Stock Behaviour and Inventory Replenishment Strategy

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Abstract

HUUB was a technological start-up whose aim was to manage the supply chain of retailers and connect the various players involved. Its services were focused on a platform that allowed it to offer its clients, the retailers, transparency regarding the processes involved in the supply chain. In 2021 HUUB was acquired by the multinational Maersk to strengthen a new branch of the company, the supply chain, and the integrated logistics sector. This means that HUUB now has a different reality and is exposed to larger customers. With this new dimension there are new challenges, one of which is the need to offer retailers a tool that guides them in their stock management.

This challenge arises essentially because e-commerce has been growing at a peak in the last few years and, although it allows retailers to profit from online transactions, it has also broken the geographic barriers which, in turn, has dispersed the demand and generated a greater difficulty regarding inventory management. Therefore, this dissertation focuses on the development of a model capable of recommending to retailers a stock replenishment plan at the product level that guarantees the satisfaction of the predicted demand, while minimizing the associated logistics costs. So far, this need had no solution in the HUUB reality.

The first step was an in-depth investigation of the operational process of purchasing and transportation of goods to understand the sources and structure of the costs involved in the process of restocking. Based on the cost structure explored, four different methods for obtaining the replenishment plans were developed, three methods based on heuristics, namely Least Unit Cost, Silver Meal, and Part Period Simplified heuristics, and one optimization model, so that a comparison could be made to understand which method was best. Once developed, they were compared in terms of cost structure and runtime, and it was found that, in general, there were no significant differences in any of the two parameters evaluated. However, the best method seemed to be the optimization model because it always allows to achieve the lowest cost and no big differences in the running time. Besides, it is the only method that allows to recommend sending through the two transport modes in the same order and, furthermore, it is more easily scalable for future works.

Finally, to enrich the work done so far, a sensitivity analysis was performed. It was found that the stock replenishment plan is not very sensitive to variations in the various cost factors.

The present project is the first step toward creating a tool for recommending stock replenishment plans.

Resumo

A HUUB era uma start-up tecnológica cujo objetivo era a gestão da cadeia de abastecimento dos retalhistas e a conexão dos vários intervenientes envolvidos. Os seus serviços eram focados numa plataforma que permitia oferecer aos seus clientes, as marcas, transparência relativamente aos processos envolvidos na cadeia de abastecimento. Em 2021 a HUUB foi adquirida pela multinacional Maersk para fortalecer um novo ramo da empresa, o setor da cadeia de abastecimento e de logística integrada, o que faz com que agora a realidade HUUB passe a ser outra, estando assim exposta a clientes de maiores dimensão. Com esta nova dimensão surge mais desafios, sendo um deles a necessidade de oferecer às marcas uma ferramenta que lhes oriente relativamente à gestão de stock.

Este desafio surge essencialmente devido ao facto de, nos últimos anos, o e-commerce ter vindo a crescer a pico e, apesar do mesmo permitir às marcas lucrarem com transações *online*, também veio quebrar as barreiras geográficas o que, por sua vez, fez dispersar a procura e gerar uma maior dificuldade relativamente à gestão de inventário. Assim sendo, a presente dissertação foca-se no desenvolvimento de um modelo capaz de recomendar às marcas um plano de reposição de stock ao nível do produto que garanta a satisfação da procura prevista, ao mesmo tempo que procura minimizar os custos logísticos associados. Este necessidade até ao momento não tinha qualquer tipo de solução na realidade HUUB.

O primeiro passo foi uma investigação profunda do processo operacional de compra e transporte de mercadoria, de modo a perceber quais as fontes e a estrutura dos custos envolvidos no processo de reposição de stock. Com base na estrutura de custos explorada, foram desenvolvidos quatro métodos diferentes, três baseados em heurísticas, nomeadamente as heurísticas *Least Unit Cost*, *Silver Meal* e *Part Period Simplified*, e um modelo de otimização, de modo a poder ser feita uma comparação para perceber qual o melhor método. Depois de desenvolvidos, os mesmos foram comparados a nível da estrutura de custos e do tempo de corrida, verificando-se que, de um modo geral, não existiam diferenças significativas em nehum dos dois parâmetros avaliados. No entanto, o melhor método pareceu ser o modelo de otimização por permitir atingir sempre os custos mais baixos e sem grandes diferenças no tempo de corrida. Além disso, é o único métodos que permite recomendar enviar através dos dois modos de transporte possíveis na mesma ordem e é mais facilmente escalável para trabalhos futuros.

Por fim, para enriquecer o trabalho feito até então, foi feita uma análise de sensibilidade e verificou-se que o plano de reposição de stock é pouco sensível às variações dos vários fatores de custo.

O presente projeto é o primeiro passo para a criação de uma ferramenta de recomendação de planos de reposição de stock.

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To my brother and sister for always being by my side, for helping me and for being an unconditional support. To my grandmother for the great love, affection, and care she has given me since I was born.

To all, my sincere thank you.

"Para vencer - material ou imaterialmente - três coisas definíveis são precisas: saber trabalhar, aproveitar oportunidades, e criar relações. O resto pertence ao elemento indefinível, mas real, a que, à falta de melhor nome, se chama sorte."

Fernando Pessoa

Contents

Acronyms and Symbols

SC	Supply Chain
DIA	Dynamic Inventory Assistant
KPI	Key Performance Indicator
TPL	Third-Party Logistics
SCM	Supply Chain Management
EOQ	Economic Order Quantity
WW	Wagner-Whitin
SM	Silver-Meal
LUC	Least Unit Cost
PPS	Part Period Simplified
LL	Less than Container/Truck Load
FL	Full Container/Truck Load
SS	Safety Stock
PO	Purchase Order
SASS	Stock Above the SS
LT	Lead Time
SBD	Stock at the beginning of day
SBDASS	Stock at the beginning of day above SS
NR	Net requirements
BSA	Batch Size that should Arrive
BSP	Batch Size that should be Purchased
SED	Stock at the End of Day
MIP	Mixed Integer Programming

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Chapter 1

Introduction

For an online retailer that sells in several parts of the world, deciding on the appropriate level of stock in each of the geographies in order to meet the respective demand and reduce logistical costs can be a difficult task. As such, the emergence of this dissertation, carried out in HUUB by Maersk that now constitutes the Maersk E-Commerce Logistics department, more specifically in the area of E-fulfilment, comes in the sense of offering brands a tool capable of guiding it regarding the stock management and replenishment, since the problem addressed considers that the retailers work on a make to stock inventory approach and, therefore, keep stock on the fulfiment centers close to markets of demand.

1.1 Motivation

In recent years, e-commerce has become an increasingly important component of the global retail structure. With the emergence of the internet, the retail sector has undergone a substantial transformation and has allowed brands from several countries to benefit and profit from online transactions. The share of e-commerce in the total global retail sales in 2021 accounted for nearly 19,6 percent of retail sales worldwide and forecasts indicate that e-commerce will be close to a quarter of total global retail sales by 2025 (Coppola, 2022).

According to Bai et al. (2021), the pandemic anticipated the adhesion to e-commerce, squeezing years of digital sales penetration into months. Since the beginning of the pandemic, e-commerce purchases have increased from 40% to 60% compared to pre-pandemic levels and more than 50% of consumers are expected to continue their online shopping habits and this pattern will fuel the growth of online sales.

The great adherence to online commerce in the pandemic period resulted in a great impact on supply chains, ending up testing and exposing the vulnerabilities of the global logistics network (Keenan, 2022). Therefore, given the scenario of uncertainty experienced during this period, it has become increasingly important to have a real-time view of the stock in all stores, warehouses and in transit to see if the stock is in excess or below the limits of safety stock, i.e., identify mismatches between demand and inventory availability faster so that retailers can take immediate steps to re-balance the stock (Staub, 2021). In addition to being more important to understand the level of stock, it has also become more important to understand how much to order and when, to avoid excess working capital invested in the idle stock. The COVID-19 pandemic has prompted governments, investors, CEOs, and others to take a closer look at the working capital since this can serve as a proxy for their resilience against difficult economic times and, for this reason, companies are trying to improve their stock management to optimize the use of their working capital through strong inventory management. A disciplined approach would proportionate enough cash to provide comfort against tough economic times (Batherosse, 2022).

The transition of brands to the online world causes them to lose some ground regarding inventory management all over the world and regarding the logistic processes involved in its replenishment. As such, an opportunity arises here to offer these brands tools that allow them to be aware of the inventory level and optimize it.

These brands' needs, that is emerging even more with the explosion of e-commerce, served as motivation for this dissertation, in the sense of offering brands better control over their stock and a better understanding of the costs involved in the replenishment process.

1.2 Company Overview

HUUB is a Portuguese tech startup founded in 2015 that operates in the logistics field for the fashion industry.

Sometimes it can be challenging for a brand to manage its entire Supply Chain (SC) due to its complexity, resulting in a lack of visibility. As that, HUUB is positioned as the connection of all SC stakeholders and offers a completely digital and omnichannel experience of the SC by managing all fundamentals of a logistic operation, such as inventory, fulfillment, and delivery that is supported by a data-driven approach, which allows an all-encompassing view of the SC.

HUUB accomplish this comprehensive view of the SC through a digital logistics integrated platform - SPOKE - that manages the interaction between the different stakeholders, such as the suppliers, the partners, the fashion brands (clients), and their end-customers (brand's customers).

SPOKE is a collaborative platform that connects the brands' e-commerce platform with the entire SC and that provides an interface that allows brands to monitor their SC and manage their inventory without the burden of managing the daily operations. Since this platform manages the entire logistic process, the brands' efforts are reduced, allowing them to focus on their core business.

To increase the value proposition, besides the platform, HUUB also provides warehousing and distribution services. Regarding warehousing, HUUB provides inbound services, such as verifying goods quantities and quality, pick and pack services. Regarding the distribution, HUUB's role is to choose for each brand the best shipping partner for each country. Additionally, since HUUB manages the entire brand's value chain, it has access to a set of data that allow it to analyze the market and draw conclusions and, therefore, it enables HUUB to offer insights to brands about the market, which increase the value proposition offered.

With this value proposition, HUUB embraces the commitment of pursuing sustainable growth for every stakeholder's business and leveraging the flow of information throughout the chain.

1.2.1 Acquisition by Maersk

HUUB was, in August of 2021, the third acquisition of the Danish multinational Maersk within E-commerce Logistics.

Maersk is a Danish company active in a wide variety of business sectors but stands out for its activity in the transport and energy sectors. Additionally, it also offers supply chain management services and integrated logistics solutions to simplify customers' supply chains.

HUUB's acquisition by Maersk was accomplished to fortify the new focus in the integrated logistics field and to improve the performance in this area. The aim is that, after integrating HUUB's platform into the solutions offered by Maersk E-commerce Logistics, customers and partners can have access to easy-to-use interfaces that allow them to have visibility of stock and all logistical processes. Thus, with this omnichannel logistics product, customers can focus on their core business of producing and selling goods and will be able to offer their products faster to the end-consumers (Prevljak, 2021).

Following the acquisition, HUUB became part of the Maersk E-commerce Logistics team and is currently in a phase of transition and integration with Maersk.

1.3 Problem Addressed

As referred before, with the growth of e-commerce, online demand is growing and scattering across different parts of the world and, consequently, it is no longer centralized in one place.

However, the dispersion of demand and the increasing breakdown of geographical barriers make stock management more difficult for brands, especially when they start to have more warehouses spread across different parts of the globe since it difficult the decision of where to allocate their stock. It is the case of Maersk E-commerce Logistics customers. With the emergence of Maersk E-commerce Logistics, brands began to have the possibility to open physical operations all over the world and to have stock close to the various demand clusters due to the vast network of warehouses available. However, without a good stock management strategy, retailers can jeopardize all the benefits of having a comprehensive warehouse network and, consequently, can incur high costs due to misallocation and poor replenishment of stock.

Brands are often not capable to answer to seasonality properly or managing the trade-off between storage costs and ordering costs, leading to stock levels that do not optimize costs or that cannot meet the demand, incurring then in lost sales. Thus, creating a service that recommends brands when and how much to order based on the costs involved in the restocking process allows to avoid lost sales or high cost of last-mile delivery, due to lack of stock in the warehouse that should satisfy the respective orders, and to avoid high storage costs and idle stock.

Due to this need to offer brands a tool that allows them to manage stock and take advantage of the possibility of allocating stock in the various possible geographies, a new project emerged at

Maersk E-commerce Logistics called Dynamic Inventory Assistant (DIA). The present dissertation emerged associated with this new project, more specifically associated with the inventory control and replenishment feature. The idea is to create a tool that helps brands control the stock of each product, manage properly its inventory replenishments and, consequently, reduce their costs.

1.4 Project Objectives

The focus of this dissertation is the development of a model that recommends brands a stock replenishment plan for products individually. Since the project's implementation involved multidisciplinary domains, the main objective is subdivided into milestones to achieve more measurable results.

Firstly, as this is a new project in the E-commerce Logistics area and there is no in-depth knowledge of the replenishment process, the first milestone is to understand and outline the full shipping process from supplier to warehouse. Before being acquired by Maersk, HUUB only managed and handled the supply process from the warehouse to the final customer, and the process of transferring goods from the supplier to the warehouse is not much explored, for this reason, there is not much knowledge of this part of the supply chain. This requires that in the first stage there is an exploration of the downstream supply chain process and identification of the various stages necessary to make the goods reach the warehouse.

Secondly, since costs are the basis for building the main model, one of the intended objectives is to recognize the cost drivers involved in the process and identify the sources of lead time.

After identifying the process cost drivers, the main milestone follows up: the creation of a replenishment recommendation algorithm. In this last step, the main focus is to test different methods and find the model that provides the replenishment plan that minimizes all the costs involved while trying to satisfy all predicted demand. The replenishment plan suggested should be able to prevent stockouts, since it has a direct impact on sales and an indirect effect on customer satisfaction. But, at the same time, the replenishment quantities should avoid overstocking, since it can lead to unsold or obsolete and it implies an investment of capital.

Finally, with the implementation of this algorithm, the idea is to offer a useful tool to brands and to increase the value proposition offered.

1.5 Methodology

The first phase of this project was to learn more about HUUB, its platform, and how it works. In addition, a deeper understanding of the new DIA project that the Maersk E-commerce Logistics team intends to develop is made. Additionally, more directed towards the dissertation project at hand, a deeper understanding of the inventory replenishment process in warehouses and familiarization with general processes involved in the shipping process were made, both through contact with Maersk members and through web exploration.

After an overview of how the process of transferring goods from the supplier to the warehouse works, a literature review was conducted to become aware of the state-of-the-art and to get a scientific ground on the subjects that will serve as a basis for the practical part of this dissertation.

The next step focused on the development of an algorithm to determine the safety stock based on the demand prediction error since the safety stock is an input for the algorithms that provide the replenishment plan. Then, the development of those algorithms that would be used to obtain the replenishment plans follows, and it was also defined the indicators that would be used to compare them. After developing the various algorithms, a comparison between them followed up. The comparison was established through the cost structure and the running time.

Finally, a sensitivity analysis was performed considering the variation of the cost drivers involved.

1.6 Thesis Outline

This dissertation consists of six chapters. The present chapter introduces the project and the reason behind its emergence. The next chapter is "Literature Review" which presents the theoretical background and state-of-the-art review necessary for the project.

The third chapter elaborates on the context of the project and divides into four sections: the first focus on a deep contextualization of the project, the second presents a description of the stakeholders involved in the replenishment process, the third one describes each transport mode cost structure and, finally, the fourth section maps the replenishment process.

