Reverse logistics optimization model for a multi-warehouse network

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Abstract

Companies often saw returns as an unavoidable cost, forgetting the possibility of making them profitable or, at least, less costly for the business. However, the implementation of an efficient reverse logistics supply chain has been proving to be a competitive advantage. With return rates reaching the highest levels ever seen, corporations have begun to explore the possibility of managing product returns in a more cost-efficient manner, looking for higher profit margins and better operational performances. By linking reverse logistics with optimization algorithms, companies can enhance their decision processes and become more competitive.

The current dissertation allowed the identification of the most critical areas in HUUB's reverse logistics supply chain, proposing an optimization algorithm to give a solution capable of dynamically setting the destination warehouse of a specific return. The approach has two main phases: understanding reverse logistics operation at the company and developing an algorithm capable of answering not only HUUB today's necessities but also in conformity to its expected growth. For that, we propose a hybridization model using a Genetic Algorithm and a Simulated Annealing approach. The model is applied to distinct scenarios representing distinct situations in HUUB's reverse logistics daily operations.

The results showed that the model was able to generate great solutions, demonstrating that the applied algorithms are effective and efficient techniques to use. Moreover, we conclude that expanding the current network to send returned products is a valuable solution that can help the company saving costs.

Resumo

As empresas tendiam a olhar para as devoluções como um custo inevitável, esquecendo-se da possibilidade de as tornar lucrativas ou, pelo menos, mais económicas para o negócio. Contudo, ter uma cadeia de abastecimento com uma logística inversa eficiente tem provado trazer uma vantagem competitiva. O número de devoluções está a atingir números nunca antes vistos, criando a vontade nas empresas de começar a gerir-las de uma maneira menos custosa. A aplicação de algoritmos de otimização na área de logística inversa permite às empresas uma tomada de decisão mais eficiente, tornando-se mais competitivas.

Esta dissertação olha para a logística inversa da HUUB e identifica as áreas mais críticas, propondo um algoritmo de optimização que escolhe dinamicamente o armazém de destino para cada uma das devoluções. A abordagem passa por duas grandes fases: a compreensão de toda a logística inversa da empresa e o desenvolvimento de um algoritmo que permite à HUUB responder aos desafios actuais bem como aos do seu futuro. Para tal, é proposto um modelo de hibridização contemplando um *Genetic Algorithm* e um *Simulated Annealing*. Este modelo foi aplicado a vários cenários ilustrativos do dia-a-dia operacional da empresa.

Os resultados mostram que o modelo foi capaz de gerar boas soluções, demonstrando que a combinação dos dois algoritmos é eficiente. Para além disso, é concluído que expandir a atual rede de armazéns que recebem devoluções é uma solução proveitosa para a empresa.

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"Every journey that is successful has culs-de-sac and speed bumps. I carry a wisdom gene through my life through the good, the bad, and the ugly."

Peter Guber

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Acronyms and Symbols

ACO	Ant Colony Optimization
AM	Account Management
DB	Database
EU	European Union
EVA	Economic Value Added
FMEA	Failure Mode and Effects Analysis
GA	Genetic Algorithm
HR	Human Resources
NL	Netherlands
NHPP	Non-homogeneous Poisson Process
PBMs	Population-based metaheuristics
PSO	Particle Swarm Optimization
PO	Purchase Order
PT	Portugal
RL	Reverse Logistics
RPN	Risk Prioritization Number
RR	Return Rate
RSCM	Reverse Supply Chain Management
SA	Simulated Annealing
SL	Service Level
SO	Sales Order
SSBMs	Single solution based metaheuristics
US	United States
TS	Tabu Search
VAT	Value Added Tax
VNS	Variable Neighborhood Search
WCO	World Customs Organization

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Chapter 1

Introduction

Reverse Logistics (RL) have been viewed as an unavoidable cost of doing business, forfeiting any chance of cost savings. Due to its added complexity, the return flow is often costlier than the forward distribution of goods and it also fails to bring value to the business. Companies are adding workers, increasing warehouse space, and establishing separate departments to handle RL.

Furthermore, returns are also a driver for customer satisfaction (Rogers et al., 1999). Consumers expect returns to be frictionless. For that, return policies must be convenient and technology should help to create a smoother process that helps to enhance the customer experience.

An organization cannot improve returns management without relevant data. The process of gathering and managing the correct data goes a long way toward reducing the costs of returns processing, while also potentially improving the customer experience.

Considering the arguments aforementioned and recognizing the inherent importance of having an efficient return process, the underlying research problem is to analyze the RL of the products at HUUB and study a solution to improve the returns flow, turning it into a healthy source of loyalty and profits.

1.1 Company Overview

HUUB is a start-up, founded in 2015, that offers an end-to-end logistic platform for distinctive fashion brands. The company promises to manage all of the brands' supply chain, from its clients to its suppliers. The company ecosystem is composed of brands, end-users (retailers and customers), suppliers, carriers and other partners. In Figure 1.1 is illustrated HUUB's central position regarding its stakeholders. This solution will enable small independent brands to avoid unnecessary waste of time, money and energy, allowing them to focus only on their product development, sales, and marketing. Although in the past, HUUB was only focusing on the kids' fashion industry, nowadays, its customer segment is extending towards adult brands as well.

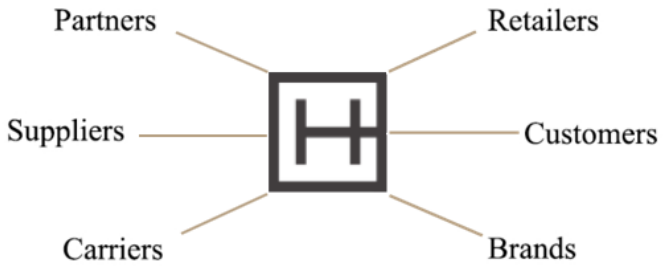


Figure 1.1: HUUB's positioning relative to its stakeholders

In order to simplify all the different and complex phases of the brand's supply chain, the company uses Spoke, a web-based platform that connects all of the HUUB stakeholders. Currently, the company boasts a portfolio of 50+ brands and has served more than 80 countries. Since the deployment of Spoke, it has handled more than 180.000 products, pertaining to 20.000 SKUs and an approximate total of 6.600 shipments, with two logistics centers, one in Maia, Portugal (PT) and another in the Netherlands (NL), via a partnership with DAMCO.

1.2 Thesis Objectives

As the company's supply chain network keeps evolving, and the network of warehouses increasing, the number of returns is also expected to rise. At this stage, there is a need to regroup and redesign the whole approach of RL, creating a practical solution with four primary objectives:

- To cope with HUUB's forecasted growth;
- To contribute positively to the Operational Margin;
- To assure a correct cycle time for the RL process, regarding the pre-defined service level agreements;
- To allow brands' development.

1.3 Project Methodology

The first phase was to understand the current state of RL at HUUB. To deep dive into the whole operation, several interviews with the most important stakeholders were done. HUUB's Portuguese warehouse was visited and the entire returns process was mapped. Additionally, all the operational costs, tools, and stakeholders were gathered.

After understanding the return operation at HUUB, the area that will bring the most favorable return for this company is identified.

The best way to solve the proposed problem is through the implementation of an algorithm that supports the decision making of one of the parts of the returns process. For this purpose,

and after understanding what the desired output of the algorithm is, all data requirements were gathered. Since there was no historical data, there was a need to generate dummy data. After that, the algorithm was developed and tested with different scenarios that could happen to HUUB in the upcoming times.

After that, we extracted results and performed scenario analysis. In the end, the key takeaways were stressed out.

1.4 Project Structure

This dissertation starts with the current chapter as an introduction to the problem, where we explain the purpose of this project, as well as its objectives and methodology.

The "State of the art", comprises a literature review on RL, the distinct areas of RL optimization problems, metaheuristics applied and a statistical distribution to model HUUB's demand.

The "Problem Context", details the organizational structure of HUUB and its current flow of products across HUUB's supply chain. Besides, we map the return process and provide insights on improvement opportunities.

The "Methodology", comprises the opportunities explored by this master thesis. In this last stage, the construction of the mathematical model created during this project is discussed. Hence, it includes the explanation of the decision variables, the objective function, and the constraints applicable to this system.

The "Implementation and Results", concerns the implementation of each stage of the algorithm and the results obtained in each step. A sensitive analysis is also conducted in this section.

Finally, the sixth and final chapter, "Conclusion and Future Work", is a conclusive reflection about the results and future improvements that would be complementary to the study developed over this dissertation.

Chapter 2

State of the art

Throughout this chapter, we explore the relevant concepts addressed in this dissertation. First, the definition of RL, the drivers and the current framework on this subject are detailed. Then, the main concepts concerning optimization models and techniques in RL areas are engaged, with a particular focus on metaheuristic approaches. Finally, on a different, but equally relevant matter, the Non-homogeneous Poisson distribution is addressed.

2.1 Reverse Logistics

RL is generally defined as the process of planning, implementing, and controlling a cost-effective flow of raw materials/in-process inventory/finished goods, from the point of consumption to the point of origin. All of this with the mindset to recapture or create value (Rogers et al., 1999). For instance, RL activities include collection, disassembly, and processing of used products/product parts/materials to reuse or to assign to an environmentally friendly recovery.

Other authors suggest a Reverse Supply Chain Management (RSCM) as an extension of traditional supply chains (Sol, 2013). The perspective of the backward flow of materials as being a symmetric view of the forward processes was common until the late '90s. However, from the beginning of the century, research showed that, in a retail environment, this was not necessarily true (Lembke and Rogers, 2002). This argument is illustrated in Figure 2.1.

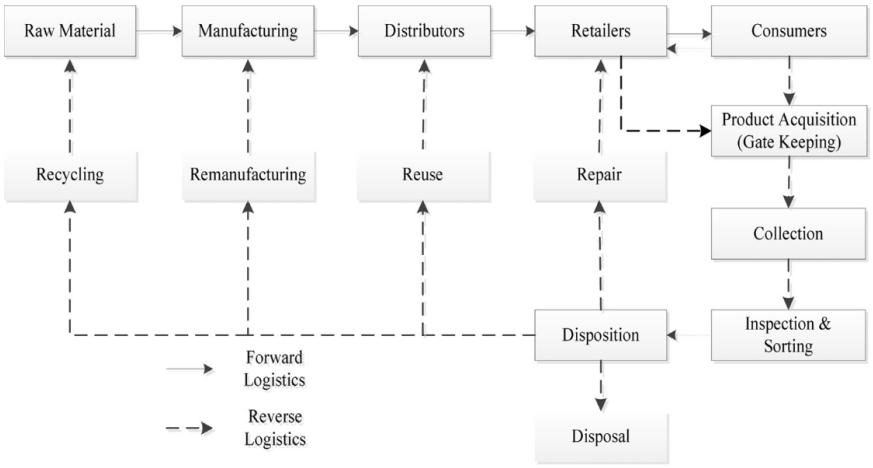


Figure 2.1: Flow of forward and reverse processes (Agrawal et al., 2015)

Thereby, the definition of RL has widened its scope over time, with the increased interest of researchers (Agrawal et al., 2015). One of the main drivers behind RL is the potential to recover value from used products (Pokharel and Mutha, 2009). On top of that, consumer awareness, legislation, directives (Ravi and Shankar, 2005) and environmental issues (Pan et al., 2015) are contributing to the interest in optimizing RL.

At HUUB, the majority of products are in good condition. Hence, the focus of this thesis is more about recovering its value rather than social or environmental responsibilities.

A typical RL structure develops over multiple stages: product acquisition, collection, inspection, sorting and disposition, as reflected in Figure 2.1. These different stages are discussed next.

Product acquisition

The first step in an RL structure is to acquire the item from the customers for further processing. Research has shown that this step is of particular importance for a profitable RL. The acquisition of the items can cause some difficulties since products have an uncertain return date as well as an undefined quantity or quality (Fleischmann et al., 2003).

Collection

After the acquisition, products are collected to have a post-processing phase which involves inspecting, sorting and disposing of the item. There are three fundamental kinds of collection strategies that rely upon where the collection occurs: from customers directly, through retailers or using an outsider 3PL company.

Inspection and Sorting

After collection, the returned items are usually brought to a single location where inspection occurs. As mentioned by Rogers et al. (1999), a customer may return the items due to known or unknown reasons. After passing through a dedicated control stage, the products are sorted. The time that this action takes depends on transportation, disposal and disassembly cost (Zikopoulos

and Tagaras, 2008).

Disposition

Finally, the last stage consists of deciding how to dispose of the item for further processing. Several authors have different visions for its classification. However, the more consensual way to classify disposition is through reuse, repair, remanufacturing, recycling and disposal (Thierry et al. (1995), de Brito and Dekker (2002), Fleischmann et al. (2003)).

Recently, many firms realized that a better understanding of product returns and efficient RL could provide a competitive advantage (Stock and Mulki, 2009). Therefore, adopting RL as a strategic tool for economic benefits and improving their corporate social image (Govindan et al., 2012) is now in the interest of many companies.

Regarding the part of this thesis which concerns about the returns process at HUUB, a further study of what the Returns Management area covers is addressed in the next section.

2.1.1 Returns Management

Returns Management is the supply chain management process by which activities associated with returns, RL, gatekeeping, and avoidance are managed within the organization and across crucial members of the supply chain (Rogers et al., 1999).

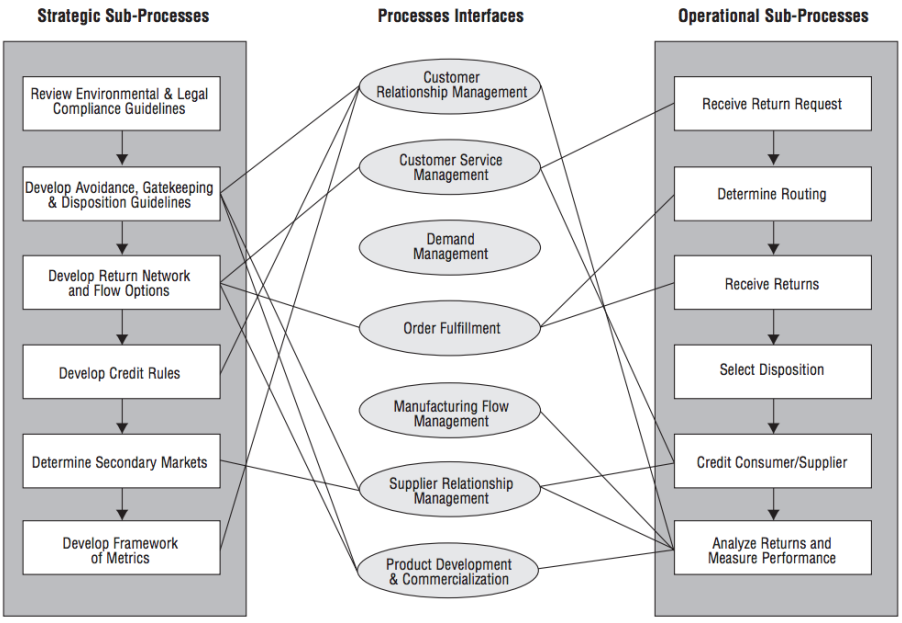


Figure 2.2: Returns Management: strategic and operational processes (Rogers et al., 1999)

The term returns in the definition above is more focused on the backward physical movement of the goods and does not include the terms of avoidance and gatekeeping. Avoidance means the minimization of the number of returns requests, ensuring for example, that the quality of products

is at the highest level attainable. Gatekeeping assures that only allowed returns are accepted and then guided to the correct location. Therefore, it increases effectiveness and efficiency (Rogers et al., 1999) by eliminating the costs associated with returning products that should not be returned or that go to inappropriate destinations.

Processes can be divided into strategic and operational, as illustrated in figure 2.2. The strategic part establishes the structure for the implementation of the process across the firm and the key members of the supply chain, while the operational part can be defined as the implementation of the process that has been established at the strategic level (Rogers et al., 1999). A brief list of the activities involved in each of the 6 processes, both strategical and operational, are detailed in Appendix A.

2.2 Reverse Logistics Optimization Areas and Metaheuristics Applied

RL has given rise to many optimization problems. Mathematical modeling in the literature includes a wide variety of sub-categories such as linear programming, non-linear programming, goal programming, and some combination of linear, stochastic and fuzzy programming. However, for solving large-scale problems, many of these approaches have proved to be limited. Most of these problems are classified as difficult and complicated to solve through exact methods or simulations. To overcome this, researchers apply methods as metaheuristics to solve them (Prajapati et al., 2019).

According to Voss and Woodruff (2006), a metaheuristic can be defined as "an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high-quality solutions." A metaheuristic can be classified as a single solution based metaheuristics (SSBMs) or as a population-based metaheuristics (PBMs), whether the output is a solution or a population of solutions, respectively. Examples of SSBMs are the Tabu Search (TS), Simulated Annealing (SA), Variable Neighborhood Search (VNS) and the GRASP method. The most widely used PBMs are Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO).

Rachih et al. (2018) review 120 published papers between the years of 2004 and 2017 on RL optimization problems. They divide RL into seven principal research subjects: (1) The Vehicle Routing Problem, (2) Network Design, (3) Inventory Management, (4) Assembly and Disassembly, (5) Production Planning, (6) Location and Allocation, and (7) Returns Management. For each of these subjects, a discussion of the principal metaheuristics adopted is presented. The results of these studies can be seen in Appendix B. It is concluded that GA and TS strategies are the most applied methods.

2.2.1 Hybridization Techniques

It is commonly found in literature the use of *hybridization methods* to improve metaheuristics results. These techniques involve the combination of different metaheuristics to exploit the power of each method and to avoid some of their limitations.

