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Quantitative Evaluation of Operations for Omni-Channel Warehousing

FMCG Warehouse Simulation Study

Delft University of Technology

TU Delft

Royal HaskoningDHV
Enhancing Society Together

Quantitative Evaluation of Operations for Omni-Channel Warehousing

FMCG Warehouse Simulation Study

by

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Preface

This research is written as final thesis for the Mechanical Engineering master at the Delft University of Technology. This thesis is written within the department of Maritime and Transport Technology, for the track Multi-Machine Engineering. The research question has been provided by Royal HaskoningDHV, where the study has been performed and supervised.

This report benefits warehousing practitioners who seek insights to base decision making on regarding omni-channel warehouse operations design. Many thanks to all the people that have supported me during this research. Special thanks to my daily company-supervisor Sander van den Brand, for his professional, flexible and cheerful support and guidance along the way. I also would like to thank Mark Duinkerken, for his accurate and practical advise and feedback.

Thanks should also go to my housemates from De Gouden Leeuw, who have made my time as a student a true pleasure. I am also grateful for all colleagues at Royal HaskoningDHV, who helped me get through the though parts of the research process. Last but not least, I would like to express my deepest appreciation to my family and girlfriend Anniek for their love, support and patience along the way.

J. van Dijk
Delft, September 2022

Abstract

In recent years E-commerce sales have been growing with a steady rate of about 20% and are expected to grow by another 10% in the upcoming years (Von Abrams, 2021). The growth in e-commerce sales has been accelerated by the coronavirus pandemic.

This e-commerce trend has been identified as the biggest potential for growth for retailers and has not gone unnoticed with the traditional physical store suppliers (Roger et al., 2015). In suppliers' rush to develop e-commerce capabilities, the e-commerce integration is often performed through bolted-on systems without regard for integration with traditional store fulfillment (Roger et al., 2015).
Little scholarly works exist exploring operational implications in the omni-channel context (Kembro et al., 2018). Moreover, of the existing omni-channel warehousing research, the gist has been on channel conflicts and managerial aspects, while the interplay between the store and e-commerce distribution channel has not received much attention (Agatz et al., 2008).

Therefore, this research presents a quantitative analysis of the effect of operational philosophy on the omni-channel warehouse performance. This is done by modeling and simulating multiple alternative operation designs and comparing the performance with each other. The aim is to shed light on the operational implications for integrated omni-channel warehousing. Furthermore, the practical implications of the operational philosophy are considered.

This leads to the following research question:

What is the Impact of Operational Philosophy on Omni-Channel Warehouse Performance?

In order to answer above question, use can be made of a case provided by RHDHV. The main research question is broken down into the following sub-questions in order for it to be answered comprehensively and structured:

1. How is warehousing characterised and what are its challenges?
2. What is the state of the research on omni-channel operations?
3. How is omni-channel warehousing characterised and what alternatives for operations exist?
4. How can omni-channel warehouse performance be quantified?
5. How is the model set up and what experiments are required to evaluate the performance of the operational alternatives?
6. How do the operational alternatives perform under different scenarios?

The operations considered do not include receiving and shipping stages, because these stages represent similarities with the processes in conventional warehouses. Also, product allocation and picker routing are not considered, these subject have already received lots of attention, and form a whole research field on their own. Automation is not considered in this research because currently automation does not play a big role for picking processes and desired flexibility and scalability do not justify the use of an automated system (Hübner et al., 2015).

The omni-channel term reflects the fact that customers can interact with suppliers through an array of channels, like mail, stores, social media, television, gaming consoles and mobile devices (Rigby, 2011). Although definitions surrounding omni-channel retail strategies are ambiguous, it is the term that is used in this paper, because omni-channel retailing is the overarching term and most advanced concept.

Two main strategies exist for omni-channel warehouse implementation, one is utilizing an integrated warehouse and the other is using a separated warehouse. Both of these methods have their benefits and downsides, in general, the opportunities for separated warehousing strategy are the challenges for the integrated strategy and vice versa.

An important determinant whether to choose for an integrated or a separated approach is the existing infrastructure of the company (De Koster, 2003). When a company wants to start internet activities, the existing assets can be exploited. Furthermore, the complexity of the assortment is a differentiator when selecting dual-channel solutions. Because results indicate that positive effects of integrated warehouses outweigh the challenges associated with added operational complexity (Hübner et al., 2016a), it is the avenue which is further explored in this research.

The challenge of designing efficient integrated omni-channel warehouses has not been researched yet, however such strategies have already been implemented by industry. These practices can be used to derive feasible operational philosophies from. Subsequently these design alternatives can be tested against each other for their performance to gain insight into omni-channel warehouse operations.

The found feasible operational philosophies can be summarized as follows:

1. Alternative I: Physically separated picking area, simultaneous picking for web and store orders
2. Alternative II: Common picking area, zoned by rotation speed, simultaneous picking for web and store orders
3. Alternative III: Common picking area, time slot separated picking for web and store orders

To analyse the performance of the three identified design alternatives, a discrete event simulation (DES) model is proposed. Furthermore, an use case is introduced to serve as a reliable basis for modeling. The case can be used to get realistic throughput values from, and assumptions regarding the stochastic values and boundaries can be related to the case. The case concerns a distribution warehouse of a Fast Moving Consumer Goods (FMCG) supplier in East-Asia. The use case provides data on order arrival patterns, order compositions, throughput, lead time targets and size of workforce. Inputs that could not be derived from the case have been based on literature and insights from warehousing experts.

The objective of the model is to evaluate the effect of operational philosophy on the performance of the omni-channel warehouse. In order to do so, the model has to be able to asses the sensitivity of the performance to the arrival patterns of the orders and the sensitivity to the order type skewness. The order type skewness indicates the ratio between the throughput of the warehouse dedicated to store order fulfillment, and the throughput dedicated to web order fulfillment. With the results from the model, a statement can be made about which design alternative performs best considering the scenarios. The inputs to the simulation model are the order volumes, order compositions, order arrival patterns, pallet size, case size and the products.

The results for alternative I are most promising. It shows a high throughput of web orders, due to the dedicated forward web order fulfillment area. It performs best, while it requires the least amount of personnel, and can handle peak web arrivals reliably. Moreover, this alternative is most future proof, when more of the warehouse throughput will be dedicated to fulfilling web orders.

However, the forward picking area puts high demands on available space and forklifts. The required area and equipment hinders the ability to scale the web fulfillment operations, because increasing the number of pickers for web order fulfillment, means adding an entire forward storage area. That is not beneficial concerning the expected increase in arriving web orders and the current lead time figures for the forward picking area. Lastly, the separate areas for web order and store order fulfillment, make it difficult for personnel to switch to web or store fulfillment.

Results for alternative II show high lead time spreads and a disability to handle peak order arrivals. However, workforce can be shifted between store and web order fulfillment, this can offer a solution for the performance, seen from the reliable lead times for alternative III. Furthermore, the operations are easily scalable due to efficient travel in the pick zones. However, the sorting area must be able to support the increase in orders as well.

The performance of Alternative III can only be seen in the light of the store orders being used as a buffer and using a tailored time slot selection. When this is the case the operations perform very reliable and is capable of processing peaks efficiently. Workforce can be easily shifted via the time slots, and space utilization is very efficient since no extra picking or sorting areas are required. However, the operations are difficult to scale because all personnel works in the same area, which can lead to bottlenecks.

The main takeaway from the results is the large effect of the amount of web orders on the operations. Although the warehouse throughput remains the same, the required work to fulfill orders increases when more throughput is dedicated for web fulfillment. For an increase of 5% of pallet throughput dedicated to web order fulfillment, which translates to an increase of web orders of 50% for the considered FMCG warehouse, the average lead time for alternative I, increases with 113%. While the number of pickers dedicated to web order fulfillment is theoretically sufficient. Therefore, for an omni-channel warehouse the amount of work is not defined by the amount of pallets processed, rather the amount of orders processed.

However, as discussed, the forward storage operations come with a high demand on required space, which makes scaling of the operations difficult, while scaling is required in order to be able to handle the foreseen increase in web orders. It should be considered to invest in warehouse space, which can be earned back through a smaller required workforce.

Considering the future throughput figures, practitioners should reconsider implementing an integrated warehouse when area usage is constraint, since non of the evaluated omni-channel warehouse operations show adequate performance. With space often being constraint when considering implementing an extra online channel in existing infrastructure, the foreseen increase in web orders forms a massive problem. For future throughput, green field integrated omni-channel warehouses should be considered or separate omni-channel warehousing strategies, rather than integrating multiple channels in existing infrastructure, as non of the considered layouts proves adequate.

List of Abbreviations

3PL	Third-Party Logistics
A/S	Accumulation/Sorting
AS/RS	Automated Storage and Retrieval Systems
B2C	Business-to-Customer
DES	Discrete Event Simulation
DIY	Do-It-Yourself
E-Commerce	Electronic Commerce
FMCG	Fast Moving Consumer Goods
IQR	Inter Quartile Range
PDL	Process Description Language
RHDHV	Royal HaskoningDHV
SKU	Stock Keeping Unit
UML	Unified Modeling Language

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I

Intro

1

Introduction

In this chapter the introduction to the research is given. First the background is described along with the problem statement and research questions. Subsequently, the approach and scope for the research are discussed. Lastly, the structure for the remainder of the report is presented.

Background

Warehousing has received a lot of attention in the last twenty years, and still the publication count is growing rapidly. Most of this research is aimed at traditional warehouses, where only one sales channel is considered, the one that delivers to physical stores. Since the rise of e-commerce, a lot of the research has shifted towards warehousing where the business-to-customer (B2C) channels are considered. E-commerce entails the buying and selling of goods or services using the internet, where money and data is transferred to execute the transactions (Shopify, 2022).

E-commerce sales have been growing with a steady rate of about 20% in the last years and is expected to grow by 10% in the upcoming years (Von Abrams, 2021). Moreover, the growth of the e-commerce market has been accelerated by the coronavirus pandemic. According to Lund et al. (2021), the rate of e-commerce growth, grew by another 20% due to the consumers staying at home and stores having to close. These developments reduces the relevancy of the traditional brick-and-mortar sales network. When referring to 'traditional retailing' or 'traditional warehousing', the retailing through one offline sales channel is meant. Where end-customers go to physical stores and stores place orders at the supplying warehouses, also known as brick-and-mortar retailing.

The increase of e-commerce retail sales has not gone unnoticed with the traditional physical store suppliers. Since less of the consumer goods are bought through stores, the store suppliers can miss out on part of the revenues when not offering their products online (Chiang et al., 2003). The rise of e-commerce prompts these traditional suppliers to start and sell online, next to their existing store activities (Boyaci, 2005, Chiang et al., 2003). Moreover, the e-commerce trend has been identified as the biggest potential for growth (Roger et al., 2015).

This large potential is the reason suppliers are looking to integrate the new sales channel into their existing supply chain. Because of the difference in nature of e-commerce orders and store orders, an overhaul of their processes is required. Aspects that differ and have consequences for the operations are: the order arrival times, order sizes, short deadlines, order picking and product characteristics (Alawneh and Zhang, 2018, Hübner et al., 2015).

Implementing new technology is difficult for many great supply chain organizations. Rigby (2011) states that these organizations are often technophobic and unattractive for young computer talent. Rigby also points out that implementation of an online channel is crucial for suppliers existence, already in 2011.

Royal HaskoningDHV identifies the need of their traditional supplier clients, for solutions when considering selling directly to customers over the internet. Roger et al. (2015) sees this need as well, and states that in suppliers' rush to develop e-commerce capabilities, the e-commerce integration is often performed through bolted-on systems without regard of integration with traditional store fulfillment. The lack of available space contributes to this phenomenon and an e-commerce department often starts out as a few tables put together in a corner, describes Royal HaskoningDHV. Since the existing infrastructure, processes and automation are not considered, the e-commerce operations lack efficiency and visibility across departments (Roger et al., 2015).

The integration of an online sales channel into traditional operations for brick-and-mortar suppliers, leads to omni-channel supply chains. Next to being able to ride the wave of e-commerce growth, such a strategy provides chances to reach new customer segments, introducing even more growth possibilities (Alawneh and Zhang, 2018). The omni-channel supply chain is now considered to be the dominant business model for the retail sector (Agatz et al., 2008, Bretthauer et al., 2010).

The omni-channel term reflects the fact that customers can interact direct with suppliers through an array of channels, like mail, stores, social media, television, gaming consoles and mobile devices (Rigby, 2011). The omni-channel supply chain presents the overarching and most advanced concept of retailing through multiple channels (Hübner et al., 2016b). Although definitions surrounding omni-channel retail strategies are ambiguous, it is the term that is used in this paper, because the broadest possible view of the logistics system is desired and it indicates that the whole spectrum of user interfaces is included (Hübner et al., 2016b). However, the focus is on warehouse operations design, which means there is no differentiation between the customer interfaces with the supplier. For warehouse operations the two defining aspects are, whether the orders come from stores, or from separate customers via an online channel.

Gap

Although omni-channel strategies are the dominant business model, most of warehousing research has been performed on single-channel warehousing and optimization for these warehouses (Boysen et al., 2019). The single-channel warehouse research focuses on traditional warehouses supplying stores, or on B2C warehouses. The research field of omni-channel warehousing is underrepresented. Of the dual-channel warehousing research, the gist has been on channel conflicts and managerial aspects, while the interplay between the physical and e-commerce distribution channel has not received much attention (Agatz et al., 2008).

Furthermore, the practical implications of implementing an online channel in a traditional warehouse have not been researched, let alone been quantified. Kembro et al. (2018) describe that, although operations-research modeling and simulation, have been widely utilized for traditional single-channel warehouses, it has not been researched for omni-channel warehousing design. Thereby identifying a lack of research on how to design in terms of layout and operations in an omni-channel warehouse, while literature stresses the importance of a tailored design solution for omni-channel warehouses (Marchet et al., 2018). Also, Boysen et al. (2019) state that the selection of a warehousing system that can process different type of orders have not received attention yet. This is backed up by Bressolles and Lang (2019), who states limited scholarly works exist exploring operational implications in the omni-channel context. Moreover, the operational implications for integrated logistics in omni-channel warehouse design have not been quantified yet (Song et al., 2019). Such research can be used to support operations decisions in omni-channel warehousing (Hübner et al., 2015).

Concluding, currently no quantitative analysis exists that considers the omni-channel warehouse operations. Such an analysis can give insights into the required changes and performance indicators for e-commerce operations implementation in traditional store supplying warehouses. Thus, the impact of omni-channel operations philosophy on warehouses performance has not been researched in the practical sense yet.

Problem Analysis

Traditional suppliers struggle with efficient integration of e-commerce operations within their existing warehouses (Hübner et al., 2015, Roger et al., 2015). According to Davarzani and Norrman (2015), orders from different type of channel require a design that can fulfill orders with different characteristic. The characteristics are different due to the nature of the e-commerce operations compared to the store supplying operations.

Currently, companies use bolted-on systems and processes, in their haste to implement e-commerce operations, without considering efficient integration with their existing operations (Roger et al., 2015). While Hübner et al. (2016a) describe that integration of operations is necessary for cost efficient dual-channel implementation. Furtermore, according to Tielbeek (2015), retailers who execute an omni-channel strategy often face unsatisfactory results, such as high operational costs and low extra revenues. Alawneh and Zhang (2018) underline the problem by stating that traditional suppliers can not function properly in a omni-channel business environment without adaptation of their warehouse.

However, no research exists on quantifying the effect of operational design on omni-channel warehouse performance. It is clear that orders from different order channels provide challenges but no research exist which explores operating philosophy alternatives and their performance. The design of operations for warehouses who try to implement e-commerce operations while considering the existing traditional operations is non existent. Practical operations design insights will benefit suppliers who try to latch on to the rise of e-commerce by implementing an efficient omni-channel warehousing strategy. This is a need which has been identified by RHDHV as well.

Research Objective

This leads to the following research question:

What is the Impact of Operational Philosophy on Omni-Channel Warehouse Performance?

In order to answer above question, use can be made of a case provided by RHDHV. The case is described in section 5.2. The main research question is broken down into the following sub-questions in order for it to be answered comprehensively and structured:

1. How is warehousing characterised and what are its challenges?
2. What is the state of the research on omni-channel operations?
3. How is omni-channel warehousing characterised and what alternatives for operations exist?
4. How can omni-channel warehouse performance be quantified?
5. How is the model set up and what experiments are required to evaluate the performance of the operational alternatives?
6. How do the operational alternatives perform under different scenarios?

The objective of this research is to develop a simulation model of an omni-channel warehouse with integrated operations for both order channels. The model is made to be able to evaluate different operational philosophies and quantify their performance. The results will benefit warehousing practitioners who seek to implement omni-channel operations by providing insight in performance and design considerations for omni-channel warehouse operations. The results give insights in the way traditional warehouses can be adapted to facilitate efficient omni-channel operations. A parametric simulation model is delivered, which evaluates the impact of multiple operational philosophies on the warehouse performance. The results for each philosophy can be compared for insights to base strategic operational decision making upon.

Approach

An overview of the approach is presented in figure 1.1. The first research sub question, 'How is warehousing characterised and what are its challenges?', is answered by performing a system analysis on the current way of operating for traditional warehouses. The trends and common design issues are introduced and the resulting challenges are identified.

Subsequently, in the theory section, the state of omni-channel warehousing research is discovered to answer the second research questions, 'What is the state of the research on omni-channel operations?'. Thereafter, in chapter 4, the state of omni-channel warehousing is presented. The advantages of omni-channel warehousing are discovered and the role of such a warehouse in the supply chain, to answer 'How is omni-channel warehousing characterised and what alternatives for operations exist?'. For the latter part of the question, a look is taken at the varying requirements for the different order channels. Furthermore, to identify the requirements for efficient omni-channel operations, the key performance indicators are discussed. Also, the criteria that are relevant for warehouse performance are identified. The theory section is concluded by discussing the required methods, in chapter 5, to be able to 'quantify omni-channel warehouse performance'.

In the following phase the modeling is discussed, where the 'model setup and experiments' are introduced. Lastly, for the evaluation section, 'How do the operational alternatives perform under different scenarios?' is answered. The results from the model are evaluated and the conclusions and recommendations are discussed.

Scope

This research is aimed a traditional suppliers who seek to integrate e-commerce operations within their existing warehouse. Therefore, this study does not regard greenfield warehouse design.. Although the e-commerce trend has been going on for a while, still some suppliers have not yet integrated the operations of store fulfillment and e-fulfillment successfully.

For this research the performance of three scenarios are compared with each other, in order to asses the impact of operational philosophy, order type skewness and order arrival patterns. The operations considered in the operational philosophies do not include receiving and shipping stages, this can be seen in figure 1.2 as well. The figure shows the typical warehouse flows and where the boundaries for the scope are. As can be seen, the central storage and sorting processes are considered in this research, although the respective in- or out-flow of products and information is not considered. The products are either considered to be available or considered to be ready for shipping.

The receiving and shipping stages are not considered because these processes are not dissimilar for traditional warehouses and omni-channel warehouses. Especially when considering that shipment of e-commerce orders is often outsourced. Also, since these stages have their own set of challenges, regardless of the warehouse type, a lot of research has already been performed in these areas.

Regarding the operational philosophies, the differences concern the separation of order picking per order channel, zoning and time-slots. The warehouses to which this research applies are distribution warehouses, where throughput and efficient order picking are essential. The theoretical warehouse considered, features an integrated inventory, meaning the inventories for the online and offline channel are present in one warehouse.

The operational philosophies considered, do not describe detailed physical design, rather, process design, requirements and product flows. The product flow consists of stages like receiving, storage, forward/reserve replenishment, order picking, sorting and shipment. Therefore, inventory allocation, path planning and return logistics are not considered. Furthermore, since warehouse operations are considered, channel conflicts, managerial aspects and network design of an omni-channel supply chain are out of scope.

Automation is not considered in this research because in practice automation does not play a big role for picking processes (Hübner et al., 2015, Petersen II, 2000). Furthermore, the considered throughput and required flexibility and scalability do not justify the use of an automated system.

Lastly, while the term omni-channel is being used in this paper, no differentiation between the customer interfaces with the retailer is made. For warehouse operations only the differentiation between supplying the stores or the online customers is relevant. The term omni-channel is used because it is the most advanced concept and it gives the broadest possible view.

Structure

The structure of the research is as follows. Chapter 2 describes a general warehousing background with the challenges it faces. Thereafter, in chapter 3 the literature review is presented along with a classification of previous works. Here the space this research occupies is further defined. In chapter 4 the omni-channel warehouse concept is further introduced with a system analysis. Chapter 5 discusses the methods used to answer the research questions and the model that is selected, which is the last section of the theory part. Subsequently, chapter 6 kicks of the modeling part, where the model content and data inputs are discussed. After which chapter 7 forms the first part of the evaluation, where the results are discussed and analysed. In chapter 8 the discussion is presented concerning the results and the research. Finally, in chapter 9 the conclusions and recommendations are presented.

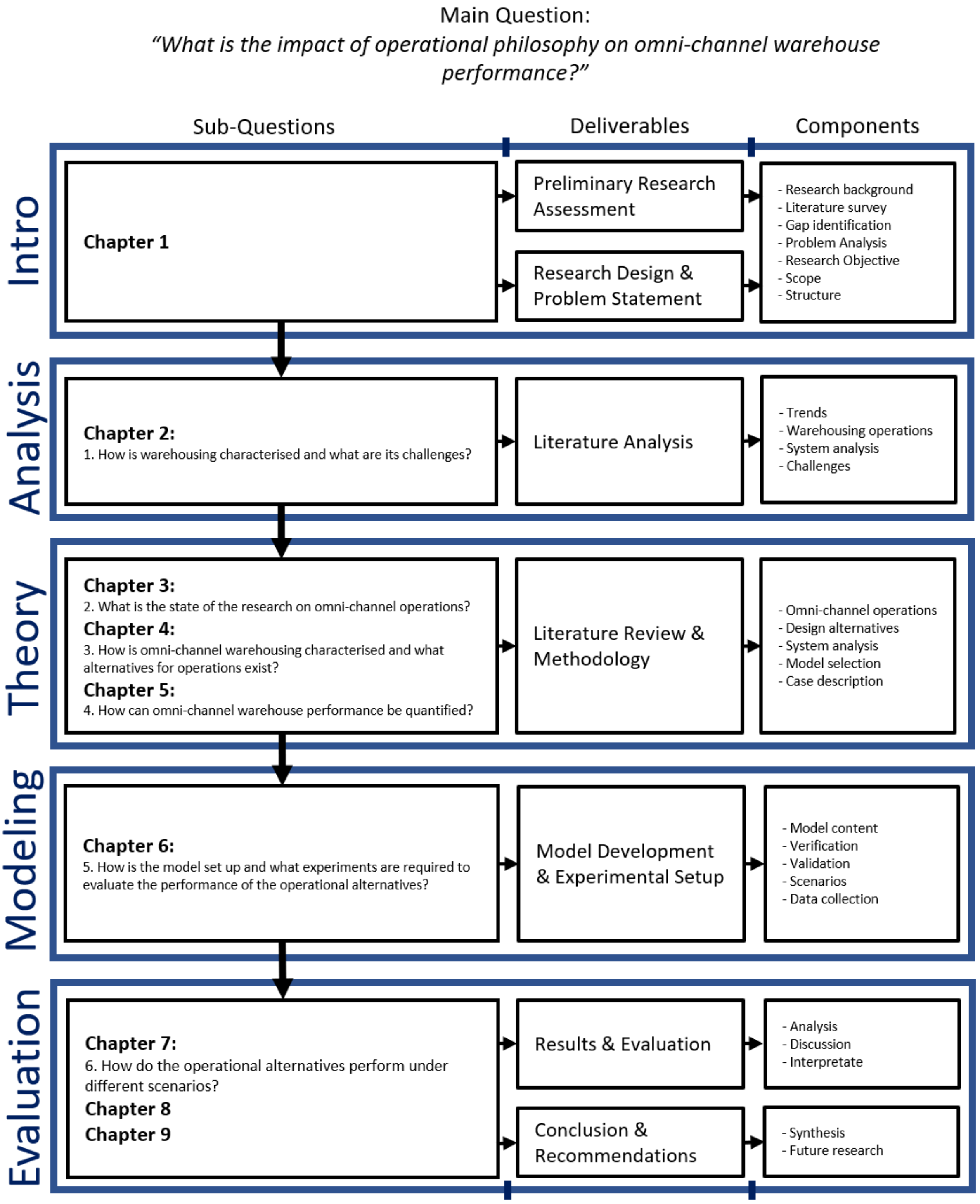


Figure 1.1: Research approach

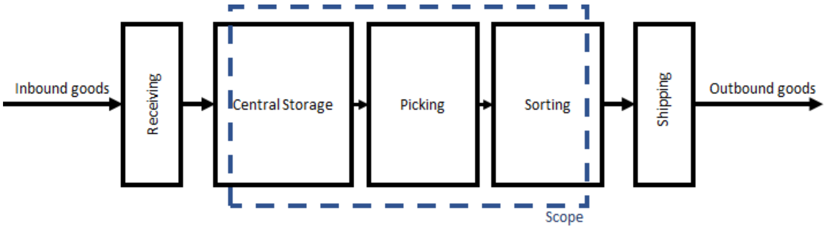


Figure 1.2: Research scope

II

Analysis

2

Warehousing

In this chapter, the current trends surrounding warehousing are discussed. With these trends, the call for efficient omni-channel warehouses can be explained. Furthermore, in this chapter, an analysis is performed to establish the current way of operating for warehouses. Through the analysis the important elements for warehouse operations design are identified, which can be used as building blocks for the omni-channel operations. Also, the inherent challenges for warehousing are presented. At the end of this chapter the first two research questions will have been answered, being: 'How is warehousing characterised and what are its challenges?'.

2.1. Trends

To understand the need for suppliers to introduce a direct channel into their warehouse operations, it is necessary to have a look at the retailing market trends. The retailing market has changed significantly in the last 20 years due to the increasing availability of the internet. Before the internet was widely available for consumers, the brick-and-mortar stores were the dominant form of commerce (Kerick, 2019). The brick-and-mortar store, refers to a physical store. Although brick-and-mortar stores still exist, they are quickly being replaced by online e-commerce stores. Moreover, for traditional suppliers the e-commerce trend has been identified as the biggest potential for growth (Roger et al., 2015).

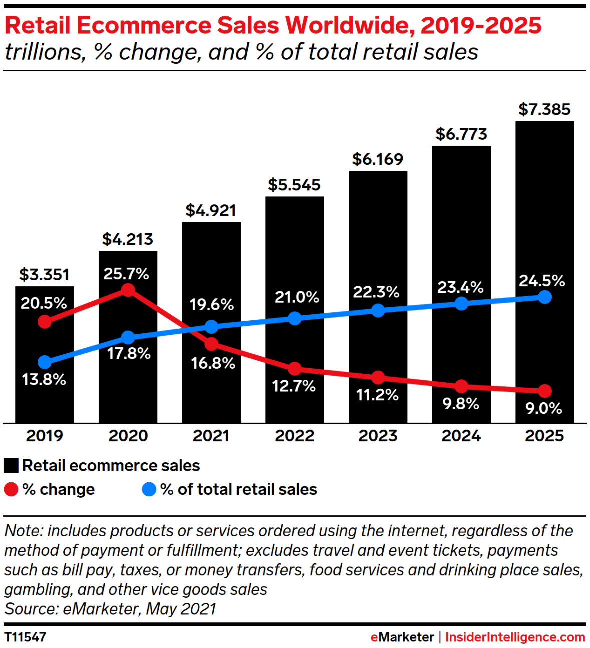
This rise in e-commerce is accelerated by the rise in use of mobile devices and online payment options. Furthermore, the online channel can offer excellent user experience, consider the 24 hour accessibility, order from home, and fast and cheap delivery benefits. Moreover, the consumer data can be used to provide product suggestions, thereby making the consumer spend more.

The number of e-commerce retail sales has not reached its peak yet. According to Lebow (2021), the e-commerce sales are forecast to grow with double digits through 2023. Furthermore, the impact of the corona pandemic has made the e-commerce market grow even faster, since people had to stay inside and physical stores had to close (Lund et al., 2021). A depiction of the growth of e-commerce can be seen in figure 2.1.

Another aspect that is relevant for traditional suppliers is the increase in market share of e-commerce versus the sales through the brick-and-mortar channel. This trend is indicated by the blue line in figure 2.1. It indicates that the online channel consumes part of the sales that would previously have been performed through the brick-and-mortar channel. Thus traditional suppliers miss out on sales when not offering their product online. Rigby (2011) even goes as far as stating that digital retail represents a major crisis for traditional suppliers. But when implemented correctly, the digital and physical arenas complement each other, with reduced cost and increased sales as a result.

The trend in warehousing research shows resemblance with the rise in e-commerce retail sales. The number of published papers on warehousing can be seen in figure 2.2. An explanation for the increase in warehousing research, can be the increased demand on the logistical chain as consequence of the different nature of online orders versus the store orders.

E-commerce requires new research, because the operations required for efficient processing of orders, are different than for traditional warehouses. The difference in operations originates from the different nature of the orders between the two sales channels. To name a few aspects: the order


Retail Ecommerce Sales Worldwide, 2019-2025

trillions, % change, and % of total retail sales

Note: includes products or services ordered using the internet, regardless of the method of payment or fulfillment; excludes travel and event tickets, payments such as bill pay, taxes, or money transfers, food services and drinking place sales, gambling, and other vice goods sales
Source: eMarketer, May 2021

T11547 eMarketer | InsiderIntelligence.com

Figure 2.1: Retail e-commerce sales and forecast worldwide (Lebow, 2021)

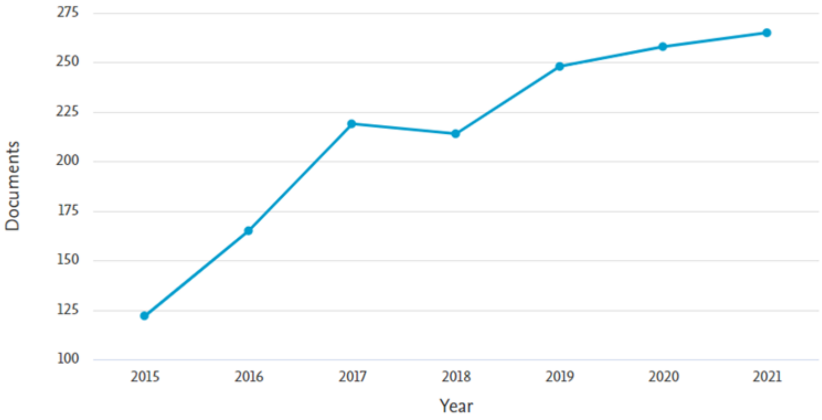


Figure 2.2: Number of published papers on warehousing from 2015 to 2021 (Scopus, 2022)

arrival times, order sizes, short deadlines, order picking and product characteristics differ enormously with traditional store orders (Alawneh and Zhang, 2018, Hübner et al., 2015). Where order times of retailers are fixed, for online customers they are not. Where a fixed number of retailers order in large batches, destined for one location, the online orders are multifold and of small proportions, with varying destinations (Le-Duc and De Koster, 2007, Leung et al., 2018).

Combined with lower processing times and greater service customization the impact on the warehousing system is tremendous (Hu and Chang, 2010). In addition, efficient operations become more important as more packages need to be handled and customers have higher expectations (Tarn et al., 2003).

2.2. Warehouse Performance & Operations

Warehousing operations depend on the type of warehouse that is considered. The type of the warehouse is defined by the role it has in the supply chain. In general a warehouse fulfills one of two functions, being a distribution function or a storage function (Rouwenhorst et al., 2000). The storage functionality of a warehouse is often seen at a production line, where products need to be stored that are required for production processes. Both type of warehouses come with their own characteristics and performance indicators.

For a distribution warehouse the number of products is often large, with small quantities per order line, resulting in a costly and complex order picking process (Rouwenhorst et al., 2000). For this type of warehouse the cost efficient order picking is the main optimization goal. The required short response time makes the throughput a prominent design criterion, while regarding the required investment and operational cost.

The characteristics for a production warehouse differ from the distribution warehouse characteristics in that its main function is to store raw materials, work-in-process and finished products, possibly for long time periods. This storage is usually done in large quantities, in order to make the storage cost efficient (Rouwenhorst et al., 2000). For this type of warehouse the storage capacity is a prominent design criterion, again, while regarding the investment and operational cost.

As an introduction to warehousing operations and to understand warehouse design decisions, an overview is presented of the main relevant operation differentiators for traditional warehousing. From this, the key operating principles and parameters will become apparent, which serves as a solid base to consider the more complex omni-channel operations. It is important to note that the different operations within the overall design, influence each other, so no choice for operations type stands on its own. Therefore, the operation descriptions mentioned in this chapter are overlapping. The subjects discussed in this section all consider the warehouse process flow, which form the most important decisions in the warehouse design stage (Rouwenhorst et al., 2000). The warehouse flow can consist of stages like receiving, storage, forward/reserve replenishment, order picking, sorting and shipment.

