Improving small-sized items replenishment process in store operations

The Case Study of Worten

Francisco Gonçalves Ferreira Cortez

Dissertation to obtain the Master of Science Degree in

Industrial Engineering and Management

Supervisors: Prof. Susana Isabel Carvalho Relvas

Eng. Pedro Maria de Sousa Araújo Ribeiro da Costa

Examination Committee

Chairperson: Prof. Ana Paula Ferreira Dias Barbosa Póvoa

Supervisor: Prof. Susana Isabel Carvalho Relvas

Member of Committee: Miguel Vieira

November 2022

Acknowledgments

In first place, I would like to thank both my supervisors, Professor Susana Relvas and Eng. Pedro Costa, for the opportunity to develop this master thesis, for the commitment and for guidance they gave me throughout its completion.

I would also like to thank my family, friends, and colleagues for their support over the years and for their willingness to help me in my assignments whenever I needed it, discussing ideas, explaining concepts, or reviewing my work.

Abstract

Driven by technological developments, people increasingly demand instant access to information, products, and services. For this reason, retail companies are currently forced to constantly adapt and optimise their operations and structures. Otherwise, they may be replaced by competitors that are better prepared to supply their consumers' needs. To increase its operational efficiency, Worten – a Portuguese retail company of consumer electronics, home appliances, and entertainment – decided to implement in its warehouse an automatic storage system for small-sized items with an integrated Goods-to-Picker system. In this sense, the company proposed challenge was to study the impact of different configurations of this system on the overall efficiency of the replenishment process of its stores. First, an academic literature review was performed on the concepts of retail operations, warehouse operations, physical store operations, and simulation models. After that, based on the knowledge acquired from the literature, a six-module methodology was composed. This methodology's final module is a stochastic simulation model, developed in software *AnyLogic*, which intends to replicate the store replenishment process of small-sized items with the Goods-to-Picker system incorporated. Through this methodology, several possible scenarios of store configurations were tested. The performance of each scenario was evaluated according to three indicators equally important to the company: the filling efficiency of the order totes, the occupation of the system resources, and the time spent to perform each operation – picking and shelf replenishment. Finally, the conclusions of this study and suggestions for future work are presented.

Key Words: Logistics; Warehouse Operations; Store Operations; Order Picking; Replenishment; Simulation model.

Resumo

Impulsionadas pelos desenvolvimentos tecnológicos, as pessoas exigem cada vez mais o acesso instantâneo a informação, produtos e serviços. Por essa razão, atualmente as empresas de retalho são obrigadas a uma constante adaptação e otimização das suas operações e estruturas sob pena, se não o fizerem, de serem substituídas por competidores que melhor enquadrem as necessidades dos consumidores. A Worten – empresa portuguesa de retalho de bens eletrónicos de consumo, eletrodomésticos e entretenimento – para aumentar a sua eficiência operacional decidiu implementar no seu armazém um sistema de armazenamento automático para os produtos de pequeno formato que desencadeia num sistema de *Goods-to-Picker*. Nesse sentido, a empresa propôs que se estudasse o impacto de várias configurações desse sistema na eficiência global do processo de aprovisionamento das suas lojas. Primeiro, foi realizada uma revisão da literatura sobre os conceitos de operações de retalho, operações de armazém, operações de loja e modelos de simulação. De seguida, com base na literatura, foi composta uma metodologia com seis módulos que desencadeia num modelo de simulação estocástico, desenvolvido em *AnyLogic*, que pretende replicar o processo de aprovisionamento de loja dos produtos de pequeno formato, incorporando o sistema de *Goods-to-Picker*. Através desta metodologia, testaram-se vários cenários possíveis de configurações de loja. Cada cenário foi avaliado segundo o seu desempenho em três indicadores igualmente importantes para a empresa: a eficiência de enchimento dos *order totes*, a ocupação dos recursos do sistema e o tempo despendido a realizar cada operação. Por fim, apresentam-se as conclusões deste estudo e sugestões de trabalho futuro.

Palavras-chave: Logística; Operações de Armazém; Operações de Loja; *Order Picking*; Aprovisionamento; Modelo de simulação.

Contents

List of Figures

List of Tables

List of Abbreviations and Acronyms

3PL	Third-Party Logistics
ABS	Agent-Based Simulation
AGV	Automated Guided Vehicle
AS/RS	Automated Storage and Retrieval System
B2B	Business-to-Business
B2C	Business-to-Consumer
BI	Business Intelligence
COI	Cube per Order Index
DES	Discrete-Event Simulation
FTE	Full-Time Equivalent
G2P	Goods-to-Picker
HDel	Home Delivery
IT	Information Technology
KPI	Key Performance Indicator
PBL	Pick By Line
PBLS	Pick By Line to Store
PBS	Pick By Store
PP	Percentage Points
PTL	Put To Light
PTS	Put To Store
PTZ	Put To Zone
RFID	Radio Frequency IDentification
SCED	Complementary Service of Home Deliveries (from the Portuguese: *Serviço Complementar de Entregas ao Domicílio*)
SD	System Dynamics
SDel	Store Delivery
SKU	Stock Keeping Unit
TCM	Transfer Conflict Manager
VLM	Vertical Lift Module
WMS	Warehouse Management System

Chapter 1 – Introduction

The first chapter of this document is an introductory chapter which aims to demonstrate summarily the core content of this dissertation. It starts by describing the problem that contributed to the emergence of this work, followed by the presentation of its most important objectives and, finally, describes the document structure.

1.1 Problem Background

Today's world is increasingly instantaneous. The information available on the internet about every topic or subject is enormous and creates the expectation that information is just one click away. Consequently, to survive, organisations of any kind are forced to adapt their structure to meet these new expectations, while maintaining their business sustainability and profitability, introducing the online flow of information and products through multiple, cross or omnichannel strategies in their supply chains (Cai & Lo, 2020).

Following the worldwide trend, the retail industry is facing several challenges reorganising its operations in warehouses and stores and automating its processes. Since customers can easily access information about the features of a product or service of any player in the market, retailers must optimise their supply chain's efficiency and accuracy to reduce costs, shorten lead times, and present lower prices for the same service level to the final consumer.

The present work focuses on Worten, a retail company leader in the Portuguese market of consumer electronics, home appliances, and entertainment. Recently, the company's business value has increased mainly due to the rise of e-commerce fuelled by the Covid-19 pandemic and the creation of a marketplace and fulfilment service where other entities can sell their products using the website and logistics chain of Worten. For the next years, Worten is expecting to maintain or increase this growth, which reflects the substantial growth of both online and retail flow of products. As it stands, Worten's supply chain cannot meet the predicted demand, because its warehouse is not designed to hold the stock that will be demanded, and the total store supply operation is costly, both in time, storage, machinery, and human resources. Thereupon, the company has decided to automate its process and redesign its operations and is analysing the implementation of a Goods-to-Picker (G2P) system for small-sized items in its warehouse. Additionally, the current picking and shipping methods in the warehouse do not regard the efficiency of the in-store reception and replenishment operations. Thus, the high efficiency in warehouse processes jeopardises the establishment of good coordination and efficiency in in-store operations. So, the approaches and linkages between these entities must be rethought in order to support the expected growth.

Therefore, the current research focuses on studying the implementation and synchronisation of a G2P system that optimises store replenishment processes.

1.2 Objectives

This master's Dissertation aims to analyse the benefits of implementing a G2P system regarding lead time, transports optimisation and the operators' occupancy rate of the Worten warehouse and store's backroom operations, reducing the total operation cost by reducing non-value-added operations in the warehouse and stores and optimizing the linkage and correlation between these entities. The accomplishment of this goal can be ensured through more tangible and specific objectives:

- Understand the context of the case study and the problem to solve.
- Select and review the scientific literature required to develop a robust knowledge base and methodology for the topic under investigation.
- Develop and implement a methodology that supports the objective of this thesis.
- Create deployment scenarios to evaluate the system according with the developed methodology, based on Worten's historical records of its flow of operations.
- Recommend the implementation of the most suitable scenario.

1.3 Dissertation's Structure

This master's dissertation is structured into six chapters, each of which is outlined below.

- **Chapter 1 – Introduction:** This first chapter introduces the dissertation, exposing its content in brief. As aforementioned, it presents the problem context, the objectives of the dissertation, and the document structure.
- **Chapter 2 – Case Study:** The second chapter presents a detailed context of the problem. It begins by introducing the company under study, and then narrows through the description of the entities and activities relevant to the problem, closing with the problem description.
- **Chapter 3 – Literature Review:** The third chapter reviews scientific literature (articles, papers and books) relevant to acquiring knowledge to comprehend the problem and develop a methodology to solve it.
- **Chapter 4 – Methodology:** This chapter describes the methodology applied to solve the problem at hand.
- **Chapter 5 – Scenarios and Results:** This chapter presents the different scenarios developed to evaluate the possible different configurations of the system in question, as well as an analysis of their results based on defined metrics.
- **Chapter 6 – Conclusions, Limitations and Future Work:** The last chapter presents the conclusion and indications for future research to build on this work.

Chapter 2 – Case Study

The purpose of this chapter is to introduce and contextualise the case study at hand. In that regard, it is organised from a higher level of contextualisation to a lower level - where the motivations for the study are presented in detail. In first place, the history and context of the corporate group to which the company belongs and the company itself are concisely described, as is its supply chain. Then, three more descriptive sections explain the current operations and organisation of the entities relevant to the case – Worten's warehouse, Worten's stores, and the distribution between them. Finally, the last section presents the context of the problem and the motivations that gave rise to this work.

2.1 Sonae

Sonae was founded on August 18th, 1959, by Afonso Pinto de Magalhães in Maia, Portugal. Initially known as *Sociedade Nacional de Estratificados*, the company began its activity as a manufacturer of wood-based panels, an innovative material for construction and real estate markets at the time (Público, 2015; Sonae, 2022).

Already under the leadership of Belmiro de Azevedo, the company took several steps to expand its activity and portfolio to what it is today during the 1970s and 1980s, such as the acquisition of NOVOPAN (a particle board manufacturing unit) or the joint venture with Promodès that resulted in the opening of Portugal's first hypermarket, the Continente in Matosinhos. At the same time, Sonae Investimentos, SGPS, SA, a holding company, was established, allowing the company to enter the capital market (Público, 2015; Sonae, 2022).

Currently, Sonae is a multinational company with operations in 62 countries across all continents and a portfolio of more than 60 brands in retail, financial services, technology, shopping centres, telecommunications, and media (Público, 2015; Sonae, 2022). This project's scope focuses on Worten, one of Sonae's companies, which will be described in section 2.2.

2.2 Worten

Established in 1996 with its first store opening in Chaves, Portugal, Worten is Sonae's specialised company in electronic retail, the second most profitable company of the group and the Portuguese leader in its business area (Worten, 2022; Sonae, 2022).

Presently, with more than two hundred physical stores of different formats and sizes spread across Portugal and Spain, the company's range of commercialised products covers over a million products (Sonae, 2022). A massive investment in the proper functioning and setting of the omnichannel, which connects and integrates the physical and digital shopping channels, allows an efficient and effortless customer experience by purchasing from the e-platform and picking up the order on the wanted store (Worten, 2022).

Despite being just one company, Worten represents three brands of Sonae's universe: Worten, the core brand of the company, which focuses on consumer electronics and entertainment; Worten Mobile, launched in 2004, directed to mobile telecommunication services; and Worten Resolve, created in 2013, focused on after-sales services (Worten, 2022). Additionally, in 2018 Worten launched the Marketplace, which allows its partners to sell their products through its website, taking advantage of the digital platform and the entire Worten operational network, promoting a symbiotic relationship between vendors and Worten.

2.3 Worten Supply Chain

Consumers' expectations and necessities change constantly over the years. Indeed, companies must rule their business and operational models by these consumers' demands if they want to prevail and be successful in the market.

Since Worten's establishment, in 1996, the world and communication changed drastically with the emergence and evolution of the internet. In the past, anyone that wanted to buy any type of goods would have to move to the physical store where that specific good was available to commercialise, with little information about the characteristics and features of the product or about its availability in the store. Now, due to the easiness of searching for information on the internet, people demand to have all the information they need to decide what they will buy whenever they want and wherever they are, especially the younger generations.

Hence, during the first years of operation, Worten had a linear supply chain. Suppliers had to deliver directly to the central warehouse in Azambuja, which in turn stored the products and prepared the orders to be shipped to all retail stores in Portugal. At that time, these retail stores were the only possible contact point between the final consumers and the products commercialised by Worten.

However, over the years, this supply chain suffered a deep reconfiguration, focusing on the omnichannel strategy and the consequent introduction of different flows of products and information between the consumers and the company. Besides the retail stores, Worten invested heavily in e-commerce, and today it uses the website to commercialise its products and promote the Marketplace, which gives customers more freedom to choose the channel in which they want to interact with the company. Afterwards, the e-commerce flows increased a lot the complexity of the supply chain ahead of the warehouse, once the customer can receive its goods in three different ways:

- the traditional process of purchasing in-store.
- Home Delivery (HDel) by ordering online and receiving the goods at home.
- Store Delivery (SDel) by ordering online and picking up the goods in a chosen store.

Moreover, another factor that increased complexity in the supply chain was the growth of the operation and the expansion into the Spanish market. In fact, one of the greatest impacts of the Covid-19 pandemic on this supply chain was the transition from physical to online commerce in Spain, with the closure of numerous Worten physical stores, even though maintaining the levels of fulfilled demand. In essence, nowadays, the warehouse in Azambuja provides online orders from Spain and Worten's warehouse near Madrid, which fulfils retail orders and some remaining online orders of that market segment.

Over the years, the changes in the supply chain configuration and its increase in flows and complexity changed the method for carrying out operations throughout the supply chain, as well as the organisational structure of each entity involved.

2.4 Warehouse

As previously stated, Worten's warehouse is placed in Azambuja, in the centre of Portugal. It has 50 000 square meters and 8 meters in height. Currently, it has a workforce of around 300 workers and 70 000 different Stock Keeping Units (SKU) in its portfolio operating from 8 am to 2 am, 6 days per week, to fulfil all the demands of Worten's retail and online flows in Portugal and Spain (by supplying the warehouse of Madrid). Through the consolidation of stock and distribution in one only warehouse, the company can take advantage of economies of scale in administration and support services and, crucially, reduce safety stock, increasing the service level and the cost of operation (Bartholdi & Hackman, 2019).

The huge diversity of products with completely different characteristics sold by Worten is one of the biggest challenges when operating the warehouse. A washing machine or a fridge has utterly distinct handling, storage, and holding requirements compared, for instance, to a video game console or a smartphone, since their value, dimensions, and volume are distinct too. Therefore, the products are categorised according to their characteristics. Generally, there are two groups of products: 701 and 708, which refer to big-sized appliances and small appliances, respectively. There are other categories of products in the warehouse that distinguish, for instance, products returned via a reverse logistics process, damaged products, or products for corporate customers. However, these are out of the scope of this study, so, they will not be presented to simplify and focus the explanation of the warehouse on the relevant matters. After this brief introduction, this section will go into more detail to explain the warehouse's flows, layout, and operations, each one of these explained in a different sub-section.

2.4.1 Warehouse Flows

The warehouse flows are the paths that one product can take from the moment it arrives at the warehouse until the moment it is shipped and leaves the warehouse. In this case, it is possible to divide Worten's warehouse flows into two main groups, inbound and outbound flows, followed by Business-to-Business (B2B) and Business-to-Consumer (B2C) flows, as shown in Figure 1.

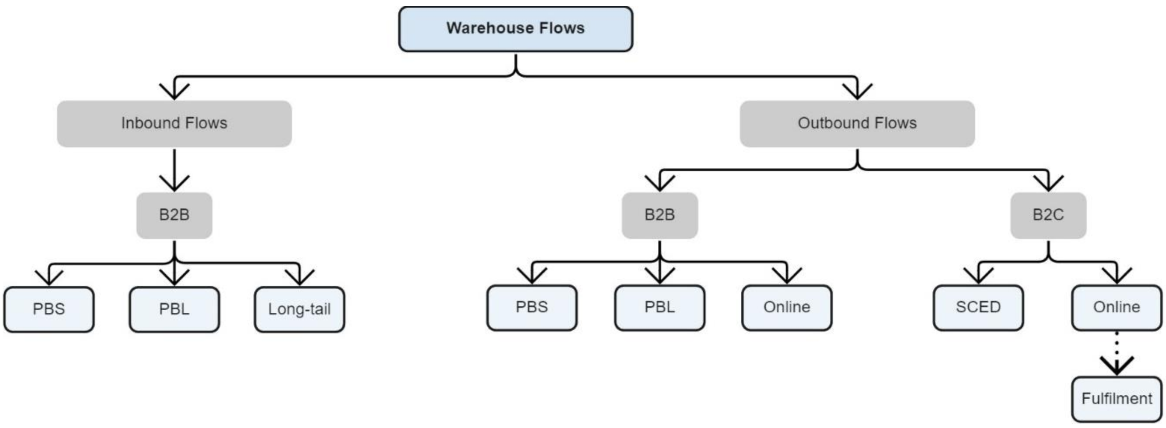

Figure 1 - *Worten's warehouse flows.*

The inbound flows – paths of goods entering the warehouse – are always B2B, once they are a transaction between the supplier companies and Worten. Afterwards, this flow is split into three different flows, fundamentally according to products and supply characteristics, like the delivery time window, the reliability and service level of each supplier: Pick by Store, Pick by Line and Long-tail.

The Pick by Store (PBS) flow is the "traditional warehousing flow" where the products are stored before shipping. There is a need to store products when the service level and trust in the suppliers are low. Typically, the products in this flow are coming from intercontinental suppliers (mostly Asian or African Worten's private label suppliers), not only because of the long delivery times that require higher levels of safety stock to account for supply fluctuations but also because they frequently do not meet the schedules of delivery or make mistakes in the quantities ordered. Due to the necessity to keep inventory at the warehouse, this is the least productive, more resource-consuming and, consequently, more expensive warehouse flow. Besides the space used to store every product, the human and machine resources used in the storage and order picking activities are significantly expensive. Although, since stores do not hold inventory of 701 products, and due to their long delivery times, these products always correspond to the PBS flow.

In opposition, the Pick by Line (PBL) is the cross-docking flow of the warehouse, thus, the goods are shipped less than 24 hours after they arrive in the warehouse. The products associated with this flow come usually from suppliers with high service levels and several delivery windows across the week – mostly worldwide companies with representation in Portugal. Ideally, PBL products are not stored. However, there is some stock to efficiently satisfy the less predictable online demand for this type of product or from online order cancellations in which the products were already at the warehouse (these products' sub-flow is unofficially called PBLS – Pick by Line to Store). Moreover, if the daily demand for one PBS good is high, that good is typically transferred to the PBL flow to minimise handling and storage activities and increase the cost-efficiency of these products.

Still on the inbound flows, the Long-tail flow considers products of highly variable demand, and so products that Worten does not want to have stored, neither in the warehouse or in-store. Therefore, they are only available to commercialise through the online channel, and every time a customer orders one of these products, Worten orders the product from the respective supplier. Worten has information about the stock available in the suppliers and its delivery lead times and based on that information, the company manages the product information passed on to customers.

In turn, the outbound flows describe the flows of products leaving the warehouse, which can be B2B or B2C, depending on whether its destination is one Worten store or the final customer, respectively. In accordance with the inbound flows, the outbound flows are divided according to products and demand characteristics (like order frequency and type of order), popularity, and demand. If the product's destination is a store and the order comes from the retail channel, it follows the PBS and PBL flows (explained above), but, if it is a SDel of an online order instead, it follows the Online flow. Alternatively, if the product is to be delivered to the customer's house, it can follow the Complementary Service of Home Deliveries (SCED – from the Portuguese: *Serviço Complementar de Entregas ao Domicílio*) flow or the Online flow, as in a SDel of online orders.

The SCED flow deals with the delivery of large-sized home appliances, like washing machines or refrigerators, and therefore it will not be analysed in detail because it is out of the scope of the study, which focused on the relationship between the warehouse and the stores.

The Online flow, on the other hand, prepares orders of 708 received through the online channel, either of products sold by Worten or through their marketplace. When there is an order to fulfil, this flow uses all the stored merchandise to accomplish it as early as possible, once Worten is committed to delivering its online orders in less than 24 hours, both in-store and at home.

2.4.2 Warehouse Layout

Warehouse management is all about the careful use of space and time, so the layout of a warehouse should be the reflection of its flows (Bartholdi & Hackman, 2019). Therefore, since the Worten warehouse flows are already explained in sub-section 2.4.1, its layout can be presented. As illustrated in Figure 2, the warehouse is divided into two main groups: the storage area, in blue and red, and the preparation area, in yellow and green. It also has several areas for value-added services, such as Reverse Logistics, Quality Control, Post Sales Service or Repair of Damaged Products for outlet selling, which are not discriminated in Figure 2 as they are out of the scope of this work.

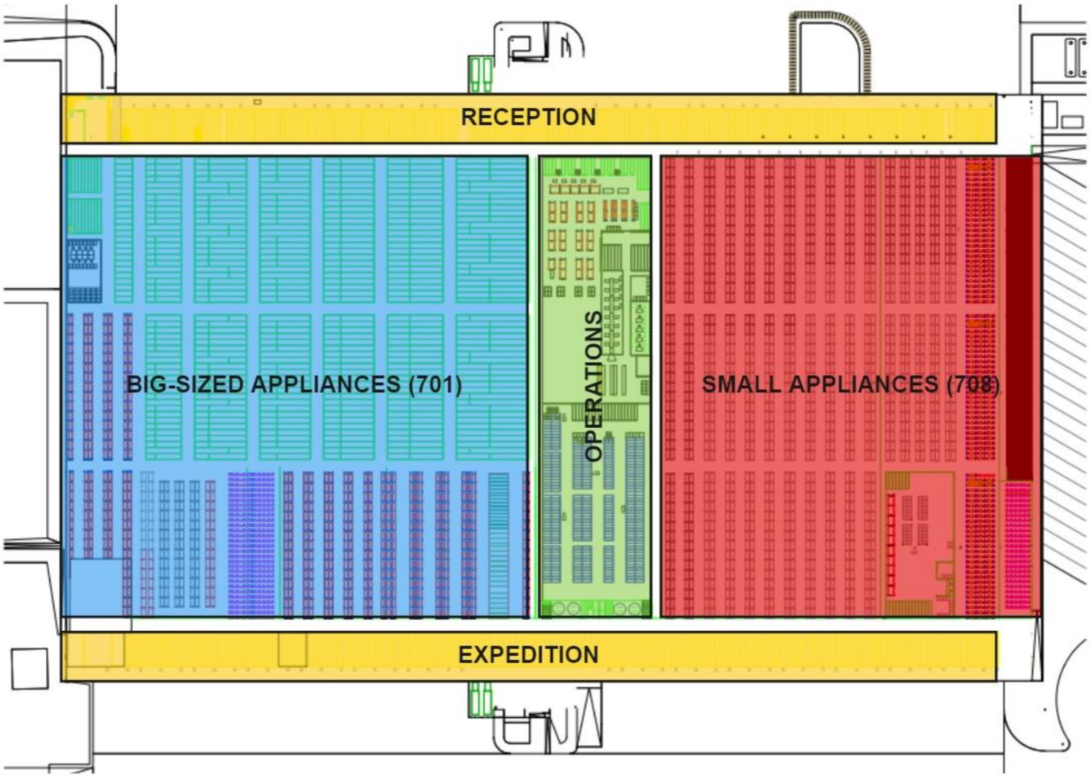

Figure 2 - *Layout of Worten's warehouse in Azambuja, 2022.*

Looking at Figure 2 it is possible to identify that warehouse is designed so that the products move on it in the most harmoniously and fluidly way possible, without having to go through unnecessary or repeated paths. That is the reason the Reception and Expedition areas are at opposite ends of the warehouse, and all the remaining operations and the storage of goods are carried out between them. Further, it is noteworthy that most of the warehouse area corresponds to storage space, which is divided into two main groups – the blue one, representing the Big-sized Appliances (701) area, and the red one, representing the Small Appliances (708) area. The details of these two areas will be explored below. However, the Reception, Expedition and Operations areas will not be fully explored here, but only in the next sub-section (2.4.3), since the most important aspect in these areas is to have a good understanding of the operational process.

701 – Big-sized Appliances

The 701 area in the Worten warehouse indicates the area of big-sized appliances, such as fridges, ovens, or televisions over 34 inches. This area is divided into two different storage sectors:

- 701 SOLO: storing sector for large products with good stowability, like fridges, ovens and dishwashers. The products are stored on the floor and block-stacked accordingly to suppliers' recommendations.
- 701 Racks: sector where the remaining big-sized appliances are stored in racked pallets. Usually, these are sensitive products, like televisions or induction stoves, that required extra careful handling and accommodation.

Since this work's scope focuses on small-format items, enclosed in the 708 area, this warehouse area will not be further detailed.

708 – Small Appliances

708 is the name given to the small appliances area, encompassing small-sized and medium-sized products, for instance, pen drives, mobile phones, or video games. The products in this area fall into three categories: (1) small-sized items (under 18 litres in volume), (2) medium-sized items that can be carried by a single person, and (3) medium-sized items that need to be carried by two workers at once.

The storage of these products is arranged in 17 longitudinal and unidirectional aisles organized by the Cube per Order Index (COI) slotting strategy, which assigns locations to products according to their popularity (picking frequency of the SKU) and volume. Thus, the most accessible locations are assigned to the products with higher COI, which is to say closer to the centre of the warehouse where is the Operations area.

Based on this strategy, the two aisles closest to the centre of the warehouse are used to stock products from the PBL flow. Since there are usually small quantities of products to stock from this flow (just the ones needed to satisfy online orders or some leftovers from the operation), instead of pallets, the products are stored in alveolus (small storage carton units). The remaining 15 aisles store in pallets the merchandise from the PBS flow. The furthest five aisles from the centre of the warehouse made up the Slow Movers area, which stores the products with lower COI, usually outdated, obsolete, or personalized items, such as products alluding to Christmas, Halloween, or Father's Day.

Besides, for security reasons the high-value 708 products are stored on the first floor of the warehouse, above the inbound area, in the Mezzanine (this area is not represented in Figure 2). This restricted access zone allows for better control of the incoming and outgoing goods because it has specific security measures, such as, a workgroup comprised of trusted employees, security cameras covering the area, the security guard of the warehouse checks everyone that leaves this place, among others.

2.4.3 Warehouse Operations

This sub-section presents the current warehouse operations, divided into Inbound and Outbound operations associated, respectively, with the Inbound and Outbound flows explained above (sub-section 2.4.1).

Inbound Operations

The inbound operations correspond to every operation that is done before starting the preparation of the order corresponding to that item. By the time the trucks arrive at the warehouse yard, they are assigned to a dock according to their time of arrival (through a "first come, first serve" logic) and the merchandise they carry (higher priority to trucks with a higher percentage of goods of the PBL flow). Once the truck is assigned to a dock, it is unloaded to the reception area, where Worten operators check the quantities and any possible damage in all the incoming cargo. During the checking operation, the operator labels the packages given the Inbound flow (PBS, PBL and Long-tail) assigned by the Warehouse Management System (WMS). Each flow has a label of a different colour, making it easier for the operators accomplishing the next activity to identify the flow of the merchandise and increase the speed and efficiency of the put-away. If the merchandise is identified with a yellow or pink label, it is part of PBL or Long-tail flows, respectively, and should be moved to the Put to Zone (PTZ) area, which is the initial activity of the cross-docking operation, or Online area, respectively. Otherwise, the merchandise identified by white labels has a lower priority of movement away from the reception area, because it belongs to the PBS or PBLS flows and will be allocated for put-away and then stored in the warehouse.

Outbound Operations

The Outbound operations of a product are the set of operations involving those from the moment the order's preparation begins. Figure 3 presents the detailed Operations area layout, where the cross-docking and consolidation activities are processed. Depending on the flow that the products follow they pass by different areas and activities. The arrows of different colours in Figure 3 represent the B2B Outbound flows (PBS, PBL and Online, described in sub-section 2.4.1).

