process becomes more stable and the warehouses are equally utilized. When all warehouses have the same start utilization, the total number of cross docks can be reduced with 32.7%, 35.9% and 54.2% respectively, and 99.9% of the containers are picked up on time before the demurrage date. Furthermore, the scheduling algorithm is not sensitive to different inbound capacities and different workload balance parameters, and it still outperforms the other scheduling procedures.

The algorithm schedules containers with a long storage time to the overflow and pick warehouses. The utilization of the reserve area of these warehouses increases faster than that in the ship warehouses because the demand for these items is lower. Accordingly, less containers are received in the pick and overflow warehouses, while items with a high turnover rate are received in the ship warehouses. As such, the pick density in the shipping warehouses increases, whereas the number of cross docks from the pick and overflow warehouses to the ship warehouses decreases. Notably, when more items are picked in the same warehouse, it costs less effort to bundle items that are purchased by the same client. Scheduling containers to receiving warehouses using the algorithm increases efficiency in the receiving, put-away, picking, packing, and shipping operations.

Contents

List of figures

List of tables

List of abbreviations

CLP	Coin Linear Programming
CSCMP	Council of Supply Chain Management Professionals
FIFO	First in first out
JTS	James Tobin Street Warehouse
MKI	Mary Kingsley Warehouse
OF	Overflow warehouses
Pen	Penalty
SAP	Systems, applications and Poducts
SLO	Storage Location Occupation
WMS	Warehouse Management System
WTR	Wetron Warehouse

1. Introduction

In 2002, management guru Peter Drucker forecasted that e-commerce would significantly impact how business is conducted. Seventeen years later, the Ecommerce Foundation expected that e-commerce would be a 621-billion-euro industry in 2019 in Europe. In 2007, only 30% of the European population bought items online, this percentage had almost doubled to 57% by 2017 (CBS, 2018).

Plunkett research Ltd. (2014) defined e-commerce: "electronic commerce refers to using the internet and intranets to purchase, sell, transport, or trade data, goods, or services." This definition shows that e-commerce is characterized by how activities are executed by the company. By fulfilling activities digitally, e-commerce companies experience advantages compared to traditional companies including increased inventory control, shortened time to market, improved market search, and lower advertising costs (Berthon, Pitt, & Watson, 1996; Burstein & Kline, 1995; Spar & Bussgang, 1996).

Logistics in e-commerce are highly complex since e-commerce typically regards small orders with low value from many different customers. They are exposed to seasonality and only large companies have their own warehouses (Turban, King, Lee, Liang, & Turban, 2017). According to the Council of Supply Chain Management Professionals (2013), logistics management plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and point of consumption in order to meet customers' requirements.

The flourishing E-commerce economy combined with new complex logistic challenges stresses the need for efficient warehouse operations. This research proposes a new scheduling algorithm to efficiently schedule the container receiving operations integrated with other warehouse operations at VidaXL. Section 1.1 provides the relevance in the literature, the research topic is defined in Section 1.2, and lastly Section 1.3 forms the outline of this report.

1.1 Relevance in the literature

Fulfilling thousands of small orders every day from different costumers requires significant effort from warehouses, which increases their throughput, storage, and accuracy requirements (Frazelle, 2002). The objective of order fulfillment is to deliver the right item to the right customer in a timely, cost effective, and profitable manner (Turban et al., 2017). Almost all warehouses fulfill customer orders through reorganization, which occurs through the warehouse operations receiving, put-away, picking, checking and packing, and shipping (Bartholdi & Hackman, 2019).

Trends in e-commerce make warehouse management one of the most important players in order to realize growth, stay profitable, and continue improving customer satisfaction. In 2007 and in 2010, Goetschalckx and McGinnes covered different aspect of warehouse design, operations, and performance evaluation by reviewing 197 articles and books from different sources. In 2015, researchers Davarzani and Norrmann identified gaps in the literature and interviewed 15 warehouse managers to suggest a practical and relevant future research agenda Both studies concluded that scheduling the receiving and shipping operations in a warehouse represents the least explored category in warehousing literature. Receiving and shipping operations have the potential to be further investigated, integrated, and independent of other operations.

1.2   Research topic

Warehousing regards the intermediate storage of goods between successive stages of a supply chain and can be implemented to reduce transportation costs and provide customer service. Most warehouses have the same material flow, whereby they receive bulk shipments, stage them for quick retrieval, retrieve and sort SKUs upon customer request, and ship them to the customer. Warehouses fulfill customer demand through reorganization, which involves the operations: receiving, put-away, order picking, checking and packing, and shipping. Each warehouse tries to increase the efficiency of its warehousing operations by reducing double handling (Bartholdi & Hackman, 2019). The objective of this thesis is to improve warehouse efficiency by scheduling the receiving operations.

The main contribution of this thesis is fourfold:

1. This is the first research focusing on efficiently scheduling the receiving operations for fast-growing e-commerce companies with multiple warehouses in the same geographical area. Fast-growing e-commerce companies are exposed to constraints that are less relevant in traditional warehousing literature.
2. While existing literature mainly focuses on improving the receiving, put-away, picking, storage, checking, and packing operations independently of each other, this thesis focuses on scheduling the receiving operation integrated with the other warehouse operations to increase the overall warehouse efficiency.
3. A new alternative rolling horizon scheduling algorithm to schedule receiving containers is developed. The algorithm can deal with uncertain container arrivals and new information availability while reducing the computation time and complexity of the problem.
4. The potential and sensitivity of the scheduling algorithm is evaluated in a realistic simulation.

1.3   Outline of the thesis

Section 1 emphasizes the relevance in literature. The structure of the remainder of this paper is as follows: Section 2 provides all relevant information regarding the problem context and emphasizes its relevance in industry, which together motivate the research subject defined in Section 2 as well. Section 3 provides a brief overview of literature relevant to the research subject. Section 4 includes the conceptual model and proposes a framework, including an algorithm, to schedule the container receiving operation. The goal of the algorithm is to schedule the receiving operations to increase the efficiency of the warehouse operations put-away, picking and shipping simultaneously, by reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date. Section 5 evaluates the effect of the scheduling algorithm on different performance measurements in a realistic simulation. Section 6 contains the overall conclusions of this research and suggests directions for further research.

2. Problem context

This section provides information relevant to the problem context and elaborates on the industry relevance. The project is commissioned by VidaXL, and the first section includes a brief company description. Secondly, the warehouse setup at VidaXL is described in Section 2.2, and thirdly the reorganization of items through the warehouse operations at VidaXL are described in Section 2.3. Fourth, the current warehouse performances are specified in Section 2.4. Finally, the problem definition, research question, project scope, and research methodology are respectively provided in Section 2.5 to 2.9.

2.1   Company background

VidaXL is a rapidly growing international online retailer established in 2006 with an annual revenue of a quarter billion euro (2017). VidaXL offers products for 'in and around the home,' mainly from their own VidaXL brand, in 29 European countries, the United States of America, and Australia via various online sales channels. However, the product assortment is shifting towards a mixture of their own brand and A-brand products and contains around 70,000 SKUs. VidaXL differentiates themselves by being able to provide customers with products for a better price by optimizing and controlling each step of the supply chain from product design, purchasing, transport, and warehousing to delivery to the regional distribution hubs of several delivery partners. In addition, VidaXL provides customer service in native languages, an open marketplace via VidaXL web shops and offers drop shipment services, which enables business-to-business customers to operate their own web shop without having to manage the logistics.

2.2   Warehouse setup

VidaXL is growing, and within a year they will double their pick and storage locations by opening two new owned warehouses. They will stop using areas of the rented warehouses. In the future, VidaXL has five warehouses in the same geographical area to store their width assortment, "the long tail". Two are shipping warehouses with a reverse area, forward area, and conveyor/sorting system, and items can be picked and shipped from these shipping warehouses. One warehouse has a reverse and forward area as well and is called the pick warehouse. Items can be picked in this warehouse, but the warehouse cannot ship the item directly to customers. The other two warehouses only have bulk storage in the reverse area and are called overflow warehouses. Items are consequently moved between the warehouses during each warehouse operation, the warehouse setup and the possible flow of goods are visualized in Figure 1 (see appendix A for a large version). Each warehouse operation will be explained in more depth in next section.
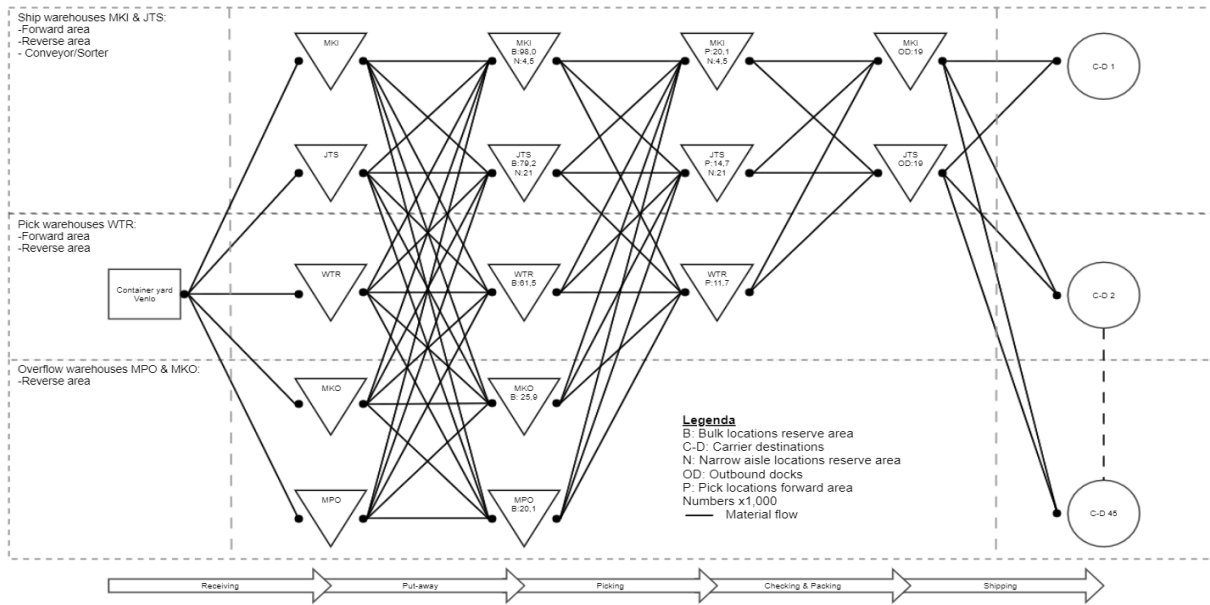
Figure 1: Flow of goods between the warehouses at VidaXL

2.3   Warehouse operations at VidaXL

Most warehouses have the same material flow: They receive bulk shipments, stage them for quick retrieval, retrieve and sort SKUs upon customer request, and ship them to the customer. Warehouses fulfill customer demand through reorganization, which involves the operations: receiving, put-away, order picking, checking and packing, and shipping (Jinxiang, Goetschalckx, & McGinnis, 2007; Bartholdi & Hackman, 2019). Each warehouse tries to increase the efficiency of warehousing operations and reduce double-handling in order to minimize handling costs (Bartholdi & Hackman, 2019). The warehouse operations receiving, put-away, order-picking, checking and packing, and shipping of VidaXL are respectively described in this section, the business process model is given in appendix B.

2.3.1   Receiving

In 2019, VidaXL received between 1 and 99 containers per day. The inbound logistics department usually receives the estimated arrival time of containers one month before the expected arrival, however due to different circumstances, the actual arrival date always differs from the expected arrival date. The forwarder transports containers to the container yard at Venlo, from which point VidaXL has ten days to pick them up before the demurrage date. However, sometimes the demurrage date is ten days after the arrival in the harbor in Rotterdam, and if the containers are not picked up on time, a penalty cost is incurred.

At the beginning of the day, the inbound logistics department receives a message signaling the actual arrival at the container yard and assigns the containers first in first out (FIFO) to one of the warehouses. From each warehouse, they receive the available storage locations per storage type and the number of containers that each warehouse can unload on a particular day. The inbound logistics department checks in the systems, applications and products (SAP) system the percent of the content which can be stored in each warehouse, this depends on the storage types available and container contents. The containers are manually assigned to a warehouse where most of the content can be unloaded without harming the capacity constraints of the warehouse. This process represents the inbound logistics department's attempt to minimize penalty costs and reduce the movements associated with putting away the goods at a storage warehouse of each container individually.

After picking up the containers at the container yard, the containers are unloaded by a team of three to four people, and the inbound logistics department tries to assign the containers so that the workload is balanced between each inbound team. Containers are categorized as A, B, and C based on the effort required to unload the container, where A containers are the easiest to unload and contain only a few SKUs. Arriving containers can contain 1 SKU or over 100 different SKUs. Items are stacked in cartons on the floor, also referred to as loose loaded, to increase transport efficiency. Before staging the items on appropriate storage units, they are inspected, and exceptions are registered. Based on the products' characteristics, they are stacked on different pallet or bin types. VidaXL has developed an algorithm to determine the right storage unit, and to utilize the warehouse storage space as well as possible, VidaXL has around 40 different storage units.

2.3.2 Put-away

Before goods can be put away, an appropriate storage location must be determined. The storage location determines to a large extent the cost of retrieving the item for a certain customer. VidaXL has multiple warehouses with different types of warehousing system, and each is equipped for a specific group of products based on their characteristics, such as: size, weight, shape, pick size, delivery quantity, type of storage module, et cetera (van den Berg, 1999). VidaXL has over 40 different storage types, and it is therefore important to receive goods at a warehouse with the right storage types available. VidaXL plans receiving operations for each container individually to minimize the put-away costs, and if the receiving warehouses lack the right storage type, the goods are cross docked according to the put-away strategy of VidaXL, which tries to minimize the picking costs.

2.3.3 Order picking

VidaXL picks the requested items in waves. At the start of a wave, the warehouse management system (WMS) checks whether enough items are ordered to simultaneously pick a pallet or box from the reserve area instead of picking items separately in the forward area. If insufficient items are ordered for a pallet pick, the WMS verifies whether the items are available in the forward area, and if not, the WMS checks whether it is possible to replenish items from the reverse area into the forward area in the pick and ship warehouses (internal replenishments). If the pick or ship warehouses lack the items in its reverse area, the items are replenished from the reverse area of the overflow warehouses (e.g. picking cross docks). The whole storage unit is replenished, if the concerning storing units are pallets with a height of 1.20 meter, the full pallet is replaced, if the items are stored in small boxes, the whole box is replenished. Picking cross docks can be prevented by receiving the containers and storing the items at the right warehouse, such that items stored in the overflow warehouse are requested less often. VidaXL does not consider picking cross docks while assigning the containers to receiving warehouses.

One SKU usually occupies one storage space in the forward area but never more than two since full pallets/boxes are picked from the reverse area if possible. In practice, replenishments can also occur from a reserve area to a reserve area in another warehouse due to items which used to be automatically labeled items but need to be manually labelled, which is only possible in the MKI warehouse.

In e-commerce, typically customers order small quantities, and to reduce travel time, picklists are generated that contain multiple order lines of multiple customers. To increase the pick density, some storage locations are divided so that two pallets with two different SKUs can be stored instead of one pallet containing one SKU.

After picking the items, conveyable items can be automatically sorted and moved into carriers via telescope conveyors in one of the shipping warehouses (MKI and JTS). Non-conveyable items are stored in different areas of the warehouses and picked according to their destination so that sorting is not necessary.

2.3.4   Checking and packing

After the order picking operations, the items are placed on a conveyor and automatically labeled. The sorter automatically checks whether the right items are picked, and the conveyor brings the items to the right outbound dock. If customers order more than one product, the items are bundled since shipping one bundled item is cheaper than shipping two single items, however items that are bundled are not always picked by the same picker. The items are therefore sometimes stored for a brief time in the bundle area.

2.3.5   Shipping

Bartholdi and Hackman (2019) assume that shipping regards an operation that does not require much effort. However, e-commerce companies typically need to ship small orders to many destinations (Turban et al., 2017). Some e-commerce companies, such as VidaXL, have different warehouses to store the width assortment. To prevent less-than-full truckloads, items must be cross docked between warehouses before they can be shipped to their finale carrier destination, which requires manual handling. Receiving and storing the items with a low demand at the picking warehouses reduces the shipping cross docks between the pick and ship warehouses. However, it is almost impossible to reduce shipping cross docks between shipping warehouses by storing the items in each ship warehouse based on the expected demand per carrier destination, since VidaXL is not able to forecast the demand pattern per carrier destination.

Forty-five different carrier destinations can be reached through the two shipping warehouses, and most of the carriers are loose loaded, which means that they are stacked without pallets or transportation cars in the carriers. In e-commerce, it is important to ship items so that customer receive their items the day after they placed their order (Wozniak, 2013; Bol.com, 2019; TNS,2019), and therefore the items must be shipped to the carrier destinations on the same day that the customer places their orders on the VidaXL website. If the items are not consolidated into one or more outgoing carriers, VidaXL will ship less than truckloads every day to the carrier destinations to satisfy customers.

2.3.6   Conclusion

Reorganizing items in the warehouse of VidaXL occurs through the operations receiving, put-away, order-picking, checking and packing, and shipping. The reorganization process is summarized in Figure 2. Almost all warehouse operations of VidaXL are equal to the preferred situation of traditional warehouses, which will be described in more depth in Section 3. Containers are received loose loaded at VidaXL to increase transport efficiency, and after receiving the items, they are staged on appropriate storage units and afterwards stored at an appropriate storage location in order to efficiently use available storage space. VidaXL tries to increase the pick density and reduce traveling time through batch picking and a conveyor system, and items are bundled to reduce parcel costs. However, VidaXL does not schedule the container receiving operation integrate with put-away, picking, and shipping operations to reduce the long-term cross docks in order to improve warehouse efficiency.

Figure 2: Product reorganization process VidaXL

2.4   Warehouse performance measures

The main performance measurement of the receiving operation is currently the total number of days containers are picked up after the demurrage date. As earlier noted, the inbound logistics department basically tries to minimize the number of days the containers are picked up after the demurrage date without considering the long-term cross docks during succeeding warehouse operations.

2.5   Problem description

E-commerce companies have a large product assortment to full fill small orders with low value from many different customers, and they typically have different warehouses to store the width assortment. Each warehouse is equipped for a special group of products. Decisions need to be made towards achieving an efficient flow of goods between the warehouses. The warehousing costs are responsible for a substantial part of the overall cost and can be reduced by avoiding cross docks. Moreover, unnecessary cross docks lead to lost items and negatively influences order accuracy (Hines & Taylor, 2000). Inaccurate orders are wrong delivered orders leading to unsatisfied customers and a return flow that is expensive to handle (Bartholdi & Hackman, 2019). The put-away, picking, checking, and packing strategy are already considered in literature and in practice to increase warehouse efficiency (Davarzani & Norrman, 2014), and therefore this research focuses on scheduling the receiving operation integrated with the other warehouse operations at VidaXL. The company is opening two new warehouses in 2020 and lacks a scheduling tool to reduce unnecessary cross docks. Cross docks are inefficient flow of goods between warehouses and occur when the succeeding warehouse operation cannot be executed in the current warehouse, the costs of a cross dock is equal during each warehouse operation. This research aims to define a scheduling algorithm which can be used daily to reduce the cross docks between the warehouses integrated with the other warehouse operations. A new scheduling algorithm is proposed to efficiently schedule the receiving operations for fast-growing e-commerce companies with multiple warehouses.

7

2.6   Research questions

Based on the problem description, the main research question is defined as follows:

"How can the container receiving operations be scheduled to increase efficiency during the warehouse operations put-away, picking, and shipping?"

According to Jinxiang et al. (2007), receiving and shipping operations include the following:

> Receiving and shipping are the interface of a warehouse for incoming and outgoing material flow. Incoming shipments are brought to the warehouse, unloaded at the receiving docks, and put into storage. Receiving and shipping operations involve, for example, the assignment of trucks to docks and the scheduling of loading and unloading activities.

In order to solve the problem description and main research question, the following sub-research questions are answered:

1. How is the receiving operation at VidaXL currently organized, planned, and controlled?
2. How does the receiving operation influence the efficiency during put-away, picking and shipping operations?
3. How can the receiving operation be scheduled to increase efficiency during put-away, picking and shipping operations?

2.7   Project scope

VidaXL has distribution centers in Europe, America, and Australia, however the distribution centers in each continent act on their own. The scope of this research considers the European distribution center, which is located at Venlo and from begin 2020 consists of five different warehouses located in the same geographical area. This research only focuses on scheduling the container receiving operations regarding the put-away, picking, and shipping operations.

2.8   Constraints

This project is executed under the following constraints:

1. Put-away strategy is fixed;
2. Network design: the number, locations, and size of the warehouses are fixed;
3. Storage units are fixed;
4. Storage types are fixed;
5. Demand cannot be forecasted per carrier destination.

2.9   Methodology

This research is conducted according to the research methodology designed by Van Aken, Van Der Bij, and Berends (2012), whose proposed method is the problem-solving cycle for design science Figure 3. Although this cycle consists of five steps, this research paper regards the first three steps of the cycle. The fourth step, the intervention is done at the logistical department of VidaXL.
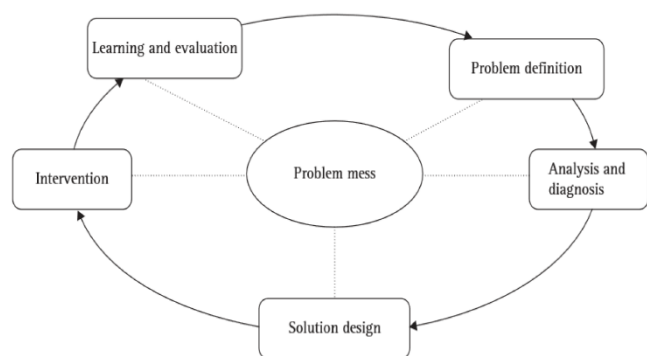
Figure 3: Problem-solving cycle (Van Aken et al., 2012)

The problem is defined in the introduction section and in the problem context section. The introduction section focuses on the research relevance in the literature, while the context section examines the relevance in industry and defines the problem. Section 3 includes a scientific literature review which includes trends and characteristics of e-commerce. Furthermore, the scientific literature review elaborates on scheduling rules and provides insight into binary decision models which functions as basis model for the scheduling algorithm.

The occurrence of cross docks is diagnosed in Section 2, while Section 4 includes an analysis of how cross docks can be prevented by scheduling the receiving operation. Moreover, a framework to schedule the receiving operation integrated with other warehouse operations is presented in Section 4. The framework first estimates the total number of cross docks during the put-away, picking and shipping operations when a container is received in one of the warehouses, followed up with a new scheduling algorithm to reduce the long-term cross docks in order to improve warehouse efficiency. The potential and sensitivity of the scheduling algorithm are evaluated in a realistic simulation, and the scheduling algorithm is implemented with an intervention at the logistical department of VidaXL. Parameter tuning is used to find proper settings to increase the performance of the scheduling algorithm. Figure 4 summarizes the research methodology.

Problem definition
- Research proposal
- Warehouse setup VidaXL
- Warehouse operations VidaXL

Analysis and diagnosis
- Literature review
- Framework including a scheduling algorithm
- Realistic simulation
- Performance evaluation
- Sensitivity analysis

Solution design
- Scheduling tool
- Parameter tuning
- Performance measurement of solution
- Company recommendations

Intervention
- Implementation of planning tool

Figure 4: Summary of research methodology

9

3. Literature review

In this section, a brief overview of literature relevant to the research subject defined in the previous sections is provided. Section 3.1 first examines the characteristics and recent trends in e-commerce companies and compares logistics in e-commerce with traditional companies to better understand the context of the problem. Section 3.2 discusses the reorganization process of items through the warehouse operations. Moreover, Section 3.3 considers the influence of prior knowledge and shows its effect on the performance of different scheduling rules, and Section 3.4 introduces the knapsack problem, which functions as basis model for the scheduling algorithm.

3.1 E-commerce retailers

In 2002, management guru Peter Drucker predicted that e-commerce would significantly impact how business is conducted. Seventeen years later, the Ecommerce Foundation has forecast that e-commerce will be a 621-billion-euro industry in Europe in 2019. In 2007, only 30% of the European population purchased items online, but this percentage had almost doubled to 57% by 2017 (CBS, 2018). The e-commerce market is growing and differs from traditional markets. This section describes the characteristics and trends of e-commerce and explains the difference between e-commerce logistics and traditional logistics to understand the context of the problem.

3.1.1 Characteristics

Companies fulfill three major activities: ordering and payments, order fulfillment and delivery to customers. Each activity can be conducted physically or digitally. Companies that execute all activities physically are called brick-and-mortar organizations, while pure e-commerce companies are referred to as virtual organizations. Increasing numbers of companies are transforming from brick-and-mortar companies to click-and-mortar companies by establishing new online sales channels (Turban et al., 2017). By fulfilling certain activities digitally, e-commerce companies gain advantages compared to traditional companies in terms of increased inventory control, shortened time to market, more efficient payment systems, improved market search and lower advertising costs (Berthon et al., 1996; Burstein & Kline, 1995; Spar & Bussgang, 1996).

3.1.2 Trends

Companies began using e-commerce in 1970, when money was first transferred electronically. After the commercialization of the World Wide Web in 1990, e-commerce companies were exposed to new trends such as growth, purchase incentives and short delivery times.

Growth: Online retail is taking business from traditional retailers. During the economic recession of 2009–2013, e-commerce realized double-digit growth every year (Knight, 2013; Wilfred, 2014). However, not every e-commerce company is successful: Multiple e-tailing companies have gone bankrupt since 1999. Around 62% of these organizations lacked financial skills, while 50% did not have sufficient experience with marketing. Moreover, many companies were unable to fulfill all customer orders and did not have large enough inventories to deal with demand fluctuations (Direction, 2005).

Purchase incentives: The three main drivers for online purchases in the Netherlands were identified as convenience, attractive pricing and large assortment (TNS, 2019).

Delivery time: Short lead times improve the conversion rate, conversion refers to the percentage of consumers that visit a website and purchase items on this website. Recently, Bol.com (2019) published a study on the effect of short lead times on conversion rates. Within one day delivery generates the best conversion rate, if items are delivered after two days, the conversion rate drops with 30%.

3.1.3 E-commerce logistics vs traditional logistics

According to the Council of Supply Chain Management Professionals (CSCMP) (2013), logistics management plans implement and control the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption to meet customers' requirements. In e-commerce companies, logistics management requires dealing with different challenges to those faced by traditional companies, Table 1.

Table 1: Logistic challanges of traditional logistics and e-commerce logistics (Turban et al., 2017)

Attributes	Traditional logistics	E-commerce logistics
Type, quantity	Bulk, large volume	Small parcels
Destination	Few	Large number, highly dispersed
Demand type	Push	Pull
Value of shipment	Very large, usually >$1,000	Very small, frequently <$50
Nature of demand	Stable, consistent	Seasonal, fragmented
Customers	Business partners, repeat customers	Unknown, many
Accountability	One link	Through the entire supply chain
Transporter	Frequently by the company, sometimes outsources	Usually outsourced, sometimes by company
Warehouse	Common	Only very large shippers have their own

Fulfilling thousands of small orders from different customers every day requires significant effort. As a result, the throughput, storage and accuracy requirements of warehouses have increased (Frazelle, 2002). The object of order fulfillment is delivering the right item to the right customer in a timely, cost-effective and profitable manner (Turban et al., 2017). Most warehouses fulfill customer orders through reorganization, which involves the operations of receiving, put-away, picking, checking and packing, and shipping.

3.1.4 Conclusion

E-commerce is significantly impacting how business is done. Increasing numbers of companies are transforming from brick-and-mortar companies to click-and-mortar companies by establishing new online sales channels. These companies typically have a large product assortment and fulfil small orders with low value to many different customers. The warehousing costs are responsible for a substantial part of the overall cost. The flourishing E-commerce economy combined with new complex logistic challenges stresses the need for efficient warehouse operations for e-commerce companies.

3.2 Warehouse efficiency in e-commerce

Warehousing, the intermediate storage of goods between two successive stages of a supply chain, can be implemented to reduce transportation costs and provide customer service. Warehouses fulfill customer demand through reorganization, which involves the operations: receiving, put-away, order picking, checking and packing, and shipping (Jinxiang et al., 2007; Bartholdi & Hackman, 2019). Each warehouse seeks to increase the efficiency of its warehousing processes and to reduce cross docks to minimize double handling (Bartholdi & Hackman, 2019). E-commerce companies have a large product

assortment to full fill small orders from many different customers, and they typically have different storage facilities to store the width assortment. Each facility is equipped for a special group of items. Decisions need to be made towards achieving an efficient flow of goods between the warehouses. Cross docks are inefficient flow of goods between warehouses and occur when the succeeding warehouse operation cannot be executed in the current warehouse. This section outlines the warehouse operations and their inherent influence on the warehouse efficiency.

3.2.1 Receiving

Ordinarily, receiving starts with a notification of the arrival of goods. Efficiently scheduling the receiving operation integrated with other warehouse operations is extremely complex for companies with multiple warehouses. The receiving warehouse determines to a large extend the efficiency during the other warehouse operations. After the items are unloaded, they are inspected, and any exceptions are noted. Next, these items are scanned so that the system knows the items are available and customer demand can be fulfilled (Bartholdi & Hackman, 2019).

Items can arrive in different quantities; typically, the receiving quantity is large compared to the shipping quantity. Multiple SKUs can be received simultaneously in one shipment. Staging the items on appropriate storage units, such as pallets and boxes, is a labor-intensive process. Receiving the items in the same unit as the storage unit reduces the labor costs. However, this procedure usually increases the transportation costs (Bartholdi & Hackman, 2019).

3.2.2 Put-away

Before goods can be put away, an appropriate storage location must be identified. The storage location determines to a large extent what it costs to retrieve the item for a certain customer. Most large e-commerce companies have multiple wareohuses with different types of warehousing systems. Each warehousing system is specially equipped for a specific group of items based on their characteristics, such as size, weight, shape, pick size, delivery quantity and type of storage module (van den Berg, 1999). It is therefore important to receive goods at the appropriate location to ensure that items can be properly stored to reduce picking, packing and shipping cross docks.

3.2.3 Order picking

The WMS accomplishes the following tasks: verifying the inventory level, producing the picklist, producing the shipping documentation and scheduling the order picking and shipping operation. Order picking costs can be reduced by minimizing non-value-added tasks. The WMS reorganizes the picklist to generate pick efficiency. If items are picked FIFO, pickers need to travel a long distance, which increases operating costs. The WMS also checks whether it is possible to pick a full carton or pallet instead of items separately. Picking a pallet rather than a single item requires different resources and is therefore a separate process. Picking pallets containing multiple items increases the pick efficiency.

Many warehouse configurations utilize a forward area and a reserve area. The forward area is used for efficient order picking, and the reserve area is used for replenishing the forward area. High pick density leads to lower traveling costs. However, not every item is always pickable in the forward area of the storing warehouse. If items are stored in a warehouse without an appropriate forward area, they are first cross docked to another warehouse before the pick tasks are executed. Orders can be picked serially or parallelly. In serial picking, one picker picks all the order lines of an order. While in parallel picking the items are picked through multiple pickers, it reduces the throughput time but requires more effort to coordinate the picking operation. The paper of Bartholdi and Hackman (2019) can be consulted for a more in-depth analyses of serial and parallel order picking.