For a more extensive review of models concerning the design and control of warehouse operations see De Koster et al. (2007) and Gu et al. (2007). In this section only the main operating differentiators are briefly discussed, the most relevant for this research are discussed more elaborate.

2.2.1. Inventory

The operations concerning the inventory can be setup in multiple ways, depending on the specific requirements for the warehouse and products. A common practice for inventory operations is to create a physical separate area for picking high-demand, fast moving products (Gu et al., 2007). Such an area is called a fast-pick area, or forward storage. The main storage is then called the reserve storage. The forward area is also referred to as a warehouse within the warehouse (Bartholdi and Hackman, 2019). In some cases products are only stored in the forward area, for example when the demand quantities are high or if the demand frequencies are low (De Koster et al., 2007).

Within the reserve storage, the products are stored in the most economical way, for example with pallet racks. While in the forward area the products are stored for easy retrieval, in smaller amounts, for example on shelves (Rouwenhorst et al., 2000). Another example of the forward pick area is the ground floor of pallet rack. The popular products can be picked from ground level and replenished by dropping overstock pallets from above (Bartholdi and Hackman, 2019). This does require more space due to the less efficient storage, however it does reduce the order-picking cost and it provides increased responsiveness to customer demand (Bartholdi and Hackman, 2019, Gu et al., 2007).

The presence of a forward area introduces additional material handling in the sense of required restocking of the forward area from the reserve area. This extra step is called a replenishment (Rouwenhorst et al., 2000). Furthermore, a company has to consider which products to store in the forward area and in what quantity, due to the limited amount of available space (Gu et al., 2007). Another constraint that needs to be considered is the, often restricted, time at which replenishment can take place, due to order picking activities (De Koster et al., 2007).

In this research a class based storage policy is assumed. This policy allocates zones to specific product groups, often based upon turnover rates (Rouwenhorst et al., 2000). In this way pick travel distances can be reduced and space can be utilized more efficient because of the random storage allocation within a class. Other storage policies include dedicated, random and correlated storage. Dedicated storage prescribes a location for each product, with the advantage of pickers becoming familiar with the layout. The disadvantage is that a location is reserved for products that are out of stock. Random storage leaves the decision for product location to the operator, with the benefit of high space utilization. The downside is the increased picking distances and a computer controlled environment in required (De Koster et al., 2007). With a correlated storage policy, products that are often required simultaneously are stored in nearby positions. The advantage of this storage policy is that it reduces picking travel times, but space utilization is not optimal and the storage decisions are more complex.

The choice for inventory policy influences the rest of the operations. For example the choice for an forward storage area influences the way the orders have to be picked.

2.2.2. Order picking

Order picking operations can be organized in multiple ways as well. A lot of research has been performed in the area of order-picking in warehouses. Order picking is considered the operation which makes up the biggest part of the warehouse operating cost (Agatz et al., 2008), therefore a lot of research has been performed in optimizing this activity.

In general two types of order picking systems can be distinguished, being a picker-to-parts system and a parts-to-picker system (De Koster et al., 2007). The picker-to-parts system are not automated, here the picker drives or walks along the aisles to pick the products. The parts-to-pickers systems, on the other hand, rely heavily on automation, such as automated storage and retrieval systems (AS/RS). In this research solely the picker-to-parts systems are considered because in practice automation does not play a big role for picking processes (Hübner et al., 2015, Petersen II, 2000). Furthermore, the considered throughput and required flexibility and scalability do not justify the use of an automated system.

The order-picking itself can be performed order by order, this is called discrete picking, or it can be performed through picking by article, known as batch picking (De Koster et al., 2007). In the latter case, a batch of customer orders are picked simultaneously by one order picker. The sorting of the orders can be done while picking, on a cart with multiple slots, or after the pick process. The advantage of batch picking is that it reduces the mean travel time per pick. However, it does require an extra sorting step (Van den Berg and Zijm, 1999).

Zoning can be applied to order-picking as well, besides applying it to inventory placement. With order-picking it refers to dedicating a order picker to a specific zone in the warehouse. With this order-picking type multiple order pickers can work on the same order at the same time in different zones (parallel) or an order can be passed from a picker to another picker in another zone for remainder of the products (sequential) (Rouwenhorst et al., 2000). Advantages of zone picking are, the short travel distances for a picker, and the picker is more familiar with where the products are. Furthermore, the reduced picking time for parallel picking is an advantage. Zoning has disadvantages as well, such as the additional cost for sorting in parallel zone picking, and the additional cost due to queuing in sequential zone picking (Gu et al., 2007).

Zoning can be applied in a pallet storage area, but also throughout entire warehouse. Also, the zones do not have to be physically separated (De Koster et al., 2007). Zones can be separated by order types or separated by turnover rate of the products, for example.

Then there is also the wave picking strategy. This is popular when batching and zoning are both applied (Van den Berg and Zijm, 1999). With this strategy all order pickers start picking in a zone at the same time, when all pickers are done the next wave starts. This strategy can be useful when a batch of orders have a common destination (De Koster et al., 2007).

Besides using a picker to move a product to an order consolidation location, a conveyor can be used to transport the picked products. The conveyor is placed within the aisle, in order for the picker to directly deposit the product on the conveyor. This operation is referred to as pick-to-belt (Van den Berg and Zijm, 1999).

The picking of less-than-carton quantities is an important operation to consider when designing the warehouse flows, because it is the most labor-intensive order-picking process (Bartholdi and Hackman, 2019). This process is also referred to as split-case or broken-case picking. For this type of picking, the smallest units of measure are considered and these units often differ in size, which makes this process difficult to automate. The flow of less-than-pallet picks should be considered as well, even when a forward storage is present.

Again, for a more detailed description of the picking processes the author refers to the works of De Koster et al. (2007) and Gu et al. (2007).

2.2.3. Sorting

The sorting processes are highly dependant of the pick processes. When a batch picking policy is selected, it directly implies that a sorting step has to be performed (Rouwenhorst et al., 2000). This would not be necessary when a discrete picking strategy is applied. With batch picking the sorting can be performed while picking and it can be done after each product has been picked. This also applies to the zone picking strategies. The sort-while-pick strategy can be modeled by inflating the item extraction time. The order-picking cart must be equipped with separate bins for individual orders to facilitate the sort-while-pick strategy (Van den Berg and Zijm, 1999). For sort-after-pick, a separate sorting step has to be performed downstream (Gu et al., 2007).

Such a sorting step is also referred to as accumulation/sorting (A/S), and is often required when picking zones are implemented. When items from the same order are assigned to multiple order pickers, to maintain high order picker efficiency, the items can be placed on a transportation conveyor and the items are transported to the sorter. Items can circulate the conveyor and enter a shipping lane when all items of the order are picked. A depiction of such a system can be seen in figure 2.3.

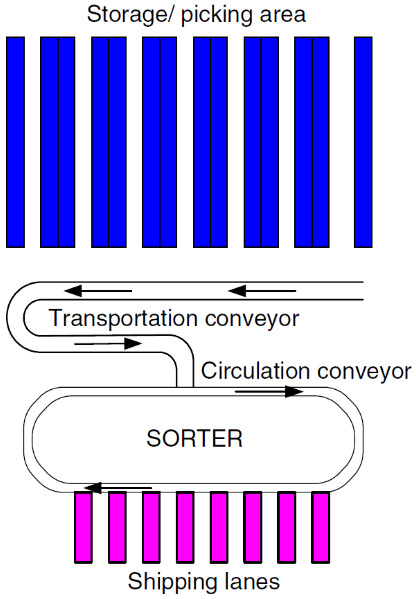


Figure 2.3: A typical A/S system (De Koster et al., 2007)

2.3. System Analysis Typical Warehouse

The warehousing operations described above can be seen back in figure 2.4, which is a depiction of all the flows that can be present in a typical warehouse. The operations surrounding inventory are present within the reserve storage processes. For this process flow overview, only the products are taken as inputs and no distinction is being made whether the warehouse processes web-orders or store-orders.

To better indicate the difference between operations required for web and store orders, depictions of the warehouse flows are made for both operation types. These process flow figures do consider the difference in input, whether the orders are coming from stores or from online customers. The depictions can be seen in figure 2.5.

As can be seen in figures 2.5a and 2.5b, the processes required for store and web orders, differ. The main difference is the requirement for web order handling, to be able to handle single items, rather than cases. Therefore, web order fulfillment requires a location where cases can be opened and the pieces can be set aside for their respective orders.

The figures indicate the required processes for fulfillment of the respective order types, in the black boxes. Since the receiving and shipping processes are out of scope, the system boundary that is relevant for this research is drawn around the storage and picking processes. For effective omni-channel

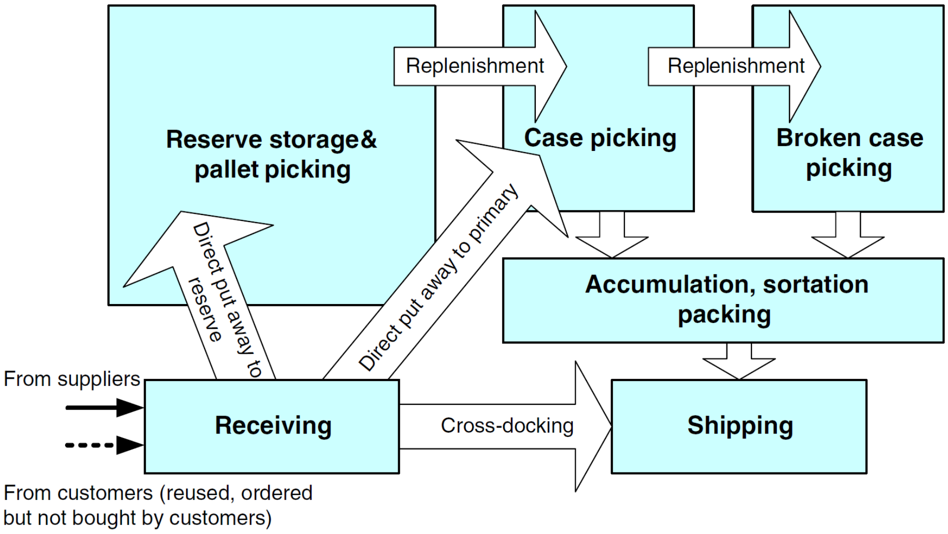


Figure 2.4: Typical warehouse functions and flows (Tompkins et al., 2010)

integration in a warehouse these two differing process flows, need to be combined. The challenges this brings are further discussed in section 2.4.

2.4. Challenges for Warehousing

The warehouse operations discussed above show the interdependencies of the different processes. Therefore, changing the requirements of the warehouse operations, can have a significant effect on every process in the entire warehouse, let alone the layout. To facilitate the need for suppliers to introduce a direct channel into their warehouse operations, as discussed in section 2.1, it is required for the warehouse to be able to handle different type of requirements. This requirement of suppliers does not only come from studying the retailing trends, the trend is identified through industry practice as well. RHDHV provides an use-case, where exactly this challenge is faced by a client. The use-case is further elaborated in section 5.

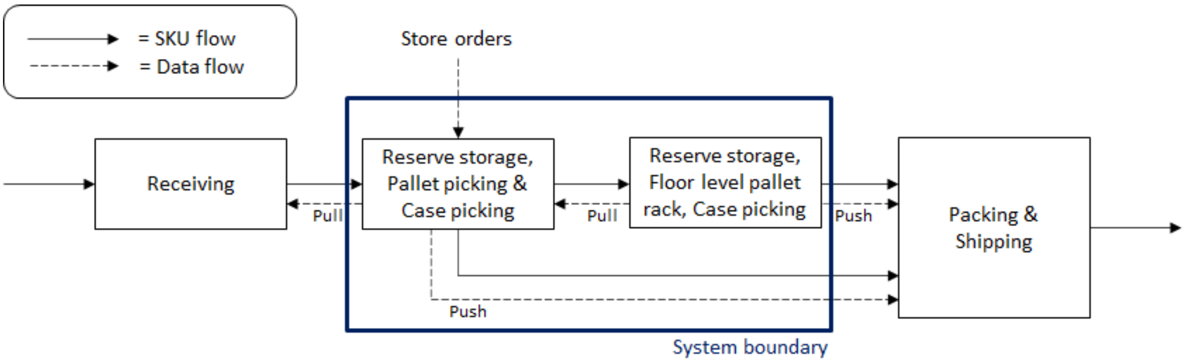
The warehouse integration for different type of operations, introduce significant challenges, as the characteristics of the direct online channel-order and the traditional retail-order differ enormously. The difference in order type brings different requirements for the warehouse operations, this is challenging to implement because processes are best suited to cater to one particular order type. The different characteristics of the order types are summarized by Leung et al. (2018) and depicted in table 2.1.

Table 2.1: Comparison between brick-and-mortar orders and e-commerce orders (adapted from Leung et al. (2018))

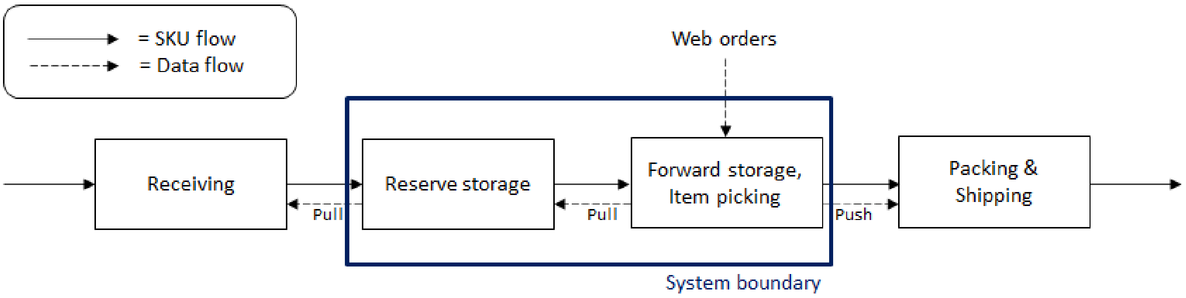
Order characteristics	Traditional store channel	Online channel
Order arrival	Regular	Irregular
Order nature	Mostly stock replenishment	Fragmented, discrete
Size per order	In bulk	In small lot-sizes
SKUs involved in each order	Very few or even identical	Many
Number of orders	Less, relatively easy to predict	More and unlimited, relatively difficult to predict
Time availability for fulfillment	Less tight	Very tight
Delivery schedule	Relatively more time buffer	Next-day or even same-day delivery

While combining fulfillment of both order types in one warehouse comes with benefits, it will require design adjustments to make these warehouses fit for efficient order picking (Agatz et al., 2008). The online channel is characterised by a large volume of small orders, single unit picking and packing, unpredictable order arrival times and short delivery lead times (Alawneh and Zhang, 2018). According to Hübner et al. (2015), most of the time the online order size is less than or equal to three items.

The required operations for the online channel have to be combined with the conventional warehouse operations for large orders, fixed order arrival times and packing on pallets. Often the warehouse



(a) Simplified warehouse flows for store-supplying warehouse



(b) Simplified warehouse flows for online customer-supplying warehouse

Figure 2.5: Typical warehouse system analysis

can be made ideal for store orders by adapting the picking sequence, to follow the shelf configuration of a standardized store. Unfortunately this layout rarely meets an online order composition (Hübner et al., 2015).

Online retailers often have a larger assortment because no costly storage space in stores is required, while the products are accessible to a broad public (Boysen et al., 2019). Furthermore, an important promise for online shops is the next-day delivery, introducing highly time critical order fulfillment processes. Another aspect that differentiates the online orders from traditional store orders, is the varying workloads due to the volatile demand of seasonal online orders. Conventional warehouses have difficulties meeting these requirements (Boysen et al., 2019, Hübner et al., 2015, Roger et al., 2015).

Current attempts to face these challenges have resulted in companies using bolted-on systems and processes, without considering efficient integration with existing operations (Roger et al., 2015). While integration of processes is necessary for cost efficient dual-channel implementation (Hübner et al., 2016a). Therefore, traditional suppliers can not function properly when consolidating different order types without adaptation of their warehouse (Alawneh and Zhang, 2018).

2.5. Conclusion

This section concludes the analysis phase of the research. First the trends surrounding warehousing have been discovered. From the trends the need for suppliers to introduce a direct channel into their warehouse operations becomes apparent. It has been established that the interest in omni-channel warehousing partly comes from the rising trend of e-commerce. Where e-commerce is being seen as providing the biggest potential for growth in retailing. Also, the implementation of multiple channels brings benefits like a larger market coverage, increased loyalty and increased profits.

Subsequently, the main warehousing types and operations are identified for traditional warehouses, in order to get an understanding of how a warehouse is characterized. It is shown that different warehousing types have different operational requirements and performance indicators. For a distribution warehouse the cost efficient order picking and throughput are relevant criteria, while for a production warehouse the storage capacity is most relevant.

Furthermore, the different operations required in a warehouse are discussed. The inventory, order picking and sorting processes have been identified as being relevant operation differentiators for warehouse process design. It is shown that no choice for an operation process stands on its own, since the operations influence each other.

To visualize the required warehousing processes and to indicate the differences for store order fulfillment and web order fulfillment, a system analysis is performed. The resulting black box process figures show the differences.

Lastly the challenges are identified. The interdependency of the processes, form a challenge when requirements of multiple order types are introduced. This challenge has to be overcome by traditional suppliers to follow the trend of introducing a direct order channel into an existing warehouse. The characteristics of traditional store orders and e-commerce orders are very different, as shown in figure 2.1. Difference in characteristics are: the order arrival times, order sizes, short deadlines, order picking and product characteristics. To combine the different order types efficiently, adaptation of traditional warehouses is required.

To summarize, the answer to the first sub-question ’How is warehousing characterised and what are its challenges?’, boils down to:

1. There is a need for efficient omni-channel warehouses
2. For a distribution warehouse throughput and cost efficient order picking are important
3. Key operating principles are inventory management, order picking and sorting, which are all interdependent
4. Different order types require different operations
5. Integrating operations for different order types in a warehouse is complex

III

Theory

3

Omni-Channel Literature

In this chapter an overview of literature concerning omni-channel warehousing and supply chains is given. First, the methodology for the literature review is discussed. Subsequently, the existing works on omni-channel warehousing are classified in order to get an understanding of the already performed research and to indicate the space this research occupies. Lastly, the insights on the state of the research field are shared, in section Results. Thereafter, in the conclusions, the second sub question is answered, being: 'What is the state of the research on omni-channel operations?'.

3.1. Method

To find relevant literature the web has been searched extensively. For the search, four databases have been used, Scholar, Scopus, Web of Science and the TU Delft repository, respectively. These databases were searched for a period of five weeks.

The used search query is as follows: warehous* AND (dualchannel OR omnichannel OR cross-channel OR multichannel OR dual-channel OR cross-channel OR omni-channel OR multi-channel OR "Retail/E-tail" OR e-fulfillment). A match with the search query was searched in the title, abstract and keywords of the papers. From the resulting papers, the abstracts were screened. When an abstract proved to be relevant for the research, the whole text was screened. When the paper still seemed relevant, the paper was included in the literature review.

For a paper to be relevant it had to meet a few criteria. The focus of the paper could not be on a production or manufacturing warehouse, nor a warehouse for groceries. Furthermore, data warehousing and networks considering e-fulfillment through stores, were excluded. No criteria was set on the date of publishing since the research field is young and all resulting papers were published after the year 2000.

To broaden the search for a more complete outlook on the research field, the references of review papers were screened. From these references, the papers matching the relevancy criteria were included, as well as papers which have made an impact (>500 citations), while not meeting all the criteria. For example papers have been selected on supply chain network design and papers considering general warehousing.

3.2. Classification

In table 3.1, an overview is given of the performed research in the omni-channel warehousing field. The table is used to classify and differentiate the works, and to indicate the research space this paper occupies. Some papers are included in the overview which have not been mentioned in this research, that is because these papers have been used to get an understanding of the research field, but have not been deemed relevant for this research because they were mostly on network designs or did not consider omni-channel operations.

The papers have been classified according to the following criteria: inclusion of omni-channel strategy, design focus, decision level, research type and whether the papers perform a case study. When the papers consider a multi-, dual- or omni-channel strategy, they are given the 'Omni-channel' check mark. The design focus has been split into the categories 'Warehouse' and 'Network'. The classification category 'Type' indicates whether the research is quantitative or qualitative.

The decision level category has been split up in three levels, being ’Strategic’, ’Tactical’ and ’Operations’. This has been done similar to the theory of Rouwenhorst et al. (2000), who splits warehouse design decision into these three categories, while mentioning that, obviously, most decisions are interrelated. The author believes this subdivision adequately describes the relevant levels for omni-channel warehouse design as well.

According to Rouwenhorst et al. (2000), the strategic design decision level concerns the process flows, level of automation and selection of basic storage and sorting systems. These decision have a long term impact and mostly concern high investments.

The tactical level is aimed at the warehouse systems dimensions and the layout design. These decisions are medium term and follow from the strategic decisions. Zoning and number of equipment are examples of tactical decisions.

Finally, the operational level concerns detailed control policies. This includes assignment and control problems of people and equipment, think of personnel routing and actual batch formation. Again, most decisions are interrelated (Rouwenhorst et al., 2000).

Table 3.1: Categorisation of Omni-Channel Warehousing Literature

				Level				
Reference	Focus	Omni-channel	Design	S	T	O	Type	Case
Alawneh and Zhang (2018)	Inventory policy for two-stage dual-channel warehouse	√	WH	√		√	QN	
Alptekinoğlu and Tang (2005)	Model for pooling at depots or stores		NW	√	√		QN	
Bartholdi III and Hackman (2008)	Optimal assignment of stock to forward picking		WH			√	QN	
Bartholdi and Hackman (2019)	Develop methodology to optimize warehouse operations		WH	√	√	√	QN	
Boyaci (2005)	Stocking decisions for manufacturer and retailer	√	NW		√		QN	
Bressolles and Lang (2019)	E-fulfillment economic performance and questionnaire	√	NW	√			QL	
Bretthauer et al. (2010)	Inventory and locations to handle online sales	√	NW		√	√	QN	
Brynjolfsson et al. (2013)	Cross-channel competition and influence of IT	√	NW	√			QL	√
Chiang and Monahan (2005)	Two-echelon dual-channel inventory model	√	NW		√	√	QN	
Chiang et al. (2003)	Game theory pricing model for manufacturer and retailer	√	NW	√			QN	
De Koster (2003)	Distribution strategies survey	√	NW	√			QL	
Dumrongsiri et al. (2008)	Game theory pricing model for manufacturer and retailer	√	NW		√		QN	
Gu et al. (2007)	Description of warehouse design and operation problems		WH		√	√	QL	
Gu et al. (2010)	Warehouse design, operation strategies and performance evaluation		WH		√	√	QL	

Continued on next page

Design: WH (Warehouse), NW (Network)
Level: S (Strategic), T (Tactical), O (Operations)
Type: QN (Quantitative), QL (Qualitative)

Table 3.1 – continued from previous page

				Level				
Reference	Focus	Omni-channel	Design	S	T	O	Type	Case
Heeswijk (2021)	Identify challenges with transition to omni-channel retailing through interviews	√	NW	√			QL	√
Heragu et al. (2005)	Determine product warehouse allocation and area sizing		WH		√		QN	
Hübner et al. (2015)	Structures, processes and interrelations in multi-channel warehouse operations	√	WH, NW	√	√	√	QL	
Hübner et al. (2016a)	Framework of the distribution concepts in omni-channel retailing	√	NW	√	√		QL	
Hübner et al. (2016b)	Survey on what companies run what strategies	√	NW	√	√		QL	
Ishfaq et al. (2016)	Interviews on realignment of omni-channel distribution processes	√	NW	√			QN	
Kembro and Norrman (2019)	Contextual factors influencing omni-channel warehouse design	√	WH		√	√	QL	√
Kembro and Norrman (2020)	Explore how retailers with multiple strategic challenges prioritize and balance these	√	NW	√			QL	
Leung et al. (2018)	E-fulfilment pre-processing system for batching		NW			√	QN	√
Mahar and Wright (2009)	Postponement in fulfillment assignment decision	√	NW		√		QN	
Marchet et al. (2018)	Survey how companies set logistics variables in omni-channel strategy	√	NW	√			QL	
Petersen II (2000)	Simulation model to investigate picking policies		WH	√	√		QN	
Piotrowicz and Cuthbertson (2014)	Focus group discussions on the role of IT in retail	√	NW	√			QL	
Rigby (2011)	Challenges for bringing digital and physical retailing together	√	NW	√			QL	
Roger et al. (2015)	Survey on requirements for re-engineering the omni-channel supply chain	√	NW	√			QL	
Russell and Meller (2003)	Decisions to automate e-fulfillment sorting process		WH		√	√	QN	
Song et al. (2019)	Relationships between logistics integration, supply chain integration, and performance	√	NW	√			QN	
Steinfield et al. (2002)	Framework of integrating e-commerce with physical infrastructures synergies	√	NW	√			QL	√
Tarn et al. (2003)	Description of e-fulfillment process		NW	√		√	QL	

Continued on next page

Design: WH (Warehouse), NW (Network)
Level: S (Strategic), T (Tactical), O (Operations)
Type: QN (Quantitative), QL (Qualitative)

Table 3.1 – continued from previous page

Reference	Focus	Omni-channel	Design	Level S	Level T	Level O	Type	Case
Tielbeek (2015)	Effect of inventory allocation strategies on performance	√	NW			√	QN	√
Van den Berg and Zijm (1999)	Classification of warehouse management problems and models		WH		√	√	QN	
Verhoef et al. (2015)	Discussing the move from multi- to omni-channel retailing and the research streams	√	NW	√			QL	
Zhang et al. (2010)	Synthesize knowledge on issues multi-channel retailing	√	NW	√			QL	
This paper	Operations Design for Omni-Channel Warehouse Integration	√	WH	√	√		QN	√

Design: WH (Warehouse), NW (Network)
Level: S (Strategic), T (Tactical), O (Operations)
Type: QN (Quantitative), QL (Qualitative)

3.3. Results

From the literature classification it can be seen that Alawneh and Zhang (2018) is the only work which considers the omni-channel warehousing operations in a quantitative way. Notice, most of the papers that do consider omni-channel warehousing are either qualitative studies or have a focus on the network design of the supply chain. This observation confirms the identified gap mentioned in the background, in chapter 1.

Alawneh and Zhang (2018), conclude after an extensive literature review, there is a lack of research into warehouse structures and operations in the omni-channel context. Only a little amount of works exist that consider a mathematical inventory model for omni-channel supply chains and although warehouse operations have been addressed for traditional single-channel warehouses, it has not been addressed in the omni-channel context. In their work, Alawneh and Zhang (2018) develop an inventory model for an omni-channel warehouse which considers capacity constraints, and demand and lead time uncertainties. The considered warehouse is divided into an area for online order fulfillment and an area for storing products and fulfilling offline orders. With the model the optimal inventory policy for a omni-channel warehouse can be considered.

Because the work of Alawneh and Zhang (2018), solely focuses on inventory policy models, the gap still remains for quantitative research into the flow of warehousing operations in an omni-channel warehouse. Therefore, the space this paper occupies is the quantitative research into omni-channel warehousing operation performance, with a focus on order-picking strategies, since these operations form a big part of the warehouse flow. This research will investigate, on a strategic and tactical level, the implications of an operational philosophy on the warehouse performance. Therefore, detailed warehouse design is not considered.

3.4. Conclusion

To conclude the overview of the existing literature, the main findings are summarized and research sub questions two is answered, being: 'What is the state of the research on omni-channel operations?'.

To answer the question, a methodical literature review has been performed, making use of multiple databases. Subsequently, the papers that are found to be relevant, are categorized for a clearer view on the research field. The classification showed little quantitative works exist on omni-channel warehousing. Therefore the gap on structures and operations in the omni-channel context, still remains. The space this paper occupies, aims to fill this gap by quantitative research, on a strategic and tactical level, on the implications of operational philosophy on the warehouse performance.

4

Omni-Channel Warehousing

This chapter forms the second part of the theory section, and introduces the omni-channel concepts found in literature. First an introduction to omni-channel warehousing is presented, where the beginnings of the concept are discussed. Subsequently, the ways in which omni-channel warehousing can be implemented in the supply chain is considered, along with multiple alternatives for implementing the required complex operations in a warehouse. For every alternative a system analysis is presented. Lastly, this chapter is concluded by stating the answer to the third research sub-question, 'How is omni-channel warehousing characterised and what alternatives for operations exist?'.

4.1. Omni-Channel Introduction

The emergence of omni-channel retailing started with the introduction of dual-channel retailing. Dual-channel firms gained a competitive advantage by the expansion of internet use and the advancements in information and manufacturing technologies (Alawneh and Zhang, 2018). A dual-channel strategy meant adding an online direct channel to an existing offline store channel, a depiction which clearly indicates the addition of the channel to the existing infrastructure is presented in figure 4.1. The figure describes online order fulfillment by a third party, 'third-party logistics' (3PL).

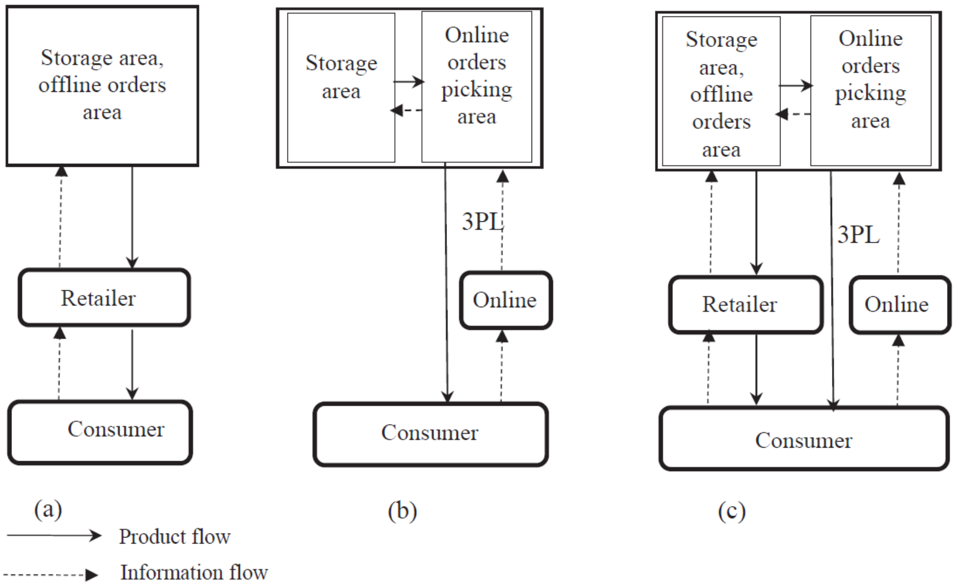


Figure 4.1: (a)–(b) Single-channel warehouses and (c) dual-channel warehouse (Alawneh and Zhang, 2018)

Chiang et al. (2003) introduced the dual-channel as a way to boost profits, even if no sales occurred in the online channel, which in those years sometimes was the case. However, in the early stages of dual-channel operations, there was resistance from retailers against the introduction of a direct channel between the supplier and the customer. The direct channel influences the number of customers going to the physical stores. Agatz et al. (2008) states that an additional distribution channel can partly cannibalize the sales of existing channels, rather than growing total sales, decreasing profits for the retailers. This led to conflicts and hostility, which were inevitable and manufacturers had to find a way to manage the conflicts. Some manufacturers even had to abandon the direct channel concept (Boyaci, 2005). Eventually the supply chains had to react in order to meet the change in consumer expectation (Dumrongsiri et al., 2008). Besides suppliers entering the world of e-commerce, pure online retailers opened physical stores, contributing to the increase of dual-channel supply chains (Agatz et al., 2008).

When considering the direct marketing channel (like catalogs), beside the offline store and web store, one can speak of multi-channel retailing. The multiple channel supply chain is now considered to be the dominant business model for the retail sector (Agatz et al., 2008, Bretthauer et al., 2010, Hübner et al., 2015). The growth of the multi-channel strategy should be considered from the perspective that this has mainly been driven by the growth of the online channel (Verhoef et al., 2015).

The multiple channel supply chain has become the dominant business model because computational outcomes indicate that the dual-channel strategy outperforms the conventional strategies in most cases. Furthermore, by making use of multiple sales channels, new buyers can be reached, increasing market coverage. This in turn, helps companies to increase customer awareness and loyalty to their products (Chiang and Monahan, 2005).

In the past ten years the omni-channel strategy has been initiated with the integration of mobile and social channels in online and offline retailing (Verhoef et al., 2015). The omni-channel term was first academically used by Rigby (2011), where he defines it as a customer sales experience which takes both advantage of physical and online touch-points jointly (Heeswijk, 2021). Therefore the definition of omni-channel is based on the customer's viewpoint (Hübner et al., 2016a). The omni-channel term reflects the fact that customers can interact with retailers through an array of channels, like mail, stores, social media, television, gaming consoles and mobile devices (Rigby, 2011). The omni-channel strategy thus involves more channels with blurred boundaries between them, emphasising the interplay between them (Verhoef et al., 2015).

The definitions surrounding multiple channel retail strategies are not well defined. This leads to the the interchangeable use of terms like dual-channel, multi-channel, cross-channel and omni-channel without clear distinction (Hübner et al., 2016a). The omni-channel supply chain is the overarching term and most advanced concept.