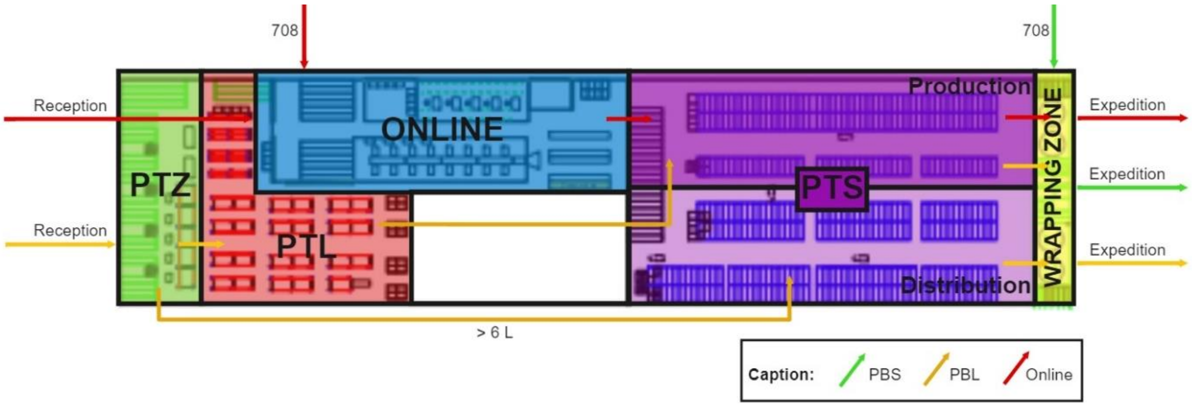

***Figure 3 -** Worten's warehouse orders' preparation area layout and main flows.*

The PBS outbound flow begins with the order picking and consolidation activities simultaneously. This process is done through a batch picking strategy inside the 708 area. The route starts at the farthest storage location from the Operations area and ends at the closest one. The operator, in an electric pallet truck, carries two pallets per route, each one of them associated with a different store, and has a voice picking technology giving instructions about the route to follow and the number of goods to pick from each SKU. This equipment is faster than other methods, like scanners, and allows a free-hand route, giving more freedom of movement to build and consolidate the pallet, which leads to productivity growth of the activity. In the end, the operator leaves the pallets in the Wrapping Zone (in yellow in Figure 3), where they are wrapped and finished. Then the pallets are placed in the corresponding outbound bay, in the Expedition area, to be loaded into the distribution trucks and delivered to the stores.

The other outbound retail flow adopts a completely different process. As aforementioned, the PBL flow is the cross-docking retail flow in the warehouse, but it also manages typical PBS products with high demand on a sporadic day. This flow operation is separated into three distinct activities completed across the Operations area (in green in Figure 3) – Put to Zone (PTZ), Put to Light (PTL), and Put to Store (PTS). PTZ and PTL are two parts of the sorting process, while PTS is the pallet assembly and consolidation activity, and is common to other flows.

The PTZ section (in green in Figure 3) is set up in three operation zones – PEQ, MED and GRA[1] – and eight sectors, six of them part of the GRA zone and the remaining two incorporated in the PEQ and MED zones. Here, the products, coming from the reception area or the 708 area, are split according to their volume. When the product's volume is equal to or greater than six litres, the product goes straight to the PTS zone. Otherwise, the products are sorted by the corresponding sector according to the WMS information.

The products are then received in the PTL zone (in red in Figure 3) which has the exact same sectors, and in each sector exists one tote for each existing Worten store. Through scanning the products assigned to a certain sector, the system turns on the lights corresponding to the stores that have demand for that SKU and indicates the number of units to deliver on each tote. Thereafter, the operator only needs to insert in each tote the right number of units until all the lights are turned off and repeat the process for the remaining SKUs. When the tote is full, it is closed, sent to the PTS zone, and replaced by another tote.

In the Online outbound flow, as in the PTL flow, the products go to the Online zone (in blue in Figure 3) from the reception area or from the 708 area, which means that this operation works, simultaneously, as a cross-docking point and a "traditional station" of order picking and preparation. This operation follows a wave picking strategy. When the wave is released, the order starts to be prepared, by picking the products and preparing the orders. If the products ordered have less than 18.5 litres, they are considered small products, thus, they are labelled, packed, and put in the conveyor that leads to the sorter. Otherwise, the products are considered large, and so, they are labelled and sorted directly according to their destination. Considering only the online orders for SDel, if the destination store has a delivery window on that day, the small products are picked from the sorter by an operator that isolates and allocates them by sector and then by store, as is done for retail orders in the PTZ and PTL zones. In the end, when the tote of the store is full, it is closed and allocated to the PTS zone, alongside the

[1] Zone PEQ, from the Portuguese *pequeno*, meaning small; Zone MED, from the Portuguese *médio*, meaning medium; Zone GRA, from the Portuguese *grande*, meaning big.

large products with the same destination. Although, if there is no delivery window, but there are online orders to deliver, the operator of the online section is responsible for the pallet preparation and wrapping to be shipped to the store on that day by the internal operator.

Finally, the PTS zone (in purple in Figure 3) is composed of two different zones, called distribution and production, each of them organized in two aisles of pallets on the floor. Each store has, at least, one pallet in each zone. The distribution zone receives the products directly from the PTZ with a volume equal to or greater than six litres. The production zone collects all the products from the PTL sector or online orders to the stores with a scheduled delivery window on that day. During the working day, the pallets corresponding to stores with a delivery window on that day are prepared. The operator starts by picking the products from the distribution zone to the master pallet, because, due to their greater volume and compactness, they form a pallet's solid base, decreasing the possibility of damaged items during transportation. Next, the items from the production zone are picked and arranged stably in the pallet. Finally, the master pallets are wrapped (in the wrapping zone) and positioned in the outbound dock to be loaded and shipped to the store.

2.5 Distribution

The merchandise transportation and distribution from the warehouse to its destination (Worten stores or customers' addresses) is outsourced by Worten to third-party logistics (3PL) companies. By doing so, the company delegates to these companies the responsibility of distribution in a specific delivery time window – a fixed interval of the day determined by Worten in which the order must be delivered – and focuses its resources on its core competencies.

All HDel or SDel from the online flow outside the delivery window are handled by independent 3PLs. At the end of each day, they receive the merchandise from the warehouse, plan the routes to operate based on the orders received, and deliver them the next day, either in-store or at the customer's address.

In addition, all the products to sell in-store, from the B2B outbound warehouse flow, are delivered by a 3PL company which works as Worten's internal distributor. In this case, both companies have an established agreement on the weekly delivery windows for each store. Once these are pre-set, it is possible to aggregate the SDel from the online flow whenever a store has a delivery window. Every day the logistics team of the Worten warehouse shares the number of pallets planned for each store with the internal distributor. Based on this number, the internal distributor determines which stores to aggregate in the same routes to meet all delivery windows and maximise the efficiency of its service. Then, the pallets shipment into the truck is ensured by the warehouse shipment team, and, in the end, they seal the truck's door to ensure that it is not opened, nor the products stolen between the warehouse and the first store.

2.6 Stores

From Worten's early days, stores have always been the main contact point between the company and the final consumer, as it was in any "traditional" linear supply chain before the digital era. Although, the implementation of the omnichannel, which connects the retail and online channels, changed stores' function in the supply chain. Beyond being a purchase place where customers can have a close view of the products, stores also became a place to collect online orders without delivery fees. Consequently, similarly to the warehouse outbound flow, there are two store provisioning flows, B2C (corresponding to online orders to pick in-store) and B2B (corresponding to retail orders).

2.6.1 Stores Operations

The store provisioning and shelf replenishment operations pursue a standard execution process applicable to every Worten store, as described below. For a better understanding of these operations, a flow diagram was developed, and it is presented in Figure 4.

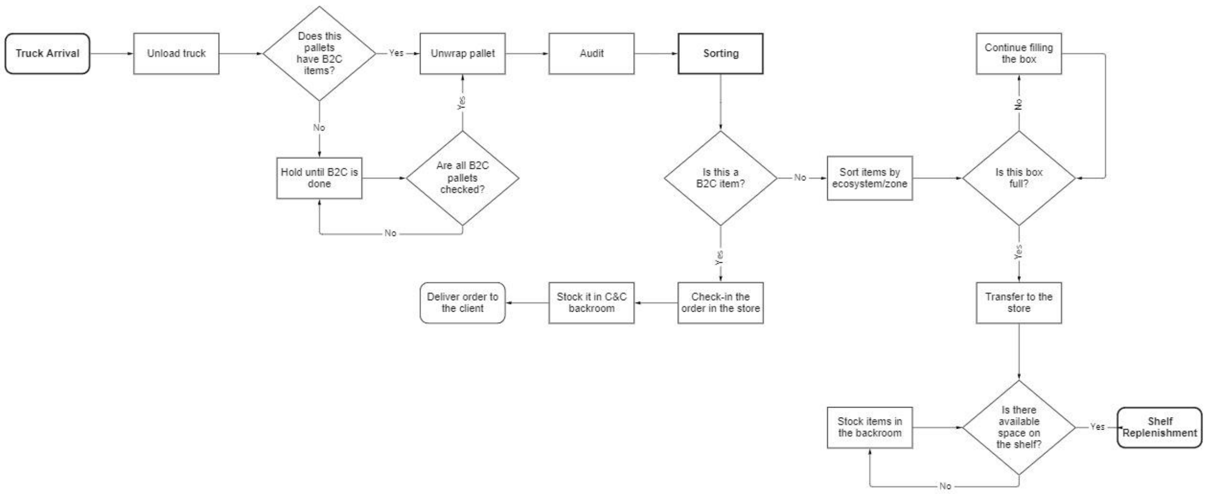

Figure 4 - *Current Store Operations process.*

When the truck arrives at the store dock, a Worten operator checks the truck seal. If the seal is untouched, the driver opens it, and the merchandise destined for that store is unloaded at the receiving dock. From that moment on, starts the Quality Control activity, in which the backroom operators unwrap the pallets and audit all the products arriving at the store and confirm the congruity between the received products and the distribution order (order from store to warehouse). In the end, if there is any discrepancy, i.e., excess or missing items, the operator opens a Transfer Conflict Manager (TCM) process. These TCM processes are then verified and handled by the warehouse management team.

It is noteworthy that there are two priority rules in this process. Firstly, priority is given to pallets with items for the B2C flow, since Worten is committed to delivering all its online orders in less than 24 hours, and so intends to have these products available to be lifted by the customers as quickly as possible. These pallets are easily identified because they have different labels than the pallet labels only with B2B items. Then, between the pallets only with B2B merchandise, the operators prioritise direct pallets, meaning pallets with few products, because these are quickly checked and stowed away, freeing up backroom floor space for the remaining operations.

During the Quality Control operation, as the operator checks each product, he/she also performs a Sorting operation, selecting and separating the items. By doing it, the operator simplifies and speeds up the task of shelf replenishment. Depending on the flow of the product, the Sorting operation procedures change. Belonging to the B2C flow, once picked by the operator, the online orders are checked-in in the store and then stocked in the Click & Collect backroom, where the customers will pick up the orders.

Nevertheless, the B2B products are sorted in different containers, like boxes or trolleys, by store ecosystem (zone with similar or related products). When the container is full, or if there are no more products part of the ecosystem in question, that container is taken into the store and placed on the shelf if there is space available. Otherwise, they are brought back to the backroom and stocked there by ecosystem and accordingly to their popularity (easier to access the best-selling items).

2.6.2 Store Types

Despite having a standard execution process for logistics and backroom operations, like store provisioning and shelf replenishment, real operations processes vary from store to store since every store is different. In the universe of 160 Worten stores in Portugal exists a wide variety of stores with different economic turnover for the company, reflected in several characteristics of their logistics process, such as selling and storage area or their provisioning frequency and volume of products.

Therefore, this study is based on three real Worten stores that represent three different groups of Worten stores (A, B, and C). All Worten Mobile stores – with smaller dimensions than type C stores – are excluded from this study by Worten's suggestion because their low frequency and small size of procurement make this analysis meaningless from a business point of view.

Type A represents the flagship store of the company, much larger than the others physically and in sales terms. This store has a selling area of around 4000 square metres, and a storage area of around 500 square metres, divided by several backroom storage places (the greater one for most of the store products, one for Worten Mobile products, one for sensitive products that come from the warehouse Mezzanine, one for Click & Collect products, and one for Worten Resolve). Moreover, its delivery window is open every weekday (from Monday to Friday), receiving usually between 20 and 30 pallets a day, increasing to between 80 and 90 pallets a day in high season (like Black Friday and Christmas). To handle the backroom operations of this store on normal days there is a team composed of 12 or 13 people, which increases in high seasons, and that is divided into four smaller teams composed of people specialised and familiarised with the routines in their operations:

- Checking team: responsible for the Quality Control and Sorting operations of the B2B flow.
- Online team: responsible for all activities related to B2C products, until storing the orders in the Click & Collect backroom space.
- Flows team: responsible for shelf replenishment and backroom storage.
- Provisioning team: responsible for the management and analysis of the in-store stock.

Then, the 52 Worten stores with around 2000 square metres of selling area and with 250 square metres of the storage area are part of type B stores in this analysis. Similar to type A stores, their storage area is also divided by several backroom spaces, and they also have their delivery window open from Monday to Friday. Although, they only receive between 10 and 15 pallets per day on common days, which increases to between 35 and 40 pallets per day in the high season. Having a lower provisioning volume than type A stores, the backroom team of type B stores is composed of around three operators without any specialised operations.

Finally, type C stands for the smaller stores considered in this study, about 107 stores in Portugal. These stores have about 500 square metres of selling area and a small but variable storage area, divided into two backroom storage spaces: one for the store (B2B flow), and the other for the Click and Collect orders (B2C flow). These stores receive between three and five pallets per delivery window (and 10 to 15 pallets on high season days), which is usually scheduled for three days a week. Due to the small number of products received per shipment, these stores do not have operators assigned only to backroom operations, so these operations are conducted by any store operator whenever available.

2.7 Problem Definition

This section presents the lower level of the problem contextualisation. Reaching this stage, in first place, it will be presented the background of the research subject. Afterwards, it is outlined the problem addressed and its significance in the context of the company under study.

As already mentioned, the entire Worten supply chain is supplied by a single Warehouse in Azambuja. Recently, Worten’s logistics operation has increased greatly due to the development of new sales channels. Beyond the in-store sales, the company has substantially increased its online sales, especially after the Covid-19 pandemic and with the development of the new Worten marketplace.

In the upcoming years, the internal expectations are for an increase in sales volume until 2026 which, if that is the case, will imply an 80% increase of the average warehouse inventory of the smaller products in the 708 area (the first category of items from the 708 area according to sub-section 2.4.2), and a 150% increase of storage area required for this category of items, maintaining the current warehouse layout, flows and operations. In a more conservative projection (identified as the company’s worst-case scenario), the average warehouse inventory of these products increases by approximately 40%, and the storage area required by 65%. In fact, all the projections point to a substantial increase in both the average warehouse inventory and the storage space required. As such, to be able to continue operating in the current warehouse space, it will be required to develop a solution which increases storage density (more locations per square metre) and the efficiency of the warehouse operations and flows, which even in the scale of the current operation are already close to the capacity limit, according to the company indicators.

Bearing this in mind and understanding that the continuous improvement of the current operations is no longer a solution to keep the service level and efficiency of the operation, as it has been so far, the company decided to implement a disruptive solution by reconfiguring its warehouse operations, installing an automated storage system for the smaller products in the 708 area (sub-section 2.4.2). To execute the picking operation of these products, the company opted to install a G2P system at the automated warehouse front end. G2P is an order picking method in which the items arrive through automated systems at the order picker and then he/she has only to pick the required quantities and allocated them to the right container.

Furthermore, the current warehouse storage and outbound flows are planned to maximise the efficiency of the warehouse operations, disregarding the downstream operations. They consider exclusively three different item characteristics: its size, its sales popularity, and the suppliers’ service level. As a result, items are dispatched to the stores based on these criteria rather than factors that help the in-store provisioning and replenishment operations, like their proximity when displayed in the store. Effectively, the items' display in the store is not uniform from store to store, thus, to organise the operations based on these criteria would greatly increase the complexity of these warehouse operations if they remain as they currently are.

While restructuring part of its warehouse operation, by installing an automated warehouse with a G2P system, Worten pretends to determine the best set-up of its order picking operation in the station, taking into consideration the downstream operations. By achieving it, the coordination between the warehouse and in-store operations will improve and, consequently, the total cost of the store replenishment processes of the company is expected to decrease.

Therefore, focusing on the B2B flow (from the warehouse to the stores) of the small-sized products in the 708 area, this research will assess for each type of store (and per period of the year), the picking operation configuration that optimises: (1) the efficiency of order picking operation in the warehouse, (2) the efficiency of the in-store replenishment process, and (3) the management of the trade-off caused by the integration of these two processes.

Chapter 3 – Literature Review

Since the previous chapters allowed the reader to become familiar with the context of the problem under study, the third chapter of this thesis presents a literature review on the theoretical topics and concepts relevant to what is being studied. To that end, this chapter is structured into five different sections, each organised in the following way. The first section introduces general retailing concepts, especially focusing on retail operations. Then, the second and third sections focus on two distinct parts of the retail sector's operations. Section 2 explores the literature related to warehouse operations, with emphasis on the order picking operation (describing types of order picking and picking policies) and the sorting operation, because this thesis is specifically focused on these two operations. Later, section 3 examines the academic literature associated with physical store operations, having one sub-section that summarises the showroom operations literature and another sub-section that focuses on backroom operations. Afterwards, in section 4, aiming to define the right methodology to apply to this study, a summary is presented of several recent and important papers on topics similar to or close to the subject in hand. To conclude, the last section starts with basic concepts about modelling and simulation, exploring in detail the model conceptualisation and the verification and validation steps of a simulation study, and ends with the introduction of some of the most used methods of modelling and simulation.

3.1 Retailing

In the Strategic Retail Management book, Zentes et al. (2016) define Retailing as the activity of purchasing products from other organisations with the intent to resell them without transformation in stores or on the internet. Retailers are the entities of the supply chain responsible for handling retailing operations, delivering the right products, in the correct quantity, at the right place, at the right time, in the right conditions, at the right price, and to the right customer (Richards, 2018).

Currently, retailing operations suffer increasing pressure mostly due to the evolution of e-commerce, mass customisation, omnichannel distribution and the just-in-time philosophy (Custodio & Machado, 2020). Retailers have an extremely demanding exercise managing the multiple trade-offs existing in retailing operations, especially in the warehouse and in the store, managing inventory, in allocation and assortment of products to shelf (Eroglu et al., 2018). Thus, improving the operations efficiency of these two supply chain facilities, and the connection between both, contribute to the evolution and development of the entire supply chain as one. Warehouses once considered an expensive and heavy burden, due to capital and operating expenses, are now seen as a strategic component of the supply chain to stay ahead of the competition (Kembro et al., 2018). The efficiency and effectiveness of any supply chain are mainly dictated by the operations in warehouses (Rouwenhorst et al., 2000). Therefore, the right management of these operations can save a lot of resources for the companies. Furthermore, besides the introduction and growth of the online channel, physical retail stores remain the principal destination for customers (Mou et al., 2018). The customer attraction for retail shopping and the usually scarce shelf space of retailers granted the latter the connotation of “the most expensive real estate of the world” (Kaikati & Kaikati, 2006). The quality and effectiveness of store operations also affect the supply chain results (Mou et al., 2018). Due to their relevance in the supply chain and to the scope of this dissertation, these entities, warehouses and physical stores, deserve an in-depth analysis of the literature related to their operations, in sections 3.2 and 3.3, respectively.

3.2 Warehouse Operations

In a perfect but utopic world where retailers knew the demand for their products over time, they would only order the products they sell, and would not have stock to manage. However, the uncertainty, that characterises societies and markets, makes it practically impossible to occur and, thus, this practice is rare or non-existent (Richards, 2018). Consequently, there are usually several stock-holding stages – warehouses – across the supply chain (Richards, 2018).

A warehouse is an entity of the supply chain that virtually all products flow through in the logistics process of a company (Davarzani & Norrman, 2015). Hence, the efficiency of its operations is critical to ensure the success of the supply chain, as well as, to achieve high customer service levels (Baker & Halim, 2007). As aforementioned, the companies' view on logistics, and the importance given to this subject, is changing. The warehouses are no longer just inventory-holding entities, although it remains one of their main functions (Baker, 2007). Many of them are being adapted (with total or partial conversion) into cross-docking, transhipment or fulfilment centres, sortation or consolidation points, and reverse logistics centres (Maltz, 2004; Richards, 2018). This transformation increased the strategic and essential role that warehouses play in the supply chain nowadays and made the efficiency of their operations a critical factor to achieve the demanded high customer service levels (Baker & Halim, 2007; Kembro et al., 2018). The new activities and roles of warehouses imply a reconfiguration of their operations, which also impacts their layouts and flows (Higginson & Bookbinder, 2005).

Current warehouses predominantly conduct six different operations: receiving, put-away, storage, cross-docking, order picking, and shipping (de Koster et al., 2007; Richards, 2018; Rushton et al., 2022). Each one of these operations will be briefly described and then, due to the context of this dissertation, the literature about order picking will be reviewed in detail in sub-section 3.2.1.

Receiving is always the first operation to execute when the merchandise arrives at the warehouse. It usually includes the unloading of incoming transportation, checking the quality control of the merchandise, and recording the incoming goods in the inventory system of the warehouse (de Koster et al., 2007; Rushton et al., 2022). Occasionally, it may be needed to label the goods, unpack and/or repack products in a format that suits better the remaining warehouse operations (Habazin et al., 2017; Rushton et al., 2022).

Afterwards, starts the put-away operation. From here, the goods may go to a storage location to be stocked, or directly to a preparation or picking location to be dispatched through cross-docking (Rushton et al., 2022). In modern retailing warehouses, the instruction about the place to take the goods is given by the installed WMS (Richards, 2018).

Storage is one of the most complex and resource-consuming activities of the warehouse, especially in terms of space resources (Gu et al., 2007). It keeps the goods in inventory until to be placed an order that requests them (Rushton et al., 2022).

When the products are not stored in the warehouse, but, instead, are directly prepared and dispatched in less than one day, they pass through a cross-docking operation (de Koster et al., 2007). This virtually direct passage from the receiving docks to the shipping docks increases the complexity of the remaining operations, as it requires a lot more coordination between receiving and shipping operational timings, as well as, between put-away operation and order picking availability (Gu et al., 2007).

Lastly, shipping is the final operation of the warehouse, after order picking or cross-docking (Habazin et al., 2017). This operation starts by sorting the items into their carriers (if it is not done while order picking or cross-docking) (Rushton et al., 2022). Then, the orders are consolidated in pallets, and placed in the outbound area of the warehouse, from where they will be loaded into the truck for distribution (Rushton et al., 2022). Occasionally, shipping also may have a control activity (Habazin et al., 2017). After this operation, the items are ready to be distributed to the next entity of the supply chain (Rushton et al., 2022).

3.2.1 Order Picking

Order picking, also called selection by some authors, is the operation of picking the right amount of the right product, from storage or other buffer areas, to satisfy customer orders (Bartholdi & Hackman, 2019; de Koster et al., 2007; Petersen & Aase, 2004; Roodbergen & Vis, 2006). Taking frequently more than half of the operational costs of warehouse management, this operation is one of the most vital activities of the supply chain, and usually, retailers prioritise the investment in the improvement of its efficiency and accuracy (Tompkins et al., 2010). An underperforming order picking operation leads to a growth of operational costs that can considerably affect the service levels of the whole supply chain (de Koster et al., 2007). This explains why order picking is one of the most documented and studied topics in warehouse operations, and even in retail. Nevertheless, there is a lot to study regarding new order picking methods and their optimal implementation, since the gap between the practice and the academic literature still exists (de Koster et al., 2007).

In fact, Vijayakumar & Sgarbossa (2021) state that the order picking methods design must be based on five key decision areas: layout design, storage assignment, zoning, batching, and routing. The layout design decisions define the shelf layout and configuration by specifying the number of blocks as well as the number, width, and length of aisles within each block. Secondly, storage assignment decisions dictate how items are assigned to storage spaces depending on item attributes. If the warehouse is divided into zones, the order picking task of the picker must be realised in a specific zone defined through zoning decisions. Batching decisions aim to consolidate efficiently customer orders into a single pick round to optimise the order picking performance. Finally, routing decisions determine the picker's movement within the warehouse to get the goods from the shelves (Vijayakumar & Sgarbossa, 2021).

Furthermore, according to Roodbergen & Vis (2006), it is possible to recognise three different moments during an order picking operation: the travel moments, picking the items, and the remaining activities. While the efficiency of picking items and of the remaining activities (like receiving picking information, picking up an empty pick carrier and dropping it off when it is full) is affected by less controllable factors, such as the operator's experience or the chosen rack type, the travel moments – the movement between picking moments – are the moments considered to be the most easily influenced through operational planning and structuring. Therefore, most of the research in this area has been directed to reduce travel times through the improvement of operational efficiency in routing, batching, and storage assignment (Roodbergen & Vis, 2006). Based on this research and retailers' operational experience, several order picking methods have been created over time to reduce or minimise the order picking operation time (Gu et al., 2007).

As shown in Figure 5, order picking may be done through manual or automated methods (Davarzani & Norrman, 2015). Through both methods, this operation is the most resource-consuming operation of the warehouse, either labour-intensive in warehouses with manual systems, or capital-intensive if it has an automated order picking system (de Koster et al., 2007). The use of automated systems is normally associated with the reduction of labour costs (Petersen & Aase, 2004). Nevertheless, numerous organisations keep using manual order picking because factors like the variety in SKU shape and size, the variability of demand, and the substantial investment involved in the automation transition of an order picking system make it a high-risk option for them (Petersen & Aase, 2004; Vijayakumar & Sgarbossa, 2021). Furthermore, it is essential to emphasise that automated systems may not always be favourable to businesses. When the automated transition is not performed with the utmost rigour, companies may end up using an inappropriate technology, or perhaps the right technology wrongly (Baines, 2004).

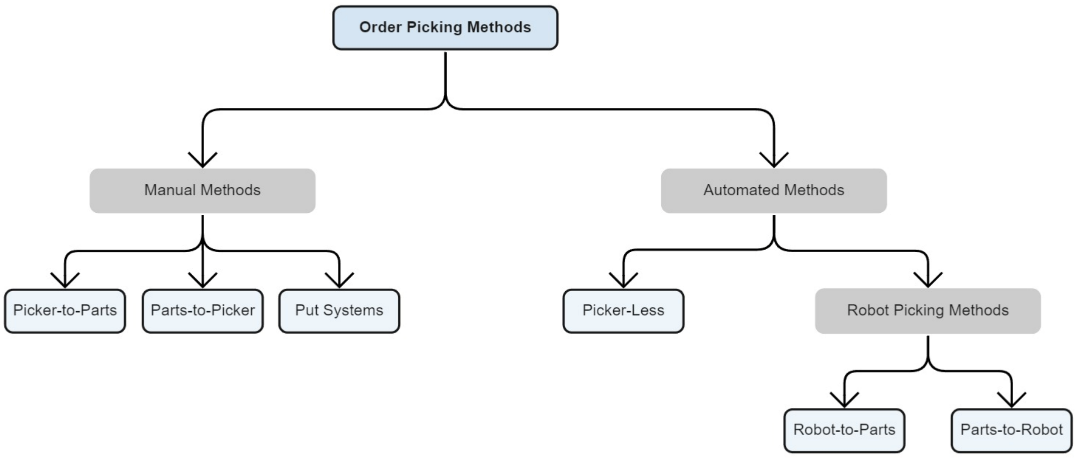

Figure 5 - *Classification of Order Picking Methods (based on de Koster, 2004; Habazin et al., 2017; Jaghbeer et al., 2020).*

According to Figure 5, there are three types of manual order picking methods – picker-to-parts, put systems, and parts-to-picker –, and three types of automated methods – picker-less, robot-to-parts, and parts-to-robot (de Koster et al., 2007; Habazin et al., 2017). In the manual order picking methods, a human performs the picking action. Otherwise, it is accomplished exclusively by machines (Jaghbeer et al., 2020).