The fourth chapter is dedicated to the project methodology, addressing the identification of the cost drivers involved in the replenishment process, followed by a brief description of the methods that will be tested and the assumptions needed to build them. Then, there is a characterization of the reasoning behind these methods, both heuristic-based approaches and optimization models. Finally, in the following three sections there is a brief description of the sensitivity analysis performed, as well as the metrics collected and the programming tools used, respectively.

In the chapter "Results and discussion" a comparison of the different methods is made based on the KPIs previously defined and a sensitivity analysis follows up.

The last chapter provides insight into the main results of the project and the impact this tool will have on the customers. In addition, opportunities for improvement and future developments are identified.

Chapter 2

Literature Review

This chapter provides an overview of the state of the art of topics covered in this dissertation. Starting with a general introduction to supply chain, there is a review of supply chain management, third-party logistics, inventory management, and its importance. This is followed by a review of the cost elements involved in the replenishment process that will influence replenishment decisions. Then, a model for determining the optimal order, its limitations, and the heuristics derived from this model are discussed. Still on stock replenishment, a review of the different stock control policies follows up. Finally, the concept of safety stock and different ways of determining it is introduced.

2.1 Supply Chain Management

According to Stadtler and Kilger (2008), in a broad sense, a supply chain (SC) consists of two or more legally separated parties that are linked by material, information, and financial flow that are involved, directly or indirectly, in fulfilling a customer request. Moreover, according to Stadtler and Kilger (2008), the inclusion of many stakeholders/ organizations all over the process brought the challenge of integrating and coordinating all the information and material in order to achieve an integrated flow over the SC, emerging then a new philosophy – Supply Chain Management (SCM).

Regarding the concept of SCM, according to Băleanu et al. (2009), many definitions have been proposed in the literature and, therefore, there is a lack of a comprehensive and encompassing SCM definition. In spite of many scholars defending that SCM includes coordination and integration among SC and the movement of goods from suppliers to the end customers, there are still varying conceptualizations of how SCM should be defined (Mentzer et al., 2001). Although many definitions of SCM from different authors occur in the literature, according to Mentzer et al. (2001) these definitions can be classified into three categories: a management philosophy, implementation of the management philosophy, and a set of management processes.

Within the scope of this project, HUUB by Maersk is responsible to manage the logistics activities for its clients and, for this reason, is one of the stakeholders of the supply chain.

2.2 Third Party Logistics

Marasco (2008) refers that, according to Coyle et al. (2003), Third Party Logistics (TPL) is an external organization that executes totally or partially the logistic function of a company and that, according to Lieb (1992), TPL consists in the usage of external companies to perform logistics functions that are traditionally performed within the organization. Both definitions have a common idea: a TPL includes any way of outsourcing logistics activities.

Despite the variety of services that could be provided by a TPL, the typical ones are transport, warehousing, inventory, value-added services, information services, and design and re-engineering of the chain, and the most common among industrial firms are the first three, according to studies referred in Hertz and Alfredsson (2003).

The interest from companies for TPL emerges from the fact that it facilitates globalization, lead time reductions, and customer orientation, which allow the company to achieve a competitive advantage in the marketplace (Hertz and Alfredsson, 2003). Moreover, in this article, the authors refer that, according to Andersson (1997), the companies could achieve many other benefits when they create logistical alliances, namely achievement of economies of scale, operations efficiency, bargaining power, faster implementation of new systems, smoother production and diversified knowledge.

Finally, according to Hertz and Alfredsson (2003), the relationship between the provider of a TPL service and the receiver is changing over time from a focus on a contract to a focus on partnership, agreement, and to mutual benefit.

2.3 Inventory Management

In any organization all functions are interlinked, being that some key areas like supply chain management, logistics, and inventory are the backbone of the business delivery and, for this reason, are extremely important for business success and efficiency. According to Nirmala et al. (2021), inventory management directs the progression of merchandise from suppliers to the warehouse and from the distribution centers to the retail location.

Inventory management involves planning and controlling (Namusonge, 2015). Planning involves determining in advance the quantity and the moments to purchase, to keep efficient stock coordination, and controlling consists of following the procedure set up at the planning stage and monitoring stock levels.

Kolias et al. (2011) refers that inventory management policies entail contradictory functional objectives. While the effort of the financial manager is to minimize the inventory level, the effort of the marketing manager is to minimize the inventory shortages. Therefore, there is a trade-off - the issue of inventory management lies in optimizing between under and overstocking costs. For this reason, one of the inventory management goals is to balance the conflicting economics of not wanting to hold too much stock due to the associated holding costs but, at the same time, make items available to prevent from not being able to meet service level and to avoid a reduction in sales (Namusonge, 2015).

2.3.1 Inventory Management Importance

Namusonge (2015) highlights that a company that neglects to manage its inventory risks having bottlenecks and, therefore, does not maximize its profit. Inefficiently managed inventories can generate irreparable losses for companies in highly competitive sectors. According to Ogbadu (2009), Lysons and of Purchasing & Supply (1996) refers that inventory control allows increasing profitability through cost reduction. With efficient stock control, goods are made available when needed, taking into account shortages, order cost, purchase price, and working capital. Finally, Capkun et al. (2009), Cannon (2008) and Koumanakos (2008) analyzed the relationship between inventory and financial performance and concluded that effective inventory management impact positively the performance of a firm.

2.4 Cost Elements

Since inventory replenishment decisions focus on minimizing total logistics costs, it is important to identify all costs that must be considered when determining order quantities (Swenseth and Godfrey, 2002).

2.4.1 Inventory Holding Costs

According to Gurtu (2021), keeping inventory is a necessity for ensuring smooth operations, however, it has a cost associated named as inventory holding cost or inventory carrying cost. In the ideal scenario, the organizations do not keep inventory - just-in-time delivery - avoiding then holding inventory costs. However, for many manufacturing, trade, or retail organizations, the conditions in which they operate do not allow them to have zero stock, thus requiring the maintenance of an ideal stock. Inventory carrying cost represents one of the highest costs in the physical distribution system and is composed of many different components (Londe and Lambert, 1977).

Cost of Warehousing and Handling

According to Krittanathip et al. (2013), empirical studies show that the cost of warehousing and holding inventory are a larger share of total logistics costs than transport costs, and approximately 61% of total logistics costs are composed of non-transport related logistics costs.

Warehousing costs are associated with the warehouse space and time management, so it is associated with the occupation of the facility (Speh, 2009). Additionally, according to the same article, warehousing costs also include costs incurred to support the operation of the distribution center - operations administration - which includes line supervision costs, administrative work, information technology, insurance, and taxes.

Regarding handling costs, these are all expenses associated with moving items in or out of the warehouse, such as receiving, packing, and loading, and may also include extra work that may be required, such as repackaging or reconditioning damaged products (Speh, 2009).

Cost of Capital

According to Rajabi (2016), Krupp (1983) refers that the average level of stock represents more than 15% of the assets of organizations and, as such, the cost of capital invested to maintain it can be significant.

Rajabi (2016) also refers Muhlemann and Valtis-Spanopoulos (1980) article, which in its instance highlights that, in addition to the capital cost incurred for acquiring the inventory, it also should be considered the interest on loans for its acquisition and insurance costs or, in alternative, the opportunity cost of not investing the money in other assets. Finally, Rajabi (2016) refers to Piasecki (2001), which defends that the cost of capital results from the interest rate which is paid on borrowed money to buy the inventory. Additionally, according to Teunter et al. (2000), the cost of capital is calculated by multiplying the interest rate by the marginal cost for ordering.

Cost of Risk

The category of inventory risk costs includes charges for obsolescence and inventory damage. The obsolescence cost component arises when items became obsolescent and it is obtained through the difference between the cost of the unit and the salvage cost (Lambert and LaLonde, 1976). Moreover, when some items suffer damage, their cost should be included in the same proportion of damage compared to the total volume of inventory held (Lambert and LaLonde, 1976).

2.4.2 Inventory Ordering Costs

Each time an organization purchases inventory, there are many costs that are incurred besides the product cost, ranging from the cost of placing the order to the cost of delivering the goods, such as administrative expenses in preparing a purchase order, transportation, receiving, inspection and registering expenses.

Transportation Costs

Freight transport costs are a significant part of the global economy and constitute a large share of the total costs of many retail companies (Swenseth and Godfrey, 2002) and the increase in fuel costs and road congestion increased the importance of taking into account transport costs and better managing it. Mendoza and Ventura (2013) analyzed the scenario of ignoring transport costs and concluded that there was an increase of 14,7% in total logistics cost and 88,9% in the transport cost in comparison with the optimal solution.

Additionally, shipping rates may depend on various factors, such as the mode of transport, the distance and weight/ volume of the shipment, and the commodity class of the items shipped. The shipment quantity may be expressed in units of weight, volume, number of pallets, or in the units applied to the specific class of goods. So, identifying all sources of shipping costs in inventory models and accurately modeling those costs is important to achieving cost-effective replenishment plans (Engebrethsen and Dauzère-Pérès, 2019).

Additional Costs

When triggering an order, the buyer incurs many costs besides the items cost and the costs of transporting it until the destination (Narayan and Subramanian, 2009). Incurring in a new order requires resources to generate, process, and handle it, which leads to a respective cost that can be translated into the portion of wages and operating expenses involved in the procurement process (Narayan and Subramanian, 2009). Additionally, when items pass through the customs unit, they are subject to customs duty payment, which also increases the transaction costs (Bassa et al., 2021).

2.4.3 Shortage Costs

As mentioned earlier, one of the major problems that logistics is facing is calibrating the level of stock. Poor stock calibration can result in an over-investment of stock or stockouts. While the cost of keeping excess stock can be easily measured, the shortage cost is more difficult to estimate and there is not much exploration of the relationship between this cost and potential lost sales (Zinn and Liu, 2001).

According to the report by Corsten and Gruen (2005), there are different active responses of consumers to stockouts, namely: replacing the item with a similar product, delaying the purchase - backlogging - or simply not waiting and buying from the competition. Thus, the first step in measuring shortages costs involves anticipating consumer behavior when there is a shortage of stock so that better stock management policies can be implemented.

According to Sampaio and Machline (2008), Nahmias and Smith (1994) stated that the cost of rupture can be estimated with the following equation:

$$Cost\ of\ rupture = number\ of\ ruptures \cdot (sale\ price - purchase\ price) \tag{2.1}$$

This formula quantifies the cost of rupture as the contribution margin of the unsold item. However, it ignores the customer's reaction to short-term and long-term stockouts, so it is only about the tangible component. Ideally, it should also be considered the intangible component, despite this being more complicated to estimate. Consumers subject to stockouts may reduce future purchases and the effect on the consumer may differ depending on the number of exposures to stockouts (Anderson et al., 2006).

There is a high difficulty in reaching a consensual conclusion regarding these costs, which demonstrates that their determination remains unknown.

2.5 Lot Sizing Algorithms

According to Erlenkotter (1990), in 1913 Ford Harris published a paper in which he aimed to determine the number of units to be ordered so that it is possible to minimize the cost of ordering and carrying a given product - the Economic Order Quantity (EOQ). According to the EOQ model, the optimal quantity to order must be obtained by balancing two factors that evolve in opposite ways: (1) the cost of acquiring and transporting inventory and (2) the cost of owning inventory (Aro-Gordon and Gupte, 2016). If the order quantity is small, the number of orders is high, resulting in higher ordering cost, while carrying cost is relatively low (Kumar, 2016). Alternately, if a higher quantity is ordered, the number of orders goes down and, hence, ordering costs also decrease. However, ordering in large quantities may not pay off in terms of storage costs over a long period of time. Thus a proper balance between carrying costs and ordering costs is necessary.

2.5.1 Economic Order Quantity

As the EOQ is a trade-off between ordering and holding costs, it is obtained by the intersection of the ordering cost curve and the holding cost line and corresponds to the point of the lot size that results in the lowest total cost Kumar (2016).

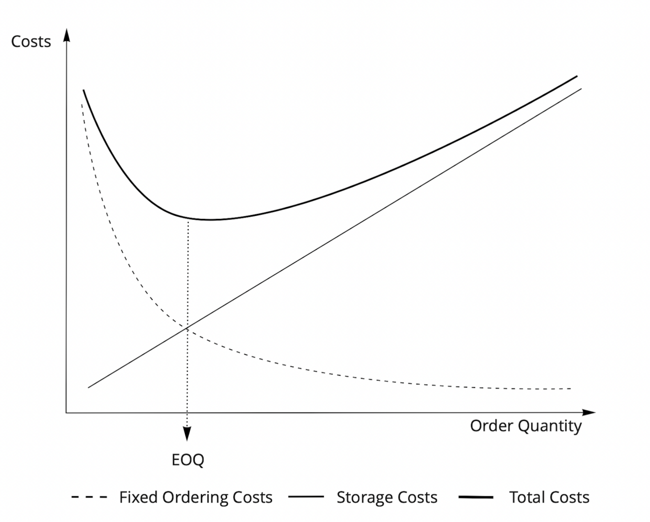

Figure 2.1: Economic Order Quantity (EOQ) model

The total cost function in period T is given in function of the order quantity, Q, by:

$$C(Q) = h\frac{Q}{2} + K\frac{D_T}{Q} \tag{2.2}$$

Considering:

Parameter	Description
T	Length of the planning horizon
D_T	Total demand over period T
h	Holding cost per unit during period T
K	Fixed cost to place an order

The minimum cost and the value of EOQ are found by setting the derivative of C(Q) to zero:

$$EOQ = \sqrt{\frac{2KD_T}{h}} \tag{2.3}$$

Nonetheless, according to Kumar (2016) and Aro-Gordon and Gupte (2016), this model makes some assumptions that do not reflect most real-life inventory systems, namely:

1. Total demand is deterministic and uniformly distributed over the period;
2. Delivery lead time is null;
3. The ordering cost is constant and independent of the quantity ordered;
4. The inventory costs are assumed constant.

2.5.2 Dynamic version of EOQ Model

In 1958, Wagner and Whitin published a paper called 'Dynamic version of the economic lot size model' in which they provide an algorithm to find the optimal solution of the classic lot-sizing problem by dynamic programming (Wagner and Whitin, 1958). However, this exact method was perceived as not working well in a rolling horizon (Axsäter, 1988). Consequently, since then, many extensions of the problem have been studied and approximate heuristic procedures have been developed (Ullah and Parveen, 2010).

Axsäter (1988) highlighted that in most practical situations a limited "forecast window" has to be used in connection with a rolling horizon implementation scheme. In these circumstances the solution obtained when applying the Wagner-Whitin (WW) algorithm is, in general, no longer optimal, once the WW algorithm finds the best solution for a fixed time period, which is not compatible with the rolling horizon applied in the real-life situations. Under these circumstances, can be beneficial the application of a simple heuristic instead of the WW algorithm. Additionally, Blackburn and Millen (1980) refers that a heuristic may in fact generate good solutions and is more understandable.

2.5.3 Lot Sizing Heuristics

As referred by Axsäter (1985), most heuristics used in practice are sequential techniques, i.e., the future requirements are divided into periods. Therefore, the decision of including the requirements of a certain period in the preceding batch is taken without taking into account the requirements beyond that period. Methods of this type do not require a long horizon to recommend a good solution and are often suitable in a rolling horizon environment (Axsäter, 1988). Examples of these heuristics are the Silver-Meal (SM), Least Unit Cost (LUC), and Part Period Simplified (PPS).