3.2.4   Checking and packing

After picking the product, the picker must check if they have picked the right item according to their pick list. Order accuracy can be a KPI to measures the service delivered to the customer. Inaccurate orders lead to unsatisfied customers and a return flow that is expensive to handle. Items can be bundled or packed to reduce the number of boxes shipped to a client, which lowers shipping and handling costs. After the item is checked and packed, it can be scanned to register its availability for shipping (Bartholdi & Hackman, 2019).

3.2.5   Shipping

Shipping normally requires less manual effort compared to other warehouse operations, since it deals with fewer items and the items have already been consolidated into larger boxes during the packing operation (Bartholdi & Hackman, 2019). However, e-commerce companies typically need to ship small orders to many destinations (Turban et al., 2017). Some e-commerce companies have different warehouses to store the width assortment. To prevent inefficient less-than-truckload shipments, item must be cross docked between the facilities before it can be shipped to its final carrier destination. While it is possible to wait until each individual facility has full truckloads, this process can be lengthy for destinations with low demand. In e-commerce, it is important to ship items on the same day the order is placed to ensure customers receive their items on time (Wozniak, 2013; Bol.com, 2013; TNS, 2019).

3.2.6   Conclusion

Each warehouse seeks to increase the efficiency of its warehouse operations by reducing double handling. Cross docks are a form of double handling and can be prevented by scheduling the receiving operation. Available containers can be assigned to a receiving warehouse to unload the items on pallets, and the put-away strategy subsequently assigns the storage location of each SKU individually. The storage location depends on the receiving location but is not always the same as the receiving location, and cross docks can consequently occur. After a customer request, the items are picked from the forward area, however not every item is pickable in the forward area of the storing warehouse. If items are stored in a warehouse without an appropriate forward area, they are first cross docked to another warehouse before the pick tasks are executed, and the picked items are subsequently checked and can be shipped to customers. However, not all warehouses are able to serve all carrier destination on time, and therefore the items are cross docked from the pick location to shipping warehouse before shipping them to customers. The warehouse efficiency of an e-commerce company with different storage facilities can be increased by scheduling the receiving operation in order to avoid cross docks during the put-away, picking, and shipping operations.

3.3   Scheduling the receiving operations

Scheduling can be done either statically or dynamically. In static algorithms, the assignment of tasks to processes and the time at which the execution starts is determined in advance. However, if the task characteristics are not known beforehand, tasks cannot be scheduled statically. In dynamic scheduling, new tasks are scheduled without affecting the deadlines of the previously scheduled tasks. Dynamic scheduling algorithms can be centralized or distributed. In centralized algorithms, all tasks are received at one central location and scheduled on the different processors. In distributed algorithms, tasks arrive independently at each processor, and the processer checks whether it can accept or needs to reject these tasks (Manimaran & Siva Ram Murthy, 1998). According to Dertouzos and Mok (1989), there does not exist a scheduling algorithm that provides an optimal solution without prior knowledge. This section examines scheduling rules and the influence of prior knowledge on the solution.

3.3.1 Prior knowledge

The receiving operation can be scheduled to prevent inefficient warehouse operations. Scheduling the receiving operation is limited by the level of prior knowledge or information that is available. Typically, three scenarios can be distinguished: 1) no knowledge is available; 2) partial statistical knowledge of the arrival or departure process and the content of the container is available; 3) perfect knowledge of the content and sequence of each arriving or departing container is available (Larbi, Alpan, Baptiste, & Penz, 2011). The second scenario is the basis for most decision models in literature since it is the most common one in practice (Jinxiang et al., 2007).

The rolling horizon policy is a useful tool in dynamic situations with uncertain arrivals in later stages of the scheduling horizon (Wilkinson, 1996). It separates the problem in a sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner. This approach results in close to optimal solutions with a significant reduction of the computation time (Dimitriadis, Shah, & Pantelides, 1997). In static scheduling policies, the arrival times of all containers must be known beforehand or must be forecasted while in rolling horizon policies only the actual arrival date need to be known. The rolling horizon policy is therefore suitable in real-time applications in uncertain environments (Fang & Xi, 1997).

3.3.2 Scheduling rules

Many large distribution centers receive many containers a day. A scheduling rule can be used to select the next container to be processed from a set of available containers. Scheduling rules are normally intended to minimize operational costs. However, there are $n!$ possible ways of sequencing n containers waiting in the queue (Rajendran & Holthaus, 1997). It is therefore not possible to select one rule that outperforms all other rules in every situation. Most scheduling rules are developed for job shop environments. A wide variety of scheduling rules for transport are derived from these rules. However, such rules often deal with minimizing the travel distance and the number of vehicles required (Le-Anh, Koster, & Yu, 2010). Scheduling rules for job shops can be adapted to schedule the container receiving operations. However, the rules must be tested through simulation to verify if they can achieve the desired results in different settings. Most researchers assume that all jobs or containers are available at the start of the scheduling period (Baker K., 1974; French, 1982; Pinedo, 1995). Only simple scheduling rules, such as shortest processing time, FIFO and longest processing time, are evaluated in situations where job arrivals are dynamic (Hunsucker & Shah, 1994).

By 1976, more than 100 different scheduling rules had already been developed. Scheduling rules can be classified into the following categories: 1a) Simple priority rules, which are based on information related to a specific job, involving sub-classifications developed according to processing times, due dates, number of operations, costs, setup times, arrival times, slack, machines and miscellaneous information. 1b) Combinations of simple priority rules, which involve the combination of rules that fall under category 1a to form other scheduling rules. 1c) Weighted priority indexes, in which each simple priority rule can be weighted to receive an overall total weight, with important characteristics having a greater influence on the outcome than less important characteristics. 2) Heuristic scheduling rules, which involve a more complex consideration such as scheduling alternate operations; such rules do not only employ mathematical tools but can also include human intelligence. 3) Other rules, which are designed for a specific situation or consist of a combination of priority indexes based on the mathematical functions of job parameters. Panwalker and Iskander's (1976) presents a summary of these rules. New scheduling rules are still being developed. However, at the foundational level, these rules are combinations of the simple priority rules or are only applicable in company-specific scenarios.

3.3.3 Conclusion

There does not exist an algorithm yet to schedule the container receiving operations of a company with multiple warehouses in the same geographical area. However, the receiving operation can be scheduled dynamically through a centralized rolling horizon algorithm to face uncertain container arrivals and information availability. The rolling horizon policy separate the scheduling problem in a sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner.

3.4 Introduction to binary decision models

Scheduling the container receiving operation to reduce cross docks require a decision process that can be formalized and validated independently of personal preferences. Quantification of variables and results is necessary. In most cases, the outcome of decisions can be measured by a single value representing profit, costs or some other category of data. Finding the option with the highest (or lowest) value can be extremely difficult when there are many possible options. This section therefore introduces the multiple knapsack problem which functions as basic model for the algorithm.

3.4.1 Multiple knapsack problem

The multiple knapsack problem originates from a cargo problem where multiple aircrafts from the same airline travel the same flight route multiple times a day. First, the airline must accept a package; afterwards, it must select a flight to transport the package. This can be formulated with a binary decision variable for every combination of a package for a flight (Kellerer, Pferschy, & Pisinger, 2004).

$$x_{ij} = \begin{cases} 1 & if\ item\ j\ is\ put\ on\ flight\ i \\ 0 & otherwise \end{cases}. \qquad (1)$$

When choosing the first alternative $x_{ij} = 1$, a certain weight w_j is required, where $x_{ij} = 0$ does not require a weight. Each alternative has a particular profit p_j. The solution is feasible if the sum of all weights over all binary decisions does not exceed capacity constraint 3. Moreover, it is not possible to assign each package twice by constraint 4. There can exist multiple feasible solutions. However, most of the time, not all feasible solutions optimize the outcome. The multiple knapsack problem can be formulated as the following linear integer programming problem:

$$Max \sum_{i=1}^{m} \sum_{j=1}^{n} p_j x_{ij}, \qquad (2)$$

subjected to:

$$\sum_{j=1}^{n} w_j x_{ij} \le c_i, \quad i = 1, \dots, m, \qquad (3)$$

$$\sum_{i=1}^{m} x_{ij} \le 1, \quad j = 1, \dots, n, \qquad (4)$$

$$x_{ij} \in \{0,1\}, \quad i = 1, \dots, m, j = 1, \dots n. \qquad (5)$$

3.4.2 Conclusion

Daily scheduling the container receiving operation is like the multiple knapsack problem since it is not always possible to select and schedule all containers. Furthermore, only partial knowledge of the arrival process and the estimated cross docks per container is available. It is therefore not possible to select and schedule all containers beforehand. The solution is feasible when all constraints are met, each container is only scheduled once, and each warehouse only receives the containers it can handle.

3.5 Conclusion

E-commerce has significantly impacted the way business is conducted. Current trends in e-commerce makes warehouse management one of the most important players in realizing growth, maintaining profitability and continuously improving customer satisfaction. Following the commercialization of the World Wide Web, e-commerce companies have been exposed to new trends such as growth, purchase incentives and short delivery times.

Warehouses of e-commerce companies typically need to fulfill thousands of small orders from different customers every day. Warehouses reorganize items, which involves the operations: receiving, put-away, order picking, checking and packing, and shipping. Receiving and shipping operations is the least explored category in warehousing literature. The flourishing E-commerce economy combined with new complex logistic challenges stresses the need for efficiently scheduling the receiving operation.

Large e-commerce companies often have different storage warehouses. Each warehouse has special equipment for a specific group of products and is therefore not always able to accomplish all warehouse operations for each item. Items are therefore cross docked to another warehouse when the succeeding warehouse operation cannot be executed in the current warehouse. The warehouse efficiency can be increased by scheduling the container receiving operation to reduce the total number of cross docks.

The receiving operation can be scheduled dynamically through a centralized rolling horizon algorithm to face uncertain container arrivals and information availability. The rolling horizon policy separate the scheduling problem in a sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner. When scheduling containers to specific warehouses, a binary decision must be made. The multiple knapsack problem can be used to make formalized decisions independently of personal preferences. The basic model is adapted in Section 4, the conceptual model improves the warehouse efficiency by reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date. The potential and sensitivity of the scheduling algorithm are evaluated in a realistic simulation in Section 5.

4. Conceptual model

E-commerce companies have a large product assortment to fulfill small orders from many different customers, and they typically have multiple warehouses to store the width assortment. Each warehouse is equipped for a special group of products. Decisions need to be made towards achieving an efficient flow of goods between the warehouses. Each warehouse tries to increase the efficiency of its operations by reducing double handling (Bartholdi & Hackman, 2019). The put-away, picking, checking, and packing strategy are already considered in literature and in practice to increase warehouse efficiency (Davarzani & Norrman, 2014), and therefore this research focuses on scheduling the receiving operation integrated with the other warehouse operations at VidaXL.

The goal of this research is to increase the warehouse efficiency by scheduling the container receiving operation in order to avoid cross docks during the succeeding warehouse operations. E-commerce companies typically ship small orders with low value to many different customers. The warehousing costs are therefore responsible for a substantial part of the overall cost and can be reduced by avoiding cross docks. Moreover, unnecessary cross docks lead to lost items and negatively influences order accuracy (Hines & Taylor, 2000). Inaccurate orders are wrong delivered orders leading to unsatisfied customers and a return flow that is expensive to handle (Bartholdi & Hackman, 2019).

VidaXL is a rapidly growing international online retailer with an annual revenue of a quarter billion euro and the product assortment contains around 70,000 different SKUs (2017). VidaXL is opening two new warehouses and will have two ship, one pick and two overflow houses in the same geographical area to fulfill all European orders. However, not all warehouses are equipped with all necessary resources to accomplish all warehouse operations for each product type, and therefore cross docks occur when the succeeding operation cannot be executed in the current warehouse. The number of cross docks associated with receiving, put-away, picking, checking and packing, and shipping operations can be estimated on the pickup day and differ per container for each receiving warehouse.

The receiving operations at VidaXL can be scheduled within ten days after confirmation of the delivery date of each container in the container yard at Venlo. VidaXL receives multiple containers per day and can therefore select the next containers to be processed from a set of available containers. During most days it is impossible to select and process al available containers since each warehouse is constrained by the available inbound capacity per day. The receiving operation must therefore be scheduled to determine which container must be processed in each warehouse on each day.

The objective of our model is reducing the number of long-term cross docks while avoiding situations where the container is picked up after the demurrage date. The main approach for accomplishing this is through scheduling containers to the preferred warehouses such that the corresponding estimated number of cross docks is reduced. Scheduling the receiving operations has a *"free operating space"*: The pickup date can be scheduled within ten days after the confirmation of arrival to prevent demurrage costs, the receiving warehouse can be chosen and the order of receiving each container can be determined. However, for some urgent critical containers there is no liberty, they must always be unloaded first at a specific warehouse. This section combines scheduling the receiving operation for critical and non-critical containers while reducing the long-term cross docks into one algorithm.

Daily scheduling the receiving operations to avoid cross docks require a decision process that can be formalized and validated independently of personal preferences. The multiple knapsack problem can be used as basic model for the new developed scheduling algorithm. This section provides a framework to reduce the long-term cross docks and demonstrates that the long-term cross docks during each warehouse operation can be reduced by scheduling the receiving operation.

Section 4.1 first provides a framework to schedule the receiving operation integrated with other warehouse operations. Section 4.2 issues the variables used in the conceptual model. Section 4.3 provides the container data existing of a distinction between critical and noncritical containers, and the quantification of the estimated number of cross docks per container regarding each warehouse operation. Moreover, Section 4.4 proposes an algorithm to subsequently schedule critical and noncritical containers while reducing the long-term cross docks and the number of days the containers are picked up after the demurrage date. Finally, the algorithm is validated and verified in Section 4.5. It is recommended to read Section 4.1 before reading the other sections since Section 4.1 elaborates in more depth on the remaining structure of this section.

4.1 Framework

The framework to schedule the receiving operation integrated with other warehouse operations will be presented in this section, the framework is visualized in Figure 5. The framework consists of three layers: input data, scheduling algorithm and output data. Each layer subsequentially fulfill certain tasks and provide the subsequent layer with information to complete the scheduling process. The provided information depends on the current state of the system and therefore differs each day the algorithm is executed, and a receiving schedule is made. Each layer will be discussed in this section.

Figure 5: Framework conceptual model

4.1.1   Input data

The input layer gathers all relevant data for the scheduling algorithm. The receiving operation will be scheduled at the start of every day and the input data will therefore be gathered at the start of every day instead of updating the input data every time new information becomes available. As a result, decisions can be taken daily, making the model less complex. This section elaborates on the available input data consisting of container data and warehouse data.

Container data

In 2019, VidaXL received between 1 and 99 containers per day and can therefore select the containers to be processed on the next day from a set of available containers. During most days it is impossible to select and process al available containers since each warehouse is constrained by the maximum inbound capacity. Consequently, a pool of containers is available at the container yard.

Containers can be classified as critical and noncritical containers. Critical containers must be received as soon as possible at a specific warehouse and it is therefore not possible to schedule the container receiving operation to achieve an efficient flow of goods. Noncritical containers are preferred to be picked up from the container yard within ten days, otherwise demurrage costs are incurred, however these containers lack any other scheduling restrictions. It is therefore possible to schedule the receiving operation in the upcoming ten days to achieve an efficient flow of goods. Section 4.3.1 provides rules to distinct critical and noncritical containers.

Arriving containers can contain 1 SKU or over 100 different SKUs. After receiving a container at one of the warehouses, items are put-away, stored, picked, checked and packed, and shipped to fulfill customer demand. However, not every warehouse operation can be executed in each warehouse for each SKU. Items must be cross docked between the warehouses when the subsequent operation cannot be executed in the current warehouse. The inherent expected number of cross docks during each warehouse operation when the container is received in one of the warehouses can be estimated on the pickup day. Section 4.3.2 to 4.3.5 provides guidelines to estimate the number of cross docks when the container will be received in one of the warehouses.

Warehouse data

The warehouse data consist of the inbound capacity per container type and the total inbound capacity per warehouse. VidaXL classifies the containers as A, B, and C based on the number of SKUs and on the number of items in each container, where A containers require less manual effort to unload than C containers. Each warehouse can be constrained with the number of A, B and C containers it can receive per day. Moreover, each warehouse is only able to receive a total number of containers per day. Note that the total inbound capacity is not always equal to the sum of the inbound capacity per container type. The receiving operations must be scheduled such that all inbound capacity constraints are met. The inbound capacity constraints are provided by each warehouse individually.

Information availability

In an ideal situation, the container and warehouse data are known far in advance. When there is enough inbound capacity, it would then be possible to schedule the receiving operation of each container before the demurrage date while minimizing the total long-term cross docks.

The container receiving operation at VidaXL is not ideal, the exact inbound capacity per warehouse is only known a few days in advance, the actual arriving date of each container almost always differs from the estimated arrival date and it is almost impossible to estimate the number of cross docks of

each receiving container far in advance. Section 4.3 shows that the estimated number of cross docks depends on the available storage locations in the receiving warehouse, and on the stock level of each SKU in the pick and ship warehouses. Both depend on the demand of each SKU and on the earlier received and stored items in each warehouse. Containers received during previous days, increases the current stock level in each warehouse and therefore affect the estimated number of cross docks of the new receiving containers. It is therefore almost impossible to calculate the container and warehouse data for all feasible solution since each decision affects the estimated cross docks of other containers. This paper therefore proposes in Section 4.4 an alternative rolling horizon scheduling algorithm to deal with uncertain container arrivals and new information availability while reducing the computation time and complexity of the problem.

4.1.2 Scheduling algorithm

The objective of our model is reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date by scheduling the receiving operation. Daily scheduling the receiving operation of noncritical container to avoid cross docks require a decision process that can be formalized and validated independently of personal preferences.

In multi container packing problems, a set of containers must be scheduled to one or more warehouses, each container can be scheduled to at most one warehouse. Each container has a weight associated with receiving the container at one of the warehouses. Furthermore, each container may also have a profit or costs which can differ or can be equal to its weight. When there is only one single warehouse, the problem is similar to the well-known knapsack problem (Fukunaga & Korf, 2007; Keller et al., 2004).

For our model, the characteristics of four well-known multi container packing problems are evaluated: bin packing, multiple knapsack, bin covering, and min-cost covering. Many other combinatorial optimization problems are variants of these multi container packing problems as constraints are added or adjusted. In the basis, the problems differ from each other in two dimensions. One key dimension is whether all containers are assigned to a warehouse or whether a subset of containers is selected and assigned to a warehouse. The second dimension is whether the inbound capacity of the warehouses cannot be exceeded, referred to as packing, or whether a minimum of containers must be assigned to each warehouse, referred to as covering (Fukunaga & Korf, 2007). The models are classified in Table 2.

Table 2: Characterizing multi container problems (Fukunaga & Korf, 2007)

	Schedule all containers	**Select and schedule subset of containers**
Packing	Bin packing	Multiple knapsack
Covering	Bin covering	Min-cost covering

In bin packing or covering problems, the goal is to schedule all containers to bins (i.e. warehouses) without harming the minimum or maximum capacity constraint of each bin. The objective is to minimize the total number of bins necessary to schedule all available containers. There are infinite bins available to schedule all containers (Delorme, Lori & Martello, 2015; Fukunaga & Korf, 2007; Martello, Pissinger & Vigo, 1998; Valerio de Carvalho, 2000). On the other hand, multiple knapsack or min-cost covering problems aims to maximize the overall profit of the selected and scheduled containers without harming the minimum or maximum capacity constraint. A subset of containers is selected since it is not possible to schedule all containers while satisfying the capacity constraints. The total

number of warehouses is fixed under the multiple knapsack problem while the total number of bins under the min-cost covering problem is infinite (Fukunaga & Korf, 2007; Keller et al., 2004; Wolsey & Nemhauser, 1999).

Daily scheduling the container receiving operation at VidaXL is similar to the multiple knapsack problem since VidaXL is only able so select and schedule a subset of containers. Each warehouse is constrained by the maximum available inbound capacity, VidaXl is therefore not able to pick up all available containers on the arriving day. VidaXL aims to select and schedule all containers before the demurrage date but is not always able and not forced to pick up all containers before the demurrage date when there is not enough inbound capacity. Furthermore, only partial knowledge of the container arrival process and the estimated cross docks per container is available. Deciding to receive a container in a warehouse increases the inventory position of the warehouse and affects the estimated cross docks for new arrived containers. It is therefore not possible to schedule all containers beforehand as a bin packing problem since new containers and information becomes available during the scheduling process. Moreover, VidaXL has a finite number of warehouse available and can therefore not minimize the number of warehouses necessary to receive all containers as they do in bin packing or covering problems. Even if the bin packing problem is constraint with the number of available bins equal to the number of warehouses is it still not a bin packing problem since it is not always possible to select and schedule all available containers. Which is a key characteristic of the bin packing problem. Furthermore, it is also not possible to minimize the number of inbound teams necessary to receive all containers. The warehouses have a restricted inbound capacity and can therefore not always receive all available containers on the same day. Moreover, the resources necessary to unload a container are equal in each receiving warehouse, it is therefore not possible to schedule the container such that as many containers as possible are received while minimizing the inbound teams necessary. Cross docks are not physically executed by the inbound teams and do therefore not impact the resources necessary to receive containers.

Basic multiple knapsack problem
The multiple knapsack problem originates from a cargo problem where multiple aircrafts from the same airline travel the same flight route multiple times a day. First, the airline must accept a package; afterwards, it must select a flight to transport the package. The airline attempts to maximize the value of the selected packages without harming the maximum capacity constraint of each flight. Each flight can have a different capacity. Furthermore, each package can only be assigned once to a flight. This scenario can be formulated with a binary decision variable for every combination of a package for a flight. If there are *n* packages available and *m* flights, there are *n*m* binary decision variables (Kellerer et al., 2004).

Daily scheduling the receiving operation at VidaXL is similar to the cargo problem, as VidaXL has w warehouses and there are j containers available with the result of w*j binary decision variables. VidaXL is not able to schedule the receiving operation on next day for all available containers and must therefore select a subset of containers; afterwards it must schedule the containers to a warehouse. VidaXL wants to reduce the long-term cross docks and the number of days the containers are picked up after the demurrage date, without harming the inbound capacity constraints of each warehouse. Furthermore, each container can only be assigned once at one of the warehouses. Container j will be assigned to warehouse w if the binary decision variable is equal to 1, and if the container is not assigned to warehouse w, the binary decision variable is equal to 0.

Myopic

The multiple knapsack problem can be used as basic model to select and schedule the next container to be processed. However, daily minimizing the number of cross docks is exposed to myopic and does not lead to the optimal answer. In fact, the total long-term cross docks are not minimized with the basic multiple knapsack problem because of:

1. Daily selecting containers to minimize the total number of cross docks automatically means not selecting "hard containers" with many cross docks at all warehouses. These containers are forced to be scheduled just before the demurrage date and are therefore most of the times scheduled at a less preferred warehouse resulting in avoidable cross docks. Forced scheduling a "hard container" with 10 avoidable cross docks at a less preferred warehouse results in more cross docks as voluntary scheduling another container with one avoidable cross dock at a less preferred warehouse.
2. Minimizing the total number of cross docks every day does not minimize the long-term cross docks, since two sub optimizations do not automatically lead to the overall optimum.
3. The total number of cross docks are minimized without harming the inbound capacity constraint by selecting zero containers.

Scheduling containers

Four adjustments must be made to the basic multiple knapsack problem to schedule noncritical containers in order to reduce long-term cross docks.

1. The model must consider the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse. This will prevent the model from not scheduling "hard containers". Moreover, this feature assist in selecting the right container to be received in a less preferred warehouse since it contemplates the profit of receiving container j at warehouse w. Section 4.4.3 proposes a method to quantify the profit.
2. The algorithm must be able to optimize the binary decision model for multiple periods to reduce the long-term cross docks. However, confirming the pickup date of all available containers makes the system inflexible to new information and leads to suboptimal answers as well. The model is therefore adapted to a rolling horizon procedure where only the immediate short-term schedule is implemented. VidaXL can confirm the pickup date of the containers scheduled on the next day and can consequently reschedule the pickup date of the other containers if new information becomes available. This working procedure is explained in more depth in Section 4.4.2 and Section 4.4.3.
3. The model must be rewritten as a maximalization function to schedule as many containers as possible in order to prevent the model from selecting zero containers, it consequently enables selecting containers for the complete scheduling horizon.
4. The possibility of selecting and scheduling a container must be increased when the container is approaching its demurrage date to prevent demurrage costs.

Scheduling critical and noncritical containers can be combined in one rolling horizon scheduling algorithm, the objective function of the algorithm will be discussed in more depth in Section 4.4.3 while Section 4.4.4 demonstrates the working procedure of the algorithm.

4.1.3   Output data

The scheduling algorithm is able to select and schedule every day as many containers as all warehouses can receive during the scheduling horizon from the available set of containers. The algorithm will

reduce the long-term cross docks while avoiding situations where the container is picked up after the demurrage date. However, VidaXL must only confirm the pickup date of the containers scheduled on the next day in order to retain flexible to new information. New containers can arrive at the container yard and the number of cross docks associated with receiving the container at a warehouse can differ over time. The list with available containers must be updated after confirming the pickup date of the scheduled containers. The potential and quality of the scheduling algorithm is evaluated in Section 5.

4.2   Variables

The sets, parameters, vectors, and decision variables used in Section 4.3 and in the proposed binary decision model in Section 4.4 are specified as follows:

Sets

I	*Set of SKUs* $(index = i)$	$1, ..., I$
J	*Set of containers* $(index = j)$	$1, ..., J$
W	*Set of warehouses* $(index = w)$	$1, ..., W$
T	*Set of periods* $(index = t)$	$1, ..., T$

Parameters

AD_j *Arriving Day container j*

AS_{tw} *Available number of storage locations of storage type t in warehouse w*

B_p *Total bulk locations in pick warehouses*

B_o *Total bulk locations in overflow warehouses*

B_S *Total bulk locations in shipping warehouses*

C_W *Capacity of warehouse w*

CPA_{jw} *Number of put-away cross docks if container j will be received at warehouse w*

CPI_{jw} *Number of picking cross docks if container j will be received at warehouse w*

CPS_{jw} *Number of pick and ship cross docks if container j will be received at warehouse w*

CT_{jw} *Total number of cross docks if container j is docked at warehouse w*

D_i *Demand in pallets per week of SKU i*

FD *Free demurrage days*

M *Big M, large positive penalty constant*

P   *Penalty when approaching due date of container j*

PA_{ijw} *Number of pallets of SKU i in container j which cannot be stored in warehouse w*

Q_{ij} *Number of pallets of SKU i in container j*

$E[SLO_j]$ The expected equivalent number of weeks container j occupies one bulk pallet place if the container is received in the ship or pick warehouse

$\overline{SLO_w}$ Average SLO at warehouse w

S_{ip} Current total bulk stock in number of pallets of SKU i at pick warehouses

S_{is} Current total bulk stock in number of pallets of SKU i at ship warehouses

S_{iw} Current total bulk stock in number of pallets of SKU i at warehouse w

S_{tw} Stock level of storage type t at warehouse w

SC_i Stock coverage of SKU i

TD Today

TS_{tw} Total storage locations of storage type t at warehouse w

μ_t Allowed utilization of storage type t

$\overline{\mu_W}$ Average utilization of bulk locations in all warehouses

W_{jw} Weight of assigning container j to warehouse w

WB_{Aw} Fraction of the capacity at warehouse w allowed to be occupied with type A containers

WB_{Bw} Fraction of the capacity at warehouse w allowed to be occupied with type B containers

WB_{Cw} Fraction of the capacity at warehouse w allowed to be occupied with type C containers

Z_P Cut-off SLO of pick warehouses

Z_S Cut-off SLO of shipping warehouses

Z_{LW} Lower-bound SLO of receiving warehouse w

Z_{UW} Upper-bound SLO of receiving warehouse w

Vectors

CT_j Vector containing all CT_{jw} of container j $CT_j = \{CT_{1w}, \ldots, CT_{Jw}\}$

D_j Vector containing all D_i of the SKUs in container j $D_j = \{D_1 \ldots, D_{50}, \ldots, D_{90}\}$

Q_j Vector containing all Q_{ij} of container j $Q_j = \{Q_{1j}, \ldots, Q_{50j}, \ldots, Q_{90}\}$

S_j Vector containing all $(S_{ip} + S_{is})$ of the SKUs that are in container j $S_j = \{(S_{1p} + S_{1s}), \ldots, (S_{Ip} + S_{Is})\}$

Decision variables

x_{jw} $\begin{cases} 0 & \text{Not assigning container j to warehouse w} \\ 1 & \text{Assigning container j to warehouse w} \end{cases}$

4.3   Container data

Multiple containers a day arrive at the container yard waiting to be picked up by VidaXL. After arrival, containers are first classified as critical and noncritical containers. Critical containers must be scheduled before scheduling noncritical containers. Section 4.3.1 first provide rules to make a distinction between critical and noncritical containers. Noncritical containers must be picked up within ten days and lack any other scheduling restriction, it is therefore possible to schedule the receiving operation to reduce long-term cross docks. Section 4.3.2 to 4.3.5 provides methods to determine the number of cross docks associated with the put-away, picking and shipping operation respectively when the container will be received in one of the warehouses. Cross docks are inefficient flow of goods between warehouses and occur when the succeeding warehouse operation cannot be executed in the current warehouse. The put-away, picking and shipping cross docks are marked red in Figure 6. Cross docks can be avoided through scheduling the receiving operation such that the flow of goods between the warehouses is organized as efficient as possible.
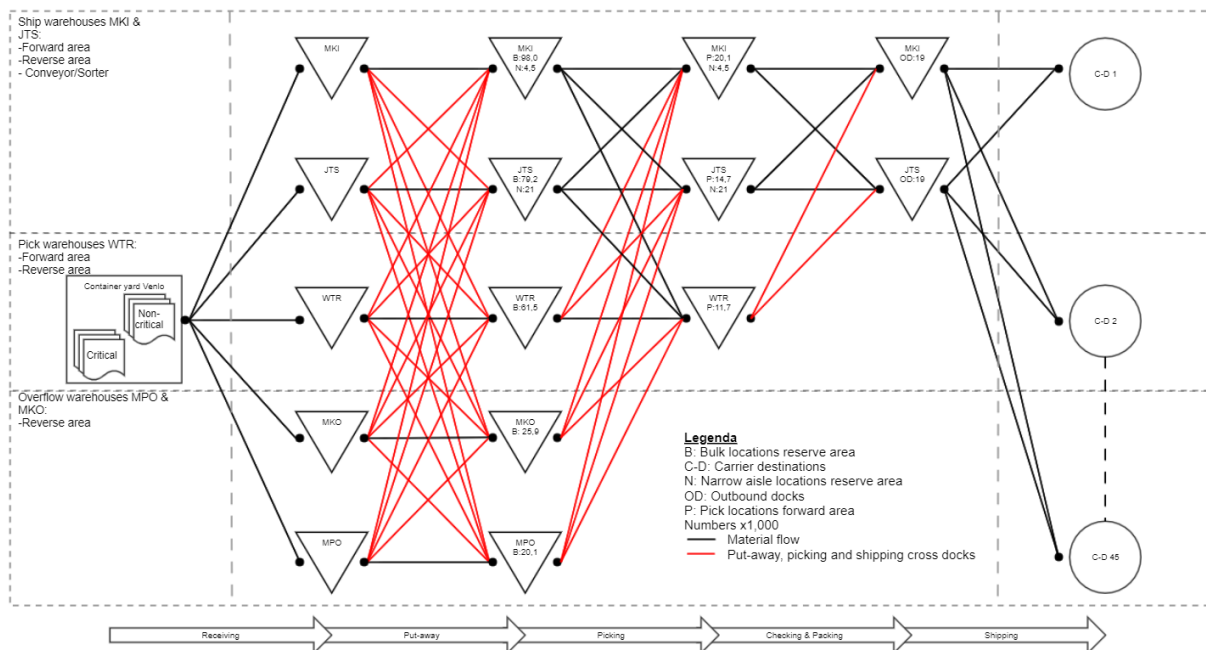
Figure 6: Put-away, picking and shipping cross docks between warehouses (marked red)

4.3.1   Distinct critical and noncritical containers

Containers available at the container yard can be classified as critical and noncritical containers. Critical containers must be received as soon as possible at a specific warehouse and it is therefore not possible to schedule the container receiving operation to achieve an efficient flow of goods. Noncritical containers are preferred to be picked up from the container yard within ten days, otherwise demurrage costs are incurred, however these containers lack any other scheduling restrictions. It is therefore possible to schedule the receiving operation in the upcoming ten days to achieve an efficient flow of goods.