According to Rachih et al. (2018) and Fister et al. (2013), GAs are the most flexible metaheuristics for hybridization. The most common combinations seen in the literature are GA-PSO and GA-SA. For example, Soleimani and Kannan (2015), used the hybridization of GA with PSO to solve the problem of modeling, design and planning for a closed-loop supply chain. GA cannot memorize the solution in each iteration, this problem can be solved through PSO. On the other hand, Li et al. (2013) used GA-SA to solve the location-inventory-routing problem and Yadegari et al. (2015) applied it to find the best locations of plants, distribution centers, and dismantling facilities. GA can find the region of the solution space that contains the optimum of the objective function. As the search for the local optimum is ineffective, the combination of GAs with local search algorithms is logical to attempt.

Having explored some of the most used techniques for local search, we concluded that SA has good results in converging faster to the optimal solution when the size of the problem is reasonable. Both GA and SA are further detailed in Sections 2.2.2 and 2.2.3.

2.2.2 Genetic Algorithm

GAs are a popular and robust strategy used in optimizing complex combinatorial systems with a large number of variables.

They represent PBMs and are inspired by Charles Darwin's theory of natural evolution. These algorithms reflect the process of natural selection where the individuals with the best fitness are selected for reproduction to produce the offspring of the next generation (Coello et al., 2006).

Before starting with the explanation of the main phases of the algorithm, it is necessary to understand the basic concepts of the technique:

- Structure/individual: encoded solution of the problem;
- Genes: a subunit of a chromosome;
- Genotype: population in the computation space. In the computation space, the solutions are represented in a way which can be easily understood and manipulated using a computing system;
- Phenotype: population in the actual real-world solution space; hence, they represent the properties coded by the individual's genotype;
- Alleles: the value of a gene;
- Chromosome: the set of genes with alleles assigned;
- Locus: gene position in the chromosome;

- Population: Set of individuals (solutions)
- Fitness: evaluation of an individual; generally, it is determined based on the objective function of the individual;
- Genetic Operators: operate on GAs population attempting to generate new solutions with higher fitness;

The three main operators that GAs embrace are the following:

Selection:

The idea of the selection phase is to choose individuals with a better fitness function and let them pass their genes to the next generation. Therefore, two pairs of individuals (parents) are selected based on their fitness scores. Individuals with high fitness have more chances to be prevailed for reproduction. There are a vast number of different selection methods, such as roulette wheel selection, tournament selection, rank selection, elitism selection, and random selection.

Crossover:

In this phase, the genetic information of two or more parent individuals is merged, producing one or more descendants. Hence, the main objective of the crossover process is to exploit the best traits of the current chromosomes. The most popular methods used are the single point crossover, the two-point crossover, Uniform Crossover, Cut and Splice and the Ordered Chromosome Crossover.

Mutation:

This phase occurs to create diversity in the population. By changing the information in a gene of a parent, GA introduces randomness avoiding local optima and paving the way towards global optima; several types of mutation techniques exist including Bit-string Mutation, Flip Bit, Boundary, Uniform and Non-Uniform.

2.2.3 Simulated Annealing

SA is a probabilistic method introduced by Kirkpatrick (1984). The annealing process in metallurgy inspired this algorithm. In the annealing process of metal or glass, the material is first heated up to a specific temperature at which its atoms can move freely and randomly within it. In the second phase of the process, called crystallization, the materials have to cool down for the particles to rearrange themselves into a lower energy state and form crystals.

Analogously, in the SA algorithm, the objective function of an optimization problem corresponds to the energy function of the material, which is minimized by introducing the temperature and an iteration number as control parameters of the search progress (Cahon et al., 2004).

Two nested loops compose this algorithm: the thermal equilibrium (inner) loop, that comprises the achievement of thermal stability at a given temperature, and the (outer) cooling loop, in which

the temperature is decreased from its initial value towards zero until achieving a specific convergence criterion when the search comes to an end. (Banchs, 1997);

Thermal equilibrium loop

1. Perturbation Scheme: It defines how the model is updated. In the SA algorithm, the exploration of the solution space is done by imposing perturbations on the estimates of the parameters that are being optimized. These perturbations depend on a 'temperature' index T and their magnitudes at any stage in the process. Hence, in this phase, a perturbation is computed and then added to the existent model f_i, to obtain the new one f_u.

2. Acceptance Criterion: It determines if the new model is either accepted or discarded. According to the literature, the most common acceptance criterion is the Metropolis algorithm. In this method, an energy variation ($\triangle E$), given by the subtraction of the error function of the initial model to error of the updated model, is computed: $E = E(f_u) - E(f_i)$. As stated above, if $\triangle E < 0$, f_u is always accepted. However, if $\triangle E \geq 0$, f_u is only accepted with the probability, given by $P(\triangle E) = \exp(-\triangle E/T)$. Using this equation, the probability of accepting f_u will decrease as the parameter T decreases. Therefore, at low temperatures, only those models with a small $\triangle E$, will have a substantial chance of being accepted. In case of not accepting f_u, the model operation will continue with f_i.

3. Thermal equilibrium achievement: In each iteration of the thermal equilibrium loop, a new model (f_u) is computed and then accepted or rejected according to the acceptance criterion. This process is repeated until it reaches thermal equilibrium. There are different strategies to define the end of this loop, for example, the use of a maximum number of perturbations, a maximum number of acceptances or even a combination of both.

Cooling loop

1. Initial Temperature: the determination of the correct initial value of the temperature is crucial for the success of the algorithm (Banchs, 1997). On the one hand, the temperature cannot be too low as it would almost never accept worst solutions and therefore restrict too much the search space. On the other hand, if the initial temperature is too high, the algorithm will perform 'random walks' over the research space during a considerable number of iterations, which will also have consequences in the computational time of the algorithm. Therefore, the initial temperature must be defined in such a way that almost any perturbation is accepted during the first iteration of the cooling loop and then gradually decreases. According to Banchs (1997), there is not a straightforward rule to compute the initial temperature. A usual approach to settle the initial temperature is to use a value in the same order of magnitude as the typical objective function values of the problem.

2. Cooling Schedule: the rate at which the temperature decreases also has a high influence on the success of the search. On the one hand, a too low cooling schedule will lead to too

many iterations. On the other hand, with a high cooling schedule the algorithm will likely not deviate much from the original solution, thus exploring a very reduced region of the parameter space.

3. Stopping criteria: the choice of the most appropriate stopping criteria depends on the search conducted. Following Banchs (1997), when the objective of the SA algorithm is to perform a local search, more relaxing stop criteria can be used. A usual technique is to perform the loop until a certain defined amount of solutions are not accepted

2.3 Modelling Returns Demand

When an item is returned to the company's warehouses (and if in conform), it is placed back in stock to fulfill future orders. Hence, the solution presented in this project takes into account the probability and the cost of an item being sold or not in the future. The probability will depend on the item's demand. Forecasting demand is a crucial issue for driving efficient operations management plans. This is especially the case in the fashion industry companies as HUUB, where demand uncertainty, lack of historical data and seasonal trends usually coexist. Poor forecasting results in stock-outs/high inventory, rush orders, obsolescence, low Service Level (SL) and inefficient resource utilization. Therefore, in order to fit the model to the real demand patterns, a Non-homogeneous Poisson Distribution is applied.

The Non-homogeneous Poisson Process (NHPP) has been successfully applied to model non-stationary processes. The distribution can be defined as being a time-dependent Poisson process. Therefore, the number of events of this distribution by time t, called, $N(t)$, is equal to the number of counted events of the Poisson process by time t. Therefore, the mean value function of the NHPP is given by:

$$E[N(t)] = \int_0^t \lambda(t)dt \tag{2.1}$$

The probability of zero or n events occurring is given by the following equations, respectively:

$$P[D(t) = 0] = exp(-\int_0^t \lambda(t)dt) \tag{2.2}$$

$$P[D(t) = n] = exp(-\int_0^t \lambda(t)dt).\frac{(\int_0^t \lambda(t)dt)^n}{n!} \tag{2.3}$$

According to the literature, NHPP models have successfully been used not only on demand forecasting but also in applications as queuing and communication network problems, traffic modeling and seismology (Ghanmi (2016), Cao et al. (2012) and Jiandong et al. (2018)).

Chapter 3

Problem Context

This Chapter aims to contextualize the problem in detail. Therefore, an extensive overview of this dissertation's case-study is presented. The current ordering and return processes at HUUB are dissected as well as their costs and return policy. The analysis performed is predominantly based in the year 2018, as it provided more completed data and, on top of that, it was a year of natural growth and with no unexpected issues.

3.1 Global Context of HUUB

The present Section aims to give a more fulfilling overview of the company, to better understand the following Sections.

3.1.1 External Structure

To ensure its goals and competitiveness in the market, the company developed relationships with other organizations. These external stakeholders can be divided into six categories: brands, suppliers, end-users, carriers, customs, and tax authorities.

Brands
Being the ones that benefit directly from HUUB's services, they represent the company's revenue source. Money-related transactions occur mainly between this partner and the company, or between this partner and other stakeholders (in this last case, the money is still handled by HUUB). As it is going to be analyzed in this Chapter, the communication to and from this stakeholder is crucial during the returns management AS-IS process.

Suppliers
The role of this stakeholder is to ensure the production of the right amount of brands' products at the right time. Then, these products are sent from the suppliers to the HUUB's warehouses to be either shipped or stocked.

End-users
HUUB operates both B2B and B2C businesses. Therefore, the end-users can be both retailers or actual end-customers.

Carriers
They represent the bridge between warehouses, suppliers, and end-users, being responsible for ensuring that the products' transit time is between the schedule established. In the case of exports, HUUB, the brands and this stakeholder have to change information that is ultimately "compiled" by the carrier and handed to customs for verification. Therefore, these carriers can be obstructed by customs. For each flow done by these partners, different informational objects are generated, for e.g., carrier-specific labels, invoices, bills of landing, certificates of origin, etc.

Customs
As mentioned before, they are responsible for document validation in the case of exports. The information takes time to validate, which makes this process a severe bottleneck for supply chain management. The carrier has to make sure that the information that arrives at customs is correct.

Tax authorities
Tax Authorities ensure that every commercial monetary transaction is compliant with the country's law. Despite being a "backstage actor", the amount of money transferred across parties is significant, which makes their mention relevant in this Section.

3.1.2 Internal Structure

Before reviewing the returns' process, the company structure should be pointed out. HUUB is divided into six departments: Account Management (AM), Business Intelligence & Artificial Intelligence (BI &AI), Financial & Human Resources (HR), Information & Technology (IT), Marketing & Sales and lastly, Operations.

Account Management
AM represents the bridge between HUUB and its current clients. They communicate with the client when it concerns to the assurance of a good onboarding process, support of the brands' use of Spoke platform, report of the status of the operations and, finally, business insights that may be helpful for their performance as a brand. The department is also responsible for the information that allows the operation planning through the season. They provide the dates and quantities of inbound deliveries in the warehouse, establishing the daily work to be accomplished regarding the wholesale sales channel.

Business Intelligence & Artificial Intelligence
The BI &AI Intelligence team develops tasks related to descriptive, predictive and also prescriptive analytics. The main purpose is to improve the operational performance of HUUB, through

business insights extracted from the data.

Financial & Human Resources
The main activities of the Financial team include the control of company finances, assuring that all transactions are conducted according to all norms. This department also carries the responsibility of developing a cost framework where key performance indicators are established. Plus, the HR division is responsible for the management of human resources and all the processes inherent to it.

Information & Technology
The I&T department is responsible for the development and maintenance of the Spoke platform, mentioned in the Introduction Chapter. Therefore, their tasks include the continuous support for the current version of the platform and the improvement and development of new features and functionalities.

Marketing & Sales
The Marketing & Sales division focuses on customer acquisition and retention. They represent the point of contact with new possible clients, promoting the company's service through fairs or direct contact.

Operations
The Operations team is responsible for all warehouse management, meaning this the control of the inbounds, outbounds, packing, and labeling to ensure the fulfillment of customer orders. A warehouse planning is performed, in each season, concerning the estimated quantities and dates of the orders coming from the suppliers. This information is communicated to HUUB by the brand, which contracted these terms directly with the vendor. Thus, this information is not directly communicated by the vendor to HUUB. AM and Operations teams need to be coordinated to keep a smooth operational flow.

3.1.3 HUUB's Top Markets

To gain perspective into HUUB's e-commerce top markets, the first step is to understand the geographical distribution of demand. Despite having the United States (US) leading the demand, Europe still represents the core of e-commerce orders (see Figure 3.1). The demand pattern also supports HUUB's choice of establishing its second warehouse in the NL, close to Central and Northern Europe.

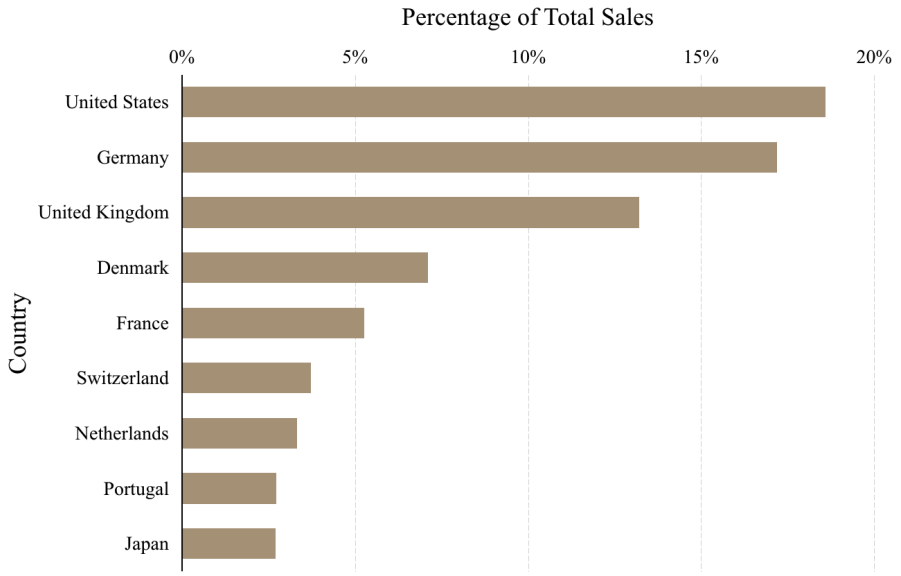


Figure 3.1: HUUB demand in % of orders of 2018

3.2 Returns at HUUB

At HUUB, a return order can have three distinct origins, depending on the stage of the supply chain that the return is identified: at the end-user, at the warehouse or at the carrier. We explore the three cases next.

The end-user can claim a return order (i.e., the end-user can allege the return), or not. For HUUB, the non-claimed return starts at the carrier (observe Figure 3.2). This can happen when it is impossible to find the end-user, for example, due to a wrong address inserted or due to not find the end-user at home. A claimed return can have two different triggers. It can start at the warehouse (when end-users send back their parcels directly to the warehouse), or at the end-user (due to several types of reasons such as the end-user did not like the item, HUUB sent a wrong item, etc.). HUUB only organizes the return transportation when the return is originated at the end-user, which happens more than 95% of the times.

Today, all the returns organized by HUUB are addressed to the warehouse in PT.

After analyzing the different types of return triggers and their destination points, it is necessary to stress out what can happen to a return after the parcel arriving at the warehouse. A return can result in three different types of actions and it is of brands' responsibility deciding which action should the process follow. After being received at the warehouse, and passing through all the returns process stages (which will be further explained), a return can be either placed back in stock, resent to the end-user, or destroyed in case the items are non-conforming. According to a recent study at HUUB, the most common action for a return is to be placed back in stock, which happens 77% of the times. Also, it is essential to note that the majority of the non-conforming returns can be fixed, being placed in stock afterward.

A return can stay at NL only when its trigger is in that warehouse or at the carrier. In these cases, the item is assumed to be in conformance and it is then resent or placed back in stock.

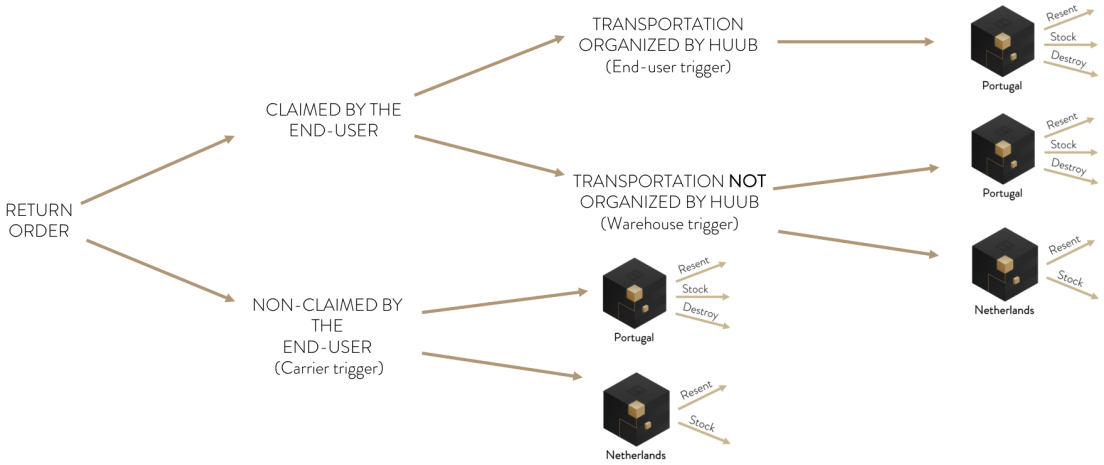


Figure 3.2: Returns triggers and the following actions

3.2.1 Returns in numbers

The majority of returns come from e-commerce end-users, representing 91% of the total returns requests that the company had in 2018. (see Figure 3.3)

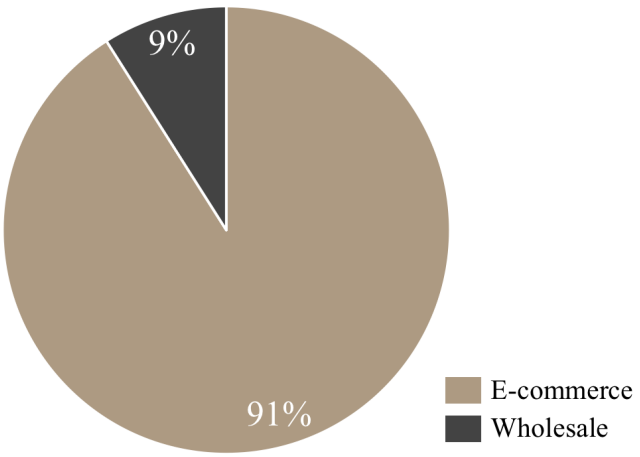


Figure 3.3: Percentage of E-commerce and Wholesale Returns at HUUB

Analyzing Figure 3.4, it is possible to understand that the countries with a higher percentage of returns are similar to the ones from the demand profile.