Moreover, exact methods, such as WW, present the optimal result but often fail to do so in a timely manner and may consume too many computational resources. Unlike complex algorithms, heuristics are simple and efficient techniques that can present acceptable results without intensive consumption of computational resources (calculation time) (Axsäter, 1988).

Silver-Meal Heuristic

One of the best-known heuristics was developed in 1973 (Ho et al., 2006). The SM Heuristic, also called Minimum Cost per Period, is an EOQ-based rule for minimizing the total of relevant costs for each replenishment period. According to this rule, the replenishment quantity is the quantity that will meet the requirements for an integer number of periods such that the average cost per period is minimized (Silver et al., 1998).

The rule consists in aggregating the requirements of consecutive periods in a single order launch unless the cost per period when including the requirements of period k+1 is higher than including just until period k (Baciarello et al., 2013).

The SM heuristic is widely researched and understood and this rule offers reduced calculation intensity when compared to the formal EOQ model under stochastic requirements (Silver et al., 1998).

The following equation was obtained from the work of Baciarello et al. (2013) and it says that the order triggered in i will aggregate the requirements from i to j until:

$$\frac{S+h\sum_{k=i}^{j+1}(k-i)d_k}{j+1} > \frac{S+h\sum_{k=i}^{j}(k-i)d_k}{j} \tag{2.4}$$

Considering for this and the next heuristics this definitions:

Parameter	**Description**
i	First period
j	Last period
d_k	Requirement in period k
S	Fixed cost to place an order
h	Inventory holding cost per unit per unit time k

Least Unit Cost Heuristic

This heuristic is based on the rule of selecting the number of periods covered by the replenishment order such that the total relevant cost per unit of demand is minimized.

According to this rule, the requirements of various consecutive periods are aggregated in a single order launch unless the cost per unit when aggregating the requirements of period k+1 is greater than that of the order that aggregates the requirements until period k (Baciarello et al., 2013). That is, instead of dividing the total costs by the number of periods for which the order will satisfy requirements, as in the Silver-Meal heuristic, it divides by the accumulated requirements.

The next equation is from Baciarello et al. (2013) and, according to this formula, the order triggered in period i will aggregate the requirements from i to j until:

$$\frac{S+h\sum_{k=i}^{j+1}(k-i)d_k}{\sum_{k=i}^{j+1}d_k} > \frac{S+h\sum_{k=i}^{j}(k-i)d_k}{\sum_{k=i}^{j}d_k} \tag{2.5}$$

Part-Period Simplified Heuristic

The PPS heuristic is another rule for determining the size of the lots over time. This rule aggregates in the same lot the requirements of k integer periods until the storage costs are much nearer to the fixed ordering cost but not higher. This technique is particularly important when the setup cost is high (Baciarello et al., 2013).

The following equation was obtained from the work of Baciarello et al. (2013) and it says that the condition to aggregate the requirements in the same batch is given by:

$$\sum_{k=i}^{j}(k-i)d_k \leq \frac{S}{h} \tag{2.6}$$

2.5.3.1 Comparison

Several authors have focused their contributions on trying to demonstrate that among the various dynamic lot-sizing rules there are big differences in terms of performance that can not be neglected (Baciarello et al., 2013).

A study done by Florim et al. (2019) evaluated many heuristics under different seasonality and demand variation scenarios. The percentage error of the total costs was used to act as a benchmark and was calculated using as comparison the results of the exact WW method.

Firstly, Florim et al. (2019) analyzed the performance of the heuristics when subject to different variations in demand. The EOQ presented the highest error and it increases when the demand variation increase. The results obtained also show that SM and LUC heuristics achieve the optimal result when under low variation in demand and produce results very close to the optimal when the demand data has high variability.

Secondly, scenarios with different seasonality indexes were analyzed - a moderate and a high peak of demand. According to the results exposed it is possible to realize that the EOQ presents the higher error in both scenarios, which increases when the peak on demand increase. The results obtained also show that SM and LUC heuristics presents a low error when under low peaks on demand and an increase in the error when under a high peak on demand.

In all scenarios, the EOQ method always presents a higher percentage of errors when compared with the heuristics, which leads to the conclusion that heuristic methods are, in general, a good option (Florim et al., 2019).

Additionally, a study done by Jeunet and Jonard (2000) measured the performance of some heuristics in different environments and concluded that the SM and the PPS represent the best trade-off between cost-effectiveness and robustness.

Finally, Ho et al. (2007) mentions some studies in which the efficiency of the SM heuristic is praised over a wide range of tested factors. The author states that the heuristic presents a high level of precision concerning the optimal solution and computational speed quality compared to more complex heuristics.

Regarding PPS heuristic, not many studies regarding its performance were found.

2.6 Inventory Control Policies

Inventory control policies are decision rules that indicate the quantities and ordering times, considering the trade-off between the costs involved. Briefly, inventory policies are classified as continuous and periodic review policies (Silver et al., 1998).

2.6.1 Continuous reviewing policy

In this system, the stock level is continuously reviewed and when the inventory level on-hand falls below the replenishment point, r, which is set as the trigger level, it should be generated a replenishment order of quantity Q (Horenbeek et al., 2013).

These two control variables have different purposes. The amount to replenish, Q, results from the trade-off between the ordering costs and the storage costs: high values of Q lead to a low number of replenishments but to a high level of inventory and, consequently, to high inventory costs. On the other hand, a small value of Q leads to a low level of inventory but more frequent purchases. Regarding the reorder point, r, it has an impact on the probability of stockout: a high reorder point ensures higher safety regarding the probability of stockout while a low value increases the susceptibility to stockouts (Castellano, 2015). The order quantity and the reorder point must be defined at the beginning of the planning horizon and are decided once and for all (Bookbinder and Tan, 1988).

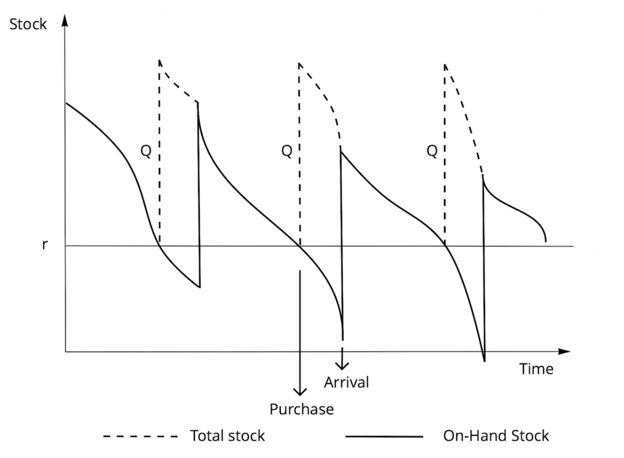

Figure 2.2: Continuous Review Policy

2.6.2 Periodic reviewing policy

In many situations, a continuous review of the inventory level may not be practical and, in these cases, the level of inventory is checked at certain time periods – periodic reviewing policy (r,S) (Horenbeek et al., 2013). Under this policy, an inventory replenishment is placed every r period to raise the inventory level to the order-up-to-level S (Tarim and Smith, 2008).

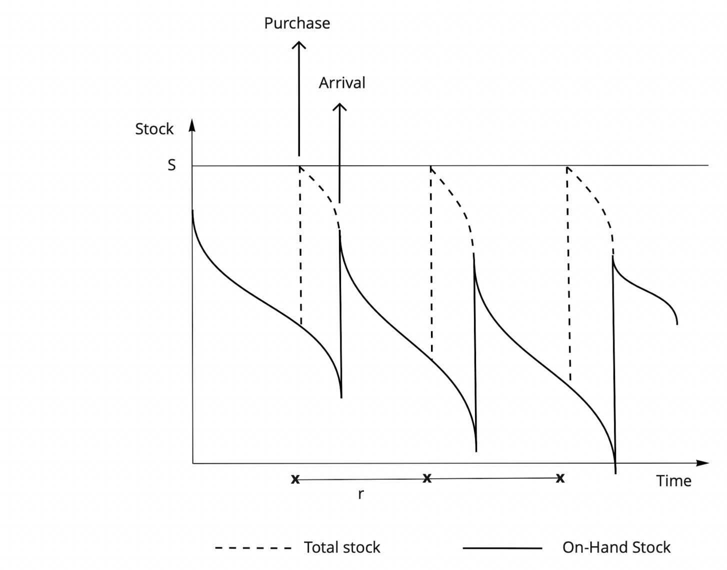

Figure 2.3: Periodic Review Policy

2.6.3 Hybrid policy

There is also a system that combines the continuous review system with the periodic review system, resulting in a hybrid strategy. This system (R, s, S), also called (T, s, S) or (s, S, T), is characterized by checking the inventory position every R units of time. If the inventory position is below s an order is placed in order to increase it to S, otherwise, nothing is ordered until the next inventory review.

The main advantage associated with this strategy is the low associated inventory costs. However, the calculation of the three control parameters makes this strategy more complex (Visentin et al., 2020).

2.7 Safety Stock

According to Kanet et al. (2010), in a survey including producers, distributors, and retailers, the major desired goal reported by the majority of them was improving the service level. One strategy to improve the service level is by leveraging the stock in order to reduce stockouts and Koh et al. (2002) highlights that safety stock (SS) is one of the most robust strategies to soften supply and demand uncertainty.

Additionally, as stocking high inventory generates high inventory costs, it is necessary to find the right level of SS to be small enough to reduce inventory-related costs (Gonçalves et al., 2020), but enough to satisfy the uncertainty associated with demand and replenishment time, in order to avoid stockouts (Boulaksil, 2016).

Schmidt et al. (2012) exhibits some mathematical-stochastic methods for determining SS that are generally described and discussed in publications. And Gonçalves et al. (2020) recalls standard stochastic approaches for dimensioning SS, based on other studies.

As referred on Schmidt et al. (2012), one of the rules for calculating SS is dependent on a safety factor, the standard deviation of demand, and lead time. In this formula, the safety factor is based on the service level and is obtained through the application of the inverse of the standard normal distribution for the respective service level. As the safety factor results from the application of the standard normal distribution for the respective service level desired, it assumes a normally distributed demand during the replenishment time.

The following equation for determining the SS was obtained from the work of Schmidt et al. (2012):

$$SS = SF(SL) \cdot \sigma_D \cdot \sqrt{LT} \tag{2.7}$$

Where:

Parameter	**Description**
$SF(SL)$	Inverse of the standard normal distribution for a service level SL
σ_D	Demand standard deviation
LT	Average lead time

According to Schmidt et al. (2012), Alicke (2005) provides a similar calculation rule, however the author uses the forecast error derived from forecasting data:

$$SS = SF(SL) \cdot \sigma_F \cdot \sqrt{LT} \tag{2.8}$$

Considering:

Parameter	Description
σ_F	Standard deviation of the forecast error for the demand during LT

The author considers that the standard deviation of the error is calculated through historical data and is the mean squared deviation of the predicted demand from the actual.

According to Schmidt et al. (2012), Axsäter (2015) also explores the SS and extends the preceding formula to a new formula that considers a stochastic replenishment time resulting then in the following formula:

$$SS = SF(SL) \cdot \sqrt{LT \cdot \sigma_D^2 + D^2 \cdot \sigma_{LT}^2} \tag{2.9}$$

Considering:

Parameter	Description
D	Mean demand per time unit
σ_{LT}	Standard deviation of LT

Taking into account this information, it is observed that the SS calculation is influenced by the demand and lead time uncertainty, in case it exists, and that there are several alternative calculating formulas suggested by different authors.

Chapter 3

Problem Framework and Description

This chapter will present the context of the current dissertation.

The first section focuses on presenting an in-depth contextualization of the dissertation. The second focuses on identifying the external partners involved in the operational replenishment process and their relevance. Then, the third section highlights the different transportation modes used to ship merchandise, since it is important to understand the cost drivers involved in the replenishment process. Finally, the fourth is dedicated to mapping the operational replenishment process, considering only maritime and road transportation - the main transport channels used by the actual Maersk E-commerce Logistics customers.

3.1 Problem Context

As mentioned earlier, e-commerce has had a boom in recent years. Before the pandemic period, e-commerce accounted for a large portion of retail sales, even so, the pandemic has further intensified its growth.

With this e-commerce growth, the brand's demand is becoming more dispersed across different parts of the world. This lifting of the geographic barrier could be a benefit for customers, as they will benefit from a wider range of products and brands at their disposal, however, it could be difficult for brands to manage their stock and meet the demand.

With the creation of more sales channels and the emergence of more demand clusters, demand is no longer centralized in one place and this lifting of the geographical barrier makes stock management more difficult for brands, especially when they start to have more warehouses at their disposal, making it more difficult to decide where to allocate their stock, when and in what quantity to replenish their warehouses.

With the emergence of Maersk E-commerce Logistics, customers acquired the ability to easily open physical operations and store near multiple demand clusters around the world due to the wide range of over 200 warehouses spread across North America, Europe, and Asia.

Nevertheless, there is no point in having access to a wide range of warehouses if the brand does not know what quantity to allocate to each warehouse nor how to manage the stock that is in each one. Poor stock management and control can undermine all the advantages of having a wide range of warehouses available and incur great losses. Therefore, it is important for the brand to have a sense of future sales and it is also important to have a sense of the best time to order inventory so that it arrives in time to meet demand and to ensure that it never incurs overstock.

Given the need to provide services that allow brands to optimize their inventory management, a new project emerged in Maersk E-commerce Logistics - DIA - which is supposed to be a set of resources to enhance the brand experience and help them manage their inventories, recommending how to optimize logistics costs.

The present dissertation is related to DIA project and the main idea is to create a functionality capable of notifying the brand of the best purchase moment and the respective quantities in order to avoid stockouts, based on expected stock levels, demand, production lead times, and transit times, desirable service levels and production constraints.

3.2 Inventory Replenishment Stakeholders

To transport the goods from the supplier to the warehouse, there is a complex operational process with the intervention of several stakeholders that contribute to the chain value. Therefore, it is important to identify the stakeholders and their respective roles in the chain.

The main stakeholders involved in the replenishment process are Brands, Suppliers, Consolidation Warehouses, Freight Forwarders, Liner Agents, Ports, Carriers, and Warehouses.

3.2.1 Suppliers

The supplier is the actor that guarantees the production of goods that will later be sold by brands. Since the supplier is the most downstream stakeholder in the supply chain, the variability in production time, the order preparation, and the bureaucracy processing are the first components that contribute to the lead time.

3.2.2 Consolidation Warehouse

The consolidation warehouse is a logistics facility that receives individual orders from other centers and suppliers and combines these small shipments into larger and more economical container loads that are bound for a similar destination.

The consolidation process carried out in these logistics centers consists of organizing and sorting orders before shipping them.

One of the main objectives of load consolidation is to lower the transportation costs for each order, combining the orders of multiple customers in a single shipment makes it possible to divide the delivery costs and dispatch full container loads. Moreover, with consolidation, brands can purchase smaller orders more frequently while reducing costs, which is relevant when observing demand fluctuations.

3.2.3 Freight Forwarder

The freight forwarder assumes the representation of the shipper - the entity who puts goods in the care of others to be delivered to the receiver - and arranges the transportation of goods on his behalf by concluding affreightment contracts with the carrier.

The freight forwarder itself is not responsible to transport the goods, it is commissioned with the planning and organization of the transport operation.