Critical containers are the containers which must be unloaded as soon as possible at a specific warehouse, which only occurs when a container at the container yard contains items which are almost out of stock. To fulfill customer demand on time, it is desirable to reduce the throughput time between the moment the critical container arrives at the container yard and when the item is shipped to the customer. Therefore, these containers are preferred to be received as soon as possible in a ship

warehouse, even if the number of cross docks in the ship warehouse is higher than in another warehouse. Containers are classified as critical when the current stock coverage is below a certain value. The current stock coverage of SKU i can be calculated as follows:

$$SC_i = \frac{\sum_{w \in W} S_{iw}}{D_i} \qquad (6)$$

When the stock coverage is lower than the desired stock coverage, container j with SKU i must be received as soon as possible in a shipping warehouse. The critical containers must be scheduled before the noncritical containers, which is included in the scheduling algorithm in Section 4.4.3.

4.3.2 Put-away cross docks

Put-away cross docks occur when the receiving warehouse is not the same as the storage warehouse. Items cannot be stored in the receiving warehouse when the receiving warehouse lacks the right storage type or when the storage type is fully utilized (as pointed out in Section 2.3.2). The number of put-away cross docks of SKU i in container j are:

$$PA_{ijw} = \begin{cases} 0 & if\ Q_{ij} \leq AS_{tw} \\ Q_{ij} - AS_{tw} & if\ Q_{ij} > AS_{tw} \end{cases} \qquad (7)$$

The number of put-away cross docks when receiving container j at warehouse w, as a consequence of not having the right storage type available, are:

$$CPA_{jw} = \sum_{i \in I} PA_{ijw} \qquad (8)$$

4.3.3 Picking cross docks

Picking cross docks occur in cases of customer demand when there is no stock available at the pick or ship warehouses while there is stock available in the overflow warehouses. Cross docks (e.g., external replenishments) are executed to replenish bulk stock from the overflow warehouse to one of the ship or pick warehouses. Pallets are always completely replenished from the reserve area into the forward area, and demand occurs in full pallets and can occur with equal probability at any day of the week. Picking cross docks can be avoided by assigning available containers to each warehouse so that the pallets stored in the overflow warehouse remain there as long as possible. More containers containing items with a short storage time can consequently be received in the preferred shipping warehouse resulting in less put-away, picking and shipping cross docks.

To determine where to receive a container, the expected storage location occupation (SLO) is calculated, along with the equivalent number of weeks the container occupies one bulk pallet place if the container is received in the ship or pick warehouse. The SLO is determined for the whole container instead of each item individually since all items will be stored in the receiving warehouse if possible. Section 4.3.3.1 elaborates on the calculations of the SLO. To increase warehouse efficiency, containers must be allocated such that the amount of picking cross docks between warehouses is reduced. Therefore, containers with a low SLO are preferably received in the pick or ship warehouses, while containers with a high SLO are preferably received in an overflow warehouse. Items stored in the overflow warehouse are consequently requested less often resulting in less cross docks. Section 4.3.3.2 proposes an equation for calculating the cut-off SLO to distinct high and low SLO. Section 4.3.3.3 provides formulas to calculate the number of picking cross docks if a container is received in a less preferred warehouse. The same example is referred to at the end of every section for clarification.

4.3.3.1 Storage location occupation

The SLO consist of two parts: The first regards the time required before the current stock is sold and VidaXL begins to sell the content of the receiving container if the container is received in the pick or ship warehouse; the second regards the time required before the content of the receiving container is sold. For simplicity is assumed that it never occurs that two containers containing the same SKU are available in the container yard.

The first part requires $(S_{ip} + S_{is})/D_i$ time units, where S_{ip} is the total current stock level of SKU i in the pick warehouses, S_{is} the total current stock level of SKU i in the ship warehouses, and D_i is the demand pattern of SKU i. In the meantime, the items are occupying Q_{ij} pallet places, so the SLO during this timeframe is $(S_{ip} + S_{is}) * Q_{ij}/D_i$. The first part is marked blue in Figure 13. The current stock level of SKU i in the ship and pick warehouse is considered instead of the overall stock since the stock level in the overflow warehouse does not affect the decision.

Demonstration A*: The stock level of SKU i in the overflow warehouse does not affect the allocation decision of the receiving container, given the restriction that first all stock is sold from the ship and pick warehouses before stock in the overflow warehouses.*

VidaXL receives one container with ten pallets of SKU i. Before assigning the container to the ship, pick, or overflow warehouse, the company checks the stock level in each warehouse and the demand pattern of SKU i. There are currently ten pallets located in the ship and pick warehouses and ten pallets located in the overflow warehouse, and the demand pattern is one pallet every week. First the stock is sold from the ship and pick warehouses before the stock in the overflow warehouses, the company therefore forecasts that the stock level will develop as shown in Figure 7 and Figure 8*. The company calculates the SLO of the receiving container using equation 10, and two situations can occur: 1) the SLO is low and the container is assigned to the pick or ship warehouse or 2) the SLO is high and the container is assigned to the overflow warehouse.*
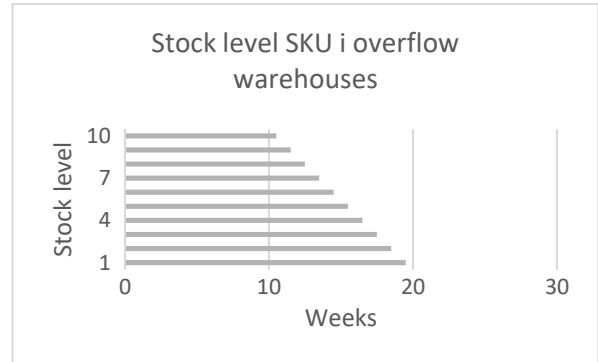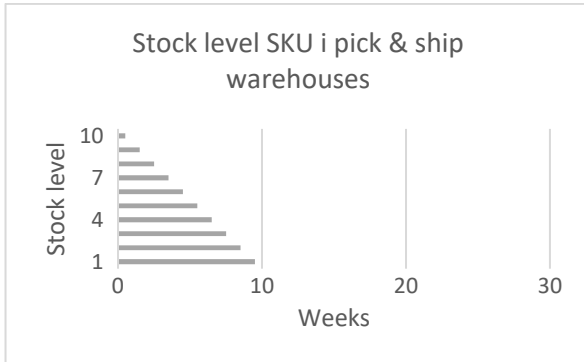
Figure 7: Current stock level SKU i pick and ship warehouses   Figure 8: Current stock level SKU i overflow warehouses

In the first situation, ten pallets of SKU i are received in the pick or ship warehouse and the current stock level of SKU i increases to twenty pallets (Figure 9). The increase in stock in the pick and ship warehouses is allowed since the demand is high enough so that the SLO of the receiving container is below the cut-off SLO Z_P (which is explained in Section 4.3.3.2). The ten pallets stored in the overflow warehouse consequently remain ten weeks longer in the overflow warehouse (Figure 10*), which is preferred since the company wants to store pallets as long as possible in the overflow warehouse in order to reduce cross docks between warehouses.*
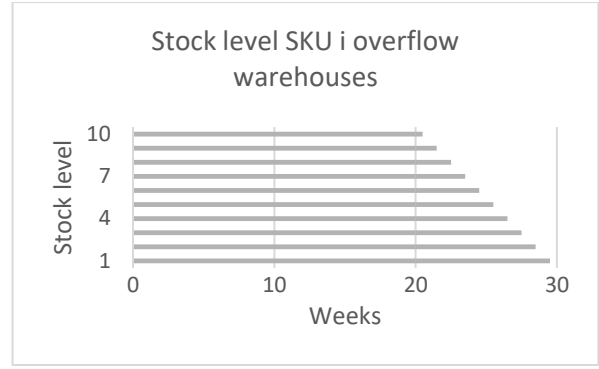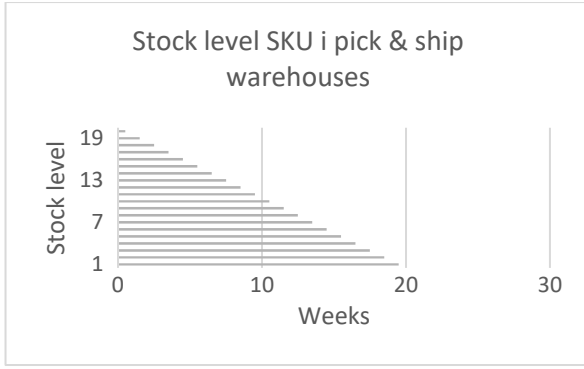
Figure 9: Stock level SKU i pick & ship warehouses $SLO < Z_P$

Figure 10: Stock level SKU i overflow warehouses $SLO < Z_P$

In the second situation, the company handles a lower cut-off SLO Z_P and the container is assigned to the overflow warehouse. The stock level in the pick and ship warehouses remains equal and the company forecasts to sell all the pallets within ten weeks (Figure 11). However, the stock level of the overflow warehouse increases by ten pallets to twenty pallets, the pallets stay in the overflow warehouse on average longer as forecasted earlier, which is desired since the throughput time of the pallets stored in the overflow warehouse must be as long as possible in order to reduce the cross docks between warehouses (Figure 12).
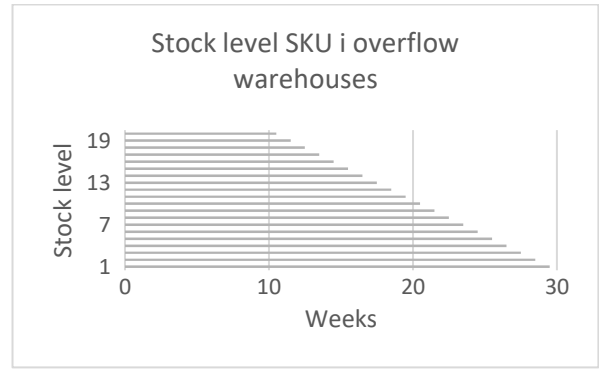
Figure 11: Stock level SKU i pick & ship warehouses $SLO > Z_P$

Figure 12: Stock level SKU i overflow warehouses $SLO > Z_P$

The stock level in the overflow warehouses does not affect the decision to receive the container in the overflow warehouses or in the pick or ship warehouses. The stock level in the pick and ship warehouses represents the sole crucial stock affecting the decision to receive containers in one of the warehouses.

The second part of the SLO consists of the time required before all pallets of SKU i of container j are sold, which can be calculated by summing the time that each pallet remains in the warehouse. For example, container j contains ten pallets of SKU i with a demand of one pallet per week. The first pallet demand occurs within one week on a random day, so it occupies one pallet place for half a week on average, while the second pallet is sold within two weeks, so it occupies one pallet place for one and a half weeks on average, and so on. In total, the pallets occupy the equivalent of one pallet place for 0.5+1.5+2.5+3.5+4.5+5.5+6.5+7.5+8.5+9.5=50 weeks. It is possible to calculate the sum of consecutive numbers using the Gauss sum formula (equation 9). Demand occurs at a random day of the week and not always at the end of the week, and therefore the formula of Gauss must be adjusted to (n^2)/2. In addition, the demand is not always one pallet per week, and the Gauss formula can be divided with the demand pattern D_i to calculate the equivalent number of weeks the item occupies one pallet place

(marked red in Figure 13). The SLO can be calculated with equation 10, which represents a combination of the first and second equation.
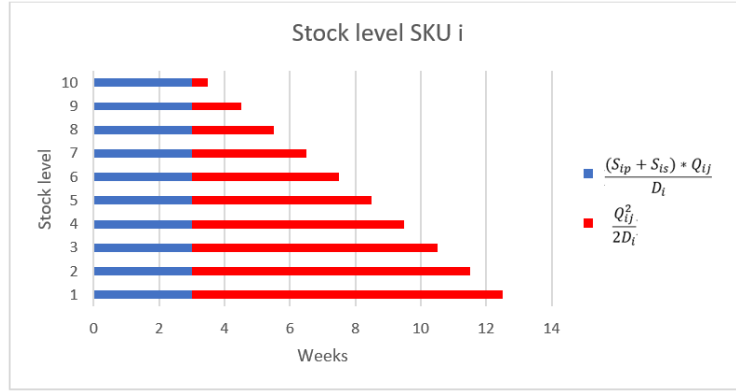
Figure 13: Stock level evolution SKU i container j with marked SLO denotation

$$1 + 2 + 3 + \cdots + n = \sum_{k=1}^{n} k = \frac{n(n+1)}{2} \qquad (9)$$

$$E[SLO_j] = \sum_{i=1}^{I} (\frac{(S_{ip} + S_{is}) * Q_{ij}}{D_i} + \frac{Q_{ij}^2}{2D_i}) = \sum_{i=1}^{I} \frac{Q_{ij}^2 + 2 * (S_{ip} + S_{is}) * Q_{ij}}{2D_i} \qquad (10)$$

Example 1 : Calculating the SLO

VidaXL receives one container j, which has eight SKUs inside which can be stored on fifty-five pallets in total. The container contains six pallets of the first item, the demand pattern for this item is one pallet per week, and there are currently fourteen pallets stocked in the pick and ship warehouses. Container j also contains seven pallets of the second item, the demand pattern for the second item is one pallet per week, and the current stock level in the pick and ship warehouses is twenty-six pallets. The content of container j, the demand pattern of the SKUs in container j, and the current stock level of those SKUs are summarized in the following vectors:

I: 8
Q_j: {6,7,10,7,5,12,1,7}
D_j: {1,1,2,1,2,3,2,1}
S_j: {14,26,23,15,25,29,10,18}

The SLO of container j can be calculated using equation 10:

$$E[SLO_j] = \sum_{i=1}^{8} \frac{Q_{ij}^2 + 2 * (S_{ip} + S_{is}) * Q_{ij}}{2D_i} = 999.5$$

Container j is expected to occupy the equivalent of 999.5 storage locations for one week if it is received in a pick or ship warehouse.

29

4.3.3.2 Cut-off SLO

For every receiving container, the appropriate receiving warehouse needs to be determined. As previously mentioned, the efficiency of the warehousing system can be increased by assigning the containers so that the amount of picking cross docks between the warehouses is reduced. Therefore, containers with a low SLO are preferred to be received in one of the pick or ship warehouses, while containers with a high SLO are preferred to be received in an overflow warehouse. This section provides equations to specify low and high SLO.

Demonstration B: *Containers with a low SLO are preferred to be received in one of the pick or ship warehouses, while containers with a high SLO are preferred to be received in an overflow warehouse.*

VidaXL receives four containers in the next thirty weeks. For simplicity, the warehouses currently do not have stock of the SKUs that are in the containers (which is also the case when new SKUs are received). The first three containers each contain ten pallets, and the demand is one pallet per week. The SLO of each container is calculated using equation ten and is equal to fifty. The fourth container has ten pallets, but the demand pattern is one pallet per three weeks. The SLO of the fourth container is also calculated with equation 10 and is equal to 150. To equalize the usage of the storage space between the pick, ship, and overflow warehouses, the containers can be divided into two sets. Set A contains the first three containers, where 3*10=30 pallets with a total SLO of 50+50+50=150. Set A uses five storage places on average in the upcoming thirty weeks, see Figure 14 *for the expected stock level evolution of set A. For calculating the average storage places in the upcoming thirty weeks, it does not matter whether all three containers are received from the start 30*(5+0+0)/30=5 or whether one container is received every ten weeks 10*(5+5+5)/30=5). Set B contains the fourth containers with ten pallets and a SLO of 150 as well. Set B uses five storage places on average in the upcoming thirty weeks as well, see Figure* 15 *for the expected stock level evolution of set B. To reduce the number of cross docks between warehouses, it is better to assign set B to an overflow warehouse. Ten pallets are consequently cross docked in the upcoming thirty weeks to fulfill customer demand. If set A is assigned to an overflow warehouse, VidaXL needs to cross dock ten pallets from set A every ten weeks, resulting in thirty cross docks in the upcoming thirty weeks.*

Figure 14: Stock level evolution set A (SLO=150)   *Figure 15: Stock level evolution set B (SLO=150)*

The example shows that containers with a low SLO are preferred to be received in the pick and ship warehouses and shows that the storage locations in the warehouses can be equally utilized if the total SLOs of each set are equal. However, in practice the bulk storage locations are not equally divided over the pick, ship, and overflow warehouses. Therefore, the overall SLO must be divided according to the distribution of the bulk storage places between the pick, ship, and the overflow warehouses, which is represented by the right side of equation 11. The left side illustrates the sum of all expected SLOs lower

than Z_P so that all containers with a SLO lower than Z_P are preferred to be received in the pick and ship warehouses to achieve balanced storage location utilization. Parameter Z_P must be set so that the following equation holds:

$$\sum_{j \in J \,|E[SLO_j] \leq Z_P} E[SLO_j] \; = \; \frac{B_p + B_s}{B_o + B_p + B_s} * \sum_{j \in J} E[SLO_j] \qquad (11)$$

Example 1 : Calculating the cut-off SLO

VidaXL received 7,100 containers in 2019. The SLO per container can be determined from historical data and yields the result of Figure 16. The SLO faces a "long tail," where all values above 3,000 are given in the last column. A SLO value of 3,000 is on average almost equivalent to storing all items of a container for one year without selling any items. When items are not sold within one year, VidaXL tries to sell the items via other sales channels or they scrap the items.
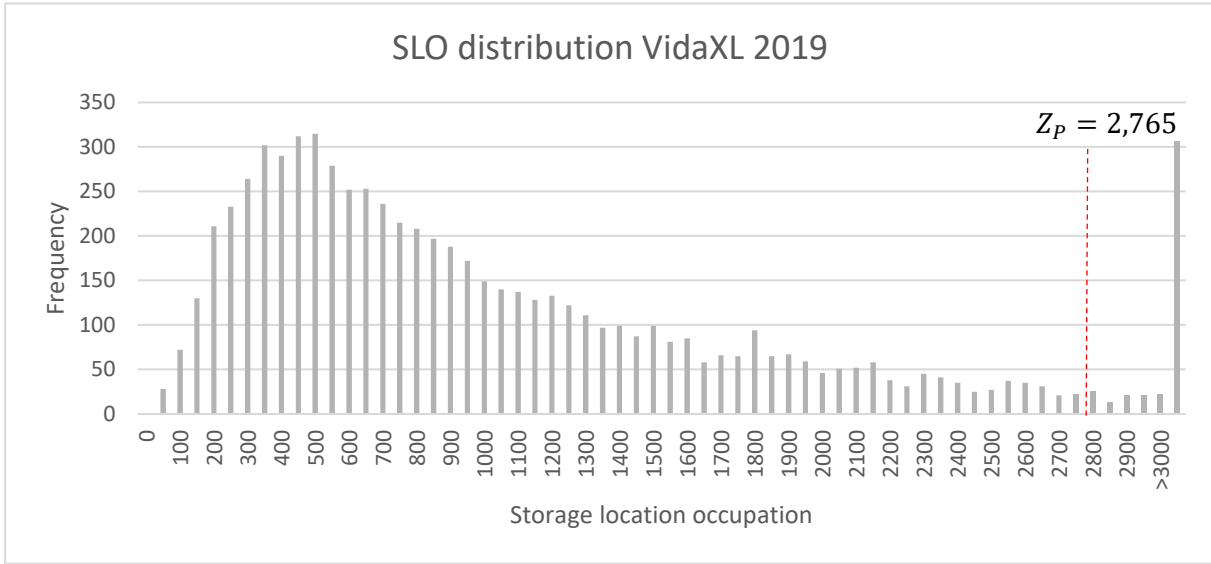
Figure 16: Storage location occupation and cut-off SLO Z_P VidaXL (2019)

The "long tail" makes the warehouse operations at VidaXL highly suitable for assigning containers with a high SLO to overflow warehouses. As earlier noted, ten containers with a SLO of 300 occupy the same amount of storage places as one container with a SLO of 3,000.

Vida XL has 284,700 bulk storage locations divided across three overflow warehouses, one pick warehouse, and two ship warehouses, they have 238,700 bulk storage locations in the pick and ship warehouses and 46,000 bulk storage locations at overflow warehouses. VidaXL wants to utilize the storage locations equally over the warehouses while reducing the number of cross docks. To achieve this result, 84% of the overall SLO must be assigned to the pick and ship warehouses and 16% to overflow warehouses. To reduce the number of cross docks between the warehouses, the containers with a high SLO must be received in the overflow warehouses. In other words, containers with a SLO lower or equal to Z_P must be stored in the pick and ship warehouses so that the sum of the SLO of those containers divided by the overall SLO is equal to 84%.

After evaluating the historical data of VidaXL, the cutoff score Z_P must be set to 2,765.

$$\sum_{j \in J \,|E[SLO_j]\leq 2,765} E[SLO_j] \;=\; \frac{61,500 + 177,200}{46,000 + 61,500 + 177,200} * 7,322,506 = 6,138,549$$

4.3.3.3 Additional cross docks if received in another warehouse as preferred

If containers are received in another warehouse as preferred (according to the cutoff SLO), the items occupy storage locations so that other containers must be received in other warehouses as well. Pallets are consequently cross docked between the pick and ship warehouses and the overflow warehouses unnecessary. Two events cause cross docks: 1) The wrong container is received in the pick or ship warehouse or 2) the wrong container is received in the overflow warehouse. The expected unnecessary cross docks in the first event can be calculated by multiplying the additional fraction of time that the items unnecessarily occupy the storage location with the average pallets per container and subtracting it by the average pallets per container. The additional fraction of time that the items occupy the storage location can be calculated by dividing the expected SLO of container j with the average SLO of the pick and ship warehouses. However, the outcome needs to be divided by two since in practice such cross docks only occur for the items wrongly stored in the overflow warehouse rather than to the items wrongly stored in the pick and ship warehouses (equation 12).

The expected unnecessary cross docks caused by the second event can be calculated by multiplying the average pallets per container with the expected SLO of container j and dividing this result by the average SLO of the received containers in the overflow warehouse. This value can be subtracted from the average pallets per containers to calculate the unnecessary cross docks. Moreover, the outcome needs to be divided by two since additional cross docks only occur for the containers assigned to the overflow warehouse (equation 13).

If $E[SLO_j] > Z_P$ and container is assigned to the pick or ship warehouse:

$$E[CPI_{jw}] = \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO}_{pick\ and\ ship\ wh}} - \frac{\bar{Q}}{2} \qquad (12)$$

If $E[SLO_j] < Z_P$ and container is assigned to the overflow warehouse:

$$E[CPI_{jw}] = \frac{\bar{Q}}{2} - \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO}_{overflow\ wh}} \qquad (13)$$

Example 1 : Calculating additional picking cross docks

Container j from example 1 is received in the overflow warehouse, and therefore container j+1 must be received in the pick or ship warehouse to equalize the utilization of the storage locations. Container j+1 has an expected SLO of 3,000, and the average SLO of the containers received in the pick and ship warehouses is 1,000. Therefore, the additional pallet cross docks of receiving container j+1 in the pick or ship warehouse instead of the overflow warehouse are:

$$E[CPI_{jw}] = \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO}_{pick\ and\ ship\ wh}} - \frac{\bar{Q}}{2} = \frac{56.5 * 3,000}{2 * 1,000} - \frac{56.5}{2} = 56.5$$

Container j+1 occupies the equivalent of 3,000 storage places for one week in the pick or ship warehouse. Three other containers with a SLO of 1,000 must consequently be received in the overflow warehouse to equalize the utilization between the ship, pick, and overflow warehouses.

Container j in example 1 has an expected SLO of 999.5, and the container must be received in the pick or ship warehouse because its expected SLO is below 2,765. If the container is received in the overflow warehouse, avoidable cross docks occur. Therefore, the additional pallet cross docks due to the wrong receiving location are calculated as follows:

$$E[CPI_{jw}] = \frac{\bar{Q}}{2} - \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO}_{overflow\ wh}} = \frac{56.5}{2} - \frac{56.5 * 999.5}{2 * 3,000} = 18.8$$

In total, four containers are wrongly assigned. Container j+1 is assigned to the ship and pick warehouse. Equation 12 assigns 56.5 additional cross docks to container j+1. Three containers with a SLO of 999.5 are assigned to the overflow warehouse, and 18.8 additional cross docks are assigned to each container. In total, 56.5+18.8+18.8+18.8=112.9 cross docks are equally assigned to the four containers.

In practice, three containers with on average 56.5 pallets are stored in the overflow warehouse, resulting in 3*56.5=169.5 cross docks. If the containers were assigned correctly, the container with a SLO of 3,000 was stored in the overflow warehouse, resulting in 56.5 cross docks. The wrong assignment results in 169.5-56.5=113 unnecessary avoidable cross docks, which is equal to the sum of all additional assigned cross docks to all four containers.

4.3.4   Shipping cross docks

Shipping cross docks occur when the pick warehouse is not the same as the shipping warehouse. This section first elaborates on the occurrence and prevention of shipping cross docks. Moreover, it proposes a method to reduce shipping cross docks and it presents an example for clarification.

VidaXl has one pick warehouse which is not equipped for shipping items directly to the customer, and they have two shipping warehouses which can pick and ship items directly. Items picked in the pick warehouse are always cross docked to one of the shipping warehouses.

VidaXL currently ships items to forty-five carrier destinations in Europe, carrier destinations with low demand are not reach by both shipping warehouse. They are not able to forecast the demand pattern per item per carrier destination since the demand pattern is exposed to multiple trends and seasonality, and it is therefore not possible to assign the right shipping warehouse to receiving containers based on forecasted customer demand. In addition, the expected utilization of the pick locations will deviate between 70% and 90% in 2020. VidaXL lacks sufficient pick locations to make items pickable in multiple warehouses, and shipping cross docks will consequently occur when the pick warehouse is not the same as the ship warehouse.

The shipping cross docks from the pick warehouse to the ship warehouses can be reduced by storing items with a high demand in the ship warehouse, items with an average demand in the pick warehouse and items with a low demand in the overflow warehouse. More containers containing items with a short storage time can consequently be received in the preferred shipping warehouse resulting in less put-away, picking and shipping cross docks. After observing Figure 6, it looks like it does not matter if the items stored in the pick and overflow warehouse are cross docked to the ship warehouse during the picking or shipping operation. However, scheduling the receiving operation does not affect the current replenishment procedure and the warehouse network design of VidaXL.

Items are not always directly cross docked (e.g. replenished) from the overflow warehouse to the ship warehouses. Sometimes, they are first cross docked to the pick warehouses, the items are consequently cross docked to the ship warehouses before shipping them to the customers. The picking cross docks are executed to the pick or ship warehouse based on the utilization of the forward area of those warehouses. Moreover, it is only possible to pick some items in the pick warehouse and not in the ship warehouse since the forward area of the ship warehouses are not always equipped with all storage types. Pallets must therefore first be cross docked from the overflow warehouse to the pick warehouses before cross docking the items to the ship warehouses.

When receiving containers in the overflow warehouse, it is not possible to determine beforehand if the items will be cross docked to the ship or pick warehouse. It is therefore desirable to reduce all cross docks during the shipping and picking operation from the overflow warehouses, by receiving container with a low SLO in the shipping warehouse, containers with an average SLO in the pick warehouse and containers with a high SLO in the overflow warehouse. More containers containing items with a short storage time can consequently be received in the preferred shipping warehouse resulting in less put-away, picking and shipping cross docks. Receiving containers can be assigned to the warehouses in the same manner as described in Section 4.3.3. Equation 11 must be adjusted as follows to calculate the cut-off SLO Z_S:

$$\sum_{j \in J \,|E[SLO_j] \leq Z_S} E[SLO_j] \;=\; \frac{B_S}{B_O + B_P + B_S} * \sum_{j \in J} E[SLO_j] \qquad (14)$$

The right side of the equation is adjusted so that the containers are equally distributed over the warehouses according to the distribution of the storage locations. There are consequently two cut-off SLOs: The cut-off SLO Z_S is the upper bound SLO of the shipping warehouses, Z_S is also the lower bound of the pick warehouses, and the cut-off SLO Z_P is both the upper bound of the pick warehouses and the lower bound of the overflow warehouses.

If the container is not received in the preferred warehouse, the estimated number of additional cross docks can be calculated in the same manner as in Section 4.3.3. However, equations 12 and 13 must be adjusted to:

If $E[SLO_j] > Z_{UW}$ where Z_{UW} is the upper bound of the receiving warehouse w:

$$E[CPS_{jw}] = \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO_W}} - \frac{\bar{Q}}{2} \qquad (15)$$

If $E[SLO_j] < Z_{LW}$ where Z_{LW} is the lower bound of the receiving warehouse w:

$$E[CPS_{jw}] = \frac{\bar{Q}}{2} - \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO_W}} \qquad (16)$$

Example 1 : Calculating Z_{LW}, Z_{UW}, and the additional number of cross docks.

VidaXL still has the same amount of bulk locations in each warehouse: 62% are located in the shipping warehouses, 22% in the pick warehouses, and 16% in the overflow warehouses. To reduce the number of cross docks, the receiving containers must be allocated so that the overall SLO is divided according to the same distribution. The same historical data from the previous section is evaluated (Figure 17).
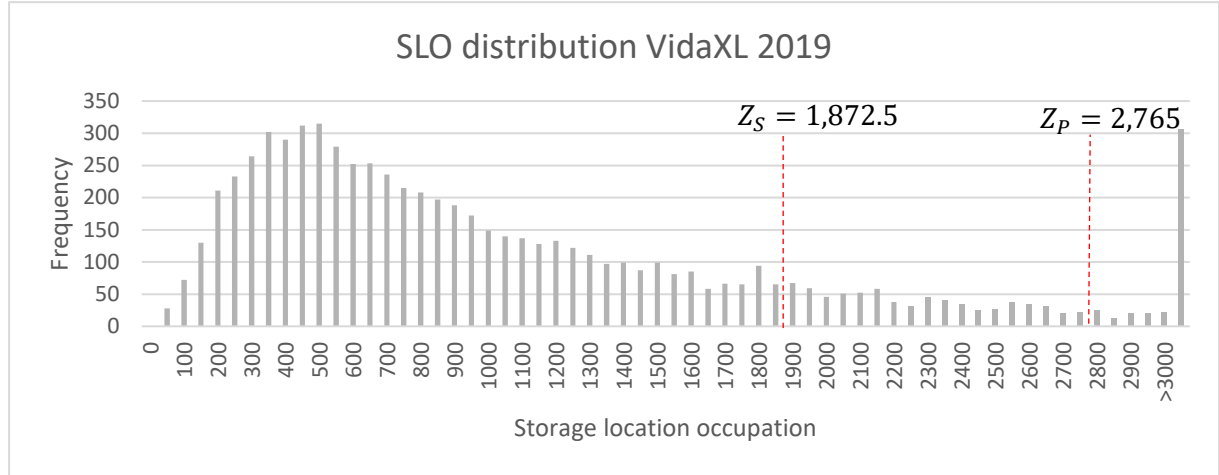
Figure 17: Storage location occupation and cut-off SLO Z_P and Z_S VidaXL (2019)

The cut-off SLO Z_S is equal to Z_{UW} of the shipping warehouses and to Z_{LW} of the picking warehouses, which can be calculated as follows:

$$\sum_{j \in J \,|E[SLO_j]\leq 1,872.5} E[SLO_j] \ = \ \frac{177,200}{46,000 + 61,500 + 177,200} * 7,322,506 = 4,556,382$$

The cut-off SLO Z_S is equal to 1,872.5. Every receiving container with a SLO lower or equal to 1,872.5 must be received in one of the shipping warehouses to reduce the number of shipping cross docks. The cut-off SLO Z_P is equal to the Z_{UW} of the picking warehouses and to the Z_{LW} of the overflow warehouses, which can be calculated as follows:

$$\sum_{j \in J \,|E[SLO_j]\leq 2765} E[SLO_j] \ = \ \frac{61,500 + 177,200}{46,000 + 61,500 + 177,200} * 7,322,506 = 6,138,549$$

Receiving containers with a SLO lower than 1,872.5 are consequently preferred to be received in the shipping warehouse. Containers with a SLO between 1,872.5 and 2,765 are preferably received in the pick warehouses, while containers with a SLO above 2,765 are preferably received in the overflow warehouses to reduce put-away, picking and shipping cross docks.