4.2. Omni-Channel Implementation

An omni-channel strategy can be implemented in three ways, according to De Koster (2003) and Agatz et al. (2008). They describe 1): the order picking and delivery from local stores, 2): order picking at distribution centers which supply stores, and 3): order picking from dedicated direct-channel distribution centers. For the purpose of this research, only the latter two strategies are considered, since network design is out of scope. This is in line with what Hübner et al. (2016a) describe. Furthermore, a significant amount of research has already been performed considering the optimal strategy for e-fulfillment through stores.

Hübner et al. (2016a) describe a separated and an integrated strategy, and state that both strategies are equally common. The separated strategy entails setting up a separated e-fulfillment channel, that is separated warehouses and operations. In this way processes are simplified and order picking space is not constraint. With the integrated strategy, the e-commerce operations are integrated in the existing warehouse infrastructure. In this way the warehouse delivers to retail stores and directly to customers. Integrating an e-commerce department in the already existing infrastructure reduces initial investment, facility cost, and provides potential for inventory pooling (Hübner et al., 2016a, Steinfield et al., 2002). Moreover, the integrated strategy provides a higher coordination ability and flexibility (Alawneh and Zhang, 2018). However, it does mean more complex operations. In the following sections the opportunities and challenges of both strategies are further discussed.

4.2.1. Integrated omni-channel warehouse

The main advantage of an integrated warehouse strategy is the potential for inventory pooling (Hübner et al., 2015). The inventory of the online and offline channels can be balanced, reducing inventory levels and storage space, while increasing availability. This flexibility reduces cost as well, by decreasing duplicate storage and lost sales. Furthermore, no transshipment is required between warehouses for inventory adjustment, leading to fewer required product touches and contributing to the effect of economy of scale (Hübner et al., 2015). The reduced number of transshipments leads to a reduced CO2 footprint of the supply chain as well. Moreover, according to Alawneh and Zhang (2018), using a decentralized policy for all channels can result in inefficiency in many situations. Companies with separated distribution systems have difficulty developing an effective inventory policy to reach an optimal channel performance. Another benefit of an integrated warehouse, mentioned by Bartholdi and Hackman (2019), is the reduction of safety stock, which is required to protect against variability in the product flow. This benefit leads to smaller investments in stock and saving of warehouse space. Bartholdi and Hackman (2019) describe it as the integrated warehouse being smaller than the sum of its parts. Another benefit of integrated omni-channel warehouses is the possibility for constant capacity utilization (Hübner et al., 2015). When online orders cannibalize orders from the store channel, the throughput of the warehouse can remain roughly the same.

However, the required operations for cost efficient integrated processes are more complex, and so the gains from integrated inventories must outweigh the increased complexity, or the flows can be better separated into different warehouses (Kembro et al., 2018). The integrated warehouse requires extensive re-engineering of the operational processes. This complexity comes from channel-specific order sizes, delivery times and stocking layouts, which have to be considered simultaneously (Hübner et al., 2015).

4.2.2. Seperated omni-channel warehouse

As described above, an integrated warehousing strategy requires complex processes, resources and know-how for picking orders for both channels. Flexible systems are required to perform the picking of orders with a large variety. From this follows the biggest advantage of a separated warehousing strategy, the simple operations and processes required. Furthermore, no preconditions are required for the infrastructure and space is often less constrained. Without the space constraints there is a possibility of introducing new products to the online assortment. Another benefit of a separated supply chain strategy, is the reduced risk when setting up a new operation channel, because the new channel can have its own legal entity (Hübner et al., 2016a). Also, the online channel can be implemented quickly when not part of a long-term plan, but driven by dynamical online retail growth. Then the fast entry through outsourcing is a solution with relatively low risks and investments (Hübner et al., 2015).

Challenges for the separated omni-channel warehousing strategy are the cost associated with transshipment between storage locations. Furthermore the initial cost for setting up a separate warehouse can be an issue. In general, the opportunities for separated warehousing strategy are the challenges for the integrated strategy and vice versa.

According to De Koster (2003), an important determinant whether to choose for an integrated or a separated approach is the existing infrastructure of the company. When a company wants to start internet activities, the existing assets can be exploited. Furthermore, the complexity of the assortment is a differentiator when selecting omni-channel solutions. The assortment is simple when it has a small width of products and nonperishable and not fragile products. A simple assortment requires less complicated logistics and systems because products can be stored closer to one another with fewer moves required for the assembly of orders. Furthermore, a smaller range of handling procedures is required to handle all products, leading to fewer and simpler systems.

This research is aimed at already existing warehouses seeking to integrate operations for an online sales channel. Also, results from Hübner et al. (2016a) indicate that positive effects of integrated warehouses outweigh the challenges associated with added operational complexity.

4.3. Omni-Channel Operations Design Alternatives

Since an integrated warehouse is considered in this research the problem of complex integrated processes has to be overcome. While this challenge has been faced in industry before, no quantitative models have been used to compare the industry solutions. The industry practice can be used however, to derive feasible operational philosophies from. These design alternatives can be tested against each other for their performance to design efficient omni-channel warehouse processes. This section describes the practices found in literature.

Hübner et al. (2016b) performed an exploratory study among 60 internationally operating omni-channel suppliers in Germany and found three possible ways to integrate a omni-channel strategy, based on the level of integration for the inventory and picking processes with regard to the different order channels. First, Hübner et al. (2016b) describe the possibility for separated inventory and separated picking for the offline and online channels. Secondly, they describe a philosophy with integrated inventory and separated picking. And thirdly, a completely integrated method where inventory and picking for both channels is integrated. Their results indicate that the positive effects of integrating the inventories for the online and offline channel into one warehouse, outweigh the resulting complexities. Furthermore, they find that 6 out of 10 omni-channel retailers integrate the picking operation for both channels. From these retailers a quarter separates the channel picking activities with time slots. From the questioned omni-channel suppliers, 4 out of 5 confirmed a higher warehouse efficiency with a common pick zone. Concerning the inventory, all participants indicated the need for integration. Integrated inventory refers to managing the inventories for both order channels from one warehouse location, while integrated picking refers to picking in a common zone for both order channels.

Hübner et al. (2015) have investigated 33 European-based leading companies in omni-channel retailing, and found that nearly half of them separate the picking activities per order channel. They mention the leveraging of picking zones by rotation speed as a positive factor for integration, because it shortens the picking for both channels. Picking distance can be saved because slow-movers can be picked separately and fast-movers can be grouped within one area. Furthermore, they found that separate picking time slots per channel harmonizes processes. In this way the faster pickers with small order quantities are not overtaking or crossing the slower store-order pickers. With this strategy, store orders can serve as a buffer for the higher priority, shorter lead time web orders. Hübner et al. (2015) also state that a common picking zone is favored when separating picking by rotation speed zones and time slots.

Kembro and Norrman (2019), who explore warehouse configurations in omni-channel retailing by conducting case studies with six large omni-channel retailers, describe that the integration of inventory and picking, is step-wise. It starts with both processes separated, then separated inventories but common pick zones, and subsequently, the last step, integrated storage and picking. In case of integrated storage and picking, processes can still be separated in time. Kembro and Norrman (2019) also find the order picking for web orders is mostly in batches while single large volume orders for stores are picked using one or more pallets.

Concluding, from the literature on industry practice it becomes apparent that integrated inventories is desirable, this means inventories for the online and offline channels are present in one warehouse. However, multiple methods for the order-picking processes are implemented. The industry is divided almost 50/50 for whether to integrate or separate the picking for each order channel. Furthermore, when an integrated picking strategy is chosen, the processes can still be separated by product rotation-speed zones or by time slots.

Therefore, the first relevant warehouse operational philosophy to research, is a configuration where order-picking is physically separated per channel. Secondly, an operational philosophy where the pick zones are not physically separated, but the picking is zoned by product rotation speed, where store orders and web orders are picked simultaneously. Lastly, an alternative where the picking zones for both channels are equal, but picking is separated by time slots, is a relevant operational philosophy to compare. The operational philosophies are summarized in table 4.1.

Table 4.1: Design alternatives for omni-channel operations from literature

Operational Philosophy	Inventory	Picking
Alternative I	Integrated	Physically separated area, simultaneous for web and store orders
Alternative II	Integrated	Common area, zoned by rotation speed, simultaneous for web and store orders
Alternative III	Integrated	Common area, time slot separation for web and store orders

Note: Integrated inventory refers to managing the inventories for both order channels from one warehouse location

4.4. System Analysis of the Omni-Channel Design Alternatives

This section provides the system analysis of the three alternative operational philosophies found in literature. By comparing the three alternatives with each other, the impact of the operational philosophy on the performance of the processes can be identified. For each alternative it is indicated how it changes the typical system, as analysed in section 2.3. Also for each operational philosophy a schematic layout is presented to give a rough idea of the effects the operational philosophy has on the flow of SKUs. The black boxes in the figures represent the process steps required for fulfillment of orders from two different types. The system boundary indicates which processes are considered within this research, as the receiving and shipping stages are out of scope.

4.4.1. Alternative I: physically separated web-order picking

This operational philosophy features a physical separation of picking zones for the web and store order channels. This configuration makes use of a forward storage area where the web orders are picked, as introduced in section 2.2.1. Pickers stand in between gravity racks which can be replenished by forklifts from the reserve storage area.

In this forward picking area, the pickers pick orders discrete rather than in batch, and can deposit the picked orders directly on an conveyor leading to the shipping area, therefore, no traveling is required after the order is completed. The forward picking area is supplied by the forklifts when inventory levels become low. The forklifts give priority to refilling the forward storage area. When the forklift is not available the picker waits until the product is replenished before continuing.

From the reserve storage area the store-orders are picked by forklifts, which fulfill the full pallet orders, after which the orders are moved to the shipment area by the forklift. The pallet racks present in the warehouse are drive-in racks, where each lane of racks is dedicated to one product. The less-than-pallet orders are fulfilled from the reserve storage as well, by case pickers. These pickers can pick cases from pallets at the ground level of the pallet racks. This happens discrete for each order. After an order is complete the picker moves the pallet to the shipment area.

A depiction of the process flow for the first design alternative can be seen in figure 4.2. A visual schematic depiction of this operational philosophy is shown in figure 4.3. This represent a top down view of the warehouse and shows the rough layout of such a process flow. This is meant for illustration purposes, for the reader to form a better understanding of the physical implications of the operational philosophy.

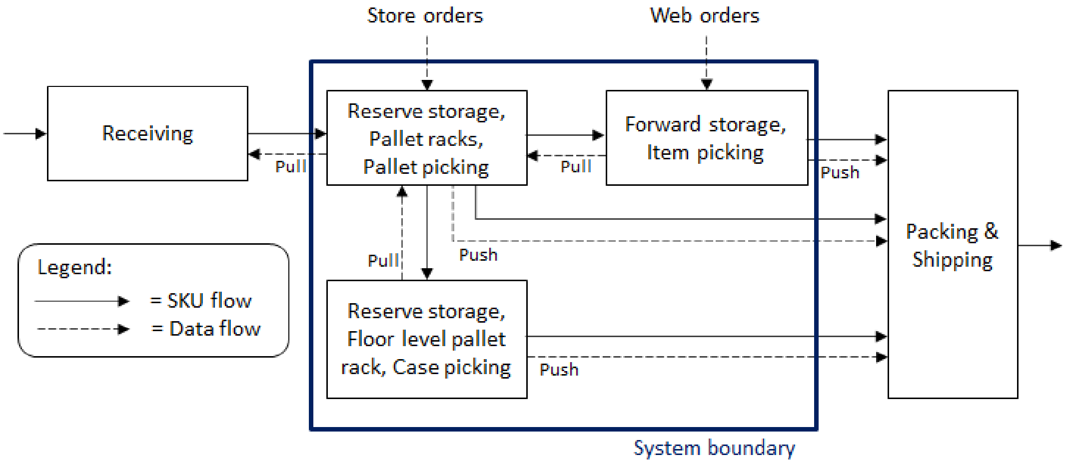


Figure 4.2: Process model Alternative I: physically separated web-order picking

What can be noticed in figure 4.2, the processes are similar to the processes in figure 2.5, albeit combined together in one warehouse. This does require a lot of forklift travel, since forklift need to fulfill orders and need to replenish the forward storage areas.

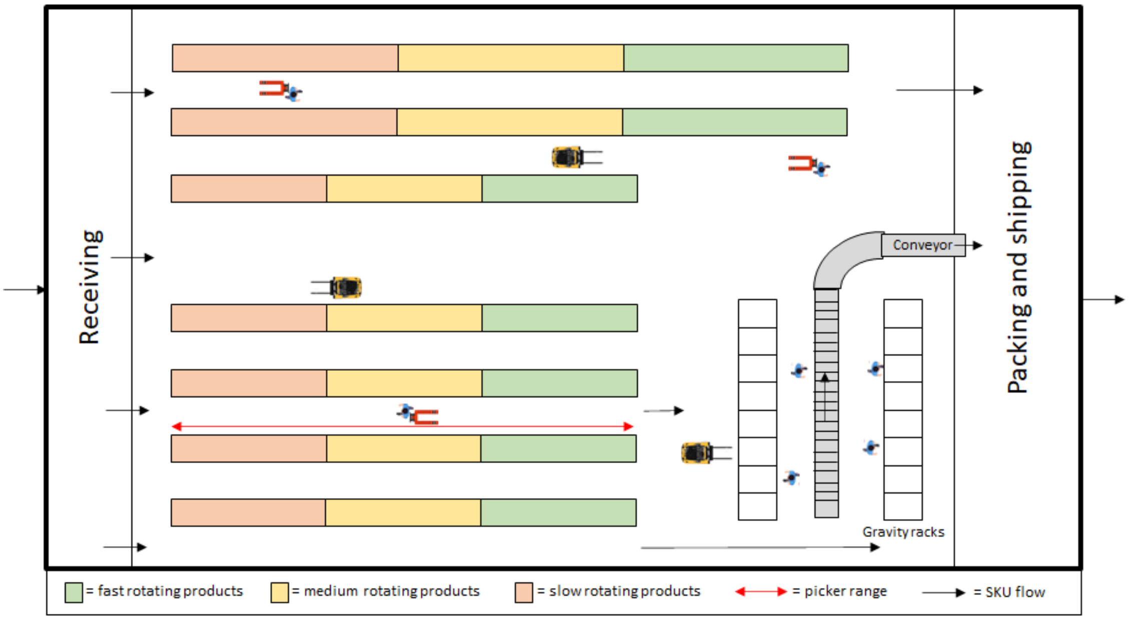


Figure 4.3: Schematic layout Alternative I: physically separated web-order picking

4.4.2. Alternative II: zoned and common picking area

The second operational philosophy alternative identified, describes a warehouse configuration where the picking zones for store orders and web orders are not separated, unlike the first philosophy. With this philosophy the picking operations for both order channels are performed simultaneously. To make this operation more efficient, pickers are dedicated to a specific zone in the warehouse, where they pick only parts of each order. This ensures pickers not having to cross each other too often, while being able to pick store and web orders simultaneously in the same area.

The web-orders are picked in batches, while the store-orders are picked discrete. The web orders are picked in batches because often a high amount of orders need to be fulfilled and by batching, the travel time per order is significantly reduced, as discussed in section 2.2.2. Furthermore, the orders often are small, therefore, multiple orders can be placed on one cart.

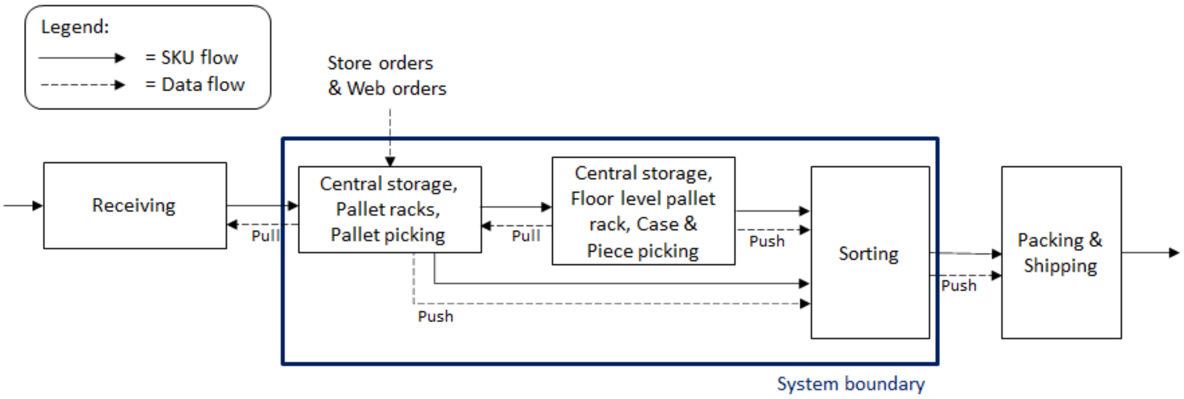


Figure 4.4: Process model Alternative II: zoned and common picking area

For the batch picking the pickers are assumed to have trolleys with separate bins for different orders, which results in a sort-while-pick operation. Hereafter, the picker deposits the picked products at a sorting stage where the products are consolidated to fulfill the order. The pickers all pick from the ground level of the pallet racks in the storage area. The ground level of the pallet racks are replenished from the higher levels with a forklift. When the forklift is not available the picker waits until the product is replenished before continuing. Furthermore, forklifts fulfill the full pallet orders directly from the same storage area, after which the products are transported to the sorting stage.

The defining features for this operational philosophy, are the picking zones and the necessity for a sorting step, to consolidate the products coming from different zones. A depiction of the process flow for the second design alternative can be seen in figure 4.4. The schematic depiction of the operational philosophy can be seen in figure 4.5.

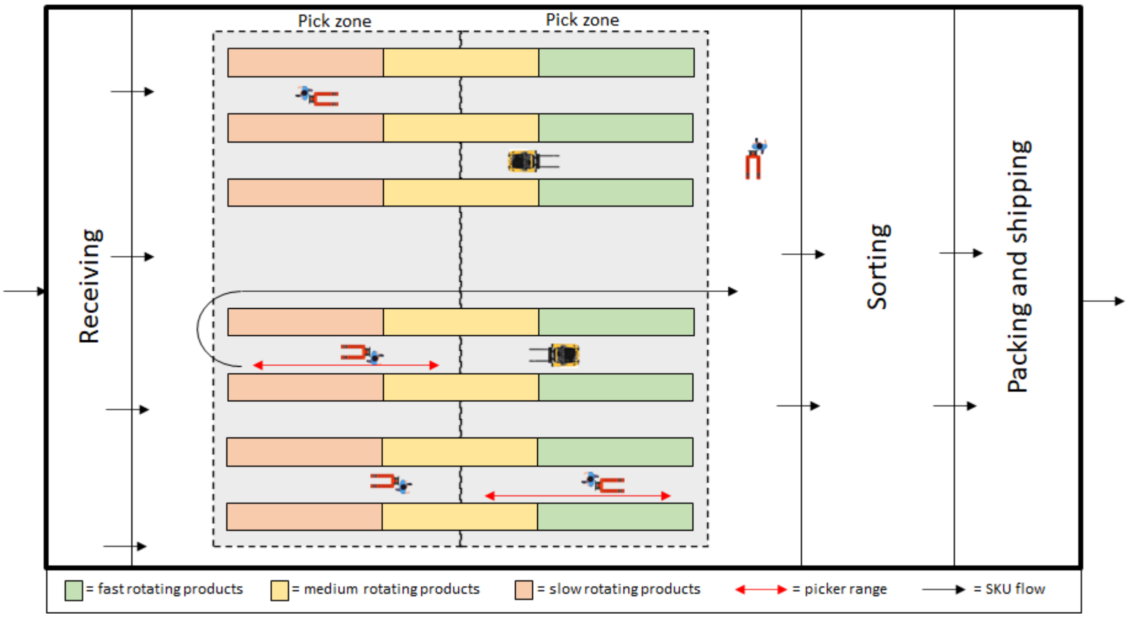


Figure 4.5: Schematic layout Alternative II: zoned and common picking area

4.4.3. Alternative III: time slot separated picking

The third alternative, identified in literature, has the least complex process flow. That is because the processes are not separated by space, but by time. The processes required for web-order picking are performed in the same area and with the same equipment as for the store-order processes. For store-orders the orders will be picked discrete, where forklifts fulfill the full pallet orders and pickers perform the less-than-pallet order picking. The pickers can, again, pick from the ground level of the pallet racks, which will be replenished from the higher racks by forklifts.

At a dedicate time, the store-order picking will switch to web-order picking. The web-order picking will be performed in batches, for the same reasons as explained in section 4.4.2, for this operations the pickers are assumed to have trolleys with separate bins for different orders, which results in a sort-while-pick operation.

A depiction of the process flow for the third design alternative can be seen in figure 4.6. The green markings indicate the main difference of this alternative compared to the other alternatives. The green markings stand for the time dependency of the relevant processes, where either the store order processes are called upon, or the web order processes. The schematic depiction of the operational philosophy can be seen in figure 4.7, which is be a simplified top down view.

4.5. Conclusion

This section concludes the second chapter of the theory section, where the literature on omni-channel warehousing has been discussed. First, a description has been given of the emergence of the omni-channel strategies, where the definition comes from the customer's viewpoint. The omni-channel terms reflects the fact that customers can interact with retailers through an array of channels and the term is the most advanced concept of retailing. However, for operations design, the only relevant distinction is

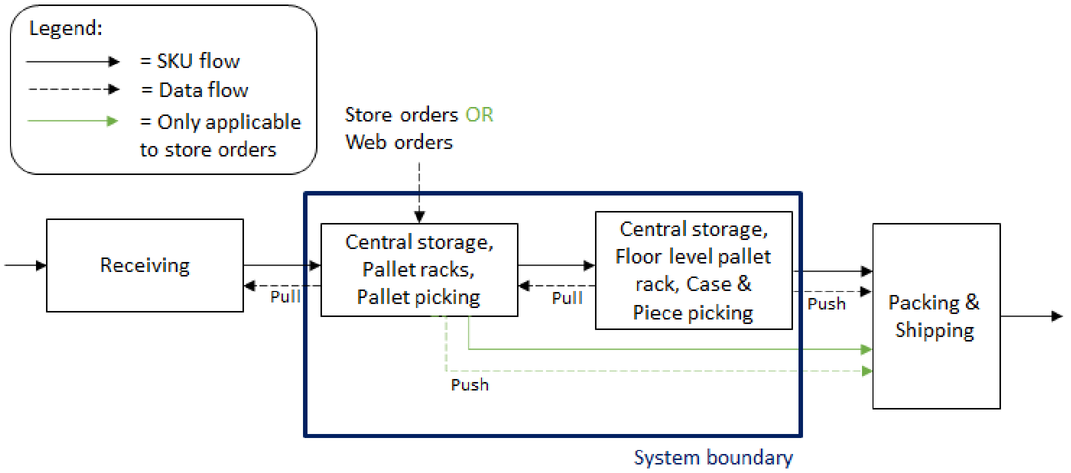


Figure 4.6: Process model Alternative III: time slot separated picking

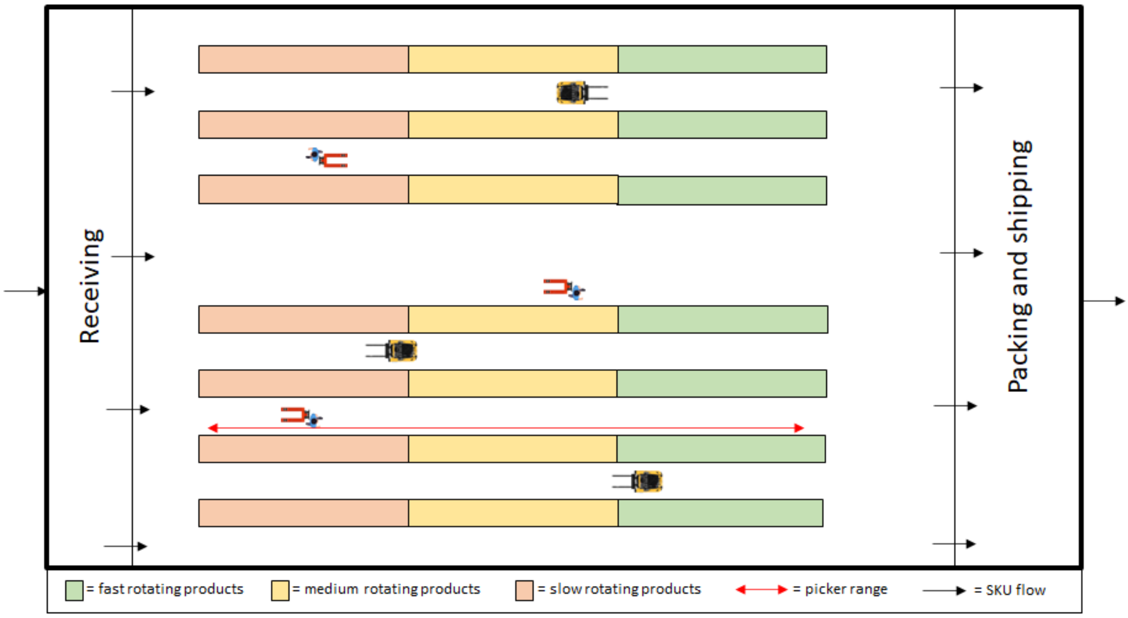


Figure 4.7: Schematic layout Alternative III: time slot separated picking

the origin of the order, whether the orders come from a physical store or from the direct online channel, since that dictates its characteristics. The omni-channel strategy has gone on to become the dominant business model in retailing.

Secondly, the ways in which an omni-channel strategy can be implemented in the supply chain, has been discussed. Where it became apparent that operations can be integrated or separated, mostly depending on the existing infrastructure and assortment. Because the positive effects of integrated warehouses, outweigh the challenges associated with added operational complexity, integrated warehousing is considered as design direction.

When looking at literature on the industry practice for integrated omni-channel warehouse operations, it is apparent that integrated inventories for both order channels is essential for efficient warehouse operations. Furthermore, it is shown that order-picking practices vary in industry, from picking in different physical zones for each order channel, to picking in common zones. Also when picking in a common zone the picking processes can be separated by product rotation speed, while picking store orders and web orders at the same time. Another operational alternative is the order type separation by time slots. This variety in feasible configurations, form the alternatives for operational philosophies for omni-channel warehousing.

In summary, the third research sub-question, ’How is omni-channel warehousing characterised and what alternatives for operations exist?’, is answered by:

1. It is the dominant business model in supply chains
2. Omni-channel reflects the fact that customers can interact with retailers through an array of channels
3. Omni-channel strategy can be implemented with an integrated or separated warehouse
4. Integrated omni-channel warehousing is operationally complex, due to having to handle orders of different types
5. Multiple alternatives exist for implementing integrated omni-channel warehouses
   (a) Alternative I: Physically separated picking area, simultaneous picking for web and store orders
   (b) Alternative II: Common picking area, zoned by rotation speed, simultaneous picking for web and store orders
   (c) Alternative III: Common picking area, time slot separated picking for web and store orders

5

Methodology

The theory section of the research is concluded with this chapter. From industry practice and research literature, the need for efficient omni-channel warehouses has become apparent. In literature three feasible operational philosophies have been identified. To quantify the performance of these alternatives, a model is required, which is introduced in this chapter. With the results from the model, the performance of the operational philosophies can be compared. Eventually the comparison gives an indication for the impact of the operational philosophy in the omni-channel warehouse. Furthermore, the method for modeling the alternatives is introduced. When it is known how the alternatives perform, one is able to say something substantial about the way omni-channel warehousing can be implemented Subsequently, to serve as a basis for modeling and serve as a realistic scenario, a use case is introduced. This chapter sees the fourth research sub-question answered, 'How can omni-channel warehouse performance be quantified?'.

5.1. Discrete Event Simulation

For the comparison of performance of the operational philosophies, a model is required. The goal of the model is to quantify the omni-channel warehouse performance. For this purpose a simulation is ideal, as for testing in real-life, the impact of the alternative philosophies become visible only after months, with a chance that the situation has becomes worse. Experimenting with a simulation model of the warehouse, with the multiple operational philosophies, and using a real warehouse order flow as model input, is an inexpensive, fast and safe way of evaluating performance, while maintaining credibility.

The main goal of any logistic system is to 'keep the flows flowing' at the lowest costs, preserving demands on quality, quantity and service (Otjjes and Veeke, 2014). In case of the warehouse the main flows are products and orders. The handling of products in a warehouse, is a typical discrete process, see for example the picking of the product and placing it at the shipment area.

Warehousing systems are characterized by a number of processes and events. These events have a discrete start and end time. This suits warehousing operations because the movement of products and pickers can be modeled as two events, from point A to point B, with a time delay. In other words, the warehouse system is discrete because the products, pickers and forklifts can be modeled to change value or state at discrete time points. Their processes and states do not change continuously. When the aggregation level of the model is set correctly, continuous processes do not have to be considered in a warehouse. The aggregation level needs to be set in such a way that the model represent an simple version of reality while maintaining a satisfactory level of accuracy.

Therefore, Discrete Event Simulation (DES) is a method which is particularly suitable for modeling logistical systems. DES is based on the statistical paradigm of the queuing theory.

With DES a logistical system is represented as a chronological sequence of events. The events occur in a system with a fixed structure and can change the state of the system, including the state of the components in the system which can trigger new events. DES is a representation of components, such as products and orders, that travel through a flow chart of processes, such as pickers or forklifts, where they stay in queues and are processed (TU Delft OpenCourseWare, 2022).

With the queuing theory it is possible to estimate labor requirements with a given product count and inventory turns per year (Bartholdi and Hackman, 2019).

With the queuing theory a warehouse can be modeled by setting an order or SKU as a ’customer’ that arrives and is stored (joins a queue), to wait for picking (service). Therefore, Little’s Law is applicable to a warehousing process (Bartholdi and Hackman, 2019). Little’s Law entails that for a queuing system in steady state the average length of the queue, or the average number of elements in a system, denoted here as L, equals the average arrival rate, λ, times the average waiting time, or throughput time, W, like so:

$$L = \lambda W \tag{5.1}$$

This equation still holds for a large number of different SKUs and orders, with every order and SKU being able to have their own arrival rate, waiting time and queue length. This means Little’s Law can be applied on a family of SKUs and orders, or even to an area within a warehouse (Bartholdi and Hackman, 2019).

The processes in many cases have a stochastic character which are subject to variation. These variations cause tuning problems and are the main cause of unreliable throughput times, waiting times and waiting queues or extra storage capacity needed. The implementation of such stochastic values, make the model able to simulate probabilities of complex real world processes.

A simulation is well suited for capturing dynamic behaviours and complex interdependencies over time. Also, with simulation, one is able to add measurements and statistical analysis at any time. When looking to implement analytic models, the required simplified conditions often do not hold in real world, while more realistic models are too complex to solve (Gu et al., 2010). Analytic analysis is suitable to verify theoretical implementation, while simulation can show physical implementation. Therefore, simulation is the most widely used tool in literature and practice for warehouse performance evaluation (Gu et al., 2010). Moreover, unlike Excel or linear programming, the model can be analyzed while it runs. This interaction builds understanding and trust (Wilkinson, 2020). Also, simulation allows for experimenting with scenarios, which in general are not possible with existing real systems, while grasping complex systems and behaviours.

5.2. Use Case Introduction

For this research a use case is used to serve as a realistic basis for the model. The case is provided by Royal HaskoningDHV (RHDHV), and concerns a distribution warehouse of a Fast Moving Consumer Goods (FMCG) supplier in East-Asia, which is the biggest market for e-commerce retailing (Lebow, 2021). RHDHV is an independent, international, engineering, design and project management consultancy. The company operates in several areas with multiple branches, one of which is the supply chain and logistics consultancy branch. This branch caters to the need of multinationals who often still rely on traditional warehouse operations to supply their customers.

The use case in question, is selected because the company is at the verge of implementing online order fulfillment within their existing store-supplying operations. The company sees a big future for e-commerce in value creation, therefore, they aim to add the online order channel into their existing warehouse operations. The company already has extensive experience with fulfilling traditional store orders and has not yet found a way to efficiently add the e-commerce operations within their compound. Because the e-commerce operations need to be implemented in existing operations, efficient integration has an even higher priority. The considered supplier is an excellent example of a previously traditional supplier, which solely supplied brick-and-mortar stores, who now wants to add a second online sales channel to their operations. For the company it is not relevant through which online interface the customer places its order.

The e-commerce processes are currently performed by a third party, where the e-commerce processes are completely separated from the rest of the warehouse flows. The company does not own any brick-and-mortar stores, therefore, the fulfillment of the online orders have to be performed from the warehouse.

The considered company is seeing part of their sales from the traditional store channel be cannibalized by the online channel. This benefits constant capacity utilization, as mentioned by Hübner et al. (2015). The operations currently envisioned by the company, show big resemblance with the scenario described by Alawneh and Zhang (2018), and is similar to the first identified feasible operational philosophy 'Alternative I: Physically separated web order picking'. Concerning the flows, the warehouse gets all of the products supplied by other production companies, so the warehouse only fulfills distribution duties. As earlier identified in section 2.2, for this type of warehouse, efficient order picking and high throughput is essential.