Thus, the main function of the freight forwarder is the affreightment, which includes chartering the shipping entity, booking space in the shipping entity, taking care of the inland transportation in case of non-ground transportation or in case the merchandise needs to be previously consolidated, and goods handling including loading, unloading, reloading, temporary storage of goods.

The contract of the forwarder allows to speed up the transportation and reduce transaction costs due to its know-how and experience which increases the value of the supply chain.

3.2.4 Liner Agent

While the freight forwarder represents the shipper, the liner agent represents the carrier within a certain geographical area.

The function of the liner agent consists in close contracts of affreightment with the shipper in name of the carrier and their main assets are the local network and expertise on local matters and on the shipping line.

Once the liner agent is a bridge between the shipper and the carrier, as the freight forwarder, many services are overlapped, like arrangement of inland transportation, container logistics, port operations, and documentation handling. But, as the liner agents represent the carrier, they usually provide marketing in order to secure goods for the ships.

3.2.5 Ports and Terminal Operators

Ports and terminal operators are important actors in overseas transportation.

Many services are provided in the terminals. More general logistics services are provided, such as loading and unloading, and more complex logistics services may be provided, like quality control, customizing, and packing of goods.

3.2.6 Carrier

The carrier is the main actor in the process of transporting merchandise from the supplier to the destination warehouse.

Since transportation costs are a big driver of overall logistic costs involved in the purchase of merchandise, the optimized choice of carrier and negotiation of transportation features and fees is relevant to be able to control the quality of service and expenses.

Additionally, the choice of the type of transportation and the carrier depends on many factors such as the delivery speed, the service level, and the origin and destination point.

3.2.7 Warehouse

This partner is responsible for receiving items from suppliers, storing them, and processing the orders for shipment. In the inbound process, when the cargo arrives at the warehouse, the merchandise passes through a quality control stage, the items are sorted, counted, and transported to the designated area in the warehouse and a reception validation is processed.

They are the last stakeholder involved in the process of reception from the supplier and the first stakeholders involved in the physical delivery of products to the end customer, as that, they are the main connection between the supplier and the brand's customer.

Warehouses are a crucial partner to delivering Maersk E-fulfilment operations and have a significant role in the business.

3.3 Transportation Modes

Transport is one of the main sources of costs in the replenishment process of the warehouse and, in many cases, it is one of the most time-consuming phases of the entire process and, as such, is the main source of lead time. For these reasons, it is important to understand and identify the different modes of transport used by Maersk E-fulfilment customers to comprehend the cost structure of each one.

For the present dissertation, only the case of customers who sell in Europe will be considered. These Maersk E-fulfilment customers are customers that sell in Europe and who are supplied from suppliers located mainly in Europe and Greater China via road and sea, respectively. As such, although there are other ways of transport used by current customers, such as air transport and rail, these transport ways will not be considered for the algorithm design since they are less requested.

Concerning road transport, it is the most used way of transport to carry from suppliers located in Europe to warehouses located in Europe due to the effectiveness and speed of short-distance deliveries and the ease of delivery, since it allows delivery directly to the final warehouse without the need for a distribution center.

Regarding the transport by sea, it is the most used by customers who are supplied by suppliers located in Great China. This transport way requires a longer transit time, greater bureaucracy, and more administrative processes, however, it allows brands to transport bulky and heavy loads, carry large amounts of cargo and have access to suppliers that are not accessible by road.

Within each of the physical modes, different loading options exist depending on the shipment size: Less than Container or Truck Load - that from now on will be referred as Less than Load (LL) - and Full Container or Truck Load - that from now on will be referred as Full Load (FL) - for different container sizes.

FL transportation

FL is the loading option used when the cargo is sufficient to compensate for incurring a freight rate charged in a container-truck base and, in this case, there is no consolidation and the container-truck is filled only with the respective shipment cargo. Sometimes the container-truck may not be full filled, but the rate is charged on the basis of a full container-truck and is the standard form for shipping large charges.

FL shipments are loaded directly at the supplier's warehouse and delivered straight to the destination warehouse. That means uninterrupted cargo transport without any intermediary consolidation needed and, thus, it requires less handling time.

LL transportation

LL is used when the cargo has a small volume or dimensions that will not take enough space in the container-truck to incur in FL. In this case, the cargo is combined with other shipments to fill the container-truck.

However, LL shipments have a longer delivery time when compared with FL shipments. As LL shipments are combined with other shipments, it takes more time to plan such loads, consolidate with other merchandise, and pass through the customs checks once several cargoes are to be inspected.

3.4 Process Mapping

After understanding who are the main players involved in the process of replenishment, it is important to understand the flow of merchandise from the suppliers until the final warehouse, especially to notice the sources of costs and lead time involved in the process of replenishment, and the connection with the SPOKE, the platform that manages the interaction between the stakeholders involved in the brand's supply chain.

As this is a new project for the company and there is no in-depth knowledge regarding the flow from supplier to the warehouse with rail and air freight and, additionally, the main transportation ways actually used by E-fulfilment Maersk customers are road and sea shipping, these are the only transportation ways considered and analyzed in this dissertation. As that, only the road and sea transportation ways are considered for the design of the process replenishment outline to supply brands in Europe supplied, respectively, from Great China and Europe.

A flowchart of the replenishment process was made (see Figure A.1 in Appendix A) and should be consulted for a better understanding of the process mapping that follows.

The process starts when the brand triggers a Purchase Order (PO) to the supplier. After the brand receives this PO and confirms that they could satisfy it, the supplier sends an order confirmation and a proforma invoice that represents a faith estimate of the purchase price, in order to avoid exposing the buyer to any unexpected and significant charges once the transaction is concluded.

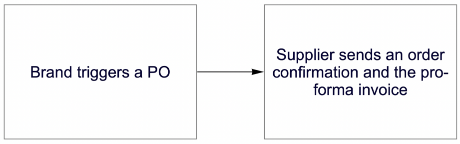

Figure 3.1: Creation of a PO

After receiving this confirmation, the brand creates the PO in the platform SPOKE and, if the brand is not a regular supplier's customer, the brand should do a pre-payment of 25-50% of the value established in the proforma. Otherwise, if the brand is a regular customer, there is no need for a pre-payment and the brand starts handling the delivery process. In case the supplier produces to order it starts producing the merchandise, otherwise, it starts picking and packing the goods to be delivered, then creates the packing list and sends a notification to the brand to inform them that merchandise is ready to be delivered. In case the merchandise needs to be consolidated due to the low volume, the freight forwarder or the liner agent, depending on who is involved in the process, books the shipment to the consolidation warehouse, which receives the merchandise and prepares the consolidation of the small shipments into large and more economic loads. After that, the freight forwarder or the liner agent handles the logistics documentation necessary for the delivery process.

Figure 3.2: Order production and dispatch by supplier

Then, depending if the transport will be overseas or not, the container or the truck is, respectively, filled with merchandise in the supplier or consolidation warehouse and, at this moment, there is a bifurcation in the process, depending on its transportation mode.

In case of overseas transport, after filling the container, the freight forwarder/ liner agent handles the transportation until the shipping area, then handles the export customs clearance if necessary and other possible diligences necessary for the process and contacts the shipping company to arrange the movement of goods overseas. After that, the container is loaded in the carrier by the departure port and terminal operators and then transported from the departure port to the arrival port by the carrier. When the carrier arrives at the port, an arrival notice is sent by the shipping company to the receiver, and the container is unloaded and moved to a container yard by the terminal operator. At this moment, import customs clearance is handled if it is required and an inspection is also done, if necessary. When there is no need for customs clearance, the container is soon shipped to the destination warehouse.

In the case of road transport, the freight company is contacted to arrange the movement of the goods, then the truck is filled and any necessary customs clearance or other diligences are handled

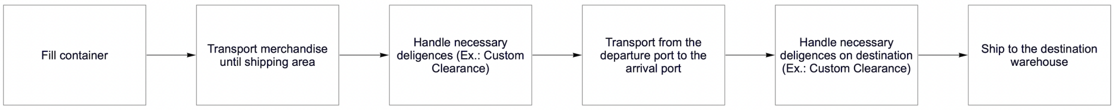

Figure 3.3: Sea transportation

if necessary. After that, the freight company transports the merchandise from the supplier/ consolidation warehouse to the destination warehouse, and, again, if necessary, the customs clearance is accomplished in the destination country.

Figure 3.4: Road Transportation

Finally, when the warehouse receives the merchandise and the packing list, they pick the merchandise to stock, and the SPOKE is automatically updated with the information sent by the warehouse. In turn, SPOKE updates the brand platform, and the process of merchandise inbound is concluded.

Chapter 4

Methodology

This chapter explains the steps taken to achieve the final goal: creating an algorithm that provides a stock replenishment plan based on predicted demand.

Firstly, it explains the discovery of the cost structure involved in the stock replenishment process. Then, a description of the algorithm developed to determine the SS value follows up. After that, it explains the sequence to develop the algorithms based on lot-sizing heuristics and the formulation of the optimization models. The chapter ends with an explanation of the sensitivity analysis performed and a description of the metrics collected.

4.1 Cost Drivers Identification

For the construction of the algorithms that recommend when and how much to replenish from a certain product, it is first necessary to understand the structure of the costs involved in the replenishment process, since it is the fuel for the algorithms.

The costs involved are of two types: storage costs and ordering costs.

Regarding the first group, brands pay a cost associated with storing the products in Maersk E-fulfilment warehouses, which depends on the daily square footage used.

Regarding the second group, it is composed of more elements. The first component is associated with the administrative costs incurred when an order is triggered, namely the administrative costs involved when processing an order, such as the remuneration of the elements responsible for processing an order, the materials and documents involved in processing it, and costs associated with customs clearance, when they exist. These types of costs are incurred every time an order is triggered and, for this reason, this component depends on the number of orders. In addition, another cost component involved in the process consists of the costs associated with the transport of goods and, regarding these costs, its structure differs depending on the transport mode: FL or LL.

FL is a shipment type where the rate is paid for the full size of the container or truck, even if it is not fully filled. The total shipping costs are expressed in function of the quantity transported, Q, as:

$$C(Q) = A \cdot int(\frac{Q \cdot v}{K}) \tag{4.1}$$

Table 4.1: Description of the parameters involved in FL-transport cost

Parameter	**Description**
A	Flat rate per container-truck
K	Container-truck capacity (m^3)
v	Item volume (m^3)

As this cost depends on the number of containers, every time a new container is required, the cost increase in A currency units.

LL is the shipment type used when the charges have small volumes and, in this case, the charge is consolidated with other charges to be shipped together in the same container-truck and the rate is allocated to the shipper according to the proportion of volume occupied. The total shipping costs are expressed in function of the quantity transported, Q, as:

$$C(Q) = P \cdot Q \cdot v \tag{4.2}$$

Table 4.2: Description of the parameters involved in LL-transport cost

Parameter	**Description**
P	Flat rate per volume
v	Item volume (m^3)

This cost is dependent on the items purchased quantity and, therefore, if the order quantity increases one unit, the total cost will increase $P \cdot v$ currency units.

Taking this information into account, the cost drivers involved in a replenishment process depend on the transportation mode.

Table 4.3: LL and FL transport cost drivers

Transportation Mode	**Cost drivers**
FL	volume of items in storage number of orders number of containers
LL	volume of items in storage number of orders order volume

4.2 Approaches Introduction

Different methods were tested in order to compare and find the best one for three transportation contract scenarios

The three transportation contract scenarios are:

1. Brands have transportation contracts that only allow the transport of goods through LL transportation mode;
2. Brands have transportation contracts that only allow the transport of goods through FL transportation mode;
3. Brands do not have transportation modes restrictions and, therefore, will use the one which allow to incur in the least costs.

Regarding the methods tested, the first three consist of applying three different heuristics - Least Unit Cost, Silver-Meal, and Part-Period Simplified - and the last one consists of an optimization model. Different methods have been implemented so that a comparison can be made.

Table 4.4: Methods tested for each transport constraint scenarios

Transportation Constraint Scenarios	**Methods Tested**
LL-restricted transport	Least Unit Cost Heuristic Silver-Meal Heuristic Part-Period Simplified Heuristic Optimization Model
FL-restricted transport	Least Unit Cost Heuristic Silver-Meal Heuristic Part-Period Simplified Heuristic Optimization Model
Without transport mode constraints	Least Unit Cost Heuristic Silver-Meal Heuristic Part-Period Simplified Heuristic Optimization Model

4.3 Assumptions

For the development of the algorithms, it was necessary to consider some assumptions.

The first assumption is the one associated with the frequency at which the algorithm is run. A company algorithm that predicts the number of sales at the granularity of the product will feed this replenishment algorithm. Since the sales forecast algorithm updates constantly its forecasts and can change it from day to day, it assumes at the outset that this algorithm would be run every day. However, considering this assumption has some drawbacks. If the model is not actually run daily, it may not provide the best recommendations. The recommendations will always be improved as the present algorithm receives updated sales forecast data and, therefore, if the model receives outdated forecasts, it will, in turn, make recommendations that could be improved because the respective forecasts are not updated and, consequently, not closer to the real. However, requiring both this model and the sales forecast model to be run every day implies that resources must be invested to do so, and as such, it is time-consuming and has associated costs.

It is also assumed that there are no-cost benefits of ordering different products simultaneously and, as such, the models will be designed to make replenishment plan recommendations for only one product at once. This assumption does not correspond to a completely real world context, however there are customers with few products or customers whose products have large volumes on average and as such, they tend to purchase different products separately, making the model suitable for these customers.

Additionally, regarding the costs involved, it assumes that the costs involved in the ordering process and in the warehousing are constant for the entire recommendation time horizon each time the algorithm is run. This assumption could be a problem if there is knowledge of a large variation in any of these costs for the next periods in the forecast horizon. But, since the algorithm is to be run on a daily basis, these costs may be updated on the next run of the algorithm, reducing the consequences of this assumption.

Moreover, it assumes that there are no quantity discounts. Quantity discounts are usually offered by suppliers to encourage buyers to purchase larger volumes. Nonetheless, since data on the costs associated with suppliers, which includes the prices of purchased items, will be scarce and difficult to obtain for the time being, and in the near future, they will be ignored for the formulation of the problem.

Finally, it assumes that the LT is the same for the entire recommendation time horizon each time the algorithm is run. Furthermore, it will consider that the low variations that may arise in the lead time are insignificant, i.e., there is no uncertainty associated to lead time.

4.4 Safety Stock Approach

A replenishment plan is important for brands to be able to optimize total logistic costs. However, the replenishment recommendation algorithms are fed by a sales forecast model developed by the Artificial Intelligence team. The sales forecast model, in turn, is not perfect and presents deviations from the actual sales values. Due to the forecast error, it is necessary that the brand invests in SS to avoid the occurrence of situations in which the forecast deviation is such that the brand cannot meet the estimated demand, incurring shortages. Thus, the first step before creating the stock replenishment recommendation algorithms, which is done independently from the rest of the procedure, is to create an algorithm that calculates the value of the SS to be used for the entire planning horizon.

It assumes that the LT is constant and, therefore, the safety stock is used to cover only uncertainty on the forecasting model.

The algorithm receives as input the service level, lead time, and historical data of the forecast value and the real sales value for the same day. Then, the algorithm determines the standard deviation of the difference between the forecast demand and the actual value. The safety stock recommended by the algorithm is calculated using the equation 2.8.