Consider the containers j, j+1, and the new introduced container j+2, which have SLOs of 999.5, 3,000, and 2,000 respectively. Imagine that container j is received in the overflow warehouse, container j+1 in the pick warehouse, and container j+2 in the ship warehouse.

For container j holds $E[SLO_j] < Z_L$, the additional number of cross docks are:

$$E[CPS_{jw}] = \frac{\bar{Q}}{2} - \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO_W}} = \frac{56.5}{2} - \frac{56.5 * 999.5}{2 * 3,000} 18.8$$

35

For container j+1 holds $E[SLO_j] > Z_U$, the additional number of cross docks are:

$$E[CPS_{jw}] = \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO_W}} - \frac{\bar{Q}}{2} = \frac{56.5 * 3{,}000}{2 * 2{,}500} - \frac{56.5}{2} = 5.65$$

For container j+2 holds $E[SLO_j] > Z_U$, the additional number of cross docks are:

$$E[CPS_{jw}] = \frac{\bar{Q} * E[SLO_j]}{2 * \overline{SLO_W}} - \frac{\bar{Q}}{2} = \frac{56.5 * 2{,}000}{2 * 1{,}000} - \frac{56.5}{2} = 28.3$$

4.3.5 Total number of cross docks

The total number of cross docks as a result of assigning container j to receiving warehouse w can be calculated by summing the number of cross docks during the put-away, picking, and shipping operations (equation 17). The total number of cross docks during put-away are defined as CPA_{jw}, while the expected total number of avoidable cross docks during picking and shipping are defined as CPS_{jw}.

$$CT_{jw} = CPA_{jw} + CPS_{jw} \qquad\qquad (17)$$

4.4 Scheduling container receiving operation

In an ideal situation, the inbound capacity per warehouse, the arriving date and the number of cross docks of each receiving container is known far in advance. When there is enough inbound capacity, it would then be possible to schedule the receiving operation of each container before the demurrage date while minimizing the total long-term cross docks. A binary decision must be made, containers must be picked up by a warehouse on a specific date resulting in J*W*T binary decision variables. The triple sum objective function can minimize the total long-term cross docks by assigning the containers to warehouses on specific periods. Container j will be assigned to warehouse w on period t if the binary decision variable is equal to one, the container is not assigned to warehouse w on period t if the binary decision model is equal to zero. Triple sum objective functions are complex to solve and requires high computational effort, the solution space increases exponentially.

The container receiving operation at VidaXL is not ideal, the exact inbound capacity per warehouse is only known a few days in advance, the actual arriving date of each container almost always differs from the estimated arrival date and it is almost impossible to estimate the number of cross docks of each receiving container far in advance. Previous section showed that the estimated number of cross docks depends on the available storage locations in the receiving warehouse, and on the stock level of each SKU in the pick and ship warehouses. Both depend on the demand pattern of each SKU and on the earlier received and stored items in each warehouse. Containers received during previous periods, increases the current stock level in each warehouse and therefore affect the estimated number of cross docks of the new receiving containers. Scheduling the container receiving operation for many periods in advance with a triple sum objective function is therefore almost impossible since each receiving operation during previous periods affects the estimated cross docks of to be received containers in future periods.

It would be possible to resolve the triple sum objective function each period when new information becomes available. However, solving a triple sum objective function with J*W*T binary decision variables requires computational effort and there is only limited time available to complete the

calculations. VidaXL schedules its container receiving operation each day, there will only be a few hours available during the night to provide a proper receiving schedule for each warehouse. Applying a rolling horizon and resolving a triple sum objective function for the coming months each day new information becomes available would therefore not be possible.

The solution space can be decreased significantly through daily assigning the containers to warehouses while meeting the inbound capacity constraints, resulting in W*J binary decision variables. However, minimizing the total cross docks daily is exposed to myopic and does not reduce the total long-term cross docks. Section 4.4.1 provides three examples to discuss all three myopias and proposes a method to conquer them. This paper proposes an alternative rolling horizon scheduling algorithm to deal with uncertain container arrivals and new information availability while reducing the computation time and complexity of the problem. First, an aggregate solution for multiple periods is provided with a binary decision model. The binary decision model has a double sum objective function and selects the next containers to be processed at each warehouse for the upcoming periods. The binary decision model only assigns the containers to warehouses, resulting in J*W binary decision variables and a double sum objective function. Second, the FIFO dispatch rule is applied to gather a detailed solution for the first scheduling's period. The FIFO dispatch rule schedules the container to specific receiving periods such that the throughput time decreases, and the containers are picked up before its demurrage date. The algorithm can be resolved each period new information becomes available. Section 4.4.2 first elaborates in more depth on the rolling horizon policy whereas Section 4.4.3 proposes a binary decision model including the objective function. Finally, the complete algorithm to schedule the receiving operation of critical and noncritical containers is provided in Section 4.4.4.

4.4.1 Reducing the total number of cross docks

The goal if this research is to increase the efficiency of warehouse operations by reducing the total number of cross docks. First, this section provides evidence that unnecessary cross docks are not avoided through daily selecting containers to minimize cross docks since this automatically means not selecting "hard containers" with many cross docks at all warehouses. Second, this section provides evidence that minimizing the number of cross docks daily does not minimize the total long-term cross docks. Third, this section provides evidence that the total number of cross docks are minimized without harming the inbound capacity constraint by selecting zero containers. Afterwards, it proposes a method to tackle these myopias through maximizing the long-term profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse.

Myopic 1
Selecting containers to minimize the total number of cross docks automatically means not selecting "hard containers" with many cross docks at all warehouses. These containers are forced to be scheduled just before the demurrage date and are therefore most of the times scheduled at a less preferred warehouse resulting in avoidable cross docks. Forced scheduling a "hard container" with ten avoidable cross docks at a less preferred warehouse results in more cross docks as voluntary scheduling another container with one avoidable cross dock at a less preferred warehouse.

There are six containers available in the container yard waiting to be picked up, and VidaXL can receive one container per day in the upcoming five days in each of the two warehouses. VidaXL must pick up all available containers within four days to prevent itself from demurrage costs. Moreover, VidaXL receives two containers per day in the upcoming two days. The cross docks associated with receiving the containers at MKI or JTS are provided in Table 3.

Container	A	B	C	D	E	F	G	H	I	J
MKI	5	5	5	5	6	6	5	5	5	5
JTS	6	7	8	9	12	13	0	0	0	0
Available date	t	t	t	t	t	t	t+1	t+1	t+2	t+2
Demurrage date	t+3	t+3	t+3	t+3	t+3	t+3	t+4	t+4	t+5	t+5

To minimize the number of cross docks daily, the containers can be scheduled as shown in Table 4.

Table 4: Receiving schedule daily minimize cross docks myopic 1

Day	t	t+1	t+2	t+3	t+4
MKI	C	G	D	F	J
JTS	A	H	B	E	I

The total number of cross docks are 5 + 6 + 5 + 0 + 5 + 7 + 6 + 12 + 5 + 0 = 51.

Through minimizing the number of cross docks daily, the containers G and H are scheduled on day t+1 and VidaXL is therefore forced to pick up the "hard containers" E and F on day t+3 since these containers are approaching the demurrage date. Container E is assigned to a less preferred warehouse, causing 12-6=6 unnecessary avoidable cross docks. The containers can also be assigned as in Table 5.

Table 5: Receiving schedule conquer myopic 1

Day	t	t+1	t+2	t+3	t+4
MKI	C	D	E	F	J
JTS	A	B	G	H	I

The total number of cross docks are 5 + 6 + 5 + 7 + 6 + 0 + 6 + 0 + 5 + 0 = 40.

Minimizing the total number of cross docks automatically means not selecting "hard containers" with many cross docks at all warehouses. These containers are forced to be scheduled just before the demurrage date and are therefore most of the times scheduled at a less preferred warehouse resulting in unnecessary avoidable cross docks.

Myopic 2
Minimizing the total number of cross docks every day does not minimize the total long-term cross docks since two sub optimizations do not automatically lead to the overall optimum.

There are eight containers available in the container yard waiting to be picked up, and VidaXL can receive two containers per day in the next two days in each of the two warehouses. The number of cross docks associated with receiving the containers at the MKI and JTS warehouse are presented in Table 6.

Table 6: Container data myopic 2

Container	A	B	C	D	E	F	G	H
MKI	4	4	4	4	7	7	8	8
JTS	6	6	6	6	6	6	6	6
Available date	t	t	t	t	t	t	t	t
Demurrage date	t+5	t+5	t+5	t+5	t+5	t+5	t+5	t+5

Minimizing the number of cross docks on the first day can be achieved as presented in Table 7.

Table 7: Receiving schedule daily minimizing cross docks myopic 2

Day	t	t+1
MKI	A, B	E, F
JTS	C, D	G, H

The total number of cross docks are 4 + 4 + 6 + 6 + 7 + 7 + 8 + 8 = 50.

Minimizing the total number of cross docks over both days results in the assignment of Table 8*.*

Table 8: Receiving schedule minimizing total number of cross docks myopic 2

Day	t	t+1
MKI	A, B	C, D
JTS	E, F	G, H

The subsequent number of cross docks are 4 + 4 + 4 + 4 + 6 + 6 + 6 + 6 = 40. Minimizing the number of cross docks daily thus does not minimize the total number of cross docks.

In a static situation, scheduling all available containers for the upcoming days results in the optimal answer. However, the scheduling procedure is exposed to uncertainty, because VidaXL does not know exactly when the containers become available, and the number of cross docks associated with each container can differ each day. Containers received over the following days can influence the decision made on the previous day. The rolling horizon policy may therefore be very useful in dynamic situations with considerable uncertain arrivals in later stages of the scheduling horizon (Wilkinson, 1996). Applying the rolling horizon policy to schedule the container receiving operation is described in more depth in Section 4.4.2.

Myopic 3
The total number of cross docks are minimized without harming the inbound capacity constraint by selecting zero containers.

There are six containers available in the container yard waiting to be picked up, and VidaXL is able to pick up one container per day in the upcoming tree days in each of the two warehouses. VidaXL must pick up all available containers within three days to prevent itself from demurrage costs. The cross docks associated with scheduling the containers at MKI or JTS are provided in Table 9*.*

Table 9: Container data myopic 3

Container	A	B	C	D	E
MKI	5	5	5	5	6
JTS	6	7	8	9	12
Available date	t	t	T	t	t
Demurrage date	t+2	t+2	t+2	t+2	t+2

Minimizing the total number of cross docks while there is no minimum inbound capacity constraint yield the result of Table 10*.*

Day	t	t+1	t+2
MKI	-	-	B
JTS	-	-	A

No containers are scheduled on day t and on day t+1. However, all containers must be picked up before or on day t+2, each warehouse is only able to receive 1 container per day and not all containers are therefore picked up before the demurrage date by daily minimizing the number of cross docks.

Selecting containers to minimize the number of cross docks automatically means not selecting "hard containers" with many cross docks at all warehouses. Moreover, minimizing the number of cross docks daily does not minimize the total long-term cross docks and selects zero containers when none of the available containers are approaching the demurrage date. The total number of cross docks can be reduced by scheduling the containers for a larger scheduling horizon existing of multiple periods by maximizing the profit from assigning container j to warehouse w instead of less-preferred warehouse. This principle is a combination of a rolling horizon policy and the greedy heuristic, the latter selects the "biggest bang for the buck," yielding a better result than minimizing the number of cross docks daily.

Conquer myopic 1, 2 and 3 while reducing long-term cross docks

Scheduling containers for a scheduling horizon of multiple periods by maximizing the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse conquer myopic 1, 2 and 3.

At day one, there are eight containers with the same demurrage date available at the container yard waiting to be picked up, containers A, B, C, D, E, F, G, and H. On the fourth day, four new containers become available at the container yard, and VidaXL has the capacity to receive one container per day in two warehouses. VidaXL schedules the containers over two periods and only confirms the pickup day of the containers scheduled on next period (the scheduled for the second period can consequently still be changed). The cross docks associated with scheduling the containers at MKI or JTS are provided in Table 11.

Table 11: Number of cross docks per container per warehouse

Container	A	B	C	D	E	F	G	H	I	J	K	L
MKI	5	5	5	5	5	5	5	5	5	5	5	5
JTS	6	7	8	9	10	11	12	13	0	0	0	0
Available	t	t	t	t	t	t	t	t	t+3	t+3	t+3	t+3
Demurrage	t+3	t+3	t+3	t+3	t+3	t+3	t+3	t+3	t+12	t+12	t+12	t+12

To minimize the number of cross docks, the containers are scheduled as shown in Table 12 *(c =confirmed picked up, n=scheduled but pick up not yet confirmed).*

Table 12: Receiving schedule minimizing the number of cross docks

Day	t		t+1		t+2		t+3		t+4	
C/N	C	N	C	N	C	N	C	N	C	N
MKI	C	D	D	E	E	G	G	J	J	L
JTS	A	B	B	F	F	H	H	I	I	K

The total number of cross docks are 5 + 6 + 5 + 7 + 5 + 11 + 5 + 13 + 5 + 0 = 62.

Scheduling the containers for two periods by maximizing the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse leads to the assignment of Table 13.

Table 13: Receiving schedule "biggest bang for the buck"

Day	t		t+1		t+2		t+3		t+4	
C/N	C	N	C	N	C	N	C	N	C	N
MKI	H	G	G	F	F	E	E	I	I	K
JTS	A	B	B	C	C	D	D	J	J	L

The total number of cross docks are 5 + 6 + 5 + 7 + 5 + 8 + 5 + 9 + 5 + 5 = 50.

The total number of cross docks is reduced by maximizing the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse. Moreover, maximizing the profit daily yields a suboptimal solution, and therefore the total number of cross docks can be reduced by maximizing the profit over a larger horizon. Sections 4.4.2 to 4.4.4 elaborate on the scheduling procedure to maximize the profit over a scheduling horizon existing of multiple periods. The influence of different scheduling horizons on the total number of cross docks is investigated in Section 5.

4.4.2 Rolling horizon policy

As mentioned in the introduction of Section 4.4, each receiving operation affects the estimated cross docks of new to be received containers. Furthermore, the receiving operation at VidaXL is exposed to uncertainty and it is therefore almost impossible to apply a static algorithm to schedule all container arrivals in advance. A rolling horizon policy can therefore be applied to revise the receiving schedule every period new information becomes available. This section first introduces the rolling horizon policy, hereafter it discusses the usability of the rolling horizon policy to schedule the container receiving operation at VidaXL.

To reduce the long-term cross docks, the rolling horizon policy will be applied. The rolling horizon policy separate the scheduling problem in a sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner. This approach results in close to optimal solutions with a significant reduction of the computation time (Dimitriadis, Shah, & Pantelides, 1997). The length of the scheduling horizon has a significant impact on the performance of the model. Some simulation studies show even better performance under the rolling horizon policy as under static scheduling since it can deal with environmental changes (Fang & Xi, 1997). The rolling horizon policy may therefore be very useful in dynamic situations with considerable uncertain arrivals in later stages of the scheduling horizon (Wilkinson, 1996). In static scheduling policies, the arrival times of all containers must be known beforehand or must be forecasted while in rolling horizon policies only the actual arrival date need to be known. The rolling horizon policy is therefore suitable in real-time applications in uncertain environments (Fang & Xi, 1997). Figure 18 provides a rough idea of the outcome of the rolling horizon policy.
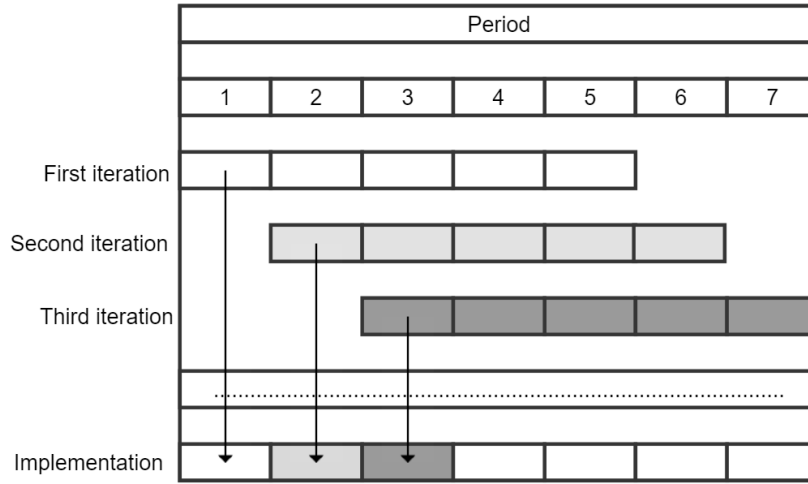
Figure 18: Rolling horizon policy

The container receiving operation at VidaXL can be scheduled with the rolling horizon policy to deal with uncertain future container arrivals. The rolling horizon policy can reschedule the receiving operation every period new information becomes available. Most rolling horizon policies optimizes the objective function over multiple periods, schedules the container to a warehouse and assigns the containers directly to one of the scheduling blocks (e.g. periods). The detailed schedule of the first period will be implemented and the other containers will be rescheduled during next period when new information becomes available. However, solving a triple sum objective function with J*W*T binary decision variables is complex and requires computational effort, there is only limited time available to reschedule the containers. VidaXL schedules its container receiving operation each day, there will only be a few hours available during the night to provide a proper receiving schedule for each warehouse. Applying a rolling horizon and resolving a triple sum objective function each day new information becomes available would therefore not be possible.

The computational effort can be reduced through splitting the problem in sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner. This approach results in close to optimal solutions with a significant reduction of the computation time (Dimitriadis, Shah, & Pantelides, 1997). At VidaXL, an aggregate solution can be provided with a binary decision model thereafter the FIFO dispatch rule can be applied to gather a detailed solution for the first scheduling's period, Figure 19.
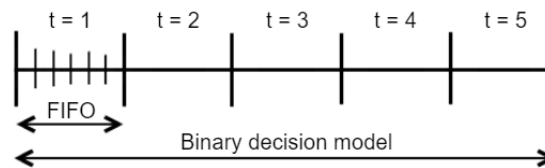
Figure 19: Aggregate and detailed schedule

The solution space can be decreased significantly, the binary decision model selects a subset of containers out of the available containers and schedules them to a warehouse, resulting in J*W binary decision variables. However, the containers are not yet assigned to one of the scheduling blocks (e.g. periods). The FIFO dispatch rule can be used to complete the detailed schedule for the first period by assign the containers FIFO to the scheduling blocks. The rule is effective in minimizing the maximum throughput time and variance of throughput times. The FIFO dispatch rule is therefore chosen to avoid

situation whereas the container is picked up after its demurrage date. The detailed schedule of first period can immediately be implemented. The receiving operation can be rescheduled during succeeding periods when new information becomes available, Figure 18.

Assigning containers directly to one of the scheduling blocks with a triple sum objective functions has the potential to be investigated in more detail when facing tight demurrage dates. The weight variable of the triple sum objective function differs per schedule block since it aims to schedule containers with a tight demurrage date first without using a dispatch rule. We expect that the triple sum objective function therefore will assign more containers in an earlier stage to less preferred warehouses when the preferred warehouse is not able to receive all containers on time, resulting in less containers scheduled after the demerge date. However, when demurrage dates are loose, the triple sum objective function can also assign fewer desirable containers to less preferred warehouses since it contemplates the demurrage and pick up date as well, which can result in unnecessary avoidable cross docks. The double sum objective function only considers the demurrage date when selecting the next containers to be processed but treats containers with different demurrage dates equally when deciding which container is desired to be received at a less preferred warehouse. The double sum objective function only contemplates the long-term cross docks and can therefore avoid unnecessary cross docks in some situations. Notably, the outcome of both models strongly depends on the parameters used and it is therefore not possible to conclude beforehand which method suits best (Addis, Carello, Grosso, & Tanfani, 2015; Monch & Habenicht, 2003). VidaXL is opening two new warehouses and will extend their inbound capacity, the probability of facing tight demurrage dates consequently decreases. In consultation with VidaXl is therefore decided to apply a rolling horizon policy where the aggregate schedule is provided with a binary decision model whereas the detailed schedule is made with the FIFO dispatch rule.

4.4.3   Binary decision model

Complex professional environments require a decision process that can be formalized and validated independently of personal preferences. This section therefore presents a binary decision model which provides an aggregate mid-term container receiving schedule through selecting a subset of containers out of the available containers and schedule them to warehouses, while reducing the long-term cross docks and the total number of days the containers are picked up after the demurrage date. Moreover, it explains the logic behind each constraint and proposes a method to solve the binary decision model.

The problem can be defined as a maximization function since it aims to maximize the profit from assigning container j to warehouse w instead of another warehouse, which seems contractionary since our goal is to reduce the total number of cross docks. However, if the problem is rewritten to a minimization function, the total number of cross docks on the long-term increases as concluded in Section 4.4.1. Furthermore, the model includes a double sum objective function instead of a triple sum objective functions to reduce the computational effort. The model only selects a subset of containers and schedules them to one of the warehouses, the containers are not yet assigned to one of the scheduling blocks (e.g. periods). The FIFO dispatch rule will afterwards be used to assign the containers to specific scheduling blocks as mentioned in the previous section. The binary decision model is incorporate in the scheduling algorithm proposed in Section 4.4.4.

Deciding where to receive which container can be formulized as the following binary decision model:

$$Maximize \sum_{w \in W} \sum_{j \in J} W_{jw} * x_{jw} \qquad (18)$$

subjected to:

$$\sum_{w \in W} x_{jw} \leq 1, \qquad\qquad j = 1, \dots, J \qquad (19)$$

$$\sum_{j \in J} x_{jw} \leq T * C_w \qquad\qquad w = 1, \dots, W \qquad (20)$$

$$\sum_{j \in J_A} x_{jw} \leq WB_{Aw} * T * C_w \qquad w = 1, \dots, W \qquad (21)$$

$$\sum_{j \in J_B} x_{jw} \leq WB_{Bw} * T * C_w \qquad w = 1, \dots, W \qquad (22)$$

$$\sum_{j \in J_C} x_{jw} \leq WB_{Cw} * T * C_w \qquad w = 1, \dots, W \qquad (23)$$

$$\sum_{j \in J} x_{jw} \geq C_w \qquad\qquad w = 1, \dots, W \qquad (24)$$

$$S_{tw} \leq \mu_t * TS_{tw} \qquad\qquad w = 1, \dots, W \qquad (25)$$

$$x_{wj} \in \{0,1\}, \qquad\qquad w = 1, \dots, W \; j = 1, \dots, J \qquad (26)$$

Where:

$$W_{jw} = 1000 - (CT_{jw} - \min(CT_j) - (TD - AD_j) * P) \qquad (27)$$

$$P = \begin{cases} M & if \; TD - AD_j > FD - 1 \\ P & else \end{cases} \qquad (28)$$

The aggregate receiving schedule can be provided through solving a binary decision model, as VidaXL has w warehouses and receives j containers with the result of w*j binary decision variables. Container j will be assigned to warehouse w if the binary decision variable x_{jw} is equal to 1, and if the container is not assigned to warehouse w, the binary decision variable is equal to 0. The binary decision model provides an aggregate mid-term container receiving schedule for each warehouse.

Each container has a weight W_{jw}, which depends on the receiving warehouse w and on the demurrage date of container j. The weight contemplates the profit from assigning container j to warehouse w instead of another warehouse by subtracting the least possible number of cross docks of container j from the number of cross docks if it is received in warehouse w. Additional penalty costs P are included so that containers approaching the demurrage date are preferred to be selected first when it is not possible to select and schedule all available containers. The value of the penalty sole depends on number of days the container is already available in the container yard, since the model aims to contemplates the long-term cross docks when considering which container is desired to be received at a less preferred warehouse. The binary decision model only schedules the containers to warehouses

and does not assign the actual receiving date, the detailed schedule will be completed in a later stage by the FIFO dispatch rule. Furthermore, the structure of W_{jw} prevent weights equal to zero such that the model always schedules as many containers as possible under the specified constraints.

The goal of the binary decision model is to maximize the product of all weights W_{jw} and decision variables x_{jw} under constraints 19 to 26. Because this model tries to maximize the profit from assigning container j to warehouse w, it schedules as many containers as possible and proposes an aggregate schedule for the upcoming T periods. If the binary decision model was defined as a minimization function by adjusting the weight W_{jw}, it would only schedule as many containers as necessary under constraints 26 to 33, which will result in an aggregate planning for one period and would result in a suboptimal solution, as concluded in the previous sections. However, it is possible to make an aggregate schedule for the upcoming T periods with a minimization function by adding and adjusting constraints (Addis, et al., 2015).

Containers are received loose loaded and can contain multiple SKUs, and items of the same SKU can be staged at the beginning and end of the container. The complete container is therefore unloaded at the receiving warehouse. Moreover, the warehouse operations at VidaXL are not designed to receive and unload one container in multiple warehouses. Constraint 19 ensures that each container cannot be allocated to multiple warehouses.

Each warehouse can receive multiple containers per period; however the maximum inbound capacity is constrained by the available resources at each warehouse. The binary decision model provides an aggregate mid-term container receiving schedule for each warehouse. Constraint 20 ensures that the model does not schedule more containers at each warehouse than the warehouse can handle during the aggregate scheduling period.

The performance of the inbound teams can be improved by balancing the workload between the warehouses. VidaXL categorizes its containers as A, B, and C containers, where A containers are easy to unload and cost little manual effort, while C containers typically contain many different SKUs which require significant effort from the inbound teams to unload the container. Constraints 21 to 23 assure that the workload is balanced between each warehouse for the aggregate mid-term receiving schedule.

The containers are unloaded by an inbound team, and if the warehouse does not receive enough containers, the performance of the inbound team decreases since it cannot unload as many containers as desired. Constraint 24 ensures that at least C_w containers are scheduled at warehouse w for the aggregate schedule such that the FIFO dispatch rule can complete the detailed container receiving schedule for at least one period in advance.

Warehouses can only receive containers when they have storage locations available to store the items. If containers are unloaded at a fully utilized warehouse, all items need to be cross docked to another warehouse to store all items. Therefore, constraint 25 ensures that VidaXL only receives containers at a warehouse which has storage space available in the warehouse.

The PulP library in python is used to solve the integer linear programming problem. The PulP library generates mathematical programming systems or linear programming files, and calls GLPK, CLP, CPLEX, and Curobi to solve linear problems (Hall, 2016). The default solver is the Coin Linear Programming (CLP) model which is open-source mixed integer programming and is free to use. The code is designed by COIN-OR and uses branch-and-cut algorithms to solve the problem. Branch and cut algorithms are

computation effective and are very powerful approaches to solve integer programming problems (Hillier & Lieberman, 2001). The CLP uses three hierarchical levels: The first two contain all the problem data which define the model, while the third contains the algorithmic aspects of the CLP model (Coin-Or, sd).

The PulP library can validate whether the provided solution is optimum or not using the function LpStatusOptimal (Mitchell, Kean, Mason, O'Sullivan, & Phillips, 2009). However, solving the binary decision model optimal for each iteration leads to close to optimal long-term solutions (Dimitriadis, et al. 1997). The length of the aggregate scheduling horizon has a significant impact on the performance of the model. Different scheduling horizons are therefore evaluated in Section 5.

4.4.4 Scheduling algorithm

This section proposes a scheduling algorithm to schedule critical and non-critical containers while accomplish fewer cross docks and avoiding situations where the container is picked up after the demurrage date. The algorithm applies the rolling horizon policy proposed in Section 4.4.2 and uses the binary decision model suggested in Section 4.4.3. This section illustrates the working procedure of the scheduling algorithm with an example.

The total long-term cross docks can be reduced by solving a binary decision model to make an aggregate receiving schedule for the upcoming T periods while completing the detailed schedule with the FIFO dispatch rule. The binary decision model selects and schedules containers to one of the warehouses by maximizing the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse while considering the demurrage date, the objective function is provided in Section 4.4.3. The binary decision model selects and schedules under constraint 20 as many containers as all warehouses can receive during the upcoming T periods. The total inbound capacity of all warehouses during next period will never exceed the number of container available in the container yard. Furthermore, under constraint 24 the binary decision model schedules at least as many containers to each warehouse as each warehouse can receive in the next period. The FIFO dispatch rule will otherwise not be able to complete the detailed schedule for next period as mentioned in Section 4.4.3. The binary decision model only selects a subset of containers and schedules them to warehouses. The FIFO dispatch rule is used afterwards to complete the detailed schedule for the first period by assign the containers FIFO to the scheduling blocks. The rule is effective in minimizing the maximum throughput time and variance of throughput times. The FIFO dispatch rule is therefore chosen to avoid situation whereas the container is picked up after its demurrage date. The detailed schedule of first period can immediately be implemented. The receiving operation can be rescheduled during succeeding periods when new information becomes available.

At VidaXL, one scheduling's period is equal to one day and the scheduling algorithm will therefore be executed every day. If there are enough containers available, the binary decision model will select and schedule as many containers to each warehouse as each warehouse can receive in the upcoming T days. Afterwards, the FIFO dispatch rule assigns the scheduled containers FIFO to pickup days. VidaXL needs to confirm the pickup date to the forwarder one day in advance, the detailed schedule of next day is therefore immediately implemented and communicated to the forwarder. However, the forwarder is sometimes not able to make the container available for pickup on time. VidaXL therefore wants to inform the forwarder two days in advance with the expected pickup date of each container such that the forwarder can anticipate on the request. The detailed schedule must therefore be completed with the FIFO dispatch rule for at least next day and preferred for the upcoming two days. On day t+1, VidaXL executes the algorithm again, due to new information availability, the best receiving

schedule for day t+2 differs from the expected receiving schedule communicated to the forwarder. VidaXL is still able to revise the expected detailed receiving schedule of day t+2 on day t+1. Sometimes there are not enough containers available to complete the detailed schedule two days in advance. VidaXL can therefore only inform the forwarder two days in advance when there are enough containers available at the container yard. New containers and information become available every day which can affect the receiving schedule, and therefore the scheduling algorithm must be executed at the start of every day to revise the receiving schedule for next days. Furthermore, it makes no sense to update the container receiving schedule during the day since the forwarder must be informed at the beginning of the current day to make the container available for next day.