Under a study performed in Europe about return rates (RR) from the website de Best (2019), Northern and Western European countries tend to have higher RRs than Southern and Eastern European fellow countries. This is explained since countries like Germany and Denmark have wealthier buyers who are more prone to do impulse shopping, while the other countries tend to behave more carefully in proceeding to the shopping cart. Also, according to the research done in

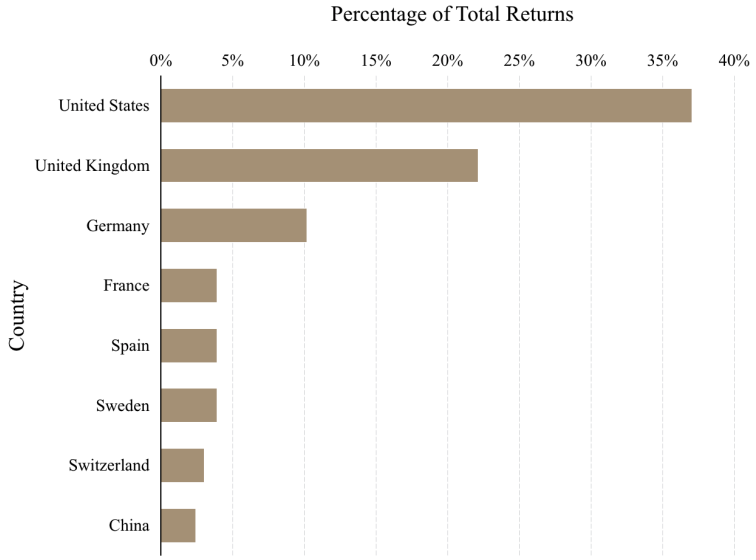


Figure 3.4: Countries with higher percentage of returns

Benchmark (2016), the percentage of e-commerce returns have been growing year over year. The study shows that more than half of the population in Germany and NL sent at least one purchased good back to an online store between early 2017 and spring 2018. France could be found in third place. From the company's point of view, this seems to be an excellent opportunity to start thinking as DAMCO as a possible warehouse to assign returns.

In e-commerce, HUUB's RR in 2018 was around 1%. Only this year, HUUB's sales growth is expected to reach 300%. Therefore, with the fast speed with which HUUB is growing, and considering the e-commerce trends for the RRs in the studies mentioned above, it is expected that the number of returns will also increase, being urgent for the company to have a returns process well structured.

3.3 Operation AS-IS

To understand how to make future improvements, it is essential to do a deep-dive on the current state of the whole return operation.

It is important to mention that the returns process at HUUB is in its beginning and is not standardized. An extensive analysis was done to catch all the necessary information to construct the AS-IS operation. As it is going to be observed in this Section, the number of different people involved in this process is considerable, being necessary to bring together information from different teams and stakeholders. In these analyses, three main points were addressed:

- Process Flow: identification of the different stages involved in each of the RL process phases and the intervening parties;

- Informational Flow: identification of the roles of each actor, analysis of the necessary data inputs and outputs in each returns process stage, as well as the identification of the communication tools used;
- Financial Flow: costs involved in each one of the phases.

By rethinking on these three aspects, the goal is to highlight what and where are the returns processes' most critical areas and to identify the most urgent actions to take.

3.3.1 Process Flow

It is possible to divide the returns management process into four main phases:

Phase 0: Outbound Shipment

This phase incorporates the decisions done in the Sales Order (SO) process that will impact the returns operation.

During the outbound shipment of an order, some brands require a return label [1]. Only 2% of the brands use the return label policy. Its use is not in the HUUB's interest once it prevents the flexibility to select the carrier and warehouse that could minimize the associated costs with a possible return. Besides, some brands want to include a return form inside their orders. These return forms are used for the end-user to specify the reason for their return. This information is not saved and is only used to communicate the reason to the brand afterward. 15% of HUUB's universe of brands use these forms. Appendix C.1 illustrates all the stages of phase 0.

Phase 1: Inbound Shipment Organization

As seen in Figure 3.5, this phase is split into two sub-phases. The first sub-phase captures the moment from when the return order is requested until the moment that all the necessary info to schedule the return transport is collected. The second sub-phase goes from that point till the time when the return transport is scheduled. In this phase, it is important to mention what are the returns policy used. A brand can choose between using their return policy or be subject to HUUB's policy, which states that an end-user should create a return within 14 days of receiving the item. When the brand communicates to the account manager a return request, HUUB is responsible for transportation. If the return is inside the European Union (EU), the cheapest carrier is chosen according to the origin country of the return and the SL chosen by the brand (Express or Standard). When the return is outside the EU, the carrier chosen is the same as the one in the outbound shipment. This is done to avoid the necessity of creating a new export certificate that could delay the returns process to more 1 to 2 days. Appendix C.2, C.3 and C.4 encapsulate all this phase stages.

[1] postage paid label addressed to the end-user so he can send the item back without paying the postage his self

Phase 2: Shipment

The present phase encompasses the return shipment, from its origin to its final destination. When a return is from outside the EU, the confirmation of goods inside the return may be necessary. This can happen due to three different situations: when HUUB is not responsible for creating the proforma invoice, the carrier can request a match between the information in the brand's invoice and the return; when customs want to be sure that the shipment refers to a return and not to an import; when the carriers' system fails. Appendix C.5 and C.6 details all the process discussed.

Phase 3: Warehouse Process

This phase combines all the warehouse operations. First, the return status is analyzed. In the case of non-conformities, the brand is notified to decide what should be done with the return. When everything is in conform, the return can have one of the two other ending points addressed above in section 3.2. This phase is represented in Appendix C.7 and C.8.

3.3.2 Informational Flow

To better clarify the communication flow between the distinct parties involved, and help to identify all the different data inputs and outputs, a responsibility assignment matrix is presented in Figure 3.5.

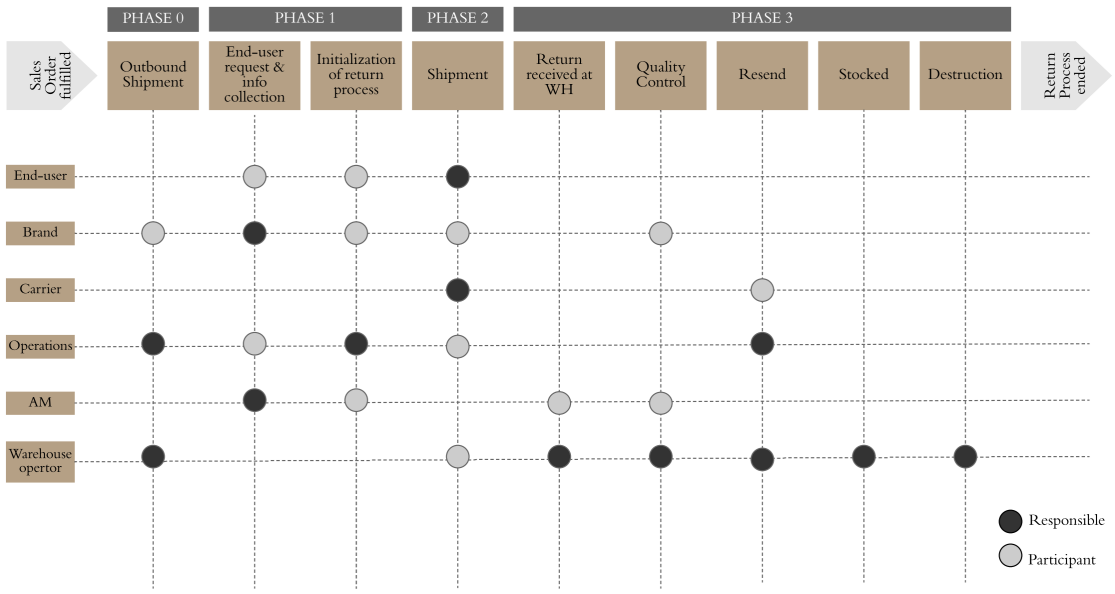


Figure 3.5: Responsibility assignment matrix

After analyzing the operational flow, it is possible to recognize the use of six distinct tools to communicate between the different parties:

1. E-mail: used in all phases between the brand and AM. It is also used by the Operations team and the account manager for sending/receiving necessary documents, as for example, the return label;

2. Phone calls: besides the use of e-mail, phone calls are also done by the Brand and the account manager.

3. Trello: a card is created once a return is communicated to HUUB. When the return is received at the warehouse, the card is moved as it goes through the different stages of phase 3. This task management app helps the communication between the warehouse operator and the account manager that has a visual overview of what is being done and the status of the return.

4. Slack: When a return is in non-conformity the operator uses this tool to notify the account manager; it is also used between the operations team and AM to communicate smaller things then the ones communicated throw e-mail.

5. Carriers Platform: used by the operations team to do the return labels;

6. Excel: where Operations team save information about the return label done;

7. Spoke: in HUUB's database (DB) there is no object as a "return". Therefore, when a return is received at the warehouse, it is created in the DB as a fake purchase order (PO) from a supplier, losing important information. Excel and trello are the only tools that allow HUUB to keep tracking of the return and the original SO that gave rise to it.

3.3.3 Financial Flow

After analyzing both processual and informational flow, it is important to have an overview of the cost structure of the return operation. The distribution of the costs in the different phases is illustrated in Figure 3.6.

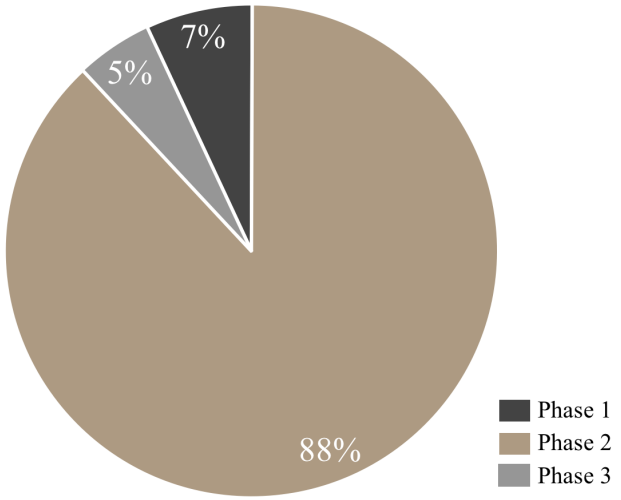


Figure 3.6: Cost distribution between the different phases of the returns

As it is seen above, the biggest chunk of costs are concentrated in phase 2. The costs involved in that phase can be unfolded into four major types: transportation costs, duties, tax, and extra charges.

Transportation costs

Represent the cost of moving a product from one place to another. It varies with volume/weight and, as stated above, it depends on the origin/destination and SL chosen by the brand (Express: 1-3 days in transit or Standard: 2-5 days in transit).

Duties

Tax on incoming products as stated by the destination country customs authority. This cost depends strongly on the type of product, its value and on the country of entrance. Currently, the EU is a free trade zone, where no Duties neither Taxes are applied to products moving across borders inside the EU. On the other hand, when a product comes from outside the EU, as it happens for example with the US, there are rates applied that depend on the Harmonized System of product classification, as predicted by the World Customs Organization (WCO).

Tax

On top of all duties, customs can charge over a product a Value Added Tax (VAT), depending mainly on the value of the product and on the country.

Extra charges

When a courier has to perform an action that does not belong to the regular span of events such as delivering in a remote area, fuel surcharges or heavier packages than usual, additional charges are applied.

3.4 Improvement Opportunities

To highlight the opportunities for improvement in HUUB's RL supply chain, a Failure Mode and Effects Analysis (FMEA) was conducted (see Figure 3.7). FMEA is utilized in vast areas and various industries. Therefore, the scale used to perform this analysis was based on Feili et al. (2013) and posteriorly adapted to the scope of this thesis.

Using a Risk Prioritization Number (RPN), the failures associated with the process are categorized according to their severity, occurrence and detection. The identification of the failure modes as well as the quantification of their effects was done through several interviews with the distinct actors highlighted in Figure 3.5.

The possible failures during phase zero can be considered of low importance. As observed, the values of the severity of failures, as well as their probability of occurrence, and the possibility of detection are below the middle of the scale. However, this can't be applied to phase 1 and 2. Despite the low occurrence values, the high rate of RPNs is due to its impacts on the process and the impossibility of being detected before they happen. Phase 3 is the one that comprises the higher number of possible failures. Some returns arrive at the warehouse with no information about its original SO and not identifying the items inside. Besides this, HUUB's space to process

the returns seems to be limited concerning the expected growth for the next years. Nevertheless, the RPNs in this stage are low comparing to other phases.

Hence, it is possible to conclude that failure modes in phases 1 and 2 are the ones which should receive more attention.

PHASE	ACTIVITY	REQUIREMENTS	POTENTIAL FAILURE MODE	POTENTIAL EFFECTS OF FAILURE	SEVERITY	POTENTIAL CAUSES OF FAILURE	OCCURANCE	CURRENT PROCESS CONTROLS DETECTION	DETECTION	RPN
PHASE 0	SO Preparation	Orders shipped with the require documents	Missing return label	Return process is slowed down	4	Operational Process	2	Order confirmation	3	24
			Missing return form	Loss of information	2	Operational Process	2	Order confirmation	3	12
PHASE 1	Collect the necessary info to start the return schedule	Brand has to give the necessary info about that return	Brand doesn't give all the info	Downstream cannot proceed	5	Communication failure	4	No detection opportunnity	10	200
PHASE 2	Customs	All Documents in conformity	Wrong Info	Carrier cannot proceed	7	Operational Process/ End-user fault/Carrier fault	3	No detection opportunnity	10	210
			Document Missing	Carrier cannot proceed	7	Operational Process	3	No detection opportunnity	10	210
	Shipment with Post	Fill the necessary documentation	Client is the responsible for the shipment	Return takes too much time to proceed	4	Brand's return policy	3	No detection opportunnity	10	120
PHASE 3	Return identification	Visibility of the returns that are arriving at warehouse	Don't know if warehouseat arrived is a return or not	Operator cannot do the planning previously. Operator is unable to proceed	6	Not using the correct approach to collect data	3	The returns arriving to the warehouse are most likely to be detected	10	84
	SO identification	Return label or return form have to inform about warehouseat was the original order	Return without SO info	Operator has to find the SO searching on spoke by its customer, #ref or address	3	Not using the correct approach to collect data	6	The SO identification is most likely to be detected	9	54
	EAN identification	Identify the EAN'S returned	Return without EAN info	Operator is unable to proceed	3	Not using the correct approach to collect data	6	The EAN identification is most likely to be detected	9	54
	Non-confomity return	Decsion of warehouseat to do with the return	Communication between AM, brand and Operations takes too much time	Operator is unable to proceed	3	Not using the correct platform to communicate	2	No detection opportunnity	10	60
	Non-confomity return	Allocate item to a special position, waiting for brands' answer	No special positions in stock for this items	Space is not organized for the oprrator to work	4	No defined space for the returns process	2	No detection opportunnity	10	80
	Placed back to stock	Creation of different purchase order's in case of items of different suppliers	Time Consuming	Affects the efficiency of the process	2	Not using the correct approach to collect data	6	No detection opportunnity	10	120

Figure 3.7: Failure Mode and Effective Analysis

3.5 Operation TO-BE

After an initial overview of HUUB's main markets and having the returns' process mapped and dissected, it is now possible to pinpoint the second phase as the one which improvement seems to have the most significant impact on the RL supply chain costs. As discussed above, nowadays, when a return order is requested, the only possibility that a return has is to be allocated to the warehouse in PT. To analyze if the consideration of DAMCO as a possible warehouse to allocate a return is an opportunity to save costs, the inbound transportation costs from HUUB's top markets to the two warehouses are compared. According to Figures 3.8 and 3.9, the allocation to DAMCO is clearly a point to explore. Regarding the distinct SLs, the price to the warehouse in NL is lower for almost all the countries in the study.