4.5 Heuristic's Based Algorithms

As referred before, several methods were tested to understand which one recommends a replenishment plan that allows incurring fewer costs. The first methods tested were based on lot-sizing heuristics, more specifically using Least Unit Cost, Silver Meal, and Part-Period Simplified heuristics. As mentioned in the literature review, some authors consider heuristic methods for batch sizing to be effective methods, thus they are appealing and, as such, were studied in this dissertation.

The heuristics' algorithms implementation is divided into three steps. In the first step, the net requirements are obtained through the difference between the predicted demand and the expected inbounds planned to arrive on the planning horizon. The next two steps occur along the planning horizon, the second consists in determining when the brand should place the orders and the third is to determine the respective quantity.

Step 1: Determine net requirements The model receives as inputs the expected demand for the planning horizon and a list of the inventory inbounds that are planned to arrive at the warehouse in the same time interval. These expected inbounds resulted from orders placed a-priori at the moment the model is being run. Hence, part of the demand that is predicted can be satisfied through the inventory inbounds that were already planned to arrive and, as such, the quantities needed to order in the replenishment plan from the supplier are reduced. Therefore, the first step is to determine the net requirements to meet the demand.

Additionally, the demand before the arrival of the first replenishment order can only be satisfied through stock from expected inbounds during this interval or stock already in the warehouse. If the stock in the warehouse or the expected inventory inbounds can not satisfy the demand, the brand will incur lost sales.

Step 2: Trigger replenishment Regarding this step, it consists in anticipating the expected stock in LT days. If the Stock Above the SS (SASS) expected after LT days is not enough to satisfy the requirements of the respective day, a new purchase is triggered. It is done because the merchandise takes LT days to arrive and, for this reason, if it is expected that the brand runs out of SASS on day x, then a new purchase should be done on day x-LT to arrive on day x.

Anticipating the SASS LT days before is done so that the brand is able to purchase in time and does not run out of stock. That is, the purpose of the anticipation of future needs is that the order arrives at the warehouse the instant after the previous SASS is exhausted, and, as such, there is no consumption of SS.

It is important to highlight that each day the algorithm is run, the forecast demand for the planning horizon is considered to be deterministic and, as such, the quantities ordered should equal the inventory requirements to meet the demand and, therefore, at no time the SS must be consumed.

The SS is only intended to cover uncertainties associated with the LT and the demand forecast because it is not actually deterministic. In a deterministic environment, the SS must not be used to cover expected requirements, those future requirements should be anticipated and, consequently, covered through recommended inventory purchases. The exception is the net requirements during the days before the first arrival, since no order can arrive in time to cover that, and, consequently, the SS should be used to cover the requirements.

To clarify the ideas presented in this step, an example is given for a prediction day 0 and a planning horizon of seven days, considering a LT of two days and that at the beginning of the day 0 there is nine inventory units of product in warehouse and wants to have a SS of two units. The Stock at the Beginning of the Day (SBD) consists in the stock before considering the arrival of stock of the respective day and before satisfying the Net Requirements (NR) that occurs during the day. The Stock at the Beginning of Day Above SS (SBDASS) consists in the component of SBD above the SS. If the stock is lower than SS, then its value is 0. The Batch Size that should Arrive (BSA) consists in the quantity that should arrive in order to satisfy the NR that can not be satisfied by the SBDASS of the day. Consequently, it is important to highlight that a new batch should arrive when the SBDASS is lower than the NR. As referred before, the batch should be ordered with an antecedence equal to LT, in order to guarantee that the goods arrive in time to satisfy the needs and, consequently, there is no SS expense - Batch Size that should be Purchased (BSP). Finally, the Stock at the End of Day, i.e., after the arrival of the purchased batch and after satisfying the net requirements that occurred during the day is designed as SEB.

To simplify the example, a lot-for-lot rule will be used to determine the batch size instead of the heuristics that were used in practise:

Table 4.5: Example of order triggering step using lot-for-lot lot-sizing rule

Day	SBD	SBDASS	NR	BSA	BSP	SED
0	9	7	4	0	4	5
1	5	3	2	0	1	3
2	3	1	5	4	4	2
3	2	0	1	1	3	2
4	2	0	4	4	2	2
5	2	0	3	3	4	2
6	2	0	2	2	0	2
7	2	0	4	4	0	2

When looking at day two, SBDASS < NR and, consequently, a batch should arrive at this day - BSA - in a quantity that is equal to the difference between BBDASS and NR. To guarantee that the batch arrives in time to satisfy the requirements, it should be ordered at day 0 - BSP.

Step 3: Replenishment Quantity At the moment the algorithm is run, the stock in the warehouse can not be enough to cover the needs during the days that follow in an interval equal to the

LT - the minimum period that will take until the first order arrives. Therefore, in that case, SS may have to be consumed and, consequently, the first recommended inventory order may have to incorporate a quantity to replace the expended SS.

Regarding the purchased quantity that is not to replenish SS, i.e., the purchase that is to satisfy the predicted future net requirements, it is determined based on the heuristics. The heuristics determine how many consecutive days' requirements are aggregated in the same batch.

4.5.1 Method 1: Least Unit Cost Heuristic

The first method tested to determine the lot size was the LUC heuristic. As referred before, according to this rule, the requirements of consecutive days are aggregated in the same order until the unit cost of aggregating k days is lower than the unit cost of aggregating k+1 days.

For each transport mode scenario, it is taken into account different costs to determine the lot size:

1. When under LL transportation mode constraint, the unit cost is calculated considering the cost per order, the transport cost per volume, and the storage cost.
2. When under FL transportation mode constraint, the unit cost is calculated considering the cost per order, the container cost, since in LL the transport is charged based on the a container basis, and the storage cost.
3. When under no transport mode constraint, two different batch sizes are determined, one considering LL transportation and another considering FL transportation. Both unit costs are compared and it is chosen the batch with the lower unit cost. In other words, two different batch sizes are determined independently considering the rule of minimizing the unit cost, and then the minimum unit cost obtained for each one is compared and the batch size recommended is the one whose unit cost is lower.

4.5.2 Method 2: Silver-Meal Heuristic

According to this rule, the requirements of various consecutive days are joint in a single order until the period cost of aggregating k days is lower than the period cost of aggregating k+1 days.

For each transport mode scenario, it is considered different costs to determine the lot size:

1. For the case of the LL transport mode constraint to determine the period cost it is considered the order cost, and the storage cost. It is important to highlight that the variable ordering cost, i.e. the transport cost/ volume, is not considered since this cost depends on the lot quantity and, consequently, the period cost would inherently increase due to the increase of the lot quantity caused for adding the requirements of one more period.
2. For the case of FL transport mode constraint, it is also taken into account the container cost since this cost can be considered as a fixed cost for a certain quantity interval - the quantity equal to the container capacity. It was assumed that the container cost is a fixed ordering cost and is equal to the container cost multiplied by the number of minimum containers necessary to satisfy the minimum order quantity.

3. When there is no transport mode constraint, the two minimum period costs are determined considering separately each one of the transportation modes and then compared. Nevertheless, since when in LL transport the period cost does not include the variable transport cost component while in FL the period cost takes into account all the costs involved, the period costs are not comparable. In order to make the period cost comparable, the variable cost component is then added to the LL period cost. After that, the transportation mode and the order quantity are decided based on the lower period cost between both.

4.5.3 Method 3: Part-Period Simplified Heuristic

This heuristic is based on the rule of aggregating the requirements of consecutive days in a single order while the storage cost is lower than the fixed ordering costs.

As in the previous heuristics, it takes into account different costs depending on the transport mode scenario:

1. For the case of the LL transport mode constraint, as in the previous method, only the fixed ordering cost and the storage cost are considered since they are the only costs relevant for the decision rule.
2. For the case of the FL transport mode constraint, as in the previous method, the fixed ordering cost and the storage cost, the container cost was also considered based on the same reasoning.
3. When there is no transportation restriction, the quantity recommend is based in the transportation mode whose difference between the ordering costs and the storage costs is lower.

4.6 Optimization Models

Optimization models were also tested to make a comparative analysis against the heuristics applied since the exact methods allow obtaining the optimal solution and, consequently, the costs presented are expected to be lower.

As in the heuristic's methods, three optimization models were developed, a first one that assumes FL-constraint transportation, another that assumes LL-constraint transportation, and the last one that considers the possibility of send merchandise through any transportation mode - FL or LL.

The parameters and the indexes considered for the following models are presented in Table 4.6.

Table 4.6: Mixed integer programming inputs

Input	Description
O^F	FL fixed ordering cost
C^F	FL container cost
O^L	LL fixed ordering cost
R^L	LL variable ordering cost
h	Storage cost per day per volume
V^F	FL container volume
v	Item volume
m	Minimum order quantity
LT	Lead time
SB	Stock after a period equal to lead time
SS	Safety stock level
i_t	Inventory inbound expected during the day t
d_t	Demand expected during the day t

Additionally, Table 4.7 exhibits the decision variables and the respective description considered for this model. The binary variables have a description that translates their meaning when they are set to 1.

Table 4.7: Mixed integer programming decision variables

Variables	Description
Q_t^F	Quantity ordered in day t to be transported through FL
Q_t^L	Quantity ordered in day t to be transported through LL
y_t^F	1 if an order occurred in t to be transported through FL
y_t^L	1 if an order occurred in t to be transported through LL
w_t	1 if an order occurred in t
N_t^F	Number of FL containers used for the order at day t
s_t	Stock at the end of day t

4.6.1 Optimization Model considering none-transport mode restrictions

The goal of the optimization model is to provide the replenishment plan to satisfy the demand after a period equal to the lead time until the end of the time horizon. Therefore, the output is the quantities recommended to purchase in each instant t and the respective transportation mode.

This can be translated into the following objective function:

$$min(\sum_{t=0}^{T-LT}(O^F \cdot y_t^F + C^F \cdot N_t^F + O^L \cdot y_t^L + R^L \cdot Q_t^L \cdot v) + \sum_{t=LT}^{T}(h \cdot s_t \cdot v)) \tag{4.3}$$

The first and third parcels concern the fixed ordering costs involved in FL and LL transportation, respectively. The second parcel is related to the container costs involved in FL transportation and the fourth parcel concerns the transport cost that is dependent on the volume in the LL transportation. Finally, the last parcel concerns the storage costs of the items.

Regarding the constraints of the model, the first one is related to the stock in the warehouse, it should be greater or, at least, equal to safety stock:

$$s_t \geq SS, \forall t \in \{LT, ..., T\} \tag{4.4}$$

The next two constraints are related to whether or not there is an order that is going to be transported through FL and LL transportation, respectively, on day t:

$$Q_t^F \leq M \cdot y_t^F, \forall t \in \{0, ..., T-LT\} \tag{4.5}$$

$$Q_t^L \leq M \cdot y_t^L, \forall t \in \{0, ..., T-LT\} \tag{4.6}$$

The next two constraints guarantee that if an order is placed, its quantity is higher than the minimum order quantity:

$$(y_t^L + y_t^F) \leq 2 \cdot w_t, \forall t \in \{0, ..., T-LT\} \tag{4.7}$$

$$m \cdot w_t \leq Q_t^L + Q_t^F, \forall t \in \{0, ..., T-LT\} \tag{4.8}$$

The following constraint is related to the number of containers. Since containers have a limited capacity, the number of containers increases each time a container is full:

$$Q_t^F \cdot v \leq N_t^F \cdot V^F, \forall t \in \{0, ..., T-LT\} \tag{4.9}$$

The next two constraints are related to the stock in the warehouse. The stock at the end of the day is equal to the stock at the end of the previous day plus the quantity that arrived at the warehouse less the quantity that left the warehouse during the day:

$$s_t = SB + Q_{t-LT}^F + Q_{t-LT}^L + i_t - d_t, t = LT \tag{4.10}$$

$$s_t = s_{t-1} + Q_{t-LT}^F + Q_{t-LT}^L + i_t - d_t, \forall t \in \{LT+1, ..., T\} \tag{4.11}$$

Finally, to guarantee the binary nature of binary variables and the other variables are positive, the following restrictions are applied:

$$Q_t^L, Q_t^F \geq 0, \forall t \in \{0, ..., T-LT\} \tag{4.12}$$

$$y_t^L, y_t^F, w_t \in \{0, 1\}, \forall t \in \{0, ..., T-LT\} \tag{4.13}$$

4.6.2 Optimization Model for FL Transportation Mode

When the only transportation mode considered is the FL, constraints, variables and inputs associated with the other transport mode are disregarded. That is, all the inputs are kept, except O^L and R^L. Regarding the variables, the ones that are not necessary for this model are Q_t^L, y_t^L and w_t.

In this case, the new objective function is:

$$min(\sum_{t=0}^{T-LT}(O^F \cdot y_t^F + C^F \cdot N_t^F) + \sum_{t=LT}^{T}(h \cdot s_t \cdot v)) \tag{4.14}$$

And the only difference observed in the constraints is that 4.6, 4.7, and 4.8 are no more necessary.

To guarantee that the quantity ordered is higher than the minimum order quantity, the following constraint is added:

$$m \cdot y_t^F \leq Q_t^F, \forall t \in \{0, ..., T-LT\} \tag{4.15}$$

Regarding the restrictions 4.10 and 4.11, in order to exclude the LL component, they are expressed as:

$$s_t = SB + Q_{t-LT}^F + i_t - d_t, t = LT \tag{4.16}$$

$$s_t = s_{t-1} + Q_{t-LT}^F + i_t - d_t, \forall t \in \{LT+1, ..., T\} \tag{4.17}$$

4.6.3 Optimization Model for LL Transportation Mode

When the only transportation mode considered is the FL, constraints, variables and inputs associated with the other transport mode are disregarded. That is, all the inputs are kept, except O^F, C^F and V^F. Regarding the variables, the ones that are not necessary for this model are Q_t^F, y_t^F, N_t^F and w_t.

Regarding the objective function, it can be translated through the following formula:

$$min(\sum_{t=0}^{T-LT}(O^L \cdot y_t^L + \sum_{t=LT}^{T}(h \cdot s_t \cdot v)) \tag{4.18}$$

And the only difference observed in the constraints is that 4.5, 4.7, 4.8 and 4.9 are no more necessary.

The new constraint to guarantee that the order quantity is higher than the minimum order quantity is expressed as:

$$m \cdot y_t^L \leq Q_t^L, \forall t \in \{0, ..., T-LT\} \tag{4.19}$$

Regarding the restrictions 4.10 and 4.11, in order to exclude the FL component, they are expressed as:

$$s_t = SB + Q^L_{t-LT} + i_t - d_t, t = LT \tag{4.20}$$

$$s_t = s_{t-1} + Q^L_{t-LT} + i_t - d_t, \forall t \in \{LT+1, ..., T\} \tag{4.21}$$

4.7 Sensitivity Analysis

The ordering costs involved in this process are values with some uncertainty, especially when it comes to transportation costs. Transportation costs have shown a large increase in recent years and there are several news reports of this increase in peak freight prices since the outbreak of the pandemic.

In addition to internal data from Maersk that reveals a great volatility in shipping costs in recent years, according to Carrière-Swallow et al. (2022a), the cost of shipping full containers suffered a high increase in 2020 and the cost of shipping bulk commodities had an even higher increase. Additionally, in a study by Carrière-Swallow et al. (2022b), the authors state that by October 2021, indicators of the cost of transporting full containers through sea had suffered an increase of 500% when compared to pre-pandemic levels and the cost of shipping bulk commodities tripled. Finally, in Smith et al. (2021) the authors state that the cost rising is generalized, it is increasing both in ocean and truck transport and the warehousing costs are also increasing.