Picker-to-Parts

The most common order picking method is the picker-to-parts (also called picker-to-goods by some authors). In this method, after having the picking list prepared, the human picker travels through the aisles, searches for the items ordered and collects the quantities ordered from that item (de Koster et al., 2007; Vijayakumar & Sgarbossa, 2021). There are two types of picker-to-parts systems: low-level picking (the items are requested by the picker during the picking task while moving on the storage aisles) and high-level picking (the picker travels across the aisles on an automatic lifting order-pick truck, which stops in the pick locations and waits for the task to be completed by the picker) (de Koster et al., 2007).

In the recent years, the important development of business digitalisation provided numerous improvements in order picking methods (Qi et al., 2020). Beyond the traditional picker-to-parts method – in which the picker performs all the tasks manually – there are now better, faster, and more effective solutions, for instance, paperless picking or AGV (Automated Guided Vehicle) assisted picking (Vijayakumar & Sgarbossa, 2021). In the paperless picking methods, the human picker uses picking devices, like pick-to-light, pick-to-voice, or RFID systems, which improves his/her ease of perception, reducing picking errors (Vijayakumar & Sgarbossa, 2021). The picker still performs most of the tasks manually, so, this method is more suitable to pick small and medium items (Vijayakumar & Sgarbossa, 2021). Alternatively, in the AGV assisted picking is mostly used on heavy or mixed-shelves order picking operations and, as the name implies, an AGV accompanies the picker to the picking locations, and waits for the picker to place the items on it (Boysen et al., 2019). Once full, the AGV returns to the depot, and the picker gets an empty AGV to continue the operation (Boysen et al., 2019).

Parts-to-Picker

The order picking method called the parts-to-picker method, or goods-to-picker, consists of the items moving in the direction of the order picker from storage supported by automated solutions, instead of being the picker to find the items on the shelves (Vijayakumar & Sgarbossa, 2021). In this method, the task of picking the items from the shelves is fully or partially automated, and later the human picker is responsible for picking the items from the distribution system, e.g., a conveyor, and sorting them by customer order line (de Koster et al., 2007).

Compared with the picker-to-parts methods explained above, this method reduces the theft and the heating or lighting requirements in the storage area, as well as greatly improves the efficiency of the operation and the ergonomic conditions of the picker, contributing to the maintenance of the worker's performance over time (Hwang et al., 1999; Vijayakumar & Sgarbossa, 2021). Evidently, reducing the repetitive tasks of travelling, bending, lifting, and picking items increases the performance of the order picking system, since it reduces the risk of injuries, like musculoskeletal disorders or low back pain which would certainly reduce the performance of the picker (Grosse et al., 2017). Besides, the parts-to-picker method ensures better space utilisation, once it is possible to take advantage of vertical storage space (Daria et al., 2015; Hwang et al., 1999).

This method has also various topologies with different levels of automation, different integration in the warehouse, and, consequently, different capital investments (de Koster et al., 2007). One of the most common systems used is the Automated Storage and Retrieval System (AS/RS), which is a computer-controlled warehousing system that incorporates one or more parallel aisles, each with two storage racks (van den Berg, 2002). The system uses aisle-bound cranes to take unit loads (called mini-loads in the case of bins) and transport them to the human picker location, where the ordered number of items is taken by the picker, and the leftovers go back to storage (de Koster et al., 2007). It is also worth mentioning the Vertical Lift Modules (VLM) and the Vertical and Horizontal Carousel systems, parts-to-picker systems widely adopted by companies to pick small-sized items, and already addressed in the academic literature (Daria et al., 2015; de Koster et al., 2007). These systems have similar high-density storage in a small footprint, with rotating shelves (Dukic et al., 2015). VLM and both Carousels consist of a storage column of extractable trays with items stored, which are moved and extracted by an automated device to present in front of the picker the right tray for that specific order picking task (Daria et al., 2015). However, while in VLMs and Vertical Carousels the shelves rotate in a vertical plane, in Horizontal Carousels the rotating plane is horizontal (Dukic et al., 2015; Đukić et al., 2021). Traditionally, they have just one picking place, which could potentially lead to a high picker's idle time (Daria et al., 2015). Thus, to reduce this time, operators are usually responsible for more than one picking unit at the same time (Dukic et al., 2015). Furthermore, a dual-tray system emerged recently, doubling the order picking places, and enabling to handle and operate two trays at the same time (Daria et al., 2015; Dukic et al., 2015). In fact, the main difference between the VLM and the Carousels systems is that VLM moves and extracts only one tray at the same time, while Carousels move all the trays together, and during the picking of items all the system stops (Daria et al., 2015). Overall, VLM systems have a reduced risk of damaging the stored products due to the less movement and are also cheaper to install and operate, but Carousels operate usually faster (Daria et al., 2015; Dukic et al., 2015).

Since parts-to-picker methods need much more specific equipment and machinery, compared to picker-to-parts methods, the investment costs are higher and the flexibility to change the system is lower. Although, the Return on Investment of these types of systems is usually lower than two years (Dukic et al., 2015).

Put Systems

In addition to the methods described above, there is still one more type of order picking manual method, the put systems. These are mostly used for small items and are especially common when a high number of client orders must be picked in a short time window (de Koster, 2004). In this method, the order picker takes the carriers of items (commonly, bins) from the shelves by one of the methods explained above (picker-to-parts or parts-to-picker), and then distributes the right quantity of items over the customer orders (de Koster et al., 2007).

Automated Methods

The automated methods are significantly less explored in the academic literature because they are a lot more recent and less explored by companies (Jaghbeer et al., 2020). The picker-less methods are entirely automated systems and do not require any kind of picker external to the system, like a human or a robot (Jaghbeer et al., 2020). The robot picking methods, robot-to-parts and parts-to-robot have great similarities with the picker-to-parts and parts-to-picker methods, respectively. The main difference between them is that the order picking is carried out by a robot, instead of a human. Effectively, robot-to-parts systems have mobile robots moving through the storage areas to pick up the items ordered, whereas parts-to-robot systems have fixed robotic arms picking the items at a picking station (Huang et al., 2015). Considering that these technologies are recent, they still have some flaws and weaknesses, and the robotic arm is not configured to pick all types of items (Lee & Murray, 2019). Hence, it is common to have hybrid systems where humans and robots complement each other weaknesses (Lee & Murray, 2019).

Picking Policies

Whichever order picking method is used, the items on the pick list of a picking operation are influenced and determined by the picking policy adopted in that area of the warehouse (Petersen & Aase, 2004). Three of the most used types of picking policies – single order picking, batch picking and zone picking – will be explored below:

1) **Single Order Picking:** also known as strict-order picking, this policy is the simplest order picking policy, where the picking operation tour is exclusively to pick up all the items from a single order (Petersen & Aase, 2004). This policy is easy to implement and keeps the cohesion of the order without the need for consolidation or sorting afterwards (Petersen & Aase, 2004).
2) **Batch Picking:** it groups a set of orders into batches that can be picked in a single picking route, to reduce travel times and, consequently, total picking time (de Koster et al., 2007; Petersen & Aase, 2004). There are some different types of batch picking policies mainly based on two criteria: priority to the proximity of pick locations and priority to time windows (de Koster et al., 2007). If the priority is given to the proximity of pick locations, the WMS attributes to one batch orders with items close to other orders' items in the same batch (de Koster et al., 2007). On the other hand, if the priority is the order's time windows, the orders are grouped according to the time interval of their arrival, or the proposed time interval of their shipping (de Koster et al., 2007). The first-come-first-served batch picking policy, where the orders are assigned to a batch according to their arrival time until the batch is full, is one example of this type of batch picking (Petersen & Aase, 2004). Furthermore, there are types of batch picking policies which consider other factors, like the order size or the dimensions of the product, though these are more complex policies, which usually are difficult to implement in the warehouses, and so, they are not contemplated in this literature review (Petersen & Aase, 2004).
3) **Zone Picking:** the warehouse is divided into different zones, and pickers are assigned only to one specific zone (de Koster et al., 2007; Petersen & Aase, 2004). The greater the warehouse, the more beneficial this policy becomes, once it reduces the picker's area of intervention, reducing the travel time of operation, the traffic congestion of the warehouse, and increasing the chances for each picker to be familiarised with each SKU's location (de Koster et al., 2007; Petersen & Aase, 2004). In contrast, in zone picking the orders are split, which forces an activity of order consolidation before the shipping (de Koster et al., 2007). To minimise the impact of an extra activity of consolidation, there are two possible approaches: pick-and-pass and parallel picking (de Koster et al., 2007). A pick-and-pass approach is a progressive approach where the order picking starts in one of the zones, and passes from picker to picker, aggregating progressively the SKUs of each warehouse zone, until it passes through all the relevant zones for the order (de Koster et al., 2007). In the second approach, parallel picking, all the pickers realise the picking operation in the same time window in each of their picking zones, and the order is merged right after picking (de Koster et al., 2007).

It is also possible to have merged order picking policies, such as wave picking that combines both batch and zone picking (de Koster et al., 2007). If it is in place a wave picking policy, each order picking operation has on its pick list SKUs from various orders but of the same warehouse zone, to minimise the maximum lead time of every batch (de Koster et al., 2007).

3.2.2 Sorting

When more than one order is picked in the same batch picking operation, there is a need to sort the batch by order (Gu et al., 2007). Sorting, according to Richards (2018), is the operation of dividing a batch of items by the different customer orders or shipment destinations. This operation may be processed in two different moments of the warehouse operations: while picking the items (sort-while-pick), or during the shipping operation after picking (pick-and-sort) (Roodbergen & Vis, 2006).

Actually, if it is a sort-while-pick sorting process, at the end of the order picking operation, the items of each order are already prepared for consolidation. Otherwise, pickers usually deposit the items of their batches in a conveyor which leads to a sorter, where all the items from this wave or batch picking operation stay, until being picked again by an operator, and assigned to a sorting lane (Gu et al., 2007). In the end, they are assigned to the container respective to their order or shipment destination, and the container is consolidated and shipped out of the warehouse (de Koster et al., 2007).

According to the author's knowledge and research, sorting operations or related topics have not been addressed in the most recent years by academics, and, when addressed, it was always approached from the perspective of maximising efficiency or reducing the operational time in the warehouse operations (Gu et al., 2007). It has never been addressed from the perspective of seeking to optimise both warehouse and store replenishment operations, which is the main objective that this thesis aims to address.

3.3 Physical Store Operations

A physical or brick-and-mortar store is “a large shop where you can buy many different types of goods” that exists in “a physical building, rather than doing business only on the online”, according to the Cambridge Dictionary[2]. In the past, it was an essential piece of the supply chain because it was the only contact point between brands and customers, and it was the only place to trade merchandise (Alexander & Blazquez Cano, 2020). With the emergence of e-commerce and the development of omnichannel, physical stores are not unique or essential anymore, although they are still relevant in retail supply chains (Berman, 2019).

In fact, web-based retailers, like Amazon, improved the easiness and speed of online shopping, which led to a market restructuring that turned out to be the closure of several physical stores, especially mall tenants, like electronics or clothes stores (Misonzhnik, 2017). Store closings harm the operational efficiency of manufacturers and retailers since they reduce their distribution points and, as a result, decrease the possibility of economies of scale in activities like storage and distribution (Berman, 2019). Consumers now choose to combine both online and physical channels to purchase something. They

[2] From the *Cambridge Dictionary* website: https://dictionary.cambridge.org/dictionary/english/store; https://dictionary.cambridge.org/dictionary/english/brick-and-mortar

usually start to search for goods online, but physical stores continue to be the most-used channel for purchase because it is possible to fully see and experience the goods (Berman, 2019).

Physical store logistics operations are divided into two major groups – showroom operations and backroom operations, which correspond approximately to 40% of the total working hours in a retail store and 40% of the total logistics retail cost (Pires et al., 2017, 2020). The most relevant academic literature for this dissertation about physical store operations will be presented in sub-sections 3.3.1 and 3.3.2.

3.3.1 Showroom Operations

The showroom (or sales area) of a store is the space where the merchandise is displayed to the customers. Therefore, there is always an added concern to ensure that it is organized and attractive to customers (Pires et al., 2017). Since this is the space that most evidently creates value, companies usually define its dimensions meticulously and consider several aspects, such as in-store traffic patterns, shopping behaviour, and expected sales (Pires et al., 2020). Yaw Wong & McFarlane (2007) believe that the efficiency of the showroom logistics process is so critical to the entire supply chain that, regardless of the efficiency of the remaining entities, inefficient showroom operations will dramatically lower the efficiency and service level of the entire chain.

The retail operation that takes place in the showroom is called shelf replenishment, i.e., the practice of refilling shelves by transporting items from the backroom (Yaw Wong & McFarlane, 2007). Retailers may use two shelf replenishment policies, that differ in the observation point at which the inventory is monitored. If the operator's basis for shelf replenishment is the observation of a low level of products on the shelf, he/she is using a "pull" replenishment policy. Instead, if the shelf replenishment starts from the observation of the products stored in the backroom, the operation is conducted by a "push" replenishment policy (Yaw Wong & McFarlane, 2007). Sometimes, these two policies can be applied simultaneously in the same retail store, as operators restock products on the shelves that they notice are out of stock, and at the same time fill the shelves with products that are in the backroom inventory, even if there is still stock of those products on the shelves.

3.3.2 Backroom Operations

The backroom space of a retail store is the area where inventory should be stored if there are no empty spaces available in the showroom (Eroglu et al., 2018). Generally, when the shelf is full, the items are sent to the backroom, which represents between 15% to 20% of the total store area (Bixler & Honhon, 2021). The benefit of using backroom areas is not at all consensual among companies and researchers, since the trade-offs between their benefits and costs have different impacts from case to case, considering as well the characteristics and objectives of each one. Hübner & Schaal (2017) illustrate these trade-offs simply and clearly. Saving stock of a few products in a backroom grants more available shelf space for other products in the showroom, however, it also creates additional costs for the products in the backroom because the replenishment frequency and the operational complexity increase.

Xue et al. (2017) defend the use of backroom spaces since they believe that stores should try to have as many products as possible on display on the showroom shelves, as a tactic to influence demand, and use the backroom to hold inventory of the products displayed so that the shelf restocking process is as quick and efficient as possible. The same authors note that cooperative replenishment of backroom and showroom inventories brings higher value to the supply chain than not having a backroom at all, especially if the inventory holding cost is low, its shortage cost is high and/or its demand volatility is small.

Moreover, Pires et al. (2020) find the backroom spaces especially useful because they behave as a buffer between the stores' showroom and the upstream supply chain entities. Having a backroom inventory space available enables a broader delivery window, allowing the entities of the supply chain directly related to the store to plan their routing decisions to their better convenience and benefit, reducing associated transportation costs. It also prevents and mitigates brand damages from delivery uncertainties or imperfections, longer lead times, or other inaccuracies related to store provisioning and shelf replenishment (Eroglu et al., 2013).

However, as aforementioned, the backroom inventory spaces increase the labour costs and the operational complexity of store operations, once stores have to keep inventory in, at least, two separate locations (Eroglu et al., 2018). The labour costs increase because the showroom inventory must be constantly monitored and checked by store operators, and every time consumers purchase something the shelf must be replenished with the same SKU from the backroom inventory, which increases the number of store employees required to preserve the service level (Eroglu et al., 2013). Operationally, the constant exchange of stock between these two store areas complicates the inventory monitoring task and may lead to recurring inventory inaccuracies (Gruen & Corsten, 2007). Further, if the shelves are not instantly restocked, the customers may not find the product in the store and purchase a substitute product, delay the purchase, or, in the worst-case scenario, not purchase there to purchase in a competitor's store, increasing the store's cost of lost sales (Eroglu et al., 2018).

Additionally, the majority of retailers' backrooms have low automation levels (using mostly labour-intensive systems, such as racks), and do not have assigned or specialised places for their items (Pires et al., 2020). Thus, the possibility of misplaced, forgotten, damaged or stolen products is substantial (Bixler & Honhon, 2021; Eroglu et al., 2018). In this regard, Pires et al. (2020) affirm that some companies are using dedicated storage policies, that fix storage locations for each SKU in the backroom, or class-based storage policies, setting the backroom in specific departments of products, although the products are randomly allocated inside each department. These strategies allow employees to be familiar with the products' locations in the backroom, and these locations usually match the showroom layout, which enables a faster and more efficient shelf replenishment service. On the other side, having an assigned location for out-of-stock products decreases the space utilisation efficiency of the backroom storage (de Koster et al., 2007).

Several authors also note the existence of a backroom effect. They argue that the existence of a backroom in a retail store leads to higher total costs of operation, and it occurs due to the poor alignment, or complete misalignment, between case packs, shelf space in the showroom, and the reorder inventory point (Bixler & Honhon, 2021; Eroglu et al., 2013). Eroglu et al., (2013) say that these three factors are the decision variables of the retailers' optimisation problem and that its optimisation would lead to a globally optimal inventory policy. However, the case pack sizes are frequently decided by the supplier alone (customizing them to the ideal size of a particular store would be absurdly expensive for retailers), and shelf space allocation decisions are usually made in medium or long periods (one or two times a year) and controlled by the merchandising department. Hence, the operations department can manage and control the reorder point, in the short run, mostly to minimise costs, instead of optimising them (Eroglu et al., 2013).

Considering all the disadvantages of managing a store with a backroom, some authors defend that the best way to operate a retail store is without it, even if it leads to some lost sales due to the absence of backup inventory (Bixler & Honhon, 2021). Some retailers hold this idea in such high regard that what is displayed in the sales area influences their customers' purchases that they give up having backroom space to increase their showroom space (Eroglu et al., 2018). For instance, Walmart uses the top shelf of their showroom as a backroom inventory space. Also, without a backroom, the retailer has more employees in the showroom, faster replenishment, reduced on-hand inventory, and less waste[3] of time, labour, cash flow, or product obsolescence (Bixler & Honhon, 2021). Other studies show that the more inventory there is in the stores, the greater the inventory recorded errors caused by errors in the activity of shelf replenishment (DeHoratius & Raman, 2008; Ton & Raman, 2010). While proposing this non-backroom approach, Bixler & Honhon (2021) recognise that some retailers may not benefit from it due to their size, or incapacity to operate like this. Nonetheless, they affirm that small changes in the size and layout of the backroom, in the design of the case packs or in the management of inventory can help to reduce waste and increase returns to retailers.

3.4 Warehouse and Store Operations: literature review summary

From the research conducted by the author of this work, it was found that there is a gap in academic research and investigation, as no studies were found that purport to study the optimisation of operation between the warehouse and retail stores. Thus, the methodology that best fits this study will be defined through the evaluation of various works carried out in several related areas that are explored in this literature review presented in Table 1. Although the works listed are not completely within the scope of this dissertation, this evaluation helps to understand the various methodologies used in similar works, enabling to draw conclusions about the methodology to use, based on some of the characteristics of these research and their similarities and differences with the work in hand. Some of the studies presented have already been mentioned throughout this research, others are exclusively mentioned in Table 1 for the above-described purpose.

From Table 1, it is possible to distinguish four different methodology methods applied in the studies mentioned: data-driven approach, optimisation models, heuristics algorithms, and simulation models. The data-driven approach is used only in one research studying a company with a single-store supplied shop (Turgut et al., 2018). This approach is useful if the case in study has a small dimension and does not have many variables. Further, the optimisation models and the heuristics algorithms are commonly used in these problems (used in four out of eight papers in Table 1). However, they frequently do not

[3] By waste Bixler & Honhon (2021) include the obsolete and expired products, as well as the non-value-added process steps, as they take a lean manufacturing definition.

support high-complexity problems, and so they are mostly useful for abstract or small-dimensioned cases (Kim & Moon, 2021; Zhuang et al., 2022).

Table 1 - *Short Literature Review on Order Picking, Sorting, Showroom and Backroom Operations.*

Title	Author	Scope	Summary/Methodology	Problem Dimension
Order picking optimization with rack-moving mobile robots and multiple workstations	(Zhuang et al., 2022)	Order Picking	Suggests a mixed integer programming model of the multi-workstation order and rack sequencing problem with rack-moving mobile robots, through a data-driven heuristic	Different problem sizes tested. Larger cases (with more than 5 racks, 20 orders and 2 units of tote capacity at a workstation) did not present optimal solutions within the time limit. Some cases cannot present a feasible solution within 30 minutes of the model running.
Route optimization for warehouse order picking operations via vehicle routing and simulation	(Shetty et al., 2020)	Order Picking	Proposes a vehicle routing problem-based approach joint with the distance matrix for finding an optimal route for order picking, through a computational simulation.	One warehouse composed of 30 parallel racks of 7 levels, each row has 124 bay locations with 3 bins.
Optimizing parcel sorting process of vertical sorting system in e-commerce warehouse	(Tan et al., 2021)	Sorting	Uses a particle swarm optimisation algorithm (simulation) to solve a mixed integer linear programming model about the problem of parcel sorting in an e-commerce warehouse where parcels are waiting to be sorted and delivered.	Algorithm tested with different values on its parameters. The population size and the maximum number of interactions are 100.
Optimizing automated sorting in warehouses: the minimum order spread sequencing problem	(Boysen et al., 2018)	Sorting	Applies a simulation study of the consolidation process of zoning and batching picking policies to minimise the spread of orders in the release sequence to have a fast assembly in the packing stations.	One warehouse of an online retailer with one linear conveyor, which receives as input a sequence of bins and considers the workers' movement.
Integrated planning for product selection, shelf-space allocation, and replenishment decision with elasticity and positioning effects	(Kim & Moon, 2021)	Showroom Operations	Implements a mixed integer non-linear programming model to solve a shelf-space allocation problem with product selection and replenishment decisions, through two heuristic algorithms to solve.	Different problem sizes tested. Larger experiments (with more than 6 product types and 2 shelf columns and rows) did not present optimal solutions within the time limit
Managing retail shelf and backroom inventories when demand depends on the shelf-stock level	(Xue et al., 2017)	Backroom and Showroom storage	Provides an optimisation and a heuristic model to study the implementation of periodic-review inventory systems for the joint replenishment of the store backroom and showroom shelves with the impact of the on-shelf inventory level on demand.	Not specified
Solving the grocery backroom sizing problem	(Pires et al., 2020)	Backroom Operations	Provides two mixed integer linear programming models to solve the backroom sizing problem, i.e., determine the dimension of storage departments in the backroom area to optimise its overall efficiency, by two optimisation models.	50 convenience stores that hold around 25 thousand SKUs on average
Data-driven retail inventory management with backroom effect	(Turgut et al., 2018)	Backroom effect	Proposes a mixed integer linear model to calculate inventory control parameters for retail stores considering the backroom effect, through a data-driven approach.	One store supplied by one warehouse

Finally, the simulation models are also commonly used in related problems, as can be seen by their appearance in three of the papers in Table 1. This methodology is mostly used in high-complexity problems, where a relatively high level of reality is intended to exist. Bixler & Honhon (2021) state that simulation models are one of the best methods to conduct company-related studies, like this one. Therefore, simulation is the methodology chosen to accomplish this work, which will be described in light of the academic literature in the following section 3.5.

3.5 Modelling and Simulation

Real-world problems are most of the time hugely complex, and people cannot test different solutions in the real system to find the right one, as it could lead to expensive costs or irreversible damage to the system (Borshchev & Grigoryev, 2013). For instance, it is not possible to build a house before having a complete and detailed scheduling. As well, it is not possible to test the best G2P system in a warehouse by implementing all the systems and checking their performance. Therefore, there are several methods to solve real-world problems without changing the real system until the final solution is found. Modelling is one possible method to use.

In fact, a simulation model is a simplified image of the real system (Banks, 1998). While it must stay complex enough to give a plausible answer to the problem raised, modelling allows some abstraction from the real world, focusing the model on the important issues to solve and disregarding those that are superfluous to the problem at hand (Banks, 1998; Grigoryev, 2021). After the model building process, starts the simulation process, exploring the model under different conditions, comparing scenarios, and understanding its behaviour to optimise the system without wasting any resources (Borshchev & Grigoryev, 2013). The simulation outputs are composed during the model runs and can be observed during and after the runs (Grigoryev, 2021). In the end, when the best solution is discovered, it is implemented in the real-world system (Borshchev & Grigoryev, 2013).

Advantages and Disadvantages of Modelling and Simulation

When compared with other methodologies, modelling and simulation present some advantages and disadvantages that must be weighted up to assess if it is the best method to use.

Firstly, simulation models are usually more reliable and simpler to develop than others (like analytic or linear programming models), since they demand less thinking and the development process is modular and incremental (Borshchev & Grigoryev, 2013). Then, the visual language used in this type of model and the flexibility to explore and animate the system in real-time facilitate the model's perception, the interpretation of results, and the processes of verification and debugging (Grigoryev, 2021). A clear example of this situation is the possibility to expand and compress time while simulating, which allows the investigator to follow carefully, through "microscopic" examination, complex parts of the simulation that are usually difficult to understand in real-time – understanding the interactions amongst entities and variables – and speed up already understood or less important parts of the simulation (Banks, 1998). Hence, using modelling and simulation, it is considered a wise investment since it represents a millesimal percentage of the total investment in a project; it prevents wasting resources; helps to identify constraints and bottlenecks of the system; and allows preparing for future changes by building different scenarios (Banks, 1998).

Nevertheless, modelling is a self-skill difficult to acquire except through experience and time (Carson, 2005). Plus, it is a resource and time-consuming task where no savings should be made, since it may lead to an undershooting model which does not meet the objectives set (Banks, 1998). Likewise, if the time devoted to analysing the output results of the simulation is not enough, it may be hard to interpret them and distinguish between what is pure randomness and what are interrelated system variables (Banks, 1998).

3.5.1 Modelling and Simulation Concepts

According to Banks (1998), a simulation study is divided into eight steps, as illustrated in Figure 6.

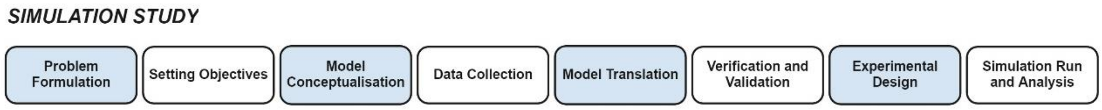

Figure 6 - *Simulation study steps (based on Banks (1998)).*

From Figure 6, the *Model Conceptualisation* and *Verification and Validation* steps are the most relevant ones, according to academia (Robinson, 2006). Consequently, these will be explored below.

Model Conceptualisation

Model conceptualisation is the part of the process that transforms the real system into a model to simulate through a certain level of abstraction and simplification of reality (Robinson, 2006). To be able to do this properly, it is relevant to have a skill that seems more like an “art than a science” once it is mostly learned by experience (Robinson, 2008). Therefore, it is difficult to find methods and procedures that define this step of the simulation study, as well as academic literature about this topic.

Effectively, this is the most crucial part of a simulation study because it will impact several key aspects of the study, like the data collection, the speed at which the model might be generated, the model’s validity, the speed testing, and the trust in the model outputs (Robinson, 2008). Consequently, the chances of a successful simulation study grow significantly if the conceptual modelling phase is effective. Given its prominence, some authors, like Balci (1994), state that the early stages of the simulation study process, where the model conceptualisation is integrated, are not just visited once at the beginning of the process, but instead are continuously repeated and reassessed throughout the process. Nance (1994), in turn, separates the notion of a conceptual model from a communicative model. In his idea, a conceptual model is only the mental reasoning behind the communicative model, which is the explicit computer-based representation of the conceptual model.

During this step, the model should stay simple enough to be easily read and understood, while still serving its intention (Robinson, 2017). It is also important to properly classify the system modelled regarding behaviour and time (Rosseti, 2015). As is shown in Figure 7, the system’s behaviour is stochastic if its output depends on a probability function; otherwise, if everything that happens is determined, it is deterministic. In terms of time, it is a static system if it represents a moment or if it does not change considerably over time; otherwise, it is dynamic. If the state of a dynamic system changes at discrete points in time, it is said to be discrete; otherwise, it is said to be continuous.