With regard to automation, the specific company considered in this case desires a flexible solution which can be run as an experiment and is easily scalable. Furthermore, the company wants cost efficient implementation and desires little constructional effort, therefore, automation is not preferred. Furthermore, the throughput and required handling speed does not justify the investment, especially when also considering the losses in order-picking flexibility, according to supply chain experts at RHDHV.

In general, practice shows that automation does not play a big role for picking processes. When it is used, it is mainly for the inbound processes, such as storage in high racks, and sorting processes (Hübner et al., 2015). Reasons for not automating the picking processes are the large spread in shapes and sizes of products, difficulties with handling most of the products, small order sizes and variety in order volume due to seasonality (Petersen II, 2000).

Furthermore, an automated system requires a big initial investment and can give difficulties with scaling of the operations. Therefore, parts-to-picker systems are not suited. The inventory allocation policy in the current warehouse is a class-based policy based on product turnover rates (ABC-policy). For the remainder of the research this policy is assumed to be in place.

The range of product the company offers are, home, health and fabric care, which are fast moving consumer goods. Also, this means that the products are non-perishable, which makes it suitable for integrated warehousing operations, as described in section 4.2. Other characteristics related to these type of products are the high inventory turnover rates and low product cost. The products are high turnover because they are used daily, consumed quickly and of high demand (Pahwa, 2022). This contrasts with low sales luxury items, DIY items and fashion articles.

Since the FMCG items are used regularly in a household, by a wide range of people, online order sizes will be larger than orders sizes for DIY suppliers, while order sizes are smaller than for clothing suppliers. Furthermore, the products are of small size, which makes manual handling of cases and pieces feasible for pickers.

Moreover, the product sizes determine the number of handling moves required per order, since large products can only be handled one at a time, while small products can be picked in larger amounts. In turn, this influences the number of pickers required and the fulfillment times. Therefore, these product characteristics influence the modeling and the generalization of the results, which will be reflected upon in section 8.

By making use of an use case for input data, it is ensured that used data is realistic and feasible. The use case provides data on order arrival patterns, order compositions, throughput and size of workforce. It is crucial for input data to be realistic as for models a well known statement is: 'garbage in = garbage out'.

5.3. Conclusion

To conclude, this chapter has described the methods the remainder of the research is approached with. The performance of the identified operational design alternatives, has to be quantified in order to compare the impact on the omni-channel warehousing efficiency.

Firstly, the model type is introduced. A discrete event simulation will be used because the movement of products and pickers can be modeled as two events, which have a discrete start and end time. The model can reduce the complexity of the simulation, while preserving relevant information for the warehouse flows. A simulation with accurate input is a cheap, fast and safe way of evaluating performance, while maintaining credibility. With the implementation of stochastic values, the model is able to simulate probabilities of complex real world processes, while keeping the model simple.

Secondly, a use case has been introduced, supplied by RHDHV. The use case will serve as a realistic source for input data and can be used as a realistic scenario to evaluate. The available data, provides throughput figures, arrival patterns and order compositions. Accurate data is crucial because as they say: ’garbage in = garbage out’. The considered case, describes processes of a FMCG retailer in East-Asia, which operates a distribution warehouse.

To summarize, the fourth research sub-question, ’How can omni-channel warehouse performance be quantified?’, is answered by:

1. Introducing a discrete event simulation model
2. Using stochastic inputs to capture probabilities of complex real world processes
3. Setting an aggregation level so that the model is simple while maintaining the required level of accuracy
4. Suggesting a sensitivity analysis for the order arrival patterns and order type skewness
5. Making use of realistic data from a suitable use case

IV

Modeling

6

Modeling

This chapter describes the modeling phase of the research. The model objective and the modeling methods are discussed, along with the verification and validation. Also, the way in which the data from the use case is adapted to be able to be used as inputs for the simulation model, is discussed. Furthermore, this chapter describes the experimental setup by which the results are collected. At the end of the chapter the fifth research question is answered, 'How is the model set up and what experiments are required to evaluate the performance of the operational alternatives?'.

6.1. Model Objective

The objective of the model is to evaluate the effect of operational philosophy on the performance of the omni-channel warehouse. Each operational philosophy exists of a different configuration of components. Furthermore, for each operational alternative the interactions between the components are different. The discrete event simulation model has to be able to evaluate each design alternative with the same inputs of data and with the same boundaries. For the effects of the operational philosophy on the performance of the warehouse to be interpretable the results have to be collected and represented by the model.

Next to evaluating the performance of the design alternatives, the model has to be able to asses the sensitivity of the performance to the arrival patterns of the order. The arrival patterns can have a significant influence on the performance, and it is interesting to see in what situation which philosophy performs best. Another aspect the model has to evaluate the sensitivity for, is the number of orders for each order type.

With the results from the model, a statement can be made about which design alternative performs best regarding the performance indicators, considering the scenarios. The resulting statement can be used to narrow down the design space for efficient omni-channel warehouse implementation. In order to do so, the model must be able to give answers on whether to implement physically separated picking zones by order channel, separated picking zones by product turnover speed or time slot separated picking for each order channel. For an overview of models that concern other segments of warehouse design see Gu et al. (2010), where models are discussed concerning sizing, department layout and storage strategies, rather than operation flows.

6.2. Inputs

The inputs for the simulation model are similar to the inputs in an actual distribution warehouse. When thinking of a warehouse, immediately two types of input come to mind, the products and the orders. Since for this research the receiving stage of the products is not considered, no logic is implemented in the model to simulate the arrival of products. However, products are required in the model. Therefore, the products have been simulated as always present in the reserve area when asked for. That would translate to an actual warehouse with always enough stock and space to store the stock products.

The second input for a warehouse, the orders, is more accurately modeled to resemble real operations. Moreover, the inputs of the order are considered to have a significant impact on the performance of the operational philosophy. Therefore, the orders are modeled so that the patterns match the actual patterns as seen in the case warehouse. The order pattern consist of three important aspects, being: the order arrival pattern, the number of orders for each order type, and the order compositions. In turn, the order composition consists of the number of unique products in an order and the amount for each product.

Both the order arrival pattern and the order composition differ for the store and web orders. The differences between these two order types have been covered extensively in section 2.4.

Besides the inputs for the products and the orders, two other important inputs exist concerning operational parameters, being the average number of cases per pallet and the average number of pieces in a case. These values are critical to get right because it can relate the throughput of the warehouse to the required number of moves required. Therefore, these values are taken from the use case, and will be used as inputs for the model.

6.3. Outputs

The outputs of the model have to shed light on the performance of the considered operational philosophy. As discussed in section 6.9.5 for a distribution warehouse the efficient order picking is the main optimization goal, while the throughput is a prominent design criterion as well. Several indicators have been identified to evaluate the performance upon. For warehousing, several key performance indicators exist, being the ’length of day’, ’order lead time’ and ’amount orders delayed’ (Petersen II, 2000).

The ’length of day’ represent the time it requires for a day’s worth of orders to be fulfilled. The length of day is measured from the time picking begins until all orders are ready for packaging and shipment (Petersen II, 2000). It is an important indicator because it can be related to the warehouse throughput and the operating cost. The shorter the ’length of day’, the higher the throughput, because more orders can be fulfilled in a given amount of time.

An important notion to this statement is that the ’length of day’ is not only dictated by the throughput, but by the order arrivals as well. Therefore, this KPI is not suited to represent every scenario accurately. The reason it is included in this research is because it gives an indication for the operating cost, as well. That is because it indicates for how many hours, and more crucially for which hours, wages have to be payed to warehouse employees. Working over-hours and working late nights shifts result in high hourly wages, especially with the shortages in workforce.

Another performance indicator which can be used for warehousing is the ’makespan’. The makespan is defined as the length of time that elapses from the start of work to the end. This is actually very similar to the ’length of day’, albeit that the makespan does not consider the time elapsed when no orders are in the system. Therefore it is solely a measure for the time spent on fulfilling orders, this does not include the time waiting for orders to arrive. Therefore, the length of day and the makespan will be the same in a scenario where all orders arrive at the start of the day. By comparing both performance indicators, the effect of the order arrival pattern on the performance of the warehouse can be easily visualized.

Table 6.1: In practice found operational philosophies summary

Indicator	Type	Description
Length of day	KPI	Time required to fulfill a day’s worth of orders (Petersen II, 2000)
Makespan	KPI	Time spent on fulfilling orders, not including waiting for orders
Percentage orders delayed	KPI	Indicator for customer service, dependant on desired fulfillment time (Petersen II, 2000)
Lead time, STD	KPI	Time spent from order arrival until it is fulfilled, the standard deviation indicates the process reliability
Utilization	Output	Measure for cost efficient operations

STD (Standard Deviation)

The ’order lead time’ is a more commonly known performance indicator for logistical systems. It stands for the time from when the order arrives until it is fulfilled. In the case of this research the order is considered fulfilled when it has been delivered to the shipment area, because the shipment processes are not considered in this research. The ’order lead time’ is important because it is again an indicator for throughput, but more importantly its standard deviation is a great indicator for process consistency and robustness. When the lead times are short, it indicates a high throughput and efficient operations. Furthermore when the standard deviation is large, it indicates inconsistent processes, where potentially small disturbances can create a significantly lower throughput.

The order lead time can also be used to determine the 'percentage orders delayed'. This indicator is relevant for distribution warehousing because it serves as a measure for customer service. Customer service is highly important to cater to the high demands of the e-commerce customers. When a too large percentage of orders is delayed, customers will start ordering at other companies. An order is delayed when it is not fulfilled within the required fulfillment time, as set by the company, further explained in section 6.9.5.

Lastly, the 'utilization' of the pickers and forklifts can give insights into effectiveness of the pickers and forklifts. It is a measure for the percentage of time pickers and forklifts are not being used to their full potential. It indicates whether the process runs cost efficient and whether possible gains can be made by adding personnel. Combined the performance indicators show the throughput, service rates and efficiency of the modeled design alternative. An overview of the KPI's and outputs is given in table 6.1.

6.4. Model Content

This section describes the way the model is set up. First the model simplifications and assumptions are discussed to set the context for the components and interactions. Secondly the components itself are discussed with their interactions. Finally, the parameters for the components and the rest of the model are introduced.

6.4.1. Simplifications

Simplifications are methods born from the desire to create simple models (Robinson, 2014). Numerous advantages are associated with simple models such as faster run time, easier interpretation, higher flexibility and faster development. Of course, the model should still be able to meet the objectives.

One way of simplifying a model is by setting an appropriate aggregation level. By making certain processes a black-box, orders and products can enter and leave the box at dedicated times. The time spent within the black-box can be sampled from a distribution to replicate actual process handling times (Robinson, 2014). By means of abstraction the details irrelevant to the research can be left out.

As discussed in section 5.1, the logistical processes in a warehouse can typically be described as a discrete system. Approaching the warehouse as a continues process, would result in unnecessary complex model. In order to evaluate the operational alternatives in a sufficiently accurate way, the required aggregation level is one where the product states and picker states are identifiable, while the details of the processes are left out. With this aggregation level the warehouse operations can be modeled as separate processes and events, with a discrete start and end time.

Another method of reducing the complexity of the model is by simulating complex real world processes with distributions (Robinson, 2014). In that way non deterministic parameters, such as handle speeds, can be simulated while the exact cause for the variations do not need to be known. To ensure accuracy, such distributions need to match approximately the actual probability distributions. The distributions by which the parameters are defined can be found in table 6.2 and table 6.9.

Another simplification of processes is introduced for the storage location of products. The exact location for each product is not considered, and average travel distances to product locations are used. This is done in order to keep the model simple, since product allocation is a whole area of research on its own. Furthermore, with exact product locations, come picker routing problems. By taking the travel distance to each product as an average, which depends on the operational philosophy, the research question can still be answered while keeping the model simple.

The assortment of the FMCG distribution warehouse, is simplified as well. An actual FMCG distribution warehouse can have more than 10.000 unique products in its assortment. In order to simulate this, the product categories are considered, rather than the actual products themselves. Every product in the warehouse is part of one of six categories, being: fabric care, baby care, home care, hair care, oral care and shave care. When a product is required, it is not necessary to know the exact product but only the product category.

With this category it is determined whether a product needs refilling or to which picking zone the product needs to be assigned. This means no SKU is considered individually, rather each product category is considered with its own stock levels or queues. By considering each product by its category, the model translates to a warehouse with only six different products. For each of these categories the demand is known.

Furthermore, the formation of order batches is considered to be a method which reduces the required travel time per order. The exact method for order batching is not considered. To simulate the effect of order batching, the average travel distance for each unique product in the order is set as a percentage of the travel distance required, when no order batching would be in place. Hereby, the effects of the alternative operational philosophy can be simulated while keeping the model simple and accurate.

The final simplifications are made considering the out of scope receiving and shipping stages. Since the receiving of the actual goods to the warehouse, is not considered, it is assumed that products are readily available for forklift to fulfill full pallet orders and to replenish lower level pallet racks and forward picking areas. Furthermore, concerning the shipping area, orders are considered fulfilled when all products are delivered at the shipping area.

6.4.2. Assumptions

Assumptions need to be made in the model in order to deal with unknowns. For a lot of parameters, the values have to be approximated by a distribution while being as close to reality as possible. The assumptions are based on expert knowledge, common sense and literature. As literature source, the research of Petersen II (2000) is used. In table 6.2, the assumed values are presented. These values have been validated by experts at RHDHV.

Table 6.2: Parameter values assumed for the simulation model

Parameter	Value
Forklift travel speed	2.5 [m/s]
Forklift product handling time	Triangular distribution (min=5, max=35, mode=14) [s]
Picker travel speed	0.8 [m/s]
Forward picker travel speed	1.4 [m/s]
Picker initial product handling time	12 [s]
Picker product handling time	6 [s]
Forward picker initial product handling time	8 [s]
Forward picker product handling time	4 [s]
Administration time after fulfillment	30 [s]
Forward administration time after fulfillment	10 [s]
Replenishment threshold	10 [cases or pieces]
Replenishment amount	1 [pallet]
Initial stock amount	1 [pallet]
Sorting time	15 [s/per order] and 5 [s/product]
Amount of orders in batch	15
Amount of pieces per web order	3
Amount of pick zones	2
Amount of picking time slots	3

The number of pieces per web order is taken from Hübner et al. (2015), where they found 75% of the investigated companies has an average order size of three items or lower. Hübner et al. (2015) have investigated 'do-it-yourself' (DIY), electronic and fashion retailers. Where the fashion retailers reported order sizes higher than three items. The FMCG warehouse considered in this research, is assumed to show more resemblance with the DIY and the electronics market, than the fashion market, albeit with order sizes assumed to be on the higher side of the average for DIY and electronics. Therefore, a value of three items per order is considered to be valid.

The forklift handling time is defined as the time required to pick-up or put-down a pallet. Whether it is from the ground or from a storage rack. The picker handling times are defined as the time required for pickers to pick up a case from the floor level of the pallet rack and place it on the respective pallet for the order.

6.4.3. Components & processes

All elements considered in this research, together, have to include all the critical processes from the warehouse operations that are within scope. Furthermore, the processes that interconnect with the operations and that have a significant influence on the operations, have to be included in the model. For this research the level of detail is such that the warehouse operations can be reduced to the components mentioned in table 6.3. The components and behaviours in this conceptual model have been validated by industry experts with knowledge of the real world system.

Table 6.3: In practice found operational philosophies summary

Component	Behaviour
Case picker	Fulfills less than pallet store orders
	Picks cases from lower level of pallet racks
	Travels with pallet jack
	Fulfills orders discrete
Piece picker	Fulfills web orders
	Fulfills orders in batches when not in forward storage
All pickers	Pickers wait when product stock is empty, until product is refilled by forklift
	Perform first order that arrives
	First product to pick at each location takes longer for scan time
Forklift	Fulfills full pallet store orders and performs replenishment tasks
	Prioritizes replenishment tasks over fulfilling orders
Sorter	Starts sorting after all products of order have arrived
All components	Finish their task before starting new one
Products	Class-based storage is present in central storage
	Same assortment for web and store orders

6.4.4. Interactions

To bridges the gap between the textual process description, from section 4.4, and the formalization required for coding, an informal Process Description Language (PDL) is introduced. A PDL is a informal pseudo language, where processes and interactions are described. This PDL has the same level of detail as the model has and is depicted in appendix B.

For a more visual representation of the processes and interactions, a Swim lane diagram has been made, according to Unified Modeling Language (UML) standards, which can be seen in figure 6.1. The process interactions for the other operational philosophies are presented in appendix C. This depiction can serve as a basis for more intuitive process understanding and depicts the relations between the different processes.

As can be seen from the UMLs, the components and processes for each operational philosophy are quit different. A reason for this phenomenon, are the interdependies between the operations, components and processes, as discussed in section 2.4. Therefore, when the operational philosophy changes, a lot of the components and their interactions change as well. For the exact workings of these processes the reader is referred to the PDL, where each process is elaborated upon.

To easily understand the Swim lane UML, each component and process has been color coded. The main model components, which are interacting with data and each other, are designated in blue. These represent the people in the warehouse, where logic is involved for their tasks. A complete explanation of the color coding is presented in table 6.4.

Table 6.4: In practice found operational philosophies summary

Color	Meaning
Blue	Components interacting with data and each other
Green	Inputs of the model
Red	Sink of the model
Yellow	Documents concerning orders
Orange	Data concerning products
Grey	Decision

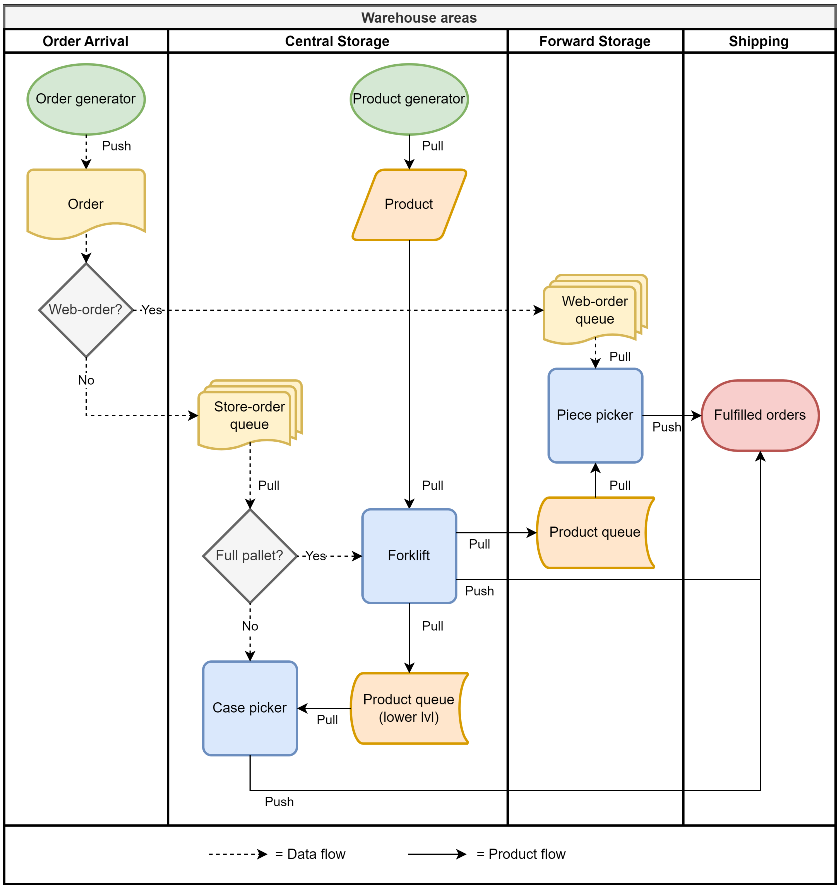


Figure 6.1: Process interactions for Alternative I: physically separated web-order picking

The PDL and the UML have both been validated by experts of RHDHV, who have knowledge of the actual processes and interaction present in a distribution warehouse. Together with the validation for the assumptions, components and processes, these methods form the white-box validation, where it is ensured that the content of the model is a sufficiently accurate representation of the real world.

6.4.5. Configurations

The three operational philosophies that have been identified in literature, all have different product flow characteristics, resulting in different average travel distances, and personnel requirements. The average travel distance is influenced by batching, zoning, forward storage and required sorting steps or replenishment steps. The difference in travel distances for each operational alternative, will lead to varying order processing speeds. These have, in turn, effect on the performance indicators. The product flow characteristics of each operational philosophy, partly dictate the amount of personnel required, because every process step requires personnel. Here below, the configuration of travel distance and personnel for each operational philosophy is presented.

Travel distance

An overview of the effects of the operational philosophies on the travel distance parameter, is presented in table 6.5. An explanation for the values is given below.

According to findings of Petersen and Aase (2004), combining class-based storage and batching of orders can lead up to savings of 50% in fulfillment time. The reduction of fulfillment time is largely due to the reduction in travel distances, since the product handling and speed is not impacted by these methods. The high savings in fulfillment time are identified for orders up to 5 SKUs, which is considered to be the case for this research.

Table 6.5: Travel distance for each operational philosophy

Alternative	Travel distance
Maximum travel distance per move (MTD)	CUD(0.8, 1.2) · 25[m]
I forward pick: web picker (forward storage)	0.2 · MTD
I forward pick: store picker (class-based storage)	0.8 · MTD
II zone pick: web picker (zone picking & batching)	0.5 · MTD
II zone pick: store picker (zone picking)	0.8 · MTD
III time slots: web picker (class-based storage & batching)	0.5 · MTD
III time slots: store picker (class-based storage)	0.8 · MTD

MTD (Maximum Travel Distance), CUD (Continuous Uniform Distribution)

Therefore, a 50% reduction in travel distance is assumed when both methods can be applied in an operational philosophy. This is the case for the web-order pickers in Alternative III: time slot separated picking. That is why, in table 6.5, the travel distance for web orders in Alternative III, is set to be half the maximum travel distance.

The same gain in process efficiency can be seen when combining zone picking and batch picking (Petersen and Aase, 2004). This is the case in Alternative II, where these two methods are applied for the web order picking. Therefore, as can be seen in table 6.5, also for this configuration, the travel distance is assumed half the maximum travel distance.

When implementing zoning, batching and class-based storage at once is not an option, the implementation of solely one of these methods, leads to an improvement of 20% in fulfillment time (Petersen and Aase, 2004). For every operational philosophy this is the case for the store-order pickers. Since for Alternative I, a class-based storage is assumed to be in place, for Alternative II, zoning is implemented, which nullifies the effect of the class-based storage, and for Alternative III, again a class-based storage is assumed. Furthermore, the store orders are picked discrete, rather than in batches.

Since the travel distances for the pickers in the forward storage area is only a fraction of the distance a picker in the central storage has to travel, the reduction in fulfillment time is assumed to be 80%. The distance the forklift has to travel for each operation is equal for each operational philosophy and is set to be the maximum travel distance, since operational philosophy does not impact the average travel distance of the forklift, as it only handles one pallet of product at a time. The maximum travel distance per move is estimated to be 25 meters, when considering an average sized warehouse. This value is verified in consultation with warehousing experts at RHDHV.

The set travel distances can give a skewed view of the actual processing time of an order. The distances in itself do not tell the whole story, for example, web-order fulfillment in the forward storage can seem really efficient, but one has to consider the extra required replenishment steps of the forward storage area. Likewise, the extra sorting step for Alternative II should be considered and the lack thereof for Alternative III.

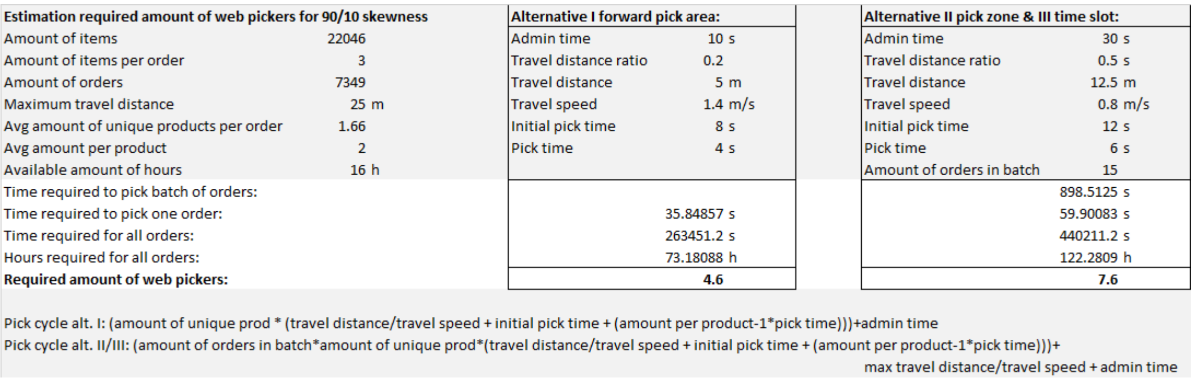
Personnel

An overview of the effects of the operational philosophies on the personnel requirements, is presented in table 6.5. An explanation for the values is given below.

Table 6.6: Personnel configuration for each operational philosophy

Alternative	Amount of personnel
I forward pick: web pickers	8
I forward pick: store pickers	4
II zone pick: web pickers	8
II zone pick: store pickers	4
II zone pick: sorters	4
III time slots: pickers	12
All alternatives: forklifts	4

The number of pickers has been set to these values for several reasons. Firstly, the number of web pickers has been set to eight pickers because in theory this amount of pickers makes it feasible for the web orders to be picked in 16 hours, which is a full workday for two shifts. For Alternative I, the theoretical required number of pickers is less, but for equal comparison the number of web pickers is set to eight as well. A depiction of the calculations is presented in figure 6.2.

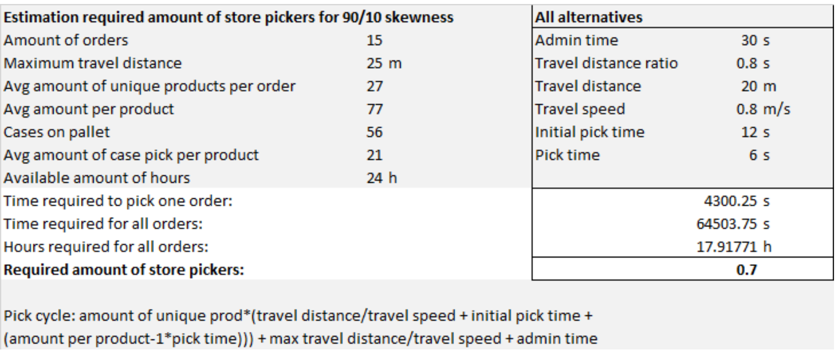


Estimation required amount of web pickers for 90/10 skewness			**Alternative I forward pick area:**			**Alternative II pick zone & III time slot:**		
Amount of items	22046		Admin time	10	s	Admin time	30	s
Amount of items per order	3		Travel distance ratio	0.2		Travel distance ratio	0.5	s
Amount of orders	7349		Travel distance	5	m	Travel distance	12.5	m
Maximum travel distance	25	m	Travel speed	1.4	m/s	Travel speed	0.8	m/s
Avg amount of unique products per order	1.66		Initial pick time	8	s	Initial pick time	12	s
Avg amount per product	2		Pick time	4	s	Pick time	6	s
Available amount of hours	16	h				Amount of orders in batch	15	
Time required to pick batch of orders:							898.5125	s
Time required to pick one order:				35.84857	s		59.90083	s
Time required for all orders:				263451.2	s		440211.2	s
Hours required for all orders:				73.18088	h		122.2809	h
Required amount of web pickers:				**4.6**			**7.6**	

Pick cycle alt. I: (amount of unique prod * (travel distance/travel speed + initial pick time + (amount per product-1*pick time)))+admin time
Pick cycle alt. II/III: (amount of orders in batch*amount of unique prod*(travel distance/travel speed + initial pick time + (amount per product-1*pick time)))+
max travel distance/travel speed + admin time

Figure 6.2: Calculation for theoretical required number of web pickers

For the store orders, the theoretical fulfillment time has been used as well. This resulted in a theoretical requirement of one store orders picker, for fulfillment within 24 hours. In the model the amount is set to four store pickers, so that two picker can be dedicated to each pick zone for Alternative II. This reduces the workload on the pickers when working in their respective zones. The possibility for bottlenecks in the process has thereby been reduced. Furthermore, this ensures robustness and a more reliable process while the number of pickers is still feasible. Again, for equal comparison the number of store pickers has been set equal for each operational philosophy. The calculation performed for setting this parameter is depicted in figure 6.3.



Estimation required amount of store pickers for 90/10 skewness			**All alternatives**		
Amount of orders	15		Admin time	30	s
Maximum travel distance	25	m	Travel distance ratio	0.8	s
Avg amount of unique products per order	27		Travel distance	20	m
Avg amount per product	77		Travel speed	0.8	m/s
Cases on pallet	56		Initial pick time	12	s
Avg amount of case pick per product	21		Pick time	6	s
Available amount of hours	24	h			
Time required to pick one order:				4300.25	s
Time required for all orders:				64503.75	s
Hours required for all orders:				17.91771	h
Required amount of store pickers:				**0.7**	

Pick cycle: amount of unique prod*(travel distance/travel speed + initial pick time +
(amount per product-1*pick time))) + max travel distance/travel speed + admin time

Figure 6.3: Calculation for theoretical required number of store pickers

Combining the two considerations for the store and web pickers, the number of pickers set for alternative III, is twelve. With twelve pickers the total amount of pickers required for each scenario is the same. This makes comparison between the alternatives more fair.

The amount of set forklifts for every operational alternative has been set equal for each scenario as well. Four forklifts have been selected for similar reasons as for the store pickers. Just an amount of one forklift is theoretically required to fulfill all orders within 24 hours, but when considering the picking zones in Alternative II, the forklift operations are sensitive to forming bottlenecks. Therefore the number of forklifts per zone has been doubled from one to two, while still remaining a feasible amount of required forklifts.

The number of sorters for Alternative II has been set to four, to represent a feasible amount of personnel within the area and while theoretically being able to process all orders within 16 hours. The fact that the theoretical required amounts of personnel are feasible, forms a verification of the model.

6.5. Verification

Verification and validation of the model has been performed throughout the simulation study. While the verification has been performed continuously by comparing the computer model with the conceptual model, the validation has been performed less frequently, since experts with knowledge of the real world system need to be involved. This is in line with the descriptions of Robinson (2014), on verification and simulation processes.

The first method implemented to ensure correct simulation model development, is a top-down approach. The model has been build in segments, with each segment introducing new components or more complexity. By only adding detail when the basis segment has proven to be correct, errors can be avoided more easily. Furthermore, while the segments of the model where not yet complex, verification has been done by comparing hand calculations with the simulation results.

The verification has been performed by checking the code, as well. The code has been read through multiple times to ensure that the data and logic are correct. The modeling scripts have not been read through in their entirety as a second check. However, the code has been explained to experts of simulation studies and warehousing operations.

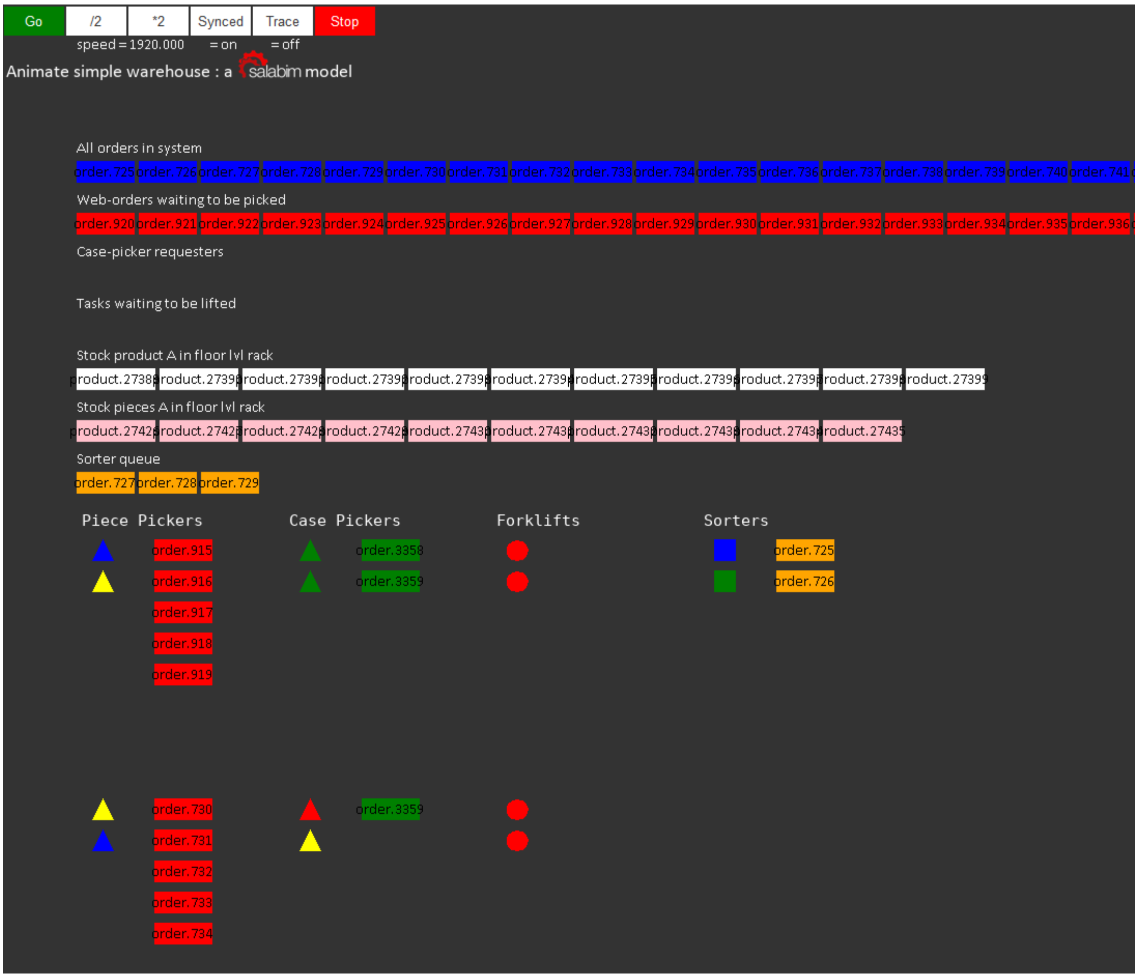


Figure 6.4: Depiction of symbolic animation used for model verification

Furthermore, the model has been verified by performing visual checks. In order to do so, a symbolic animation for the simulation has been made. With this animation it is easily visible if components follow the right logic and whether they perform the right interactions. By making sure each component in the simulation indicates which mode it is in, and what the type of tasks is it is performing, errors in the model can immediately be spotted. A depiction of the animation used for verification purposes can be seen in figure 6.4. By making this animation, people with little knowledge of the actual processes can understand and check the simulation model more easily.