The receiving operation can be scheduled for period t+1 on period t using the following algorithm:

1. Form long list with containers available at the container yard at Venlo from which the pickup date is not confirmed yet.
2. For each container j:
   a. Determine demurrage date
   b. Calculate number of cross docks CT_{wj}
   c. Verify stock coverage SC_i of each SKU i in container j
3. Schedule critical containers:
   a. If $SC_i < \underline{Y}$ do:
      i. Schedule container j to preferred ship warehouse as soon as possible
      ii. Adept C_w
4. Complete aggregate receiving schedule for noncritical containers:
   a. Solve binary decision model for T periods
5. Complete detailed receiving schedule for noncritical containers:
   a. Assign containers FIFO for next period (t+1) for each warehouse
   b. If $\sum_{j \in J} x_{jw} > * C_w$ do:
      i. Schedule containers FIFO for the period after next period (t+2) for each warehouse
6. Update list with available containers at container yard:
   a. Remove containers scheduled on period t+1 from list with available containers
   b. Update list with new container arrivals

The scheduling algorithm must be solved daily hereafter the detailed schedule is implemented for next day. The containers are consequently scheduled as shown in Figure 20 (T=5).
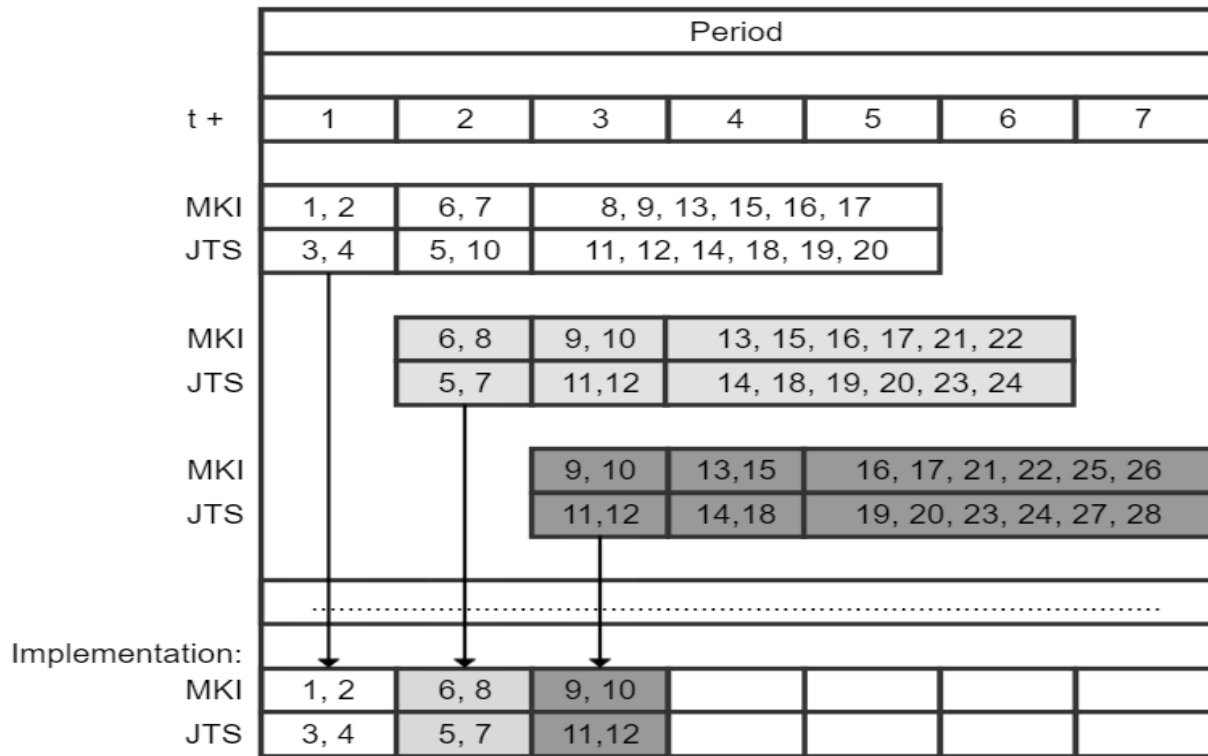
Figure 20: Outcome scheduling algorithm three iterations

First, the scheduling algorithm is executed on day t at the start of the day. A long list with available containers at the container yard is created and the container data for each container is determined by evaluating the system. Critical containers are immediately scheduled to the shipping warehouses. The aggregate receiving schedule for noncritical containers is completed by solving the binary decision model provided in Section 4.4.3. There are 55 containers available at the container yard and VidaXL can receive two containers per day in each warehouse. Under constraint 20, it is not possible to schedule the receiving operation for all available containers. The binary decision model selects a subset of containers and schedules the containers 1, 2, 6, 7, 8, 9, 13, 15, 16 and 17 to the MKI warehouse and the containers 3, 4, 5, 10, 11, 12, 14, 18, 19 and 20 to the JTS warehouse. The detailed schedule is completed by assigning the containers with the FIFO dispatch rule to the upcoming 2 days. The MKI warehouse is able to receive two containers a day, the containers 1 and 2 are consequently scheduled on day t+1 and the containers 6 and 7 on day t+2. The detailed container schedule of day t+1 is implemented and confirmed to the forwarder since VidaXL needs to confirm the pickup day one day in advance. Furthermore, it is already possible to inform the forwarder with the expected detailed schedule of day t+2. However, the detailed schedule of day t+2 can still change when new information becomes available after completing the algorithm again on day t+1. VidaXL should therefore carefully inform the forwarder that it expects to pick up the containers 5,7,8 and 9 on day t+2 without actually confirming the pickup date of these containers. Furthermore, the containers 1, 2, 3 and 4 are removed from the list with available containers since their pickup is scheduled and confirmed.

Second, the scheduling algorithm is executed on day t+1 at the start of the day, new container arrivals are added to the list with available containers at the container yard. There are no critical containers at the container yard. The aggregate receiving schedule is again completed by solving the binary decision model of Section 4.4.3. The model selects a subset of containers and schedules the containers 6, 8, 9, 10, 13, 15, 16, 17, 21 and 22 to the MKI warehouse and the containers 5, 7, 11, 12, 14, 18, 19, 20, 23,

24 to the JTS warehouse. Due to the availability of new information, the performance increases when the container 7 and 10 are swapped between the MKI and JTS warehouses. The detailed receiving schedule is completed by applying the FIFO dispatch rule to the scheduled containers. The containers 5, 6, 7 and 8 are scheduled on day t+2, the detailed schedule made on day t for day t+2 is incorrect. VidaXL need to inform the forwarded that it will pick up container 8 instead of container 10 on day t+2. Furthermore, VidaXL can again inform the forwarder that it expects to pick up the containers 9, 10, 11 and 12 on day t+3.

Third, the scheduling algorithm is repeated on day t+2. The binary decision model schedules 10 containers to each warehouse thereafter the detailed schedule is completed by scheduling containers 9 and 10 to the MKI warehouse and containers 11 and 12 to the JTS warehouse on day t+3. The detailed schedule made on day t+1 is in line with the detailed schedule made on day t+2 and VidaXL affirms the pickup date of these containers to the forwarded.

The scheduling process can be repeated every day, in this example the aggregate schedule is provided for the upcoming 5 days while the forwarder is informed with the detailed schedule for the upcoming 2 days. Section 5 investigates the influences of different planning horizons and penalty values on the performance of the scheduling algorithm.

4.5   Validation and verification

The conceptual model and simulation need to be verified and validated before conclusions can be drawn and recommendations can be made. Verification refers to the steps, processes, or techniques that are employed in the model to ensure that it behaves according to the specifications. Validations refers to validating whether the model adequately represents the actual process (North & Macal, 2007).

The model is verified using stress testing, stage-by-stage, and scenario analysis. With stress testing, the model is tested under extreme and unlikely situations such as zero containers, zero capacity, maximum capacity, and zero cross docks, which allows flaws and errors to be easily detected. Stage-by-stage verification refers to building the model piece by piece where every new stage is extensively tested using multiple test sets. Errors can be detected early in the modeling phase. Lastly, the model is verified by scenario analysis, where multiple scenarios under different conditions are tested, and the results are compared with each other in Section 5. The outcome is checked, and the results of different performance measurements are compared.

The underlying logic of the conceptual model has been validated by the logistics department of VidaXL. The scheduling algorithm is implemented at VidaXL, and the solution will be validated every day by the logistics department.

As mentioned in Section 4.4.2, the PulP library checks whether the solution is optimum. However, finding the optimum per scheduling horizon does not automatically results in the overall long-term optimum as demonstrated in Section 4.4.1. Furthermore, the rolling horizon policy separate the scheduling problem in a sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner. This approach results in close to optimal long-term solutions (Dimitriadis, et al. 1997). Calculating the long-term optimum assignment with brute force is not possible, because brute force calculates every possibility and the problem is too large for brute-force methodology according to the following example.

If there are 3 warehouses which can receive goods, the warehouses can receive 4, 4, and 2 containers per day for seven days in a row. In total, (4+4+2)*7=70 containers can be scheduled. The first warehouse can schedule 28 containers out of 70, which results in $1.17 * 10^{21}$ possible combinations.

$$\binom{70}{28} = 1.17 * 10^{21}$$

The second warehouse can schedule 28 containers of the remaining 42 containers, which results in $7.40 * 10^{11}$ possible combinations. The third warehouse can schedule 14 containers out of 14 containers, leaving only one remaining combination. In total, there are $1.17 * 10^{21} * 7.40 * 10^{11} * 1 = 8.69 * 10^{32}$ combinations to schedule 70 containers. The python function combinations can calculate 300,000 combinations per minute, which will require $2.01 * 10^{21}$ days to calculate every combination. The calculation time increases exponentially with the number of available containers, and it is impossible to validate the model using brute force.

Assuming that the branch and cut algorithm of the CLP solver from the PulP library provides the correct answer, it is possible to calculate the theoretical upper bound of the minimum number of cross docks possible. The theoretical upper bound quantifies the optimal static solution when the inbound capacity per warehouse, the arriving date and the number of cross docks of each receiving container is known one year in advance. The theoretical upper bound solution of the simulation is provided in Section 5.4.

4.6 Conclusion

The warehouse efficiency can be increased by scheduling the receiving operation in order to avoid cross docks during the put-away, picking, and shipping operations. The receiving operation can be scheduled with the usage of the proposed framework. The framework consists of three layers: input data, scheduling algorithm and output data. Each layer subsequentially fulfill certain tasks and provide the subsequent layer with information to complete the scheduling process.

The input layer gathers relevant container and warehouse data for the scheduling algorithm. The container data consist of a distinction between critical and noncritical containers, and estimates the total number of cross docks when the container is received in a warehouse. The warehouse data consist of the inbound capacity per container type and the total inbound capacity per warehouse.

The scheduling algorithm subsequently schedules critical and non-critical containers with a rolling horizon policy. The rolling horizon policy separate the scheduling problem in a sequence of iterations, each iteration only models' part of the scheduling horizon in detail, while the rest of the horizon is scheduled in an aggregate manner. The aggregate schedule is provided through solving a binary decision model, it selects and schedules containers to one of the warehouses by maximizing the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse while considering the demurrage date. The detailed schedule can be completed by assigning the scheduled containers FIFO to the upcoming scheduling periods.

The output data consist of the detailed schedule where the pickup dates of the scheduled containers are specified with the FIFO dispatch rule. VidaXL can implement the receiving operation of the containers scheduled on the next day. However, VidaXL must not confirm the pickup date of the other scheduled containers in order to retain flexible to new information and container arrivals. The potential and sensitivity of the scheduling algorithm are evaluated in a realistic simulation in Section 5.

5. Simulation

To evaluate the potential of the proposed scheduling algorithm, the receiving operation at VidaXL is simulated. The simulation setup is discussed in Section 5.1. The datasets used as input are described in Section 5.2. The output of the scheduling algorithm is compared with other scheduling procedures, which are presented in Section 5.3. Section 5.3 also shows an overview of the used performance measures. The quality of the scheduling algorithm is specified in Section 5.4. The final results are shown in Section 5.5, and the sensitivity of the model is analyzed in Section 5.6.

5.1   Simulation setup

The receiving operation at VidaXL is simulated using discrete-event simulation. Each event occurs at a particular moment in time and causes a change in the system, and therefore this type of simulation only evaluates the system after each event. Figure 21 shows the general architecture of the simulation.

Figure 21: Simulation architecture VidaXL
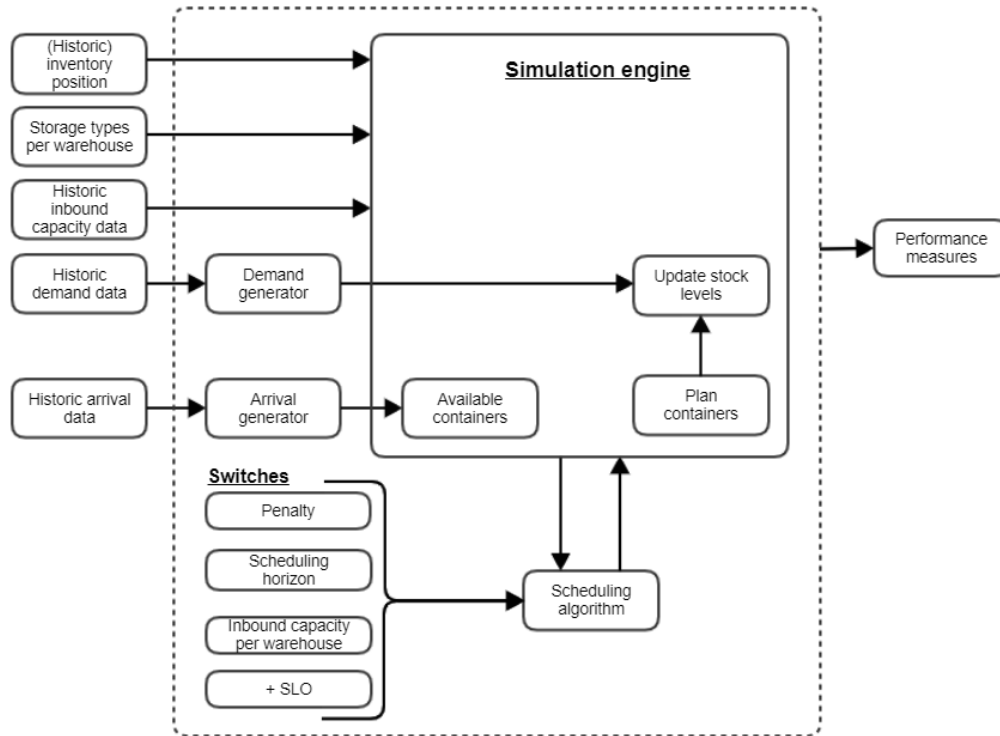
The simulation aims to represents the warehouse operations at VidaXL of 2020 as accurately as possible, and therefore the simulation setup is the same as the warehouse setup of VidaXL in 2020. The following warehouses are included in the simulation:

- MKI (ship warehouse)
- JTS (ship warehouse new: January 2020)
- WTR (pick warehouse new: November 2019)
- OF (all overflow warehouses)

The storage types and number of storage locations in each warehouse are equal to the warehouse network of VidaXL. All overflow warehouses are equipped with the same storage types and can therefore be seen as one warehouse. The company opened one pick warehouse in November 2019, one new ship warehouse in January 2020, and closed three overflow warehouses. Stock is moved from the old warehouses to the new warehouses and is currently not equally distributed over the warehouses. Therefore, the effect of the scheduling algorithm is analyzed using two different settings: First the potential of the scheduling algorithm is evaluated in a ramp-up situation where the inventory is not equally distributed over the warehouses. In this situation, VidaXL wants to equalize the utilization of the resources in each warehouse as quickly as possible without having avoidable cross docks. Second, the potential of the scheduling algorithm is evaluated when the starting inventory is equally distributed over the warehouses.

VidaXL does not receive containers during the weekend. Moreover, it is not possible to schedule containers in the first week of the simulation to generate a pool of available containers. If there is no pool of available containers, it is not possible to schedule the containers for the whole scheduling horizon and the algorithm reduces the number of cross docks per day. Reducing the number of cross docks per day does not lead to the minimum number of possible cross docks, as concluded in Section 4.4.1.

The proposed scheduling algorithm in Section 4.4 has four variables which can be adapted and immediately affect the outcome of the algorithm. The influence of different scheduling horizons and penalty values are analyzed in the results section, and the proper values are later used to compare the results with other scheduling procedures.

The inbound capacity per warehouse immediately influences the outcome of the proposed scheduling algorithm. The total inbound capacity per day is calculated by counting all containers received in the corresponding month and dividing this value with the number of workdays in that month. The inbound capacity for warehouse w is calculated using the following equation:

$$C_w = \min \left(\frac{Total\ inbound\ capacity\ *\ available\ storage\ locations\ warehouse\ w}{\sum_{w \in W} available\ storage\ locations\ warehouse\ w}, 20 \right) \qquad (29)$$

The inbound capacity cannot exceed 20 containers per day since there are insufficient resources in each warehouse to handle more than that. The sensitivity analysis investigates whether the proposed scheduling algorithm behaves independently of the inbound capacity of each warehouse.

Moreover, the following assumption is made in the simulation model:

- The maximum SLO is equal to 3,000, which is on average almost equivalent to storing a container for one year without selling any items. When items are not sold within one year, VidaXL tries to sell the items via other sales channels or they scrap the items.

5.2 Input

The simulation model uses in the basis four different input datasets, namely the arriving pattern of containers, the demand pattern per item, the inbound capacity per warehouse, and the starting inventory per warehouse.

The arriving pattern of containers corresponds to the arriving pattern of 2019. The simulation model can schedule the containers after confirmation of the actual delivery date, which can be received on the day of arrival or one day beforehand. The contents of each container correspond to the actual received containers in 2019. Each container can contain multiple items of multiple SKUs, and the number of items per SKU is divided with the Packspec to calculate the number of pallets per item per container. The Packspec regards the packing specifications and differs per SKU, as some SKUs are large and can only fit 2 items on one pallet, while other SKUs are small and can fit 1,000 items on one pallet. The containers are classified as A, B, and C based on the number of SKUs and on the number of items in each container, where A containers require less manual effort to unload than C containers.

The demand pattern per item corresponds to the demand pattern of 2019 and is converted to the demand pattern per pallet since full pallets are replenished from the reserve area into the forward area. Each demand event occurs with probability equal to the distribution of the number of storage locations between the ship and pick warehouses (e.g., if the shipping warehouse has 50% of the total bulk storage locations, the probability is 50% that the demand occurs in the shipping warehouse). If one of the shipping warehouses lacks the item in stock, the inventory of the picking warehouse is evaluated, and if the pick warehouse has the item in stock, the items are cross docked to the shipping warehouse. If the ship and pick warehouses lack the item in stock, the inventory of the overflow warehouses is evaluated, and if they have the item in stock, the items are cross docked to the ship warehouse. If the item is not in stock in any of the warehouses, the demand request is forfeited.

The total inbound capacity per day is calculated by counting all containers received in the corresponding month and dividing this with the number of workdays in that month. The inbound capacity per warehouse is calculated using equation 29 as described in Section 5.1.

The starting inventory differs regarding the ramp-up and steady-state situations. The starting inventory of the ramp-up situation is equal to the actual inventory in the reserve areas on the first of February 2020 and is measured in number of pallets. In contrast, the starting inventory in the steady-state situation is generated by running the simulation for one year for the extended FIFO scheduling procedure (explained in Section 5.3) and constraining the maximum capacity of each warehouse to 75% of actual capacity. At the end of the simulation, all warehouses are consequently equally utilized with 75% of total storage capacity. The ending inventory position is used as the starting inventory for the steady-state situation. The extended FIFO scheduling procedure is used since it most closely corresponds to the current working procedure of the logistics department of VidaXL.

5.3   Output

The output of the simulation is compared with three other scheduling procedures to evaluate the potential of the proposed scheduling algorithm. The results are compared with scheduling the containers FIFO and minimizing the number of cross docks FIFO every day. Moreover, the effect of including picking and shipping cross docks in the binary decision model is investigated by running the model with and without additional cross docks based on the SLO.

Proposed scheduling algorithm: The algorithm applies a rolling horizon policy which reschedules the receiving operation every day new information becomes available. First, an aggregate solution for the coming four days is provided with a binary decision model. The binary decision model selects a subset of containers out of the available containers and schedules each container to a warehouse. The binary decision model maximizes the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse while considering the demurrage date. Second,

the FIFO dispatch rule is applied to gather a detailed solution for the first day. The detailed schedule of first day can immediately be implemented. The receiving operation can be rescheduled during succeeding days when new information becomes available.

FIFO: In the FIFO scheduling procedure, the system is evaluated at the start of every day and the containers are scheduled for next day. The containers with the earliest arrival date are selected until the number of containers corresponds to the inbound capacity of that day. The containers are scheduled chronologically, which means that the first container is assigned to its preferred warehouse based on the number of put-away cross docks. The container is only scheduled to its preferred warehouse if the preferred warehouse has remaining inbound capacity, otherwise the container is scheduled at the second preferred warehouse and so on. The procedure is repeated until all selected containers are scheduled.

FIFO extended: The third scheduling procedure is an extension of the FIFO procedure where every day, the containers with the earliest arrival date are selected until the number of containers corresponds to the inbound capacity of next day. The scheduling procedure aims to minimize the total number of put-away cross docks for the next day by solving a binary decision model for that day. Accordingly, the scheduling procedure is repeated every day.

NoSLO: The proposed scheduling algorithm tries to reduce the number of picking and shipping cross docks by assigning containers with a high SLO to the pick and overflow warehouses. The demand for the items stored in the pick and overflow warehouses is low, and thus causes fewer cross docks. The scheduling procedure NoSLO behaves as the proposed scheduling algorithm but does not consider the SLO; it only contemplates the put-away cross docks and the demurrage date.

The following KPIs are measured for every scheduling procedure:

- Number of containers received in each warehouse;
- Number of pickup dates predicted correctly during day t for day t+2;
- Number of pickup dates predicted incorrectly during day t for day t+2;
- Real put-away cross docks from each warehouse;
- Real picking cross docks after customer demand;
- Real shipping cross docks after customer demand;
- Average throughput time per arriving container;
- Number of containers picked up after the demurrage date;
- Total number of days the containers are picked up after the demurrage date;
- The reserve area utilization per warehouse.

5.4 Quality of scheduling algorithm

Before evaluating the potential of the scheduling algorithm, a theoretical upper bound of the main performance measurement the total number of cross docks is determined. The theoretical upper bound quantifies the optimal static solution when everything is known beforehand. For the theoretical upper bound calculation is therefore assumed that perfect knowledge of the content, number of cross docks and the arrival date of each container is available. Furthermore, the containers must be scheduled under the same constraint as the algorithm does.

The default CLP solver of the PulP library in python is used to calculate the theoretical upper bound. The code is designed by COIN-OR and uses branch-and-cut algorithms to solve the problem. The PulP library can validate whether the provided solution is optimum or not using the function LpStatusOptimal (Mitchell, Kean, Mason, O'Sullivan, & Phillips, 2009).

Assuming that the branch and cur algorithm of the CLP solver provides the correct answer, the minimum number of cross docks possible are 89,148 and 64,138 in the ramp-up and steady state situation respectively. The theoretical upper bound solution has 5.7% and 10.4% less cross docks as the solution provided by the scheduling algorithm presented in Section 5.5. The scheduling algorithm does not provide the optimal solution regarding the theoretical upper bound. However, recall that there does not exist a scheduling algorithm that provides an optimal solution without prior knowledge (Dertouzos & Mok, 1989). Furthermore, the algorithm uses a rolling horizon policy which provides close to optimal solutions (Dimitriadis et al., 1997).

5.5   Results

The goal of this research is to schedule the receiving operations in e-commerce logistics to increase the efficiency of the warehouse operations put-away, picking and shipping simultaneously, by reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date. First, parameter tuning is used to increase the performance of the scheduling algorithm in Section 5.5.1. Second, the potential of the scheduling algorithm is analyzed by comparing its performance with three other scheduling procedures during the ramp-up phase. Last, the performance of each scheduling procedure is analyzed in a steady state situation.

The goal of constraints 21, 22, and 23 is to balance the workload between the warehouses and the inbound teams. The workload can also be balanced with other managerial decisions, for example, by extending certain inbound teams. The parameters WB_{Aw}, WB_{Bw}, and WB_{Cw} are therefore set equal to one since these are managerial decisions, and the purpose of this section is to evaluate the maximal potential of the scheduling algorithm. The sensitivity of the scheduling algorithm under different values for WB_{Aw}, WB_{Bw}, WB_{Cw} is evaluated in Section 5.5.

5.5.1   Scheduling algorithm parameter tuning

The proposed scheduling algorithm may behave differently with different parameters settings. As such, parameter tuning is used to determine the appropriate settings for the container scheduling process at VidaXL. An aggregate scheduling horizon equal to two, three, four or five days combined with penalty value of ten, twenty, twenty-five and thirty for each day the container is not scheduled after its arrival day in the container yard.

The main purpose of the penalty is to plan the containers before the demurrage date. Figure 22 and Figure 23 illustrate the behavior of the scheduling algorithm under the different scheduling horizons and penalties for each day the container is not scheduled after its arrival day in the container yard on the number of days the containers are picked up after the demurrage date. The results of a scheduling horizon equal to two days are excluded from these figures since the total number of days containers are picked up after the demurrage date differ between 18 and 1,650 days. The results are less visible when these values are included in the figures. A detailed overview of the simulation results for all instances is given in Appendix C.
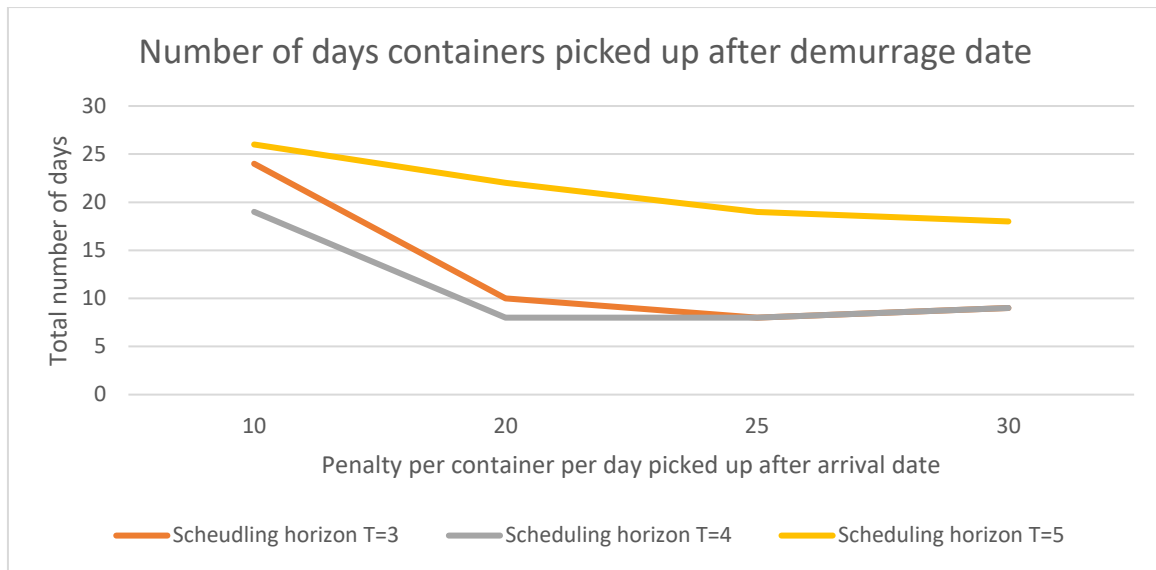
Figure 22: Simulation results, effect of different parameters on days containers are picked up after demurrage date (1)

From Figure 22 can be observed that the total number of days that the containers are picked after the demurrage date decreases when the assigned penalty increases. The effect stabilizes when the penalty rises to a value between 20 and 30. The penalty is responsible for a substantial part of the overall weight. Moreover, when there is not enough inbound capacity to receive all containers before the demurrage date, the total number of days the containers are picked up after the demurrage date increases. As such, increasing the penalty value does not decrease the total number of days the containers are picked up after the demurrage date anymore.
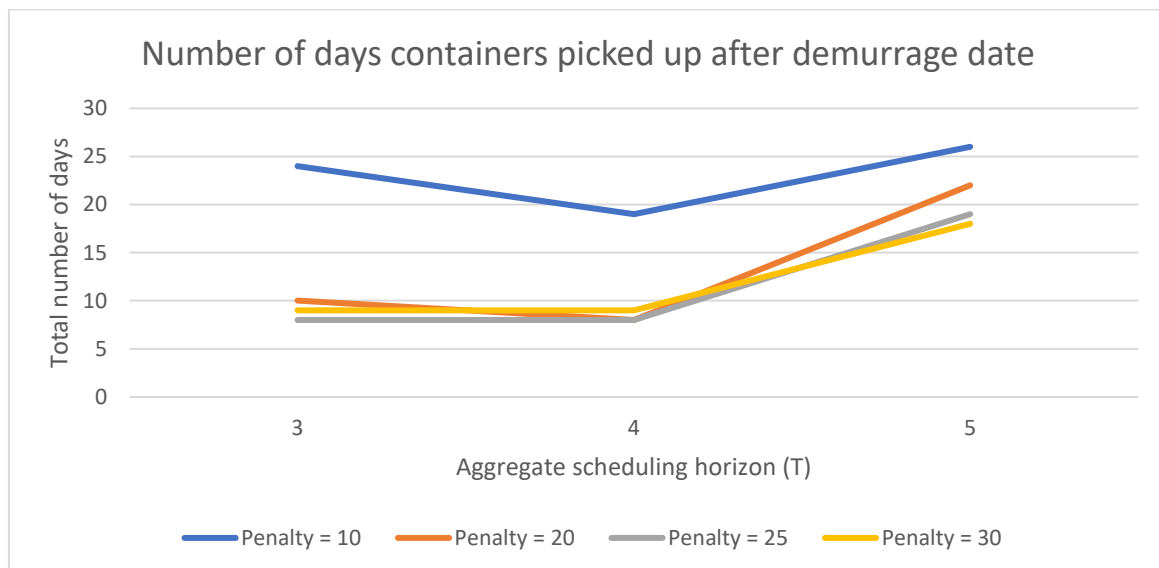
Figure 23: Simulation results, effect of different parameters on days containers are picked up after demurrage date (2)

Figure 23 shows the effect of completing the aggregate schedule for different scheduling horizons. Being able to complete the aggregate schedule for the upcoming four or five days does not reduce the total number of days the containers are picked up after the demurrage date. Notably, the scheduling algorithm performs worse with an aggregate scheduling horizon equal to five days as applying an aggregate scheduling horizon of three days. VidaXL has over 40 different storage types, the storage

types at MKI ship warehouse are more varied than those in the other warehouses. Accordingly, most containers prefer to be assigned to the MKI warehouse since most of their items can be stored there. Making an aggregate schedule by solving the binary decision model for five or more days assigns more containers to the MKI warehouse and less containers to the other warehouses. The number of containers scheduled to each warehouse depends on their inbound capacity during the scheduling horizon (i.e. constraints 20 till 23). When more containers are approaching the demurrage date as the preferred warehouse can handle, not all containers are picked up before the demurrage date. Completing the aggregate schedule for a shorter horizon assigns more containers to the second preferred warehouse so that the total number of days the containers are picked up after the demurrage date decreases.