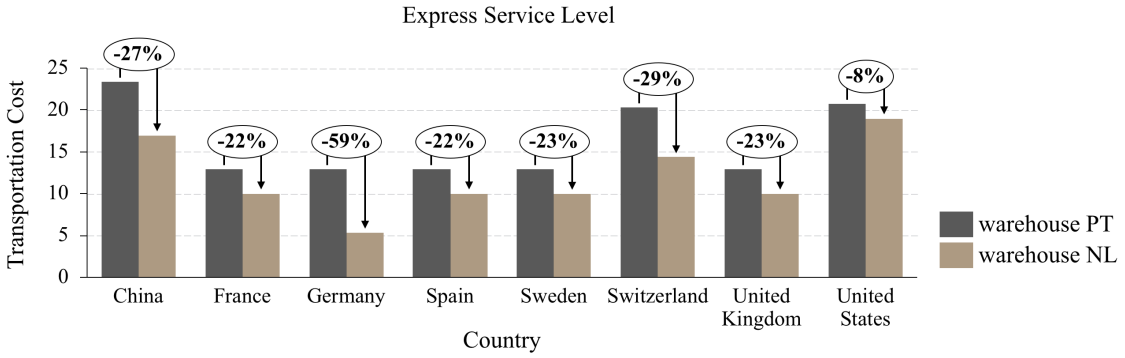


Figure 3.8: Transportation costs from HUUB's top markets to it's distinct warehouses - express Service Level

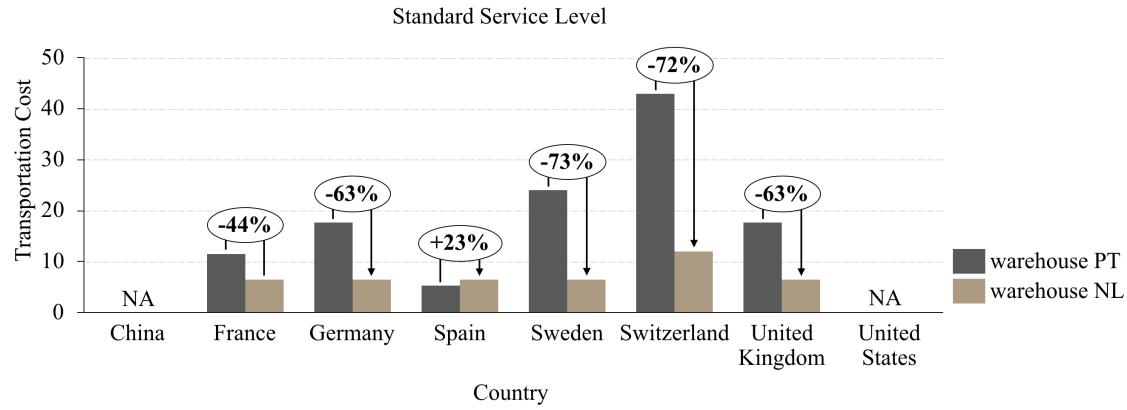


Figure 3.9: Transportation costs from HUUB's top markets to it's distinct warehouses - standard Service Level

However, not only transportation costs to the warehouses are the ones that should be taken into account. As seen in the above sections, the majority of the returns are placed back in stock.

This includes storage costs, and DAMCO storage costs are higher than the ones from PT warehouse. Therefore, the allocation of returns to DAMCO can be advantageous for the items with high rotation, and during the pick season weeks.

Based on all of this analysis, it was concluded that a mathematical optimization model that allocates a return to the better warehouse, will be a significant contribution to future management. This model will perform on a run-on-request mode and will be used by the Operations Team during phase 2 when the inbound transportation is organized. This will not only minimize costs but will also allow HUUB to have an overview of its RL operation. Consequently, it is expected that this algorithm unmasks the entire process of returns, which at this moment, due to the number of decisions, people involved and communication and management tools used, is completely non-transparent. Thus, the main focus of this project was the development and implementation of an optimization model that takes into account the inbound transportation costs, storage costs and the costs associated with the probability of the item of a return be re-sold or not, according to the weeks until the end of the season.

Chapter 4

Methodology

After an initial overview of HUUB's returns' processes and the identification of the priority areas to improve, the aim of this Chapter is to discuss the methodology used to create the optimization algorithm that will allow the company to have a fulfill overview of its RL, which is currently completely masked.

The main purpose of this algorithm is to provide knowledge about the planning of HUUB's RL operation and, consequently, allocate returns, not only to the Portuguese warehouse but also proving that DAMCO should be considered in the equation. The solution was designed keeping in mind the fast growth of the start-up, and it accounts for the possibility of adding new warehouses in the future in case HUUB expands its network. It is therefore completely scalable. Since only a low percentage of returns come from wholesale end-users, this first solution only contemplates e-commerce returns.

The chapter starts by explaining the procedures of data preparation and the methods applied to achieve the data required for the optimization algorithm. Then, the formulation of the problem is detailed, followed by the explanation of the structure of the algorithm used.

4.1 Data Preparation

4.1.1 Understanding Costs Quantification

The major costs concerning a returns' process can be divided into three distinct categories: Storage Costs, Transportation Costs and Tax and Duties.

The storage costs comprise the costs associated with having an item assigned to a warehouse of the network. This cost is given per item per week.

As stated in Section 3.6, the transportation costs, apart from depending on its origin, destination and SL, depend also on the weight/volumetric weight of a return. After consulting the used carriers' platforms, it is observed that the volumetric weight of the item being transported is only taken into account when it is greater than its actual weight. Once the algorithm only answers to e-commerce returns, the occurrence of this event is rare, and consequently, the modeling of these costs is done taking only into account the return actual weight.

As stated in the financial flow section, the Tax and Duties costs occur when a transaction is done with a country from outside of the EU. When this is the case, they represent a high percentage of the costs paid in a transaction. Besides that, as seen in Section 3.2.1, the country with the highest RR is the US, making the modeling of these costs a critical aspect to take into account. Therefore, exhaustive research, including e-mails and meetings with the carriers, was done for trying to understand how could this been included in the proposed model. After this research, we conclude that the nature of these costs depends on very distinctive factors such as the carriers' policy, the material of the product, the type of product, the amount of taxes paid, and many others. Hence, the modeling of these costs will be out of the scope of the thesis. However, we expect that in the upcoming times, a more mature version of this algorithm can comprise these costs.

4.1.2 Dummy Data Creation

As discussed in Section 3.3.2, the only tracking that exists about the returns is in Trello and in the Excel referred. Therefore, the first step consists in the creation of objects in the DB related to the returns process. The design of the new tables was done taking into account the integration with the existing ones. In Appendix D the proposed UML diagram is introduced. The tables that are already in the DB are represented in white. Hence, for the implementation of this algorithm, two main objects are created: *return* and *return item*. As seen in Appendix D, the return is linked to the original SO delivery, which contains important data for the model. The attributes flagged with a grey spot are the needed inputs and with a black one are the outputs. Only the returns without a label are going to be read by the model, since they are the ones that still need to be allocated to a warehouse. The model reads all the returns that do not have a schedule yet. When a return is allocated, the *scheduled* attribute is set to true. The table *origin type* is related to the different starting points that a return can have: at the end-user, at the carrier or at a warehouse of the network (observe Figure 3.2). As already discussed, returns starting at the carrier will not be implemented in this model.

Since nowadays, the necessary input data for the algorithm is not being collected, there was the necessity of creating dummy returns. The distribution of these returns was done, taking into account the geographic pattern analyzed in Section 3.4. The weight of each return for the calculation of the transportation costs mentioned above was estimated by the mean of 264 returns collected in the Excel created by the Operations team. The extreme outliers were removed, giving an average weight of 0.83kg (see Appendix E). The same approach was used for the average number of items comprised in each return, rounding the 1.2 items/return. Most of the returns transportation between Europe countries use the standard SL. Hence, the only returns with express SL are US and China.

The λ for each item returned was estimated with the sales of that item family (e.g., top, bathroom, bags wallets, etc.) in the previous year, concerning the distinct number of brands selling that item and the different type of products belonging to that family:

$$\lambda_{it} = \frac{\text{sales for the item family}}{\text{distinct brand * distinct products}} \tag{4.1}$$

4.2 Optimization Model

As mentioned at the beginning of the present Chapter, to answer to the fast growth of the start-up, the design of the solution was done not only taking into account the expected rise of the returns number, but also the acquisition of new warehouses.

At the beginning of the study, a first optimization model was created. This model, named as *Model 1*, read all the returns in the DB with no warehouse assigned. For each one of these returns, the assignment decision to a warehouse is independent from the decision made in the other returns' allocations. Thus, the solution given by this model is suboptimal in two distinct cases:

- **When different returns have equal items**

  The selection of the best warehouse for a return is influenced by the demand of the items comprised in the return. For an item to be sold, the demand has to be superior to its stock. With this first model, in the case of having returns with items that are equal, the increment of those items' stock from one return to another is not considered. Nevertheless, the stock increment can impact the assignment of the return to a warehouse.

  For example, DAMCO has higher storage costs than the Portuguese warehouse. However, as seen in Section 3.5, transportation costs are lower. If the stock of the items being returned is low and the demand for that particular item is significant, that item rotation in a warehouse is also high. Therefore, despite the highest storage costs, the assignment to NL could be cost-beneficial. However, with more items in stock, the selling probability decreases, and as staying in a warehouse with higher costs can be more costly, the selection of the Portuguese warehouse for the assignment could represent a better decision.

- **When the capacity of a warehouse is in its limit**

  The assignment of a return to a warehouse cannot be done, if with the returns assigned previously, its capacity reached the limit. This case is also not considered in the first model.

As the percentage of returns per day at HUUB is low, the likelihood of one of these two situations happening is small, so it could be concluded that this first approach would answer the start-up's problem nowadays. However, as stated in Chapter 3, it is expected a significant increase of the returns number in the upcoming years and a rise in the number of warehouses in the company's network, being possible to affirm that by the end of this year there will be more than two warehouses.

Therefore, there is a need for a new model, named *Model 2*, capable of following the start-up growth. In this second model, a return assignment decision to a warehouse depend from the decision made in the other returns' allocations. If returns are not independent, the number of

different possible combinations to allocate a set of returns reaches a high degree of complexity. Having this stated, it is possible to conclude that the right approach to solve this optimization problem is through the use of a metaheuristic.

Hence, to design a solution for the company, both *Model 1* and *Model 2* are considered. When none of the situations mentioned above happen, the solution given by *Model 1* is valid. Otherwise, the returns go through *Model 2*, since the solution from the first model is suboptimal.

When the first model is not valid, the solution given can still be close to a good solution. Therefore, the ouput from *Model 1* is going to be explored in *Model 2*. After the research done and presented in Section 2.2, the metaheuristic chosen to answer this problem is an GA. Figure 4.1 encapsulates the discussion above.

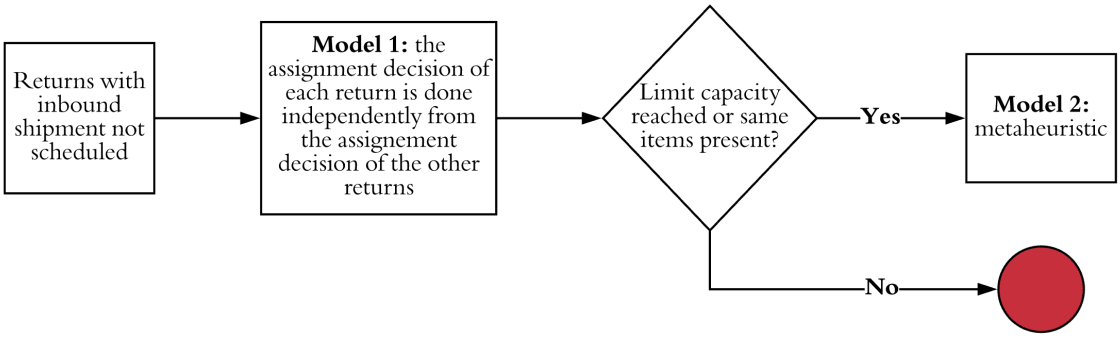


Figure 4.1: Solution Approach Diagram

4.3 Problem Formulation

In this section, we present the mathematical formulation considered in both models discussed in section 4.2. First, the assumptions made are pointed out, followed by the presentation of the problem indexes, parameters, auxiliary variables and decision variables. Finally, in the remaining Sections, the objective function and its constraints are introduced.

4.3.1 Assumptions

- Locations of customers and disposal centers are fixed and predefined;
- The returns considered are from e-commerce end-users;
- A return origin can be at the warehouse or at the end-user shipping address;
- The demand for the products takes into account the historical data of the demand of the same weeks in the year before;
- The demand follows a NNPP;
- There is at least one warehouse in the network which capacity limit is not reached;

- When an item is not sold, it stays in the cheapest warehouse for 6 months;
- One month has 4 weeks;
- Autumn/Winter season goes from 01-01 until 30-06 and Spring/Summer from 01-07 to 31-12;
- After being processed, a return stays undefined time at the warehouse.

4.3.2 Decision Variable and Objective Function

The indexes, parameters and auxiliary variables of the model are described in Tables 4.1, 4.2 and 4.3, respectively. The decision variable is binary and its description is displayed below:

W_{ra} (=1) If return r goes to warehouse a

The objective of this optimization model is to allocate returns to a warehouse, minimizing costs. The objective function was divided into three terms:

min f1:

- Cost of going to the warehouse:

$$\sum_{r=1}^{R}\sum_{a=1}^{A} W_{ra}.CT_{O_raWT_r} \tag{4.2}$$

- Cost of not selling:

$$\sum_{r=1}^{R}\sum_{a=1}^{A} W_{ra} * \sum_{i=1}^{Q_r}(CTC_{aw} + 24 * CVS_a) * P[D(T)_i \leq S_i] \tag{4.3}$$

- Cost of selling:

$$\sum_{r=1}^{R}\sum_{a=1}^{A}\sum_{i=1}^{Q_r} W_{ra} * (CTM_{aw} * P[D(t)_i > S_i] + \sum_{t=1}^{T}\sum_{p=1}^{T-1} P[D(t)_i > S_i \cap D(p)_i \leq S_i] * t * CVS_a) \tag{4.4}$$

where

$$P[D(t)_i = x] = \frac{e^{-\sum_{t=0}^{T}\lambda_{it}} * (\sum_{t=0}^{T}\lambda_{it})^x}{x!} \tag{4.5}$$

Term (4.2) comprises the transportation costs associated with the RL process. In case of a return with its origin in a warehouse, if the destination warehouse corresponds to the origin one, the value of this cost is logically zero.

Term (4.3) is the incurred costs in case the items of the return are not sold. As stated in Section 4.3.1, when an item is not sold until the end of the season, it is placed in the warehouse with the cheapest storage costs, until the end of the next season (six months). The probability of not selling an item until the end of the season follows an NHPP (see Section 2.3) where λ(t) represents a discrete variable varying from week to week. In *Model 1*, the S_i variable from one return assignment to another stays the same. However, in *Model 2*, this variable is dynamically changed as the returns are assigned.

Finally, the Term (4.4) represents the costs of an eventual posterior selling of the items being returned. It comprises the storage costs that depend on the expected number of weeks that an item is in the warehouse, and the transportation cost from the warehouse to the end-user. The probability of an item being sold in a given week is linked to the following events: the demand in the weeks before has to be inferior to the number of items available in stock, and in the current week the demand has to overcome the stock level. The transportation cost value is obtained with a weighted average of the costs from that warehouse to the destination countries. The weight takes into account the percentage of sales that HUUB had for each country in the previous year. This cost is associated with the probability of the demand for that item being superior to the items in stock. This probability follows an NHPP, like the one presented in Term (4.3).

Table 4.1: Indexes of the model

Indexes	Description
r	id of the return
i	item - from 1 to I
w	weight range from 1 to W
t, p	weeks from 1 to T
d	day from 1 to D
a	warehouse
j	returns origin from 1 to J

Table 4.2: Auxiliary Variables of the model

Auxiliary Variables	Description
S_i	Stock of items i in all warehouses network
Q_a	Quantity of items that are going to WH a
$t = 0$	First week from where the return items are available in stock
$d_r = 0$	Day at which the return r arrive at the WH

Table 4.3: Parameters of the model

Parameters	Description
SL_r	SL of return r given in time transit days
CT_{jacw}	Transport cost from j to a with carrier c for weight w
CTM_{aw}	Mean transport cost from a to the selling country for weight w per item
CTC_{aw}	Transport cost from a to the cheapest wh for weight w per item
CVS_a	Variable Storage costs at WH a per item per week
O_r	Return origin country
TT_{ab}	Transit time from a to b
WT_r	Return Total weight
Q_r	Total quantity of items of return r
$D(t)_i$	Demand of item i in t weeks
$D(t)_{im}$	Demand of item i in t weeks at market m
$P[D(t)_i = x]$	Probability of the demand of i in t weeks be equal to x items
λ_{imt}	Average number of items i sold during week t on market m
λ_{it}	Average number of items i sold during week t on all markets
T	Number of weeks till the end of the season
D_a	Number of days that takes at wh a to process a return
RP_a^d	Number of returns being processed at WH a on day d
RI_a^d	Number of returns that arrive at WH a on day d
RO_a^d	Number of returns that are already processed at WH a on day d
IP_a^d	Number of items being processed at WH a on day d
II_a^d	Number of items that arrive at WH a on day d
IO_a^d	Number of items that leave WH a on day d
Q_r^d	Total quantity of items of return r that arrive at day d
MP_a	Maximum returns process capacity at WH a per day
MN_a	Maximum number of items allowed at WH a

4.3.3 Problem Constraints

$$TT_{za}.W_{ra} \leq SL_r, \quad \forall z,a,c \tag{4.6}$$

$$Q_a = \sum_{r=1}^{R} Q_r * W_{ra}, \quad \forall a \tag{4.7}$$

$$Q_r^d * W_{ra} + RI_a^d - RO_a^d + RP_a^d \leq MP_a, \quad \forall a,r,d_r \leq d < (D_a + d_r) \tag{4.8}$$

$$RI_a^d - RO_a^d - Q_r^d * W_{ra} + RP_a^d \leq MP_a, \quad \forall a,r,d = d_r + D_a \tag{4.9}$$

$$Q_r^d * W_{ra} + II_a^d - IO_a^d + IP_a^d \leq MN_a, \quad \forall a,r,d > (D_a + d_r) \tag{4.10}$$

$$\sum_{a=1}^{A} W_{ra} = 1, \quad \forall r \tag{4.11}$$

The selection of the transportation of the return needs to consider the SL chosen by the brand, meaning that the transit time given by the selected carrier cannot exceed the days accorded between the brand and HUUB (Constraint (4.6)).