The model has been verified by checking the output reports of the simulation as well. With this method, it can be checked if the model behaves as would be expected. For example, all orders that enter the warehouse, also have to leave the warehouse, because the flows have to be conserved. When this is not the case, it can be a signal that something is wrong in the simulation model. Other outputs that have been inspected are, the 'length of day', which can not be shorter than the time that is required for all orders to arrive, and the 'utilization', which can not be greater than one.

Lastly, besides the verification of the output reports, some verification test have been performed. The performed tests are: seed independence, continuity, degeneracy, consistency and a fault injection test. The results from these verification runs are presented in table 6.7. As can be observed, each model has passed the verification. From these results, along with the results from the run-time visualization, as seen in figure 6.4, it can be concluded that the model is right.

Table 6.7: Table of verification tests and results

Test	Model	Expectation	Results	Pass/Fail
Seed independence: Makespan web orders	Alternative I forward pick	±32913[s], hand simulation without interaction and stochastic	seed 1: 36705[s] seed 2: 33560[s] seed 3: 34051[s]	Pass
	Alternative II zone pick	±54996[s], hand simulation without sorting, interaction and stochastic	seed 1: 72544[s] seed 2: 66787[s] seed 3: 54400[s]	Pass
	Alternative III time slots	±36664[s], hand simulation without interaction and stochastic	seed 1: 41133[s] seed 2: 30853[s] seed 3: 42741[s]	Pass
Continuity: Increase travel distance +20%	All alternatives	Increase makespan web orders <20%	Alt I: +1.7% Alt II: +8.9% Alt III: +9.4%	Pass Pass Pass
Degeneracy: No web orders arriving	All alternatives	Makespan web orders 0[s]	Alt I: 0[s] Alt II: 0[s] Alt III: 0[s]	Pass Pass Pass
Consistency: Double amount of personnel	All alternatives	Makespan web orders decrease by almost 50%	Alt I: -49.3% Alt II: -49.8% Alt III: -49.2%	Pass Pass Pass
Fault injection: No products available	All alternatives	Infeasible	Alt I: Infeasible Alt II: Infeasible Alt III: Infeasible	Pass Pass Pass

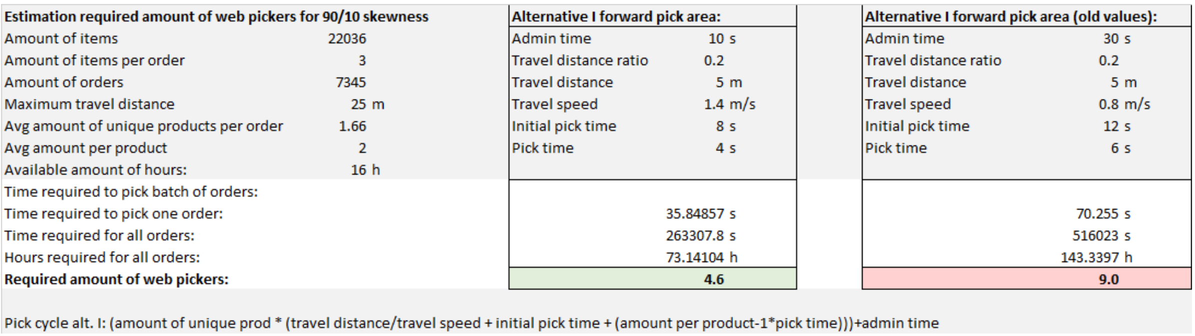
6.6. Validation

Where the micro validation of the model, has briefly been discussed in section 6.4.4, this section introduces the macro check of the simulation model, also referred to as black-box validation (Robinson, 2014). The black-box validation sees if the overall model represents the real world accurately enough.

A difficulty for performing this type of validation, is the absence of real world data to which the simulation model output can be compared. Since this simulation model evaluates alternative operating philosophies, no real world data exists to compare the model against. Therefore, the comparison has to be made with the expectations and intuition of experts with detailed knowledge of the real system (Robinson, 2014).

This type of validation has been performed throughout the modeling process. For instance, in multiple development stages the simulation animations enabled the warehousing experts to comment on the behaviour of the simulated operations, thereby providing a means for face validation. The model could be critiqued is this way, while providing suggestions for improvements, thereby increasing confidence in the model.

From the evaluation session with the experts, it became apparent that handling times for the piece picking were being overestimated. As a consequence the number of required pickers to handle the throughput, was found to be too high by a factor of four. After reconsideration with warehousing experts it was determined that handling speeds for piece picking can be simulated to be lower than case picking handling speeds. The piece picking handling times could be lower by a third, while the time in between orders was lowered by 50%. This resulted in a more feasible required number of pickers, nearly half of the old amount, which matched the experts expectations. The effect of the changes in pick speed is depicted in figure 6.5, where it can be seen that for the old values an amount of nine pickers was required, while currently just five pickers are required.



Estimation required amount of web pickers for 90/10 skewness		**Alternative I forward pick area:**		**Alternative I forward pick area (old values):**	
Amount of items	22036	Admin time	10 s	Admin time	30 s
Amount of items per order	3	Travel distance ratio	0.2	Travel distance ratio	0.2
Amount of orders	7345	Travel distance	5 m	Travel distance	5 m
Maximum travel distance	25 m	Travel speed	1.4 m/s	Travel speed	0.8 m/s
Avg amount of unique products per order	1.66	Initial pick time	8 s	Initial pick time	12 s
Avg amount per product	2	Pick time	4 s	Pick time	6 s
Available amount of hours:	16 h				
Time required to pick batch of orders:					
Time required to pick one order:			35.84857 s		70.255 s
Time required for all orders:			263307.8 s		516023 s
Hours required for all orders:			73.14104 h		143.3397 h
Required amount of web pickers:			**4.6**		**9.0**

Pick cycle alt. I: (amount of unique prod * (travel distance/travel speed + initial pick time + (amount per product-1*pick time)))+admin time

Figure 6.5: Effect of expert suggestions on model parameters

The distribution warehousing experts at RHDHV have validated the simulation model. The global behaviour of the model matches their intuition of how a real world omni-channel warehouse would behave. Their conclusion is reached after consideration of the model results, and after reviewing the simulation animation as presented in figure 6.4.

6.7. Experimental Setup

The goal of the experiment is to determine the performance for each omni-channel operational philosophy under different conditions. The conditions being varied, as discussed on section 6.1, are the order arrival pattern and the order type skewness. The results from the experiments will be compared with the key performance indicators as stated in table 6.1.

The run-length of the simulation model, is determined by the time required for a day's worth of orders to be processed. Therefore, the run-time can be different for each run. The simulation model is build to run one simulation day at the time. The model starts at the start of the day, not necessarily when the first order arrives. The models stops when all scheduled orders have arrived and have been fulfilled.

No warm-up is required at the start of each simulation day because it is assumed that when a workday starts in the actual warehouse, the orders of the previous day all have been processed, or at least the backlog of orders will not interfere with the new day's orders.

The model runs every scenario 27 times, with different random seeds. 27 replications have been selected, because this number of replications ensures that the 95% confidence interval of the length of day remains below the 1% deviation about the mean, for the most realistic scenario, i.e. the case order arrival pattern and the forward area operational philosophy. The percentage deviation of the confidence interval about the mean, acts as a measure of the narrowness of the interval (Robinson, 2014). When more replications are performed, the closer the 95% confidence interval is, to the actual mean.

The formula used is presented in equation 6.1:

$$n = \left(\frac{100 S t_{n-1,\alpha/2}}{d \bar{X}} \right)^2 \tag{6.1}$$

where:

$\bar{X}$ = mean of the output data from the replications
S = standard deviation of the output data from the replications
n = number of replications
$t_{n-1,\alpha/2}$ = value from Student's t-distribution with $n-1$ degree of freedom and a significance level of $\alpha/2$
α = significance level, 5% for 95% probability
d = the percentage deviation of the confidence interval about the mean

The program used to perform the discrete event simulation with, is Salabim (Van der Ham, 2021). Salabim is a discrete event simulation package for python. Python is used for its flexibility and scalability, and to gain understanding of the processes behind programming of complex real world logistic problems.

6.8. Scenarios

To capture the performance of the model under varying circumstances, a sensitivity analysis is proposed. By testing the model performance for different conditions, statements can be made on ideal performance, robustness and stability.

Two sensitivities have been identified to give relevant insights, being the sensitivity to order arrival patterns, and the sensitivity to order type skewness. The order type skewness, stands for the degree to which the type of arriving orders, are either store orders or web orders, assuming a constant throughput of pallets.

The order arrival pattern has been selected because it can indicate which operational alternative has the highest theoretical throughput and which alternative is least sensitive to peak order arrivals. The highest theoretical throughput can be tested by letting all orders arrive upfront. In this way it becomes clear which alternatives handles orders fastest, irrespective of arrival rate.

Furthermore, with a spread-out arrival pattern, the performance under ideal situations is shown, this is interesting in comparison with the case arrival pattern because it can indicate for each design alternative, how well a non-ideal arrival pattern, can be handled. This could lead to concluding a design alternative is a good choice, when the arrival pattern can be managed, or it can lead to concluding that an operational philosophy is particularly well suited for absorbing peaks of orders arriving. This can be used to base consideration about the robustness for each operational philosophy on.

The effect of the order type skewness is interesting in light of the expected growth of e-commerce orders, as discussed in section 2.1. A constant throughput is considered, because the growth of the online channel is expected to cannibalize part of the offline channel orders. Results from a skewness of large web order amounts can indicate which operational philosophy is best suited for future operations. Also, a scenario is investigated where the demand skewness can represent a company which is only just starting up the online channel operations, therefore receiving little amounts of web orders. For such a situation a different temporary solution can be the best option.

Demand skewness patterns of 95/5, 90/10 and 80/20 are used. Where these figures are defined as the percentage of pallets for store orders versus the percentage for web orders. The 90/10 skewness is selected because it represent the current throughput figures of the case. The 80/20 skewness type is selected because that represent the throughput numbers of the outlook for 2025 in the case situation. For more insights a skewness pattern of 95/5 is selected as well, to simulate companies who are in an even earlier stage of online channel implementation. The gained insights can shed light on potential investment decisions.

Not every KPI is relevant for each scenario. The 'length of day' does not give accurate results on order processing efficiency, when orders arrive all at the last minute, for example. Furthermore, not all scenarios of order type skewness, have to be evaluated for every order arrival pattern. Table 6.8, summarizes which scenarios are being evaluated, the resulting number of different scenarios is five. The exact input values for the scenarios will be discussed in section 6.9.

Table 6.8: Overview of scenarios

	Order skewness store/web		
Order arrival pattern	A: 95/5	B: 90/10	C: 80/20
1: Upfront		√	
2: Evenly spread		√	
3: Case	√	√	√

Scenario 1B does not consider the 'lead time' and '% orders delayed'

6.9. Input Data & Validation

As described in section 6.2, the input for the model exists of the amount of orders, the order arrival pattern, the order composition, the amount of cases on a pallet and the amount of pieces per pallet. Because the use case considered, is from an actual client of RHDHV, these order patterns and operation parameters are known. First, the number of orders for each type is determined. Secondly, the distribution for each product type of the case is analysed. All inputs are summarized in table 6.9.

6.9.1. Order volume

The input data for the number of store orders can be obtained from data from the case. The data available from the case represents a peak month of warehouse operating. From the case data a plot can be made, presented in figure 6.6, each data point represents a day. As can be seen, the amount of incoming store orders per day is very evenly spread between the values of 10 and 20 orders. Furthermore, the average of the number of orders per day is 15. Therefore, an integer uniform distribution is selected, ranging from 10 to 20, which implies an average number of orders equal to the case situation, being 15 orders per day.

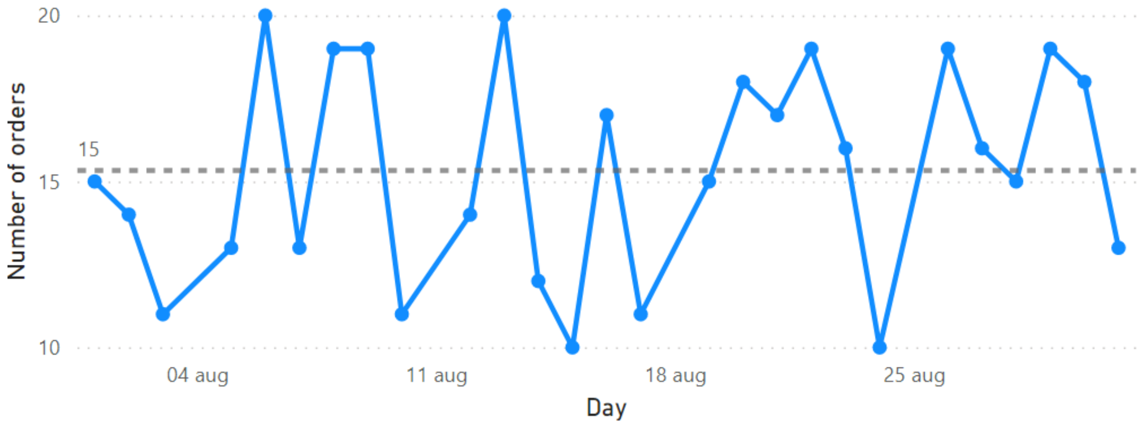


Figure 6.6: Amount of store orders per day

For the number of web orders very little data is available. The only available data on web orders is the throughput of pallets per product type per month. In order to adapt this data to amount of orders per day, several calculations need to be made. The formula used to do so is presented in equation 6.2.

$$weborders/day = \frac{pallet\ throughput \cdot cases/pallet \cdot pieces/case}{workdays/month \cdot pieces/order} \tag{6.2}$$

For this calculation to give an accurate estimation of the number of web orders per day, the weighted amount of cases per pallet and the weighted amount of pieces per case, for each product category is used.

The resulting number of pieces which are processed per day, and are used as inputs can be seen in table 6.9. For each replication the number of processed pieces per day is varied around the mean, to simulate varying day by day demand. The selected distribution is described in table 6.9. The distribution results in a mean comparable to the actual mean amount of pieces processed in the case situation.

The difference in order type skewness influences the number of store orders and pieces processed in a day. To determine the order values for the 95/5 and the 80/20 order type skewness, it is made sure that the throughput of pallet of the warehouse remained the same. In order to do so, the average number of store orders arriving is scaled with the amount of pallets, while maintaining the same spread between maximum amount of orders and minimum amount of orders. For the web orders the average number of orders per day is scaled as well, with the number of pallets for the relevant order type skewness.

6.9.2. Product category distribution

The distribution of product category for each order has to be known as well. With this information, the incoming orders can be simulated to have the same probabilities of product categories within each order. With this information the products within an order can be assigned to a picking zone and it can be traced which product categories require replenishment by a forklift. The distribution of product categories for store orders is known and presented in figure 6.7. Unfortunately the distribution of product category for web orders is no readily available. Therefore, it is constructed with known throughput values. The throughput values are given for each product sold via the web channel. By linking the product-id for every sold product, to their product category the distribution was found for web orders, as seen in figure 6.8 These distribution can exactly be replicated by probability density functions. By setting the probability for each product category, equal to the value found for the use case, the compositions of the orders in the simulation are known to be representative of the distributions for the case.

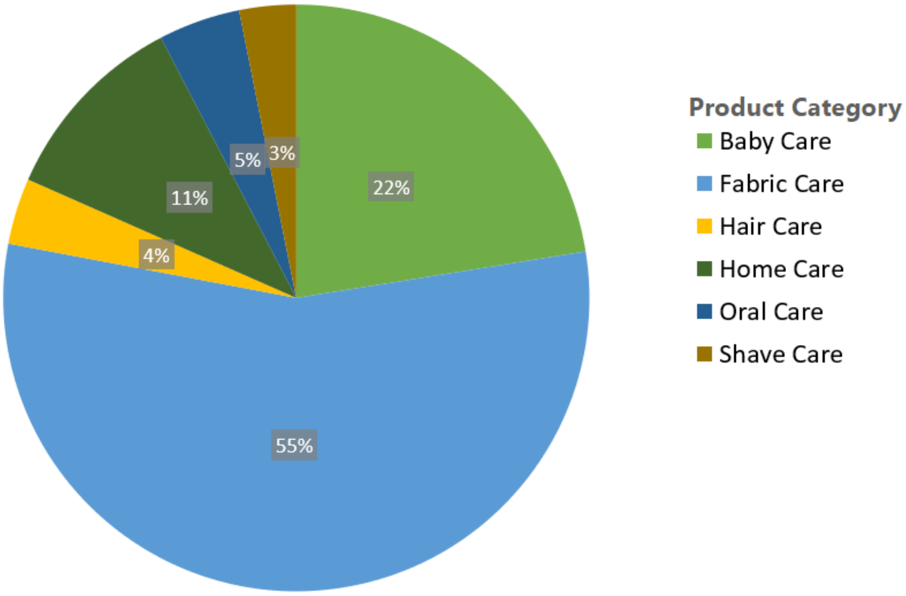


Figure 6.7: Percentage of product category for store orders

6.9.3. Order composition

To simulate the composition of each order, again data from the case is used. The order composition consist of the number of different products, and the amount for each of those products. First, the number of different products in a store order is determined. This is done by checking the amount of unique product-ids per order. The resulting histogram for number of unique products per order can be seen in figure 6.9a. The average of unique products per order for every day is taken, since the model is evaluating operations for a day of work, therefore the number of data points is the amount of work days in a month, which is 27.

As can be seen, the average amount of different products within a store order is 27. Furthermore, the minimum is 21 and the maximum is 39. To accurately represent this distribution in the simulation, a triangular distribution is selected with a minimum of 21 and a maximum of 39. The mode of the triangular distribution is set to be 21 as well, since this is the amount of products that is seen most regularly. Moreover, the resulting average of the triangular distribution, matches the average found in the data. A

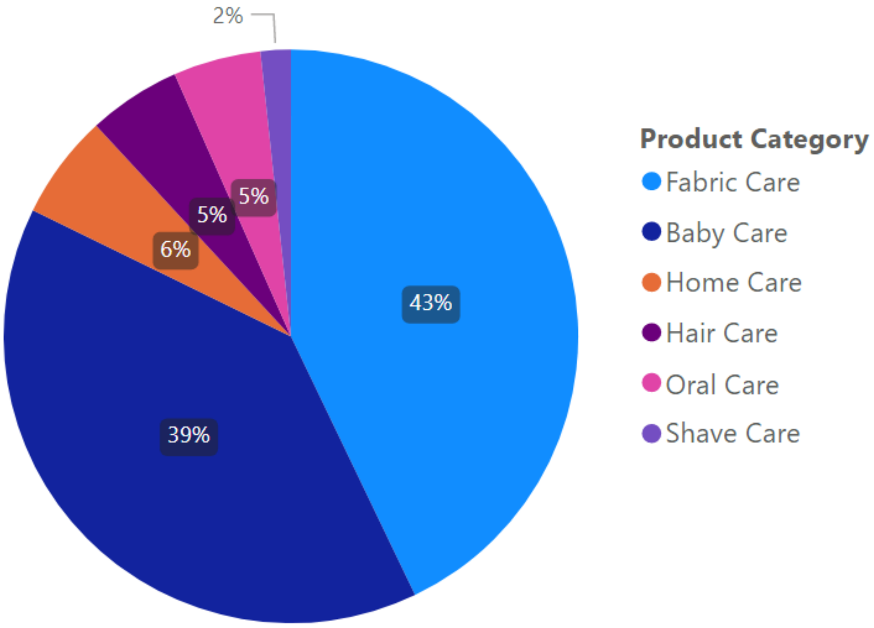


Figure 6.8: Percentage of product category for web orders

sample of 27 instances from the distribution is presented in figure 6.9b. For this approximation a visual goodness-of-fit test can be performed. As can be seen, the histograms are very much alike, which makes the chosen distribution suitable.

A similar approach has been used to determine the number of cases per product per order for each day. The results are presented in figure 6.10. This distribution has a mean of 77, a minimum of 45 and a maximum of 121. Therefore, this distribution can be approached by a triangular distribution as well, with the respective maximum and minimum, and with the mode set to 65. These values match the actual distribution, since the peak of the histogram is now similar to the mode. Again the input to the model is presented in figure 6.10b, by which the visual goodness-of-fit test can be performed. As can be seen, the sample from the distribution is very similar to the distribution of the case data, therefore the approximation is suitable.

Unfortunately, the composition distributions for the web orders are unknown. Although, it is assumed that each web order on average, consists of three pieces, as discussed in section 6.4.2. Therefore, the selected distributions for number of unique products per order and the amount for each product, need to match this assumed number.

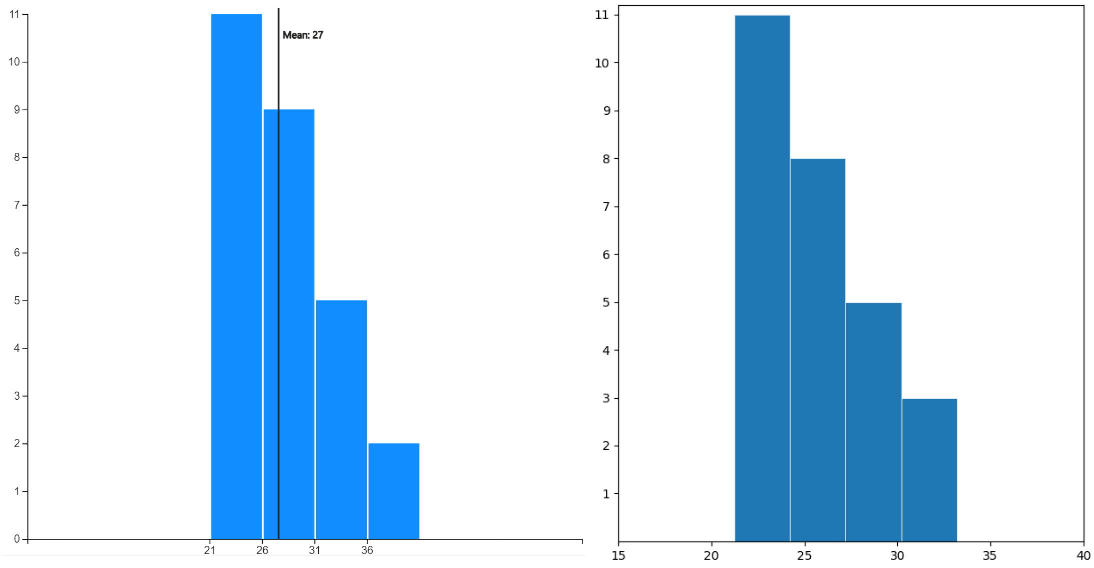
This is done by taking a triangular distribution for each parameter. The number of unique orders is taken to be triangularly distributed with a maximum of 3, a minimum of 1 and a mode of 1. This results in a mean of 1.6 unique products per order. Subsequently, the amounts for each product is set to be a triangular distribution with a minimum of 1, maximum of 4, and a mode of 1. Which results in an average of 2 pieces per product.

The resulting average amount of pieces per order is slightly higher than the earlier assumed 3 pieces per order. However, the distributions do seem realistic and feasible.

6.9.4. Order arrival patterns

The input for the order arrival patterns of the store and web orders, are partly generated and partly taken form the case. The generated arrival patterns, are the pattern where all orders arrive upfront, and the pattern where all orders are evenly spread out throughout the day.

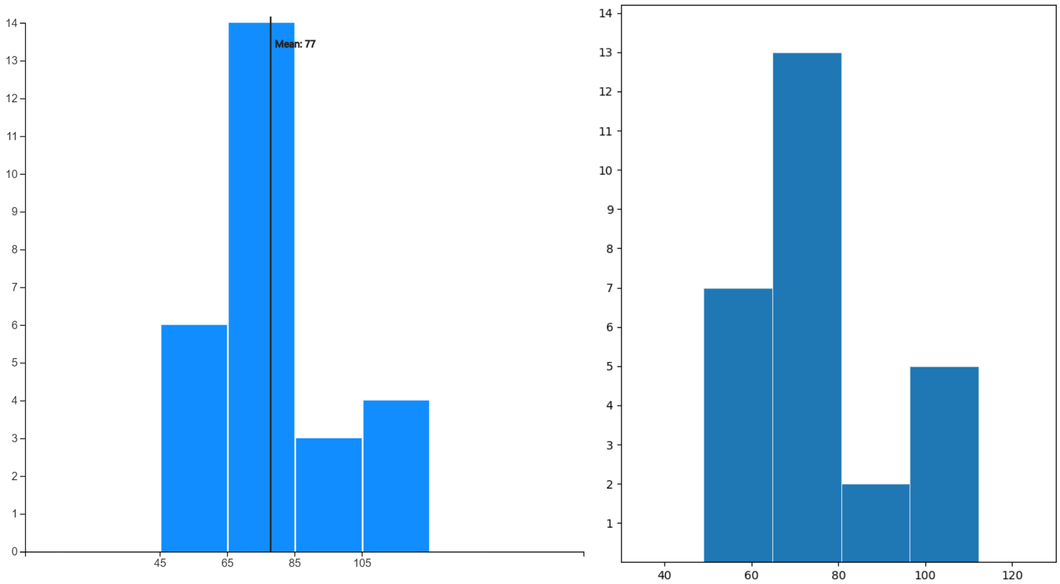
These kind of patterns, however, rarely occur in real life. Therefore, also a look is taken at the impact of an actual order arrival pattern. Figures 6.11a and 6.11b, represent the order arrival pattern from the case. As a matter of fact, these patterns actually represent the arrival pattern for the trucks collecting the orders. This pattern has been assumed as order arrival pattern because it is infeasible



(a) Average of unique products per store order per day

(b) Sample of distribution for approximation

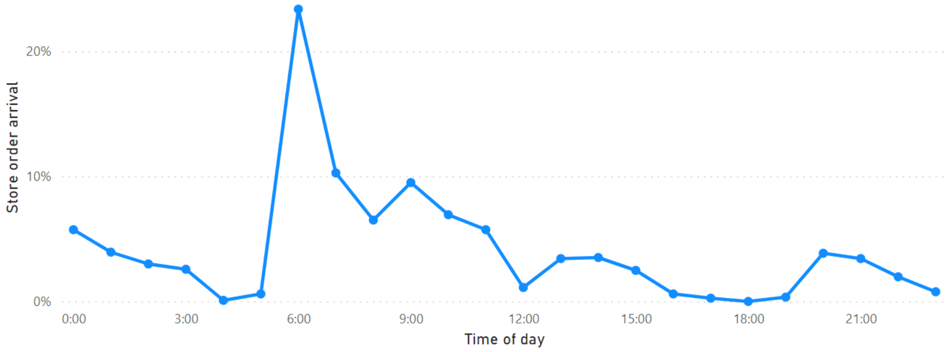
Figure 6.9: Amount of unique products per order histograms



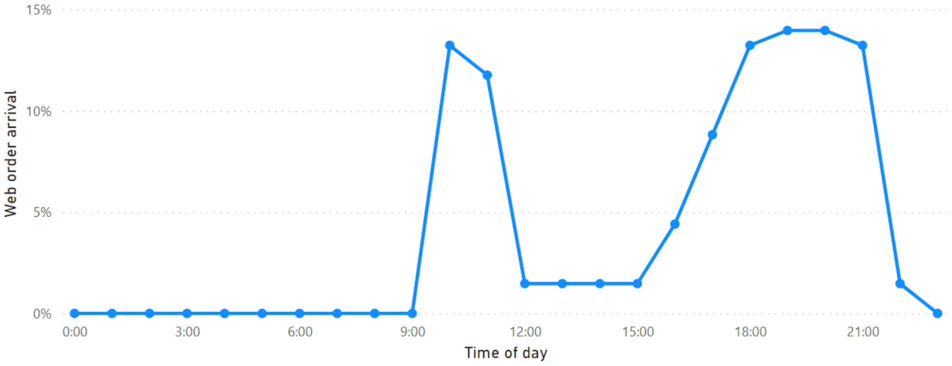
(a) Average of cases per product per store order per day

(b) Sample of distribution for approximation

Figure 6.10: Amount per product per order histograms



(a) Arrival pattern for the store orders



(b) Arrival pattern for the web orders

Figure 6.11: Order arrival patterns

for orders to be prepared for a too long time in advance, because the fulfilled orders would need to be stored at the shipment area, which often is space constrained.

For the simulation these exact order arrival patterns can be used. No approximation is necessary, as the percentage of orders arriving at a time, can be multiplied by the overall amount of orders for that day. The outcome is rounded to ensure integer amounts of orders arriving.

6.9.5. Target order lead time

As described by Rouwenhorst et al. (2000) and mentioned in section 2.2, for a distribution warehouse the order picking processes are costly and complex. Therefore, for the warehouse considered, the efficient order picking is the main optimization goal and the desired short response time makes the throughput a prominent design criterion.

The operations for the use case, consider a lead time target for the store and web orders. For the store orders, average desired lead time is two hours. The lead time indicates the time from when the order arrives, up to when the order is fulfilled. When a truck arrives to collect a fulfilled order, the truck cannot be waiting for too long, because fines can be associated with long waiting times. On the other hand, warehouse processes can become congested when the truck has not arrived yet, therefore preliminary fulfillment of the orders is currently not an option.

Furthermore, currently the average lead time of web orders is a desired two hours. When the web orders arrive, oftentimes the customer expects the package to be delivered the next day. To ensure that the picked orders can still be scheduled for delivery, a cut-off time can be used, after which orders cannot be delivered the next day, but the day after that. Another process requirement is that the standard deviation of order lead-times is small, no matter the circumstance. Even in peak hours the lead times must fall between acceptable values, this ensures reliability of the process.

The lead time targets currently used by the use case company, can be utilized to calculate the mean orders delayed performance indicator. The performance indicators have been introduced in section 6.3.

6.9.6. Summary

To summarize, an overview of the inputs is presented in table 6.9. These inputs will be the same for each operational alternative. By using inputs from an actual FMCG distribution warehouse an element of realism and validity is added.

Table 6.9: Input values for the simulation model, based on use case

Parameter	Value
Order volume store orders 95/5	IUD(11,21)
Order volume store orders 90/10	IUD(10,20)
Order volume store orders 80/20	IUD(8,19)
Pieces volume web orders 95/5	11018 · CUD(0.8, 1.2)
Pieces volume web orders 90/10	22036 · CUD(0.8, 1.2)
Pieces volume web orders 80/20	44072 · CUD(0.8, 1.2)
Product distribution store order	PDF(55, 22, 11, 5, 4, 3)
Product distribution web order	PDF(43, 39, 6, 5, 5, 2)
Unique products store order	Triangular(21, 39, 21)
Amount per product store order	Triangular(45, 121, 65)
Unique products web order	Triangular(1, 3, 1)
Amount per product web order	Triangular(1, 4, 1)
Arrival patterns	Upfront & spread out & case
Leadtime target store	2 hours
Leadtime target web	2 hours

IUD (Integer Uniform Distribution), CUD (Continuous Uniform Distribution), PDF (Probability Density Function)

6.10. Conclusion

This chapter has introduced the modeling phase of the research. First the model objective is described as being the ability to evaluate the effect of operational philosophy on the warehouse performance, while considering different order arrival patterns and order type skewness. With different operational philosophies, the warehouse flows alter, which results in different travel distances and ultimately in different processing times. The order arrival patterns are varied because it gives an indication of the ability of each operational alternative to process peak order arrivals and the theoretical most efficient philosophy can be determined.