The effect of different aggregate scheduling horizons on the average number of cross docks per container is illustrated in Figure 24.
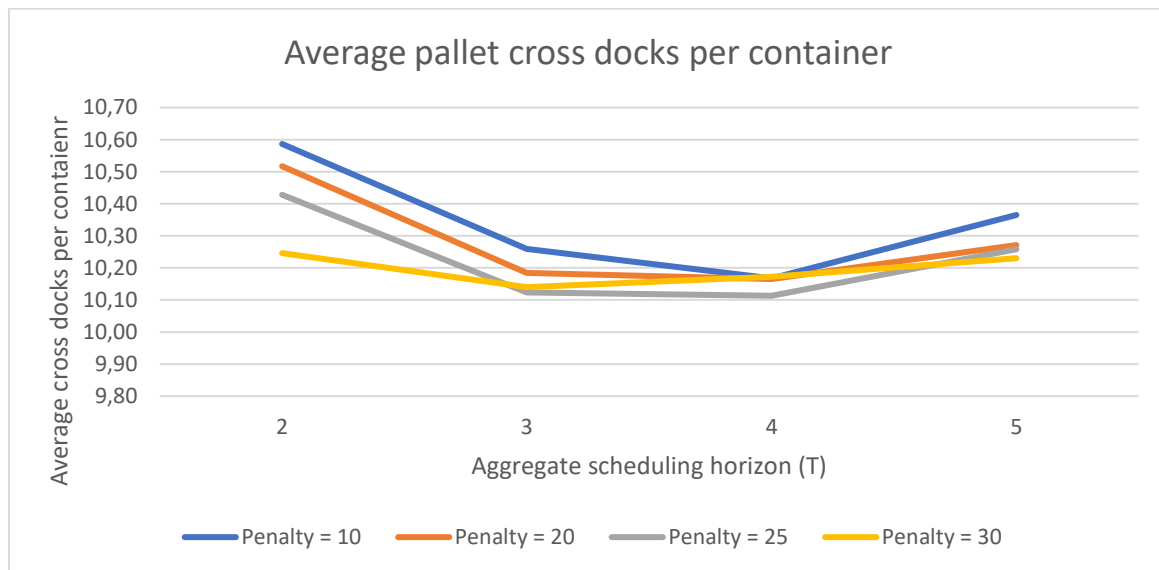
Figure 24: Simulation results, effect of different parameters on average pallet cross docks per container

As concluded in Section 4.4.1, the number of cross docks can be reduced through applying a larger aggregate scheduling horizon. Daily minimizing the number of cross docks does not lead to the overall optimum and therefore the average number of cross docks reduces when applying an aggregate scheduling horizon equal to three or four days. The average number of cross docks are at lowest under a scheduling horizon equal to four days and a penalty value equal to twenty-five.

If an aggregate scheduling horizon of five days is applied, more containers are assigned to the preferred warehouse and less containers are assigned to the other warehouses. However, each warehouse can only receive as many containers as it can handle on a day. As a result, more containers are facing tight demurrage dates and are scheduled three or less days before the demurrage date. The calculated weight of these containers depends, for a substantial part, on the penalty for each day the container is not scheduled after its arrival day. The scheduling algorithm schedules the containers such that the containers are picked up as soon as possible; it focuses less on the corresponding number of cross docks. The number of cross docks consequently increases when the aggregate scheduling horizon is equal to five days.

All parameter values together form sixteen different instances. The summary of results is presented in Table 14, while the detailed results can be found in Appendix C. The performance of the scheduling algorithm is at best through applying a scheduling horizon of four days and a penalty of twenty-five for every day the container is scheduled after its arrival date. Both the average number of cross docks and the total number of days to late are reduced at this instance.

Table 14: Summary of results parameter tuning scheduling algorithm

	Average cross docks	Total cross docks	Average TH time	Total days after demurarge	Percentage of containers on time	Containers picked up after 8 days
T = 2 Penalty = 10	10.59	73,799	7.23	1,652	87.9%	2,224
T = 3 Penalty = 10	10.26	72,523	4.07	24	99.7%	59
T = 4 Penalty = 10	10.17	71,955	3.59	19	99.7%	32
T = 5 Penalty = 10	10.37	73,333	3.58	26	99.6%	51
T = 2 Penalty = 20	10.52	73,336	7.28	1,638	88.1%	2,075
T = 3 Penalty = 20	10.18	72,054	4.01	10	99.9%	13
T = 4 Penalty = 20	10.17	71,940	3.51	8	99.9%	8
T = 5 Penalty = 20	10.27	72,803	3.59	22	99.7%	37
T = 2 Penalty = 25	10.43	72,787	6.93	943	91.8%	1,635
T = 3 Penalty = 25	10.12	71,504	3.92	8	99.9%	0
T = 4 Penalty = 25	10.11	71,551	3.57	8	99.9%	9
T = 5 Penalty = 25	10.26	72,605	3.61	19	99.7%	30
T = 2 Penalty = 30	10.25	72,511	3.56	18	99.7%	25
T = 3 Penalty = 30	10.14	71,711	3.87	9	99.9%	11
T = 4 Penalty = 30	10.17	71,993	3.60	9	99.9%	10
T = 5 Penalty = 30	10.23	72,398	3.58	18	99.7%	24

5.5.2   Ramp-up situation

In the ramp-up situation, VidaXL opened one new shipping warehouse: JTS. VidaXL aims to ramp up the usage of resources in the new warehouse as soon as possible so that the resources in each ship warehouse are utilized equally. The ramp-up situation differs from the steady state situation in that the inventory in the reserve areas is not equally distributed among the warehouses. This section describes the effect of the scheduling algorithm on the receiving operation and on the cross docks during put-away, picking, and shipping operations. The detailed simulation results can be found in Appendix D.

Receiving operations: In total, 99.7% of the containers are picked up before the demurrage date. The detailed schedule made on day t predicted the pickup date of the containers scheduled on day t+2 in 66.3% of the containers correctly. In 23.3% of the cases, the scheduling algorithm predicted the wrong pickup day and did not predicted the pickup day at all in 10.5% of the cases. The total number of containers received in the new JTS warehouse per week per scheduling procedure is visualized in Figure 25. The proposed scheduling algorithm, on average, schedules more containers to the JTS warehouse compared to other procedures. More items are consequently stored in this warehouse. However, the reserve area is less utilized under the proposed scheduling algorithm since the received items have a high turnover rate (see Figure 26); therefore, the pick density in the new warehouse increases, which positively influences the warehouse's efficiency. The resources of the new JTS warehouse are used more intensively under the scheduling algorithm in contrast to other procedures.
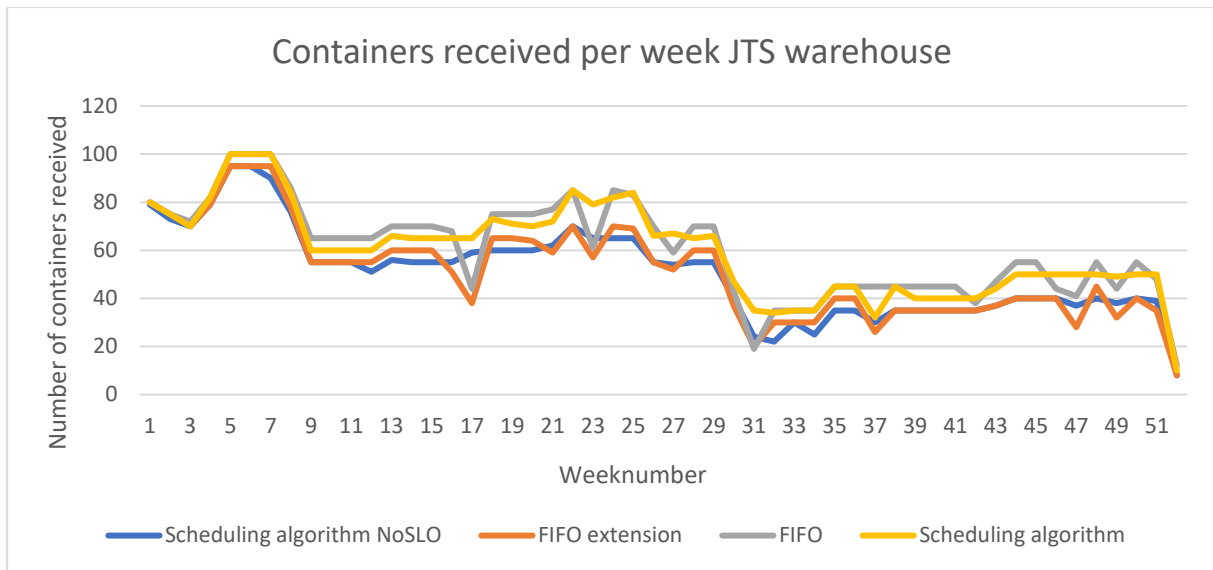
Figure 25: Simulation results, effect of different scheduling procedures on containers received in JTS warehouse
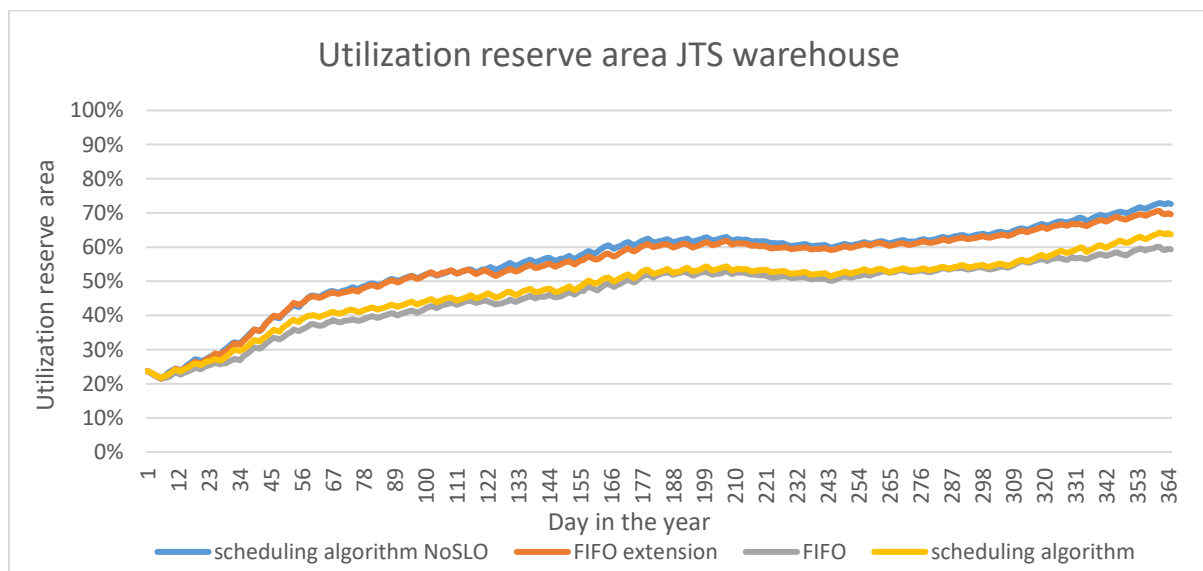
Figure 26: Simulation results, effect of different scheduling procedures on utilization reserve area JTS warehouse

Total number of cross docks

In Figure 27, the number of cross docks during each warehouse operation are graphically presented under the four scheduling procedures. The proposed scheduling algorithm uses an aggregate scheduling horizon of four days and a penalty of twenty-five for each day a container is scheduled after its arrival date. The algorithm performs at best under these settings, resulting in 94,572 cross docks during the simulation period of one year.
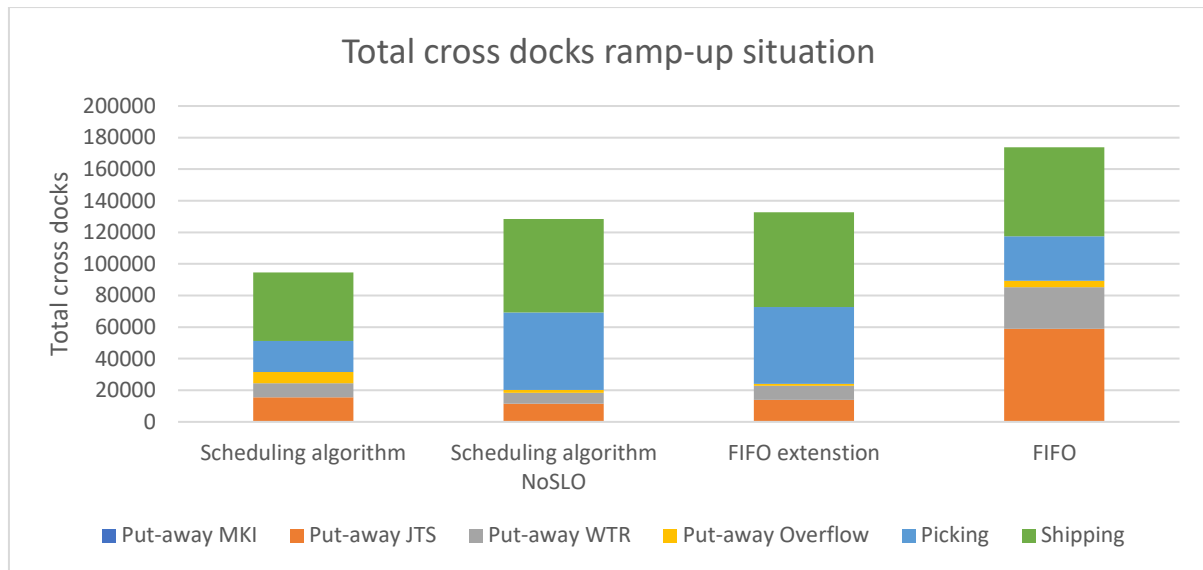
Figure 27: Simulation results, effect of different scheduling procedures on put-away, picking and shipping cross docks (1)

Put-away cross docks: Put-away cross docks occur when the receiving warehouse does not hase the right storage type available. The total put-away cross docks are lower when applying the algorithm NoSLO and extended FIFO scheduling procedures since these procedures assign less containers to JTS warehouse. Moreover, the JTS warehouse does not has all 40 storage types; therefore, more put-away cross docks occur when more containers are received in this warehouse. The total number of cross docks are still lower under the scheduling algorithm since more items are stored in JTS warehouse, and less items need to be cross docked during picking or shipping operations.

Picking cross docks: Picking cross docks occur when the item is not available after a customer demand in the ship and pick warehouse but is available in the overflow warehouse. Containers with a high SLO are stored in the overflow warehouse. Most of the items stored in the overflow warehouse consequently have a low turnover rate, reducing the number of picking cross docks when applying the scheduling algorithm.

Shipping cross docks: Shipping cross docks occur when the items are picked in a pick warehouse, which is not able to ship items. The algorithm reduces shipping cross docks through receiving containers with an above-average SLO in the pick warehouse. The items stored in the pick warehouse have a low turnover rate and are requested less often.

Figure 28 shows the total number of cross docks per week when applying the scheduling algorithm. The number of cross docks decreases as the process becomes more stable and when the warehouses are utilized equally.
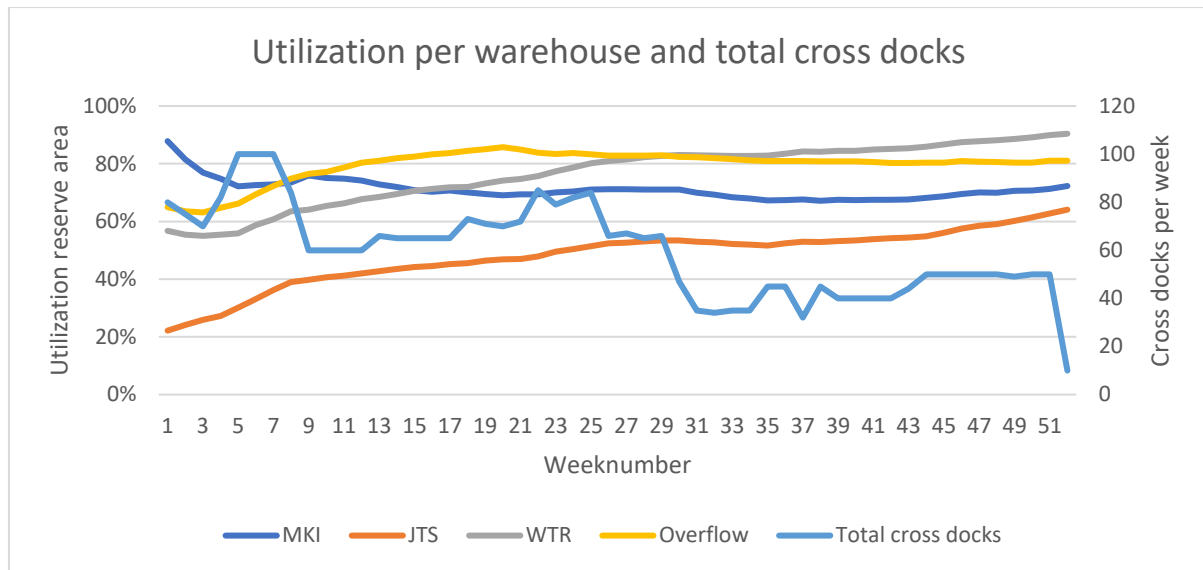
Figure 28: Simulation results, effect of the utilization rate per warehouse on the total cross docks

5.5.3   Steady state situation

In the steady state situation, each warehouse already operates for a certain amount of time; therefore, the start utilization of the reserve area in each warehouse will be the same. The scheduling algorithm again uses an aggregate scheduling horizon of four days and a penalty of twenty-five for each day a container is scheduled after its arrival date. This section outlines the results of the scheduling algorithm regarding receiving operation and the cross docks during put-away, picking, and shipping operations. The effect of including picking and shipping cross docks in the algorithm based on the SLO of each container is described at the end of this section. The detailed simulation results can be found in Appendix E.

Receiving operation: Results affirm that 99.9% of the containers are picked up on time. In total, eight containers are picked up one day after the demurrage date. The detailed schedule made on day t predicted the pickup date of the containers scheduled on day t+2 in 65.1% of the containers correctly. In 21.5% of the cases, the scheduling algorithm predicted the wrong pickup day and did not predicted the pickup day at all in 13.4% of the cases. The MKI and JTS shipping warehouses received 25.3%, 26.3%, and 10.5% more containers under the scheduling algorithm than under the scheduling algorithm without SLO, the extended FIFO procedure, and the normal FIFO procedure, respectively (Figure 29).
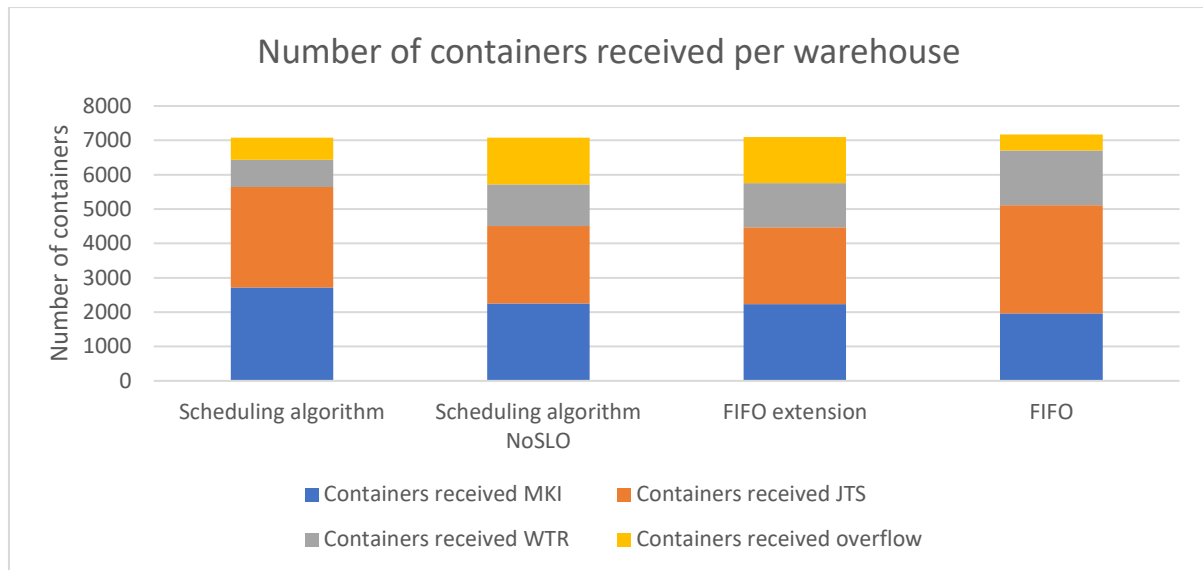
Figure 29: Simulation results, effect of each scheduling procedure on the number of containers received per warehouse

Total number of cross docks

In Figure 30, the cross docks during each warehouse operation are graphically presented under the four scheduling procedures. The proposed scheduling algorithm outperforms the scheduling algorithm without SLO, the extended FIFO procedure, and the normal FIFO procedure. The total cross docks are reduced by 32.7%, 35.9%, and 54.2%, respectively.
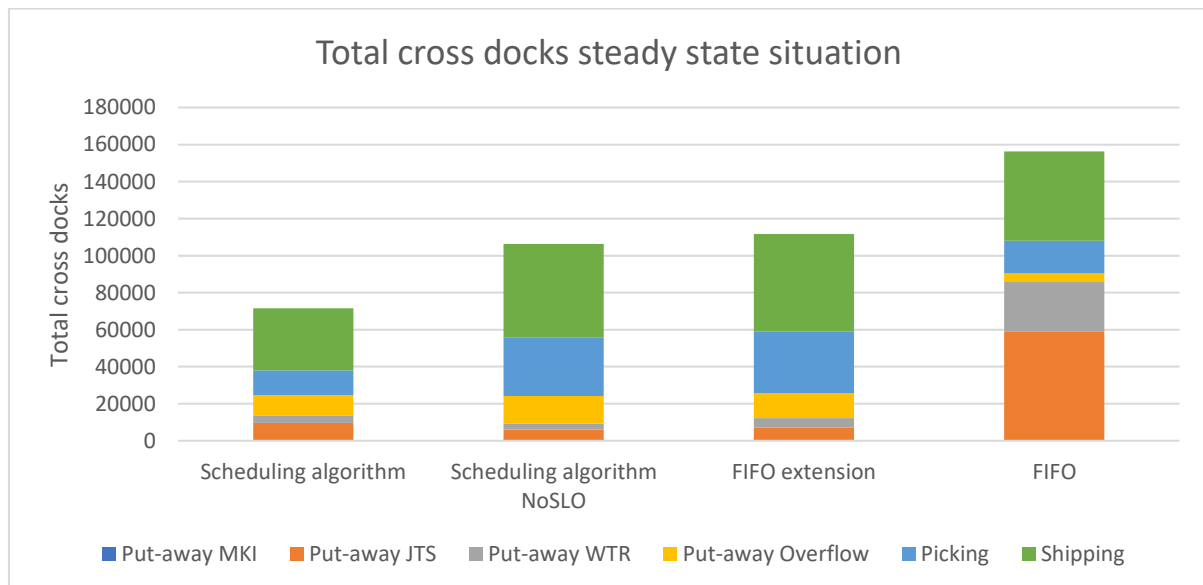
Figure 30: Simulation results, effect of different scheduling procedures on put-away, picking and shipping cross docks (2)

Put-away cross docks: There are less put-away cross docks at each warehouse under the proposed scheduling algorithm. Most containers are received in the shipping warehouses. However, the received items have a high turnover rate, and the storage location becomes available for new arrivals after a relatively short time. The ship warehouses are equipped with most of the storage types, decreasing the number of put-away cross docks.

Picking cross docks: The picking cross docks are lower under the scheduling algorithm since containers with a high SLO are received in the overflow warehouse. The items stored in the overflow warehouse are sold less often, reducing the number of picking cross docks.

Shipping cross docks: The shipping cross docks account for 46.9% of the total number of cross docks under the scheduling algorithm. However, it is hard to prevent shipping cross docks because VidaXL is not able to make items pickable in both shipping warehouses since pick locations are scare. However, the shipping cross docks are reduced by receiving containers with a SLO above average in the pick or overflow warehouses.

Effect of including picking and shipping cross docks
The previous section affirmed that the number of cross docks decreases when picking and shipping cross docks based on the SLO are considered in the scheduling algorithm. This section describes the effect of including picking and shipping cross docks on the utilization of each warehouse. The utilization of each warehouse under the scheduling procedures with and without SLO are presented in Figure 31 and Figure 32.
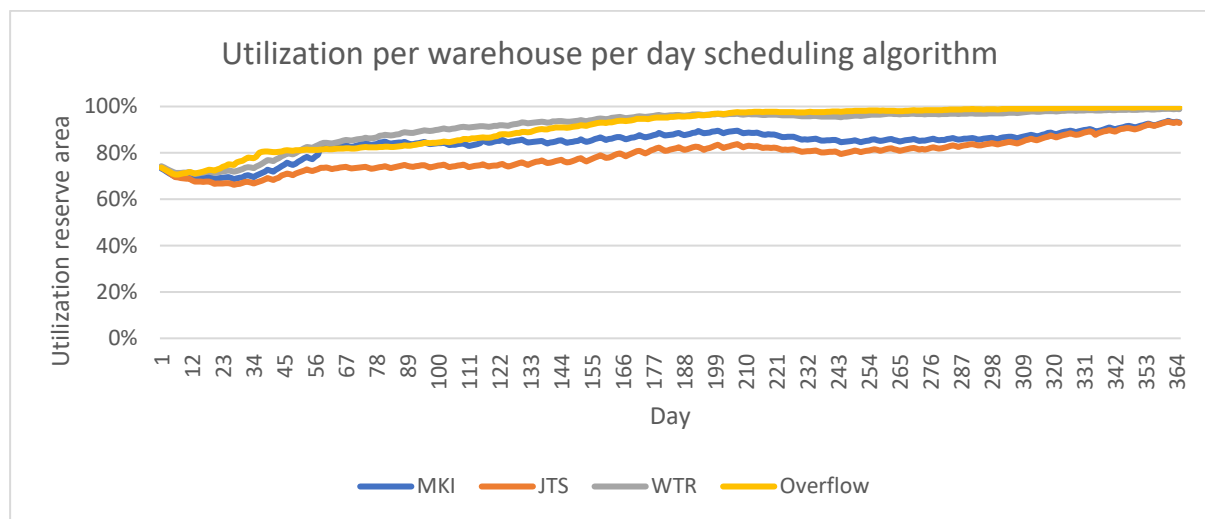
Figure 31: Simulation results, effect of considering picking and shipping cross docks on the utilization per warehouse
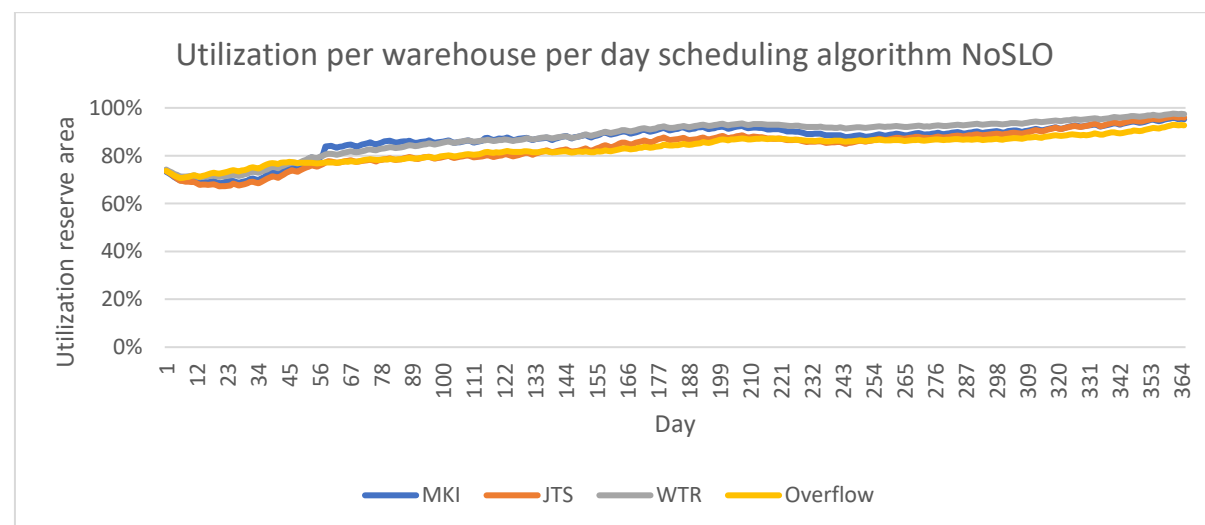
Figure 32: Simulation results, effect of not considering picking and shipping cross docks on the utilization per warehouse

63

The algorithm schedules containers with a long storage time to the overflow and pick warehouses. The utilization of the reserve area of these warehouses increases faster than that in the ship warehouses because the demand for these items is lower. Accordingly, less containers are received in the pick and overflow warehouses, while items with a high turnover rate are received in the ship warehouses. As such, the pick density in the shipping warehouses increases, whereas the number of cross docks from the pick and overflow warehouses to the ship warehouses decreases. Notably, when more items are picked in the same warehouse, it costs less effort to bundle items that are purchased by the same client. Scheduling containers to receiving warehouses using the algorithm increases efficiency in the receiving, put-away, picking, packing, and shipping operations.

5.6 Sensitivity analysis

This section determines whether the conclusions drawn in the previous section are still valid under different circumstances. First, sensitivity during the ramp-up situation is investigated in Section 5.6.1. This is done by evaluating the performance of the scheduling algorithm when the overflow warehouse is only able to receive containers if the utilization of the other warehouses is above 70%. This situation corresponds to the current ramp-up procedure at VidaXL. Second, sensitivity during the steady state situation is evaluated in Section 5.6.2. The inbound capacity per warehouse is adjusted to determine if the scheduling algorithm still outperforms the other scheduling procedures. Moreover, the workload balance parameters are modified to analyze if the model behaves the same way in different circumstances.

5.6.1 Ramp-up situation

After opening a new warehouse, VidaXL temporarily stops receiving any container in the overflow warehouses to increase the usage of resources in the new warehouse. This section analyzes the consequences of this temporary block on the inbound flow of the overflow warehouses.