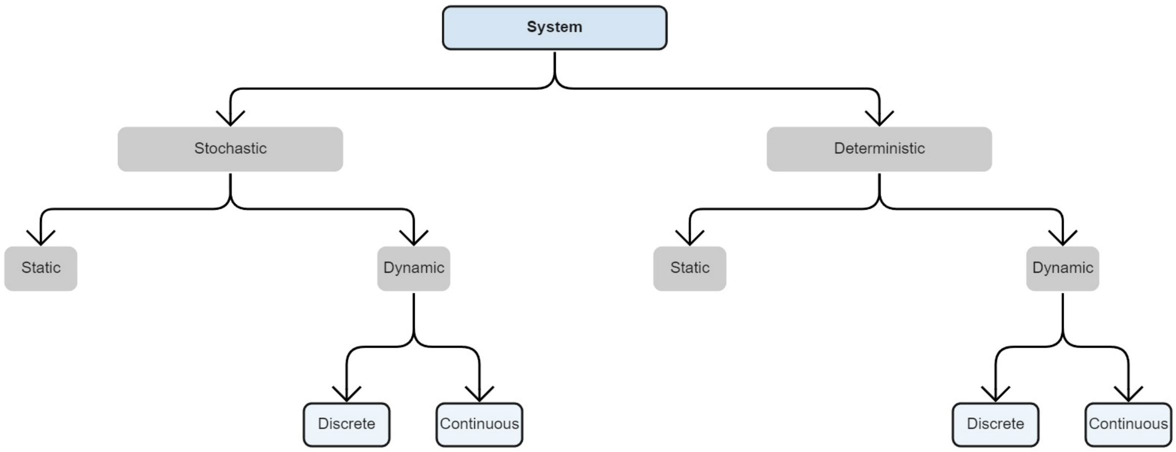

Figure 7 - *System's classification in behaviour and time.*

Verification and Validation

Further on, in the process of the simulation study, illustrated in Figure 6, there is another equally important step for the success of the study, the Verification and Validation. This step checks if the simulation model reproduces the real-world system, determining if the model may be used in the future (Banks, 1998). It should be noted that a model is not universally valid, which means that it must be used exclusively to simulate the situation for which it is created (Balci, 1994).

Essentially, the verification process focuses on the match between the simulation model and the conceptual model of the real-world system developed, while the validation process confirms if the simulation model depicts with accuracy the real-world system at a specified confidence level (Balci, 1994; Borshchev & Grigoryev, 2013; Robinson, 2006). Occasionally, it is impossible to build a logical and coherent validation process because it is difficult to draw a correct picture of the real world. Thus, the validation of simulation models is reduced to the verification of similarities between the evolution of the simulation and the perception that the analyst has about the real-world system (Pidd, 2003). The visual and interactive features of the simulation software establish conditions that help in the process of verification and validation since they promote the model's understanding and reading and create favourable conditions to easily distinguish different verification tests by monitoring the system (Pidd, 2003).

In the academic literature, there are several methods to verify the simulation model during its composition (Balci, 1994; Banks, 1998; Law, 2000; Pidd, 2003). Some authors recommend making a scheme of the simulation model before coding to clearly define the targets of the simulation. To easily identify mistakes, the coding or modelling of the system should be broken down into small parts and reviewed by more than one person with experience in the subject. Furthermore, the logic of the model can be checked by running the simulation model using distinct inputs and verifying if the outputs are plausible and consistent, or by tracing an entity throughout the entire simulation (through its metric values or the movement of its animation). In addition, it is possible to compute the sample mean and variance for every simulation input probability distribution and then compare them to the historical mean and variance to confirm that the generated distribution values are accurate.

Finally, the best test of a simulation model's validation is to directly compare the outputs of the model with the outputs of the real world system. However, at times, the data from the real world may not be accurate or lack validation (Law, 2000). In such instances, the data must be gathered and examined through sensitivity analysis to assess the effect of the inaccuracies (Robinson, 1999).

Simulation model components

The major components of a simulation model are:

- Entity: the basic component of the system. It may be permanent, if it is a resource, or temporary, if it enters and exits the system throughout the simulation (Pidd, 2003).
- Attributes: properties and characteristics that describe the entities. Important to develop the system and compile statistics through simulation (Chung, 2004; Pidd, 2003).
- Queue: it keeps groups of entities that share similar conditions. The entity is in a passive state, waiting in the queue until the materialisation of conditions to begin a new activity. To enter and exit the queue, the entities are always regulated by a predefined rule (Pidd, 2003).
- Activity: it occurs when an entity participates in the system (active state), leading to a change of state in the system (Chung, 2004; Pidd, 2003).
- Event: an occurrence that changes the state of the system. For instance, the beginning and the ending of every activity is an event (Pidd, 2003).

3.5.2 Modelling and Simulation Methods

A simulation study can be carried out using several methods, depending on the objectives set by its developers and on the scope of the project for which it is designed (Robinson, 2014). Different approaches have, for instance, different abstraction levels and are therefore suitable for different types of projects (Borshchev & Grigoryev, 2013). In this research, the three most popular methods of simulation – discrete-event simulation (DES), system dynamics (SD), and agent-based simulation (ABS) – will be succinctly defined and explained in light of existing academic literature.

3.5.2.1 Discrete-event simulation

The DES method was developed in the 1950s, guided by the principles of the Monte Carlo methods, to improve the design and operation of manufacturing plants by identifying long waiting times or queue lengths, bottlenecks in the system, the rate of resource utilisation, etc. (Grigoryev, 2021; Robinson, 2014). This methodology has been applied to a wide spectrum of businesses and social fields over the years, from health care to computer systems.

When using this methodology, the simulation developers consider that the real system can be represented by a succession of discrete events over time, like the beginning or the end of an activity (Robinson, 2014). These simulation models represent their real system from a microscopic perspective, tolerating low abstraction levels and focusing on the meticulous rules that control the system's interactions through time (Grigoryev, 2021; Pidd, 2003). The model is represented as a flowchart where the mobile agents of the system are displayed by entities that progress from the “source” block to a “sink” block through queue and activity blocks (Borshchev & Grigoryev, 2013; Robinson, 2014). The entities’ attributes play an important role in the logic and final output of the model once they may define, for instance, the time spent in an activity, the route of the entity through the system, or the rule of priorities in queues (Robinson, 2014). All the entities’ arrival times, queues and activities’ service times are typically stochastic, following the premise that “the world can be understood as a set of interconnected activities and queues that are subject to random variation”, and therefore DES models are also stochastic (Robinson, 2014).

3.5.2.2 System Dynamics

In 1958, Jay W. Forrester published a paper that introduced the concept of SD to the world (Dangerfield, 2014). Based on the previous work of Arnold Tustin, Forrester developed this methodology to solve industrial supply chain problems. From his understanding, operational research was only directed to operational problems, although it could be valuable to use this field to solve strategic or top-level policy issues in organisations or states (Dangerfield, 2014).

Hence, the focus of SD is on understanding the structure and dynamics of complex systems and how they may affect the system’s behaviour (Sterman, 2002). Although the initial stimulus of the system’s dynamics may be exogenous, this methodology explores their endogenous causes, i.e., the interactions between its elements within closed boundaries and the feedback effects that cause changes in the system over time (Dangerfield, 2014; Forrester, 2009).

The system is presented from a macroscopic perspective, with a high abstraction level that considers aggregations (e.g., of products), called stocks, instead of individual agents (Dangerfield, 2014; Pidd, 2003). Plus, it is assumed to be a continuous flow of balancing and reinforcing feedback loops, creating a circular causality that affects the aggregations composing the system state (Grigoryev, 2021).

3.5.2.3 Agent-based simulation

ABS is the most recent method for modelling and simulation presented in this research. It was created in the 1990s and since then has been applied to many disciplines, like operational research, computer science, social sciences, and economics (Siebers et al., 2010).

Unlike the aforementioned methods, ABS tolerates different abstraction levels, allowing complexed and detailed models where the agents are the physical parts/objects of the system and highly abstracted models where the agents are entities like companies or the government (Grigoryev, 2021). The agents of ABS are the entities of the model (Siebers et al., 2010). They are active entities because each agent has control over its actions, i.e., they have the initiative to decide their path in some situations (Siebers et al., 2010). This option is beneficial to the developers of the model since they can start modelling the objects (as agents) and their behaviours, even if the behaviour and interaction between agents or the dependencies between variables are not completely known *a priori* (Borshchev & Grigoryev, 2013). Later, it is easier to link the agents created to interact and create the system’s properties and behaviours, or simply place them in a system with its dynamics (Grigoryev, 2021).

Thus, this type of simulation model can prove to be very useful in various situations, such as when (Siebers et al., 2010):

- Agents move over a region, and it is important to consider spatial aspects in their behaviours.
- The future cannot be predicted based on the past, so the agents' behaviour is difficult to model.
- Agents have dynamic relationships with other agents, for instance, forming new organisations throughout the simulation.
- Agents or populations have to learn and/or adjust during the simulation.

Chapter 4 – Methodology

This chapter introduces and explains the methodology developed to approach the problem under study. The first section presents an overview of the methodology created. Then, the remaining sections present the modules that compose this methodology.

4.1 Methodology Overview

As already disclosed in section 3.4, the main method selected to support the methodology selected to address the problem at hand is simulation. However, before developing and applying the simulation model, it was necessary to create five modules that influence the simulation output and are independently conceptualised. Meaning that, while the modules influence each other's results (because the results of one module are inputs to another), the reasoning behind each module's design is unaffected by any other module. The proposed methodology, illustrated in Figure 8, was aligned with and validated by the Business Intelligence (BI) team of the company.

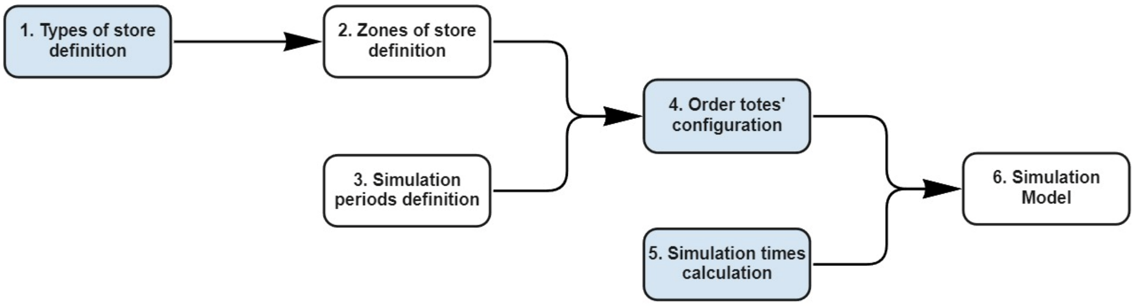

Figure 8 - *Proposed Methodology Overview.*

The first module of this methodology aims to categorise all the Worten stores in Portugal into three categories, already defined in section 2.6.2, and then, in the second module, divide them into zones according to the type of products on display and the dimensions of the store. The development of this module involved visits to the stores under study to observe and understand their configuration and operation, as well as the analysis of logistics data about each SKU and a description of all Worten stores in Portugal, both provided by Worten's BI team.

Then, the third module is set to define the periods of the year to simulate in the study. The focus is to simulate different periods of the year that represent different challenges for the company's logistics system, especially in the picking and store replenishment activities which are the core of this study's scope. To do so, the most relevant periods of the year were discussed with the BI team of the company and validated by the shipment records of the last full business year of the company between Worten's warehouse and its stores (again provided by the BI team).

The fourth module was created to determine the content of each order tote after the picking operation. To do so, it considers two system characteristics which influence this module's output: the arrival order of the inventory totes at the G2P station and the store's configuration. Inputs from the previously described modules are used to obtain results:

- a list of the type of store for all Worten stores in Portugal (from the first module).
- a list of all the SKUs associated with a store zone (from the second module).

- and historical data of the items shipped to each store in each of the periods under analysis (from the third module).

The data processing, data treatment and development of the algorithm used in this module were implemented using *Python* programming language, through the open-source web application *Jupyter Notebook* from the *Anaconda Navigator* graphical interface. In fact, the choice of the programming language and software used was based on the knowledge, preference, and past experience of the dissertation's author, but this could have been done using other programming languages (e.g., *MATLAB* or *Java*) and other software.

After running the algorithm developed, the main outputs of this module are the quantity of order totes shipped from the warehouse to each store and a detailed description of each order tote to be produced in the period considered. The description includes the tote's shipment date, its destination store, the number of items inside the tote (broken down by zone of store), the number of SKUs inside the tote (broken down by zone of store), and the tote's occupied volume.

Furthermore, the fifth module proposes a methodology to calculate the operational times so that the simulation model represents the relevant operations to the case in hand – the picking time, in the warehouse, and the shelf replenishment time, in the stores. To determine these times effectively, they were decomposed into several components, which were then calculated using different methods, depending on the ease to determine or obtain valid values at each moment of the operation. After obtaining the values of each time component, these are inputted into the simulation model.

Lastly, the sixth module of this methodology is an ABS model which represents the system under study. As stated in sub-section 3.4, simulation models are frequently used in company-related studies, like this one, where the problems have high complexity levels. They are also an excellent tool to perform scenario analysis on. This model reproduces the picking operation, in the warehouse, and the shelf replenishment, in the stores. It was developed according to the steps presented in Figure 6 in collaboration with the Worten BI team using the simulation software *AnyLogic*, which is already used in the company. Moreover, it can be run for any time length, only restricted by the maximum number of agents allowed by the software and the data available. After running the simulation, the outputs generated are the occupancy rate of the warehouse and stores resources over time, and the records of the timestamps of the start and end of the relevant activities taking place in the simulation. The results obtained from this methodology will be assessed in chapter 5.

4.2 Types of store definition

The population of Worten stores in Portugal is diverse and complex since they have different demand characteristics, dimensions, workforce, selling records, etc. There are, however, similarities between stores that allow grouping them into distinct categories.

Internally, apart from the division between Worten and Worten Mobile stores (the latter are not included in this study due to their small dimension), the company divides the common Worten stores into two groups – Mega and Super. According to the records provided by the company, there are 53 Mega stores and 107 Super stores. One of the 53 Mega stores stands out from the rest because it has a larger area and a sales volume highly above any other store, being considered Worten's flagship store. Therefore, the total population of stores in the scope of the study is composed of 160 stores, divided into three types: the flagship store (type A), the remaining 52 Mega stores (type B), and the 107 Super stores (type C). To simplify the inherent complexity of this population of stores, it was assumed that all the stores belonging to the same type are exactly the same in terms of demand characteristics, workforce, layout and display of products. The characteristics of each type are already detailed in sub-section 2.6.2. To perform this study, three real stores of the company were assumed as models, one for each type of store considered, thus, the remaining stores of each type are considered to be absolutely equal to their type's model store. The methodology of defining model stores was recommended by the company's BI team as it is a method often, used by them, that recurrently exhibits good results.

4.3 Zones of store definition

Currently, when a store receives a shipment from the warehouse, the backroom operators responsible for the Quality Control task sort the products according to their location in the store, to simplify the task of shelf replenishment that is performed in the showroom (see sub-section 2.6.1). This sorting operation is necessary because during the picking and shipping operations in the warehouse the operators are not considering the affinity of the products in the store but merely compacting all the items as much as possible to reduce the space used in the distribution operation to the stores.

If instead, there is a division of stores into zones, where each SKU is exclusively associated with one zone, and that division is followed during picking and packing in the warehouse, the sorting task can be minimised or even abolished from the store provisioning and shelf replenishment process. Therefore, the order totes are composed only by products of the same zone in the store. The idea is to create a method of shelf replenishment analogous to the zone picking policy in the warehouse (see sub-section 3.2.1). As the picker is assigned to only one warehouse zone during a zone picking activity, so the operator in charge of shelf replenishment is assigned to only one zone in the store during the shelf replenishment of all the units in a specific order tote.

Hence, this module follows two main steps:

(1) determine a logical division of each model store.

(2) assign each SKU to a zone in the store.

The determination of a logical division of each model store was reached through the observation of the articles displayed in the store and from the understanding of the replenishment operation, which was greatly helped by informal interviews with the store managers and backroom operators from the model stores.

Effectively, the number and dimensions of the zones in the store arise from an already existing store division for picking products of online waves in the type A store. If the store has available stock, online orders might be prepared in store. Thus, the backroom team, applying a zone picking policy to simplify and speed up the picking task, divides the showroom store into six zones:

- Small home appliances
- Big home appliances[4]
- Hi-Fi
- IT
- Entertainment & Gaming
- Promotions, Mobile & Printing

Although the Small home appliances zone has not the largest area, the operators usually split it into two during the sorting process, because the generalised greater volume of its items, compared to the volume of products in the remaining zones, makes it difficult to move around with the products. Further, the Promotions, Mobile & Printing zone has a panel in the wall where the responsibility of replenishment falls on the showroom team, and not on the backroom team. As a result, they chose to split the articles replenished by one team from the articles replenished by another during the sorting operation.

Overall, the type A store is divided into eight zones, one of which will not be considered, as it has no products coming from the 708 area of the warehouse, and therefore it falls outside the scope of the study. The zones considered in this study are described in Table 2. The remaining model stores are also divided in the same number of zones with identical descriptions and related product ranges. Once the area of these stores is smaller than the area of the type A store, the direct extrapolation of the zones of store implies that the zones of type B and C stores will have smaller areas than type A (see Table 30 in Appendix).

Table 2 - *Zones of store description and examples.*

Zone	Description	Examples
1 - Small home appliances 1	Small home appliances for the kitchen, housekeeping, and hygiene.	Microwaves, wands, toasters, grills, coffee machines, mixers, lamps, hair straighteners, electric toothbrushes, and shaving machines.
2 - Small home appliances 2	Small home appliances for cleaning and garden.	Vacuum cleaners, irons, ironing boards, fans, lawnmowers, chainsaws, and leaf blowers.
3 - Hi-Fi	Audio-visual equipment and devices.	TV sets, TV wires (e.g., HDMI or Scart), remote controls, radio sets, stereo speakers, and headphones.
4 - IT	Computers, other electronic equipment to store and send information, and related accessories.	Computers, laptops, keyboards, mouses, screens, memory cards, pens drive, and hard drives.
5 - Entertainment & Gaming	Electronic gaming equipment and other devices for entertainment and recreation.	Consoles, controls, console games, gaming chairs, gaming headphones, gaming mouses, CDs, DVDs, board games, and books.
6 - Promotions, Mobile & Printing	Promotional or seasonal products, high-end cell phones (and related accessories), and printing equipment.	Gift cards, smartphones, power banks, smartwatches, printers, printer cartridges, cameras, drones, and binoculars.
7 - Mobile Panel	Cell phones and small related accessories.	Cell phones, cell phone covers, earphones, and chargers.

The second step of this module is to associate each SKU with each zone of the store. To execute this step, it was used the Market Structure of Worten provided by the company. The Market Structure is an internal document of the company, where the logistics information of all the company's SKUs is broken

[4] This zone is out of the scope of this dissertation because it only receives big appliances from section 701 of the Worten's warehouse.

down (e.g., category, subcategory, base unit, description, volume, dimensions, Ti, Hi, etc.). This document was loaded, and its data was treated in *Power BI*, a data-analytics software recommended and widely used by the company. The association of each SKU to their zone of store was conducted at the category level. The category of an SKU reports the general type of the product, e.g., all the simple microwaves have the same category number, thus, it is accurate to consider that all the products of the same category belong to the same zone of store.

Afterwards, to evaluate which store's configuration is best for each of the store types, different scenarios with different numbers of zones of store will be generated by assembling the zones originally defined in this section, as presented in Table 3. The assembly of zones of store was always done through contiguous zones and making sure that, for each store configuration, the store is divided into zones with areas as similar as possible.

Table 3 - *Zones of store, depending on the store type and on the number of zones of store in the scenario.*

Number of zones	Store Type A	Store Type B	Store Type C
2	1 – Small home appliances 1 & 2 + Hi-Fi 2 – IT + Entertainment & Gaming + Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 + IT + Promotions, Mobile & Printing + Mobile Panel 2 – Hi-Fi + Entertainment & Gaming	1 – Small home appliances 1 & 2 2 – Hi-Fi + IT + Entertainment & Gaming + Promotions, Mobile & Printing + Mobile Panel
3	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT + Entertainment & Gaming + Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi + Entertainment & Gaming 3 – IT + Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi + IT + Entertainment & Gaming 3 – Promotions, Mobile & Printing + Mobile Panel
4	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT 4 – Entertainment & Gaming + Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi + Entertainment & Gaming 3 – IT 4 – Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT + Entertainment & Gaming 4 – Promotions, Mobile & Printing + Mobile Panel
5	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT 4 – Entertainment & Gaming 5 – Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT 4 – Entertainment & Gaming 5 – Promotions, Mobile & Printing + Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT + Entertainment & Gaming 4 – Promotions, Mobile & Printing 5 – Mobile Panel
6	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT 4 – Entertainment & Gaming 5 – Promotions, Mobile & Printing 6 – Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT 4 – Entertainment & Gaming 5 – Promotions, Mobile & Printing 6 – Mobile Panel	1 – Small home appliances 1 & 2 2 – Hi-Fi 3 – IT 4 – Entertainment & Gaming 5 – Promotions, Mobile & Printing 6 – Mobile Panel
7	1 – Small home appliances 1 2 – Small home appliances 2 3 – Hi-Fi 4 – IT 5 – Entertainment & Gaming 6 – Promotions, Mobile & Printing 7 – Mobile Panel	1 – Small home appliances 1 2 – Small home appliances 2 3 – Hi-Fi 4 – IT 5 – Entertainment & Gaming 6 – Promotions, Mobile & Printing 7 – Mobile Panel	1 – Small home appliances 1 2 – Small home appliances 2 3 – Hi-Fi 4 – IT 5 – Entertainment & Gaming 6 – Promotions, Mobile & Printing 7 – Mobile Panel

4.4 Simulation periods definition

Depending on the periods chosen, the system will be tested in different ways, since the demand of each store and, consequently, the dimension of the shipments to each store fluctuate throughout the year. As such, the approach to this module can be divided into three main steps:

(1) Determine the time length of the simulation periods.
(2) Divide the year into periods with similar shipping characteristics to the stores.
(3) Determine how many and which periods of the year to simulate.

The time length of the simulation run could be a full year. Although feasible, this approach would significantly increase the cost of this study since it would be necessary to pay for a premium version of the simulation software. Thus, instead of running a whole year of simulation, it was determined to run it over several shorter periods of the year, representing the different situations that the system goes through during the course of the year (especially the extreme ones). Since the shipments from the warehouse in Azambuja to the stores are planned on a weekly basis, it is logical to assume that the time length of each simulation period is one week. This way, it will be possible to evaluate the behaviour of the system throughout a complete week of simulation with days with different shipped quantities to the stores. This simulation was carried out with the latest free *AnyLogic* version (*AnyLogic 8.8.0 Personal Learning Edition*), which restricts the maximum use of dynamically created agents in a model to 50000 (Borshchev & Grigoryev, 2013).

Moreover, the aim is to have a broad study which allows a complete analysis of the different challenges that the system in question faces throughout the year. In order to select the appropriate weeks to simulate, the expedition records from the last full calendar year at the time of this work, i.e., 2021, were used. Looking at the progress of the number of items shipped over the year for each of the model stores defined (see Figure 9), it is possible to break down the year into four different periods. The expedition records of the company are confidential information, as such, they are presented in Figure 9 relative to the annual maximum values (store type A in week 48).

- **Low season:** from the start of the year until May (weeks 2 to 18). This period, which encompasses the Winter and a large part of Spring, is characterised by weeks of stable, even though, low quantities shipped to all the stores. During this period in 2021, the three stores under study reached their lowest peak of shipped items.
- **Summer holidays:** from the second week of May until the end of August (weeks 19 to 35). This period is marked by the beginning of the bathing season in Portugal (May 7th, week 19) and the start of the school Summer holidays (between weeks 24 and 25). As in the low season, the quantity of items shipped to the stores remains stable week after week. Nonetheless, during this period, there is a clear increase in the average weekly quantity shipped.
- **Back to school:** from the first week of September until the second week of October (weeks 36 to 41). The start of the new academic year in most universities and schools in Portugal causes a considerable increase in the number of items shipped to each store during the months of

September and October compared with previous periods, which is directly related to the demand increase for the stores during the same period.

- **Black Friday and Christmas:** from the second week of November until the end of the year (weeks 42 to 53). This is the period in which Worten has the greatest demand values, something that is also reflected in the number of weekly quantities shipped to the stores. Clearly, this is the period when the responsiveness and flow of picking, provisioning and shelf replenishment operations of the company are tested the most. It is characterised by weeks of large quantities shipped to the stores (similar or higher to the quantities shipped since September) together with the highest shipping peaks of all the stores in the weeks near Black Friday (weeks 48 and 49) and in the case of the type A store a second peak in the Christmas week (week 52).

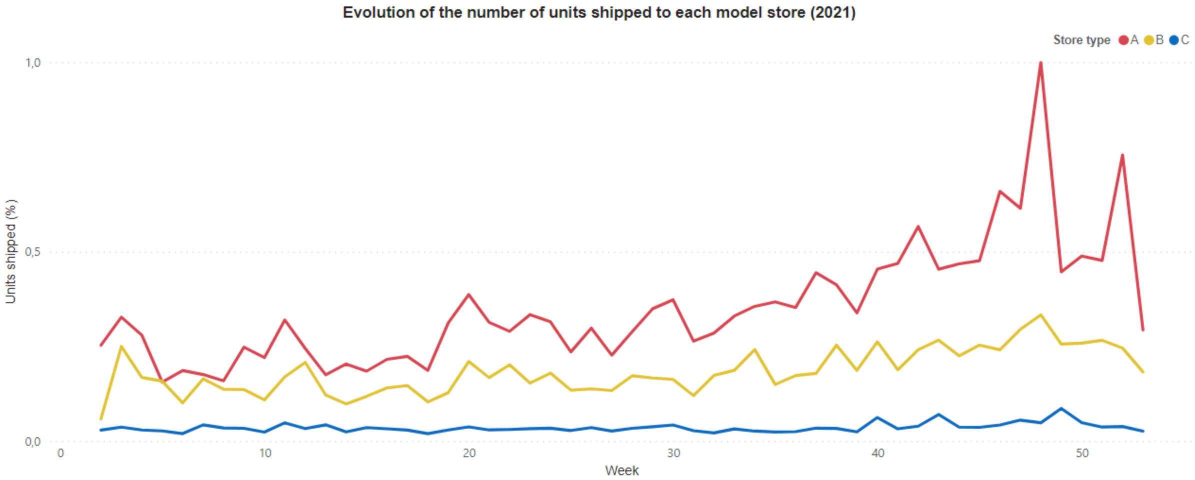

Figure 9 - *Line chart showing the weekly evolution of the number of units shipped to each model store throughout 2021.*

Based on the aforementioned information, the third step of this module intends to precise which periods of the year to simulate. In agreement with Worten BI team, it was stipulated to simulate one week per each period of the year defined above. The simulated weeks should represent important milestones of a calendar year, which help to explain the behaviour of the shipping process during that period. The description of the weeks, as well as the justification for their choice, is explained in Table 4.

Table 4 - *List and reasoning of the weeks to simulate.*

Period	Week	Days	Reason
Low season	Week 7	07/02/2021 to 13/02/2021	Following the previous year's Black Friday and Christmas period, which leads to abnormal numbers of stock-outs and surplus, the company goes through a regularisation process of store inventories that usually lasts the whole of January[5]. For this reason, to guarantee the simulation of a week representing stability after the regularisation period, it was decided to simulate the first week of the year that has no January days, week 7.
Summer holidays	Week 25	13/06/2021 to 19/06/2021	In 2021, the Summer holidays of the Portuguese public school started on June 18 (week 25), which is the reason why it was decided to simulate this week.
Back to school	Week 37	05/09/2021 to 11/09/2021	The academic year of 2021/2022 for the Portuguese public school started during week 38. Assuming that most people do their back-to-school shopping before the first week of school, the decision was to simulate week 37.
Black Friday and Christmas	Week 48	21/11/2021 to 27/11/2021	Week 38, as well as being the week in which Black Friday took place (November 26), was also the week in which the model store for types A and B had their shipping peaks. Therefore, this week was chosen to evaluate the system in the most challenging situation.

[5] Information shared by the Worten BI team.