Constraint (4.7) means that returns with more than one item cannot be divided. Therefore, all the items of a given return have to be allocated to the same warehouse.

Finally, the last three constraints are related to the warehouse capacities and are only taken into account in *Model 2*. It is considered that the warehouses have different zones for allocating returns and for assigning what can be regarded as common stock. Hence, constraint (4.8) and (4.9) are related to the maximum number of returns that a warehouse can carry, and constraint (4.10) represents the maximum number of items (common stock) that a warehouse can keep.

4.4 Genetic Algorithm

In the present section we dissect the GA procedure applied. All the parameters used are detailed in Appendix F.

4.4.1 Chromosome Representation

Very distinct approaches are found in the literature about the chromosome representations for this type of problems (Mousavi et al., Fathollahi Fard and Hajaghaei-Keshteli (2018), Min et al. (2006a) and Man). In the strategy adopted in this thesis, each chromosome is represented by a data frame, with two columns. The first column represents the return and the second one represents the warehouse to which the return is going to be assigned (see Figure 4.2). It is important to mention that all the chromosomes created during the distinct algorithm operations are feasible solutions, i.e., it is always guaranteed that the warehouse capacity is not exceeded.

4.4.2 Initial Population

In PBMs algorithms, the construction of the initial solution plays an important role in its efficiency. Therefore, the first population is astutely generated to ensure that it covers well the parameters space and that at least a few of its chromosomes have good initial parameters according to some criteria.

At the beginning of this phase, three distinct chromosomes are generated, where the assignment of a return to a warehouse is based in business understanding. One of these chromosomes comes from *Model 1* (see Figure 4.1). In case it is unfeasible, the allocation of the returns to the fulfilled warehouse is changed until the feasibility of the chromosome is achieved. These changes are applied by randomly selecting a gene of the chromosome assigned to a full warehouse. Its allocation is changed to a not full warehouse, also randomly selected. This process is repeated until the feasibility of the chromosome is achieved. Algorithm 1 in Appendix G encapsulates the logic discussed.

A second chromosome is constructed assigning the maximum number of returns to the warehouse with the cheapest storage costs. The allocation of the returns is done regarding the returns order in DB. If the warehouse gets full in the middle of the allocation, the next returns are assigned to the following warehouse with the cheapest storage costs. The pseudo-code representing this construction is illustrated in Algorithm 2 in Appendix G.

Finally, the third chromosome is constructed allocating the maximum number of returns to the warehouse that allows the lowest transportation costs. The assignment logic is the same as the one used for the previous chromosome.

The construction of the other chromosomes of the population is done having these three first chromosomes as a basis. For the creation of these chromosomes, a percentage, named as *Random fraction* (f_r), determine the number of genes in a chromosome which the assignment to a warehouse is done randomly. The allocation of the remaining returns of that chromosomes is done by adding the genes from the original chromosome. All the chromosomes generated are feasible. Algorithm 3 in Appendix G details this construction.

4.4.3 Genetic Operators

Elitism

In evolutionary algorithms, the preservation of the best solutions to the next generation should be carefully taken into account. Therefore, the parameter *Elitism probability* (p_e) will define the number of elite solutions to be directly carried over to the next generation.

Selection and Crossover

The parents selection is a necessary process that directs the algorithm search towards promising regions in the search space. For this purpose, the tournament selection method is known to provide good results in the literature (Ghezavati and Beigi (2016), Diabat et al. (2013) and Min

et al. (2006b)). In this method, the *Selection Probability* (p_s) defines the candidate's likelihood of participating in a tournament. From these individuals, the best two are selected for crossover.

To calculate the objective function, all the genes of a chromosome are ordered by transit time. For returns with the same transit time, the order considered is the observed in the chromosome genes' sequence. From the discussion in Section 4.2, it is possible to conclude that different genes' sequences in the chromosome can have distinct cost functions. Therefore, the method used is the one point crossover, where rows of different chromosomes are exchanged.

One cutting point is randomly selected for the gene sequence. The approach is illustrated in Figure 4.2where parents P1 and P2 generate two offsprings, O1 and O2. Selecting a point i, Child O1 genes sequence is generated as follows: genes at positions from the beginning of the chromosome to i are copied from P1. Other positions in O1 are filled with missing genes obtained by sweeping P2 circularly checking if a return has appeared in O1 or not. If not, then the current position in O1 is filled with genes from P2. Child O2 is obtained by exchanging the roles of P1 and P2.

Only the feasible children enter in the new population. When the parents are selected, the crossover method is applied until getting at least one feasible chromosome in a given number of tries. The maximum tries are defined according to a parameter named as *Maximum number of tries in Crossover* (C). If the number of tries is reached without a feasible chromosome produced, the parents are kept in the new population. This approach emerged from the need to ensure that the algorithm would not get stuck in this operation.

The crossover method is applied until a certain number of feasible offsprings is reached. This number is defined regarding the *Crossover Probability* (p_c) parameter.

It is noted that the crossover method applied only has meaning when there are returns in the population with the same transit time as only those can be exchanged between each other to produce a better fit solution. Exchanging the order of returns with different transit times produces no change in the cost function. After an analysis of the mean transit times regarding the possible origins and destinations of a return, it is concluded that for most countries the transit times are the same. Therefore, it is extremely unlikely for a population of chromosomes to have all different transit times. However, if this happens, the crossover method is not applied to reduce inefficient computational time.

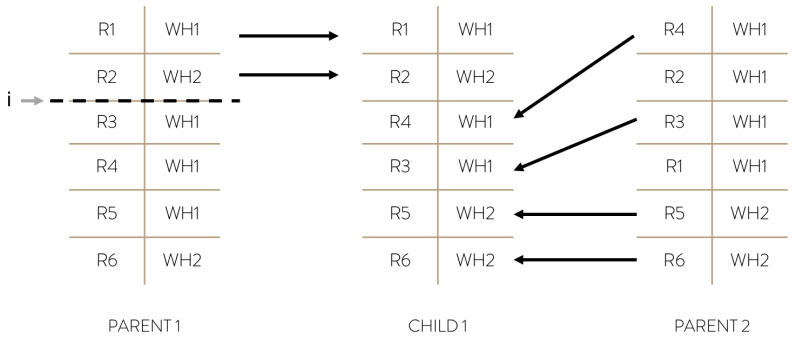


Figure 4.2: Example of the application of the crossover method

Mutation

Being the objective of the mutation to explore the search space, the strategy adopted in the thesis will involve the change of a warehouse at a random gene in the chromosome. Therefore, from the population, a random chromosome is selected. Then, the warehouse of a random gene of that chromosome is replaced for another one, also chosen randomly. When a warehouse is replaced, the new chromosome generated can be unfeasible. Therefore, the mutation involves a parameter, defined as *Maximum number of tries in Mutation* (M). When a chromosome is selected, a new mutation is applied to the original chromosome until getting a feasible chromosome or until the number of tries reaches this parameter value. If the number of tries is reached and a feasible chromosome was not found, the original chromosome is kept to the new population. As in the crossover method, the mutation is applied until a number of feasible chromosomes are generated. The number is determined by the *Mutation Probability* (p_m).

4.5 Local Search

During the first tests of the model, we noticed that the algorithm was not exploring some possibly good solutions in situations where the warehouse limit is reached. Therefore, there was a necessity to create a local search technique for this case scenario. All the chromosomes in the current population (elitism, crossover and mutation chromosomes) pass through this procedure.

For the crossover and mutation offsprings, an SA approach is used. However, in the case of elite chromosomes, SA is not applied to ensure that the best solutions are not lost from generation to generation.

The Pseudo-code regarding the elite population is described in Algorithm 4 in Appendix G. The original chromosome is divided in two: genes assigned to warehouses which, in the *model 1* solution, have reached their limit, and genes assigned to the remaining warehouses. The new chromosome is the result of swapping the warehouses of this two genes. In case the elite chromosome do not have any genes assigned to full warehouses or if all are allocated to full warehouses, a mutation is applied to a random gene selected. If the new chromosome generated is feasible, the cost function is compared with the elite chromosome. In the case of having a lower value, the new chromosome generated is added to the new population. Otherwise, the elite chromosome is kept. If the new chromosome is unfeasible, the same elite chromosome goes through the local search method again. This occurs according to a given parameter named as *Maximum number of tries in local search* (L).

For non elite chromosomes, the logic is similar to the discussed above. However, the decision of adding or not the new chromosome to the new population is determined through the SA algorithm. The acceptance criterion applied is the Metropolis algorithm mentioned in Section 2.2.3. The number of papers with different approaches for the choice of the initial temperature is vast. It is important that the initial temperature given allows the acceptance of almost any perturbation during the first iteration of the cooling loop. Hence, its value is defined taking into account the values obtained in the fitness function of the current population and adding a defined margin to it.

The cooling schedule considers a parameter defined as *maximum number of iterations in SA* (S) and is defined as:

$$New\ Temperature = Current\ Temperature - \frac{Initial\ Temperature}{S} \tag{4.12}$$

In each iteration a new chromosome is generated with the same logic mentioned for the elite chromosomes. If until the *New Temperature* reaches 0 degrees, none of the new generated chromosomes are accepted, it means that the probability of the original chromosome being a good solution is high, passing directly to the next generation.

4.6 Stopping Criteria

The algorithm will stop when any of the following criteria are satisfied:

1. If no better solution can be generated in a *Maximum number of consecutive generations* (B).
2. If the *Maximum number of iterations* (I) is reached.

Chapter 5

Implementation and Results

This chapter comprises the technical implementation of the concepts addressed in the previous sections, as well as a discussion of the results obtained. We suggest the integration of this component within Spoke.

5.1 Deployment

To develop this model, the main programming language used was Python. This high-level language is known for providing a user-friendly code and debugging can be easily done when compared with other languages such as C++ or Java. Due to the need for extracting data from a DB, SQL has also been employed for all queries concerning the selection of the data needed. These queries are directly used in the main Python code through external libraries that allow DB connection and data transfer. This algorithm will also be used to determine the viability of including DAMCO warehouse in the RL operation. The transportation costs associated with this possibility were not gathered by the time this project started. Therefore, after gathering and organizing all of this information, the costs were inserted into the DB.

Every time the user makes a request on Spoke, the algorithm will run and retrieve the results as demonstrated in Figure 5.1. Whenever a request is made, a JSON file is created. The information is sent in this lightweight format to ease the transformation of the data and to allow a faster response. All experiments were computed using an Intel® Core™ i5 2,6GHz processor with 8GB of RAM.

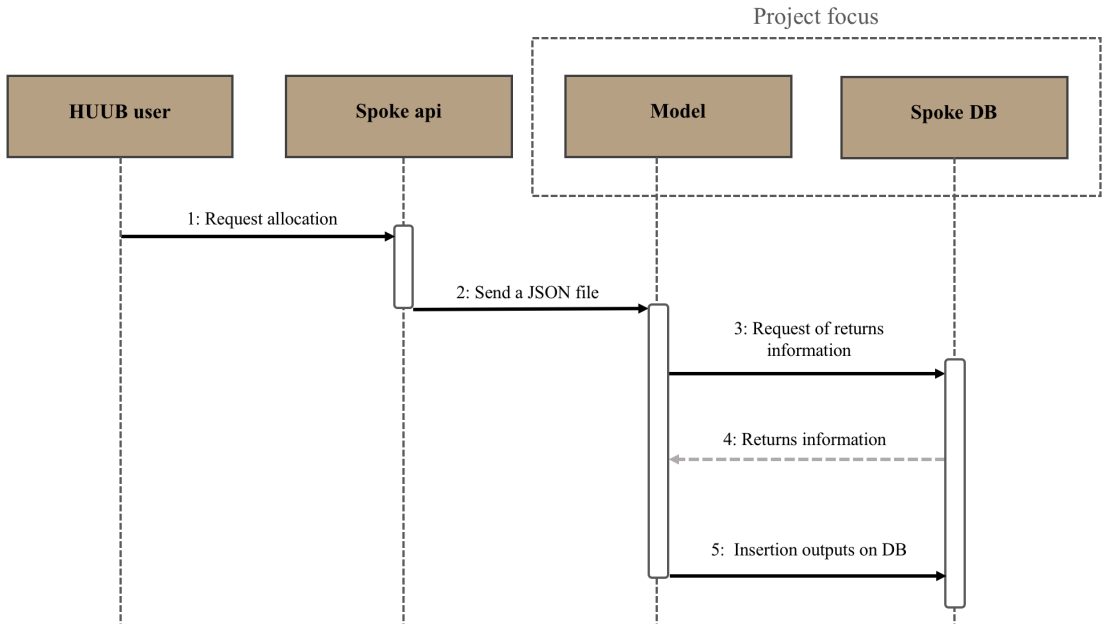


Figure 5.1: Request Planning

5.2 Scenario analyses

To gather some insights and to assure that the model is well-built, we tested distinct scenarios. After doing a research on RRs in e-commerce nowadays, the conclusion was that numbers hover around 25% of the e-commerce total orders (Dennis (2019), Saleh (2019), Douglas (2018) and Ecommerce (2018)). Therefore, the maximum and the minimum number of returns intervals were estimated, taking into account the sales pattern in 2018 and assuming a RR of 25%.

According to Appendix H, that reflects the SO pattern in 2018, the months with lower and higher demand are May (with an average of 867 orders/month) and November (averaging 6718 order/month), respectively. As this model is going to run daily, this gives an interval between 28 and 224 orders per day. Multiplying these values by the RR gives a range between 7 to 56 of returns per day at HUUB. With this set, the following scenarios were considered:

Table 5.1: Distinct Scenarios Analysed

Scenario	Situation	Method Applied	Purpose
A	Independent returns	Model 1	Test the applicability of the model; Observe patterns in the allocations;
B	Returns with same items	Model 2: GA	Test the applicability of the model; Sensitivity analyses concerning GA parameters;
C	Warehouse with limited capacity	Model 2: GA-SA	Test the applicability of the model; Sensitivity analyses concerning GA parameters;

5.2.1 Scenario A: Independent returns

To test the model, distinct samples of returns were created. For a sample of 7 returns with 1 item, the model took on average 49.29 seconds to run. First, only returns with origin at the end-user (see Figure 3.2) were tested. According to the origin country of a return, it was possible to observe some patterns. Therefore, we conducted sensitivity analyses concerning the distinct origins of a return.

The analyzed countries are the ones observed in Section 3.2. The λ_{it} highly influences the results. For the study be as closest as possible to reality, we assume that the item with the highest RR is the same as the one with the highest sales. Hence, the item belonging to each return was from the *Top* family (see Appendix H.2). Next, the time-space distribution of its sales in the previous year was observed. As the majority of *Top* items are sold in the second season, the study was conducted as if the return request is in August of the present year.

The returns' origin country that translates into more cost savings after being assigned to DAMCO is Switzerland (see Table 5.2). The results of the other countries are in Appendix I. The stock column represents the number of items that HUUB has in its network of warehouses, equal to the item that was returned. The Objective Function is calculated, either for the allocation of the return to PT or to the NL. Columns 4.2 to 4.4 correspond to the distinct terms of the objective function equation (Section 4.3.2).

After analysing the tables mentioned above, we conclude that the assignment to the warehouse in the NL can have savings from 49% to 1% comparing to the solution used today by the company of allocating all the returns to PT. As the stock increases, the cost of not selling at DAMCO gets considerably higher. In countries like China, the selected warehouse to assign the return, changes with the increasing units in stock. Nevertheless, for countries as Switzerland, Sweden, the United Kingdom and Germany, the allocation to the warehouse in the NL was always advantageous concerning the distinct stock values analyzed. This is mainly due to the high difference in the inbound transportation costs between the countries and these two warehouses.

Table 5.2: Scenario A: Sensitivity Analyses for Switzerland

Origin Country	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
Switzerland	0	PT	51,92 €	42,87 €	0,10 €	8,95 €	48%
		NL	**27,11 €**	12,03 €	2,03 €	13,05 €	
	1	PT	48,63 €	42,87 €	0,25 €	5,51 €	48%
		NL	**25,40 €**	12,03 €	5,29 €	8,08 €	
	2	PT	45,93 €	42,87 €	0,37 €	2,68 €	48%
		NL	**23,93 €**	12,03 €	7,91 €	3,98 €	
	10	PT	43,35 €	42,87 €	0,48 €	0 €	49%
		NL	**22,16 €**	12,03 €	10,13 €	0 €	

Second, we also create distinct scenarios for the returns with an origin at a warehouse (observe Figure 3.2). For high stock values, the probabilities of an item being sold or not start to stabilize. Analyzing table 5.3 it was possible to conclude that for returns with origin in the Portuguese

warehouse, the most reasonable action is to stay allocated there. Either when the stock is 0, or at a high value (we observed that when the stock value reached the 15 items, term 4.3 and 4.4 stabilizes), the chosen warehouse is PT.

However, when at NL, the number of items in stock influences the return's allocation. As the stock increases, the probability of the item not being sold also increases. As the storage costs in PT are cheaper, it is advantageous to bring the return to PT. For the scenario analyzed, when the stock is 0, term 4.3. in NL is not high enough to bring the return to the Portuguese warehouse. However, when the stock rises to 1 unit, term 4.3 also increases, and keeping the return at NL gets more costly than bringing it to PT.

Table 5.3: Scenario A: Sensitivity Analyses for returns starting at a warehouse

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4
PT	0	PT	**9,04 €**	0 €	0,10 €	8,95 €
		NL	31,08 €	16,00 €	2,03 €	13,05 €
	15	PT	**0,48 €**	0 €	0,48 €	0 €
		NL	26,13 €	16,00 €	10,13 €	0 €
NL	0	PT	15,52 €	6,48 €	0,10 €	8,95 €
		NL	**15,08 €**	0 €	2,03 €	13,05 €
	1	PT	**12,24 €**	6,48 €	0,25 €	5,51 €
		NL	13,37 €	0 €	5,29 €	8,08 €

5.2.2 Scenario B: Returns with same items

In this case scenario, we create three distinct samples of returns comprising several identical items. Two of the samples considered seven returns and the other one took into account fifty-six returns. One of the samples considers a third dummy warehouse.