5.6.1.1 Temporary block on the inbound flow

VidaXL currently abolished the temporary block on the inbound flow of the overflow warehouses when the utilization of the reserve area of all pick and ship warehouses is above 70%. The simulation is thus executed with these settings. Figure 33 illustrates the utilization per warehouse while temporary blocking the inbound flow of the overflow warehouses.
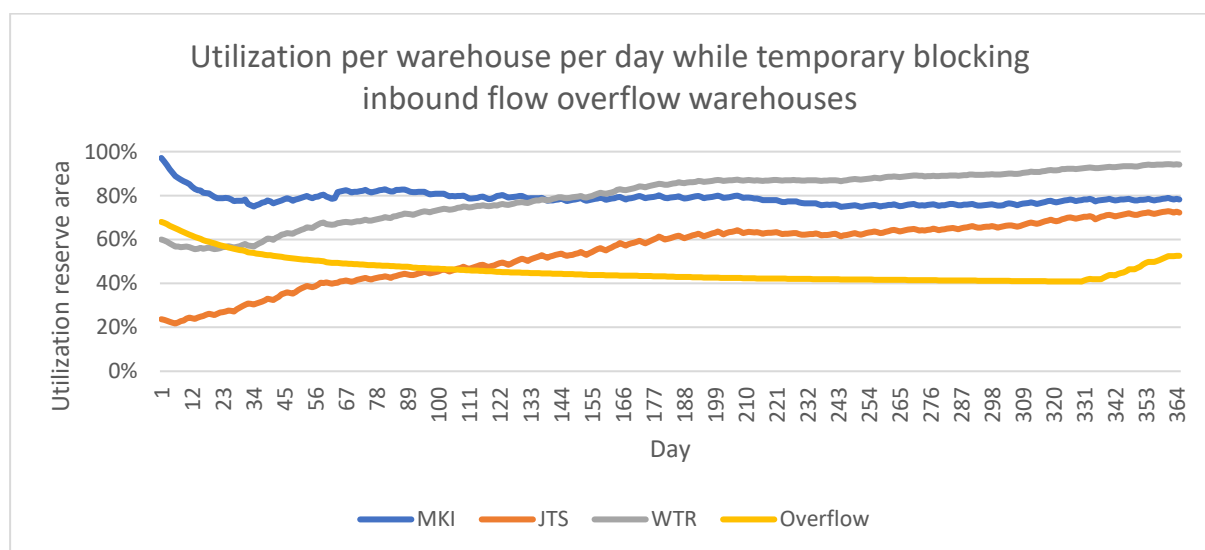
Figure 33: Simulation results, effect of temporary blocking the inbound flow on the utilization per warehouse

The temporary blockage has been abolished from day 330. Utilization in the MKI, JTS and WTR warehouses is above 70%. The effect on the number of cross docks is visualized in Figure 34. The left bar corresponds to the results presented in Section 5.5. The right bar represents the results when VidaXL temporary blocks the inbound flow of the overflow warehouses.
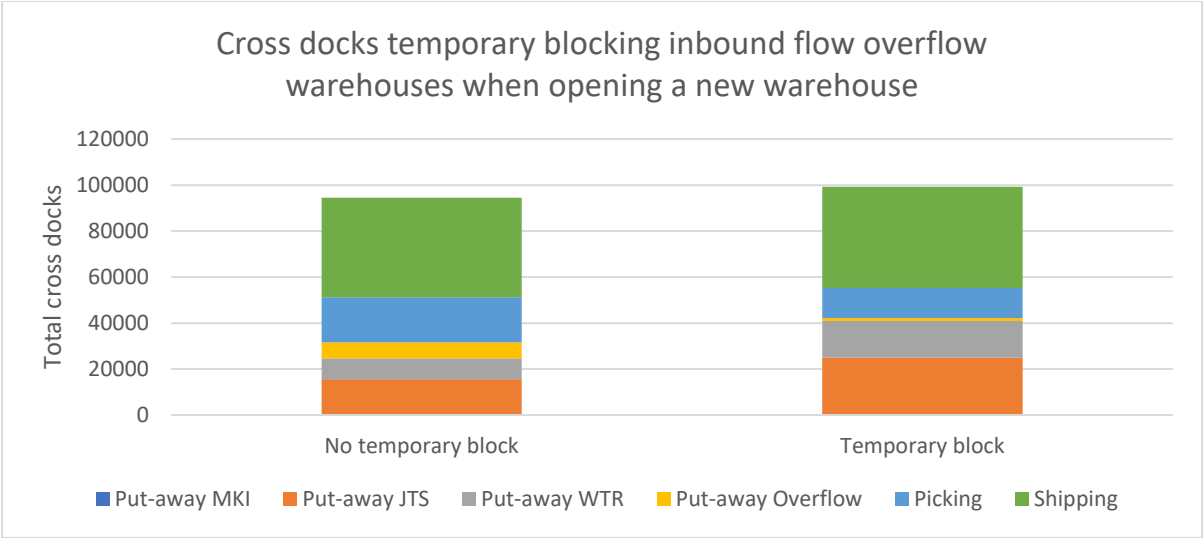
Figure 34: Simulation results, effect of temporary blocking inbound flow on the total cross docks

The total number of cross docks increases by 5.0%. The additional cross docks are mainly put-away cross docks from JTS and WTR warehouses since they receive 12.3% more containers than before. The JTS and WTR warehouse are not equipped with all storage types, causing extra put-away cross docks. The utilization of the JTS and WTR warehouses with and without temporary blocking on the inbound flow is visualized in Figure 35.
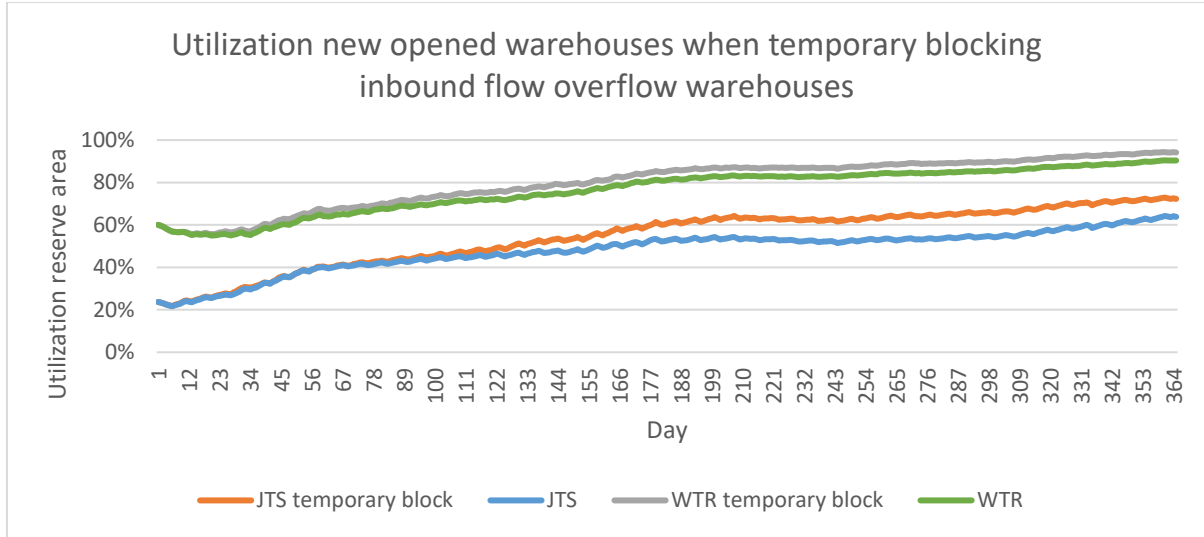
Figure 35: Simulation results, effect of temporary blocking inbound flow on the utilization new opened warehouses

The utilization of the newly opened JTS and WTR warehouses increases faster when temporary blocking the inbound flow of overflow warehouses. Containers with an average SLO are received in the new JTS ship warehouse; therefore, items with a low turnover rate are stored in the wrong warehouse. Temporarily blocking the inbound flow causes unnecessary cross docks in the short and long term.

65

5.6.2 Steady state situation

This section investigates the sensitivity of the scheduling algorithm in the steady state situation. First, sensitivity under different inbound capacities is analyzed in Section 5.6.2.1. The goal of equation 29 is to determine the inbound capacity per warehouse based on the available number of storage locations in each warehouse. The inbound capacity per warehouse determines, to a large extent, the total number of cross docks; therefore, the sensitivity of the scheduling algorithm under different inbound capacities in steady state is analyzed. Second, the behavior of the scheduling algorithm under different workload balancing parameters is investigated in Section 5.6.2.2.

5.6.2.1 Different inbound capacities

The inbound capacity per warehouse influences the total number of cross docks. When a warehouse is forced to receive a certain number of containers that it cannot store, the total number of put-away cross docks increases. Moreover, when a ship warehouse is forced to receive more containers, it also receives containers with a high SLO since there are no more containers with a low SLO available. The number of long-term picking and shipping cross docks thus increases. Accordingly, the effect of the scheduling algorithm is tested under five different inbound capacities, as used in the previous sections.

The inbound capacity of both ship warehouses decreased by 10%, while the inbound capacity of the pick warehouse increased by 10% in the first instance. In the second instance, the capacity of both ship warehouses increased by 20%, whereas the inbound capacity of the pick and overflow warehouses decreased by 10%. The third instance decreased the inbound capacity of the JTS ship warehouse by 10% and increased the inbound capacity of the MKI ship warehouse by 10%. The fourth instance is the opposite of the third instance. In the fifth instance, both shipping warehouses have 10% more inbound capacity, while the pick warehouse has 5% less inbound capacity.

Table 15 presents a summary of the results. Cross docks are expressed as percentages and compared with the total number of cross docks for the simulation period caused under the FIFO scheduling procedure. The detailed simulation results can be found in Appendix G.

Table 15: Total number of cross docks per scheduling procedure under different inbound capacities

	Scheduling alg.	NoSLO	FIFO (ext.)	FIFO
Equation 29	45.8%	68.0%	71.5%	100.0%
Ship - 10%, Pick + 10%	60.8%	70.4%	73.1%	100.0%
SHIP + 20%, Pick/OF - 10%	48.5%	75.4%	92.1%	100.0%
JTS - 10%, MKI + 10%	45.3%	67.9%	71.5%	100.0%
JTS + 10%, MKI - 10%	48.3%	69.5%	72.4%	100.0%
Ship + 10%, Pick - 5%	45.0%	66.2%	67.6%	100.0%

The proposed scheduling algorithm outperforms the three other scheduling procedures in all situations. As the inbound capacity of the shipping warehouses decreases, the benefits of the scheduling procedure also decrease. Less items are stored in the ship warehouses; consequently, the number of picking and shipping cross docks increases. Remarkable, the benefits of the scheduling procedure do not increase when the capacity of the shipping warehouses increases. The utilization rate of the reserve area of the ship warehouses consequently increases faster, resulting in more put-away cross docks. The detailed simulation results can be found in appendix F.

5.6.2.2 Workload balance parameters

This section investigates the behavior of the scheduling algorithm under different workload balance parameters. First, containers are classified as A, B, and C. Second, the total number of cross docks and the total number of days the containers are picked up after the demurrage date during the simulation period under different workload balance parameters are evaluated. Last, the effect of the workload balance parameters on the percentage of A, B, or C containers per warehouse is analyzed.

The inbound teams of VidaXL unload the received containers. Some containers may contain only a few SKUs stored in a few boxes and are thus easy to unload. Other containers may contain many small SKUs in multiple boxes, and these containers cost much effort to unload. VidaXL therefore categorizes containers as in Table 16. When a container has less than 10 SKUs inside or less than 460 boxes, the container is categorized as A. If the container is not an A container, and it contains more than 10 SKUs or more than 1,150 boxes, it is categorized as a C container. All other containers are B containers. Notably, 25% of the containers are A containers, 50% are B containers, and 25% are C containers.

Table 16: Classification of containers

Category	SKUs	Boxes
A	<=10	<=460
C	>20	>1,150
B	Otherwise	Otherwise

Since the containers are unloaded by humans, it is not fair to assign all C containers to the same inbound team. Each warehouse can divide the containers among inbound teams so that workload is equally distributed. However, when one warehouse only receives C containers, it is not possible to divide the workload equally among inbound teams in all warehouses. Constraints 21, 22, and 23 are therefore included in the scheduling algorithm. The cross docks under the scheduling algorithm with $WB_{Aw} = WB_{Bw} = WB_{Cw} = 1.0$, $WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.75$, and $WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.50$ are presented in Figure 36. The number of cross docks under the three other scheduling procedures can be found in Appendix H.
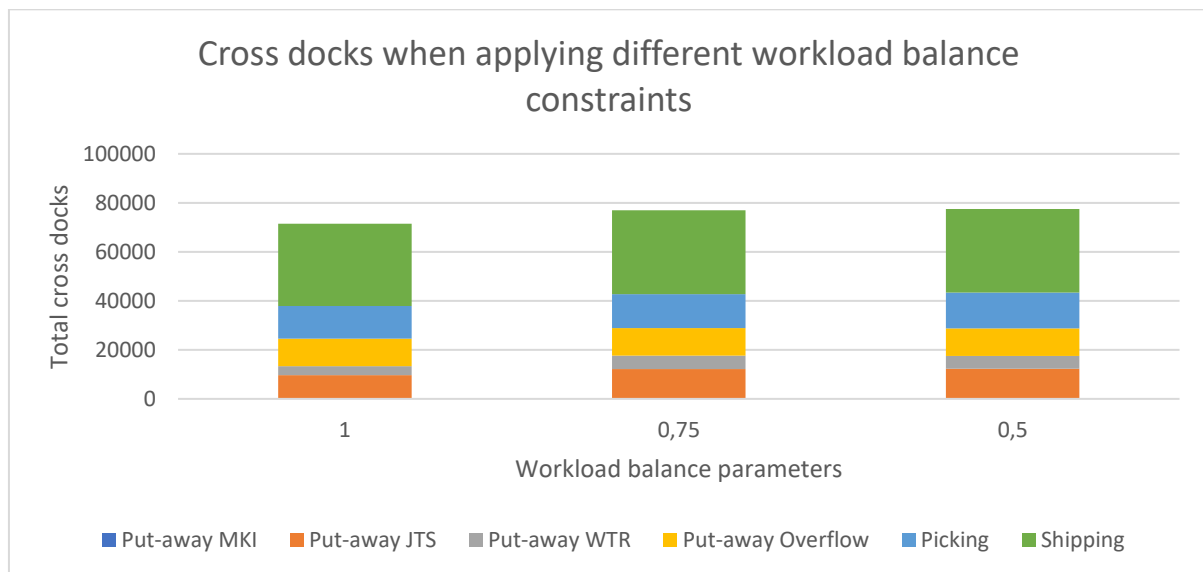
Figure 36: Simulation results, effect of applying workload balance constraints 21,22 and 23 on cross docks

When it is only possible to assign 75% of A, B, or C containers to the aggregate schedule, the total number of cross docks during the simulation period increases with almost 5,400. More than 80% of these extra cross docks are put-away cross docks. Meanwhile, when its only possible to assign 50% of A, B, or C containers to the aggregate schedule, the total number of cross docks increases with almost 6,000. Notably, 70% of those extra cross docks are put-away cross docks. Limiting the number of A, B, or C containers to 75% or 50% for the aggregate schedule increases the number of cross docks significantly although there is only a small change visible between these two parameters. Balancing the workload results in more cross docks, which consequently increases workload.

Balancing the workload negatively influences the number of containers picked up after the demurrage date. Part of the "free operating space" is used by the workload balance constraint. When $WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.75$, the total number of days the containers are picked up after the demurrage date increases to 275, and 2.7% of the containers is picked up after the demurrage date. However, when $WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.5$, the total number of days the containers are picked up after the demurrage date only increases to 19, and only 0.4% of the containers are picked up after the demurrage date. When multiple containers in the same category are available for pickup and prefer the same receiving warehouse, the aggregate schedule can only assign half of the available inbound capacity to these containers when applying the parameters $WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.5$. The scheduling algorithm assigns the leftovers to the second, third, or fourth preferred warehouse; thus, throughput time decreases. This phenomenon is illustrated in Figure 37 and Figure 38.
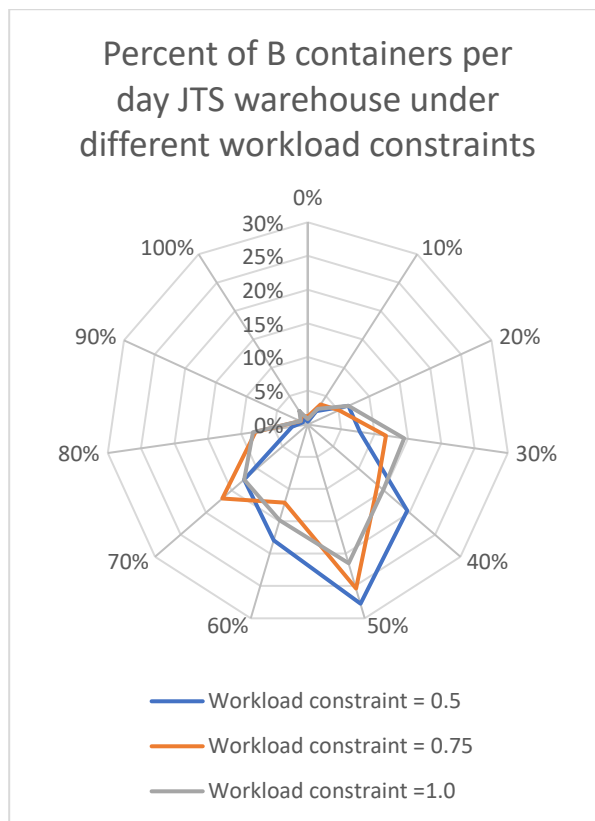
Figure 37: Simulation results, effect of different workload balance constraints on percent of B containers JTS warehouse
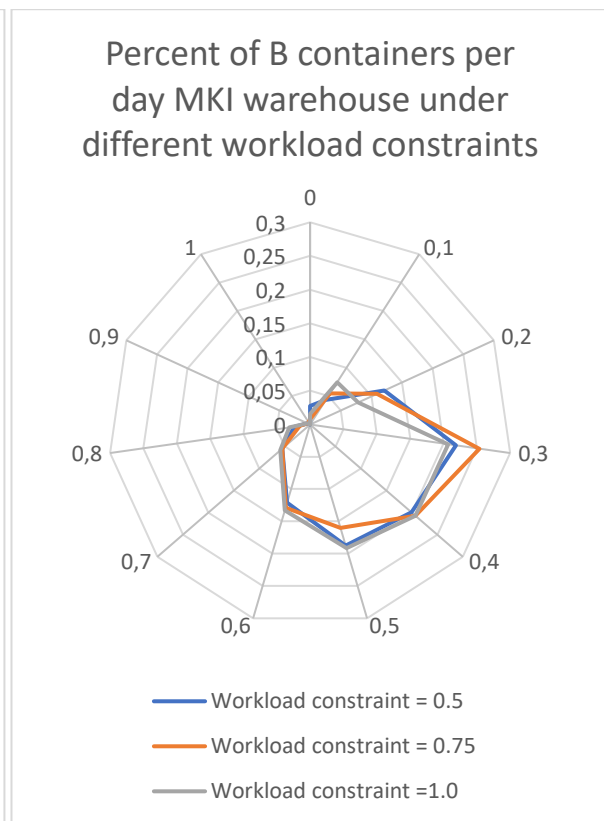
Figure 38: Simulation results, effect of different workload balance constraints on percent of B containers MKI warehouse

68

Most B containers prefer to be received at the JTS warehouse. On average, half of the received containers at JTS are B containers. When $WB_{Bw} = 0.75$, a little over 15% of the simulation period, the JTS warehouse receives 70% B containers on one day. When $WB_{Bw} = 0.5$, the JTS warehouse is not able to receive that many B containers; more B containers are assigned to the MKI warehouse. As such, the MKI warehouse receives more often 50% of B containers per day, and the throughput time consequently decreases.

The effect of the scheduling algorithm on the JTS warehouse is visible in Figure 37. The percentage of B containers received per day at the JTS warehouse is less spread under $WB_{Bw} = 0.5$. Moreover, more B containers are assigned to the other warehouses when the number of available B containers increases.

5.7   Conclusion

The potential of the proposed scheduling algorithm has been evaluated by comparing its performance with three other scheduling procedures. The proposed scheduling algorithm performs at best when applying an aggregate scheduling horizon equal to four days and a penalty value equal to twenty-five for every day the container is scheduled after its arriving day. The theoretical upper bound solution has 5.7% and 10.4% less cross docks in ramp-up and steady state situations respectively as the solution provided by the scheduling algorithm. However, recall that there does not exist a scheduling algorithm that provides an optimal solution without prior knowledge (Dertouzos & Mok, 1989). It outperforms all other procedures in the ramp-up and steady state situations. Moreover, the scheduling algorithm is not sensitive to different inbound capacities and different workload balance parameters.

In the ramp-up situation, the total number of cross docks can be reduced by 26.3%, 28.7%, and 45.6% compared with the scheduling algorithm without SLO, the extended FIFO, and the FIFO procedure, respectively. Moreover, 99.7% of the containers are picked up before the demurrage date. The number of cross docks decreases when the process becomes more stable, and the warehouses are utilized equally.

In the steady state situation, the total number of cross docks can be reduced by 32.7%, 35.9%, and 54.2% compared with the scheduling algorithm without SLO, the extended FIFO, and the FIFO procedure, respectively. Moreover, 99.9% of the containers are picked up on time.

The scheduling algorithm performs best when there is no workload balancing constraint. The scheduling algorithm assigns containers with a high SLO to the overflow and pick warehouses. The utilization of the reserve area of these warehouses increases faster than that in the ship warehouses since the demand for these items is lower. Less containers are consequently received in the pick and overflow warehouses. Accordingly, items with a high turnover rate are received in the ship warehouses. The pick density in the shipping warehouses increases, whereas the number of cross docks from the pick and overflow warehouses to the ship warehouses decreases. Scheduling containers with the proposed scheduling algorithm increases efficiency during the receiving, put-away, picking checking and packing, and shipping operations.

6. Conclusion and recommendations

The goal of this research is to schedule the receiving operations to increase the efficiency of the warehouse operations put-away, picking and shipping simultaneously, by reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date. Hereto, current scheduling procedure were captured, after which a new scheduling algorithm is proposed. The potential and sensitivity of the scheduling algorithm is evaluated in a realistic simulation. This section first answers the research questions in Section 6.1. Second, the contribution to the literature is pointed out in Section 6.2. Recommendations to VidaXL are made in Section 6.3 and directions for further research are stated in Section 6.4.

6.1 Answer on research questions

In this section, the sub research questions are answered based on the findings of previous sections.

Sub question 1: How is the receiving operation at VidaXL currently organized, planned, and controlled?

At the beginning of the day, the inbound logistics department receives a message signaling the actual arrival and assigns the containers FIFO to one of the warehouses. In 2019, VidaXL had one main ship warehouse, two small pick warehouses and multiple overflow warehouses. From each warehouse, the inbound logistics department receives the available storage locations per storage type and the number of containers that each warehouse can unload on a particular day. The inbound logistics department checks in the SAP system the percent of the content which can be stored in each warehouse. They attempt to reduce the cross docks by manually assigning the containers FIFO to a warehouse where most of the content can be unloaded without harming the capacity constraints of the warehouse.

Sub question 2: How does the receiving operation influence the efficiency during put-away, picking and shipping operations?

VidaXL is opening two new warehouses and will have two ship, one pick and two overflow houses in the same geographical area to fulfill all European orders. However, not all warehouses are equipped with all necessary resources to accomplish all warehouse operations for each product type, and therefore inefficient cross docks occur when the succeeding operation cannot be executed in the current warehouse. The total number of cross docks can be estimated on the pickup day and differ per container for each receiving warehouse.

VidaXL receives multiple containers per day and can therefore select the containers to be processed on the next day from a set of available containers. During most days it is impossible to select and process al available containers since each warehouse is constrained by the available inbound capacity.

Scheduling the receiving operations has a *"free operating space"*: The pickup date can be scheduled within ten days after the confirmation of arrival to prevent demurrage costs, the receiving warehouse can be chosen and the order of receiving each container can be determined. However, for some urgent critical containers there is no liberty, they must always be unloaded first at a specific warehouse. The efficiency can be increased through reducing the long-term cross docks by scheduling the receiving operation in the *"free operating space"*.

Sub question 3: How can the receiving operation be scheduled to increase efficiency during put-away, picking and shipping operations?

Cross docks during put-away, picking, and shipping can be estimated and prevented using the proposed scheduling algorithm. The objective of the algorithm is reducing the long-term cross docks while avoiding situations where the container is picked up after the demurrage date. The main approach for accomplishing this is through scheduling containers to the preferred warehouses such that the corresponding estimated number of cross docks are reduced.

In an ideal situation, the container and warehouse data are known far in advance. When there is enough inbound capacity, it would then be possible to schedule the receiving operation of each container before the demurrage date while minimizing the total long-term cross docks. A binary decision must be made, containers must be picked up by a warehouse on a specific date resulting in J*W*T binary decision variables. The triple sum objective function can minimize the total long-term cross docks by assigning the containers to warehouses on specific days.

The container receiving operation at VidaXL is not ideal, the exact inbound capacity per warehouse is only known a few days in advance, the actual arriving date of each container almost always differs from the estimated arrival date and it is almost impossible to estimate the number of cross docks of each receiving container far in advance. Containers received during previous days, increases the current stock level in each warehouse and therefore affect the estimated number of cross docks of the new receiving containers. It would be possible to resolve the triple sum objective function each day new information becomes available. However, solving a triple sum objective function with J*W*T binary decision variables requires computational effort and there is only limited time available to complete the calculations. This paper therefore proposes an alternative rolling horizon scheduling algorithm to deal with uncertain container arrivals and new information availability while reducing the computation time and complexity of the problem.

First, an aggregate solution for the coming four days is provided with a binary decision model. The binary decision model selects a subset of containers out of the available containers and schedules them to a warehouse, resulting in J*W binary decision variables. The binary decision model maximizes the profit associated with receiving the container at the most preferred warehouse instead of at a less preferred warehouse while considering the demurrage date. Second, the FIFO dispatch rule is applied to gather a detailed solution for the first scheduling's period. The FIFO dispatch rule schedules the container to specific receiving periods such that the throughput time decreases, and the containers are picked up before its demurrage date. The algorithm can be resolved each period new information becomes available.

The algorithm performs at best for VidaXL when applying an aggregate scheduling horizon equal to four days and a penalty value equal to twenty-five for every day the container is scheduled after its arriving day. The theoretical upper bound solution has 5.7% and 10.4% less cross docks in ramp-up and steady state situations respectively as the solution provided by the scheduling algorithm. Furthermore, cross docks can be reduced through receiving containers with a short storing time in the ship warehouses, with an average storage time in the pick warehouse and with a long storage time in the overflow warehouses. Consequently, more containers are received in the preferred ship warehouse and the efficiency of the receiving, put-away, picking, checking and packing, and shipping operations simultaneously increases.

The potential of the scheduling algorithm is evaluated through comparing the performance with scheduling the containers FIFO and minimizing the put-away cross docks FIFO every day. Moreover, the effect of including picking and shipping cross docks in the scheduling algorithm is investigated by running the model with and without additional cross docks based on the storage time. After opening a new ship warehouse, the total number of cross docks can be reduced with 26.3%, 28.7% and 45.6% compared with the scheduling algorithm without storage time component, minimizing the put-away cross docks FIFO every day and FIFO procedure respectively. The number of cross docks decreases when the process becomes more stable and the warehouses are equally utilized. When all warehouses have the same start utilization, the total number of cross docks can be reduced with 32.7%, 35.9% and 54.2% respectively. Moreover, the scheduling algorithm is not sensitive to different inbound capacities and different workload balance parameters.

6.2   Contributions to literature

The contribution to literature is three-fold and are presented in this section.

First, this is the first research focusing on efficiently scheduling the receiving operations for fast-growing e-commerce companies with multiple ship, pick and overflow warehouses in the same geographical area.

Second, while existing literature mainly focuses on improving the put-away, picking and shipping operations independently of each other, this thesis focuses on scheduling the receiving operation integrated with other warehouse operations to increase the overall warehouse efficiency.

Third, this paper proposes an alternative rolling horizon scheduling algorithm to deal with uncertain container arrivals and new information availability while reducing the computation time and complexity of the problem.

Literature on scheduling the receiving operation integrated with other warehouse operations is scare. However, this type of literature is extremely relevant for practitioners. To the authors knowledge, this is the first algorithm which schedules the receiving operation to increase the efficiency of the other warehouse operations for fast growing e-commerce companies with multiple warehouses.

6.3   Company recommendations

The company recommendations are fivefold and are presented in this section.

First, the receiving operation at VidaXL can be scheduled with the scheduling algorithm to reduce the long-term cross docks while taking the demurrage date into consideration. The potential of the scheduling algorithm is quantified with a realistic simulation, and it outperforms scheduling the containers FIFO and minimizing the put-away cross docks FIFO every day. The scheduling algorithm can be used at the start of every day by the inbound logistics department to plan the containers for next day.

Second, after opening a new ship warehouse, the usage of the resources in the new warehouse can be ramped-up with the scheduling algorithm. Many containers with a short storage time are received in the new ship warehouse and the pick density increases. As a result, the number of put-away, picking and shipping cross docks decreases. The performance of the scheduling algorithm increases when the warehouse processes stabilizes, and the warehouses are equally utilized.

Third, in the current warehouse set-up, the scheduling algorithm performs at best when applying an aggregate scheduling horizon equal to four days and a penalty value equal to twenty-five for every day the container is scheduled after its arriving day. The theoretical upper bound solution has 5.7% and 10.4% less cross docks in ramp-up and steady state situations respectively as the solution provided by the scheduling algorithm. However, the parameter settings should be evaluated with a simulation after every change in the warehouse set-up. When the average throughput time increases, the penalty value must be enlarged.

Fourth, balancing the workload between the warehouses for the aggregate schedule increases the workload as well. It is recommended to balance the workload with other managerial decisions such as dividing the workload between the inbound teams in a warehouse or providing more resources to highly utilized inbound teams.

Fifth, when the total inbound capacity is significantly lower as the expected container arrivals per month, VidaXL can adjust the workload balance parameters to schedule as many A and B containers as possible. The inbound teams can unload more containers per day and the total number of days the containers are picked up after the demurrage date decreases.

6.4   Limitations and further research

The main limitations of the scheduling algorithm are the parameter settings. Proper parameter settings differ for every warehouse set-up, and parameter tuning is necessary to determine the aggregate scheduling horizon and penalty value for every day the container is scheduled after its arrival date. Furthermore, when there is no pool of available containers, the algorithm minimized the total number of cross docks for next day. Minimizing the number of cross docks per day does not minimize the total long-term cross docks.

The effect of the scheduling algorithm on the efficiency of the warehouse operations receiving, put-away, order picking, checking and packing, and shipping can be investigated further. The scheduling algorithm reduces the long-term cross docks. However, increasing the efficiency of the reorganization process through the warehouse operations entails more as preventing cross docks between the warehouses. More in depth research is necessary to quantify for example the effect on the pick density or checking and packing operations. The algorithm functions as a basic model, constraints can be added, and the weight can be adapted to further increase the efficiency of the warehouse operations. Moreover, the scheduling algorithm assigns containers to warehouses, the effect of assigning containers to inbound docks or inbound teams can be investigated in more depth.

The algorithm applies a rolling horizon policy where the aggregate schedule is provided with a binary decision model whereas the detailed schedule is made with the FIFO dispatch rule. The theoretical upper bound solution has 5.7% and 10.4% less cross docks in ramp-up and steady state situations respectively as the solution provided by the scheduling algorithm. There is still room for improvement, assigning containers directly to one of the pickup days with a triple sum binary decision model has the potential to be investigated further.

Bibliography

Addis, B., Carello, G., Grosso, A., & Tanfani, E. (2015). *Operating room scheduling and rescheduling: a rolling horizon approach.* New York: Springer science + business media.

Baker, K. (1974). *Introduction to sequencing and scheduling.* New York: Wiley.

Baker, K., & Bertrand, J. (1981). *An investigation of due-date assignment rules with constrained tightness.* Journal of operations management.

Banks, J. (1998). *Handbook of Simulation: Principles, Methodology, Advances, Applications and Practice.* New York: John, Wiley & Sons, inc.

Banks, J. (2000). *Getting Started With Automod.* Bountiful, Utah: Autosimulations, Inc.

Bartholdi, J., & Hackman, S. (2019). *Warehouse & Distribution Science Releasse 0.98.1.* Atlanta, USA: The Supply Chain & Logistics Institute.

Berthon, P., Pitt, L., & Watson, R. (1996). *The world wide web as an advertising medium.* Journal advertising research.

Bertrand, J., Wortmann, J., Wijngaard, J., Suh, N., Jansen, M., Fransoo, J., . . . de Jonge, T. (2016). *Design of Operations Planning and Control Systems (DOPCS).* Eindhoven: Eindhoven University of Technology.