4.5 Order totes' configuration

During the order picking operation in a G2P system, the items move from the storage in the direction of the picker through an automated distribution system (explained in sub-section 3.2.1). Then, when the inventory tote[6] arrives at the picking station, the picker is responsible for selecting the number of items ordered by the stores and placing them in the correct order totes[7]. Depending on the arrival order of the inventory totes to the G2P station and on the restrictions imposed on the order totes' composition, the efficiency of the picking operation may change considerably.

This module intends to define the order totes' configuration based on the rules specified in each scenario for the order arrival of the inventory totes and stores configuration. Creating this module simplifies the simulation model by increasing the abstraction of the model at the picking operation. So, instead of developing this part of the system in *AnyLogic*, it was developed a *Python* algorithm. Given the list of the type of store for all Worten stores in Portugal (defined in the first module, see section 4.2), the list of all the SKUs associated with a store zone (defined in the second step of the second module, see section 4.3), and the list of the articles shipped to each store in each of the weeks under analysis (selected from the shipment records provided by the company and based on the conclusions from the third module, see section 4.4), it generates the order totes for the intended scenario. When creating the algorithm for this module, some simplifications and assumptions were made regarding the real system.

Simplifications:

- The assessment to check if an item fits into the order tote is accomplished by comparing the available volume of the order tote and the volume of the item. The weight and dimensions (depth, width, and height) of the items are not considered in the algorithm.
- The configuration of the system which coordinates the inventory totes' arrival at the picking station is a black box. For the case under study, it is relevant to know the conceptual order in which the inventory totes reach the station, once it impacts the composition of the order totes. Nevertheless, determining how the system is configurated is not within the scope of this study and would greatly increase the complexity of the problem at hand.

Assumptions:

- The order totes considered are 60 centimetres deep, 40 centimetres wide and 40 centimetres high (resulting in 96000 cubic centimetres). The use of these dimensions is justified because these are the true dimensions of the reusable boxes the company is implementing as order totes for the shipping operation between its warehouse and stores.
- An order tote can only be filled to 79.20%[8] of its volume (maximum order tote occupancy rate), to consider the wasted space generated by incompatible package formats.
- One order tote contains only items to be shipped on the same day and for the same store.

---

[6] An inventory tote is a box in which the warehouse inventory is stored while it is not ordered by any store.
[7] An order tote is a box that circulates between the warehouse and the company stores with the articles ordered by the stores.
[8] Conservative value considering a heterogeneous type of cargo (source: Bortfeldt & Gehring, 2000).

- One order tote contains only SKUs assigned to same zone of store.
- The passage of items from the inventory tote to the order tote follows the order in which the inventory totes arrive at the picking station.

Before running the algorithm to determine the order totes' configuration, the data received as input is treated. The data treatment follows two steps:

- Since the study focuses on the small-sized items, enclosed in the 708 area of the warehouse which fit into an order tote, drop out, from the shipment list, all the rows whose SKU:
  - does not come from the 708 area of the warehouse,
  - has a volume greater than the order tote volume.
- Associate each row of the final shipment list to a zone of store based on the type of store receiving the shipment and on the number of zones that each store has in the scenario in question, according to Table 3.

Then, as already mentioned, the arrival order of the inventory totes was considered. Three possible set-ups have been identified:

(1) Random arrival order.
(2) Arrival order priority to SKUs with higher volume.
(3) Arrival order priority to SKUs with lower volume.

Each one of these scenarios leads to a different order tote configuration for the same shipment list. In the first scenario, the inventory totes arrive from the automated warehouse in random order. In the set-ups that follow, the arrival order priority to SKUs with higher (or lower) volume means that, when the shipment orders for the day are launched in the WMS, the system that commands the selection of the inventory totes from the automated warehouse is configured to receive inventory totes sequentially so that the SKUs with higher (or lower) volume are placed first in the order tote. In this case, abstracting the algorithm from the manner to configure the real system, the effect was developed in *Python* by sorting the rows of the shipment list either randomly, in descending or ascending order of unit volume, depending on the desired set-up.

After the arrival order set-up, the algorithm goes through the shipment list, from top to bottom, to associate every item in the list with an order tote. The algorithm follows the rationale described below (also represented in the flowchart of Figure 10):

(1) The first item in the shipment list not assigned to any tote is associated with an order tote, and the volume available in that order tote is updated.
(2) Then, if there is any item to be shipped on the same day, to the same zone and store, which fits in the order tote, that item is also associated with that order tote, and its available volume is updated.
(3) Otherwise, it creates new order totes and repeats step 2, until all the items to be shipped on that day, to that zone and store are assigned to an order tote.

(4) When all the items to be shipped on that day, to that zone and store are assigned, the algorithm creates a new order tote and repeats steps 1, 2 and 3 to the items to be shipped on the same day, to the same store, but to a different zone.
(5) When all the items to be shipped on that day and to that store are assigned, the algorithm creates a new order tote and repeats steps 1, 2, 3 and 4 to the items to be shipped on the same day, but to a different store.
(6) When all the items to be shipped on that day are assigned, the algorithm creates a new order tote and repeats steps 1, 2, 3, 4 and 5 for the items to be shipped on a different day.
(7) The algorithm ends when all the items in the list are assigned.

To conclude, this module provides outputs that serve two different purposes:

- A list with the order tote's shipment date, its destination store, and the number of items and SKUs assigned to it, broken down by zone of store. This list is used as input to the simulation model.
- The number of order totes to be shipped to each store and the total volume occupied per order tote. These outputs are used to create metrics that assess each of the scenarios presented.

4.6 Simulation times calculation

The determination of the simulation model times is vital to have a model which represents the real system with the levels of detail and abstraction wanted by the model developers. Generally, the time of the relevant activities in the system under study is calculated with accuracy and detail. Additionally, the activities taking place in the real system which do not interfere with the study results, are disregarded, or ignored, and their times are simplified or ignored too.

In this case, the focus is on the performance of picking and shelf replenishment operations. Thus, the time duration of these activities is strictly calculated. Each of them is divided into three components that help to accurately determine a valid time for each of the operations. All time parameters of each component follow a triangular distribution. The time representation through this type of distribution allows a suitable approximation to the real variation of each component time, knowing only the minimum, maximum and mode time of each component. The methodology to determine the picking and shelf replenishment times is described in the following sub-sections 4.6.1 and 4.6.2.

The time of the outbound operation is reduced since the activity is simplified due to its irrelevance to the problem. Furthermore, the times of the remaining operations of the real system – inbound, storage, distribution, and quality control – are not considered in the model since their consideration does not influence the study in question but would only increase the complexity of this module (as described in the following section 4.7). Hence, the end-to-end time of the model has no logical value.

4.6.1 Picking time

Picking time is the duration of an order picking operation for one order tote, or, in other words, the time it takes to pick all the units that make up an order tote to be shipped to store. In this study, it is assumed that this time is calculated as the sum of three elements that characterise different moments of the picking operation:

$$Picking\ time = switchSKUtime + setToteTime + pickItemTime \quad (1)$$

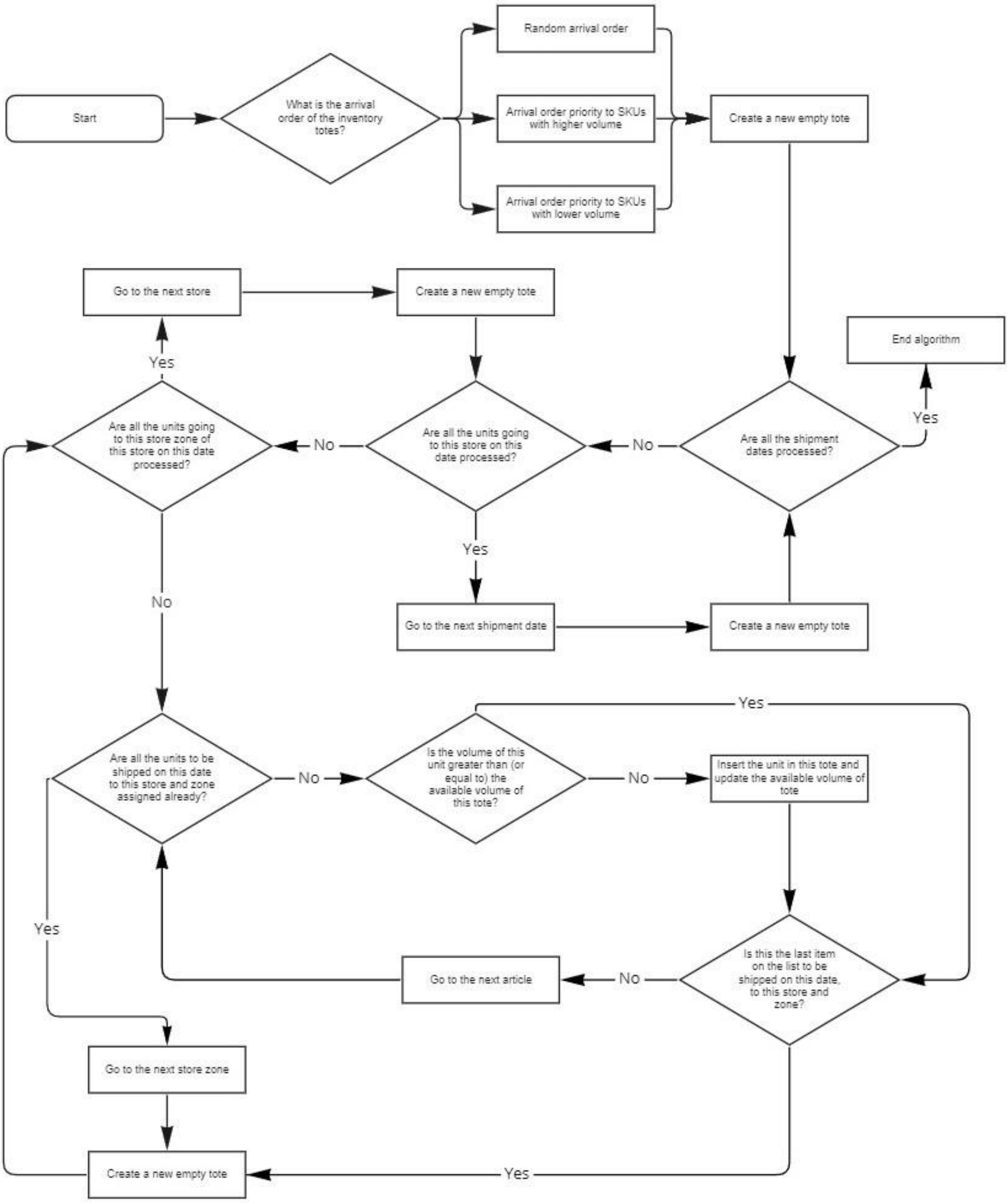

Figure 10 - *Flowchart of the Order Totes' Configuration algorithm.*

SwitchSKUtime

The first component of the picking time, the switchSKUtime, is linked to the moment of changing inventory totes in the picking station, from the moment the last inventory tote leaves the station until the moment the new inventory tote is set in the station and ready for the operator to start picking. To calculate this component some simplifications and assumptions were made.

Simplifications:

- The demand of a period is fulfilled by a single inventory tote per SKU. In the real system, depending on the volume of the inventory totes and on the unit volume of each SKU, a single inventory tote per SKU may not be enough to meet the demand.

Assumptions:

- The inventory totes are queued in the order defined by the system configuration and ready to enter the station.
- The inventory totes store units of one and only one SKU (Worten's storage policy).

Since the automated warehouse and the G2P station are not installed in the Worten warehouse yet, it is impossible to conduct empirical experiments to determine this time component. Hence, it was determined using values provided by suppliers[9] of G2P stations, similar to the station that Worten intends to install in its warehouse. The values provided by two G2P suppliers refer to three different stations. It follows the triangular distribution described in Table 5. Because there were no repeated values in the times provided by the suppliers, the mean value of the values provided was assumed as the mode of this triangular distribution.

Table 5 - *Description of the triangular distribution defining the switchSKUtime component (in minutes).*

Minimum value (a)	Maximum value (b)	Mode (c)
0.02017 min	0.05517 min	0.03567 min

The total value of the switchSKUtime component during the picking operation for a single order tote (equation 2) equals the summation of values taken from the triangular distribution described in Table 5:

$$switchSKUtime\ (x) = \sum_{1}^{qtySKUs} \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}\ for\ a \le x < c \\ \frac{2}{b-a}\ for\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}\ for\ c < x \le b \\ 0\ for\ any\ other\ case \end{cases} \qquad (2)$$

SetToteTime

The setToteTime component represents the time required to replace full order totes with new empty ones, during the time of a picking operation. As explained in Figure 10, this action may occur whenever the products picked are going to a different zone of store, or when no more items fit into the order tote being filled. The assumptions made to determine this component are described below.

[9] Sources: Dematic (official website: https://www.dematic.com/pt-pt/) and Vanderlande (official website: https://www.vanderlande.com/)

Assumptions:

- The picker only needs to remove the full order tote from the picking station and pick an empty one. All the shipping and outbound activities are taken over by another warehouse operator.
- There are always empty order totes available to replace those that get full.

For the same reasons as the switchSKUtime component, this component cannot be determined through empirical experiments. Consequently, it was determined again using values from the same G2P stations' suppliers. It follows the triangular distribution characterised in Table 6 and equation 3. Again, not having any repeated values in the times provided by the suppliers, the mean value from the sample used was assumed as the mode of this triangular distribution.

Table 6 - *Description of the triangular distribution defining the setToteTime component (in minutes).*

Minimum value (a)	Maximum value (b)	Mode (c)
0.13333 min	0.16667 min	0.15000 min

$$setToteTime\ (x) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}\ for\ a \leq x < c \\ \frac{2}{b-a}\ for\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}\ for\ c < x \leq b \\ 0\ for\ any\ other\ case \end{cases} \qquad (3)$$

PickItemTime

Finally, the pickItemTime component stands for the time it takes for the operator to move the items from the inventory tote to the order tote during the picking operation. The simplifications and assumptions made to determine this component are stated below.

Simplifications:

- The items are picked from the inventory tote and placed into the order tote, one by one. In the real system, smaller items from the same SKU are often picked up at once. Although, in the worst-case scenario, they may be picked singly. That is the scenario chosen in this study.

Assumptions:

- All the items picked up by the operator will be shipped to the stores.

As noted above, the G2P station is not yet installed in Worten's warehouse, thus, it is impossible to have a sample of empirical experiments from a real G2P station. However, in this case, given the nature of this component, which depends only on human action (and not on the settings of electronic or automated systems), it is possible to determine the distribution that it follows, replicating the conditions of the system and reproducing a sample of appropriated size to faithfully describe it. According to Israel (1992), the determination of the appropriate sample size is based on four factors: the size of the population, the level of precision, the confidence level, and the degree of variability.

Knowing that the population of this pick product task is virtually infinite (since it is an action that repeats whenever the picker collects a product from an inventory tote and places it into an order tote), the sample size was defined based on the population of one year of pick product activities. In fact, in the week in which the combined number of units shipped to the model stores (A, B and C) was the lowest of 2021 (week 6), 10281 units were shipped. Extrapolating this figure to a whole year (with 52 weeks), considering the same number of units shipped every week of the year, the annual number of units shipped would have been 534612. Thus, the population size is certainly greater than this number.

The level of precision is the range in which the true population value is expected to be (Israel, 1992). In this case, it is considered that a level of precision of 0.1 is enough, meaning that the true population size is 534612 +- 10%, i.e., between 481151 and 588073.

Then, the confidence level determines the true population value within the range of precision specified (Israel, 1992). Having a confidence level of 0.95 means that 95% of the samples will have their population value within the range of precision previously established.

Finally, the degree of variability refers to the distribution of the population's attributes (Israel, 1992). Logically, the more heterogenous the population (higher degree of variability), the larger the sample size required to obtain the desired level of precision. In this study, to have a conservative sample size, the degree of variability defined is 50%. This value indicates the maximum variability in the population, leading to a sample size probably larger than the true sample size required if the degree of variability was lower.

According to Israel (1992), for a population size greater than 100000, a level of precision of 10%, a confidence level of 95%, and a degree of variability of 50% the minimum valid sample size is 100 (Table 7). Effectively, to increase the sample coverage, knowing that this activity will be performed by several operators, and assuming that each operator performs the task at slightly different speeds, it was decided to perform the experiment with three different operators, aged between 18 and 24 years old. Each operator realized the activity 100 times with 25 different SKUs. Thus, the sample size becomes 300, making the sample precision level higher than 7%, as shown in Table 7 (Israel, 1992).

Table 7 - *Summary of factors determining the sample size for the pickItemTime (adapted from Israel (1992)).*

Population size	Level of precision	Confidence level	Degree of variability	Sample Size
<100000	0.05	0.95	0.5	**400**
>100000	0.07	0.95	0.5	**204**
>100000	0.1	0.95	0.5	**100**

The triangular distribution that defines the pickItemTime component is described in Table 8.

Table 8 - *Description of the triangular distribution defining the pickItemTime component (in minutes).*

Minimum value (a)	Maximum value (b)	Mode (c)
0.01183 min	0.11300 min	0.03567 min

The total value of the pickItemTime component during the picking operation for a single order tote (equation 4) equals the summation of values taken from the triangular distribution described in Table 8:

$$pickItemTime\ (x) = \sum_{1}^{qtyUnits} \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}\ for\ a \leq x < c \\ \frac{2}{b-a}\ for\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}\ for\ c < x \leq b \\ 0\ for\ any\ other\ case \end{cases} \quad (4)$$

4.6.2 Shelf Replenishment time

The shelf replenishment time is the time it takes to stock the showroom shelves with all the items inside an order tote receive in the store. As in the picking time, the shelf replenishment time is calculated by the sum of three components, which refer to three different moments of the shelf replenishment operation:

$$Shelf\ Replenishment\ time = interZoneTime + intraZoneTime + putTime \quad (5)$$

InterZoneTime

The interZoneTime component describes the time an operator spends travelling between zones of store during the shelf replenishment operation. To calculate this time component several simplifications and assumptions were made.

Simplifications:

- The distance between two zones is the distance between the centroid points of each zone.
- The minimum travelling distance in a store is zero, whereas the order tote to replenish next is intended for the same zone as the last one replenished.
- The mode travelling distance considered in a store is the average value of travelling between any two zones in that store.
- The maximum travelling distance considered in a store is the maximum travelling distance between any two zones in that store.
- Due to the simplifications above, this component does not depend on the zones between which the operator travels, but exclusively on the type of store he/she is working.
- All order totes (with the items inside) are taken from the backroom to the showroom at once. Thereupon, trips between the backroom and the showroom to bring more items for shelf replenishment are not considered.

Assumptions:

- The walking speed of the operator is 1.434 m/s, which is the mean speed for men between 40 and 49 years old (Bohannon & Andrews, 2011). By extrapolation, this is the walking speed considered in the study for any operator, regardless of age or gender.
- The shelf replenishment of the order totes is random. In the real system, the operators may organise the activity to replenish all the order totes from the same zone in a row.

The determination of the values of this component took place in five steps:

(1) Determination of coordinates of all the vertices of all the seven zones of each model store, using the blueprint of each model store.

(2) Determination of the centroid coordinates for each of the seven zones of each store type, from the coordinates of all the vertices of all the zones of each model store (see Table 30 in Appendix).
(3) Calculation of the distances between the centroids of all zones, for each model store.
(4) Calculation of the minimum, average, and maximum distance travelled between zone centroids, for each model store.
(5) Determination of the values that define the interZoneTime triangular distribution for each store type, by multiplying the minimum, average, and maximum distance travelled between zone centroids for each model store and the assumed walking speed.

The values of this component, for each type of store, are shown in Table 9 and equation 6.

Table 9 - *Description of the triangular distribution defining the interZoneTime component, for each type of store with seven zones of store (in minutes).*

Type of Store	Minimum value (a)	Maximum value (b)	Mode (c)
A	0 min	1.14340 min	0.69148 min
B	0 min	1.11206 min	0.61123 min
C	0 min	0.52681 min	0.28014 min

$$interZoneTime\ (x) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}\ for\ a \leq x < c \\ \frac{2}{b-a}\ for\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}\ for\ c < x \leq b \\ 0\ for\ any\ other\ case \end{cases} \qquad (6)$$

IntraZoneTime

The second component of the shelf replenishment time, the intraZoneTime, represents the time spent travelling within each zone of store. The simplifications and assumptions made to quantify this time component are presented below.

Simplifications:

- The minimum travelling distance is one metre, considering that the operator places on the shelf units from two SKUs which are side by side, consecutively.
- The mode travelling distance inside a zone is the distance between the centroid and its furthest point belonging to that zone.
- The maximum travelling distance inside a zone is the distance between the two furthest apart points in that zone.

Assumptions:

- As in the interZoneTime component, the walking speed of the operator is 1.434 m/s, which is the mean speed for men between 40 and 49 years old (Bohannon & Andrews, 2011).
- All the SKUs taken from the backroom to the showroom are placed on the shelf.

With the centroids of each zone already defined to determine the interZoneTime component, the determination of the intraZoneTime component took place in four steps:

(1) Determination of the coordinates of the furthest point from the centroid belonging to each of the seven stores of each model store, using the blueprint of each model store.
(2) Determination of the two furthest apart points in each zone of each model store.
(3) Calculation of the distances between the centroids and their furthest point belonging to the same zone, for each model store.
(4) Determination of the values that define the intraZoneTime triangular distribution for each zone of store and type of store, by multiplying the minimum, mode, and maximum distance travelled inside each zone of each model store and the assumed walking speed.

The parameter of this component for each zone of each type of store may be compared in Figure 11 (their values are presented in Table 31 in the Appendix).

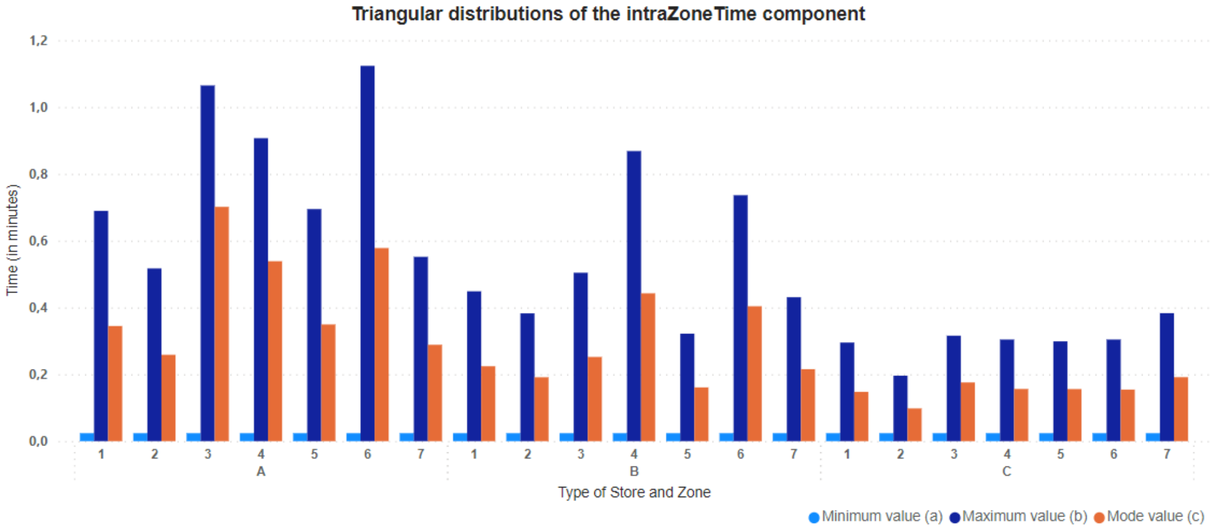

***Figure 11** - Parameters of the triangular distribution of the intraZoneTime component, for each zone of store and type of store (in minutes).*

The total value of the intraZoneTime component during the shelf replenishment operation for an order tote (equation 7) equals the summation of values taken from the triangular distribution for each zone of each store described in Table 31:

$$intraZoneTime\ (x) = \sum_{1}^{qtySKUs} \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}\ for\ a \leq x < c \\ \frac{2}{b-a}\ for\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}\ for\ c < x \leq b \\ 0\ for\ any\ other\ case \end{cases} \tag{7}$$

PutTime

The last component of the shelf replenishment time, the putTime, stands for the time that the operator takes to place the items on the shelf when he/she is right in front of the shelf for that SKU. The simplifications and assumptions made to determine this component are presented below.

Simplifications:

- The items are placed one by one on the shelf. In the real system, several items of the same SKU may be replenished at once, if they are small or when the shelf is empty. However, the worst-case scenario in this situation is to replenish one item at a time. Conservatively, this was the scenario chosen.

Assumptions:

- All the items taken from the backroom to the showroom are placed on the shelf.

The methodology to determine the values of this component is the same used to determine the pickItemTime component of the picking time (see sub-section 4.6.1). This component follows the triangular distribution described in Table 10.

Table 10 - *Description of the triangular distribution defining the putTime component (in minutes).*

Minimum value (a)	Maximum value (b)	Mode (c)
0.00583	0.20300	0.01383

The total value of the putTime component during the shelf replenishment operation for a single order tote (equation 8) equals the summation of values taken from the triangular distribution in Table 10:

$$putTime\ (x) = \sum_{1}^{qtyUnits} \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}\ for\ a \leq x < c \\ \frac{2}{b-a}\ for\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}\ for\ c < x \leq b \\ 0\ for\ any\ other\ case \end{cases} \qquad (8)$$

In conclusion, this module defined the time components of the relevant operations (picking and shelf replenishment) and calculated their values. Table 11 gathers all the information on each of the components.

Table 11 - *Summary of the Simulation times calculation module outputs (results presented in minutes).*

Operation	Component	Minimum value	Mode	Maximum value
Picking	switchSKUtime	0.02017 min	0.03567 min	0.05517 min
	setToteTime	0.13333 min	0.15000 min	0.16667 min
	pickItemTime	0.01183 min	0.03567 min	0.11300 min
Shelf Replenishment	interZoneTime[10]	-	-	-
	intraZoneTime[11]	-	-	-
	putTime	0.00583 min	0.01383 min	0.20300 min

4.7 Simulation Model

To create this module, the steps proposed in sub-section 3.5.1 (Figure 6) were followed. The first and second steps (Problem Formulation and Setting Objectives, respectively) have already been covered in the first and second chapters. The last two steps will be addressed in the next chapter. Thus, the focus of this module is the middle steps of the simulation study: Model Conceptualisation, Data Collection, Model Translation, and Verification and Validation (see Figure 6).

[10] See Table 9
[11] See Table 31

4.7.1 Model Conceptualisation

As aforementioned in sub-section 3.5.1, the Model Conceptualisation step is the basis for the simulation. At this stage, the level of detail of the simulation model is defined through the decision to abstract or detail specific parts of the real system, depending on the problem to solve and on the objectives defined for the study in question.

For this reason, a synthesised review of the problem statement (section 2.7) helps to understand the way this model has been conceptualised. Indeed, Worten needs to analyse the benefits of implementing an automated storage system and a G2P system in order to increase the efficiency of its operations and therewith be able to meet the demand the company expects in the medium and long term. While changing the design of its warehouse, the company pretends to achieve better coordination between the warehouse and store operations, increasing the overall efficiency of the in-store replenishment process.

In this regard, the challenge proposed in this thesis is to define a model for the picking operation in the G2P station that optimises the in-store replenishment processes. To this end, an academic and field research was carried out, which led to the methodology already described, which concludes with a simulation model.

This simulation model receives six inputs that influence the final outputs of the system:

- Initial number of order totes available.
- The order tote dimensions and its maximum occupancy rate (see section 4.5).
- Daily number of order totes to be shipped from the warehouse based on orders from stores (see section 4.5).
- A list describing each order tote, which details their destination store and the number of items and SKUs destined for each zone of store (see section 4.5).
- The number of operators (human resources) allocated to the warehouse operations and each store.
- The values for each time component of the picking, outbound and shelf replenishment operations (see section 4.6).

The outputs generated from this module are the occupancy rate of warehouse and store resources over time, the number of order totes actually shipped to the stores, and the records of the timestamps of the start and end of the activities taking place in the simulation. All output values depend on the input values given in each scenario; hence, these are useful metrics to evaluate the generated scenarios.