The large variability expected in costs was the motivation for the sensitivity analysis of the costs involved in the replenishment process, to observe the variation in the total cost and other factors, such as average lot size and order frequency.

Additionally, the quantity that triggers the change of the transport mode that minimizes costs is also determined and sensitivity analysis of this quantity of the cost of transport is also performed.

The sensitivity analysis was done separately for each variable and is resumed by Table 4.8.

Table 4.8: Parameters and variations tested in the sensitivity analysis for each transport constraint scenario

Transportation Constraint Scenarios	Unit Cost	Variation
LL-restricted transport	Transport cost/ m^3 Cost/ order Storage cost/ m^3/ day	±10% ±20% ±30% ±40% ±50%
FL-restricted transport	Transport cost/ container Cost/ order Storage cost/ m^3/ day	±10% ±20% ±30% ±40% ±50%
None-transport mode restriction	Transport cost/ m^3 Transport cost/ container	±10% ±20% ±30% ±40% ±50%

Regarding the cost of transport, as mentioned above, they have undergone large increases in a short time and, for this reason, variations up to ±50% are tested. Furthermore, given the large discrepancy between storage costs and ordering costs, it is expected that small variations of both costs will not have a great impact on the replenishment plan, thus being one more reason to test variations up to ±50%, to observe if large variations can impact the stock replenishment plan.

4.8 Metrics

The evaluation of each of the methods used to obtain the replenishment plan requires the usage of evaluation metrics to assess the performance of each one.

The metrics collected are the replenishment plan ordering cost, which includes the cost of triggering an order and transporting it, storage cost, total cost, and algorithm runtime.

Total cost is the primary metric for comparing the tested methods since it is the main metric that is intended to be minimized. However, the algorithms' execution time is also collected to compare its value between the different methods tested. This helps to understand how long it would take to obtain the replacement plan in a real scenario.

Regarding the two cost components, storage costs and ordering costs, they are metrics that allow understanding of which are the main sources of cost for the brand and allow understanding, in the sensitivity analysis, where the impact of each cost variation is reflected.

In addition, other metrics are collected for the sensitivity analysis, namely the average lot size and the total number of recommended orders, to understand if the variation of the unit cost value just influences the total costs or also influences the replenishment plan recommended.

4.9 Programming Tools

Regarding the development of the models, Python 3.10.4 was the programming language of choice due to the ease of syntax and the extensive library of packages available. Furthermore, this choice was made to ensure consistency with the programming language already used in the algorithms within the company.

The code was programmed with the support mainly of the Pandas and Numpy libraries provided in Python. Additionally, it also used statistics functions that are part of the Python Standard Library in the statistics module.

In the optimization models, Pulp Library was used for integer programming modeling. In the optimization models, an academic license of the Gurobi Solver version 9.0 was used.

All experiments were calculated using an Apple M1 Pro chip with 32GB RAM.

Chapter 5

Results and discussion

The goal of this chapter is to analyze each of the algorithms mentioned in the previous one. The idea is to compare the algorithms according to the total costs incurred with the replenishment plan recommended by each of them, and their runtime.

This study was conducted considering two different products with different sales profiles: product 1 has a low daily demand when compared to product 2.

Table 5.1 has a quantitative description of each product demand during the planning horizon. It was recorded the prediction done at 2021-01-01 for the period since 2021-01-01 until 2021-04-30, which corresponds to a prediction for 120 days.

Table 5.1: Quantitative description of the demand of product 1 and product 2

Parameter	**Product 1**	**Product 2**
Mean	5,16	101,10
Standard Deviation	2,84	7,09
Median	6,00	102,00
Mode	6,00	105,00
Maximum Value	10,00	116,00
Minimum Value	1,00	81,00

Additionally, for this analysis it was considered that the products had no expected inbounds to be received in the warehouse in the planning horizon and, as such, the list of "expected inbounds" is a list of null values.

Regarding the value of the other inputs necessary for the algorithms, it was considered oversea transport from Shanghai to Hamburg, which justifies the transport costs and lead time values. Those inputs are presented in Table 5.2.

Table 5.2: Input values

Input	Value
Lead Time (days)	35,00
Container Capacity (m^3)	67,70
Item volume (m^3)	0,05
Safety Stock (units)	0,00
Minimum Order Quantity (units)	0,00
Initial Stock (units)	0,00
FL Transport Cost (€/ container)	6 500,00
FL Order Cost (€/ order)	100,00
LL Transport Cost (€/ m^3)	120,00
LL Order Cost (€/order)	200,00
Storage Cost (€/ day/ m^3)	0,95

As referred in Table 5.2, it was considered that the warehouse stock, the desired safety stock and the minimum quantity are zero. These considerations were done because the impact of considering different values for these inputs would impact equally the results obtained in the different methods tested and, for this reason, it is not relevant for its comparison. Additionally, each time the algorithm is run it assumes deterministic demand for the planning horizon and, as such, considering a null safety stock will never lead to stockouts from the moment the first order arrives because the total ordering recommendations will equal the sum of the forecast net requirements.

Even so, it is important to point out that when considering that there is no initial stock in the warehouse, the demand during the days before the first arrival of stock will not be satisfied and, consequently, there will be shortage.

Finally, the planning horizon considered for this analysis is 120 days because it was considered to be a reasonable period for planning. As the lead time is already 35 days, this period allows to give brands a reasonable visibility of the next purchases estimate. It is important to highlight that a much longer forecast horizon would provide purchasing recommendations that might be too far away and, therefore, irrelevant to the moment the model is being run. Moreover, the forecast error increases as the forecast horizon is longer and, as such, the latest recommendations would not be good ones.

Additionally, a sensitivity analysis is performed considering that there are transport mode constraints:

1. Under LL-restricted transport - merchandise can only be transported in LL mode;
2. Under FL-restricted transport - merchandise can only be transported in FL mode;
3. Without transport mode constraints - there are no transport constraints, i.e. the cheapest transport mode is selected each time an order is triggered.

In the sensitivity analysis considering LL-restricted transport, the cost/ order and the transport cost/ m^3 are varied, while when FL-restricted transportation the cost/ order and the transport cost/ container are varied. Additionally, a variation of the storage costs is made in both cases.

When there is no transport mode constraints, the sensitivity analysis performed was carried out to understand the impact of the transport cost variation on the threshold quantity that triggers the change from LL-transport to FL-transport. Additionally, a similar analysis was done regarding the amount left over the full container, i.e., when the quantity to be transported is such that it is capable of filling some containers, but there is still a quantity left over.

5.1 Algorithms Comparison

The first analysis was performed with the product with the lowest demand. For this product, each scenario regarding the transport mode constraints was run with each of the four different methods, as mentioned in Table 4.4.

The results obtained are presented in Table (see Table B.1 in Appendix B) and in the following graph:

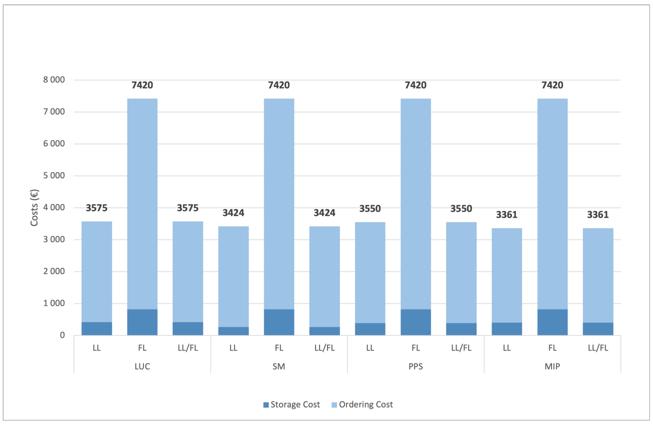

Figure 5.1: Total costs of the replenishment plan recommended for product 1 by each method under three transport-constraint scenarios

It is observed that when subject to LL-transport, the costs equal the costs of when there are no transport mode constraints, being 3 575€, 3 424€, 3 550€, and 3 361€ when applying the LUC, SM and PPS heuristic methods and Mixed Integer Programming (MIP), respectively. The Table B.3 in Appendix B shows the increase of costs when applying the heuristics methods comparatively to the costs when applying the optimization model. Furthermore, when subject to FL-transport mode, the total cost is 7 420€ for all methods, which is much higher compared to the previous transport scenarios under the same method. This highlights that for the product in question the most appropriate transport mode is always the LL since without transport constraints the algorithm always recommends shipping in LL.

The same analysis was done for product with higher demand (see Table B.2 in Appendix B) and the results achieved were the following:

When applying the same reasoning to product 2 for all transport mode scenarios it was found that, in general, when under the LL-transport mode constraint the cost is always higher and equal

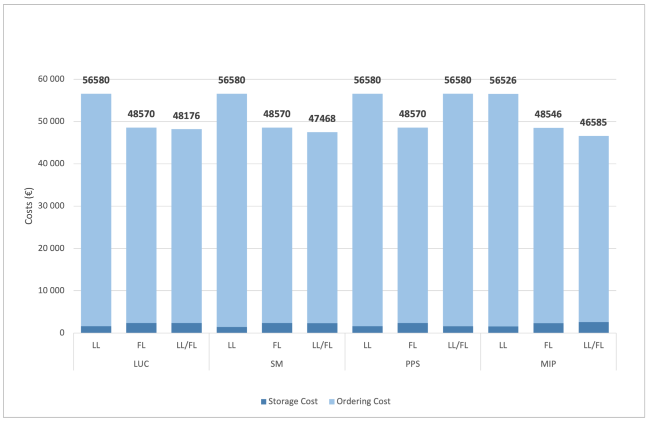

Figure 5.2: Total costs of the replenishment plan recommended for product 2 by each method under three transport-constraint scenarios

to 56 580€ for all the heuristic based algorithms and 56 526€ for the optimization model. Additionally, it is also verified that when under the FL-transport mode constraint the cost resulting from the heuristic based methods present the same value - 48 570€ - and slightly higher than the value resulting from the optimization model - 48 546€.

When there are no transport mode constraints, the costs are 48 176€, 47 468€, 56 580€ and 46 585€ for the LUC, SM, PPS heuristic based algorithm and optimization model, respectively. As that, the costs are related as follows: PPS > LUC > SM > MIP. So it is observed a common pattern to all transport mode constraints: the method that results in the lowest cost is the optimization model. The Table B.4 in Appendix B presents the increase of costs when applying the methods based on heuristics comparatively to the costs when applying the optimization model.

It should be noted that in the PPS method, when there are no transportation constraints, the algorithm recommends ordering always in LL. However, as shown in the graph, the value of total costs is lower when under FL-transport constraint and, as that, the non-restricted transport is not regretting the lowest cost. It happens because the difference between ordering costs and storage costs are smaller in LL transportation (reasoning of PPS), however, the rule of comparing this difference might be a bad decision rule since it does not imply the transport mode that results in lowest cost.

It is important to highlight that the non-restricted transport presents a slightly lower total cost than when under FL-transport constraint because the last order arrives through LL-transport instead of FL-transport. All first orders recommended are transported through FL, but the quantity of the last batch is not large enough to compensate for shipping by FL. Probably this happens because the planning horizon is limited to 120 days. If there was no time horizon limitation, possibly all orders would be recommended to be sent through FL.

It is observed that for both products, regardless of the method used and the transportation scenario, there is a general pattern: ordering costs is a much larger component than storage costs. For product 1, the average of the storage cost represent 11% of the total costs while the average ordering cost comprise 89% and, for product 2, the average storage cost comprise 4% of the total cost while the average ordering cost compose the majority - 96%.

Additionally, it is observed that the best transport mode for product 1, which has a lower demand pattern, is LL transportation and for product 2, which has a higher demand pattern, is FL transportation.

Finally, regarding the running time (see Table B.1 and Table B.2 in Appendix B), there is no significant differences observed between the methods tested.

5.2 Sensitivity Analysis

As previously mentioned, the sensitivity analysis can be divided into three parts, considering, respectively, each transport mode constraint.

5.2.1 LL-restricted transport

Under the LL-restricted transport scenario merchandise is only transported through LL mode. For this analysis it was used product 1 since it is the product for which this transport mode is most suitable, as mentioned above.

The first source of cost tested is the transport cost/ m^3 and the impact on costs are summarized in Table 5.3.

Table 5.3: Impact of LL-transport cost/ m^3 variation on replenishment plan costs

Value	Variation	Storage Costs	Ordering Costs	Total Costs
60	-50%	405,1	1 678,0	2 083,1
72	-40%	405,1	1 933,6	2 338,7
84	-30%	405,1	2 189,2	2 594,3
96	-20%	405,1	2 444,8	2 849,9
108	-10%	405,1	2 700,4	3 105,5
120	0%	405,1	2 956,0	3 361,1
132	+10%	405,1	3 211,6	3 616,7
144	+20%	405,1	3 467,2	3 872,3
156	+30%	405,1	3 722,8	4 127,9
168	+40%	405,1	3 978,4	4 383,5
180	+50%	405,1	4 234,0	4 639,1

The results show that when varying the transportation cost/ m^3 only the ordering costs change and they increase or decrease if the unit transport cost/ m^3 is incremented or decremented, respectively. However, its variation has no impact on the number of orders since the lot-size and purchase timing are influenced only by the trade-off between the fixed ordering costs and storage costs (see Table B.5 in Appendix B).

Regarding the cost/order, as its value increases/decreases, the total costs also increase/decrease, respectively, as can be seen in Table 5.4.

Table 5.4: Impact of unit LL-order cost variation on replenishment plan costs

Value	Variation	Storage Costs	Ordering Costs	Total Costs
100	-50%	259,4	2 856,0	3 115,4
120	-40%	259,4	2 916,0	3 175,4
140	-30%	259,4	2 976,0	3 235,4
160	-20%	405,1	2 876,0	3 281,1
180	-10%	405,1	2 916,0	3 321,1
200	0%	405,1	2 956,0	3 361,1
220	+10%	405,1	2 996,0	3 401,1
240	+20%	405,1	3 036,0	3 441,1
260	+30%	405,1	3 076,0	3 481,1
280	+40%	405,1	3 116,0	3 521,1
300	+50%	405,1	3 156,0	3 561,1

Furthermore, when this unit cost increases/decreases it is expected that the number of orders decrease/increase since this cost influences the replenishment plan. However, the number of orders is only sensitive to large negative variations, i.e. only reductions equal to or higher than 30% increase the number of orders from 2 to 3 (see Table B.5 in Appendix B). When the number of orders increase, the quantity of each order decrease and, as such, inventory keeps in storage for less time, leading to a lower storage cost, as can be observed in the Table 5.4. Regarding the smallest negative variations (10 and 20%), they are not enough to increase the number of orders because the increase in ordering costs would not compensate the decrease of storage costs that would result from the decrease of the batch size. Regarding the positive variations, they are not enough to decrease the number of orders. Decreasing the number of orders would results in larger lot-sizes and, therefore, in higher storage cost which would not compensate the decrease in ordering costs that would result form the decrease of the number of orders. So, even for high positive variations, the number of orders is insensible because decreasing the number of orders would result in higher costs.

Regarding the unit storage cost, it is very low compared to the cost/order and as such, only very positive variations tested (40 and 50%) caused an increase in the number of orders from 2 to 3 (see Table B.5 in Appendix B). Regarding the negative variation of this cost, it shows that even for a high decrease of unit storage cost, the number of orders does not decrease. It shows that the reduction in total ordering costs caused by the reduction of the number of orders would not compensate the increase on total storage costs (as verified with the positive variation of the cost/order).