BOL.com. (2019). *Whitepaper Razendsnel verkopen.* Bol.com.

Boysen, N., De Koster, R., & Weidinger, F. (2018). *Warehousing in the e-commerce era: A survey.* European Journal of Operational Research.

Boysen, N., Stephan, K., & Weidinger, F. (2018). *Manual order consolidation with put walls: the batched order bin sequencing problem.* EURO Journal on Transportation and Logistics.

Bukchin, Y., Khmelnitsky, E., & Yakual, P. (2012). *Optimizing a dynamic order-picking process.* European Journal of Operational Research.

Burstein, D., & Kline, D. (1995). *Road warriors.* New York: Dutton Books.

CBS. (2018, 09 19). *Netherlands in EU top 5 online shopping*. Retrieved from Centraal Bureau voor de statistiek: https://www.cbs.nl/en-gb/news/2018/38/netherlands-in-eu-top-5-online-shopping

Coin-Or, f. (n.d.). *CLP*. Retrieved from Gitub: https://coin-or.github.io/Clp/basicmodelclasses

Conway, R., Johnson, B., & Maxwell, W. (1964). *An experimental investigation of priority assignment in a job shop.* The Rand corporation.

Davarzani, H., & Norrman, A. (2014). *Toward a relevant agenda for warehousing research: literature review and practitioners' input.* Logistic research.

Delorme, M., Lori, M., & Martello, S. (2015). *Bin packing and cutting stock problems: mathematical models and exact algorithms.* Bologna: DEI "Guglielmo Marconi".

Dertouzos, M., & Mok, A. (1989). *Multiprocessor on-line scheduling of hard real time tasks.* IEEE transaction on software engineering.

Dimitriadis, A., Shah, N., & Pantelides, C. (1997). *RTN-based rolling horizon algorithms for medium term scheduling of multipurpose plants.* London: Elsevier Science Ltd.

Direction, S. (2005). *DotCom boom en bust.* Emerald Group Publishing Limited.

Ecommerce, N. (2019, August 23). *90% pakketten binnen één dag bezorgd*. Retrieved from Ecommerce news: https://www.ecommercenews.nl/90-pakketten-binnen-een-dag-bezorgd/

Fang, J., & Xi, Y. (1997). *A Rolling Horizon Job Shop Rescheduling Strategy in the.* London: International journal advanced manufacturing technology.

Frazelle, E. (2002). *World-class warehousing and material handling.* New York: McGraw Hill.

Fukunaga, A., & Korf, R. (2007). *Bin completing algorithms for multicontainer packing, knapsack, and covering problems.* Journal of artificial intelligence research.

Hall, J. (2016). *Projects*. Retrieved from COIN-OR Foundation: https://www.coin-or.org/projects/#ffs-tabbed-118

Hartog, G. (2019, 11 29). *People Plaza*. Retrieved from People Plaze VidaXL.

Hillier, F., & Lieberman, G. (2001). *Introduction to operations research.* New York: McGraw-Hill.

Hooper, N. (1996). *Dynamic distribution planning techniques: progressive logistics optimization for manufacturers.* Logistics information management.

Hunsucker, J., & Shah, J. (1994). *Comperative performance analysis of priority rules in a constraned flow shop with multiple processors environment.* European Journal of Operational Research.

Jinxiang, G., Goetschalckx, M., & McGinnis, L. (2007). *Research on warehouse operation: A comprehensive review.* European Journal of Operational Research.

Kellerer, H., Pferschy, U., & Pisinger, D. (2004). *Knapsack Problems.* New York: Springer.

Knight, K. (2013). *ComScore: Desktop Spending Up.* BizReport.

Larbi, R., Alpan, G., Baptiste, P., & Penz, B. (2011). *Scheduling cross docking operations under full, partial and no information on inbound arrivals.* Cumputers and operations research.

Le-Anh, T., Koster, R., & Yu, Y. (2010). *Performance evaluation of dynamic scheduling approaches in vehicle-based internal transport systems.* International journal of production research.

Manimaran, G., & Siva Ram Murthy, C. (1998). *An efficient dynamic scheduling algorithm for multiprocessor real-time systems.* IEEE Transactions on parallel and distributed systems.

Martello, S., Pissinger, D., & Vigo, D. (1998). *The three-dimensional bin packing problem.* Maryland: Institute for operations research and management sciences.

Micheal, P. (1998). *Competitive Advantage Creating and sustaining superior performance.* New York: Simon & Schuster.

Mitchell, S., Kean, A., Mason, A., O'Sullivan, M., & Phillips, A. (2009). *Optimization with PuLP*. Retrieved from Coin-or: https://coin-or.github.io/pulp/

Monch, L., & Habenicht, I. (2003). *Simulation-based assesment of batching heuristics in semiconductor manufacturing.* Winter Simulation Conference.

North, M., & Macal, C. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation.* Oxford University Press.

Rajendran, C., & Holthaus, O. (1997). *A comparative study of dispatching rules indynamic flowshops and jobshops.* European journal of operational research.

Ronway, R., & Maxwell, W. (1962). *Network dispatching by the shortest operation descipline.* OPNS res.

Spar, D., & Bussgang, J. (1996). *The net rules.* Harverd business review.

Strader, T., & Shaw, M. (1997). *Characteristics of electionic markets.* Decision Support Systems.

TNS, K. (2019). *Nieuwe strijd staat voorde deur in online retail.* ING economisch bureau.

TU/e. (2018). *Graduate School Master Thesis Manual Industrial Engineering.* Eindhoven: Technical university Eindhoven.

Turban, E., King, D., Lee, J. K., Liang, T.-P., & Turban, D. (2017). *Electronic commerce.* Cham: Springer International Publishing AG.

Valerio de Carvalho, J. (2000). *LP models for bin packing and cutting stock problems.* European journal of operational research.

van den Berg, J. (1999). *A literature survey on planning and control of warehousing systems.* Enschede, the Netherlands: Taylor & Francis group.

Vepsalainen, A., & morton, T. (1987). *Priority rules for job shops with weighted tardiness costs.* Management science.

Wilfred, M. (2014, februari 2). *Struggling retailers report change in shopping trends*. Retrieved from sproutwired.com: sproutwired.

Wilkinson, S. (1996). *Aggregate formulations for large-scale process scheduling problems.* Londen: University of Londen.

William, S., & Gere, J. (1966). *Heuristics in job shop scheduling.* Management science.

Wolsey, L., & Nemhauser, G. (1999). *Integer and Combinatorial Optimization.* New Jersey: Wiley-Interscience.

Wozniak, C. (2013, July 30). *5 Keys to maximizing ecommerce profitability & customers satisfaction*. Retrieved from Rakuten: https://www.rakutensl.com/post/5-keys-to-maximizing-ecommerce-profitability-customer-satisfaction

Appendixes

Appendix A
Warehouse setup VidaXL
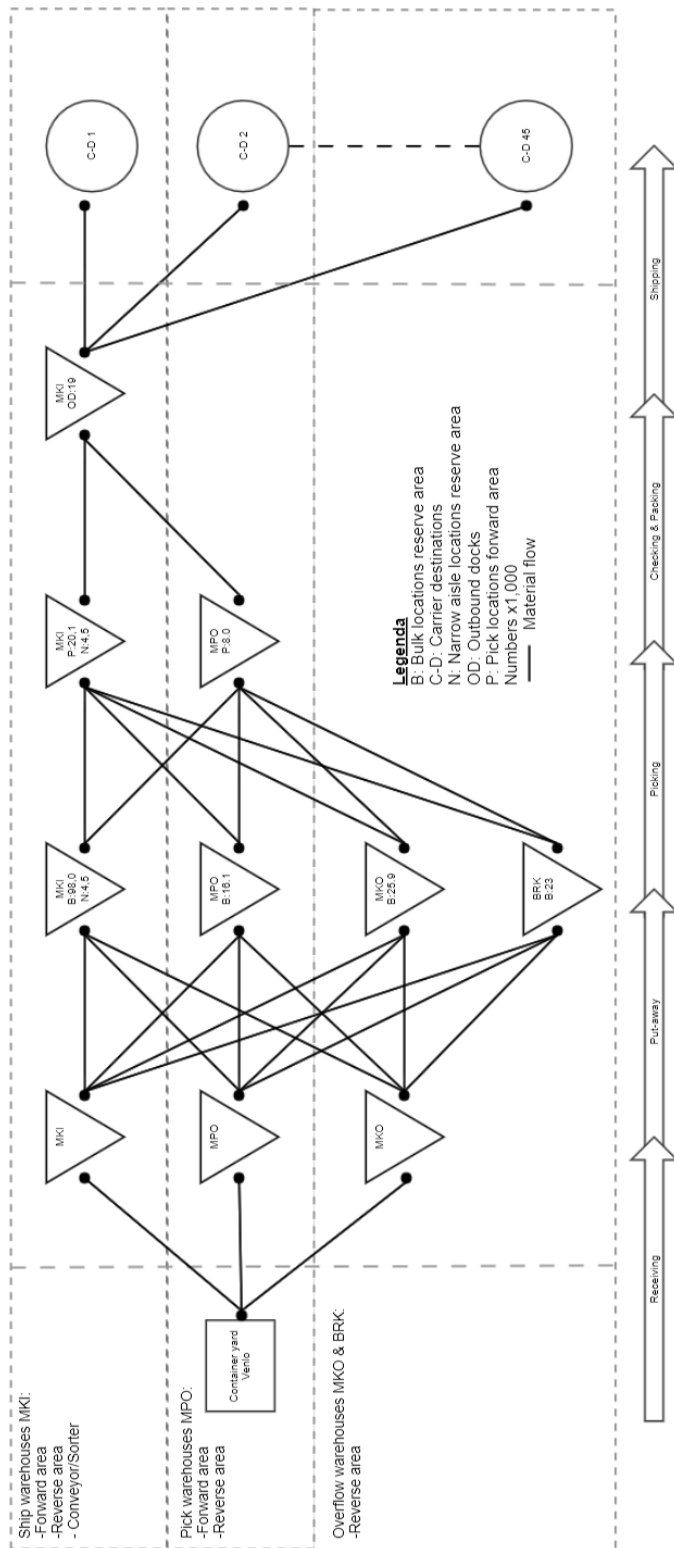
Figure 39: Warehouse setup VidaXL (2019)
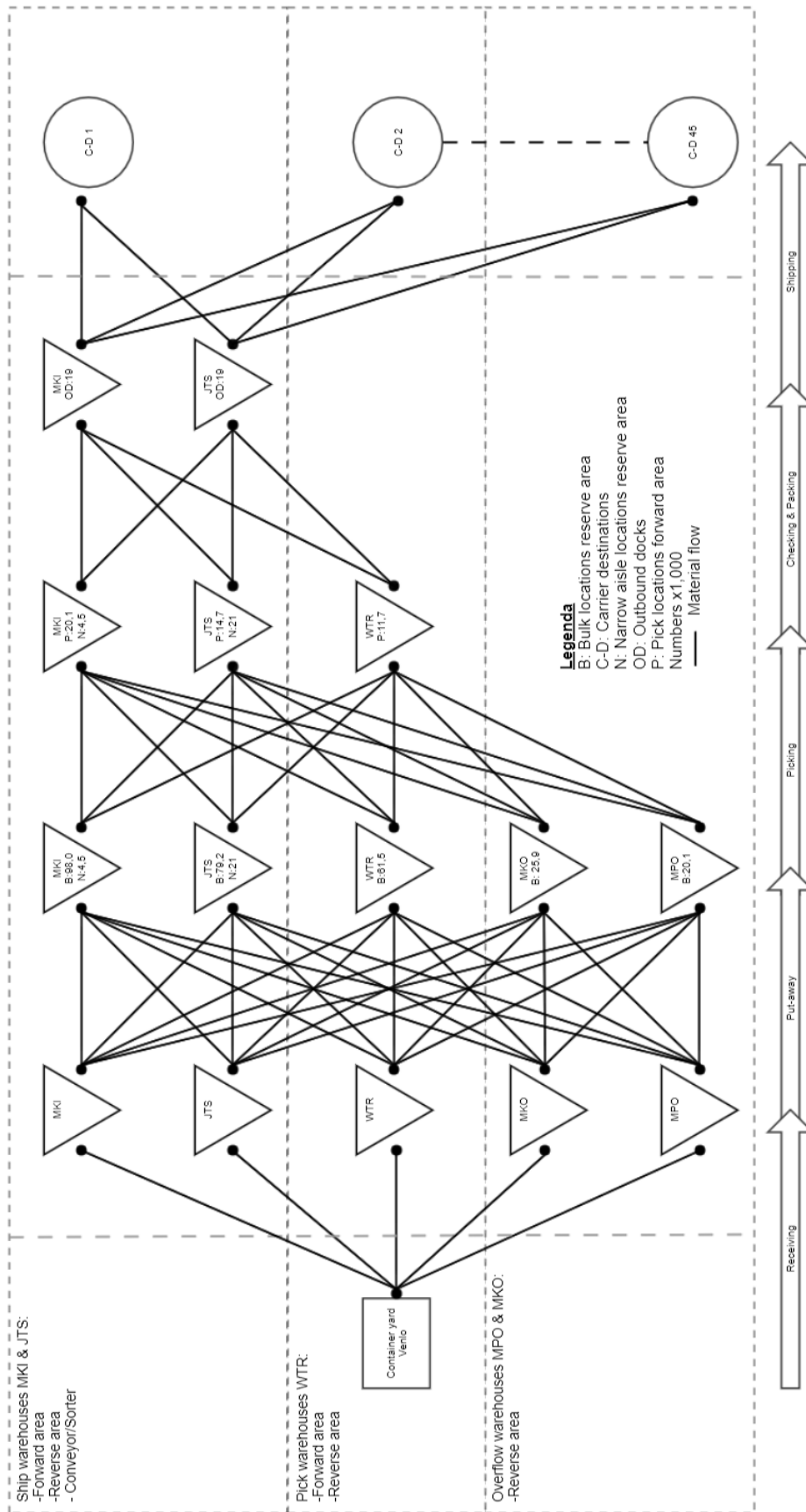
Figure 40: Warehouse setup VidaXL (2020)

Appendix B

Business process model VidaXL
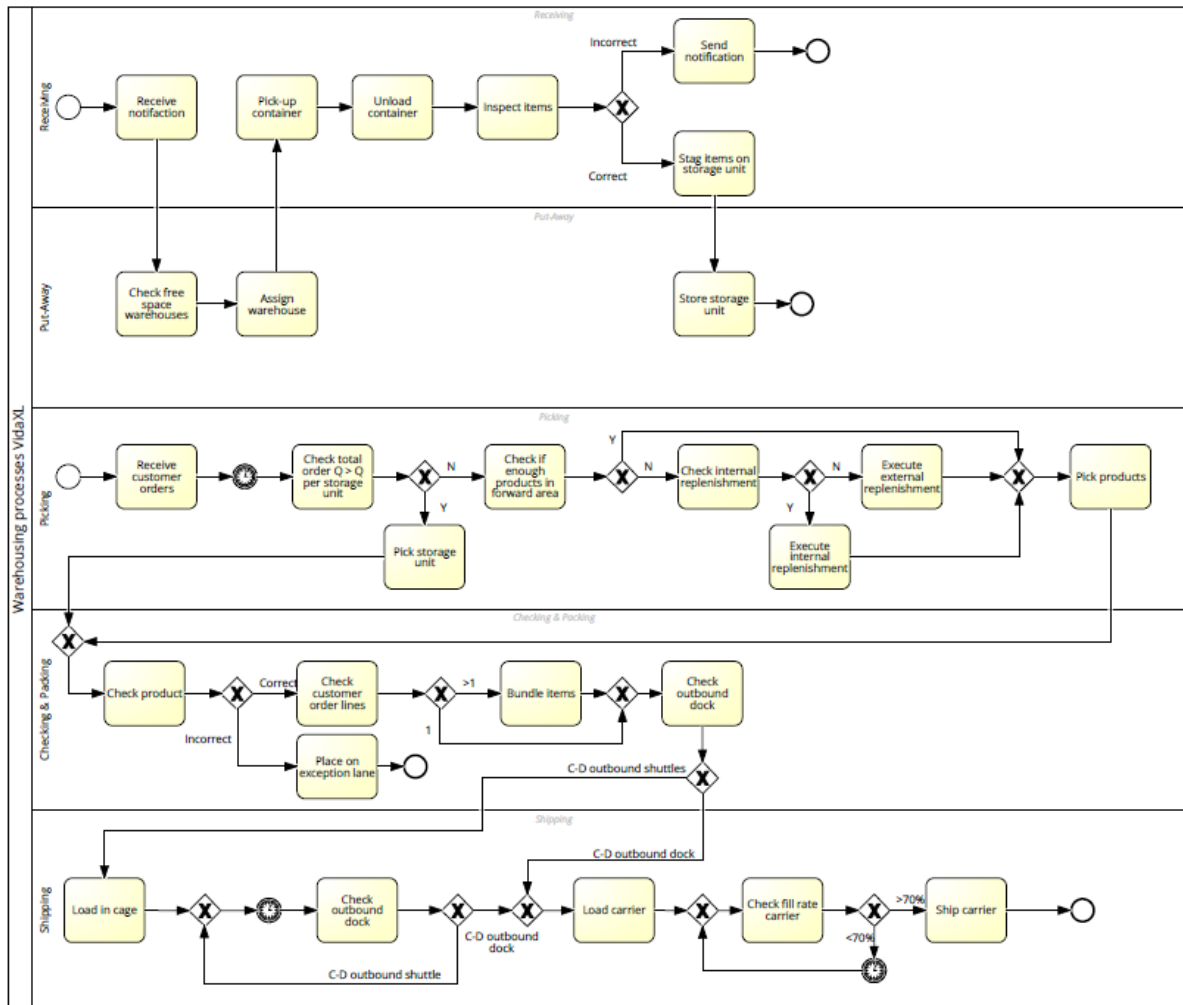
Figure 41: Business process model warehouse operations VidaXL

Appendix C
Parameter tuning scheduling algorithm

Table 17: Detailed results parameter tuning scheduling algorithm penalty = 10 and penalty = 20

	T = 2 Penalty =10	T = 3 Penalty =10	T = 4 Penalty = 10	T = 5 Penalty =10	T = 2 Penalty =20	T = 3 Penalty =20	T = 4 Penalty = 20	T = 5 Penalty =20
Nr containers MKI	2,629	2,697	2,709	2,682	2,643	2,702	2,703	2,689
Nr containers JTS	2,877	2,934	2,939	2,957	2,875	2,935	2,939	2,956
Nr containers WTR	791	796	788	793	790	786	792	787
Nr containers Overflow	674	642	641	643	665	652	643	656
Nr containers not right predicted	2,603	1,995	1,525	1,387	2,448	1,863	1,492	1,363
Nr containers right predicted	3,859	4,731	4,625	4,371	4,006	4,846	4,592	4,395
Put-away cross docks MKI	126	119	142	162	138	131	133	139
Put-away cross docks JTS	9,723	9,489	9,735	10,436	9,454	9,358	9,792	10,245
Put-away cross docks WTR	3,928	3,992	3,790	4,094	4,315	3,860	3,611	3,699
Put-away cross docks overflow	12,446	11,673	11,427	11,324	12,106	11,600	11,334	11,813
Picking cross docks	13,359	13,322	13,375	13,433	13,533	13,508	13,386	13,136
Shipping cross docks	34,217	33,928	33,486	33,884	33,790	33,597	33,684	33,771
Total nr crossdocks	73,799	72,523	71,955	73,333	73,336	72,054	71,940	72,803
Average throughput time	7.23	4.07	3.59	3.58	7.28	4.01	3.51	3.59
Nr containers picked up after demurrage	843	24	19	26	833	10	8	22
Nr days containers picked up after demurrage	1,652	24	19	26	1,638	10	8	22
Nr containers picked up after 8 days	2,224	59	32	51	2,075	13	8	37

Table 18: Parameter tuning scheduling algorithm penalty = 25 and penalty = 30

	T = 2 Penalty =25	T = 3 Penalty =25	T = 4 Penalty =25	T = 5 Penalty =25	T = 2 Penalty =30	T = 3 Penalty =30	T = 4 Penalty =30	T = 5 Penalty =30
Nr containers MKI	2,658	2,716	2,716	2,699	2,682	2,717	2,709	2,697
Nr containers JTS	2,871	2,919	2,931	2,949	2,954	2,917	2,928	2,954
Nr containers WTR	795	787	788	793	790	789	794	786
Nr containers Overflow	656	641	640	637	651	649	646	640
Nr containers not right predicted	2,344	1,871	1,522	1,381	1,345	1,819	1,503	1,348
Nr containers right predicted	4,086	4,783	6,407	4,385	4,388	4,798	4,649	4,400
Put-away cross docks MKI	140	133	133	172	158	123	147	151
Put-away cross docks JTS	9,490	9,189	9,567	10,326	10,359	9,144	9,448	10,242
Put-away cross docks WTR	3,884	3,841	3,668	3,877	3,675	3,981	3,857	3,866
Put-away cross docks overflow	11,575	11,252	11,242	11,105	11,331	11,450	11,520	11,268
Picking cross docks	13,769	13,447	13,363	13,417	13,138	13,376	13,240	13,266
Shipping cross docks	33,929	33,642	33,578	33,708	33,850	33,637	33,781	33,605
Total nr crossdocks	72,787	71,504	71,551	72,605	72,511	71,711	71,993	72,398
Average throughput time	6.93	3.92	3.57	3.61	3.56	3.87	3.60	3.58
Nr containers picked up after demurrage	569	8	8	19	18	9	9	18
Nr days containers picked up after demurrage	943	8	8	19	18	9	9	18
Nr containers picked up after 8 days	1,635	0	9	30	25	11	10	24

Appendix D
Results ramp-up situation

Table 19: Results ramp-up situation per scheduling procedure

	Scheduling algorithm	Scheduling algorithm NoSLO	FIFO extension	FIFO
Nr containers MKI	2,133	1,989	1,952	1,722
Nr containers JTS	3,103	2,654	2,675	3,138
Nr containers WTR	1,127	1,452	1,503	1,688
Nr containers Overflow	697	978	963	598
Nr containers not right predicted	1,643	2,247		
Nr containers right predicted	4,679	4,407		
Put-away cross docks MKI	98	135	154	42
Put-away cross docks JTS	15,410	11,425	13,876	58,911
Put-away cross docks WTR	9,044	6,756	8,805	26,300
Put-away cross docks overflow	7,084	1,974	1,251	4,031
Picking cross docks	19,615	49,038	48,580	28,264
Shipping cross docks	43,321	59,051	59,992	56,311
Total nr crossdocks	94,572	128,379	132,658	173,859
Average throughput time	3.80	3.97	2.51	2.42
Nr containers picked up after demurrage	19	118	0	0
Nr days containers picked up after demurrage	19	225	0	0

Appendix E
Results steady state situation

Table 20: Results steady state situation per scheduling procedure

	Scheduling algorithm	Scheduling algorithm NoSLO	FIFO extension	FIFO
Nr containers MKI	2,716	2,251	2,229	1,959
Nr containers JTS	2,931	2,257	2,243	3,152
Nr containers WTR	788	1,209	1,283	1,590
Nr containers Overflow	640	1,360	1,339	466
Nr containers not right predicted	1,522	1,808		
Nr containers right predicted	4,607	4,326		
Put-away cross docks MKI	133	151	161	84
Put-away cross docks JTS	9,567	5,932	6,834	59,009
Put-away cross docks WTR	3,668	3,281	5,304	26,713
Put-away cross docks overflow	11,242	14,732	13,496	4,597
Picking cross docks	13,363	31,495	33,139	17,568
Shipping cross docks	33,578	50,647	52,751	48,246
Total nr crossdocks	71,551	106,238	111,685	156,217
Average throughput time	3.57	3.61	2.56	2.37
Nr containers picked up after demurrage	8	7	0	0
Nr days containers picked up after demurrage	8	7	0	0

Appendix F
Results Temporary blockage OF warehouse

Table 21: Detailed simulation results temporary blocking inbound flow overflow warehouses

	Scheduling algorithm	Scheduling algorithm NoSLO	FIFO extension	FIFO
Nr containers MKI	2,133	2,143	1,965	19,999
Nr containers JTS	3,103	3,507	3,030	3,043
Nr containers WTR	1,127	1,244	1,715	1,689
Nr containers Overflow	697	175	360	346
Nr containers not right predicted	1,643	1,824	2,757	
Nr containers right predicted	4,679	5,106	4,244	
Put-away cross docks MKI	98	98	117	92
Put-away cross docks JTS	15,410	24,740	21,923	23,371
Put-away cross docks WTR	9,044	16,038	14,472	14,740
Put-away cross docks overflow	7,084	1,333	2,929	2,196
Picking cross docks	19,615	13,090	15,953	17,770
Shipping cross docks	43,321	43,997	63,698	62,089
Total nr crossdocks	94,572	99,296	119,092	120,258
Average throughput time	3,80	6,25	6,12	4,31
Nr containers picked up after demurrage	19	437	721	31
Nr days containers picked up after demurrage	19	830	2,443	37

Appendix G
Results different inbound capacities

Table 22: Results different inbound capacities (1)

	SHIP -10%, Pick + 10%				SHIP +20%, Pick/OF - 10%			
	Scheduling algorithm	Schedu-ling algorithm NoSLO	FIFO exten-sion	FIFO	Scheduling algorithm	Schedu-ling algorithm NoSLO	FIFO exten-sion	FIFO
Nr containers MKI	1,995	1,820	1,924	1,656	3,037	2,560	2,492	2,482
Nr containers JTS	2,478	1,997	2,072	2,750	3,181	2,603	2,770	3,316
Nr containers WTR	1,063	1,352	1,411	1,759	758	1,142	1,375	1,496
Nr containers Overflow	982	1,379	1,369	589	462	1,100	835	305
Nr containers not right predicted	3,078	3,125			342	453		
Nr containers right predicted	3,440	4,423			2,804	2,439		
Put-away cross docks MKI	113	115	89	65	2,658	3,872	9,962	4,258
Put-away cross docks JTS	7,437	5,975	7,661	53,906	13,007	15,348	23,620	56,236
Put-away cross docks WTR	17,123	5,558	6,942	32,661	5,594	4,371	12,885	21,913
Put-away cross docks overflow	18,943	16,427	15,101	5,061	7,767	10,264	7,951	2,545
Picking cross docks	19,138	33,411	33,277	19,778	10,424	26,031	24,812	13,661
Shipping cross docks	37,688	54,733	57,618	53,685	30,308	48,576	53,304	45,324
Total nr crossdocks	100,442	116,219	120,688	165,156	69,758	108,462	132,534	143,937
Average throughput time	19.68	19.96	14.12	13.97	1.21	1.22	2.34	1.03
Nr containers picked up after demurrage	5,056	5,122	4,409	4,419	0	0	0	0
Nr days containers picked up after demurrage	67,728	69,896	34,127	33,106	0	0	0	0

Table 23: Results different inbound capacities (2)

	JTS -10%, MKI + 10%				JTS +10%, MKI - 10%			
	Scheduling algorithm	Scheduling algorithm NoSLO	FIFO extension	FIFO	Scheduling algorithm	Scheduling algorithm NoSLO	FIFO extension	FIFO
Nr containers MKI	2,942	2,441	2,439	2,194	2,426	2,018	1,991	1,731
Nr containers JTS	2,728	2,097	2,081	2,901	3,201	2,457	2,451	3,358
Nr containers WTR	797	1,180	1,257	1,557	786	1,237	1,309	1,574
Nr containers Overflow	620	1,346	1,299	465	663	1,357	1,327	470
Nr containers not right predicted	1,462	1,939			1,573	1,971		
Nr containers right predicted	4,691	4,358			4,652	4,347		
Put-away cross docks MKI	164	131	153	71	135	116	116	65
Put-away cross docks JTS	6,786	4,345	5,200	54,472	14,410	8,408	9,806	64,168
Put-away cross docks WTR	3,561	2,350	4,087	26,213	4,252	5,018	6,895	26,374
Put-away cross docks overflow	10,650	14,535	13,506	3,831	11,669	14,755	13,643	4,619
Picking cross docks	12,740	30,063	30,970	17,452	14,257	32,562	33,627	17,647
Shipping cross docks	34,057	50,369	53,256	47,876	33,104	51,188	52,636	48,297
Total nr crossdocks	67,958	101,793	107,172	149,915	77,827	112,047	116,723	161,170
Average throughput time	3.56	3.96	3.51	2.38	3.64	3.92	2.78	2.33
Nr containers picked up after demurrage	13	12	4	0	8	11	0	0
Nr days containers picked up after demurrage	13	12	21	0	8	11	0	0

Table 24: Results different inbound capacities (3)

	SHIP +10%, Pick -5%			
	Scheduling algorithm	Scheduling algorithm NoSLO	FIFO extension	FIFO
Nr containers MKI	2,840	2,421	2,384	2,098
Nr containers JTS	3,053	2,396	2,351	3,525
Nr containers WTR	756	1,151	1,204	1,579
Nr containers Overflow	507	1,160	1,092	382
Nr containers not right predicted	636	780		
Nr containers right predicted	3,341	3,020		
Put-away cross docks MKI	151	134	95	58
Put-away cross docks JTS	11,457	8,591	7,921	59,344
Put-away cross docks WTR	4,283	3,611	5,565	25,769
Put-away cross docks overflow	9,125	11,645	11,138	3,467
Picking cross docks	11,191	27,145	26,452	15,068
Shipping cross docks	31,655	48,683	50,712	47,086
Total nr crossdocks	67,862	99,809	101,883	150,792
Average throughput time	1.67	1.74	4.14	1.31
Nr containers picked up after demurrage	0	0	41	0
Nr days containers picked up after demurrage	0	0	56	0

Appendix H
Results different workload balance parameters

Table 25: Results workload balance paremeters equall to 0.75 and 0.5

	$WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.75$				$WB_{Aw} = WB_{Bw} = WB_{Cw} = 0.50$			
	Scheduling algorithm	Schedu-ling algorithm NoSLO	FIFO exten-sion	FIFO	Scheduling algorithm	Schedu-ling algorithm NoSLO	FIFO exten-sion	FIFO
Nr containers MKI	2,631	2,273	2,247	1,705	2,623	2,277	2,262	1,690
Nr containers JTS	2,970	2,094	2,086	3,147	2,957	2,079	2,112	3,126
Nr containers WTR	810	1,154	1,138	1,692	820	1,159	1,127	1,679
Nr containers Overflow	665	1,282	1,223	602	676	1,272	1,222	637
Nr containers not right predicted	1,366	621			1,460	611		
Nr containers right predicted	4,260	2,304			4,457	2,306		
Put-away cross docks MKI	140	146	0	42	140	146	0	38
Put-away cross docks JTS	12,067	4,270	5,334	59,812	12,165	4,226	5,308	57,707
Put-away cross docks WTR	5,406	1,916	2,988	26,396	5,217	1,870	3,042	27,672
Put-away cross docks overflow	11,323	13,453	13,445	3,898	11,220	13,425	13,466	4,771
Picking cross docks	13,845	30,173	29,482	28,680	14,676	29,862	29,650	28,835
Shipping cross docks	34,149	50,371	50,208	56,263	34,125	50,799	49,049	56,901
Total nr crossdocks	76,930	100,329	101,457	175,091	77,543	100,328	100,515	175,924
Average throughput time	4.36	10.76	13.68	2.42	3.66	10.96	13.12	2.39
Nr containers picked up after demurrage	192	2,139	3,184	0	26	2163	3,206	0
Nr days containers picked up after demurrage	283	42,108	39,484	0	27	43,208	36,271	0