In order to have the simplest model possible, the model system considers only the operations of picking and outbound, in the warehouse, and shelf replenishment, in the store. All the remaining operations in Worten's supply chain (explained in chapter 2) are not relevant to the scope of the problem at hand and are thereby excluded from the model system. The decisions about the inclusion or the level of abstraction of each element of the model were based on the simplifications and assumptions stated below.

Simplifications:

- Abstraction of the number of inventory totes being used simultaneously during the picking operation. The relevant factor is to determine the capacity of the system and not the arrival order configuration of inventory totes.
- The trucks are all loaded at the same time in the warehouse every day of the week. Since the distribution operation between the warehouse and the stores is not considered in the system, all restrictions related to this operation (like the trucks' arrival time at the warehouse or the number of available docks in the outbound area) have been ignored.
- The trucks are all unloaded at the same time in the stores every day of the week. Likewise, since the distribution operations between the warehouse and the stores are not considered, all restrictions related to this operation (like the distance travelled between the warehouse and the stores or the existence of trucks that distribute to more than one store at the same time) have been ignored.
- The working hours of the store backroom operators of each type of store are the same since what matters, in this case, is the occupancy rate of resources and the time it takes to execute the activities. In the real system, the opening hours of the store (which determine the working hours of the store backroom team) depend on circumstances involving the store. For instance, if the store is in a shopping centre, its opening and closing hours depend on the opening and closing hours of the centre.
- The shipments are prepared the day before they arrive in the stores since what matters, in this case, is the occupancy rate of resources and the time it takes to execute the activities. In the real system, the picking and outbound operations of a shipment may occur during some days or even on the day it is sent to the store, depending on the delivery window frequency and schedule of each store.

Assumptions:

- There are never inventory shortages and/or order totes shortages in the warehouse since the study does not address these problems. This ensures that the picking process is completed.
- The human resources are never a limitation of the warehouse or store operation as the simulation model is intended to evaluate the system's maximum capacity. The number of human resources required in each operation is assessed by evaluating the occupancy rate of the system's installed capacity.
- It was considered that the maximum number of order totes being filled up simultaneously during the picking operation by a single picker is six. The G2P station is not yet installed in Worten's warehouse, so it was decided to use this value, since, according to the company's knowledge, similar systems implemented in other warehouses have this configuration.
- Both the picking and shelf replenishment operations of an order tote cannot be performed by more than one operator at the same time.

Based on the simplifications and assumptions stated, Table 12 denotes the level of abstraction of each constituent of this model. The intention of this table is not to have an exhaustive list, but rather a list to comprehend the model conceptualised and the details considered for each component of the system.

Table 12 - *Level of abstraction of each component of the modelling system.*

Component type	Component	Detail	Description	Included?
Entities	Warehouse	Schedule	Working time	Yes
		Area	Warehouse area	No
		Layout	Operations and zones display	No
		Location	Store's location	No
	Store	Schedule	Working time	Yes
		Type	Type of store	Yes
		Zones	Division of the stores by zones	Yes
		Area	Store area	No
		Layout	Products display in the store	No
		Location	Store's location	No
		Shipment quantity	Daily shipment quantity from the warehouse	Yes
	Tote	Volume	Order tote volume	Yes
		Maximum occupancy rate	Utilisation rate of tote volume	Yes
		Reusable	Capacity to be used more than one time	Yes
		Weight	Maximum permissible load weight	No
		Capacity	Available capacity	No
		Location	Current location	Yes
		Quantity	Real quantity of order totes in the system	No
		Destination	Zone of store destination	Yes
		Quantity of SKUs	Quantity of SKUs inside the tote	Yes
		Quantity of units	Quantity of items inside the tote	Yes
	Worker	Experience	Acquired know-how	No
		Job	Execute the warehouse and store operations	Yes
		Morphology	Physical attributes	No
		Biological characteristics	Gender and age	No
Queues	Picking Queue	Queue rule	First-in-first-out (FIFO)	Yes
		Capacity	Available capacity	No
		Arrival order	Arrival order of inventory totes from the automated storage	Yes
	Outbound Queue	Queue rule	FIFO	Yes
		Capacity	Available capacity	No
	Replenishment Queue	Queue rule	FIFO	Yes
		Capacity	Available capacity	No
Activities	Picking	Capacity	Totes for which a worker can do picking simultaneously	Yes
		Duration	Time to perform picking operations	Yes
		Quantity of SKUs	Quantity of SKUs to pick	Yes
		Quantity of units	Quantity of units to pick	Yes
		Resources	Human resources required	Yes
		System's configuration	Configuration of the G2P automated system	No
	Outbound	Capacity	Maximum number of totes in the outbound docks	Yes
		Loading time	Truck loading time	Yes
		Flows	Outbound flows in the warehouse	No
		Duration	Time for the outbound operations	No
		Resources	Human resources required	No
	Shelf Replenishment	Capacity	Number of totes a worker can replenish simultaneously	Yes
		Duration	Time to perform shelf replenishment operations	Yes
		Quantity of SKUs	Quantity of SKUs to replenish on the shelf	Yes
		Quantity of units	Quantity of units to replenish on the shelf	Yes
		Resources	Human resources required	Yes
		Shelf type	Type of shelf to replenish	No
		Shelf state	Prior shelf occupancy	No

The model conceptualisation was discussed and composed in cooperation with the BI team of the company.

4.7.2 Data Collection

The Data Collection step gathers all the data to feed the model, i.e., the model inputs which, depending on their configuration, will generate different scenarios for evaluation. As mentioned in sub-section 4.7.1, this simulation model receives inputs from six different sets, four of which result from the preceding modules developed in this methodology. From the Order totes' configuration module (section 4.5), the model receives (1) the order tote dimensions and its maximum occupancy rate, (2) the daily scheduled number of order totes to be shipped from the warehouse to the stores, and (3) a list describing the content inside each order tote. From the Simulation times calculation module (section 4.6), it receives (4) the values for each time component of the picking and shelf replenishment operations (the value of the outbound time was simplified and will be explained in the next section 4.7.3).

Following, the remaining two inputs of the model, (5) the initial number of order totes available and (6) the number of operators allocated to the warehouse operations and to each store, were defined on the assumption (already expressed in sub-section 4.6.1) that they would never be a limiting element of the model's results. As such, the values considered were based on the simulation dimensions.

All collected data is then entered into an *Excel* file connected with the simulation model in *AnyLogic*. Thus, the user of the simulation model does not amend the *AnyLogic* file during the running of scenarios, avoiding modifications on the model core and preventing differences on it during the model runs.

4.7.3 Model Translation

The Model Translation step aims to convert the system defined during the model conceptualisation into a computer model.

Hence, the first stage of this step is to choose the software that will be used to create the simulation model. In this case, as aforementioned, the choice fell on a software called *AnyLogic*[12]. The main reason for this decision was the experience and expertise in this software of the company's BI team, derived from its recurrent use to develop other simulation studies for the company. Moreover, this software has several practical and valuable features when compared with other simulation software. Firstly, it allows to combine the modelling methods (explored in sub-section 3.5.2) in the same model, depending on the developer's interpretation of the system's characteristics. In addition, its graphical display is easy to understand during the model development, and during the simulation run, allowing to track the path taken by any model component and its attributes status while running the model. It also has the option to link the model to external files (e.g., *Excel* or CSV files), enabling users to easily import data into the model and extract the simulation results after the run.

Once selected the simulation software, the second stage is to build the model which reproduces the system as it was conceptualised. In this case, the model is stochastic (because the time of its activities depends on triangular distributions, see section 4.6), dynamic and continuous (because it changes continuously over time). The simulation run covers a whole week of picking and shelf replenishment, based on the results from the Simulation periods definition module (section 4.4). Once the shipments

[12] Used the latest free *AnyLogic* version: *AnyLogic 8.8.0 Personal Learning Edition*

are prepared on the day before they arrive at the store, the model time is eight working days: from Saturday at 6:00:00 to the next Saturday at 23:59:59.

The model developed is based on the ABS method, since this method fits well systems where entities move over a region or disruptive systems to the past where their behaviours are difficult to predict from historical data (see sub-section 3.5.2). The system to be modelled matches both statements. However, having the possibility of joining together other modelling and simulation methods, some parts of the model are based on the DES method (see sub-section 3.5.2), as the operations in the warehouse and the stores are represented by a succession of discrete events over time (beginning and end of activities and queues).

In the ABS method, the entities of the model are also called agents due to their active role in the system (sub-section 3.5.2). The model created has three main agents – Tote, Warehouse, and Store – and an auxiliary agent – Worker – which is used to embody the resource pool of each operation. All agents interact with each other during the simulation run. Each main agent is characterised by attributes and relates with the other agents of the model through a specific method. The attributes can be parameters, variables, or collections. A parameter describes the objects statically, thus, it is a constant during one simulation. On the contrary, a variable represents a model state during the simulation run, which might change over time. Finally, a collection is a data object that groups and stores elements of the same type into a list. The attributes and methods of each main agent of the model are explained below.

Warehouse Agent

The first part of the model to be developed was the Main environment. This environment commands the entire simulation model. All the attributes that describe the scenario to simulate are imported from the *Excel* file into this environment. The CSV files which record the outputs are set here. Moreover, the Main environment was used to build the process that describes the operation of the Warehouse agent.

As aforementioned, the warehouse operations are described by applying the DES methodology, as illustrated in Figure 12. In simulation terms, it means that the Warehouse agent takes part in all the activities and queues presented in Figure 12. The simulation run starts at 6 am, although, the working hours in the Warehouse are set to start at 7 am every day of the week by a schedule. That schedule determines that at 7 am the wave of orders placed by the stores for the following day is released, and the number of Tote agents needed to fulfil the orders enters the Warehouse operations (from the parameter *initialTotePop*). Since the daily quantities in the wave change throughout the week, the value scheduled comes from the collection *al_qtyScheduledWaves*. This collection saves in an array list the values imported from the input *Excel* file.

Already in the Warehouse, the Tote agents will first pass through the picking activity, which in this model is represented by four blocks – seize, one queue, *picking* and release (see Figure 12). The seize and release blocks are used whenever an activity requires a certain number of resources available from a resource pool. In this case, to realise the picking activity, Workers from the *rPool_Pickers* must be available (this resource pool has two Workers exclusively allocated to this activity). When there are

Workers available, the first Tote in the queue embedded in the seize block exits the block and starts the picking activity, occupying the Worker that was available until the end of the activity. Arriving at the picking block, the Tote agent remains there until the end of the picking activity. To simulate the picking activity, it was used a delay block. As the name suggests, this type of block delays the agents for a given amount of time. The time it takes to perform the picking activity is not a concern of the Warehouse but rather of the Tote agent, thus, it will be explained further in this section. It was established a maximum capacity to perform the activity with twelve Tote agents simultaneously, since there are two Workers in this activity, and it was assumed a picker can fill simultaneously six order totes (see sub-section 4.7.1). Once the picking activity of a Tote finishes, the Tote passes to the release block, and the Worker engaged with this task becomes available to perform the picking activity with another agent Tote.

Figure 12 - *Print Screen of the Modelling of Warehouse operations.*

Afterwards, the Tote agent moves on to the outbound activity which, like the picking activity, is modelled in four blocks – one seize block, one queue, *outbound* (delay block), and one release block. The seize and release blocks are used because, to perform this activity, a Worker from the resource pool *rPool_GeneralWH* must be available. This resource pool groups all the Worker agents who have other tasks than picking in the Warehouse. By simplification, the only activity in the model beyond picking is the outbound activity. Since this activity is not the target of the simulation model, this resource pool has only one Worker, which is ample enough to perform the activity without affecting the simulation results. The time it takes a Tote agent to perform this activity follows the triangular distribution[13] described in Table 13. The distribution was set as the delay time of the outbound block by using the Warehouse agent parameters – *outBndTime_min*, *outBndTime_max*, and *outBndTime_mod*. The utilisation of queues before the delay block in both activities is just a good practice of modelling and simulation.

Table 13 - *Description of the triangular distribution defining the outbound activity time (in minutes).*

Minimum value (a)	Maximum value (b)	Mode (c)
0.01 min	0.10 min	0.05 min

Finally, before leaving the Warehouse, the Tote agents enter the *waitShip* block, which forces them to wait until 11 pm of the day they were prepared to be shipped and sent to the respective stores. This ensures the Tote agents are all sent to the stores at the same time and that they are never processed in the store on the same day they are prepared in the warehouse, as it was previously conceptualised. At 11 pm, the event *ev_Shipment* occurs which causes the *waitShip* block to free all the Tote agents in this block. Once freed from the *waitShip* block, the Tote agents leave the Warehouse to go to their assigned Store in the *popStores* (the agent population of Store agents, which size is defined by the user in the input *Excel* file).

[13] The values considered in the triangular distribution are not representative of the real time spent in the outbound activities. These values were assumed as way of simplifying this part of the simulation model which is not relevant to the problem at hand.

Store Agent

Likewise, the store operations are also described using the DES methodology (see Figure 13) and with a similar modelling configuration. When the Tote agents leave the Warehouse, they enter directly into the agent Store to which they are assigned. Although to simulate the distribution activity from the warehouse to the stores in a simple way, the Totes are firstly queued in the *onTransit* block until the *arriveStore* event takes place. The *arriveStore* event takes place at the same time (7 am) in every Store in the *popStores*, as assumed in the model conceptualisation.

Therefore, when the *arriveStore* occurs, the Tote agents in the *onTransit* block move to the seize block of the shelf replenishment activity. Like in the Warehouse, the shelf replenishment activity in the Stores is described by four blocks of the same kind – seize, one queue, *replenish* and release (see Figure 13). The queue before the delay block (*replenish*) is just a good practice of modelling and simulation. As already explained, the seize and release blocks are used when it is required a certain number of resources available to use in a resource pool to perform the activity. In fact, to perform the shelf replenishment activity in a Store is needed one Worker available from the resource pool *rPool_Str* of that Store and one Worker can only be occupied with one Tote agent at the time. The working time of the Stores' resource pools is set to be between 7 am and 11 pm (as in the Warehouse). The schedule associated with the resource pool defines that out of the working time there are no Workers in the resource pool. In contrast, during the working time, the size of the *rPool_Str* of each Store agent depends on the value of the parameter *rpoolsize* of that specific store. This parameter is defined by the user and imported to the model through the input *Excel* file.

When there are Workers available in the *rPool_Str*, the first Tote in the queue of the seize block starts its shelf replenishment activity associated with the Worker that was available. This activity occurs at the *replenish* block, which is a delay block, as in the picking and outbound activities of the Warehouse. Similar to the picking activity, the time to perform the shelf replenishment activity is associated with the Tote agent, and not with the Store, thus, it will be explained further on. Once the shelf replenishment activity of a Tote finishes, the Tote leaves the *replenish* block to the release block, and the Worker engaged with this task becomes available to perform the same activity with another Tote.

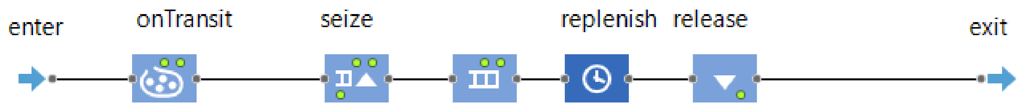

Figure 13 - *Print Screen of the Modelling of Store operations.*

Apart from the *rpoolsize* parameter, each Store agent is characterised by two more parameters (also defined by the user and imported from the *Excel* file): the *ID* which gives an identification number to each Store agent, and the *type* which associates each Store agent to the type of stores defined in section 4.2. Both these parameters are useful to identify the Store during the simulation run and in its output results.

Tote Agent

Lastly, the Tote agent is defined in the model through a different method from the other agents. In this case, the modelling method used is described by a statechart (see Figure 14). This statechart recognises the place where the agent Tote is and controls the activity it is performing at every moment.

When the simulation run starts, at 6 am of the first day simulated, the entire population of Tote agents in the system are idle, i.e., empty and ready to use, in the *popBacklog* agent population. During the simulation run, the agent Tote population may be dispersed among four distinct agent populations, depending on their state at each moment in time.

As schematically represented in Figure 14, while idle, Tote agents only change their state when they are triggered by a message to enter the Warehouse or a Store. If the message received is “pick”, the Tote agent enters the diagram of the Warehouse to be used in the picking and outbound activities. On entering the diagram, the Tote agent moves from the *popBacklog* to the *popWIP* agent population, where it stays until exits the Warehouse, passing to the *popTransit*. Otherwise, the Tote is called by a Store to perform the shelf replenishment activity, therefore, it enters that Store operations diagram, passing from the *popTransit* agent population (since it came from the Warehouse) to the *popAtStore* population, in that moment it leaves the seize block in the Store to go to the *replenish* block. At the end, when it exits the Store operations diagram, the Tote agent switches back to the idle state and, thus, to the *popBacklog* population.

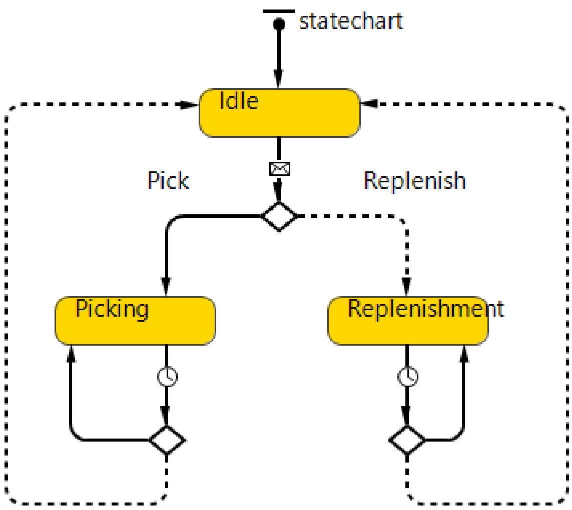

Figure 14 - *Print Screen of the agent Tote decision statechart diagram.*

Each agent Tote is identified through a unique *ID* numerical parameter. Moving on from the idle state, it is associated with another unique parameter called *reqID*, which is the identification number of the order request to fulfil that Tote. Hence, an agent Tote (with a singular *ID*) may be associated with more than one *reqID* in the same simulation run, if it is used on more than one task in the same week (run).

Moreover, the duration of each activity is determined by the expressions defined in section 4.6.

Effectively, the picking time of each agent Tote is estimated by the function *pickTime* when the Tote enters the Picking block of the statechart. This function uses the variable *qtySKUs* (which dictates the number of SKUs within a Tote, based on the input *Excel* file) and the parameters displayed in Table 14 to define the time components of the picking time described in sub-section 4.6.1 and represented in the model by the variable *timePicking*. The variable *collIdxPick* increments the store zone index during the picking activity in the simulation run. Furthermore, the timestamps of the start and end times of the picking activity for that specific Tote agent (which correspond to the Tote exit of the seize block and its entering in the release block of the picking activity in the Warehouse) are also saved in the Tote parameters *tm_startPick* and *tm_endPick*, respectively. These timestamps are then useful to calculate the lead time of the picking activity of each specific Tote.

Table 14 - *Tote agent parameters to model the picking time components.*

Operation	Component	Minimum parameter	Mode parameter	Maximum parameter
Picking	switchSKUtime	switchSKUtime_min	switchSKUtime_mod	switchSKUtime_max
	setToteTime	setToteTime_min	setToteTime_mod	setToteTime_max
	pickItemTime	pickItemTime_min	pickItemTime_mod	pickItemTime_max

In addition, the shelf replenishment time of a Tote agent (described theoretically in sub-section 4.6.2) is calculated by the function *replenishTime* when the Tote arrives at the Replenishment block of the statechart. This function uses the variables *qtySKUs* and *destFacility* (which locates the Tote agent in a Store based on its *reqID*) and the collection tm_*trvtimes* (which saves all the interZoneTime and intraZoneTime components considered in the simulation run, according to the number of zones in each store in the experience running, from the input *Excel* file) to calculate both the interZoneTime and the intraZoneTime components of the shelf replenishment time. At last, the putTime component is calculated using the parameters displayed in Table 15. For a given Tote agent, the variable *timeReplenish* has the value of the shelf replenishment time of that agent at any moment. The variable *collIdxReplenish* increments the store zone index during the replenish activity. Besides, the timestamps of the start and end times of the shelf replenishment activity of each Tote agent (corresponding to the Tote exit of the seize block and its entering in the release block of the shelf replenishment activity in the Stores) are saved in the parameters *tm_startStore* and *tm_endStore*, respectively, in order to calculate the lead time of its shelf replenishment activity.

Table 15 - *Tote parameter to model the putTime component of the shelf replenishment time.*

Operation	Component	Minimum parameter	Mode parameter	Maximum parameter
Shelf Replenishment	putTime	putTime_min	putTime_mod	putTime_max

4.7.4 Verification and Validation

Finally, the Verification and Validation step from the Simulation Study methodology illustrated in Figure 6 intends to check if the simulation model correctly replicates the real system for which it has been created (see sub-section 3.5.1). This is an essential step to understand if the results obtained from the simulation model are reliable enough to extract conclusions about the real system.

To remind the reader, Verification is the procedure which scrutinises and analyses the correspondence between the conceptualised model from the real system and the simulation model. To reduce the complexity of the process and to prevent major adjustments at the end, the Verification process was conducted while developing the model. In this case, the process was conducted using some of the practices outlined in the academic literature (already exposed in sub-section 3.5.1). The coding and modelling were split into small parts which were developed both incrementally and separately to avoid making mistakes that affect the whole model. The entire model was reviewed by more than one person to identify errors that would escape if it was only one person checking it. Further, during the development of the model, it was run with different inputs to verify its consistency, by assessing the plausibility of its outputs and tracing entities throughout the simulation.

In turn, Validation attests to whether the model actually represents the real world system in the metrics to be assessed at a high confidence level. This process usually requires outputs from the real-world system to compare to the ones obtained in the model, to progressively adjust it to the real world. Unfortunately, in this study, it is impossible to have real world outputs since the system under study is not installed yet, nor is any comparable process. Thus, as predicted in the academic literature for these cases, the validation of the simulation model was reduced to analysis and verification of the similarities between the simulation and the acquired perception of the real system, while monitoring several simulation runs with different inputs.

To ensure the results from the simulation are meaningful to evaluate the system, it is essential to define the warm-up period and the replication of simulation runs for a certain experiment.

The warm-up period is the time it takes for the model to reach a steady state. To acquire meaningful results, the simulation model should only start to collect the system's behaviour after completed the warm-up period. There are numerous approaches for predicting the length of this period (Mahajan & Ingalls, 2004). In this case, this simulation model depicts a week-long operation in a warehouse and stores which is not continuous, but instead, it starts and ends every day according to the working periods in each establishment, and all the resource pools are completely emptied at the end of the period. Furthermore, for the same day, all the Totes and Workers arrive at the Warehouse and the Stores at the same time. With these starting conditions, there is no initialisation bias in the output results. Therefore, there is no need for a warm-up period[14].

In turn, the replication of simulation runs for a certain experiment lies in the minimum number of simulation runs to achieve meaningful results. It is determined based on the system's behaviour, the desired confidence level, and the confidence interval width for the model to fit a given proportion (Byrne, 2013). Once the simulation model is stochastic, in order to have meaningful results, the same experiment must be reproduced multiple times. According to Byrne (2013), at least 19 runs should be executed to achieve a confidence level of 95%, with a confidence interval of 15% and a proportion of 5%. Thus, each experiment or scenario developed must be run 19 times on the *AnyLogic* software, with 19 different seed values. In truth, to obtain a wider confidence interval each scenario could have been run more times, however, these parameters were found adequate for this study. Therefore, the simulation study was carried out with the confidence parameters described above. The results for a certain experiment or scenario should be the average of the result obtained in the 19 model runs.

[14] Source: https://www.simul8.com/support/help/doku.php?id=features:clock:warm_up_period

Chapter 5 – Scenarios and Results

The fifth chapter of this dissertation presents and analyses the results obtained. The first section presents the metrics used to evaluate the results, followed by a description of the scenarios developed. In the last section, the results are presented and discussed.

5.1 Evaluation metrics

For a correct analysis of any model's results, it is essential to define the metrics according to which it will be evaluated. Based on the objectives set for this study, to evaluate the results from the scenarios generated, four different metrics have been established:

1) **System Throughput:** reports the number of order totes processed in the warehouse to be shipped to the stores in each scenario. If the stores' demand is met by the warehouse, for the same quantity of items ordered by the stores, the lower the system throughput, the higher the efficiency of the generated scenario. If the stores' demand is not fully met by the warehouse, it means that the installed capacity of the system is not enough. However, in this study, the system resources are not a limitation for the results, as already explained in sub-section 4.7.1.
2) **Order Tote Occupancy Rate:** the average ratio of the volume occupied by the items inside the tote to the total volume of the order tote in each scenario. It is important to remember that the order totes can only be filled to 79.20%, to consider the wasted space generated while picking (see section 4.5). This metric is inversely related to the first metric, as they both assess the efficiency of filling the order totes. For the same number of items to pick, the lower the system throughput, the higher the average occupancy rate of the order totes, and vice-versa.
3) **Full-Time Equivalent (FTE) Occupancy Rate:** the ratio of time the resources of the operation are occupied during the working hours of the warehouse and the stores in each scenario (considering every day simulated, even those in which the store does not receive any orders). For each scenario, this metric is assessed for the global operation of the simulation and individually in the warehouse operations and in the operation of each store. The analysis by entity allows to evaluate the impact of the store's configuration on the resource occupation. For the same demand, the higher the FTE occupancy rate, the lower the efficiency of the operation.
4) **FTE Occupancy:** the lead time, on average per tote, to execute the operation (picking or shelf replenishment). The picking and shelf replenishment lead times are determined by the difference between the simulation parameters that store the start and end timestamps of each activity (see sub-section 4.7.3). As in the previous metric, this is evaluated for the global operation and individually for each operation of the warehouse and store. This indicator enables the understanding of the influence of the store's configuration on the time spent performing each operation since the longer the time spent, the less efficient the operation with that configuration.

The performance assessment of the multiple scenarios tested will be accomplished through a function. This Performance Function (equation 9) summarises the achievement of the scenarios in each of the in-evaluation metrics, by weighting each of the metrics based on their relevance to the problem at hand. As a matter of fact, in this case, given the connection between the first two metrics, it would not make sense to account for both in the function, because that would mean considering the same effect twice in the performance results. Hence, the Performance Function considers the Order Tote Occupancy Rate metric and discards the System Throughput.

To sum the metrics in the same function, it is required to normalise their values. Effectively, the values from the Order Tote Occupancy Rate and the FTE Occupancy Rate metrics are already normalised, since their values are presented as a percentage of the total order tote volume and of the total number of working hours in the simulation run, respectively. Therefore, the only metric to normalise is the FTE Occupancy, which will be presented as a ratio of the maximum value obtained for this metric in all the scenarios tested.

$$Performance\ Function_{ScXX} = \alpha \times OT\ Occup\ Rt_{ScXX} + \beta \times (1 - FTE\ Occup\ Rt_{ScXX}) + \gamma \times \left(1 - {FTE\ Occup_{ScXX}}/{FTE\ Occup_{MAX}}\right) \qquad (9)$$

$$Subject\ to: \alpha + \beta + \gamma = 1, \qquad \forall \alpha, \beta, \gamma \in [0,1] \qquad (10)$$

The metrics assessed were considered to have a similar relevance for the problem at hand, based on the internal knowledge of the company. Thus, the weight of each metric is equally distributed by the coefficients α, β and γ ($\alpha = \beta = \gamma = 1/3$).

The closer to one the Performance Function score is in a given scenario, the better the scenario is.

5.2 Scenarios

To assess the most efficient system configuration, several scenarios were drawn up and tested. These scenarios were generated based on six parameters described in Table 16.