It should be noted that the most extreme variations of this cost are not realistic but were performed to verify if there was sensitivity to extreme variations.

The sensitivity of total costs is exhibit in Table 5.5.

Table 5.5: Impact of unit storage cost variation on replenishment plan costs

Value	Variation	Storage Costs	Ordering Costs	Total Costs
0,475	-50%	202,6	2 956,0	3 158,6
0,57	-40%	243,1	2 956,0	3 199,1
0,665	-30%	283,6	2 956,0	3 239,6
0,76	-20%	324,1	2 956,0	3 280,1
0,855	-10%	364,6	2 956,0	3 320,6
0,95	0%	405,1	2 956,0	3 361,1
1,045	+10%	445,6	2 956,0	3 401,6
1,14	+20%	486,2	2 956,0	3 442,2
1,235	+30%	526,7	2 956,0	3 482,7
1,33	+40%	363,2	3 156,0	3 519,2
1,425	+50%	389,2	3 156,0	3 545,2

For the last two variations tested, there was a reduction in storage costs because more orders were placed over the planning horizon. Even though the unit storage cost increased, there were fewer units in storage, leading to a lower storage cost in the end. As the number of orders increased in one unit, total ordering costs also increased by the fixed cost of triggering a new order - 200€.

5.2.2 FL-restricted transport

The analysis considering the FL-restricted transport followed and, in this case, product 2 was used because it is the type of product that most fits the FL transport, when compared to product 1.

The impact of the unit container cost variation on costs is shown in Table 5.6.

Table 5.6: Impact of FL-transport cost/ container variation on replenishment plan costs

Value	Variation	Storage Costs	Ordering Costs	Total Costs
3250	-50%	2 345,6	23 450,0	25 795,6
3900	-40%	2 345,6	28 000,0	30 345,6
4550	-30%	2 345,6	32 550,0	34 895,6
5200	-20%	2 345,6	37 100,0	39 445,6
5850	-10%	2 345,6	41 650,0	43 995,6
6500	0%	2 345,6	46 200,0	48 545,6
7150	+10%	2 345,6	50 750,0	53 095,6
7800	+20%	2 345,6	55 300,0	57 645,6
8450	+30%	2 345,6	59 850,0	62 195,6
9100	+40%	2 345,6	64 400,0	66 745,6
9750	+50%	2 345,6	68 950,0	71 295,6

The results show that, when varying the unit container cost, only the ordering costs vary and they increase or decrease if the unit cost is incremented or decremented, respectively.

Additionally, all variations do not impact the number of orders (see Table B.6 in Appendix B). Regarding the positive variation tested, in fact, it is not expected that the number of containers would be reduced because the number of containers actually used is already the minimum possible to satisfy all the needs. Regarding the negative variation, the number of containers do not increase with the decrease of the container unit cost. In fact, increasing the number of containers would generate an increase in the number of orders and, therefore, a decrease in the lot-size. The decrease on lot-size would generate a decrease on storage costs, however the increase on the number of orders and containers would generate a higher increase in total ordering costs and, therefore, in general, an increase in total costs. Therefore, the replenishment plan is insensitive to variations of this unit cost.

The impact of the unit order cost variation on costs is shown in Table 5.7.

Table 5.7: Impact of unit FL-order cost variation on replenishment plan costs

Value	Variation	Storage Costs	Ordering Costs	Total Costs
50	-50%	2 345,6	45 850,0	48 195,6
60	-40%	2 345,6	45 920,0	48 265,6
70	-30%	2 345,6	45 990,0	48 335,6
80	-20%	2 345,6	46 060,0	48 405,6
90	-10%	2 345,6	46 130,0	48 475,6
100	0%	2 345,6	46 200,0	48 545,6
110	+10%	2 345,6	46 270,0	48 615,6
120	+20%	2 345,6	46 340,0	48 685,6
130	+30%	2 345,6	46 410,0	48 755,6
140	+40%	2 345,6	46 480,0	48 825,6
150	+50%	2 345,6	46 550,0	48 895,6

Regarding the number of orders and the lot-size, there is no sensibility to this unit cost variation (see Table B.6 in Appendix B). Regarding the positive variation of this unit cost, there is no sensibility because when compared to the transport cost/ container, the cost/order is low and, therefore, the impact of this cost is low in influencing the number of orders. Regarding the insensitivity to the negative variation of this unit cost, it happens because if the number of order increase, the number of containers would also increase since in each order is used a container, but, as the cost/ container is very high, it does not compensate to increase the number of orders because it would also increase the total containers cost.

Finally, regarding the storage cost variation, the impact on total costs is exhibit on Table 5.8.

Table 5.8: Impact of unit storage cost variation on replenishment plan costs

Value	Variation	Storage Costs	Ordering Costs	Total Costs
0,475	-50%	1 172,8	46 200,0	47 372,8
0,57	-40%	1 407,4	46 200,0	47 607,4
0,665	-30%	1 642,0	46 200,0	47 842,0
0,76	-20%	1 876,5	46 200,0	48 076,5
0,855	-10%	2 111,1	46 200,0	48 311,1
0,95	0%	2 345,6	46 200,0	48 545,6
1,045	+10%	2 580,2	46 200,0	48 780,2
1,14	+20%	2 814,8	46 200,0	49 014,8
1,235	+30%	3 049,3	46 200,0	49 249,3
1,33	+40%	3 283,9	46 200,0	49 483,9
1,425	+50%	3 518,5	46 200,0	49 718,5

This variation only affects the storage cost component because the replenishment plan remains the same and, therefore, the ordering cost component does not change. The impact on total storage costs is only due to the unit storage cost variation.

This variation does not impact the number of orders nor, consequently, the lot-size (see Table B.6 in Appendix B). The fact of not impacting the number of orders reflects the previous conclusion: the positive variations tested of the unit storage cost are not enough to change the replenishment plan due to its high difference compared to the unit ordering cost and unit container cost and the negative variations tested are also not enough to change the replenishment plan for the same reason concluded in LL-transport restricted.

5.2.3 Without transport mode constraints

The last sensitivity analysis performed was to understand the sensitivity of the threshold quantity for which it is no longer worthwhile to transport merchandise in LL, and order FL instead, to LL-transport cost/ m^3 and to FL-transport cost/container (see Table B.7 in Appendix B).

For the current cost structure, the volume that triggers the transition from LL to FL transport mode is 53,33m^3, which corresponds to 1 067 units.

Testing the variation of the transport cost/ m^3, it was found that the quantity that triggers the shipment of goods by FL is inversely proportional to the transportation cost/ m^3 as shown in Figure 5.3.

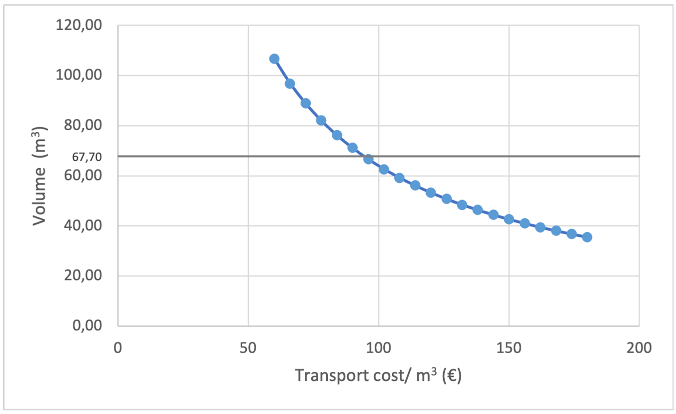

Figure 5.3: Sensitivity of the volume that triggers FL transport to transport cost/ m^3

Additionally, as can be seen through the container limit capacity in the graph (67,70 m^3), there is a negative variation in LL-transport cost/ m^3 that makes total costs through LL mode equal to costs through FL mode, and this decrease is 25,47€. So, in a real context, the LL-transport cost/ m^3 will never decrease more than 25,47€ while keeping the same FL-transport cost/ container because in this case it would never compensate to send merchandise through FL mode, which is unrealistic.

$$\Delta = 120 - \frac{6\ 500 + 100 - 200}{67,7} = 25,47\ € \tag{5.1}$$

As referred before, the same analysis was done but regarding the quantity that remains after filling full containers and that is not enough to fill the last one. The value of the volume for which it compensates to send through FL instead of LL is 52,50 m^3, which corresponds to 1 050 units (see Table B.7 in Appendix B). When analysing the sensitivity of this quantity to the transport cost/ m^3, it is observed that the threshold quantities are very close to the quantity previously analysed for the same variation but slightly lower (see Table B.7 in Appendix B).

A similar analysis was performed by varying the transportation cost/container and it was found that the quantity that triggers FL-transport is directly proportional to this cost.

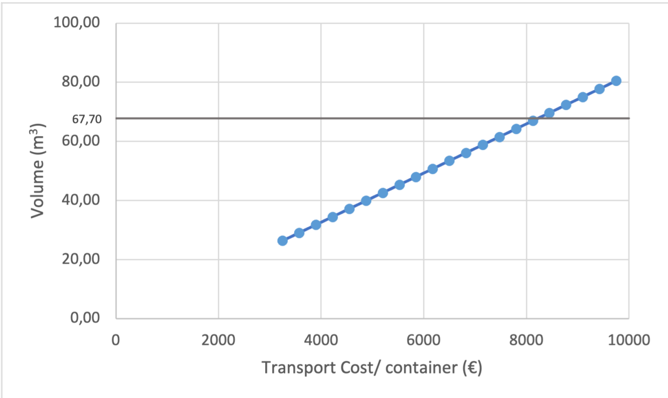

Figure 5.4: Sensitivity of the volume that triggers FL transport to transport cost/ container

It was observed that when the FL transport cost/container reaches 8 224€, an increase of 1 724€ compared to the actual value, the two modes of transport have the same total cost (see Table B.8 in Appendix B). It shows that, in a real context, the FL-transport cost/ container will never increase more than 1 724€ while keeping the same LL-transport cost/ m^3 because, in reality, the price charged for a FL container is always cheaper than the price charged for a full container in LL.

$$\Delta = 120 \cdot 67,7 + 200 - 6\,500 - 100 = 1\,724\text{ €} \tag{5.2}$$

In addition, the amount left over above the full container from which it compensates to send through FL transport was also analyzed (see Table B.8 in Appendix B). It was found that the threshold quantities are very close to the previous analysed quantity, however slightly lower.

Chapter 6

Conclusions and Future Work

In recent years there has been a major shift by brands to the e-commerce world. However, this transition causes them to lose some inventory management ground due to the breakdown of geographic barriers. Thus, efficient inventory management is an increasing challenge that brands have to face, and the decision of when and how much to order becomes even more difficult.

Thus, the present dissertation, carried out in a logistics company that is concerned with offering increasingly better resources to its customers, seeks to develop a tool that allows the customer to improve its logistics operations and reduce its costs, in order to increase the value proposition offered.

At the beginning of this dissertation, there was no tool that allowed its customers to make a recommendation regarding inventory replenishment. The complete absence of such a tool led to the investigation of this topic and possible solutions to help brands regarding it. Thus, this dissertation focus on investigating methods for recommending a replenishment plan that seeks to minimize costs and, at the same time, meet the expected demand.

6.1 Main Outcomes

One of the goals was to understand the operational process required to replenish inventory in the warehouse and to identify the sources and structure of the costs involved that are the fuel for the creation of the models that recommend inventory replenishment plans. Having the model's cost drivers identified, it followed the development of the various methods for each of the transportation mode constraint scenarios.

It was possible to verify that the various methods offered replenishment plans with costs very close to each other, and sometimes equal, within each of the transportation mode constraint scenarios. When product 1 was tested under the LL transport constraint and without transport constraint, the methods based on the LUC, SM, and PPS heuristics resulted in replenishment plans whose associated costs are 6,352%, 1,876% and 5,634% higher than the optimization model, respectively. When under the FL transport constraint, the methods based on the heuristics and the optimization model presented the same total costs. When tested for product 2 under the LL and FL transport constraints, the heuristic-based methods always obtained a solution with costs equal or higher than the cost associated with the replenishment plan provided by the optimization model by 0.096% and 0.050%, respectively. When there are no constraints on the transport mode, the models based on the LUC, SM, and PPS heuristics result in replenishment plans with higher costs than the one obtained through the optimization model in 3,415%, 1,894%, and 21,455%, respectively.

Despite having very close costs, the optimization model obtained almost always slightly lower costs than the heuristic-based methods, and no significant differences in algorithm runtime. Additionally, the optimization model is the only method that allows having both transport modes in the same order while the heuristic-based methods do not allow this condition, allowing only to recommend one transport mode per order. Finally, the optimization model is more scalable for future improvements, namely, scale the model to provide a replenishment plan for multiple products at the same time.

Furthermore, a general pattern was observable for all methods tested and all transportation mode constraint scenarios: the ordering cost is a much larger component than the storage cost. Ordering costs were found to constitute 89% and 96% of total costs for products 1 and 2, respectively. In fact, in the real context, what we have been seeing recently is a peak growth in freight costs, especially after the pandemic, which promotes an increasing discrepancy between storage costs and ordering costs. As such, the fact that this cost component is taking up an even larger proportion means that brands have to increasingly focus their attention on this cost component and exploit transportation contracts to the fullest in order to get the carrier that allows reducing this cost as much as possible.

Furthermore, taking into account the current situation of high variation in logistics costs, a sensitivity analysis was performed. In general, it was observed that the stock replenishment plan presents a low sensitivity to variations in each of the cost sources, both in LL transport mode and FL transport mode.

The insensibility to the lowest positive variations of unit storage cost and to the lowest negative variations of unit order cost proves the discrepancy between unit order cost and unit storage cost: only extreme variations impact on the replenishment plan. The insensitivity of the replenishment plan in FL transport mode to all the negative variations of the unit order cost and unit container cost and to the positive variations of the unit storage cost also proves the discrepancy between the costs of order plus container relatively to storage costs.

It was also concluded that the order volume that triggers the transition from LL to FL transport mode is 53,33m^3, while the volume that exceeds the full-container for which it compensates to send through FL instead of LL is 52,50m^3.

Finally, it was found that the FL transport cost is 25,47€ lower per m^3 in the case of a full container and, for this reason, for the same cost/container, the cost/m^3 charged in LL transport can never decrease more than 25,47€/m^3 because in that it would no longer be beneficial to ship by FL, which do not correspond to a real context. The same analysis was made for the cost/container and it was verified that while keeping the same cost/m^3 in LL shipping, the cost/container can never increase 1 724€ or more because it is somewhat unrealistic, the price charged for a FL container is always cheaper than the price charged for a full container in LL.

6.2 Future Work

The following natural step is to deploy the replenishment recommendation algorithm in SPOKE.

Additionally, there is still space for improvement of the present recommendation algorithm, namely, one of the main constraints of this project is the absence of a framework with information regarding the costs, lead time, minimum quantities, and expected inbounds. Thus, it is crucial to have a database with information constantly updated on these inputs to feed the recommendation model and to give recommendations based on updated inputs.

Furthermore, another point for improvement would be the scalability of the model, in order to recommend a replenishment plan that includes the replenishment of several products simultaneously. Currently, the model predicts individually how much to order from a given product, however, especially with small products, sometimes brands aggregate the purchase of more than one product in the same order. Therefore, the model has applicability when it comes to products of reasonable volume, such as the case of Maersk E-fulfilment customers' products, where brands usually order only that product, however when it comes to very small items, such as fashion products, it is limited.