The order type skewness is varied to get insights on the effectiveness of each alternative in future situations or in situations where an online channel is just recently added.

The inputs have been discussed as being the order volumes and compositions, while the products are assumed to be readily available in the reserve storage area. For the outputs, several KPIs have been identified as being relevant for the research question. The KPIs are: Length of day, Makespan, Percentage of orders delayed and the Order leadtime. The makespan is defined as the time it takes for all orders to be fulfilled, given the order queue is not empty. For the leadtimes the standard deviation is considered, as a measure of process reliability.

Another output considered to be important is the Utilization. This is not a KPI but it does give insights in the efficiency of each operational philosophy and it can be used for an indicator for associated costs.

Simplifications have been introduced in order to keep the simulation model simple, while maintaining the required amount of accuracy. The main method for simplification is using a black-box approach to the warehousing processes. Furthermore, the exact product storage locations are not considered. This is done because this information is not required to answer the research question, and product allocation, picker routing and batching problems do not have to be considered.

The model components have been presented in a Swimlane flowchart along with a PDL to indicate each component and its interactions. These visual representations can be found in appendix B and C.

Five scenarios have been identified as being relevant to investigate. The scenarios exist of a combination of arrival patterns with the order type skewness. An overview of the scenarios has been presented in table 6.8. Furthermore, for every operational alternative the configurations have been discussed. For each alternative the picker travel distances have been determined and the number of pickers has been set. The values have been set in such a way that the comparison between the alternatives is as fair as possible, while being based on literature and expert knowledge.

Finally, model inputs have been discussed. It is described how certain data elements have been implemented directly from information of the considered case, and how other data has been fabricated, either from case information, literature sources or expert knowledge. For each input the validity has been considered, as well as the exactness of the approximation of the chosen distributions. To summarize all simulation model inputs, a table has been presented, being table 6.9.

The goal of this chapter is to answer the fifth research question, which is: ’How is the model set up and what experiments are required to evaluate the performance of the operational alternatives?’. In summary, this is answered as follows:

1. Inputs to the simulation model are order volumes, compositions and arrival patterns
2. Output performance is measured by ’Length of day’, ’Makespan’, ’Percentage order delayed’ and ’Leadtime’
3. The alternative operational philosophies have influence on the process flows and average travel distances
4. Relevant scenarios consist of variable order type skewness and order arrival patterns
5. Input values are matched to simulate real warehousing values

V

Evaluation

7

Results & Analysis

This chapter describes the results form the simulation model, it forms the first part of the evaluation section. Five scenario's have been evaluated by the simulation model. For every scenario the results are presented and the notable observations are mentioned, along with an analysis of the results. At the end of this chapter the sixth research sub-question is answered, 'How do the operational alternatives perform under different scenarios?'.

The results are presented in box-plots. These are ideal for representing the locality, spread and skewness of the results. The box plots can be defined by five aspects, being the minimum, maximum, median, first quartile and third quartile. The minimum and maximum are defined by the respective lowest and highest data points, excluding the outliers. A data point is regarded as an outlier when it is outside of 1.5 times the inter quartile range (IQR). The IQR is defined by the distance between the first and the third quartile. The first and third quartile represent the median of the respective lower or upper half of the data set.

The box plots feature a comparison interval around the median as well, also known as a notch. The notch represents the approximate 95% confidence intervals for the median. According to Chambers et al. (2018), when the notches do not overlap there is evidence for statistically significant difference between the medians. The size of the notch is determined as follows:

$$\text{median} \pm 1.57 \times \frac{IQR}{\sqrt{n}} \tag{7.1}$$

Where n is the number of data points. Box plots are extremely useful for representing lead times because it gives immediate insight in the spread of the results and therefore the reliability of the processes.

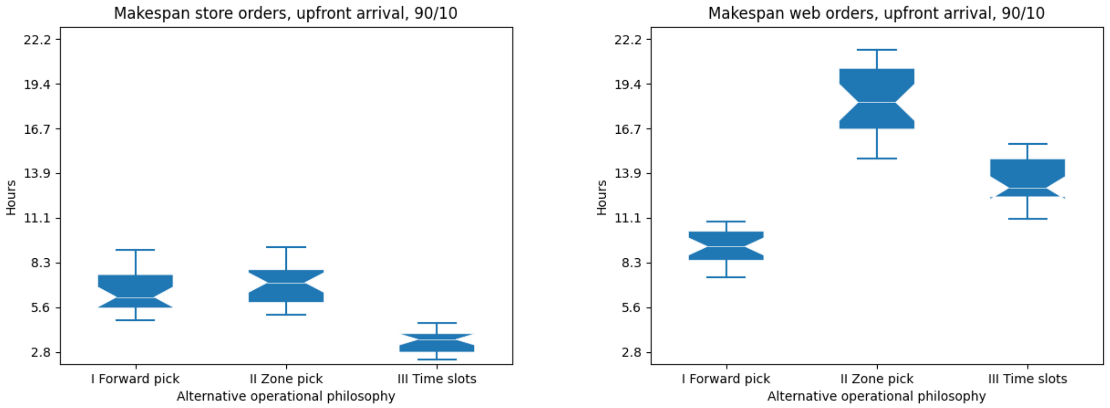
7.1. Sensitivity to the Order Arrival Pattern

This section presents the simulation model results for the varying order arrival patterns. These results give an indication for the sensitivity of the operational philosophies to the arrival pattern. The skewness for the store and web orders is set to 90/10 for these simulations. That skewness is similar to the current throughput numbers for the use case.

7.1.1. Upfront pattern

Here the results for the upfront order arrival pattern are presented. For this scenario only the makespan and the utilizations give representative insights. The lead times are not shown because due to the orders arriving upfront, the orders bunch up, which results in high lead times for the orders last in queue, while the first orders can be served immediately. Therefore, the lead times do not give a fair representation of the efficiency of the operational philosophy for this order arrival pattern. The results belonging to this scenario can be found in figure 7.1.

For this order arrival pattern, it is chosen to present the makespan for both order types. These results give an indication of the maximum throughput for each operational alternative because the time it takes to handle all orders is not constraint by the order arrivals. Furthermore, the length of day is determined by the highest makespan from both order types.



(a) Makespan store order with orders arriving upfront

(b) Makespan web order with orders arriving upfront

(c) Average performance over runs

		Utilization		
Alternative	Length of day [s]	Store pickers	Web pickers	Forklifts
I forward pick	33579	0.65	0.99	0.24
II zone pick	65700	0.33	0.90	0.12
III time slots	48201	0.93	0.93	0.17

Figure 7.1: Results upfront order arrival 90/10

Analysis

From the results is becomes apparent that operational alternative I, the forward pick area, fulfills all order the fastest when orders arrive upfront. This indicates that alternative I has the highest throughput. Operational alternative III, time slots, has the second best throughput, before alternative II with the pick zones. The operations of alternative I are more dependant on the forklift performance, as can be seen from the forklift utilization.

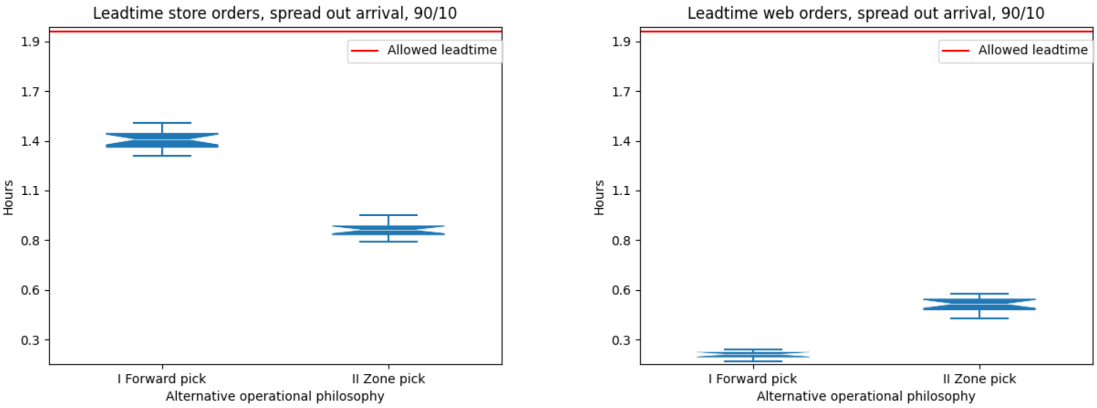
It can be seen that the store orders take significantly less time to fulfill than the web orders, while the amount of pallets that require handling is nine times higher for store orders. This can be attributed to the fact that store orders exist of full pallet orders and cases, these can be handled more efficiently than the pieces for the web orders. Moreover, the amount of orders has influence on the efficiency since each order comes with a set of required handling steps, independent of the order composition.

For this scenario, Alternative III with time slots, performs best on the store order fulfillment. That is because the complete workforce can be dedicated to fulfilling the store orders, after which the complete workforce switches to fulfilling web orders. Such efficient picking is normally not feasible for other order arrival patterns. Also, alternative I and II perform similar for the store order fulfillment, the difference in performance is not significant.

Another observation can be made regarding the utilization of the store pickers for Alternative II zone picking. This utilization value is significantly lower than the values for the other alternatives. This can be explained by the long web order fulfillment in comparison with the store order fulfillment time. When the store order pickers are done, they have to wait for the web pickers to be ready, which is measured as not productive time.

7.1.2. Spread out pattern

The results for the spread out order arrival pattern are presented in this section. It must be noted that for the figures, the results of Alternative III: 'time slot separated picking' are not presented. The values for this alternatives are not shown because they are not representative. The performance of this alternative is highly dependant on the selected time slots for each order type, and is often dictated by the



(a) Leadtime store order with orders arriving spread out

(b) Leadtime web order with orders arriving spread out

(c) Average performance over runs

	% Delayed orders		Utilization		
Alternative	Store (max)	Web (max)	Store picker	Web picker	Forklift
I forward pick	1.5 (8.3)	0.0 (0.0)	0.34	0.37	0.14
II zone pick	0.0 (0.0)	0.0 (0.0)	0.35	0.68	0.15
III time slots	58.6 (62.5)	62.3 (70.3)	0.50	0.50	0.13

Figure 7.2: Results spread out order arrival 90/10

efficiency to switch time slot at the right time. The author has not optimized the time slot selection for this scenario, therefore the results would not have been valid. The results for this arrival pattern are presented in figure 7.2.

The spread out order arrival pattern, represents the scenario where the total throughput of the warehouse is similar to the other scenarios, while the workload is evenly spread. In theory this is the scenario where all lead time targets should be met, since orders are less likely to bunch up, resulting in short lead times.

Analysis

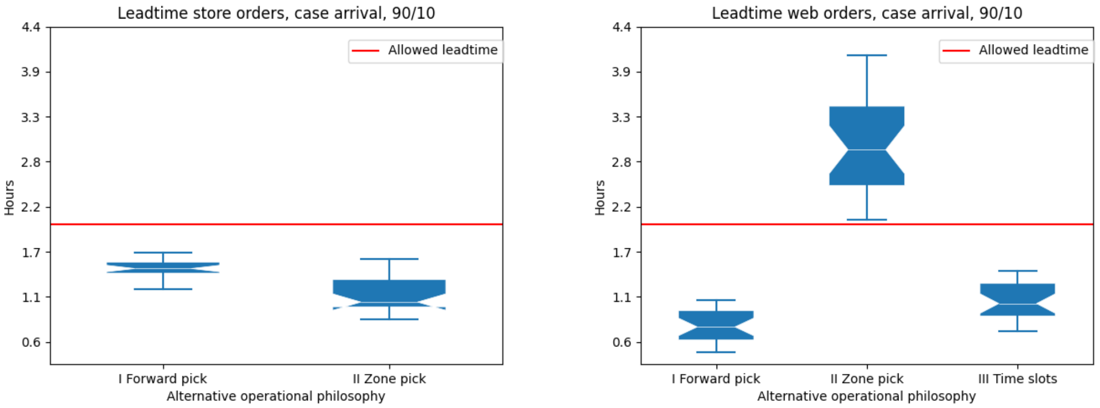
Firstly, the extreme dependency of the time slot selection for the performance of operational alternative III has become apparent. A choice has to be made, whether to fulfill the store orders or the web orders. When one type of order is being fulfilled, the lead times for the other type increase. Therefore, a time slot pattern is required tailored to the arrival pattern of the orders.

Another observation can be made for the efficiency of the store order picking for operational alternative II. In contrast to the results from the upfront order arrival, here the difference is significant. This can be explained by the ability for alternative II to pick a single order parallel, this brings a benefit when only a few orders need to be picked at a time. For a large queue of orders this gain is nullified due to each picker having to fulfill double the amount of orders.

Operational alternative I, with the forward picking area, performs significantly better for the web order fulfillment. Moreover, the utilization of the web pickers is significantly less than the utilization for Alternative II. Therefore, with alternative I it is possible to fulfill web orders faster and with less people.

It is notable that although the plots indicate lead times well below the allowed lead time, still an average of 1.5% of the orders for alternative I is being fulfilled too late. This can be explained by the fact that the plots only indicate average values over the multiple runs, while within each run some orders can be fulfilled too late.

As expected, Alternative I and II can handle the spread-out arrival pattern easily, seen from the low per-



(a) Leadtime store order with orders arriving as for case

(b) Leadtime web order with orders arriving as for case

(c) Average performance over runs

		% Delayed orders		Utilization		
Alternative	Leadtime store [s]	Store (max)	Web (max)	Store picker	Web picker	Forklift
I forward pick	5249	5.4 (15.0)	2.5 (11.2)	0.21	0.38	0.09
II zone pick	4083	6.8 (35.0)	60.0 (73.2)	0.18	0.55	0.07
III time slots	15841	32.4 (55.5)	9.0 (26.6)	0.45	0.45	0.08

Figure 7.3: Results case order arrival 90/10

centages of orders delayed. Furthermore, the spread of lead times is small, which indicates a reliable process, with a maximum spread of 16 minutes.

7.1.3. Case pattern

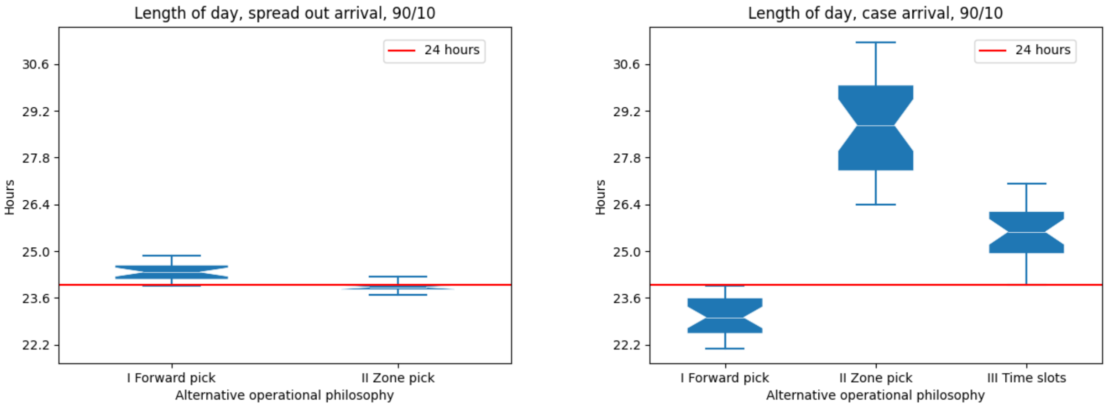
The sensitivity of the operational alternatives to the order arrival patterns is finalized with this section. The results for the case order arrival pattern are presented here. It can be seen that the lead time for the store orders for Alternative III is not presented. This is due to the big difference with the lead times for the other operational alternatives. This difference can be attributed to the fact that the fulfillment of the store orders is set on hold, while the web orders are being fulfilled. The time slots are set in such a way that the pickers start with the web orders as soon as the first web order arrives. The store orders are being fulfilled again when all web orders have been processed. This means the store orders are used as a buffer, which leads to high store order lead times, but fast web order fulfillment. The results for the case arrival pattern with a skewness of 90/10 are presented in figure 7.3.

The arrival patterns from the case are presented in figure 6.11, and represent orders arriving according to an actual pattern as seen in industry. This pattern features order arrival peaks, which puts large strain in the operations. Moreover, the peak for web order arrival, is right before the end of the day. This can lead to personnel having to work over-hours, which is more expensive than working during regular hours.

Analysis

From the results it can be seen that the overall performance of alternative I is the best, although it performs not the fastest for the store order fulfillment. However, its performance on the store orders is very constant. Furthermore, it outperforms alternative II significantly for the web orders. This presents a huge benefit for the forward storage operational alternative, the abiity to handle peak order arrivals.

It becomes apparent that alternative II, with zone picking, is not suited for sudden web order arrivals. This is best seen by the percentage orders delayed for web orders. Explanations for this behaviour can be the fact that the benefit of parallel picking of a single order is lost when a large amount of orders arrive, due to each pickers having to process more orders with lower quantities.



(a) Length of day spread out order arrival

(b) Length of day case order arrival

Figure 7.4: Length of day for varying order arrival patterns

The performance of Alternative III, with time slots, is better than alternative II for the web orders. This is, again, due to the fact that the entire workforce is dedicated to fulfilling the web orders. This goes with the cost of a large amount of store orders being fulfilled too late.

7.1.4. Length of day

The difference in length of day for the spread out arrival and the case arrival, can give an indication for the amount of late night hours the personnel has to work in order to fulfill all orders. It is currently difficult for warehouse operators to find enough staffing, let alone staffing for the late hours. The results are presented in figure 7.4

From the length of day results it can be seen that late hour peak arrivals form a big problem for work planning. Only alternative I can fulfill the orders within a day. Its performance for the spread out arrival is worse than its performance for the case arrival due to the late arrival of an order in the spread out case.

Furthermore, where alternative II performed decent for the spread out arrival, it falls short when peak arrivals are introduced, seen from the day being ended on average five hours late. The performance of Alternative III can only be seen in the light of the store orders being used as a buffer. However, even still the average day takes two hours too long.

7.2. Sensitivity to the Order Type Skewness

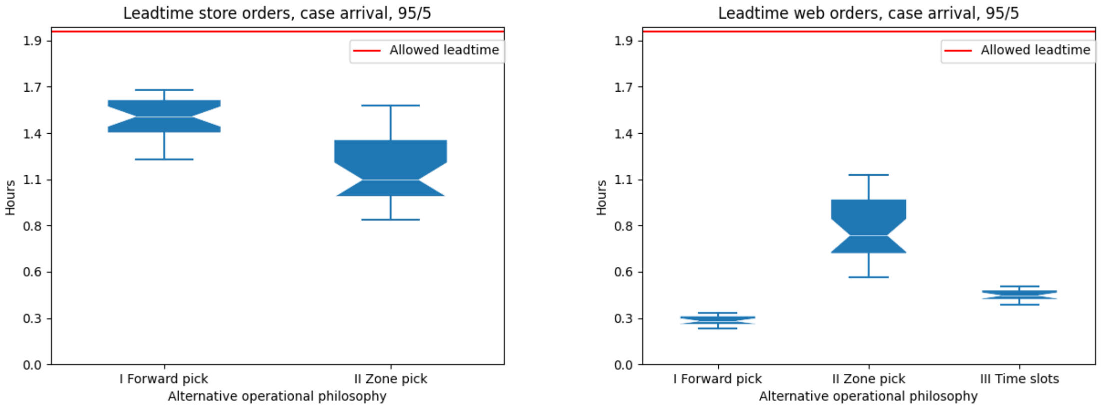
In the following sections the impact of the order type skewness is analysed. The skewness indicates the ratio between throughput of pallets for store orders and the throughput of pallets for web orders. The results for order skewness 90/10, are already presented above. The order arrival pattern set for the evaluation of the skewness sensitivity is the case order arrival pattern.

7.2.1. Skewness of 95/5 store/web orders

The skewness of 95/5 presents a situation where warehouse operations are less dominated by online orders. This can be the case for companies who have recently started with integrating the online channel in the warehouse. However, the skewness does mean that more store orders pas through the warehouse, which can have negative effects for efficiency for the more online oriented warehouse layouts. The results are presented in figure 7.5.

Analysis

Although the average store order fulfillment for alternative II is better than the store order fulfillment for alternative I, it can be seen that alternative II has a higher amount of orders delayed. This can be due to the larger spread in order leadtimes, which can be seen in figure 7.5a.



(a) Leadtime store order with 95/5 skewness

(b) Leadtime web order with 95/5 skewness

(c) Average performance over runs

		% Delayed orders		Utilization		
Alternative	Leadtime store [s]	Store (max)	Web (max)	Store picker	Web picker	Forklift
I forward pick	5336	8.0 (22.0)	0.0 (0.0)	0.24	0.20	0.10
II zone pick	4178	10.4 (33.3)	2.7 (12.9)	0.24	0.34	0.09
III time slots	14194	35.2 (52.9)	0.0 (0.0)	0.28	0.28	0.09

Figure 7.5: Results case order arrival 95/5

Another observation is the good performance of the operational alternatives on the fulfillment of the web orders, even while the orders still arrive in peaks. This can be explained by the lower amount of incoming web orders, which therefore form less of a bottleneck and a smaller queue for the web order pickers.

Furthermore, the large spread in web order leadtimes for alternative II catch the eye, while web order fulfillment operations are similar to the operations of alternative III. This indicates that the addition of personnel to the web order fulfillment can relieve dependency on the pickers, thereby making web order fulfillment faster and more reliable.

7.2.2. Skewness of 80/20 store/web orders

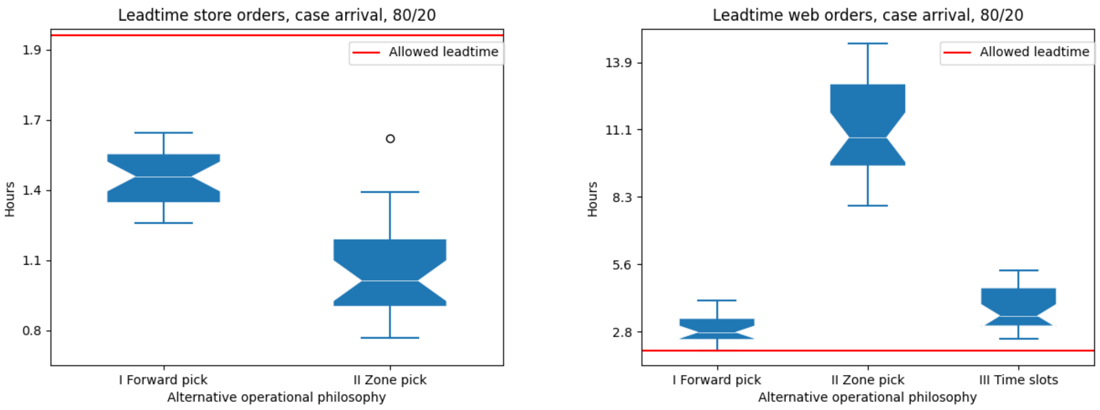
The results for the order type skewness of 80% store throughput and 20% web throughput, are presented in figure 7.6. This scenario simulates the expected throughput figures for 2025 for the case company. This means that the expected web order amount will be doubled from the current situation. Although, the overall throughput of the warehouse is the same to other scenarios, the amount of orders that are processed is not. Rising from an approximated 7000 web orders, up to 14000 web orders that have to be processed.

It should be noted that the y-axis for figures 7.6a and 7.6b, are not equal. This is done because the results have a different order of magnitude. When plotting the results on equal scale, the spread for the store order lead times would be lost.

Analysis

When looking at the percentage web orders delayed, it becomes apparent that non of the alternative operating philosophies is suited to handle the increase in web orders. All alternatives show a delayed order percentage above 50%. From the alternatives, alternative I shows the most promise, with the least amount of orders delayed.

Another observation is the outlier seen at alternative II for the leadtime of the store orders. This outlier can be linked to the high maximum percentage store orders delayed, and is an indicator for the spread



(a) Leadtime store order with 80/20 skewness

(b) Leadtime web order with 80/20 skewness

(c) Average performance over runs

		% Delayed orders		Utilization		
Alternative	Leadtime store [s]	Store (max)	Web (max)	Store picker	Web picker	Forklift
I forward pick	5159	5.1 (22.2)	58.6 (72.2)	0.15	0.62	0.07
II zone pick	3862	4.6 (44.4)	94.5 (95.5)	0.10	0.69	0.04
III time slots	22891	29.9 (44.4)	70.4 (86.7)	0.66	0.66	0.06

Figure 7.6: Results case order arrival 80/20

of the store order leadtimes, an indication for unreliable operations, although the spread remains to be around only one hour.

7.2.3. Length of day

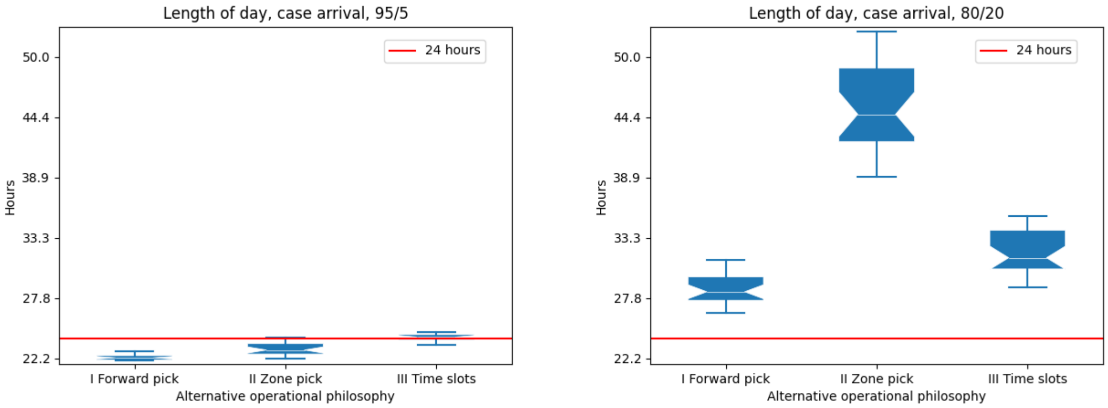
The consequences to the length of day for the different order type skewness' are presented in figure 7.7. What is apparent is the similarity between the results of the 90/10 skewness and the 80/20 skewness. Although the actual values of the results are very different, the pattern is the same. From this it can be derived that alternative II is least suited for high web order arrival volumes. Furthermore, it can be seen that alternative I performs best yet again. Also when shifting the order skewness even more towards more web orders, the relative performance between the operational alternatives remains the same.

Another observation that can be made is the short length of day for all alternatives for the 95/5 skewness compared with the 90/10 and the 80/20 skewness. This implies a high sensitivity to the amount of web orders for the performance of the operational alternative.

7.3. Conclusion

To conclude the sixth research sub-question is answered, which is: 'How do the operational alternatives perform under different scenarios?'. The information on the performance of the operational philosophies has been gathered through two sensitivity analysis, one regarding the order arrival patterns and one regarding the order type skewness. The performance for the different scenarios can be summarized as follows:

1. Alternative I shows highest theoretical throughput, with small required workforce
2. Alternative I shows reliable operation
3. Alternative I handles peaks well
4. Alternative II shows efficient operations for small order quantities



(a) Length of day case order arrival 95/5 skewness

(b) Length of day case order arrival 80/20 skewness

Figure 7.7: Length of day for varying order arrival patterns

5. Alternative II shows less reliable operations
6. Alternative II cannot handle peak arrivals efficiently
7. Alternative III shows promising theoretical throughput
8. Alternative III shows dependant performance on time slot selection
9. Alternative III is feasible when store orders can be used as buffer

8

Discussion

In this section the interpretation of the results is presented. Furthermore, the results are considered in context of the practical operational implications and further generalization is discussed. Finally, the limitations of the research are discussed.

8.1. Performance Evaluation Operational Philosophies

In this section the results from the sensitivity analysis are gathered and interpreted as a whole. The combined insights can lead to the understanding of the performance for each alternative operational philosophy. The sensitivity to the order arrival pattern has been evaluated to get insight in the effect of non ideal conditions on the efficiency of the operations. Furthermore, with the orders arriving upfront a benchmark is set for the theoretical maximum throughput.

Also, the sensitivity to the order type skewness has been evaluated. With these scenarios the performance is tested for companies in different phases of omni-channel warehouse integration. Where the 95/5 skewness represents companies at the start of omni-channel integration and the 80/20 is more representative of companies where the online channel already forms a significant portion of the warehouse throughput.

The following sections discuss the performance of each operational philosophy. The insights come from the sensitivity analysis, the aggregation of the results and from using general knowledge of the operational philosophies.

8.1.1. Alternative I: physically separated web-order picking

The results for alternative I are most promising. It shows a high throughput of web orders, due to the dedicated web order fulfillment area, i.e. the forward picking area. Because of this dedicated area, large amounts of web orders can be fulfilled quickly and efficiently. It performs best, while it requires the least amount of personnel. Furthermore, it is well suited for non ideal situations where orders arrive in peaks during the day, due to its efficiency.

Where this alternative does not always score best on store order fulfillment, it more than makes up for it with the web order fulfillment, also while maintaining a low spread in lead times. Which makes the processes reliable. Moreover, because of the efficient web order fulfillment, this alternative operational philosophy performs best for future scenarios where more of the warehouse throughput will be dedicated to fulfilling web orders.

Another benefit of this operational alternative can be found in the layout, which ensures little amounts of crossing paths, due to the dedicated picking areas. Furthermore, this results in fewer people in the reserve storage, which is beneficial for forklift movements.

However, the forward picking area does require more forklift movements than other operational alternatives, due to the replenishment requirement of the forward pick area. This can lead to a higher required investment for forklifts and a higher sensitivity to forklift down times.

Furthermore, the forward picking area requires a lot space for the conveyors to be easily accessible and for the gravity racks to be accessible for the replenishment by forklifts. The area usage for this operational alternative hinders the use of space for extra storage racks. Moreover, when operational alternatives require lots of space, it can be extra costly due to land being expensive at preferred distribution center locations, located centrally and close to the customer market.

Moreover, the required area and equipment hinders the ability to scale the web fulfillment operations. That is not beneficial concerning the foreseen increase of web orders. Also the costs for the required infrastructure is a let down. Lastly, the separate areas for web order and store order fulfillment, make it difficult for personnel to switch to web or store fulfillment. Due to the separate areas the working principles are different.

8.1.2. Alternative II: zoned and common picking area

The benefit of operational alternative II is that picking can happen in one area, simultaneously. Therefore product allocation and replenishment is relatively simple, as is the planning. Also, when orders arrive in small batches, the orders can be fulfilled rapidly due to the ability of parallel picking in both the fast product turnover zone and the slow turnover zone. This does however come with the downside of a required sorting area, which requires extra personnel and equipment. Furthermore, the benefit of parallel picking is quickly negated when orders arrive in large amounts, and need to wait for an available picker. The pickers are less available because they need to pick more orders, albeit of fewer products. Moreover, the operations of alternative II show the biggest spread in order lead times, which makes the processes unreliable. Also, operational alternative II is least suited for handling peak arrivals.

The presence of pick zones make it possible for a lot of people to work in the same area. This benefits scaleability of the operations, even more when considering the constant throughput, so personnel can be shifted from working on store orders to fulfilling web orders. The addition of personnel has a positive effect on the order lead times, and seems to decrease the lead time spread, when looking at figure 7.5b. However, the sorting area must be able to support the increase in orders as well.

8.1.3. Alternative III: time slot separated picking

As seen from the results, the performance of operational alternative III is highly dependant on the tailoring of the time slots to the order arrival pattern. Therefore, the results have not been shown in every plot. The results for the alternative are promising when looking at the throughput for the upfront order arrivals. Here the time slot selection is less relevant. Furthermore, the operations perform very reliable.

The overall performance of the alternative is good when store orders can be used as a buffer. To reach acceptable lead time figures for the web orders, the store order fulfillment will have to be put on hold.

Shifting the workforce from working on web orders, to working on store orders is relatively simple since longer time slots can be selected for the operations that require it. Although shifting these time slots real time and optimally is very complicated. This operational alternative is furthermore space efficient and low cost to implement, since no extra processing steps are required, such as sorting or replenishment of forward storage areas.

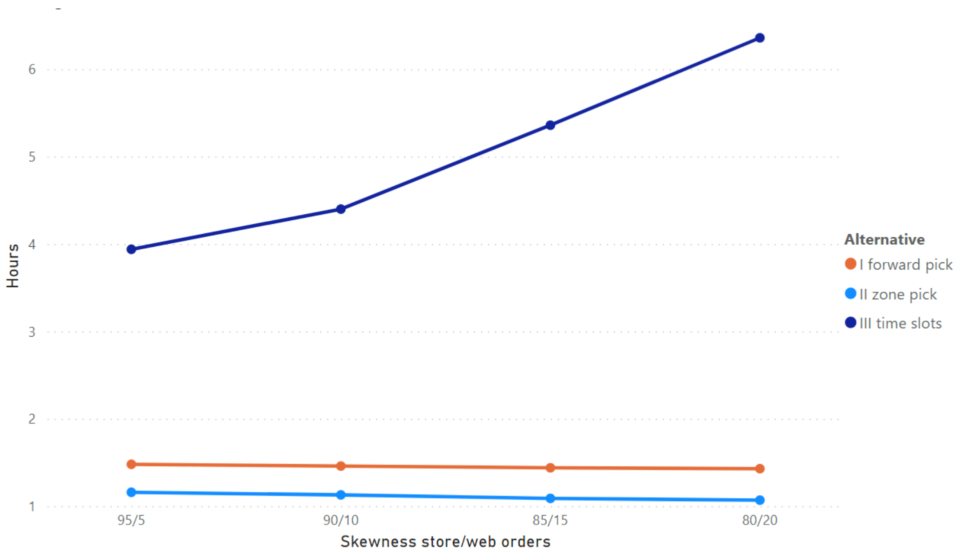
The downsides of the alternative are the high the dependency on the time slot selection, which is a complicated task, especially when demands are unknown, and the disability to scale the operations. The operations are difficult to scale because all personnel works in the same area. Therefore when the throughput is increased, choke points can arise when picker paths can regularly cross.