Table 16 - *Scenario-setting parameters*

Parameter	Description
1	Initial number of order totes available
2	Order tote dimensions and its maximum occupancy rate
3	Resource pool of the picking and shelf replenishment operations for each type of store
4	Week to simulate
5	Arrival order set-up of inventory totes to the G2P station
6	Number of zones considered for each type of store

From the parameters defined, it was decided that (1), (2), and (3) would be steady, or unchangeable, throughout the analysis, so the scenarios differ in the remaining parameters. Effectively, once assumed that the order totes and the human resources are never a limitation to the simulation model (sub-section 4.7.1), the initial number of order totes available (parameter 1) and the resource pool of the picking and shelf replenishment operations (parameter 3) will never impact the results of the simulation run. Nevertheless, by changing these parameters, the complexity of scenario development would increase. Further, changing parameter 3 in different scenarios would cause a variation in the basis of analysis for the FTE Occupancy Rate metric (see section 5.1), which would be prone to misinterpretations of its results. The determination of these two parameters was done through attempts, in order to get figures that would not affect the simulation run.

Therefore, the initial number of order totes available considered in this study was 3000. No scenario proposed uses more than 3500 order totes in a week and not even more than 800 on the same day, thus, this figure ensures that there is never order tote shortage, whilst guaranteeing an acceptable computational cost.

Similarly, the determination of the resource pool of each activity of the simulation was made to guarantee that all items ordered by the stores are shipped and shelf replenished at the end of the simulation run. Hence, the values considered for the resource pool of the picking operation in the warehouse and of the shelf replenishment in the stores of type A, B, and C were, respectively, 2, 6, 2, and 1. Knowing that the warehouse and stores in this system work from 7 am to 11 pm, the weekly working time in each entity is, respectively, 224 hours, 672 hours, 224 hours, and 112 hours.

Parameter (2) is kept unchanged for a different reason. In this case, it was decided to keep the actual dimensions of the returnable order totes that are being implemented in the distribution operation of the items from the warehouse to the stores of the company under study, since these are the only order totes the company intends to have in the near future. Consequently, as explained in section 4.5, the order totes considered are 40 centimetres long, 40 centimetres wide, and 60 centimetres high, and their maximum occupancy rate is 79.20%.

Table 17 summarises the information about the parameters that are kept fixed throughout all the simulation runs.

Table 17 - *Summary of the parameters (1), (2), and (3).*

Initial number of order totes	Order tote dimensions			Maximum Occupancy Rate	Resource Pool (Weekly working time)			
	Length	Width	Height		Warehouse	Store type A	Store type B	Store type C
3000	40 cm	40 cm	60 cm	79.20%	2 (224 h)	6 (672 h)	2 (224 h)	1 (112 h)

On the other hand, the parameters that will be tested throughout the different simulation runs are parameters (4), (5), and (6). Their testing leads to several different scenarios. The settings of parameters (4) and (5) were defined in the modules of the methodology explained in chapter 4. Firstly, parameter (4) is tested for the four weeks to simulate defined in section 4.4 – weeks 7, 25, 37, and 48. Keeping everything else constant, except this parameter, enables to assess the similarities and differences of the company's operation throughout the year. Then, it is also relevant to study the best way to configure the arrival order set-up of the inventory totes at the G2P station. In that regard, parameter (5) assesses three different configurations – random, priority to higher volume SKUs, and priority to lower volume SKUs – as explained in section 4.5.

Finally, parameter (6) defines the number of zones for each store in each scenario. Based on the Zones of the store definition module (section 4.3), each type of store may be organised into between one and seven zones (see Table 2 and Table 3). Different configurations affect the number of order totes to be shipped to each store as well as the interZoneTime and intraZoneTime components of the shelf replenishment operational time. However, testing all configurations for each of the three types of stores would be a time-consuming and complex process, which would be an unreasonable effort when compared to the advantage of such a process. Thus, according to the company's operational best practices and know-how, it was decided to test only four possible configurations for each type of store:

- 1-zone stores – as close as possible to the "As is" scenarios of shelf replenishment in-store, since there are no zones defined. It is useful as a basis for comparison between the current operation and the remaining scenarios.
- 2-zones stores – division into two zones of store.
- 7-zones stores – store division in the maximum number of zones considered.
- Customised number of zones, according to each type of store dimensions and items flow. Respectively, types A, B, and C have 6-zones stores, 5-zones stores, and 3-zones stores.

Overall, mixing all these parameters results in 48 different scenarios to test, described in Table 18.

Table 18 - *Description of each scenario considered based on the parameters (4), (5), and (6).*

Scenario	Week	Arrival Order set-up	#Zones (type A)	#Zones (type B)	#Zones (type C)
Sc01	7	Priority to higher volume SKUs	1	1	1
Sc02			2	2	2
Sc03			6	5	3
Sc04			7	7	7
Sc05		Priority to lower volume SKUs	1	1	1
Sc06			2	2	2
Sc07			6	5	3
Sc08			7	7	7
Sc09		Random	1	1	1
Sc10			2	2	2
Sc11			6	5	3
Sc12			7	7	7
Sc13	25	Priority to higher volume SKUs	1	1	1
Sc14			2	2	2
Sc15			6	5	3
Sc16			7	7	7
Sc17		Priority to lower volume SKUs	1	1	1
Sc18			2	2	2
Sc19			6	5	3
Sc20			7	7	7
Sc21		Random	1	1	1
Sc22			2	2	2
Sc23			6	5	3
Sc24			7	7	7
Sc25	37	Priority to higher volume SKUs	1	1	1
Sc26			2	2	2
Sc27			6	5	3
Sc28			7	7	7
Sc29		Priority to lower volume SKUs	1	1	1
Sc30			2	2	2
Sc31			6	5	3
Sc32			7	7	7
Sc33		Random	1	1	1
Sc34			2	2	2
Sc35			6	5	3
Sc36			7	7	7
Sc37	48	Priority to higher volume SKUs	1	1	1
Sc38			2	2	2
Sc39			6	5	3
Sc40			7	7	7
Sc41		Priority to lower volume SKUs	1	1	1
Sc42			2	2	2
Sc43			6	5	3
Sc44			7	7	7
Sc45		Random	1	1	1
Sc46			2	2	2
Sc47			6	5	3
Sc48			7	7	7

5.3 Presentation and discussion of results

Following the methodology proposed in the previous chapter, this study's results are obtained in two distinct phases: after running the order totes' configuration *Python* algorithm (section 4.5), and after running the simulation model in *AnyLogic* (section 4.7). It was tested with the expedition records of 2021.

Wherefore, all the scenarios defined were first set up and run on the *Python* algorithm. By configuring the order totes of each scenario, a detailed list of the items to be placed in each order tote is obtained. From that list, it is computed the maximum number of order totes to be prepared in the warehouse and shipped to the stores during that week (i.e., the maximum system throughput) and the average order tote occupancy rate in each scenario. The results from the algorithm are listed in Table 19. When analysing these results, keeping all the other parameters unchanged apart from arrival order set-up (parameter 5), the scenarios in which the arrival order priority set-up is given to higher volume SKUs are always the winning scenarios, when compared with the scenarios of random priority and the scenarios of priority to lower volume SKUs. Looking at Table 19, where the results from the scenarios with priority to higher volume SKUs are highlighted in bold and blue, for any given week, the Maximum System Throughput is always lower in these scenarios (and the Order Tote Occupancy Rate always higher) than in their peers of the same week, i.e., they have higher efficiency filling the order totes.

Table 19 - *Results from the fourth module: Order totes' configuration.*

Scenario (week 7)	**Sc01**	**Sc02**	**Sc03**	**Sc04**	**Sc05**	**Sc06**	**Sc07**	**Sc08**	**Sc09**	**Sc10**	**Sc11**	**Sc12**
Maximum System Throughput	**815**	**822**	**854**	**874**	980	986	1004	1013	822	830	880	903
Order Tote Occupancy Rate	**78.6%**	**77.9%**	**75.0%**	**73.3%**	65.4%	65.0%	63.8%	63.2%	77.9%	77.2%	72.8%	70.9%
Scenario (week 25)	**Sc13**	**Sc14**	**Sc15**	**Sc16**	**Sc17**	**Sc18**	**Sc19**	**Sc20**	**Sc21**	**Sc22**	**Sc23**	**Sc24**
Maximum System Throughput	**890**	**903**	**943**	**967**	1102	1109	1121	1129	905	931	968	1008
Order Tote Occupancy Rate	**78.7%**	**77.5%**	**74.2%**	**72.4%**	63.5%	63.1%	62.4%	62.0%	77.4%	75.2%	72.3%	69.5%
Scenario (week 37)	**Sc25**	**Sc26**	**Sc27**	**Sc28**	**Sc29**	**Sc30**	**Sc31**	**Sc32**	**Sc33**	**Sc34**	**Sc35**	**Sc36**
Maximum System Throughput	**1222**	**1234**	**1267**	**1292**	1513	1518	1525	1535	1233	1264	1305	1331
Order Tote Occupancy Rate	**78.7%**	**77.9%**	**75.9%**	**74.4%**	63.5%	63.3%	63.0%	62.6%	77.9%	76.0%	73.6%	72.2%
Scenario (week 48)	**Sc37**	**Sc38**	**Sc39**	**Sc40**	**Sc41**	**Sc42**	**Sc43**	**Sc44**	**Sc45**	**Sc46**	**Sc47**	**Sc48**
Maximum System Throughput	**2737**	**2761**	**2817**	**2874**	3381	3385	3401	3414	2765	2809	2882	2968
Order Tote Occupancy Rate	**78.9%**	**78.2%**	**76.6%**	**75.1%**	63.9%	63.8%	63.5%	63.2%	78.1%	76.9%	74.9%	72.8%

Taking these results into account, it was decided to run the simulation model only for the sixteen scenarios in which the arrival order priority set-up is given to higher volume SKUs, i.e., Sc01, Sc02, Sc03, Sc04, Sc13, Sc14, Sc15, Sc16, Sc25, Sc26, Sc27, Sc28, Sc37, Sc38, Sc39, and Sc40. The remaining scenarios were excluded from further analysis. As established in sub-section 4.7.4, each scenario was performed with nineteen distinct seed values (ranging from one to nineteen), and the results correspond to the average of all nineteen runs.

Although the scenarios generated to run in the *Python* algorithm and in the simulation consider the three types of store together, the results' assessment will be conducted by type of store. The assessment approach is to scale each type of store for the stress peak period in the operation (week 48), and then evaluate the loss of this scaling in the other periods of the year.

Assessment of the type of store A

Looking at the Performance Function scores for the type of store A, exhibited in Table 20, it is noted that there are no major differences between the scores obtained, especially in the scenarios of the same week, but also between the various simulated weeks. Nevertheless, it is also noted a significant drop in the score of scenarios from week 48 when compared to the other weeks, which will be discussed later. Among all the scenarios tested, the system performs best in week 7 for a 7-zone store (performance function score of 0.8367). Similarly, in the peak period of operation, the system has its most efficient performance for a 7-zones store as well (performance function score of 0.6813).

Table 20 - *Type of store A Performance Function score for each week simulated and number of zones of store.*

No. of Zones	Week			
	7	25	37	48
1	0.8327	0.8219	0.7852	0.6756
2	0.8261	0.8079	0.7454	0.6643
6	0.8355	0.8185	0.7719	0.6745
7	0.8367	0.8229	0.7742	0.6813

Regarding week 48, the best and worst (2-zones store) scenarios have close scores. Nevertheless, when analysing and comparing the scenarios in depth, it can be found that similar results do not mean similar scenarios. Table 21 shows the comparison of these scenarios in several relevant parameters for this study.

Table 21 - *Comparison between the best and worst-case scenarios for stores of type A, in week 48.*

Scenario	No. of Zones	System Throughput	Order Tote Occup. Rate	FTE Occup. Rate	FTE Occup. normalised	Avg. lead time Picking	Avg. lead time Shelf Replenishment
Best-case	7	1640	76.21%	69.88%	1.93%	0.70 min	8.96 min
Worst-case	2	1590	78.61%	76.44%	2.89%	0.72 min	13.75 min

Opting for a 7-zones store, instead of a 2-zones store, causes an increase of 50 order totes in the system throughput of the week, which leads to less occupied order totes on average – decreases by 2.40 percentage points (pp). Yet, both the FTE Occupancy Rate and the FTE Occupancy normalised metrics are lower for the best-case scenario, meaning that, when splitting the store into seven zones both the overall operation lead time and the average lead time of an order tote in the system reduce.

Extrapolating the average lead time figures of each operation to determine the total time spent in each operation during a week, it is evident the time gained when configuring the store as a 7-zones store, instead of 2-zones store. Despite the residual loss of 4.8 minutes in the picking operation (which represents less than 0.04% of the available time for picking in a week), it is in the shelf replenishment operation that the difference in the operating time is most notable. The average lead time of shelf replenishment in a store of type A divided into two zones is 13.75 minutes, which implies 21862.5

minutes of operation. In turn, in a store divided into seven zones, the average lead time of this operation is 8.96 minutes, that is, 14694.4 minutes of operation in a week. Therefore, the 7-zones store configuration, where the distances travelled during the operation are minimised, saves 7168.1 minutes in a week (almost 120 hours), i.e., 17.8% of the time for shelf replenishment of the type A store in a week.

If the company intends to have a fixed store configuration based on the configuration that best serves its interests in the stress peak period, the system might lose efficiency whenever this is not the best configuration. For the type of store under analysis, the loss shall not be highly significant since the 7-zones store configuration has also the highest score in weeks 7 and 25, and the second highest in week 37, moreover with a minimal difference to the best solution, as presented in Table 20.

According to the information displayed in Table 22, in week 37, the 1-zone store Performance Function score surpasses the score of the 7-zones configuration due to a higher order tote occupancy rate and, consequently, lower system throughput. The Performance Function components that evaluate the efficiency of the operation have similar figures for both scenarios (the FTE occupancy rate is slightly higher for the 7-zone configuration, but the FTE occupancy normalised is slightly higher for the 1-zone configuration). Thus, there is no notable superiority from one configuration over the other, in terms of the total time of operation. If the 7-zones configuration is kept, in a week the picking operation will save 13.11 hours, but 11.72 extra hours will be spent on the shelf replenishment operation.

Table 22 - *Comparison between the 1-zone and 7-zones scenarios for stores of type A, in week 37.*

Week	No. of Zones	System Throughput	Order Tote Occup. Rate	FTE Occup. Rate	FTE Occup. normalised	Avg. lead time Picking	Avg. lead time Shelf Replenishment
37	1	720	79.00%	38.96%	4.46%	2.40 min	19.95 min
	7	753	75.53%	39.02%	4.25%	1.25 min	20.01 min

As reported above, the scenarios from week 48 present significantly lower scores compared to the remaining scenarios (see Table 20). In other weeks, the Performance Function scores for any scenario are between 0.75 and 0.84, but in week 48 the scores drop considerably to around 0.67. Looking in detail at the components of the Performance Function it is noticeable that both the order tote occupancy rate (always between 70% and 80%) and the FTE occupancy normalised (always below 6%) vary minimally over the weeks. As a result, the major difference is the variance of the FTE occupancy rate. While in weeks 7, 25 and 37 the FTE occupancy rate never achieves 50%, in the peak period, the FTE occupancy reaches figures between 69.88% and 76.44%.

Assessment of the type of store B

When performing the same type of analysis for the type of store B, it can be found that the difference between the Performance Function score figures is even smaller than for type A (see Table 23). The highest system performance score is 0.8700 for a 5-zones store configuration in week 25. However, on its busiest time (week 48), the system performs most effectively for a 7-zone store (score of 0.7969).

Table 23 - *Type of store B Performance Function score for each week simulated and number of zones of store.*

No. of Zones	Week			
	7	**25**	**37**	**48**
1	0.8573	0.8648	0.8481	0.7961
2	0.8391	0.8477	0.8158	0.7422
5	0.8614	0.8700	0.8427	0.7932
7	0.8592	0.8634	0.8447	0.7969

Concerning the peak season, the best and worst-case (2-zones store) scenarios are separated by 0.0547 points. Although close, they are further apart than the performance scores for the store of type A. A thorough analysis and comparison of the metrics of each scenario reveal the differences in the impact on the system of each store configuration. In this case, there are 52 stores belonging to this type, thus, the difference in the impact on the system is magnified by this figure. Table 24 compares the best and worst-case scenarios for week 48 through several important parameters for this study.

Table 24 - *Comparison between the best and worst-case scenarios for stores of type B, in week 48.*

Scenario	No. of Zones	System Throughput	Order Tote Occup. Rate	FTE Occup. Rate	FTE Occup. normalised	Avg. lead time Picking	Avg. lead time Shelf Replenishment
Best-case	7	1093	74.23%	30.42%	3.83%	1.78 min	20.47 min
Worst-case	2	1044	77.71%	50.31%	4.74%	1.21 min	21.00 min

Looking at Table 24, it can be found that choosing a 7-zones store configuration over a 2-zones configuration increases the weekly system throughput by 49 order totes per store (i.e., 2548 processed order totes for the entire population of type B stores) since by increasing the stores' division the constraints on joining items increase, leading to a decrease in the number of possible combinations to form an order tote. However, the FTE occupancy rate and the FTE occupancy normalised of the best-case scenario for week 48 are, respectively, 19.89 pp and 0.91 pp lower than in the worst-case scenario, meaning that, especially the overall operation lead time per store, but also the average lead time of an order tote, are substantially lower under the 7-zones configuration.

Moreover, the operational average lead time values from picking and shelf replenishment operations are very similar for both configurations. It is interesting to note that, when extrapolating these values, in order to determine the total time spent in each operation during a week, it is held that the 2-zones configuration turns out to be more efficient in the picking and shelf replenishment operations. According to this method, compared to the 7-zones configuration, the 2-zones configuration spends, in a week, less 682.3 minutes (around 11.4 hours) per store in picking operations and less 449.71 minutes (around 7.50 hours) in the shelf replenishment operations of a single store. Considering the entire population of type B stores, dividing the store into only two zones saves 592.4 hours of picking (which represents 5.09% of the total available time for picking in a week) and 390 hours of shelf replenishment (which represents 3.35% of its total shelf replenishment time).

In theory, since the resource pool in both scenarios is exactly the same, it would make sense to affirm that a higher FTE occupancy rate would translate into lower time of operation. However, that is not the case. The 7-zones scenario has a much lower FTE occupancy rate (30.42% to 50.31% in the 2-zones scenario), but it is the 2-zones scenario that has the least overall time of operation. Conceptually, this phenomenon occurs due to one of the assumptions defined in the simulation model. Considering that the picking and shelf replenishment of a single order tote can only be done by a single operator causes that, at the end of each operation, when there is only one order tote remaining, instead of having both workers processing the order tote together to finish their work as quickly as possible, the simulation, as it was conceptualised, allows only one of the workers to be associated to that operation leaving the other worker free. Therefore, although the total capacity of the resource pool is not being used, the operation extends in time. Given the model's stochasticity, if the last order tote to replenish contains many units, the phenomenon will extend over a long period, giving rise to the discrepancy mentioned above.

From the comparative data displayed in the histogram of Figure 15, it is possible to see that the 2-zones scenario creates 245 order totes with a shelf replenishment lead time higher than 25 minutes (23.5% of its total system throughput), whereas the 7-zones scenario creates only 202 order totes with a lead time exceeding this figure (18.5% of its total system throughput). However, while in the 2-zones scenario the maximum shelf replenishment lead time presented is 227.92 minutes, the samples of the 7-zones scenario have much more dispersed values, being its maximum 367.49 minutes. Further, the 2-zones scenario has only 8 lead time samples above 100 minutes (0.77% of its total system throughput), whereas the 7-zones scenario has 41 samples above that value (3.75% of its total system throughput). Therefore, the differences in the shelf replenishment lead time distributions of the samples from the scenarios under analysis explain the phenomenon described above. The samples with lead times between 0 and 25 minutes were excluded from this display, since the size of the columns representing this class (which has the vast majority of the samples) would distort the presentation of the remaining columns that are intended to be highlighted in this analysis.

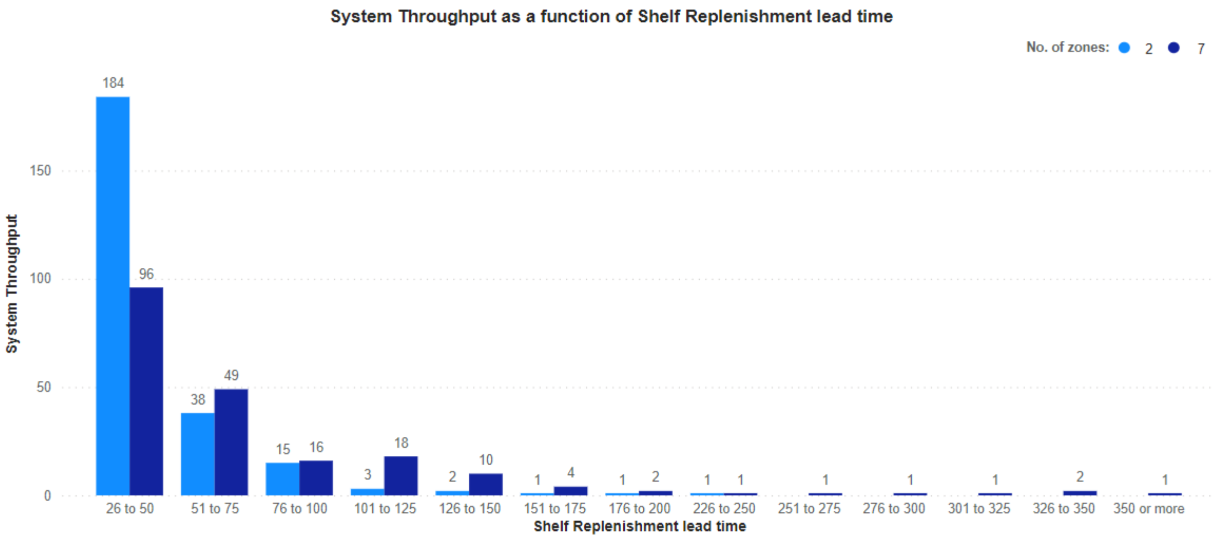

Figure 15 - *Histogram of System Throughput of 2-zones and 7-zones store configurations of type of store B in week 48 as a function of Shelf Replenishment lead time divided by classes (excluding samples with lead times of less than 26 minutes)*

Then, considering the peak season to determine the number of zones to consider during the picking operation, the system will lose more efficiency than when using the same strategy in type A stores since the 7-zones configuration is not the highest-scoring configuration in any of the remaining weeks (see Table 23). According to the parameters extracted from the simulation model runs and presented in Table

25, despite always showing similar figures, the 7-zones configuration outperforms the best-case scenario configuration in the metrics that evaluate the efficiency of the operation (FTE occupancy rate and FTE occupancy normalised) and also in the average lead times of each operation. Nonetheless, the best-case scenario configuration for each week presents a higher order tote occupancy rate. Since this metric has a larger discrepancy between the two scenarios in comparison, than the remaining metrics in the Performance Function, the performance score is lower for the 7-zones configuration.

If Worten decides to fix the 7-zones configuration the whole year, per week:

- in low season (week 7), the system will process 6 more order totes per store (i.e., 364 order totes for the entire population of type B stores) and will save only 2.76 minutes in picking per store (2.39 hours for the entire population of type B, 0.02% of the total weekly picking time), and 124.78 minutes in shelf replenishment in each store (108.14 hours in the entire population of type B, 0.93% of the total weekly shelf replenishment time available).
- on Summer holidays (week 25), the system will process 12 more order totes per store (i.e., 624 order totes for the entire population of type B stores) and spend 31.67 more minutes in shelf replenishment operations in each store (56.48 hours in the entire population of type B, 0.48% of the total weekly shelf replenishment time available), but will save 341.12 minutes in picking per store (608.33 hours for the entire population of type B, 5.22% of the total weekly picking time).
- in the Back to school season (week 37), the system will process 27 more order totes per store (i.e., 1404 order totes for the entire population of type B stores) but will save 438.24 minutes in picking per store (379.81 hours for the entire population of type B, 3.26% of the total weekly picking time), and 1278.06 minutes in shelf replenishment in each store (1107.65 hours in the entire population of type B, 9.51% of the total weekly shelf replenishment time available).

Table 25 - *Comparison between the best-case scenario of each week (7, 25, 37) and the 7-zones configuration for stores of type B.*

Week	No. of Zones	System Throughput	Order Tote Occup. Rate	FTE Occup. Rate	FTE Occup. normalised	Avg. lead time Picking	Avg. lead time Shelf Replenishment
7	5	338	75.57%	15.21%	1.95%	1.26 min	7.87 min
	7	344	74.25%	14.65%	1.84%	1.23 min	7.37 min
25	5	337	75.24%	12.69%	1.55%	1.82 min	6.42 min
	7	349	72.65%	12.13%	1.51%	0.78 min	6.29 min
37	1	435	78.22%	19.71%	4.07%	2.42 min	16.66 min
	7	462	73.65%	17.18%	3.04%	1.33 min	12.92 min

Although each simulated week represents a different period of the year in which demand and operation have different challenges and behaviours (as explained in section 4.4), for this type of store there is no difference between the figures of the operational metrics in weeks 7 and 25, as shown in Table 25. Since there is no noticeable operational change in these periods, it can be concluded that for the dimension of type B stores these two periods ought to be addressed as one.

Assessment of the type of store C

Finally, from the assessment of the Performance Function score values for stores of type C in Table 26, it is possible to declare that the best performance of the system occurs in week 37, for a 1-zone store configuration with a performance score of 0.9116. Nevertheless, during the peak season (week 48) the system performs better in a 3-zones configuration (performance score of 0.8940). The impact on the system of different scenarios is accentuated by the number of incumbent stores of type C, which is 107.

Table 26 - *Type of store C Performance Function score for each week simulated and number of zones of store.*

No. of Zones	Week			
	7	25	37	48
1	0.9091	0.9035	0.9116	0.8808
2	0.9037	0.8899	0.9017	0.8740
3	0.8991	0.8857	0.9024	0.8940
7	0.8809	0.8601	0.8812	0.8792

Again, looking at the Performance Function figures in the peak season, the best and worst-case scenarios for week 48 (respectively, 3-zones and 2-zones configuration) are only 0.0200 points away from each other. In fact, compared to the other two types of stores, type C is the one that presents Performance Function scores with a smaller gap between them (the difference between the scores of the most and least quoted scenarios is only 0.0515 points).

As already demonstrated for store types A and B, smaller differences between the performance scores of the scenarios do not mean similar scenarios since there are differences in the scores of each metric in each scenario. The best and worst-case scenarios for stores of type C in week 48 are contrasted in Table 27.

Table 27 - *Comparison between the best and worst-case scenarios for stores of type C, in week 48.*

Scenario	No. of Zones	System Throughput	Order Tote Occup. Rate	FTE Occup. Rate	FTE Occup. normalised	Avg. lead time Picking	Avg. lead time Shelf Replenishment
Best-case	3	131	74.89%	4.17%	2.51%	1.19 min	13.70 min
Worst-case	2	127	77.25%	4.57%	10.48%	5.33 min	56.82 min

From Table 27, for the same reasons explained for the type of store B, increasing the number of zones configured in stores of type C from 2 to 3, increases the weekly system throughput by 4 order totes per store (which for the entire population of type C stores equals 428 order totes) and, consequently, reduces the average order tote occupancy rate. Nevertheless, the performance of the remaining components of the Performance Function favours the 3-zones scenario.

In fact, the FTE occupancy rate figures of both scenarios are low and similar, given that this rate expresses the workers' occupation regarding the total time available to perform the operations and this type of store receives smaller quantities of items less frequently, which makes their occupancy lower than in the other types of store. However, it is the discrepancy between the figures of the FTE occupancy normalised component that is the most noticeable and that affects the most the difference in the values of the Performance Function of both scenarios.

The 7.97 pp gap between the best-case and worst-case scenarios for stores of type C in week 48 is given by the large difference in the average lead time values in the two considered operations, as shown in Table 27. Comparing the difference in their total time of operation by extrapolating the average lead time values of each operation, it is found that if implemented a 3-zones configuration, weekly the system will take less 521.02 minutes to perform the picking operation per store (equivalent to 929.15 hours for the entire population of type C stores and 7.75% of the available time) and less 5421.44 minutes (around 90 hours) to perform the shelf replenishment operation in a store (i.e., 9668.23 hours for the entire population of type C stores and 80.68% of the available time). It is important to remind the reader that these results do not mean a direct improvement of the operational time since several factors were not considered (e.g., the other activities to be performed simultaneously), but only a reduction in the time spent on this specific activity.