In order to make the problem more robust, it would also be interesting to include the storage cost from several warehouses, making it possible to decide what quantity to order to satisfy at once all of them, as well as quantity discounts, which are typically provided by suppliers and influence the choice of how much to buy. It should be noted that heuristic-based methods could be very limited when it comes to this scalability, however, the optimization model could allow scaling and provide a model capable of making recommendations for several products simultaneously to more than one warehouse and considering quantity discounts. However, with the implementation of these improvements, it would be necessary to rethink whether it would make sense to maintain a daily recommendation since it incorporates much more integer variables and, therefore, can be more time-consuming.

Finally, further on, it would be important to explore air transportation and prepare the model for this transport cost structure.

These potential new improvements should be deeper explored in order to be aligned with Maersk E-fulfilment and to guarantee that it contributes to the improvement of its value proposition and promotes its future growth.

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Appendix A

Replenishment Process Outline

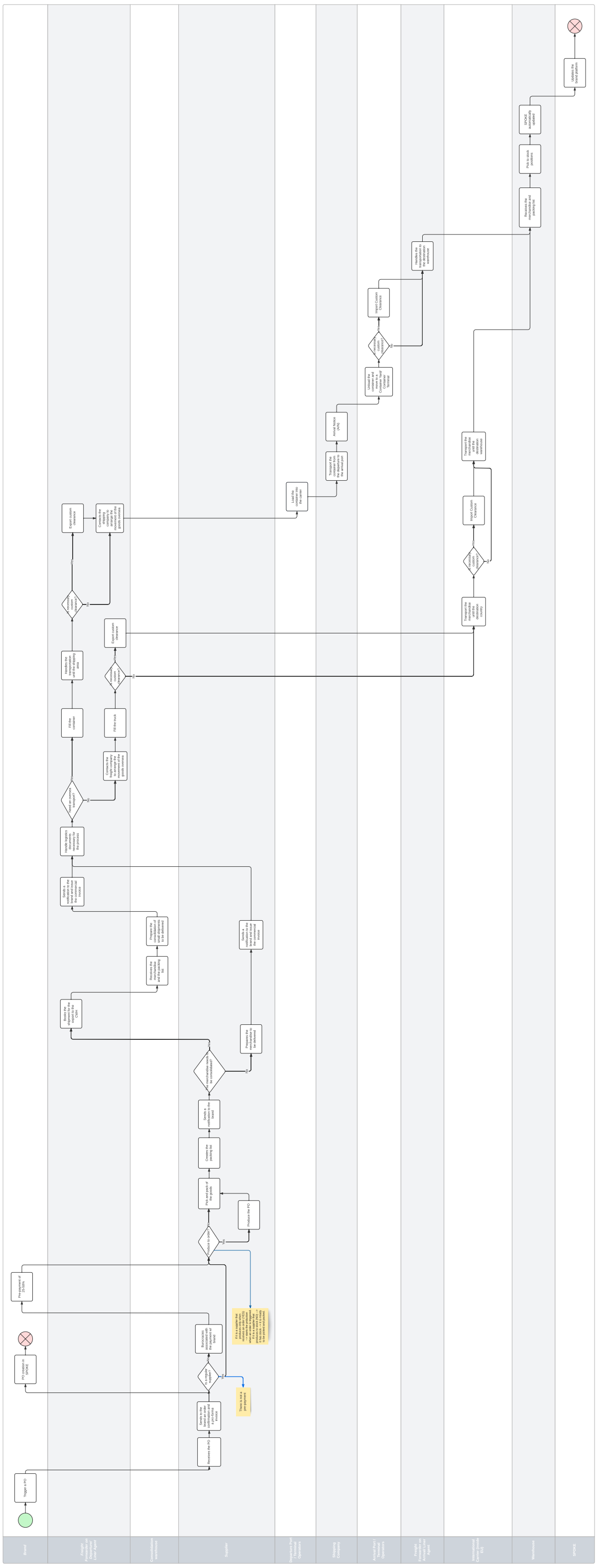

Figure A.1: Replenishment process outline

Appendix B

Results

Table B.1: Metrics collected from the replenishment plans suggested for product 1

Method	Transport Mode	Storage Cost (€)	Ordering Cost (€)	Total Cost (€)	No of Orders	Avg Storage Cost/ Order (€)	Avg Ordering Cost/ Order (€)	Avg Cost/ Order (€)	Avg Storage Cost/ Item (€)	Avg Ordering Cost/ Item (€)	Avg Total Cost/ Item (€)	Avg Lot Size	Total Running Time (s)
	LL	419	3156	3575	3	140	1052	1192	0,983	7,408	8,391	142	0,08429
LUC	FL	820	6600	7420	1	820	6600	7420	1,925	15,493	17,418	426	0,08740
	LL/FL	419	3156	3575	3	140	1052	1192	0,983	7,408	8,391	142	0,10488
	LL	268	3156	3424	3	89	1052	1141	0,630	7,408	8,038	142	0,07938
SM	FL	820	6600	7420	1	820	6600	7420	1,925	15,493	17,418	426	0,08549
	LL/FL	268	3156	3424	3	89	1052	1141	0,630	7,408	8,038	142	0,10880
	LL	394	3156	3550	3	131	1052	1183	0,926	7,408	8,334	142	0,08548
PPS	FL	820	6600	7420	1	820	6600	7420	1,925	15,493	17,418	426	0,08662
	LL/FL	394	3156	3550	3	131	1052	1183	0,926	7,408	8,334	142	0,12310
	LL	405	2956	3361	2	203	1478	1681	0,951	6,939	7,890	213	0,05587
MIP	FL	820	6600	7420	1	820	6600	7420	1,925	15,493	17,418	426	0,02052
	LL/FL	405	2956	3361	2	203	1478	1681	0,951	6,939	7,890	213	0,072490

Table B.2: Metrics collected from the replenishment plans suggested for product 2

Method	Transport Mode	Storage Cost (€)	Ordering Cost (€)	Total Cost (€)	No of Orders	Avg Storage Cost/ Order (€)	Avg Ordering Cost/ Order (€)	Avg Cost/ Order (€)	Avg Storage Cost/ Item (€)	Avg Ordering Cost/ Item (€)	Avg Total Cost/ Item (€)	Avg Lot Size	Total Running Time (s)
	LL	1630	54950	56580	10	163	5495	5658	0,185	6,227	6,411	883	0,08121
LUC	FL	2370	46200	48570	7	339	6600	6939	0,269	5,235	5,504	1261	0,08145
	LL/FL	2370	45806	48176	7	339	6544	6882	0,269	5,190	5,459	1261	0,09186
	LL	1430	55150	56580	11	130	5014	5144	0,162	6,249	6,411	802	0,07886
SM	FL	2370	46200	48570	7	339	6600	6939	0,269	5,235	5,504	1261	0,08098
	LL/FL	2328	45140	47468	7	333	6449	6781	0,264	5,115	5,379	1245	0,09200
	LL	1630	54950	56580	10	163	5495	5658	0,185	6,227	6,411	883	0,08477
PPS	FL	2370	46200	48570	7	339	6600	6939	0,269	5,235	5,504	1261	0,08655
	LL/FL	1630	54950	56580	10	163	5495	5658	0,185	6,227	6,411	882,5	0,10841
	LL	1576	54950	56526	10	158	5495	5653	0,179	6,227	6,405	883	0,82896
MIP	FL	2346	46200	48546	7	335	6600	6935	0,266	5,235	5,501	1261	10,23345
	LL/FL	2579	44006	46585	7	368	6287	6655	0,292	4,987	5,279	1261	11,23878

Table B.3: Increase of total costs of the recommended plan for product 1 when comparing each heuristic method with the optimization model

	LL	FL	LL/FL
LUC	6,352%	0,000%	6,352%
SM	1,876%	0,000%	1,876%
PPS	5,634%	0,000%	5,634%

Table B.4: Increase of total costs of the recommended plan for product 2 when comparing each heuristic method with the optimization model

	LL	FL	LL/FL
LUC	0,096%	0,050%	3,415%
SM	0,096%	0,050%	1,894%
PPS	0,096%	0,050%	21,455%

Table B.5: Metrics collected from the sensitivity analysis under LL-transport constraint

Variable	**Value**	**Variation**	**Total Costs**	**Storage Costs**	**Ordering Costs**	**Nº of Orders**	**Average Lot Size**
Transport cost/ m^3	60	-50%	2083,1	405,1	1678,0	2	213
	72	-40%	2338,7	405,1	1933,6	2	213
	84	-30%	2594,3	405,1	2189,2	2	213
	96	-20%	2849,9	405,1	2444,8	2	213
	108	-10%	3105,5	405,1	2700,4	2	213
	120	0%	3361,1	405,1	2956,0	2	213
	132	+10%	3616,7	405,1	3211,6	2	213
	144	+20%	3872,3	405,1	3467,2	2	213
	156	+30%	4127,9	405,1	3722,8	2	213
	168	+40%	4383,5	405,1	3978,4	2	213
	180	+50%	4639,1	405,1	4234,0	2	213
Cost/ order	100	-50%	3115,4	259,4	2856,0	3	142
	120	-40%	3175,4	259,4	2916,0	3	142
	140	-30%	3235,4	259,4	2976,0	3	142
	160	-20%	3281,1	405,1	2876,0	2	213
	180	-10%	3321,1	405,1	2916,0	2	213
	200	0%	3361,1	405,1	2956,0	2	213
	220	+10%	3401,1	405,1	2996,0	2	213
	240	+20%	3441,1	405,1	3036,0	2	213
	260	+30%	3481,1	405,1	3076,0	2	213
	280	+40%	3521,1	405,1	3116,0	2	213
	300	+50%	3561,1	405,1	3156,0	2	213
Storage cost/ m^3/ day	0,475	-50%	3158,6	202,6	2956,0	2	213
	0,57	-40%	3199,1	243,1	2956,0	2	213
	0,665	-30%	3239,6	283,6	2956,0	2	213
	0,76	-20%	3280,1	324,1	2956,0	2	213
	0,855	-10%	3320,6	364,6	2956,0	2	213
	0,95	0%	3361,1	405,1	2956,0	2	213
	1,045	+10%	3401,6	445,6	2956,0	2	213
	1,14	+20%	3442,2	486,2	2956,0	2	213
	1,235	+30%	3482,7	526,7	2956,0	2	213
	1,33	+40%	3519,2	363,2	3156,0	3	142
	1,425	+50%	3545,2	389,2	3156,0	3	142

Table B.6: Metrics collected from the sensitivity analysis under FL-transport constraint

Variable	**Value**	**Variation**	**Total Costs**	**Storage Costs**	**Ordering Costs**	**Nº of Orders**	**Average Lot Size**
Transport cost/ container	3250	-50%	25795,6	2345,6	23450,0	7	120
	3900	-40%	30345,6	2345,6	28000,0	7	120
	4550	-30%	34895,6	2345,6	32550,0	7	120
	5200	-20%	39445,6	2345,6	37100,0	7	120
	5850	-10%	43995,6	2345,6	41650,0	7	120
	6500	0%	48545,6	2345,6	46200,0	7	120
	7150	+10%	53095,6	2345,6	50750,0	7	120
	7800	+20%	57645,6	2345,6	55300,0	7	120
	8450	+30%	62195,6	2345,6	59850,0	7	120
	9100	+40%	66745,6	2345,6	64400,0	7	120
	9750	+50%	71295,6	2345,6	68950,0	7	120
Cost/ order	50	-50%	48195,6	2345,6	45850,0	7	120
	60	-40%	48265,6	2345,6	45920,0	7	120
	70	-30%	48335,6	2345,6	45990,0	7	120
	80	-20%	48405,6	2345,6	46060,0	7	120
	90	-10%	48475,6	2345,6	46130,0	7	120
	100	0%	48545,6	2345,6	46200,0	7	120
	110	+10%	48615,6	2345,6	46270,0	7	120
	120	+20%	48685,6	2345,6	46340,0	7	120
	130	+30%	48755,6	2345,6	46410,0	7	120
	140	+40%	48825,6	2345,6	46480,0	7	120
	150	+50%	48895,6	2345,6	46550,0	7	120
Storage cost/ m^3/ day	0,475	-50%	47372,8	1172,8	46200,0	7	120
	0,57	-40%	47607,4	1407,4	46200,0	7	120
	0,665	-30%	47842,0	1642,0	46200,0	7	120
	0,76	-20%	48076,5	1876,5	46200,0	7	120
	0,855	-10%	48311,1	2111,1	46200,0	7	120
	0,95	0%	48545,6	2345,6	46200,0	7	120
	1,045	+10%	48780,2	2580,2	46200,0	7	120
	1,14	+20%	49014,8	2814,8	46200,0	7	120
	1,235	+30%	49249,3	3049,3	46200,0	7	120
	1,33	+40%	49483,9	3283,9	46200,0	7	120
	1,425	+50%	49718,5	3518,5	46200,0	7	120

Table B.7: Metrics collected from the sensitivity analysis to LL-transport cost/ m^3 variation without transport mode constraints

Transport Cost/ m^3	**Variation**	**Total Volume (m^3)**	**Total Quantity**	**Amount Left (m^3)**	**Amount Left Quantity**
60	-50%	106,67	2133	105,00	2100
66	-45%	96,97	1939	95,45	1909
72	-40%	88,89	1778	87,50	1750
78	-35%	82,05	1641	80,77	1615
84	-30%	76,19	1524	75,00	1500
90	-25%	71,11	1422	70,00	1400
96	-20%	66,67	1333	65,63	1313
102	-15%	62,75	1255	61,76	1235
108	-10%	59,26	1185	58,33	1167
114	-5%	56,14	1123	55,26	1105
120	0%	53,33	1067	52,50	1050
126	+5%	50,79	1016	50,00	1000
132	+10%	48,48	970	47,73	955
138	+15%	46,38	928	45,65	913
144	+20%	44,44	889	43,75	875
150	+25%	42,67	853	42,00	840
156	+30%	41,03	821	40,38	808
162	+35%	39,51	790	38,89	778
168	+40%	38,10	762	37,50	750
174	+45%	36,78	736	36,21	724
180	+50%	35,56	711	35,00	700

Table B.8: Metrics collected from the sensitivity analysis to FL-transport cost/ container variation without transport mode constraints

Transport Cost/ container	**Variation**	**Total Volume (m^3)**	**Total Quantity**	**Amount Left (m^3)**	**Amount Left Quantity**
3250	-50%	26,25	525	25,42	508
3575	-45%	28,96	579	28,13	563
3900	-40%	31,67	633	30,83	617
4225	-35%	34,38	688	33,54	671
4550	-30%	37,08	742	36,25	725
4875	-25%	39,79	796	38,96	779
5200	-20%	42,50	850	41,67	833
5525	-15%	45,21	904	44,38	888
5850	-10%	47,92	958	47,08	942
6175	-5%	50,63	1013	49,79	996
6500	0%	53,33	1067	52,50	1050
6825	+5%	56,04	1121	55,21	1104
7150	+10%	58,75	1175	57,92	1158
7475	+15%	61,46	1229	60,63	1213
7800	+20%	64,17	1283	63,33	1267
8125	+25%	66,88	1338	66,04	1321
8450	+30%	69,58	1392	68,75	1375
8775	+35%	72,29	1446	71,46	1429
9100	+40%	75,00	1500	74,17	1483
9425	+45%	77,71	1554	76,88	1538
9750	+50%	80,42	1608	79,58	1592