8.1.4. General insights

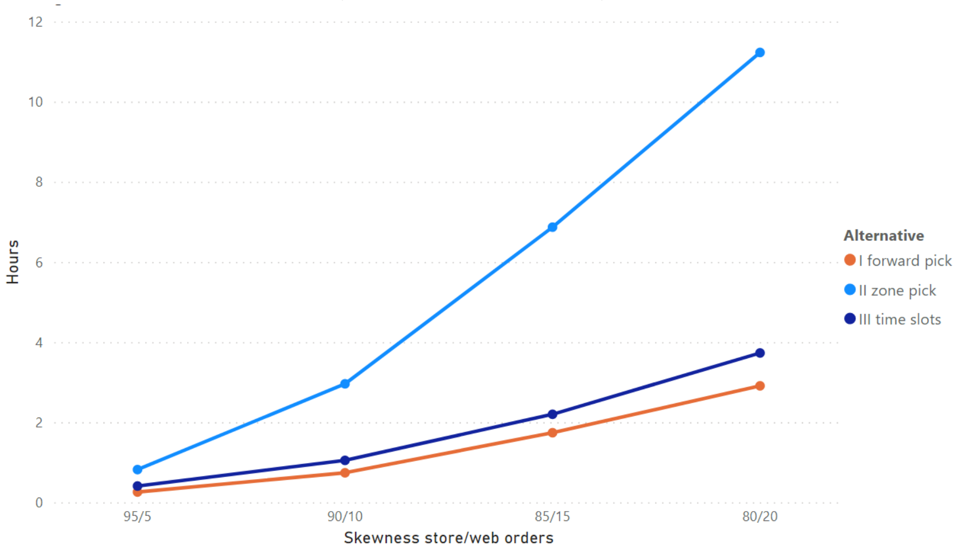
The main observation from the results is the large effect the amount of web orders has on the operations. Although the warehouse throughput remains the same, the required work to fulfill all orders increases.

Therefore, the amount of work is not defined by the amount of pallets processed, rather the amount of orders processed. A clear representation of the non linear relation between the amount of pallets processed for each channel and the fulfillment time can be seen in figure 8.1.

What is significant from figure 8.1b, is that for an increase of 5% of pallet throughput dedicated to web order fulfillment, which translates to an increase of web orders of 50%, the average lead time for alternative I, increases with 113%. While the number of pickers dedicated to web order fulfillment is theoretically sufficient.



(a) Sensitivity store order leadtime to order type skewness



(b) Sensitivity web order leadtime to order type skewness

Figure 8.1: Sensitivity of operational alternatives to order type skewness

Already from the upfront order arrival, it becomes apparent that the web orders are the driver for the overall length of day. This is why operational philosophy I performs so well in comparison with the other operational philosophies. It has a dedicated area for web orders, where a large amount of web orders can be processed efficiently, without having someone to walk through the warehouse and back with a picking cart.

Another insight is the value of flexibility when being able to shift workforce from store order fulfillment to web order fulfillment, or the other way around. Due to this ability alternatives II and III can be made to work. When picking is performed in a common area, the shifting of order type fulfillment can be used to resolve peak arrivals for example. This can become highly useful in future since no alternative is currently able to process the expected future number of web orders.

However, shifting personnel does not solve the entire problem, because the decrease in throughput for store orders, results in a decrease of just one order per day, which does not justify reducing the workforce for store fulfillment. Moreover, few pickers are dedicated to store order fulfillment already, reducing their workforce can therefore easily lead to bottlenecks.

The results indicate that the dedicated web order fulfilment area of Alternative I, is best suited for handling the expected increase in number of web orders. However, for proper handling of future throughput, more personnel is required. This forms a problem for implementing the forward picking area of alternative I, because these operations are difficult to scale. A lot of area is required when setting up a new forward storage zone, which is often not available or very expensive.

Operational alternative II, with the picking zones, is better suited for scaling of the operations, since pickers are dedicated to picking zones, thereby making picking paths less likely cross. Operations for alternative II are less reliable however. Time slot picking in alternative III, does suffer from scalability constraints. Due to all pickers being in the same area, paths are likely to cross.

From the results it can be seen that peak arrivals form a problem for efficient warehouse operations. When possible, the forming of order arrival peaks should be prevented, making every operational philosophy perform better. This goal can be reached by creating a large enough area for fulfilled orders to be stored until collection by the logistics party, in order for orders to be fulfilled in advance of shipment. However, for web orders, it is unknown when and what orders are to arrive.

Another method of dealing with peak order arrivals is setting a cut-off time, after which incoming orders are processed the next day. By doing so, previous day's order fulfillment can be spread out over the current day. The cut-off time can be set so that orders can be fulfilled before the last shipment to customers leaves. However, this does lead to lower service rates and possibly people choosing for other suppliers in order to receive their order the next day.

When contemplating the financial implications of the operational alternatives with industry experts, it became apparent that the operation costs are not significantly different from one alternative to the other. The costs for each alternative is highly dependant on the available area, but for each design alternative the same area is considered. For the total cost of the layout it does not make a significant difference whether the available space is filled with storage racks, conveyor belts or sorting systems.

A more important differentiator is, as previously mentioned, the scalability of the operations. Can a change in throughput characteristics be mitigated by assigning more personnel or does it immediately require reallocating scarce space?

8.2. Limitations

The simplifications of processes and assumptions of parameters have influence on the outcome of the research. Therefore the expected influence of the assumptions are discussed here.

An exact warehouse layout with detailed equipment selection, product allocation, replenishment and routing policies is not considered. Rather a generic warehouse layout is considered with estimations of travel distances and product handling processes. The consequences of these simplifications are that results cannot be used to base detailed warehouse design upon. Like the model, the results should not be considered detailed and more research is required to provide more detailed guidance for warehouse designers. Rather, the results can be used to get initial understanding of operational philosophy implications and can be used as considerations to base decision making upon in early stages of warehouse operations design.

Furthermore, the influence of product characteristics are not considered. The simulation model considers equal sizes and handling characteristics for each product. However, in reality some products can not be stored in equal amounts or cannot be handled as quickly as others can. This could lead to higher replenishment frequencies and larger product handling times. This can have effect on the results by increasing the spread of order lead times, which in turn can lead to higher length of days. Therefore, results from the model are indicative rather than predictive.

Another aspect not considered is the forklift reliability and the ability for the model to handle perturbations, such as breakdowns. These aspects are not required to answer the research question but can have influence on the operations. It could indicate the robustness of certain operational philosophies, which can be an important consideration for practitioners when reliability is of the essence.

It should be noted that model travel parameters are based on a maximum travel distance of 25 meters. Because the influence of picking strategy is assumed by means of a fraction of the maximum travel distance, a change of maximum travel distance influences the results. When a large travel distance is assumed the simulation results will have a larger spread between the operational alternatives, while a smaller distance will decrease the spread. However, the patterns will remain the same, therefore results can be used as an indication for actual warehouse behaviour.

Moreover, the assumed effect of picking strategy on the travel distance, is based on literature, which is based on an assumed warehouse layout. This makes applying the results one to one to an actual warehouse inadvisable, since operations are highly interdependent, as already seen in section 2.4. However, the results can be used as an indication for the solution direction.

An amount of three pieces per web order is assumed. This number has large consequences for the amount of orders in the simulation, because the amount of orders is decided by the known throughput of pieces. For example, when the amount of pieces is estimated as four rather than three, the amount of orders scale by a factor of 25%, which has large consequences on the simulation because, as seen, the amount of web orders dictate the operations efficiency. Although order volumes might turn out smaller, the observation remains that the amount of orders dictate process efficiency and non of the alternatives is currently able to process the foreseen order amounts.

Automation has not been considered in any operational alternative, because currently in practice it does not play a big role for picking processes and the operations are not considered scalable and flexible (Boysen et al., 2019, Hübner et al., 2015, Petersen II, 2000). However, when looking at the performance of the evaluated operational alternatives, automation might prove to be the best solution for handling large amounts of orders efficiently.

Moreover, for this research, the costs, area usage and scalability of the operational alternatives play a small role. However, when these factors are considered to be more prominent, it can change the outlook on the conclusions. More research is required to consider each operational alternative with detailed cost and practical implications.

Also it should be noted that, for the consideration of order lead times and length of day, the average values for each run are considered. Although this gives a good overview of the amount of times the target values are not reached, the extend to which this happens is unknown. This can lead to skewed conclusions when it appears only a few order are late while in fact they are late by an entire day. While an alternative with higher amounts of orders delayed, by maybe five minutes, scores worse. Therefore, the results obtained from the simulation model have to be interpreted within this context. The lead time for each order is considered however, in the calculations for the percentage orders delayed.

The choice of case forms a limitation as well. By considering a certain type of warehouse or company, it automatically implies excluding other types. Therefore when considering the results, it should be noted that they are obtained by evaluating an FMCG warehouse with relatively non-complex assortment. Due to this starting point the products have a higher turnover rate than when considering a DIY or fashion supplier warehouse.

Due to the large amount of movements the differences in efficiency of the operational alternatives are amplified. Which helps is representing the effect of each operational philosophy. Although turnover rates are different for other warehousing types, the patterns remain in operational efficiency, which fits the goal of the research. Although patterns remain, the worries for other type of warehouse operators will be less pressing, as a small shift in throughput, does not have to lead to an significant amount of web order increase.

Another consideration that needs to be made is the effect of the selected number of pickers on the results. Currently the amount of pickers is set to the theoretical amount required to fulfill orders within a day. The number of workers during the day is static and does not increase when orders increase. Due to the workforce being static, the peaks in order arrival can not easily be processed. Orders will start to bunch op faster and lead times will increase. Therefore, for handling variable demand, a flexible workforce is best suited, where more pickers work during peak order arrivals.

Furthermore, the amount of pickers is currently set in such a way that they are the same for every scenario and each order type skewness. When the demand on the operations shifts, the workforce should ideally shift with it. Although, for alternative I the amount of pickers is enough to theoretically fulfill orders within a day for multiple skewness levels, still a large increase in lead times can be observed.

9

Conclusions & Recommendations

In section the conclusions to the research sub questions are reconsidered and the answer to the main research question is given. Furthermore, the recommendations are presented along with suggestions for future research.

9.1. Conclusion

The main research question this research answers is: *'What is the impact of operational philosophy on omni-channel warehouse performance?'*. To get to a complete answer the question is approached through several sub questions, which are described below, along with their corresponding answers.

The first sub question answered, by analysis of general warehousing trends and operations, is: *'How is warehousing characterised and what are its challenges?'*. After consideration of the fundamental warehousing working principles, the interdependence of the operations stood out. Furthermore, order picking and throughput where identified as important performance indicators. Challenges that are identified are the requirements for different order types in combination with the process interdependencies. Furthermore, it can be concluded that warehousing practitioners are looking to implement a direct sales channel to their traditional warehouse.

Secondly a closer look has been taken at omni-channel warehousing, to answer the second research question: *'What is the state of the research on omni-channel operations?'*. Through a methodical literature review and classification, it is found that little quantitative works exist on omni-channel warehousing, which consolidated the gap of quantitative research, on a strategic and tactical level, on the implications of operational philosophy on the warehouse performance.

The third sub question used to answer the main question is: *'How is omni-channel warehousing characterised and what alternatives for operations exist?'*. From literature it was found that omni-channel supply chains are now the dominant business model, although the operation of the required warehouses are complex, especially when the warehouses are integrated for both the offline and online channel. Three feasible operational alternatives were found to be general ways of current integrated omni-channel warehouse implementation, being:

1. Alternative I: Physically separated picking area, simultaneous picking for web and store orders
2. Alternative II: Common picking area, zoned by rotation speed, simultaneous picking for web and store orders
3. Alternative III: Common picking area, time slot separated picking for web and store orders

To answer the fourth and last research sub question of the theory phase, *'How can omni-channel warehouse performance be quantified?'*, a discrete event simulation model is proposed. Such a simulation is perfectly suited to model logistical systems, due to the discrete start and end nature of logistical operations. Furthermore, a use case has been introduced to function as a reliable and feasible basis for modeling and data.

'How is the model set up and what experiments are required to evaluate the performance of the operational alternatives?', is the fifth research sub question answered, by which the modeling phase of the research is concluded. It is answered by taking the order compositions, volumes and patterns as input for the model, while the length of day, makespan, % orders delayed, lead time and utilization are taken as outputs. A sensitivity analysis is proposed to capture the model performance under varying relevant circumstances. The simulated scenarios are set to be able to evaluate the sensitivities. Lastly, to ensure realistic results, the inputs are based on data provided by the case.

The sixth research question, *'How do the operational alternatives perform under different scenarios?'*, is answered by analysing the results of the model. Through the sensitivity analysis, the performance of each alternative under varying situation became apparent. It is seen that alternative I, with the forward picking area, performs best, while zone picking in alternative II is less reliable and cannot handle peak arrivals. Alternative III can only perform well when store orders can be used as a buffer when selecting time slots.

From the interpretation of the results in the discussion, it can be concluded that alternative I benefits from a designated web order fulfillment area, which can handle large amounts of orders efficiently and reliably. Which makes this alternative best suited for future expected throughput numbers. Its downside is however the difficulties with scaling of operations, considering the requirements on available space and hardware.

For alternative II it has been identified that its biggest benefit is the scalability aspect gained from assigning pickers to a pick zone, which can be used to handle peak arrivals better and to increase lead time reliability. Furthermore, when web order volumes increase, workforce can easily be shifted from store order fulfillment to web order fulfillment, although not many personnel becomes available from store order fulfillment.

Alternative III presents reliable operations due to the large available workforce for the respective order type fulfillment. However, the good performance for web order fulfillment goes at the cost of store order lead times, which are high due to pausing store order fulfillment when web orders arrive. Moreover, the operations are not easily scaled due to the potential for crossing pick paths.

From overall insights it has become apparent that a high amount of web orders generates a high amount of stress on warehousing operations. The operations are almost entirely dominated by handling web orders. Although the warehouse throughput remains the same, the required work to fulfill all orders increases. It is concluded that the amount of work is not defined by the amount of pallets processed, rather the amount of orders processed. This forms a problem when considering the future shift in order type skewness and the often constraint space in omni-channel warehouses.

Concluding, the main research question, *'What is the impact of operational philosophy on omni-channel warehouse performance?'*, can be answered as follows. The most important impact of operational philosophy on the omni-channel warehouse performance is the ability to handle web orders. It is seen that the amount of web orders impacts operations more than the overall throughput.

Moreover, a small shift in throughput from store orders to web orders of 5%, leads to an increase of web order lead times of 113% for FMCG suppliers. This increase is even higher for the operational philosophies which are less dedicated to efficient web order fulfillment.

Therefore, when an operations design is tailored for web order handling, it performs better than more generic designs. The stresses that come with large order volumes, dictate the requirement for highly efficient web order picking, which is only possible when operations are specifically designed to do so.

Therefore, Alternative I, with the separate picking area for web orders, performs best. More so when regarding the low amount of required personnel. In these times this is a large benefit, considering the current staff shortages. Moreover, having a dedicated web order picking area, produces reliable performance, even for peak order arrivals, this benefits the reduction of personnel having to work over hours.

However, as discussed, the forward storage operations come with a high demand on required space, which makes scaling of the operations difficult, while scaling is required in order to be able to handle the foreseen increase in web orders. It should be considered to invest in warehouse space, which can be earned back through a smaller required workforce.

The operational philosophies of alternatives II and III can only serve as a temporary, flexible and low cost solution to operating the online channel. Ultimately they are not suited to handle the large amounts of orders.

However, the operations with the pick zones of alternative II do allow for increasing the workforce, without requiring extra investments in warehouse space or equipment. Because of the pick zones more pickers can work in the same area, which eventually is a temporary solution, as with a small shift in throughput, the amount of web orders requiring processing will be significant.

Therefore, more long lasting solutions need to be considered. Working with any of the considered philosophies is not durable. Especially not when considering the initial idea of an omni-channel warehouse, where web order fulfillment is often added to existing operations. This inherently forms the problem of limited available space, unless a green field integrated omni-channel warehouse is considered.

The dilemma is that efficient operations require lots of space, while easily implemented operations are less reliable and have a hard time processing peak order arrivals. Solutions can be to reduce service rates and process orders the next day, thereby mitigating the peak arrivals. It could also be considered to invest in space and infrastructure. These investments can potentially be earned back by requiring less personnel.

Since space is a huge constraint on operations, more long lasting solutions regarding automation should be considered. With limited space, automation can make omni-channel warehousing performance adequate for future rise in online orders. Some pure online suppliers have already made the gamble, and successfully so, of automating all operations to be able to handle the increase in online orders. This argues for reconsidering the separate omni-channel warehousing strategy, as it is future proof.

This is a bold statement considering the risks and downsides of high investment cost and little flexibility, but integrating omni-channel operations in one warehouse proves to be a temporary solution, when web orders are expected to increase and space in inherently often constrained.

9.2. Recommendations

As discussed in the discussion, more research is required on the effects of exact routing and product allocations in the behaviour of the simulation model. Also, the model could be adapted to consider variable pallet and product sizes. When these parameters are linked to handling times as well, the model provides even more realistic results which can be used for more detailed operations design.

Furthermore, future research should be dedicated to estimating the influence of picking strategy on the operation efficiencies. Although this is influenced by warehouse specifics, a more accurate prediction can benefit academics who try to simulate overall warehouse performance.

For future research it can be beneficial to have accurate data regarding online order volumes and compositions. This is important because a large part of the warehouse performance is dependant on the web orders, therefore this data should be accurate.

To support the conclusion regarding automation, future research should be focused on quantifying the effect of implementing automation in omni-channel warehouses. Findings could lessen uncertainties and reduce the risks associated with the high cost investments.

The practical implications of operational philosophies for omni-channel warehousing should be further investigated, as cost, flexibility and ease of implementation play a large role for practitioners, while most of research is focused on throughput and reliability.

Moreover, the effect of semi-automated solutions has not yet been considered. Future research could indicate such an increase in operation efficiency, that current omni-channel solutions can be made to work with existing infrastructure for the foreseeable future.

Regarding the required investment in space and cost for forward storage solutions, more research is required to quantify the trade off between higher space demands, while requiring less personnel to fulfill all orders. Should this trade off actually be considered, or are investments in warehousing space not easily earned back? Furthermore, is reducing the workforce such a gain that operations should be changed?

Furthermore, it is recommended to quantify the effect of flexible workforce on the warehouse performance. By assigning extra personnel when peak orders are expected to arrive, the orders could be handled more efficiently while not requiring changes in warehouse operations.

Also, the impact of reducing service levels for online orders should be investigated. Warehouse operations become more manageable when orders arrive spread out over the day, this can be reached by fulfilling orders the next day. Currently it is unclear what the consequences are for warehousing operations and supplier revenue.

More research is required into the effects of operational philosophy on warehouses other than FMCG suppliers warehouses. The decrease in product turnover rate and order volumes could change the outcome of the research. Potential effects on the results when considering lower turn over rate products, could be a smaller effect of future web throughput numbers, which could lead to easier handling of the expected online orders. Which can mean integrated omni-channel integration in existing infrastructure is adequate for future throughput numbers, due to lower requirements on extra space and pickers.

Lastly, more research is required into the performance of time slot driven operational philosophies. It shows promising performance, albeit highly dependant on time slot selection. When this selection can be optimised, based on real time order data, it can prove to be a solution for the high demands on the web order fulfillment processes.

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A

Scientific Paper

Omni-Channel Warehouse Operations Design

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Abstract—**This study evaluates the impact of operational philosophy on the efficiency of omni-channel warehouses. Suppliers want to integrate an online order channel in existing infrastructure, while efficient integration of omni-channel operations is challenging due to the difference in nature of e-commerce orders and store orders. Integration of operations is necessary for cost efficient omni-channel implementation, however little scholarly works exist exploring operational implications in the omni-channel context. The impact of operational philosophy is analysed through a discrete events simulation of the alternative operation designs. Through a sensitivity analysis on order arrival pattern and order type skewness, the performance of the design alternatives are compared. The considered operation designs have been found in literature. For realistic input values a case is considered of a distribution warehouse from a Fast Moving Consumer Goods (FMCG) supplier. From the results it is apparent that in an omni-channel warehouse, a dedicated zone is required to handle expected web order throughput efficiently, although such an operations design requires lots of space, which is often constrained. Space is constraint due to supplier seeking to integrate the online channel into existing operations, which turns out not to be durable. Therefore, it is concluded that for future throughput non of the considered operational philosophies is adequate.**

Index Terms—**omni-channel, warehousing, operations design, discrete event simulation, case study**

I. INTRODUCTION

In recent years E-commerce sales have been growing with a steady rate of about 20% and are expected to grow by another 10% in the upcoming years [1]. The growth in e-commerce sales has been accelerated by the coronavirus pandemic.

This e-commerce trend has been identified as the biggest potential for growth for retailers and has not gone unnoticed with the traditional physical store suppliers [2]. Since less of the consumer goods are bought through stores, the store suppliers can miss out on part of the revenues when not offering their products online [3]. The integration of an online sales channel into traditional operations for brick-and-mortar suppliers, leads to omni-channel supply chains, which is currently considered to be the dominant business model for the retail sector [4], [5].

However, in suppliers' rush to develop e-commerce capabilities, the e-commerce integration is often performed through bolted-on systems without regard for integration with traditional store fulfillment [2]. Efficient integration of omni-channel operations is challenging due to the difference in nature of e-commerce orders and store orders, while integration of operations is necessary for cost efficient omni-channel implementation [6]. Therefore, single channel suppliers cannot function properly in a omni-channel business environment without adaptation of their warehouses [7].

However, little scholarly works exist exploring operational implications in the omni-channel context [8]. Although, warehousing research has shifted towards warehousing where the business-to-customer (B2C) channels are considered, the most of warehousing research has been performed on single-channel warehousing and optimization for these warehouses [9]. Moreover, of the existing omni-channel warehousing research, the gist has been on channel conflicts and managerial aspects, while the interplay between the store and e-commerce distribution channel has not received much attention [4].

Therefore, this research presents a quantitative analysis of the effect of operational philosophy on the omni-channel warehouse performance. This is done by modeling and simulating multiple alternative operation designs and comparing the performance with each other. The aim is to shed light on the operational implications for integrated omni-channel warehousing. Furthermore, the practical implications of the operational philosophy are considered.

The results will benefit warehousing practitioners who try to latch on to the rise of e-commerce and seek to implement omni-channel operations, by providing insight in performance and design considerations for omni-channel warehouse operations. Thereby aiding the decisions making for omni-channel warehousing operations.

The operations considered do not include receiving and shipping stages, because these stages represent similarities with the processes in conventional warehouses. Also, product allocation and picker routing are not considered, these subject have already received lots of attention, and form a whole research field on their own. Automation is not considered in this research because currently automation does not play a big role for picking processes and desired flexibility and scalability do not justify the use of an automated system [10].

The structure of this paper is as follows. First, in section II, an analysis of warehousing trends and challenges is presented. Thereafter, the literature review and findings are presented in section III. In section IV the methods for the research are introduced. Subsequently, in section V, the modeling is discussed with the model content and experimental setup. The results are presented in section VI along with an analysis. Finaly, the paper is concluded by section VII, where the conclusion in presented.

II. ANALYSIS

To understand the need for suppliers to introduce a direct channel into their warehouse operations, a look can be taken at the retailing market trends. Before the internet was widely available for consumers, the brick-and-mortar stores were the dominant form of commerce [11]. The brick-and-mortar store, refers to a physical store. Although brick-and-mortar stores still exist, they are quickly being replaced by online e-commerce stores. The online sales channel consumes part of the sales that would previously have been performed through the brick-and-mortar channel. Therefore, digital retail can be seen as a major crisis for traditional suppliers [12]. Although when implemented correctly, the digital and physical arenas complement each other, with reduced cost and increased sales as a result.

However correct implementation is hindered by the different requirements for the operations for store orders and web orders. This originates from the characteristics of the web and store orders. The order arrival times, order sizes, short deadlines, order picking and product characteristics differ between the two. An overview of the differences can be seen in table I. Because warehouse processes show high interdependencies, the change of requirements for the warehouse operations, has significant effects on every process in the warehouse. Often warehouse operations, are best suited to cater to one particular order type, therefore introducing a second order type brings challenges. The order type is defined by the channel through which the order is placed, a store order is received from the traditional offline order channel of a store, while the web order is received from customers at home via the online channel.

III. LITERATURE

A. Literature review

After an extensive literature review, the work of Alawneh and Zhang [7] is the only work found which considers the omni-channel warehousing operations in a quantitative way. Most of the papers that do consider omni-channel warehousing are either qualitative studies or have a focus on the network design of the supply chain. In their work, Alawneh and Zhang [7] develop an inventory model for an omni-channel warehouse which considers capacity constraints, and demand and lead time uncertainties. The considered warehouse is divided into an area for online order fulfillment and an area for storing products and fulfilling offline orders. With the model the optimal inventory policy for a omni-channel warehouse can be considered. Because the focus is solely on inventory policy models, the gap still remains for quantitative research into warehousing operations design in an omni-channel warehouse.

B. Omni-channel warehousing

In literature the definitions surrounding multiple channel retail strategies are not well defined. This leads to the the interchangeable use of terms like dual-channel, multi-channel, cross-channel and omni-channel without clear distinction [6]. The omni-channel term reflects the fact that customers can interact with suppliers through an array of channels, like mail, stores, social media, television, gaming consoles and mobile devices [12]. Although definitions surrounding omni-channel retail strategies are ambiguous, it is the term that is used in this paper, because omni-channel retailing is the overarching term and most advanced concept. However, the focus of this research is on warehouse operations design, which means there is no differentiation between the online customer interfaces with the supplier. For warehouse operations the defining aspect is, whether the orders come from stores, or from the online channel.

Two main strategies exist for omni-channel warehouse implementation, one is utilizing an integrated warehouse and the other is using a separated warehouse. Both of these methods have their benefits and downsides, in general, the opportunities for separated warehousing strategy are the challenges for the integrated strategy and vice versa.

With the integrated strategy, the e-commerce operations are integrated in the existing warehouse infrastructure. In this way the warehouse delivers to retail stores and directly to customers. An integrated warehouse brings benefits in inventory pooling and flexibility, however it makes operations complex and it extensive re-engineering of the operational processes.

The separated strategy entails setting up a separated e-fulfillment channel, that is separated warehouses and operations. In this way processes are simplified and order picking space is not constraint, however costs are higher for initial setup and for the extra required inventory. Furthermore, the transshipment between storage locations is not efficient.

An important determinant whether to choose for an integrated or a separated approach is the existing infrastructure of the company [14]. When a company wants to start internet activities, the existing assets can be exploited. Furthermore, the complexity of the assortment is a differentiator when selecting dual-channel solutions. Because results indicate that positive effects of integrated warehouses outweigh the challenges associated with added operational complexity [6], it is the avenue which is further explored in this research.

C. Design alternatives

The challenge of designing efficient integrated omni-channel warehouses has not been researched yet, however

TABLE I: Comparison between brick-and-mortar orders and e-commerce orders (adapted from [13])

Order characteristics	Traditional store channel	Online channel
Order arrival	Regular	Irregular
Order nature	Mostly stock replenishment	Fragmented, discrete
Size per order	In bulk	In small lot-sizes
SKUs involved in each order	Very few or even identical	Many
Number of orders	Less, relatively easy to predict	More and unlimited, relatively difficult to predict
Time availability for fulfillment	Less tight	Very tight
Delivery schedule	Relatively more time buffer	Next-day or even same-day delivery

such strategies have already been implemented by industry. These practices can be used to derive feasible operational philosophies from. Subsequently these design alternatives can be tested against each other for their performance to gain insight into omni-channel warehouse operations.

From literature describing current omni-channel practices it becomes apparent that integrated inventories are desired, this means inventories for the online and offline channels are present in one warehouse. However, multiple methods for the order-picking processes are implemented by industry. Practitioners are divided, almost 50/50, whether to integrate or separate the picking for the online and offline order channels. Furthermore, when an integrated picking strategy is chosen, the processes can still be separated by product rotation-speed zones or by time slots.

Therefore, the first relevant warehouse operational philosophy to research, is a configuration where order-picking is physically separated per channel. Secondly, an operational philosophy where the pick zones are not physically separated, but the picking is zoned by product rotation speed, where store orders and web orders are picked simultaneously. Lastly, an alternative where the picking zones for both channels are equal, but picking is separated by time slots, is a relevant operational philosophy to compare. The operational philosophies are summarized in table II.

IV. METHODS

To analyse the performance of the three identified design alternatives, a discrete event simulation (DES) model is proposed. The handling of products in a warehouse, is a typical discrete process. The warehouse systems can be modeled as discrete systems because the products, pickers and forklifts can be modeled to change value or state at discrete time points.

DES is based on the statistical paradigm of the queuing theory. With the queuing theory a warehouse can be modeled by setting an order or SKU as a 'customer' that arrives and is stored (joins a queue), to wait for picking (service). Therefore, Little's Law is applicable to a warehousing process [15].

A simulation models is particularly suited because it allows for experimenting with scenarios, which in general are not possible with existing real systems, while grasping complex systems and behaviours. The aggregation level needs to be set in such a way that the model represent an simple version of reality while maintaining a satisfactory level of accuracy. Warehouse processes in many cases have a stochastic character which are subject to variation. These variations cause tuning problems and are the main cause of unreliable throughput times, waiting times and waiting queues or extra storage capacity needed. The implementation of stochastic values in the model, make it able to simulate probabilities of complex real world processes.

An use case is introduced to serve as a reliable basis for modeling. The case can be used to get realistic throughput values from, and assumptions regarding the stochastic values and boundaries can be related to the case. The case concerns a distribution warehouse of a Fast Moving Consumer Goods (FMCG) supplier in East-Asia, who is at the verge of implementing online order fulfillment within their existing store-supplying operations. By making use of a suitable use case it can be ensured that used data are realistic and feasible. The use case provides data on order arrival patterns, order compositions, throughput, lead time targets and size of workforce.

V. MODELING

A. Objective

The objective of the model is to evaluate the effect of operational philosophy on the performance of the omni-channel warehouse. In order to do so, the model has to be able to asses the sensitivity of the performance to the arrival patterns of the orders and the sensitivity to the order type skewness. The order type skewness indicates the ratio between the throughput of the warehouse dedicated to store order fulfillment, and the throughput dedicated to web order fulfillment. With the results from the model, a statement can be made about which design alternative performs best considering the scenarios.

B. Inputs & outputs

The inputs to the simulation model are the order volumes, order compositions, order arrival patterns, pallet size, case size and the products. Since the receiving stage of the warehouse is not considered, the products are assumed to be always in stock. Therefore, the model creates the products whenever these are required in the reserve storage area.

The outputs of the model have to shed light on the performance of the considered operational philosophy. For a distribution warehouse, efficient order picking is the main optimization goal, while the throughput is a prominent design criterion as well. Several key performance indicators (KPIs) have been identified as being suitable for accurate performance evaluation. Next to the KPIs, an interesting output is the utilization. A list of the KPIs and outputs, with their relevancy, is given below:

TABLE II: Design alternatives for omni-channel operations from literature

Operational Philosophy	Inventory	Picking
Alternative I	Integrated	Physically separated area, simultaneous for web and store orders
Alternative II	Integrated	Common area, zoned by rotation speed, simultaneous for web and store orders
Alternative III	Integrated	Common area, time slot separation for web and store orders

Note: Integrated inventory refers to managing the inventories for both order channels from one warehouse location

- Length of day: Time required to fulfill a day's worth of orders. It can be related to the warehouse throughput and the operating cost. Is not only dictated by the throughput, but by the order arrivals as well. It indicates for which hours, wages have to be payed to warehouse employees.
- Makespan: Time spent on fulfilling orders, not including waiting for orders. By comparison of the length of day with the makespan, the effect of the order arrival pattern on the performance of the warehouse can be visualized.
- % Orders delayed: Indicator for customer service, dependant on lead time target
- Order lead time: Time spent from order arrival until it is fulfilled, the standard deviation is a measure for reliability.
- Utilization: Measure for efficient operations and cost efficiency.