Genetic operators have an important impact on many factors, such as running results and the time of calculation, and they will directly affect the convergence speed of the model as well as the quality of results. Therefore, distinct parameter values were tested. The results of the study are displayed in Table 5.4.

In every scenarios p_e is assigned with a low value to do not impair the ability of an GA to find better solutions.

After analyzing Section 5.2.1, it is possible to conclude that as the stock increases, the chosen warehouse stays the same in most of the studied countries. Once the initial population comprises the chromosome from model 1, the probability of the best solution be already in the first generation is high. Therefore, in these scenarios, we recommend the use of small values for the stopping criteria.

Nevertheless, for countries like China, the number of equal items in distinct returns will influence the warehouse selection. For a more interesting analysis, all the samples created comprise

several returns with origin in countries like China, where the number of items in stock impacts the allocation decision. The stopping criteria used stayed unaltered during all the tests performed.

For the N parameter, we specified two distinct levels for each sample. As expected, the results show better solutions for the highest N values. The increased computational time regarding a higher N value is large. However, as the computational time stills within an acceptable limit, we recommend the use of more significant values.

We investigate the influence of f_r by varying it from 10% to 50%. The results seem to show that for high values of f_r, the objective function gets better values. Particular attention should be given to these results. As the samples created contained countries where the stock influenced the allocation, it was expected better results for greater f_r. However, when the stock has not effect, what happens for most of the countries studied, we suggest the use of smaller values.

For crossover and mutation probabilities, two distinct levels were specified. The solutions seem to be better for higher values of p_c. Reminding the crossover method discussed in Section 4.4.3, we endorse the importance of using high values for the p_c parameter in this case scenarios. When the stock of the items influences the allocation, the order of the returns comprised in the chromosome can affect the function cost. Therefore, a high p_c value will allow the exploration of these solutions.

Table 5.4: Scenario B: Parameter Sensitivity Analyses

Sample	Number of Warehouses	Number of Returns	N	f_r	p_e	p_c	p_m	Obj. Function	Time (sec)
B.1	2	7	10	10%	5%	45%	50%	184.62 €	39.79
			20	10%	5%	45%	50%	**184.25 €**	70.58
			20	50%	5%	60%	35%	**184.25 €**	114.25
B.2	3	7	10	10%	5%	45%	50%	190.16 €	35.39
			20	10%	5%	45%	50%	187.18 €	70.33
			20	50%	5%	60%	35%	**183.53 €**	115.06
B.3	2	56	60	10%	5%	45%	50%	1226.31 €	1019.48
			80	10%	5%	45%	50%	1227.67 €	1602.90
			80	50%	5%	60%	35%	**1124.33 €**	2113.23

5.2.3 Scenario C: Warehouse with limited capacity

To understand the impact of GA parameters in this scenario, we create four distinct samples. We believe that this scenario will only occur for a high number of RR. Therefore, all the scenarios comprised fifty-six returns. As in the scenario above, one of the samples considers a third warehouse. The stopping criteria used, as well as the parameters regarding the SA, stayed unaltered during all the tests performed. The outcomes of the study are illustrated in Table 5.5.

Concerning the N parameter, the results support the conclusion made in Section 5.2.2.

For the f_r parameter two levels were studied, from 20% to 40%. The best results were found for smaller values of the referred parameter.

In this case scenarios, we believe that the mutation method discussed in Section 4.4.3 plays an important role. When the capacity of a warehouse reaches its limit, it is essential to search other

assignments for the returns. Therefore, two levels of 60% and 80% were considered. We found better results for a higher p_m.

As discussed in Section 4.5, there was a necessity to create a local search technique for this case scenario. To understand the impact of using the applied method, for each of the samples studied, the best combination of parameters was used in a scenario without local search. As seen in Table 5.5, for all the samples the result without local search is considerably worst. Therefore, the results show that the applied methodology improved the performance of the algorithm.

Table 5.5: Scenario C: Parameter Sensitivity Analyses

Sample	Number of Warehouses	Number of Returns	Local Search	N	f_r	p_e	p_c	p_m	Obj. Function	Time (sec.)
C.1	2	56	Yes	60	20%	5%	35%	60%	1322.45 €	1990.58
			Yes	60	20%	5%	15%	80%	1319.12 €	2342.46
			Yes	60	40%	5%	15%	80%	1319.93 €	1892.54
			Yes	80	20%	5%	15%	80%	**1318.83 €**	2969.02
			No	80	20%	5%	15%	80%	1324.78 €	1345.56
C.2	2	56	Yes	60	20%	5%	35%	60%	1325.46 €	2170.39
			Yes	60	20%	5%	15%	80%	1326.27 €	3022.65
			Yes	60	40%	5%	15%	80%	1328.27 €	2258
			Yes	80	20%	5%	15%	80%	**1323.94 €**	2942.78
			No	80	20%	5%	15%	80%	1328.27 €	1238.77
C.3	2	56	Yes	60	20%	5%	35%	60%	1286.22 €	2015.78
			Yes	60	20%	5%	15%	80%	1279.79 €	1655.96
			Yes	60	40%	5%	15%	80%	1281.83 €	2553.55
			Yes	80	20%	5%	15%	80%	**1276.17 €**	2903.12
			No	80	20%	5%	15%	80%	1303.94 €	1477.18
C.4	3	56	Yes	60	20%	5%	35%	60%	1255.40 €	1055.45
			Yes	60	20%	5%	15%	80%	1273.05 €	971.68
			Yes	60	40%	5%	15%	80%	1256.65 €	2031.64
			Yes	80	20%	5%	15%	80%	**1248.01 €**	2875.53
			No	80	20%	5%	15%	80%	1258.76 €	1671.47

Chapter 6

Conclusions and Future Work

The study was set out to develop a solution for the HUUB RL supply chain. To this intent, the first steps of the project involved mapping all the processes comprised in the operation. Three main flows were covered: process, informational and financial. The conclusion was that as the decision of allocating a return was not being made in the most efficient way, the deployment of a solution capable of dynamically setting a route of a specific return would allow high saving costs.

To do this, we propose to use an optimization model. First, the construction of an approach that took into account the returns independently was performed. However, the pace at which the start-up is growing has been quite high. Moreover, the tendency of the RRs in HUUB's top markets is to increase in the next years. Therefore, a more complex model using GA and SA was developed, capable of answering to the increasing number of returns and the number of warehouses that the company will have in a short period of time.

We tested the model through different case scenarios representing distinct cases on the RL daily operation. The optimization model designed can answer not only to today's HUUB needs but also for the future needs emerging from the start-up growth. We concluded that partnering with DAMCO is a viable option that enables cost savings. Furthermore, as being close to the companies top markets, this solution can also have an impact on the service level agreement between HUUB and its customers.

Regarding the metaheuristics used, we conclude that GA parameters should vary according to the instance. In order to not use unnecessary computational time and also to not restrict too much the search space, the population size has to be adjusted according to the number of returns in the problem. The results showed that the metaheuristics applied have an excellent performance in this type of problematic areas. It is important to highlight that the number of scenarios created are low and to better support the conclusions made, more instances should be analyzed.

The work undertaken in the present thesis offered to the company not only a tangible solution capable of dynamically assigning a warehouse for a specific return, but also full visibility of its RL processes and its main improvement areas. Moreover, this solution will allow HUUB to cut on its return costs, thus positively impacting its bottom line.

This research uncovered some directions for future work. Once the majority of the returns

received at HUUB are from e-commerce, only the modulation of this case was developed. In the future, it is expected to incorporate wholesale returns. The returns with a starting point at the carrier will also have to be included.

According to what was highlighted in Chapter 3, the possible improvements regarding the returns process are vast. A solution easy to implement and with a high impact in the process would be the integration with the brand's websites, enabling the end-user return request to go directly into the company's system. This process will become more efficient and less time-consuming since the return claim will not need to be communicated by the brand to HUUB.

Concerning the proposed model in the thesis, SA parameters were not totally explored. Therefore, it is suggested to analyze the use of distinct initial temperatures. Besides, the impact of different cooling schedule techniques should be studied. We noticed that for scenarios where the capacity of the warehouses is reached, the computational time raises considerably. This is because in this case, the algorithm takes more time constructing feasible chromosomes. To make the case scenario less time consuming, a list with possible failed combinations already tried should be created. Also, special attention should be given to the construction of the initial population. With the number of warehouses increasing, it is crucial to ensure that the initial population has every warehouse represented.

The design of this optimization algorithm was done, taking into account a posterior integration with two other models developed in the company. The first one is created to plan the shipment of an order to an end-user. Therefore, if after passing through the returns operational process, the decision is to resend that item to the client, then the return would pass through this model. Also, when a return is an exchange, the new order requested should be integrated. The second model considers the allocation of stock between every warehouse in the network. Hence, to have the correct level of stock per day in each warehouse, both models should be linked. Otherwise, the possibility of allocating stock/return to a warehouse that does not have that capacity is high.

As described in Chapter 4, the Tax and Duties costs were out of this thesis scope but will be considered in the near future.

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Appendix A

Strategic and Operational Processes

Strategic Processes

1. Determine Returns Management Goals and Strategy:
    - Determine the role of returns in firm's strategy
    - Determine how to best recapture value and recover assets
    - Review environmental and legal compliance issus
    - Understand supply chain constraints and capabilities
2. Develop Avoidance, Gatekeeping Disposition Guidelines:
    - Determine types of returns firm might face
    - Establish structure to identify avoidance opportunities
    - Develop returns policies and screening mechanisms
    - Develop disposition options
3. Develop Returns Network and Flow Options:
    - Develop RL network
    - Determine transportation modes and methodologies
    - Structure plans for recalls
4. Develop Credit Rules:
    - Determine how returned product will be valued
    - Develop credit authorization guidelines
    - Establish credit policies
5. Determine Secondary Markets:
    - Find and examine potential secondary markets
    - Determine rules for using secondary markets
    - Develop re-manufacturing/refurbishing strategies
6. Develop Framework of Metrics

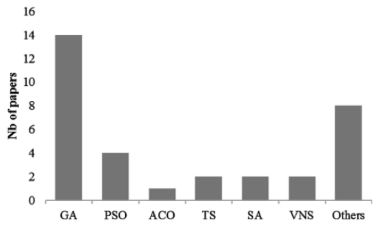
- Link returns performance to economic value added (EVA)
- Determine appropriate metrics and set goals

Operational Processes

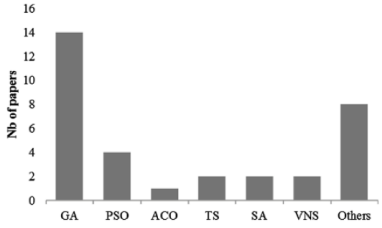
1. Receive Return Request
    - Initiate customer return request
    - Implement gatekeeping guidelines
2. Determine Routing
    - Review routing guidelines
    - Plan routing
    - Generate return material authorizations
3. Receive Returns
    - Receive returned material
    - Verify inspect and process return (gatekeeping)
    - Determine return reason
4. Select Disposition
    - Apply disposition guidelines
    - Transport product to final disposition
5. Credit Customer/Supplier
    - Coordinate credit authorization across supply chain
    - Negotiate settlement
6. Analyze Returns and Measure Performance
    - Analyze returns and identify opportunities for avoidance
    - Calculate process metrics and link to EVA
    - Set goals for performance improvement

Appendix B

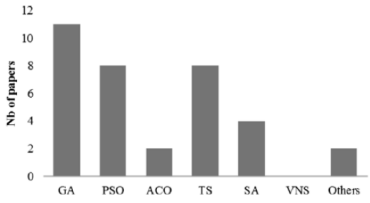
Most Commonly Used Metaheuristics per Area



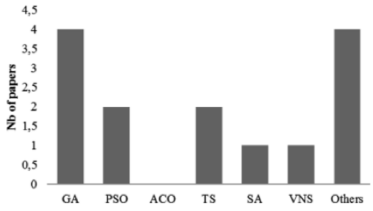
(a) Most used methods in Vehicle Routing Problem



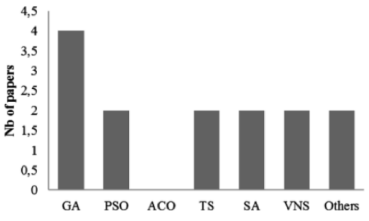
(b) Most used methods in Network Design Problem



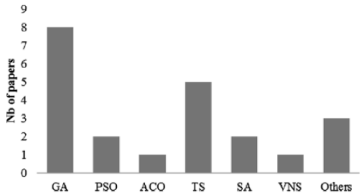
(c) Most used methods in Inventory Management Problem



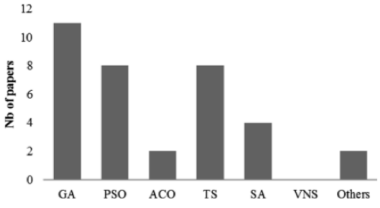
(d) Most used methods in Assembly Disassembly Problem



(e) Most used methods in Production Planning Problem



(f) Most used methods in Location and Allocation Problem



(g) Most used methods in Returns Management Problem

Appendix C

Reverse Logistics Process at HUUB

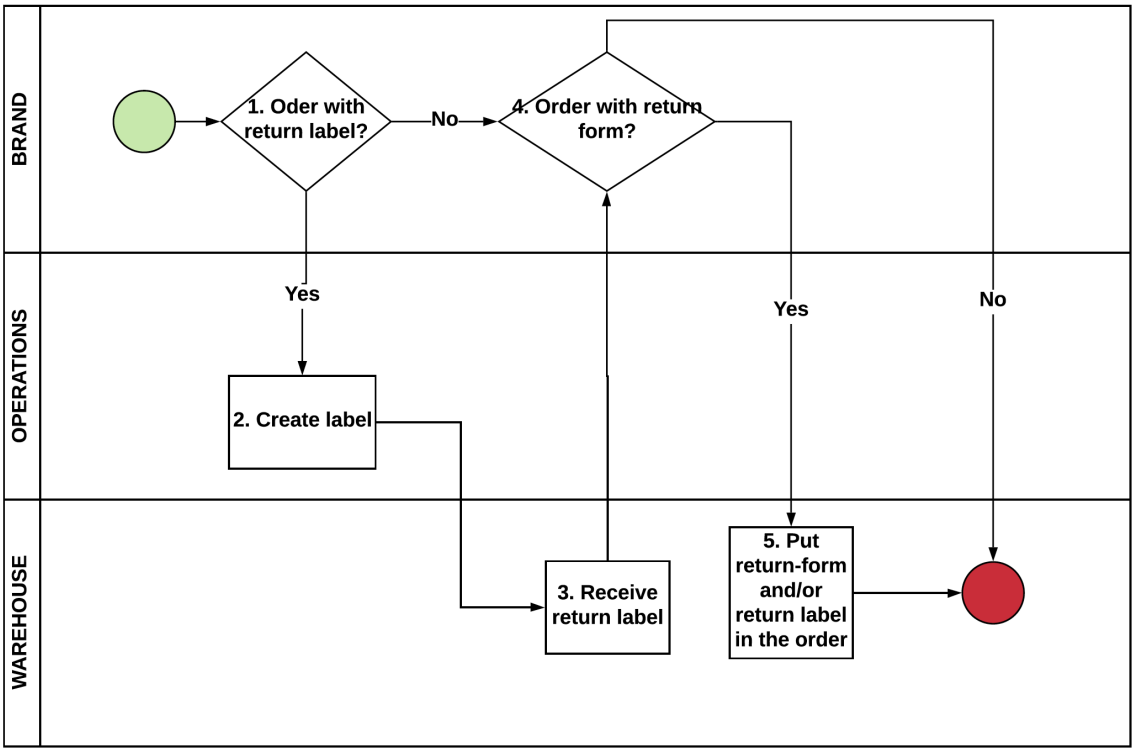


Figure C.1: Phase 0

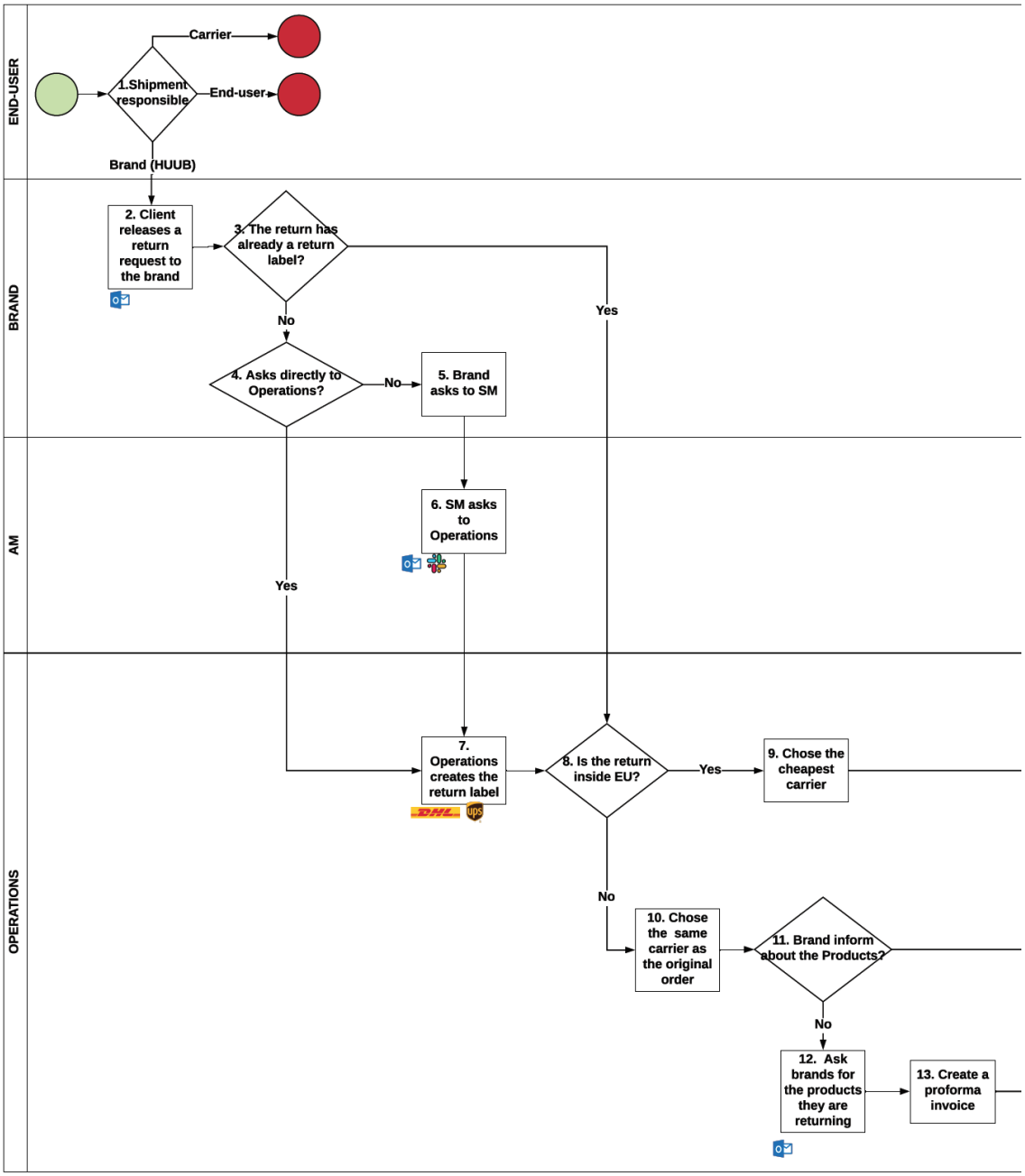


Figure C.2: Phase 1 (Part A)