In the remaining weeks simulated, the store configuration that presents the best performance is always the configuration in which the whole store is considered as one zone (see Table 26). Looking at Table 28, it shows that if it is considered that these stores keep the configuration that allows the system to perform better during the most pressured period of the operation (3-zones configuration), the system will always have a higher weekly system throughput, when compared to the ideal configuration in this period (between 3 and 4 extra order totes per store). Then, both the FTE occupancy rate and the FTE occupancy normalised have closely matched values for each of the simulated weeks presented in Table 28. Through the average lead time for each operation, it is possible to establish a comparison between the differences in the total time spent in each operation over a week for each of the periods. If implemented the 3-zones store configuration:

- in the low season (week 7), the system will save 133.44 minutes of picking per store (equivalent to 237.97 hours for the entire population of type C stores, 0.99% of the total weekly picking time) and 120.44 minutes of shelf replenishment per store (equivalent to 214.78 hours in the entire population of type C, 1.79% of the total weekly shelf replenishment time available).
- on Summer holidays (week 25), the system will save 81.06 minutes of picking per store (equivalent to 144.56 hours for the entire population of type C, 0.60% of the total weekly picking time) but lose 401.59 minutes of shelf replenishment per store (equivalent to 716.18 hours in the entire population of type C, 5.98% of the total weekly shelf replenishment time available).
- in the Back-to-school season (week 37), the system will save 73.46 minutes of picking per store (equivalent to 131 hours for the entire population of type C, 0.55% of the total weekly picking time) and 43.59 minutes of shelf replenishment per store (equivalent to 77.74 hours in the entire population of type C, 0.65% of the total weekly shelf replenishment time available).

Similar to the developments in type B stores, the comparison between the operational metrics in Table 28 denotes great operational similarity in weeks 7, 25 and 37 for the type C stores. Thus, it can be determined that for this type of store dimensions the periods represented by these three weeks may be treated alike.

Table 28 - *Comparison between the 1-zone and 3-zones scenarios for stores of type C, in weeks 7, 25 and 37.*

Week	No. of Zones	System Throughput	Order Tote Occup. Rate	FTE Occup. Rate	FTE Occup. normalised	Avg. lead time Picking	Avg. lead time Shelf Replenishment
7	1	84	77.84%	3.56%	1.54%	3.16 min	5.97 min
	3	88	74.30%	3.60%	0.98%	1.50 min	4.33 min
25	1	63	77.19%	2.09%	4.05%	2.85 min	21.17 min
	3	67	72.58%	2.26%	4.62%	1.47 min	25.90 min
37	1	67	77.73%	3.08%	1.17%	1.88 min	5.07 min
	3	70	74.40%	0.84%	0.84%	0.75 min	4.23 min

Overall system assessment

From the methodology proposed, the best store configurations for each type of store at each period of the year are exposed in Table 29, considering the results obtained from the Performance Function defined. Table 29 presents the time spent on each operation per type of store given the best store configuration, and their equivalent in weekly FTEs.

Table 29 - *Total lead time and FTEs per week for Picking and Shelf Replenishment operations for the entire population of each type of Worten store, considering the best store configuration at each period of the year.*

Store Type	Period	Store Configuration	Total lead time Picking	FTEs Picking	Total lead time Shelf Replenishment	FTEs Shelf Replenishment
A	Low season	7-zones	7.38 hours	2	140.98 hours	22
	Summer holidays	7-zones	10.21 hours	2	152.21 hours	24
	Back-to-school	1-zone	28.80 hours	5	239.40 hours	37
	Black Friday & Christmas	**7-zones**	**19.13 hours**	**3**	**244.91 hours**	**38**
B	Low season	5-zones	369.10 hours	57	2305.39 hours	355
	Summer holidays	5-zones	531.56 hours	82	1875.07 hours	289
	Back-to-school	1-zone	912.34 hours	141	6280.82 hours	967
	Black Friday & Christmas	**7-zones**	**1686.13 hours**	**260**	**19390.55 hours**	**2984**
C	Low season	1-zone	473.37 hours	73	894.31 hours	138
	Summer holidays	1-zone	179.55 hours	28	2378.45 hours	366
	Back-to-school	1-zone	224.63 hours	35	605.78 hours	94
	Black Friday & Christmas	**3-zone**	**278.00 hours**	**43**	**3200.55 hours**	**493**

As a result, following this methodology and adopting the best performance store configurations for each type of store in a period with demand similar to the peak season of 2021 (Black Friday & Christmas), Worten would spend in the warehouse the equivalent to 1983.26 hours per week in the picking operations of small-sized items to ship for its stores in Portugal, and the equivalent to 22836.01 hours per week in shelf replenishment operations of these items in store. Considering, for illustrative purposes, that a Worten operator works 6.5 hours a day (8 working hours, less one hour for lunch and half an hour of resting time), during the Black Friday & Christmas period of the year, the company would need the equivalent to 306 FTEs per week in the picking operation (approximately, 44 FTEs per day). In the same period, Worten would need the equivalent to 3515 FTE per week in the shelf replenishment operation of its entire population of stores (approximately, 503 FTEs per day), i.e., the equivalent to 38 FTEs per week for a type A store, the equivalent to 58 FTEs per week for a type B store, and the equivalent to 5 FTEs per week for a type C store.

Chapter 6 – Conclusions, Limitations and Future Work

As a retail company, the development and growth of Worten's business are directly related to the efficiency and productivity of its operations, the integration between entities, and the response that the company can give to new logistical challenges. Over the years, the increase in the number of stores and the establishment of new channels to meet customers' expectations lead to a highly complex supply chain. The warehouse in Azambuja is the heart of that supply chain. It is an essential entity in the inventory holding and distribution of items through every channel (either online or retail).

The internal projection for the growth of the company's operations, based on the projected growth of the sales volume, concludes that the current capacity of the warehouse owned by the company will not be sufficient to accomplish its needs in the incoming years. Therefore, to continue operating in the same space, there is a need to find solutions to increase storage density and operational efficiency, which can be achieved through the implementation of automation solutions in the warehouse.

The company intends to install an automated storage system for small-sized products, which allows compacting storage of this type of products, with an integrated G2P system. Considering all this, the objective purposed for this dissertation was to investigate the impact of different configurations of the G2P system to implement on the combined efficiency of the order picking and the in-store replenishment operations.

Extensive research on academic literature was conducted to acquire theoretical foundation for this work. This research focused on four main topics: retailing, warehouse operations, physical stores operations, and modelling and simulation. This latter topic was studied after concluded (through analysis of academic studies with similar characteristics) that this work's methodology should encompass a simulation study. Doing this research, it was also found that the subject under consideration constitutes a gap in academic research since the combined improvement of warehouse and retail stores is not explored.

In order to solve the problem at hand, a six-modules methodology was developed, which concludes with a simulation study to replicate the store replenishment process since the order picking operation in the warehouse. The first module divided the entire population of Worten stores in Portugal according to their dimensions and sales volume, resulting in three types of stores. Secondly, possible store divisions for carrying out the picking operation were defined for each type of store, based on the structure and operations of one model store for each type. Then, the third module defined the periods to consider in the simulation study, according to the expedition records of the company of 2021 and the company's shipment planning.

Additionally, the fourth module aimed to define the order totes' composition based on the arrival order of the inventory and on the store configuration restrictions imposed in each scenario. To this end, it was developed an algorithm in *Python* programming language which retrieves the composition of each order tote given the type of stores, the items belonging to each zone of store, and the expedition records (or predictions) to each store in the analysis.

The fifth module determined the activity times of the operations under analysis: picking and shelf replenishment. The time of each operation was divided in several components according to the activity morphology. To develop this module, it was necessary to overcome the limitation of the impossibility to study the duration of each activity empirically since the system under study was not yet implemented. As a result, these time components were determined by experiments with different levels of accuracy.

Finally, the last module was a stochastic simulation model which was built to replicate the replenishment process of small-sized items to the stores with an integrated G2P system. All previous modules were composed to determine the inputs to this module. The simulation model was developed in *AnyLogic*. A rigorous verification, while developing the model through academic approved techniques, declared the model valuable to replicate the system Worten's store replenishment process of small-sized items with a G2P system installed.

To assess the impact of the different configurations of the system in each store and at each period, 48 scenarios were developed to test different simulation periods, arrival order set-up of inventory totes, and number of zones considered in each type of store. From all these scenarios, only the ones in which the priority of arrival order set-up of inventory totes is given to higher volume SKUs were simulated in *AnyLogic*, as they presented a clear advantage over the remaining scenarios. Each scenario was evaluated through metrics which determine their performance in three important aspects: the efficiency of filling the order totes (measured by the system throughput and the average order tote occupancy rate in each scenario), the resource occupation (measured by the FTE occupancy rate) and the average time spent to perform the operation for a single order tote (measured by the average time spent by an FTE in each operation). At last, a function was elaborated to assign a score to each scenario according to its performance in each of these three aspects.

Assuming Worten intends to maintain a fixed configuration throughout the year in each store, it is recommended a 7-zones store configuration for type A and B stores and a 3-zones store configuration for type C stores, as these are the configurations with best performance scores for each type of store in the Black Friday and Christmas period (peak season of the company).

Having concluded this study, it is relevant to highlight its limitations so that they are clear to the reader. Regarding the calculation of the simulation times, none of the time components was determined from empirical measurements, which would be more accurate. Further, the impact of the weight of the products was not considered in the traveling time components (interZoneTime and intraZoneTime), and the number of products on the shelf was not considered to calculate the putTime component, although these factors may have relevance in the components pointed out. In respect of the order totes' configuration, the only characteristic of the items considered was their volume. Although considered a factor for the wasted space with incompatible package formats, if other characteristics were considered (as the weight or dimensions), determination of the order totes' configuration would be more precise and realistic. In the simulation model, the agent Worker could be more detailed since their experience, morphology or biological characteristics may affect their picking and shelf replenishment performance. Additionally, in the shelf replenishment activity, the sequence of the order totes processed is considered as completely random. However, operators organise their activity to make as few trips as possible in the showroom, thus, it would make sense to consider that the same agent Worker processes sequentially order totes from the same zone.

Furthermore, some suggestions for future work are provided based on the knowledge acquired. First, regarding the order tote configuration, in this research was assumed that the order totes could only be filled by SKUs belonging to the same zone of store. In future research would be interesting to study the impact of joining SKUs from contiguous zones in the same order tote, if the volume of items separated by zones resulted in an order tote with low occupancy rate. Then, regarding the G2P system to install in the warehouse, it was concluded that the system is favoured when the priority of arrival order set-up of the inventory totes is given to higher volume SKUs. Thus, as future work it is important to study how to configurate the automated warehouse and G2P system to be able to implement this set-up in the system. In that case, should be considered that there is a limited number of order totes that can be filled in the G2P station at the same time, as well as the capacity of the inventory totes for each SKU (both excluded from this work). Concerning the in-store replenishment operation, this study considered that one order tote could only be processed by a single operator as a valid simplification of the real system since it does not significantly change the total time of operation. In future work, it would be interesting to study the system without this restriction since this will certainly have an impact on the resource occupation and on the average time spent to replenish a single order tote.

Finally, the fourth suggestion of this work is to perform a cost benefit analysis of each scenario, to complement the performance analysis shown in this work. In this way, the company's decision-makers will have more comparative data on the implementation of each scenario and will be able to decide with greater certainty on the configuration to implement for each type of store.

References

Alexander, B., & Blazquez Cano, M. (2020). Store of the future: Towards a (re)invention and (re)imagination of physical store space in an omnichannel context. *Journal of Retailing and Consumer Services*, *55*.

Azevedo, C. (2022, March 17). *Sonae increases turnover by 5% to record figure above 7 billion euros*. Sonae.pt. Retrieved April 5, 2022, from https://www.sonae.pt/en/media/press-releases/sonae-increases-turnover-by-5-to-record-figure-above-7-billion-euros/

Baines, T. (2004). An integrated process for forming manufacturing technology acquisition decisions. *International Journal of Operations and Production Management*, *24*(5–6), 447–467.

Baker, P. (2007). An exploratory framework of the role of inventory and warehousing in international supply chains. *The International Journal of Logistics Management*, *18*(1), 64–80.

Baker, P., & Halim, Z. (2007). An exploration of warehouse automation implementations: Cost, service and flexibility issues. *Supply Chain Management*, *12*(2), 129–138.

Balci, O. (1994). Validation, verification, and testing techniques throughout the life cycle of a simulation study. *Ann Opns Res*, *53*, 121–173.

Banks, J. (1998). *Handbook of Simulation - Principles, Methodology, Advances, Applications and Practice*. Engineering & Management Press.

Bartholdi, J. J., & Hackman, S. T. (2019). *Warehouse & Distribution Science*.

Berman, B. (2019). Flatlined: Combatting the death of retail stores. *Business Horizons*, *62*(1), 75–82.

Bixler, M. J., & Honhon, D. (2021). Exploring the connections between backrooms, inventory record inaccuracies, and waste. In *Sustainability (Switzerland)* (Vol. 13, Issue 17). MDPI.

Bohannon, R. W., & Andrews, A. W. (2011). Normal walking speed: a descriptive meta-analysis. *Physiotherapy*, *97*(3), 182–189.

Borshchev, A., & Grigoryev, I. (2013). *The Big Book of Simulation Modeling*.

Bortfeldt, A., & Gehring, H. (2000). *Theory and Methodology A hybrid genetic algorithm for the container loading problem*.

Boysen, N., de Koster, R., & Weidinger, F. (2019). Warehousing in the e-commerce era: A survey. In *European Journal of Operational Research* (Vol. 277, Issue 2, pp. 396–411). Elsevier B.V.

Boysen, N., Fedtke, S., & Weidinger, F. (2018). Optimizing automated sorting in warehouses: The minimum order spread sequencing problem. *European Journal of Operational Research*, *270*(1), 386–400.

Brands of companies by Sonae, in different areas of business. Sonae.pt. (2022). Retrieved April 5, 2022, from https://www.sonae.pt/en/sonae/brands/

Byrne, M. D. (2013). *How Many Times Should a Stochastic Model Be Run? An Approach Based on Confidence Intervals*.

Cai, Y. J., & Lo, C. K. Y. (2020). Omni-channel management in the new retailing era: A systematic review and future research agenda. *International Journal of Production Economics*, *229*.

Carson, J. S. (2005). Introduction to modeling and simulation. *Proceedings of the Winter Simulation Conference*, *IEEE*, 16–23.

Chung, C. A. (2004). Simulation Modeling Handbook: A practical approach. *CRC Press*.

Custodio, L., & Machado, R. (2020). Flexible automated warehouse: a literature review and an innovative framework. *International Journal of Advanced Manufacturing Technology*, *106*(1–2), 533–558.

Dangerfield, B. (2014). System thinking and system dynamics: A primer. In Brailsford S, Churilov L, & Dangerfield B (Eds.), *Discrete-even Simulation and System Dynamics for Management Decision Making* (pp. 26–51). Wiley Series in Operations Research and Management Science.

Daria, B., Martina, C., Alessandro, P., Manuel, R., & Fabio, S. (2015). *Dual-tray Vertical Lift Module for order picking: a performance and storage assignment preliminary study*.

Davarzani, H., & Norrman, A. (2015). Toward a relevant agenda for warehousing research: literature review and practitioners' input. *Logistics Research*, *8*(1).

de Koster, R. (2004). *How to assess a warehouse operation in a single tour*.

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

DeHoratius, N., & Raman, A. (2008). Inventory record inaccuracy: An empirical analysis. *Management Science*, *54*, 627–641.

Đukić, G., Opetuk, T., & Gajšek, B. (2021). Space, Time and Ergonomics Assessment of Order Picking Using Horizontal Carousel. In *Ergonomics 2020: Proceedings of the 8th International Ergonomics* (pp. 73–83). Springer.

Dukic, G., Opetuk, T., & Lerher, T. (2015). A throughput model for a dual-tray Vertical Lift Module with a human order-picker. *International Journal of Production Economics*, *170*, 874–881.

Eroglu, C., Williams, B. D., & Waller, M. A. (2013). The backroom effect in retail operations. *Production and Operations Management*, *22*(4), 915–923.

Eroglu, C., Williams, B. D., & Waller, M. A. (2018). Using the Pack-and-a-Half Rule to Eliminate Backroom Inventories in Retail Operations. *Journal of Business Logistics*, *39*(3), 164–181.

Forrester, J. W. (2009). *Some Basic Concepts in System Dynamics*.

Grigoryev, I. (2021). *Anylogic in three days* (5th ed.).

Grosse, E. H., Glock, C. H., & Neumann, W. P. (2017). Human factors in order picking: a content analysis of the literature. *International Journal of Production Research*, *55*(5), 1260–1276.

Gruen, T. W., & Corsten, D. (2007). A Comprehensive Guide to Retail Out-of-Stock Reduction in the Fast-Moving Consumer Goods Industry. *Grocery Manufacturers Association (GMA), Food Marketing Institute (FMI), National Association of Chain Drug Stores (NACDS), The Procter & Gamble Company (P&G), the University of Colorado at Colorado Springs*.

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

Habazin, J., Glasnović, A., & Bajor, I. (2017). ORDER PICKING PROCESS IN WAREHOUSE: CASE STUDY OF DAIRY INDUSTRY IN CROATIA Picking Process in Warehouse: Case Study of Dairy Industry in Croatia. In *Promet-Traffic&Transportation* (Vol. 29, Issue 1).

Higginson, J. K., & Bookbinder, J. H. (2005). Distribution centres in supply chain operations. *Logistics Systems: Design and Optimisation*, *Springer*, 67–91.

History. Sonae.pt. (2022). Retrieved April 4, 2022, from https://www.sonae.pt/en/sonae/history/

Huang, G. Q., Chen, M. Z., & Pan, J. (2015). Robotics in ecommerce logistics. *HKIE Transactions*, *22*(2), 68–77.

Hübner, A., & Schaal, K. (2017). Effect of replenishment and backroom on retail shelf-space planning. *Business Research*, *10*(1), 123–156.

Hwang, H., Kim, C.-S., & Ko, K.-H. (1999). *Performance analysis of carousel systems with double shuttle*.

Israel, G. D. (1992). *Determining Sample Size 1 The Level of Precision*.

Jaghbeer, Y., Hanson, R., & Johansson, M. I. (2020). Automated order picking systems and the links between design and performance: a systematic literature review. *International Journal of Production Research*, 4489–4505.

Kaikati, J. G., & Kaikati, A. M. (2006). Slotting and Promotional Allowances: Red Flags in the Supply Chain. *Supply Chain Management: An International Journal*, *11*(2), 140–147.

Kembro, J. H., Norrman, A., & Eriksson, E. (2018). Adapting warehouse operations and design to omni-channel logistics: A literature review and research agenda. In *International Journal of Physical Distribution and Logistics Management* (Vol. 48, Issue 9, pp. 890–912). Emerald Group Holdings Ltd.

Kim, G., & Moon, I. (2021). Integrated planning for product selection, shelf-space allocation, and replenishment decision with elasticity and positioning effects. *Journal of Retailing and Consumer Services*, *58*.

Law, A. M. (2000). Simulation Modeling and Analysis. *McGraw-Hill Education*.

Lee, H. Y., & Murray, C. C. (2019). Robotics in order picking: evaluating warehouse layouts for pick, place, and transport vehicle routing systems. *International Journal of Production Research*, *57*(18), 5821–5841.

Mahajan, P. S., & Ingalls, R. G. (2004). Evaluation of methods used to detect warm-up period in steady state simulation. *Proceedings - Winter Simulation Conference*, *1*, 663–671.

Maltz, A. (2004). *Warehousing: The Evolution Continues Stochastic lead-times View project*.

Misonzhnik, E. (2017). Store closing data looks foreboding for malls. *National Real Estate Investor*.

Mou, S., Robb, D. J., & DeHoratius, N. (2018). Retail store operations: Literature review and research directions. In *European Journal of Operational Research* (Vol. 265, Issue 2, pp. 399–422). Elsevier B.V.

Nance, R. (1994). The conical methodology and the evolution of simulation model development. *Ann Opns Res*, *53*, 1–45.

Petersen, C. G., & Aase, G. (2004). A comparison of picking, storage, and routing policies in manual order picking. *International Journal of Production Economics*, *92*(1), 11–19.

Pidd, M. (2003). *Computer Simulation in Management Science* (John Wiley & Sons inc, Ed.).

Pires, M., Camanho, A., & Amorim, P. (2020). Solving the grocery backroom sizing problem. *International Journal of Production Research*, *58*(18), 5707–5720.

Pires, M., Pratas, J., Liz, J., & Amorim, P. (2017). A framework for designing backroom areas in grocery stores. *International Journal of Retail and Distribution Management*, *45*(3), 230–252.

Público. (2015, March 15). *Cronologia: Acontecimentos Marcantes da História da Sonae*. Cronologia: acontecimentos marcantes da história da Sonae. Retrieved April 4, 2022, from https://www.publico.pt/2015/03/15/economia/noticia/cronologia-acontecimentos-marcantes-da-historia-da-sonae-1689182

Qi, M., Mak, H. Y., & Shen, Z. J. M. (2020). Data-driven research in retail operations—A review. *Naval Research Logistics*, *67*(8), 595–616.

Richards, G. (2018). *Warehouse Management: A complete guide to improving efficiency and minimizing costs in the modern warehouse* (3rd ed.). Kogan Page Limited.

Robinson, S. (1999). Simulation verification, validation and confidence: a tutorial. *Transactions of the Society for Computer Simulation*, *16*(2), 63–69.

Robinson, S. (2006). Conceptual modeling for simulation: Issues and research requirements. *Proceedings - Winter Simulation Conference*, 792–800.

Robinson, S. (2008). Conceptual modelling for simulation Part I: Definition and requirements. *Journal of the Operational Research Society*, *59*(3), 278–290.

Robinson, S. (2014). Discrete-event simulation: A primer. In S. Brailsford, L. Churilov, & B. Dangerfield (Eds.), *Discrete-event Simulation and System Dynamics for Management Decision Making* (pp. 10–25). Wiley Series in Operations Research and Management Science.

Robinson, S. (2017). A Tutorial on Simulation Conceptual Modeling. In W. K. v. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, & E. Page (Eds.), *WSC : 2017 Winter Simulation Conference : 3-6 December 2017.* (pp. 565–579).

Roodbergen, K., & Vis, I. (2006). A model for warehouse layout. *IIE Transactions (Institute of Industrial Engineers)*, *38*(10), 799–811.

Rosseti, M. (2015). Simulation Modeling and Arena. *John Wiley & Sons*.

Rouwenhorst, B., Reuter, B., Stockrahm, V., van Houtum, G. J., Mantel, R. J., & Zijm, W. H. M. (2000). Warehouse design and control: framework and literature review. *European Journal of Operational Research*, *122*(3), 515–533.

Rushton, A., Croucher, P., & Baker, P. (2022). *The Handbook of Logistics and Distribution Management: Understanding the Supply Chain* (7th ed.). Kogan Page Publishers.

Shetty, N., Sah, B., & Chung, S. H. (2020). Route optimization for warehouse order picking operations via vehicle routing and simulation. *SN Applied Sciences*, *2*(2).

Siebers, P. O., MacAl, C. M., Garnett, J., Buxton, D., & Pidd, M. (2010). Discrete-event simulation is dead, long live agent-based simulation! In *Journal of Simulation* (Vol. 4, Issue 3, pp. 204–210). Palgrave Macmillan Ltd.

Sonae in the World. Sonae.pt. (2022). Retrieved April 4, 2022, from https://www.sonae.pt/en/sonae/where-we-are-in-the-world/

Sterman, J. D. (2002). *SYSTEM DYNAMICS: SYSTEMS THINKING AND MODELING FOR A COMPLEX WORLD*.

Tan, Z., Li, H., & He, X. (2021). Optimizing parcel sorting process of vertical sorting system in e-commerce warehouse. *Advanced Engineering Informatics*, *48*.

Tompkins, J. A., White, J. A., Bozer, Y. A., & Tanchoco, J. M. A. (2010). *Facilities Planning*. John Wiley & Sons.

Ton, Z., & Raman, A. (2010). The effect of product variety and inventory levels on retail store sales: A longitudinal study. *Prod. Operations Management*, *19*, 546–560.

Turgut, Ö., Taube, F., & Minner, S. (2018). Data-driven retail inventory management with backroom effect. *OR Spectrum*, *40*(4), 945–968.

van den Berg, J. P. (2002). Analytic expressions for the optimal dwell point in an automated storage=retrieval system. In *Int. J. Production Economics* (Vol. 76).

Vijayakumar, V., & Sgarbossa, F. (2021). A literature review on the level of automation in picker-to-parts order picking system: Research opportunities. *IFAC-PapersOnLine*, *54*(1), 438–443.

Xue, W., Caliskan Demirag, O., Chen, F. Y., & Yang, Y. (2017). Managing Retail Shelf and Backroom Inventories When Demand Depends on the Shelf-Stock Level. *Production and Operations Management*, *26*(9), 1685–1704.

Yaw Wong, C., & McFarlane, D. (2007). Radio frequency identification data capture and its impact on shelf replenishment. *International Journal of Logistics Research and Applications*, *10*(1), 71–93.

Zentes, J., Morschett, D., & Schramm-Klein, H. (2016). *Strategic Retail Management* (3rd ed.).

Zhuang, Y., Zhou, Y., Yuan, Y., Hu, X., & Hassini, E. (2022). Order picking optimization with rack-moving mobile robots and multiple workstations. *European Journal of Operational Research*, *300*(2), 527–544.

Appendix

***Table 30 -** Relevant characteristics of each zone in each type of store*

Store type		Type A			Type B			Type C		
Zone	#SKU	Area (m^2)	Centroid	X (m)[15]	Area (m^2)	Centroid	X (m)	Area (m^2)	Centroid	X (m)
1 - Small home appliances 1	30842	384	(12, 42)	14.42	175	(7, 6.25)	9.38	68.25	(10.25, 13.25)	6.17
2 - Small home appliances 2	10709	216	(30, 43)	10.82	125	(19, 6.25)	8.00	32.5	(18.75, 12.5)	4.10
3 - Hi-Fi	29950	632.5	(53.99, 34.21)	29.35	198	(46.5, 24)	10.55	79.25	(26.16, 5.23)	7.35
4 - IT	41578	604	(15.72, 24.17)	22.54	355	(21.02, 19.80)	18.52	71	(11.99, 5.78)	6.54
5 - Entertainment & Gaming	101692	309	(37.45, 21.73)	14.62	80.5	(37.5, 27.25)	6.73	62.25	(19.14, 4.85)	6.52
6 - Promotions, Mobile & Printing	41411	467	(30.30, 8.49)	24.19	262.5	(10.39, 28,47)	16.90	73	(4.12, 5.23)	6.46
7 - Mobile Panel	43117	22	(19.98, 0.56)	12.07	18	(0.5, 31)	9.01	16	(8, 0.5)	8.02

***Table 31 -** Description of the triangular distribution defining the intraZoneTime component, for each zone of store and type of store (in minutes).*

Type	Zone	Minimum value (a)	Maximum value (b)	Mode (c)
A	1	0.0239	0.68938	0.34469
	2	0.0239	0.51704	0.25852
	3	0.0239	1.06482	0.70139
	4	0.0239	0.90694	0.53866
	5	0.0239	0.69475	0.34936
	6	0.0239	1.12355	0.57807
	7	0.0239	0.55177	0.28850
B	1	0.0239	0.44856	0.22428
	2	0.0239	0.38259	0.19129
	3	0.0239	0.50417	0.25209
	4	0.0239	0.86841	0.44258
	5	0.0239	0.32176	0.16088
	6	0.0239	0.73626	0.40381
	7	0.0239	0.43086	0.21543
C	1	0.0239	0.29514	0.14757
	2	0.0239	0.19599	0.09800
	3	0.0239	0.31572	0.17575
	4	0.0239	0.30420	0.15622
	5	0.0239	0.29875	0.15587
	6	0.0239	0.30420	0.15435
	7	0.0239	0.38315	0.19157

[15] Distance from the centroid to the furthest point of the zone