Combined the performance indicators indicate the throughput, service rates and efficiency of the modeled design alternative

C. Model content

1) Simplifications & assumptions: The logistical processes in a warehouse can typically be described as a discrete system. In order to evaluate the operational alternatives in a sufficiently accurate way, the required aggregation level is one where the product states and picker states are identifiable, while the details of the processes are left out.

Therefore, the exact product locations and picker routing are not considered. Instead, the travel distances to each product is taken as an average for the considered operational philosophy and the process in question. Hereby the research question can still be answered while keeping the model simple. In the same spirit the exact formation of the order batches are not considered, instead the batch formation is assumed to have a certain impact on the travel distance per product, based on literature.

The parameters for the simulation model are subject to assumptions, since exact values can vary and are often not known. The assumptions made, are based on expert knowledge and literature. An overview of the assumed values for the simulation model parameters is presented in table III.

2) Components: All elements considered in this research, together, have to include all the critical processes from the warehouse operations that are within scope. Also, the processes that interconnect with the operations and that have a significant influence on the operations, are included in the model. Here below, a list is presented of all the components and their behaviours:

TABLE III: Parameter values assumed for the simulation model

Parameter	Value
Forklift speed	2.5 [m/s]
Forklift handling time	TRD(5, 35, 14) [s]
Picker speed	0.8 [m/s]
Forw. picker speed	1.4 [m/s]
Picker init. handling time [16]	12 [s]
Picker handling time [16]	6 [s]
Forw. picker init. handling time	8 [s]
Forw. picker handling time	4 [s]
Admin time	30 [s]
Forw. admin time	10 [s]
Replenish threshold	10 [cases or pieces]
Replenish amount	1 [pallet]
Init. stock amount	1 [pallet]
Sorting time [16]	15 [s/order], 5 [s/prod]
Orders in batch [16]	15
Pieces per web order [10]	3
Pick zones	2
Picking time slots	3

TRD (Triangular Distribution)

- Case picker: Fulfills less than pallet store orders. Picks cases from lower level of pallet racks. Travels with pallet jack. Fulfills orders discrete.
- Piece picker: Fulfills web orders. Fulfills orders in batches when not in forward storage.
- All pickers: Pickers wait when product stock is empty, until product is refilled by forklift. Perform first order that arrives. First product to pick at each location takes longer for scan time.
- Forklift: Fulfills full pallet store orders and performs replenishment tasks. Prioritizes replenishment tasks over fulfilling orders.
- Sorter: Starts sorting after all products of order have arrived.
- All components: Finish their task before starting new one.
- Products: Class-based storage is present in central storage. Same assortment for web and store orders.

The components and their interactions and relation to the other components is visually represented in appendix A. These depiction can be used to get an understanding of the consequences of the operational philosophy on the process flow in the warehouse. As represented the components and interactions are implemented in the DES model.

3) Configurations: The three considered design alternatives each have an influence on the model configurations. Besides having influence on the process flow, the design alternatives influence the required travel distance for order fulfillment. The implementation of a certain picking strategy influences the pick efficiency, which is due to a change in travel distances per pick. Values for the change in efficiency associated with each picking strategy are described in literature [18]. The values used in the simulation model are presented in table IV, along with the picking strategy that causes the reduced travel distances. The travel distances can give a skewed view of the actual processing time of an order. The required extra processing steps should be considered as well. In an attempt to make the boundary conditions for each operational alternative equal, for each scenario the total amount of order pickers is the same. The total amount of pickers is set to be twelve, where for operational alternatives I and II the amount of piece pickers for the web orders is set to be eight, which implies four case pickers. Furthermore, for every scenario four forklifts are available.

TABLE IV: Travel distance for each operational philosophy

Alternative	Travel distance
I forw. pick: piece (forward storage)	$0.2 \cdot$ MTD
I forw. pick: case (class-b. storage)	$0.8 \cdot$ MTD
II zone pick: piece (zone picking & batch)	$0.5 \cdot$ MTD
II zone pick: case (zone picking)	$0.8 \cdot$ MTD
III time slots: piece (class-b. storage & batch)	$0.5 \cdot$ MTD
III time slots: case (class-b. storage)	$0.8 \cdot$ MTD

MTD (Maximum Travel Distance) = CUD(0.8, 1.2) $\cdot$ 25[m]
CUD (Continuous Uniform Distribution)

D. Experimental Setup

The run-length of the simulation model, is determined by the time required for a day's worth of orders to be processed. Therefore, the run-time can be different for each run. The simulation model is build to run one simulation day at the time.

No warm-up is required at the start of each simulation day because it is assumed that when a workday starts in the actual warehouse, the orders of the previous day all have been processed, or at least the backlog of orders will not interfere with the new day's orders.

The model runs every scenario 27 times, with different random seeds. 27 replications have been selected, because this amount of replications ensures that the 95% confidence interval of the length of day remains below the 1% deviation about the mean. The formula used is presented in equation 1.

$$n = \left(\frac{100 S t_{n-1,\alpha/2}}{d\bar{X}} \right)^2 \tag{1}$$

where:

$\bar{X}$ = mean of the output data from the replications
S = standard deviation of the output data from the replications
n = number of replications
$t_{n-1,\alpha/2}$ = value from Student's t-distribution with n–1 degree of freedom and a significance level of $\alpha/2$
α = significance level, 5% for 95% probability
d = the percentage deviation of the confidence interval about the mean

The program used to perform the discrete event simulation with, is Salabim [17]. Salabim is a discrete event simulation package for python. Python is used for its flexibility and scalability.

E. Scenarios

To asses the performance of the three operational philosophies in multiple situations, two types of scenarios have been selected. The first scenario type, provides simulation runs for varying order arrival patterns. These scenarios are interesting, because it can indicate for each design alternative, how well a non-ideal arrival pattern, can be handled. This could lead to concluding a design alternative is a good choice, when the arrival pattern can be managed, or it can lead to concluding that an operational philosophy is particularly well suited for absorbing peaks of orders arriving.

The second type of scenarios, are scenarios where the order type skewness is varied. These scenarios are interesting in light of the expected growth of e-commerce orders. A constant throughput is considered, because the growth of the online channel is expected to cannibalize part of the offline channel orders. Results from this scenario can indicate which operational philosophy is best suited for future operations. Also, a scenario is investigated where the demand skewness can represent a company which is only just starting up the online channel operations, therefore receiving little amounts of web orders. A total of five scenarios are evaluated, each for the three operational alternatives. An overview of the selected scenarios is presented in table V.

TABLE V: Overview of scenarios

	Order skewness store/web		
Order arrival pattern	A: 95/5	B: 90/10	C: 80/20
1: Upfront		√	
2: Evenly spread		√	
3: Case	√	√	√

F. Data

Most of the input data has been available from the case. Inputs that could not be derived from the case have been based on literature and insights from warehousing experts.

The order volumes for the store orders were readily available and have been approximated with a distribution. Also data on order composition and arrival patterns have been supplied by the case. For each approximation, it is made sure that spreads and average values are similar to the actual data values. Furthermore, visual validations have been performed to ensure an accurate fit.

Little data is available on web order volumes and composition, however. These inputs have been fabricated from literature, where it is described that average online order composition in 75% of the cases is equal or less than three items [10]. Because this research considers a FMCG warehouse, the order composition is assumed to be on the high side of this observation, which brings it to three. All input data is listed in table VI. The supplied order arrival patterns from the considered case warehouse are represented in figure 1.

TABLE VI: Input values for the simulation model, based on use case

Parameter	Value
Order volume store orders 95/5	IUD(11,21)
Order volume store orders 90/10	IUD(10,20)
Order volume store orders 80/20	IUD(8,19)
Pieces volume web orders 95/5	$11018 \cdot$ CUD(0.8, 1.2)
Pieces volume web orders 90/10	$22036 \cdot$ CUD(0.8, 1.2)
Pieces volume web orders 80/20	$44072 \cdot$ CUD(0.8, 1.2)
Product distribution store order	PDF(55, 22, 11, 5, 4, 3)
Product distribution web order	PDF(43, 39, 6, 5, 5, 2)
Unique products store order	Triangular(21, 39, 21)
Amount per product store order	Triangular(45, 121, 65)
Unique products web order	Triangular(1, 3, 1)
Amount per product web order	Triangular(1, 4, 1)
Arrival patterns	Upfront & spread out & case
Leadtime target store	2 hours
Leadtime target web	2 hours

IUD (Integer Uniform Distribution), CUD (Continuous Uniform Distribution), PDF (Probability Density Function)

VI. RESULTS

A. Arrival pattern sensitivity

From the orders arriving upfront it can be seen that design alternative I has the highest throughput, these results are presented in figure 6 in appendix B. Furthermore, the processes are most reliable with a small lead time spread.

The spread out arrival pattern proves easy to handle for alternative I and II, with little amounts orders delayed and small spread in lead times. Alternative III does not give representative results due to the high dependency of time slot selection. The results for the spread out pattern can be found in figure 7.

Results for the case arrival pattern, in figure 8, show alternative I performs best in handling peak store order arrivals, while alternative II cannot handle the peak. Alternative III performs decent when store orders are allowed to be used as buffer.

Considering the length of day, alternative I performs best again. The ability to handle peak arrivals means no expensive late work shift for the employees. The results are presented in figure 9.

B. Order skewness sensitivity

For the 95/5 store/web throughput skewness results, presented in 10, it can be seen that although the average lead time for store orders is larger for Alternative I, it has less orders delayed than Alternative II. This is due to the larger spread in store order lead times for alternative II. While orders arrive in peaks, the web orders are fulfilled efficiently. This can be explained by the lower amount of incoming web orders, which therefore form less of a bottleneck for the web order pickers.

The results for the 80/20 skewness are presented in figure 11. The results show no operational alternative is capable of handling this amount of web orders, while the overall warehouse throughput remains the same. Alternative I performs most promising.

The length of day results, in figure 12, show a significantly better performance of the alternatives for the 95/5 skewness compared to the other skewness'. This implies a high sensitivity to the amount of web orders for the performance of the operational alternative. The sensitivity to order amounts is clearly visible when plotting the lead times against the order type skewness, as seen in figure 2.

VII. CONCLUSION

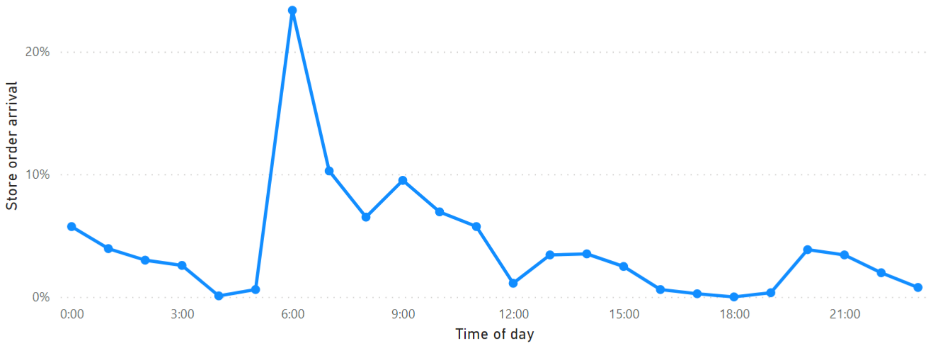
The results for alternative I are most promising. It shows a high throughput of web orders, due to the dedicated forward web order fulfillment area. It performs best, while it requires the least amount of personnel, and can handle peak web arrivals reliably. Moreover, this alternative is most future proof, when more of the warehouse throughput will be dedicated to fulfilling web orders.

However, the forward picking area puts high demands on available space and forklifts. The required area and equipment hinders the ability to scale the web fulfillment operations, because increasing the number of pickers for web order fulfillment, means adding an entire forward storage area. That is not beneficial concerning the expected increase in arriving web orders and the current lead time figures for the forward picking area. Lastly, the separate areas for web order and store order fulfillment, make it difficult for personnel to switch to web or store fulfillment.

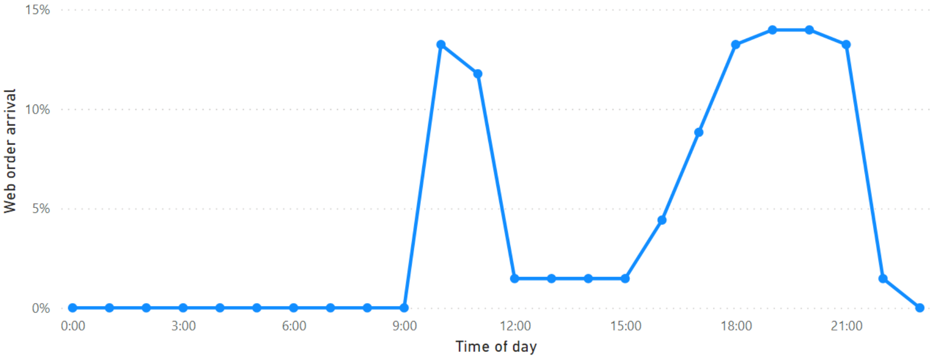
Results for alternative II show high lead time spreads and a disability to handle peak order arrivals. However, workforce can be shifted between store and web order fulfillment, this can offer a solution for the performance, seen from the reliable lead times for alternative III. Furthermore, the operations are easily scalable due to efficient travel in the pick zones. However, the sorting area must be able to support the increase in orders as well.

The performance of Alternative III can only be seen in the light of the store orders being used as a buffer and using a tailored time slot selection. When this is the case the operations perform very reliable and is capable of processing peaks efficiently. Workforce can be easily shifted via the time slots, and space utilization is very efficient since no extra picking or sorting areas are required. However, the operations are difficult to scale because all personnel works in the same area, which can lead to bottlenecks.

The main takeaway from the results is the large effect of the amount of web orders on the operations. Although the



(a) Arrival pattern for the store orders



(b) Arrival pattern for the web orders

Fig. 1: Order arrival patterns

warehouse throughput remains the same, the required work to fulfill orders increases when more throughput is dedicated for web fulfillment. For an increase of 5% of pallet throughput dedicated to web order fulfillment, which translates to an increase of web orders of 50% for the considered FMCG warehouse, the average lead time for alternative I, increases with 113%. While the number of pickers dedicated to web order fulfillment is theoretically sufficient. Therefore, for an omni-channel warehouse the amount of work is not defined by the amount of pallets processed, rather the amount of orders processed. A clear representation of this relation between the amount of pallets processed and the fulfillment time can be seen in figure 2.

Therefore, the amount of web orders is the driver for the length of day. Operational philosophy I performs so well in comparison with the other operational philosophies because it has a dedicated area for web orders, where a large amount of web orders can be processed efficiently.

Another takeaway is the value of being able to shift workforce between store and web fulfillment. Due to this ability of alternatives II and III, the alternatives can be made to work, since peak arrivals can be catched. This ability is useful in future since no alternative is currently able to process the expected web throughput numbers. Alternative I seems best suited, although the operations are difficult to scale.

Considering the future throughput figures, practitioners should reconsider implementing an integrated warehouse when area usage is constraint, since non of the evaluated omni-channel warehouse operations show adequate performance. With space often being constraint when considering implementing an extra online channel in existing infrastructure, the foreseen increase in web orders forms a massive problem. For future throughput, green field integrated omni-channel warehouses should be considered or separate omni-channel warehousing strategies, rather than integrating multiple channels in existing infrastructure, as non of the considered layouts proves adequate.

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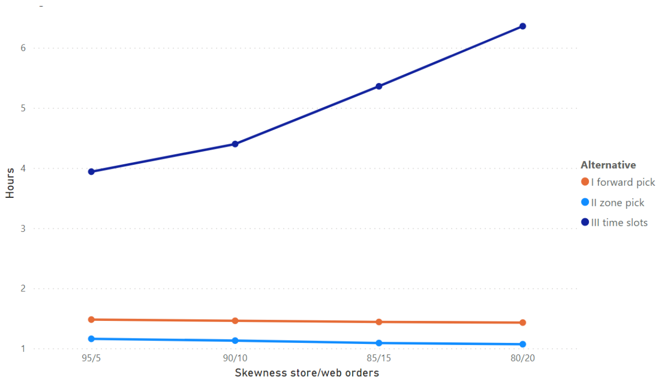
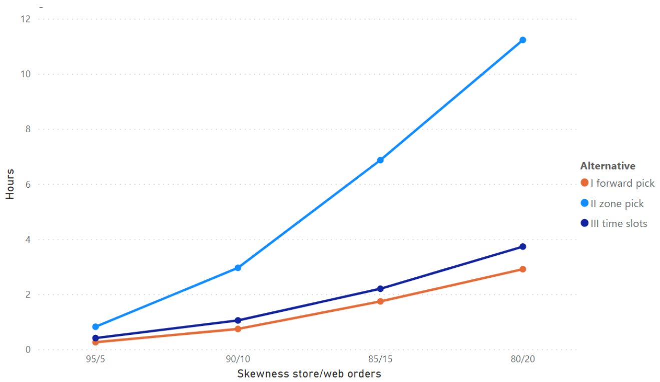


(a) Sensitivity store order leadtime to order type skewness



(b) Sensitivity web order leadtime to order type skewness

Fig. 2: Sensitivity of operational alternatives to order type skewness

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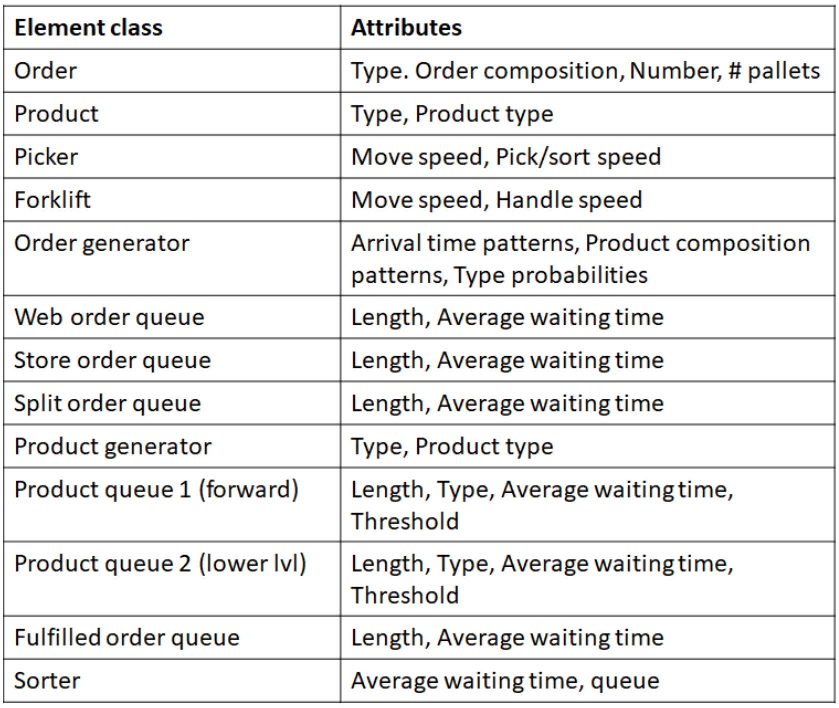
APPENDIX A
INTERACTIONS UML

APPENDIX B
PLOTS AND TABLES OF RESULTS

B

Process Description Language



Element class	Attributes
Order	Type. Order composition, Number, # pallets
Product	Type, Product type
Picker	Move speed, Pick/sort speed
Forklift	Move speed, Handle speed
Order generator	Arrival time patterns, Product composition patterns, Type probabilities
Web order queue	Length, Average waiting time
Store order queue	Length, Average waiting time
Split order queue	Length, Average waiting time
Product generator	Type, Product type
Product queue 1 (forward)	Length, Type, Average waiting time, Threshold
Product queue 2 (lower lvl)	Length, Type, Average waiting time, Threshold
Fulfilled order queue	Length, Average waiting time
Sorter	Average waiting time, queue

Figure B.1: Processes and attributes for the warehouse simulation model

```
Process of a picker (piece)
Repeat the following actions:
    Wait while web order queue is empty
    Remove first order from the web order queue
    While still products in order:
        Move short distance to next product
        While products in queue 1:
            Pick required amount of the product
            Activate forklift if product below threshold
            Remove product from product queue 1
    Hold for administration time
    Add order to fulfilled order queue
```

```
Process of a picker (case)
Repeat the following actions:
    Wait while split store order queue is empty
    Remove first split order from the store order queue
    While still products in order:
        Move to product
        While products in queue 2:
            Pick required amount of product
              Activate forklift if product below threshold
            Remove product from product queue 2
        Move to fulfilled order queue
    Hold for administration time
    Add order to fulfilled order queue
```

```
Process of sorter
Repeat the following actions:
    Wait until orders with same number are in the fulfilled order
    queue
    Remove respective order from the fulfilled order queue
    Handle
    For every product in order:
        Handle
    Add order to true fulfilled order queue
```

```
Process of order generator
Repeat the following actions:
    Wait until the next order should arrive
    Create new order with its product composition and type
    Put order into order queue for the type
```

```
Process of a forklift
Repeat the following actions:
    Wait while task queue is empty
    Remove first order from the task order queue
    If task is web product refill:
        Move to product
        Handle pallet
        Move to forward storage
        Handle pallet
        Activate product generator
        Move to dock
    If task is store product refill:
        Move to product
        Handle pallet twice
        Activate product generator
        Move to dock
    If task is store order:
        While still pallets in order:
            Move to product
            Handle pallet
            Move to shipping
            Handle pallet
        Hold for administration time
```

```
Process of Order
Repeat the following actions:
    If order type is web:
        Enter web order queue
        Activate piece picker
    If order type is store:
        Determine # pallets
        Determine split store order
        Activate forklift
        Activate case picker
```

```
Process of product generator
Repeat the following actions:
    Wait
    Create the requested product
    Put product into queue for requested type
    Activate picker
```

Figure B.2: PDL for the warehouse simulation model

C

Simulation Model Process Interactions

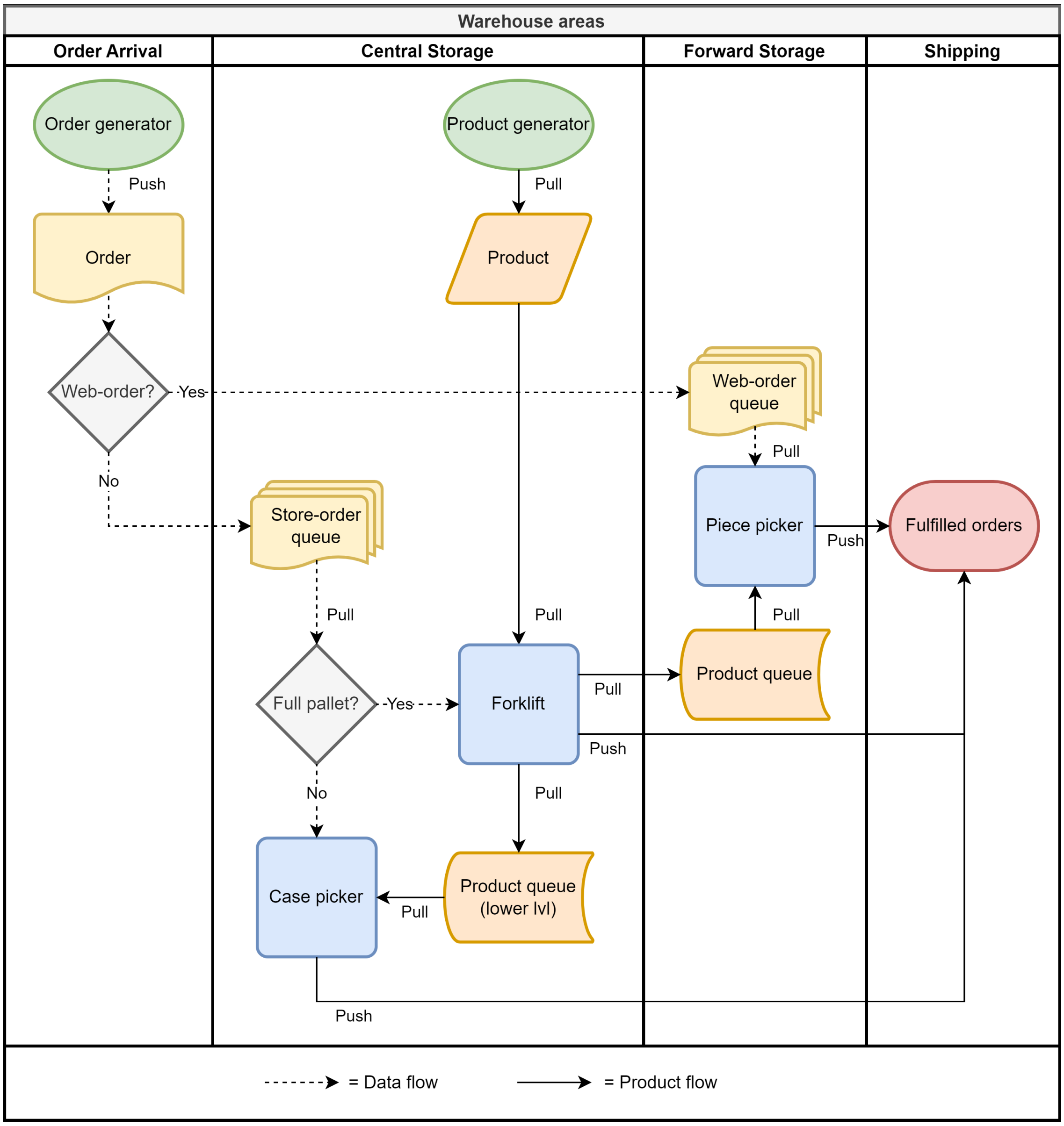


Figure C.1: Process interactions for Alternative I: physically separated web-order picking

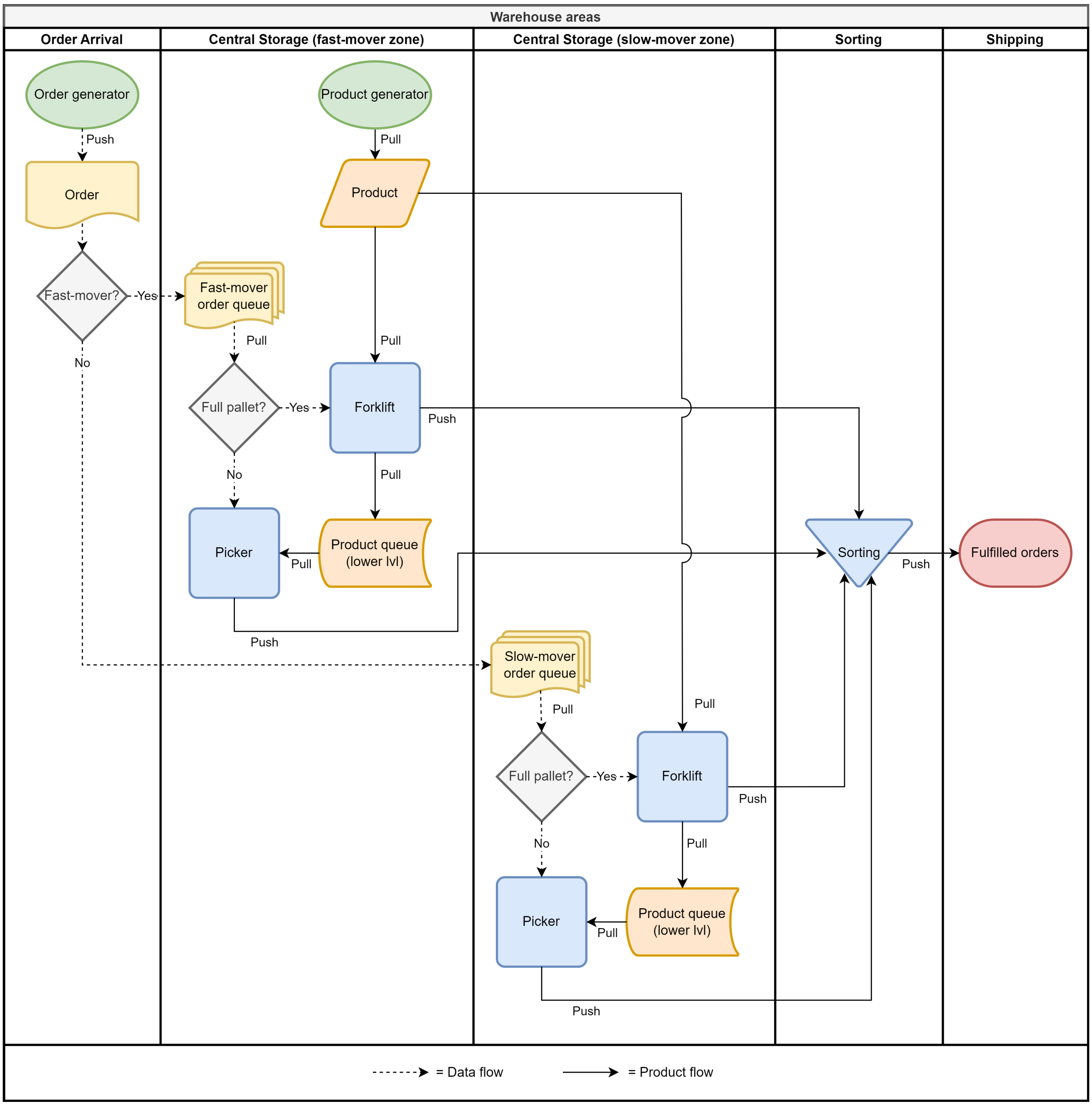


Figure C.2: Process interactions for Alternative II: zoned and common picking area

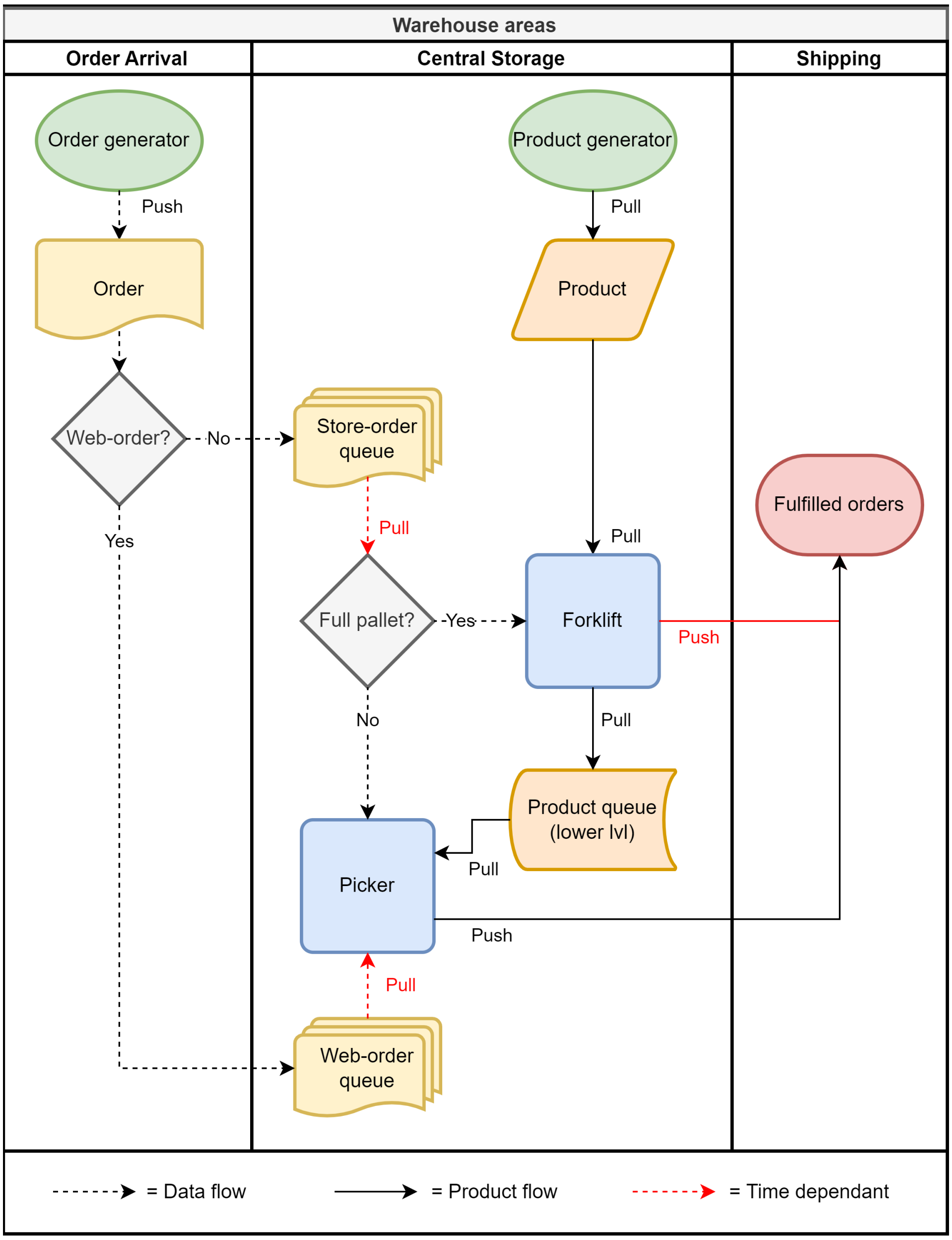


Figure C.3: Process interactions for Alternative III: time slot separated picking