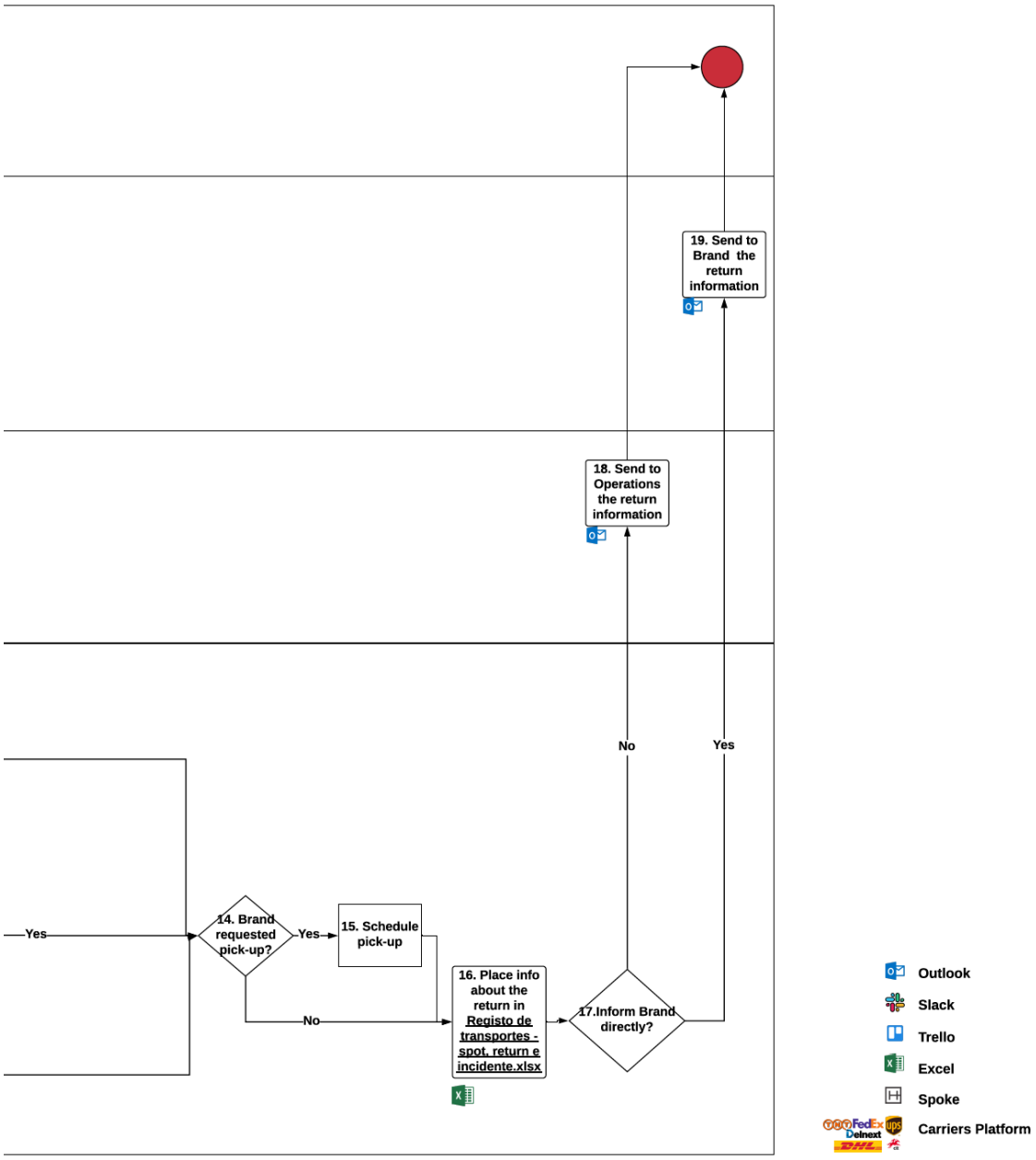


Figure C.3: Phase 1 (Part B)

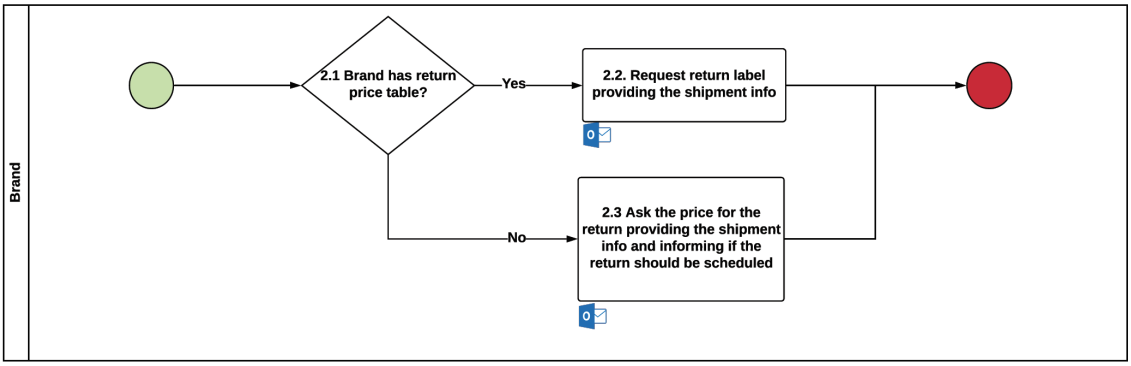


Figure C.4: Phase 1 (Activity 2)

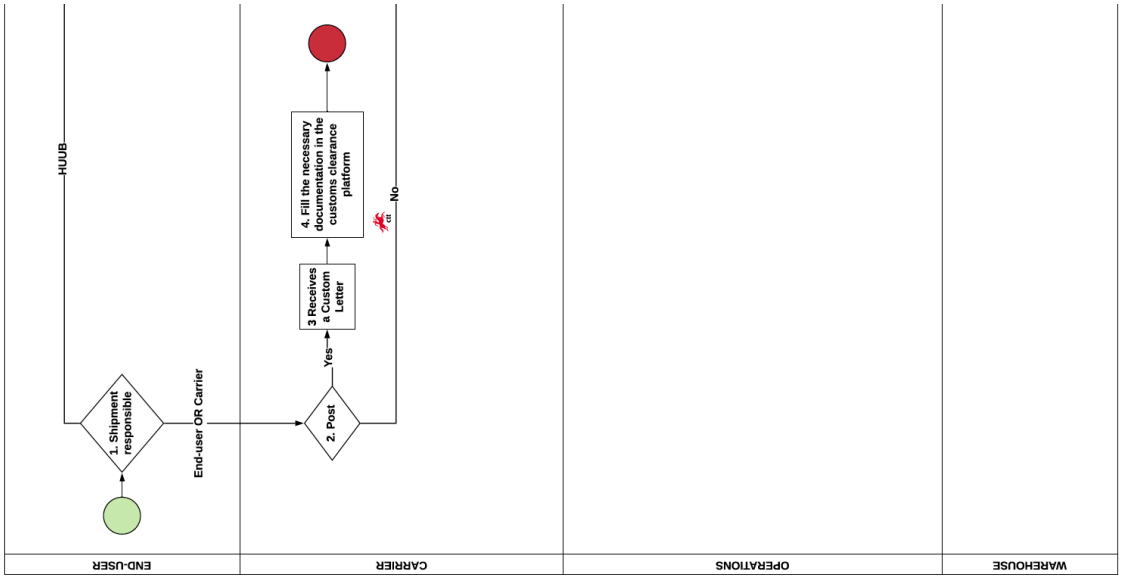


Figure C.5: Phase 2 (Part A)

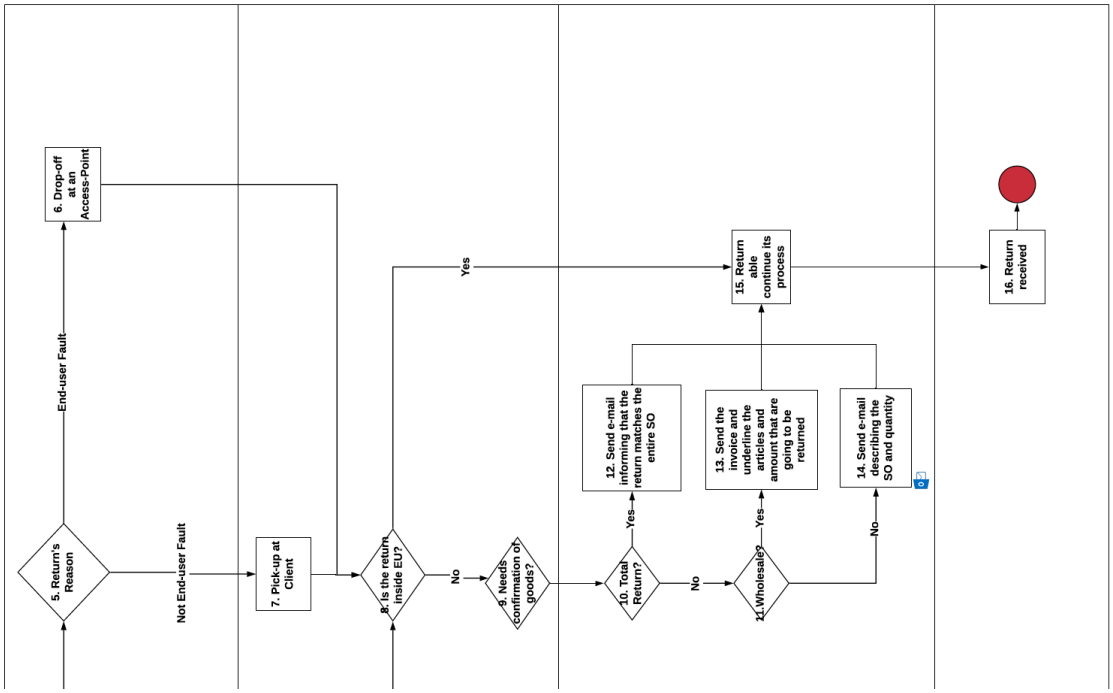


Figure C.6: Phase 2 (Part B)

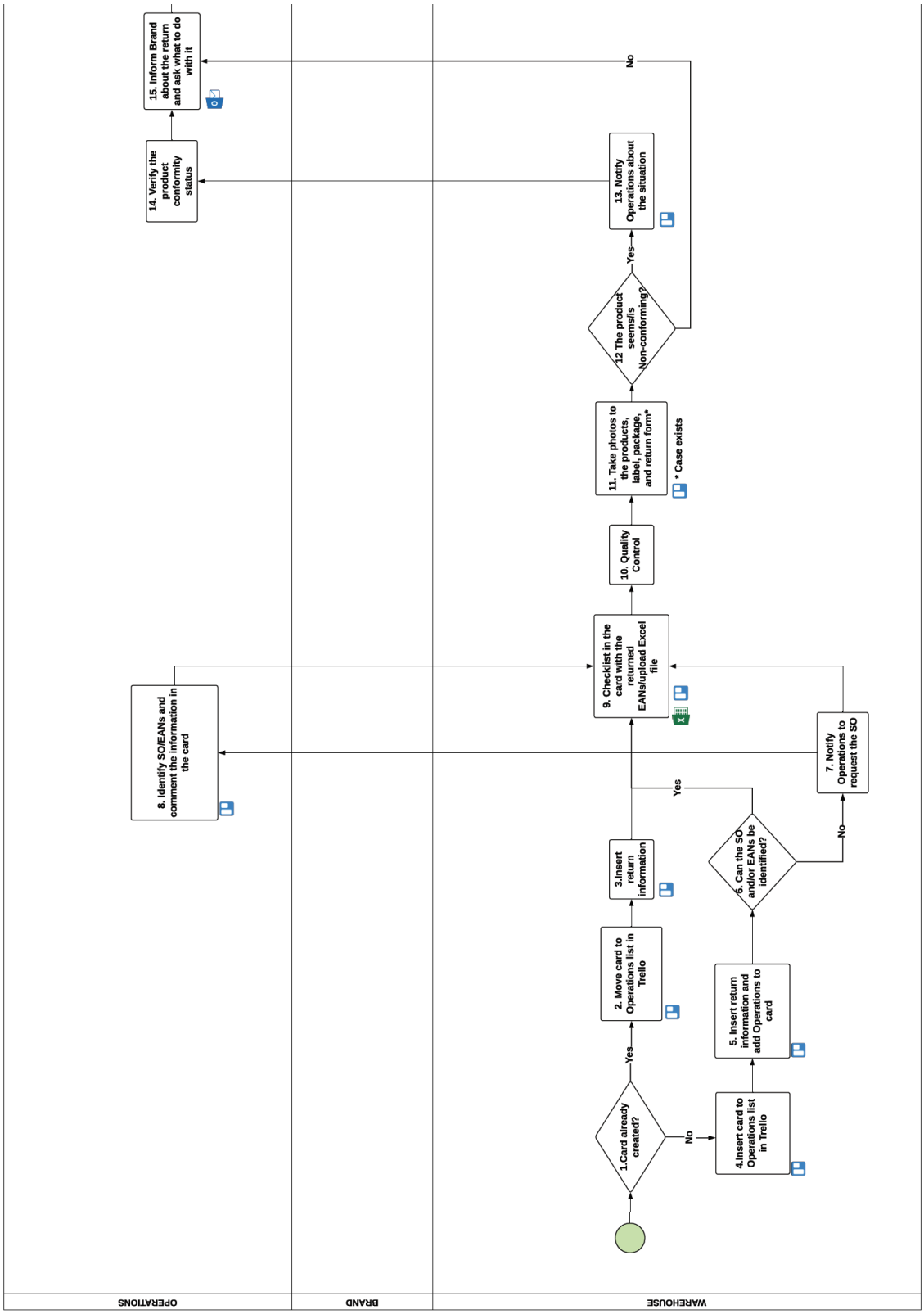


Figure C.7: Phase 3 (Part A)

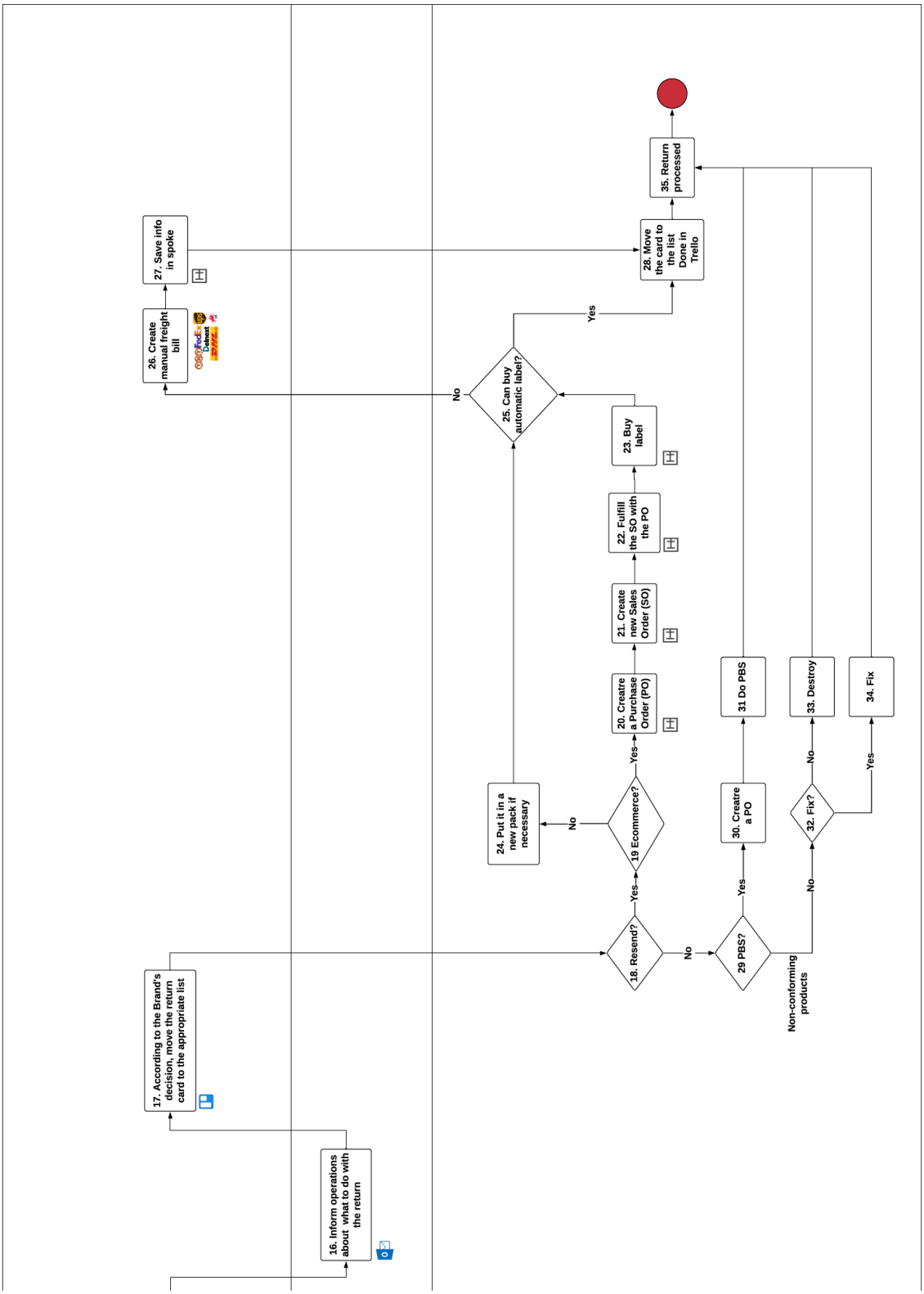
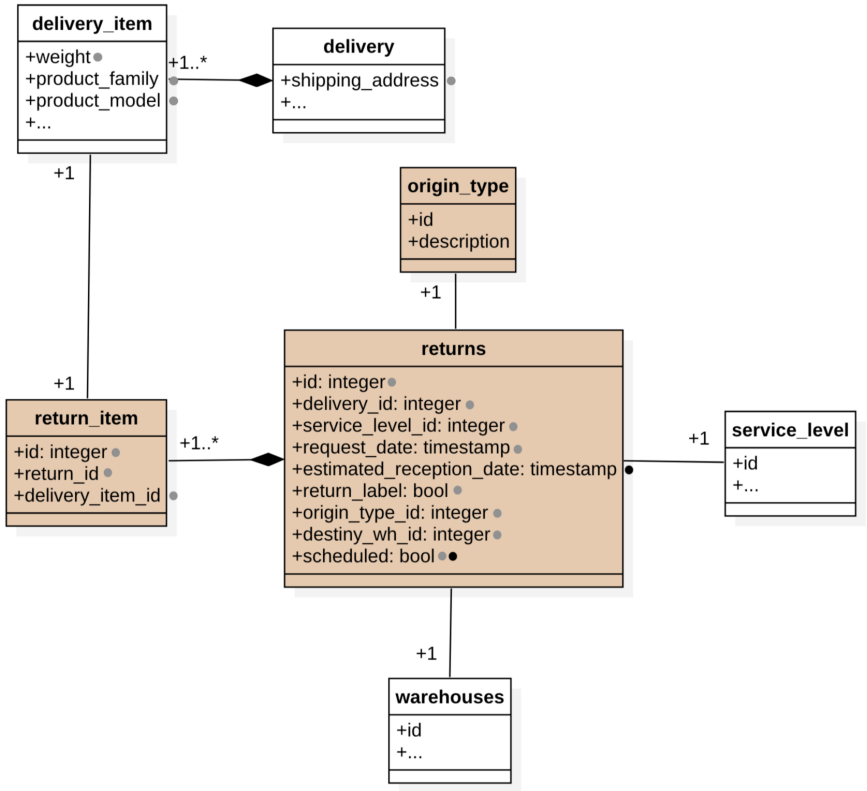


Figure C.8: Phase 3 (Part B)

Appendix D

Proposed UML Diagram



Appendix E

Weight Distribution

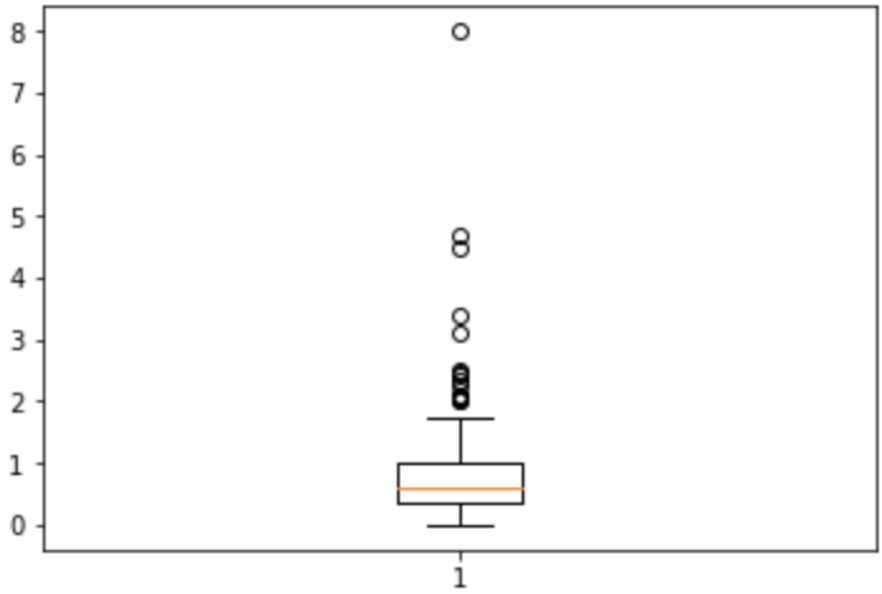


Figure E.1: Returns' weight distribution with outliers

Appendix F

Model 2 Parameters

Parameter	Description
f_r	Random fraction
p_e	Elitism probability
p_c	Crossover probability
p_m	Mutation probability
p_s	Selection probability
N	Population size
C	Maximum number of tries in Crossover
M	Maximum number of tries in Mutation
L	Maximum number of tries in Local Search
S	Maximum number of iterations in SA
T_i	Initial temperature in SA
I	Maximum number of iterations
B	Maximum number of consecutive generations with the same F_{cost}

Appendix G

Pseudo-code

Algorithm 1 Initial Population: chromosome from model 1

Input: returns, original chromosome ▷ The original chromosome is the one from model 1
Output: chromosome
$feasible \leftarrow$ check if original chromosome is feasible
if $feasible$ **then**
  add original chromosome to initial population
else
  $genes_{full} \leftarrow$ genes from the original chromosome assigned to the full warehouse
  while not $feasible$ **do**
    $gene_{selected} \leftarrow$ randomly select a gene from $genes_{full}$ to change warehouse
    $w \leftarrow$ randomly select a warehouse which capacity is not full
    $gene_{modified} \leftarrow gene_{selected}$ with new w
    replace $gene_{selected}$ by the $gene_{modified}$ in original chromosome
    $feasible \leftarrow$ check the feasibility of the chromosome
    remove $gene_{selected}$ from $genes_{full}$
  end while
  add chromosome to initial population
end if

Algorithm 2 Initial Population: create cheapest storage costs chromosome

Input: returns, cheapest storage costs warehouse
Output: chromosome
foreach *return* **do**
  $iteration \leftarrow \emptyset$
  $feasible \leftarrow$ False
  while not $feasible$ **do**
    if $iteration = \emptyset$ **then**
      gene ← the return is assigned to the cheapest warehouse
    else
      warehouse ← select the warehouse not full with cheapest storage costs
      gene ← *return* is assigned to *warehouse*
    end if
    chromosome ← add *gene*
    $feasible \leftarrow$ check the feasibility of genes already in *chromosome*
    if not $feasible$ **then**
      remove last *gene* added from *chromosome*
      $iteration \leftarrow iteration + 1$
    end if
  end while
end for

Algorithm 3 Initial Population: create chromosome with random allocations

Input: original chromosome, f_r
Output: chromosome
$genes_{selected} \leftarrow$ randomly select f_r genes from the original chromosome
chromosome ← add genes not selected
for *gene* in $genes_{selected}$ **do**
  $feasible \leftarrow$ False
  $W \leftarrow$ all warehouses of HUUB's network
  while not $feasible$ **do**
    $w \leftarrow$ randomly select a warehouse from W
    $gene_{modified} \leftarrow$ assign return in *gene* to w
    add $gene_{modified}$ to *chromosome*
    $feasible \leftarrow$ check the feasibility of genes already in *chromosome*
    if not $feasible$ **then**
      remove $gene_{modified}$ from *chromosome*
      remove w from W
    end if
  end while
end for

Algorithm 4 Local Search for elite chromosomes

Input: full warehouse, elite chromosomes, maximum tries
Output: chromosomes
foreach elite chromosome **do**
  $try \leftarrow \emptyset$
  while $try <$ maximum tries **do**
    $genes_{full} \leftarrow$ genes in the elite chromosome assigned to the full warehouse
    $genes_{not\,full} \leftarrow$ genes in the elite chromosome not assigned to the full warehouse
    if $genes_{full} = \emptyset$ or $genes_{not\,full} = \emptyset$ **then**
      $gene_{selected} \leftarrow$ randomly select a gene from the original chromosome
      $w \leftarrow$ randomly select a distinct warehouse from the one in $gene_{selected}$
    else
      randomly select a gene from $genes_{full}$ and a gene from $genes_{not\,full}$
      exchange the warehouses between the two genes selected
    end if
    chromosome $\leftarrow$ new chromosome with the applied changes in genes
    $feasible \leftarrow$ check the feasibility of *chromosome*
    if $feasible$ **then**
      $try \leftarrow$ maximum tries
      $chromosomeF_{cost} \leftarrow$ calculate the *chromosome* cost function
      if $chromosomeF_{cost} <$ elite chromosome F_{cost} **then**
        chromosome is added to new population
      else
        keep elite chromosome
      end if
    else
      $try = try + 1$
    end if
  end while
  if not $feasible$ **then**
    keep elite chromosome
  end if
end for

Appendix H

Scenario Analyses

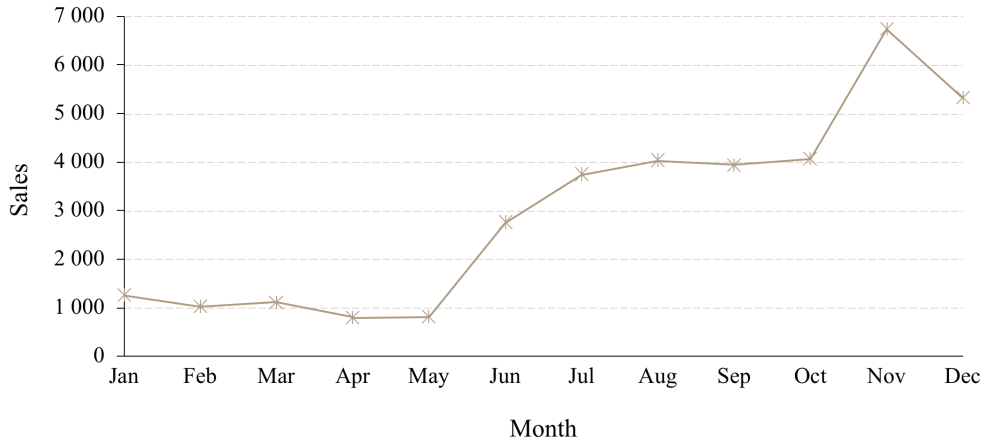


Figure H.1: Sales Order distribution

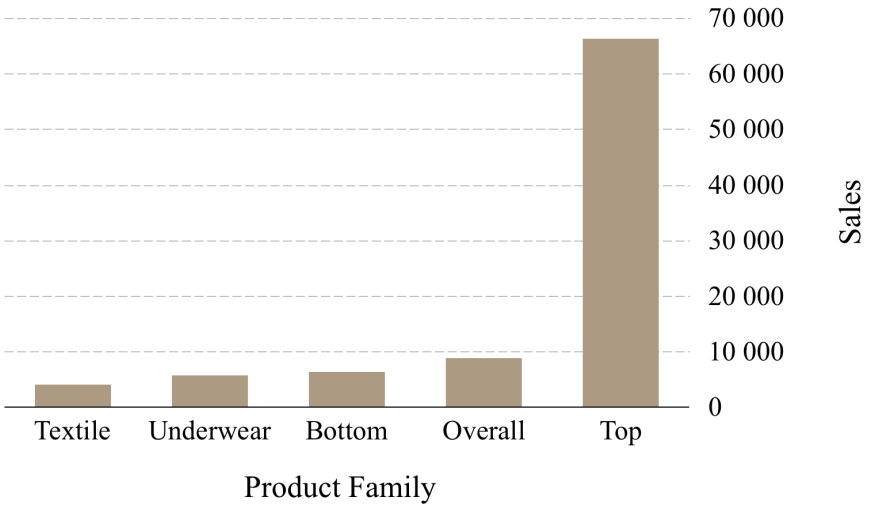


Figure H.2: Item families with highest number of sales

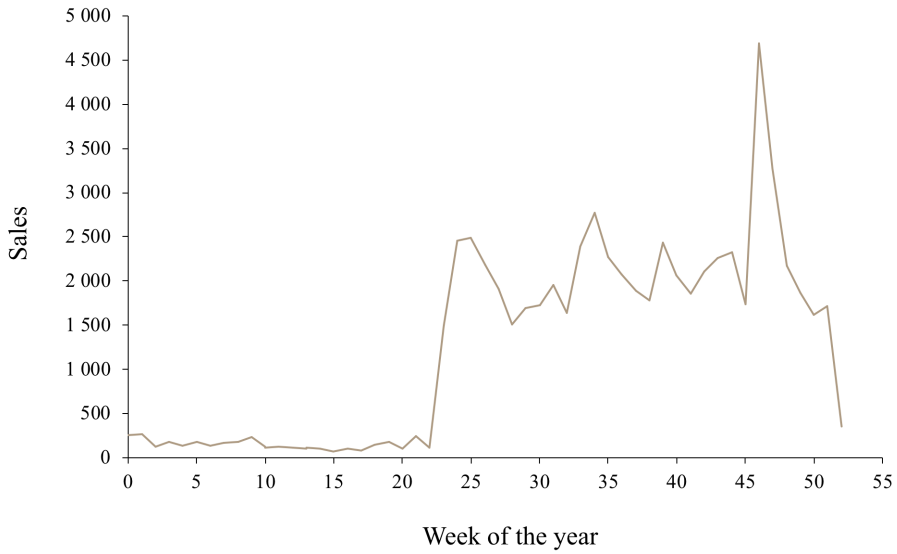


Figure H.3: Sales Distribution in 2018 for *Top* item family

Appendix I

Sensitivity Analyses: Scenario A

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
Sweden	0	PT	33,01 €	23,97 €	0,10 €	8,95 €	35%
		NL	**21,56 €**	6,48 €	2,03 €	13,05 €	
	1	PT	29,72 €	23,97 €	0,25 €	5,51 €	33%
		NL	**19,85 €**	6,48 €	5,29 €	8,08 €	
	2	PT	27,02 €	23,97 €	0,37 €	2,68 €	32%
		NL	**18,38 €**	6,48 €	7,91 €	3,98 €	
	10	PT	24,45 €	23,97 €	0,48 €	0 €	32%
		NL	**16,61 €**	6,48 €	10,13 €	0 €	

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
United Kingdom & Germany	0	PT	26,73 €	17,68 €	0,10 €	8,95 €	19%
		NL	**21,56 €**	6,48 €	2,03 €	13,05 €	
	1	PT	23,44 €	17,68 €	0,25 €	5,51 €	15%
		NL	**19,85 €**	6,48 €	5,29 €	8,08 €	
	2	PT	20,74 €	17,68 €	0,37 €	2,68 €	11%
		NL	**18,38 €**	6,48 €	7,91 €	3,98 €	
	10	PT	18,16 €	17,68 €	0,48 €	0 €	9%
		NL	**16,61 €**	6,48 €	10,13 €	0 €	

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
China	0	PT	32,39 €	23,35 €	0,10 €	8,95 €	1%
		NL	**32,03 €**	16,95 €	2,03 €	13,05 €	
	1	PT	**29,11 €**	23,35 €	0,25 €	5,51 €	0%
		NL	30,32 €	16,95 €	5,29 €	8,08 €	
	2	PT	**26,41 €**	23,35 €	0,37 €	2,68 €	0%
		NL	28,85 €	16,95 €	7,91 €	3,98 €	
	10	PT	**23,83 €**	23,35 €	0,48 €	0 €	0%
		NL	27,08 €	16,95 €	10,13 €	0 €	

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
US	0	PT	**29,76 €**	20,72 €	0,10 €	8,95 €	0%
		NL	34,05 €	18,97 €	2,03 €	13,05 €	

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
France	0	PT	**20,60 €**	11,56 €	0,10 €	8,95 €	0%
		NL	21,56 €	6,48 €	2,03 €	13,05 €	

Origin warehouse	Stock	Allocation	Objective Function	4.2	4.3	4.4	Saved
Spain	0	PT	**14,30 €**	5,26 €	0,10 €	8,95 €	0%
		NL	21,56 €	6,48 €	2,03 €	13,05 €	