FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

A Different Approach on Reverse Logistics — A Retailer's Case Study

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Abstract

Reverse logistics are, according to the *Reverse Logistics Executive Council, "the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from their typical final destination for the purpose of capturing value, or proper disposal."* In other words, reverse logistics include all the material flow from the consumers to the manufacturers.

This project was conducted in the Food and Non Food Department from a retailer company with the objective of making reverse logistics more efficient and systematized. Intense promotional activity and frequent product assortment review characterize the retailer's business resulting in high variability in demand and consequent need for overstocking. Hence, there is the need of Reverse Logistics to deal with exceeding stocks, avoiding stock-outs and creating space for new products in backroom facilities.

The problem was approached in two phases: firstly, all reverse logistic costs and benefits were identified and estimated; next, a decision tree entailing two optimization models was developed to maximize reverse logistics benefits.

When stores' product assortment is reviewed, several products are delisted losing their shelf space. Therefore, although there is stock on hand, those products are hardly sold. The End-Of-Life Stock Model (EOLS) was developed. It is based on the hypothesis that these products concentration and highlight in few stores boost their sales. Another approach to the problem — the Stock Coverge Balancing Model (SCB) — entails the prevention through balancing stocks' coverage. Besides the straightforward transportation and warehousing costs, Reverse Logistics comprises several costs that allow the decision-making. On the one hand, delisted stocks concentration and highlight allows these products sales that were not to happen in the as-is scenario. On the other hand, balancing stock coverages anticipates sales increasing their likelihood to occur within the life cycle. Furthermore, sales anticipation decreases the holding cost. Another hidden but extremely important benefit to the retailer is the backroom space release that may translate in out of shelf occurrences decrease.

The attained results prove that reverse logistics have significant benefits. The SCB resulted in a gain of 0,5% and 1,4% of the Food and Non Food Departments, respectively. The EOLS also has potential. Its gains are of 0,4% and 1,2% in the referred departments in the first year. The project estimates a total benefit of 1,2% of both departments sales in the first year, evidencing the opportunity reverse logistics represent to the retailer.

Reverse logistics, including the methodology and optimization models developed, has a broad scope and can be applied to different cases and industries. On pharmaceutical industry, reverse logistics are necessary to collect and further dispose spoiled medicines. Moreover, lateral transshipments on the distributor echelon may help complying with the legislation and increase the service level. Finally, the proposed methodology may add value by decreasing spoilage and shortage costs.

Resumo

A logística inversa é, segundo o *Reverse Logistics Executive Council*, "*o processo de movimentação de bens e produtos, desde o seu destino final típico até outro elo da cadeia de abastecimento, com o propósito de reaver valor ou de eliminação apropriada*". Por outras palavras, a logística inversa é todo o fluxo de material no sentido dos consumidores para os produtores.

Este projeto foi desenvolvido nos departamentos alimentar e não alimentar de um grande retalhista com o objetivo de sistematizar e tornar a logística inversa mais eficiente. A intensa atividade promocional e elevada revisão dos artigos em gama caracterizam o negócio do retalhista, traduzindo-se numa elevada variabilidade na procura e consequente necessidade de aprovisionamento em excesso. Dado isto, é evidente a necessidade de logística inversa para dar destino ao stock em excesso, evitando rupturas e criando espaço para novos artigos na retaguarda das lojas.

A abordagem ao problema dividiu-se em duas fases: primeiramente, mapearam-se todos os custos e benefícios da logística inversa; em seguida, foi desenvolvida uma árvore de decisão que inclui dois modelos de optimização que visam maximizar o benefício da logistica inversa.

Aquando das revisões de gama, vários artigos são descontinuados, deixando de ter espaço na placa de vendas. Assim, apesar de existir inventário destes artigos, os mesmos não vendem. Foi desenvolvido um modelo de escoamento que se baseia na permissa de que a concentração destes artigos em poucas lojas em que lhes é dado destaque potencia a sua venda. Uma outra abordagem ao problema é a prevenção através do equilibrio das coberturas dos artigos nas diferentes lojas - modelo de balanceamento de coberturas. Para além dos custos óbvios de transporte e armazenamento, a logistica inversa tem vários benefícios que alimentam ambos os modelos para a tomada de decisão. A concentração de artigos descontinuados e o seu destaque na loja potencia a sua venda, que de outra forma não aconteceria por estes se encontrarem armazenados na retaguarda. O balanceamento, ao equilibrar as coberturas, coloca os artigos noutras lojas em que a venda acontece dentro do seu tempo de vida. A antecipação da venda dos artigos diminui também o custo de posse que lhes está associado. Outra vantagem, não tão evidente, mas de extrema importância para o retalhista, é a libertação de espaço na retaguarda que se traduz num menor número de rupturas com stock em loja.

Os resultados obtidos provam que a logística inversa tem benefícios significativos. O balanceamento de stock nas lojas resultou num ganho de 0,5% e 1,4% face às vendas nos departamentos alimentar e não alimentar, repetivamente. O modelo de escoamento também tem potencial, permitindo obter um ganho de 0,4% e 1,2% nos referidos departamentos no primeiro ano em que é executado. O projeto estima, no primeiro ano de implementaçao, um benefício total de 1,2% face às vendas de ambos os departamentos, evidenciando a oportunidade que a logística inversa representa para o retalhista.

A logística inversa, incluindo a metodologia e modelos desenvolvidos, é abrangente a passivel de ser aplicada a diferentes casos e indústrias. Na indústria farmaceutica, a logística inversa torna-se necessária para a recolha e o correto tratamento dos medicamentos estragados. Mais ainda, ao nível do grossista, as transferências entre lojas podem ajudar a cumprir a legislação e aumentar o

nível de serviço. Por fim, a metologia desenvolvida pode acrescentar valor ao diminuir os custos de quebra e ruturas.

Aknowledgements

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Raquel Vieira

“Pose ta question, tu seras idiot une seconde.
Ne la pose pas, tu seras idiot toute ta vie”

Albert Einstein

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Acronyms, Indexes and Parameters

Acronyms

EOLS	End-Of-Life Stock Model
EOQ	Economic Order Quantity
FD	Food Department
NFD	Non Food Department
SCB	Stock Coverage Balancing Model
SKU	Stock keeping unit

Indexes and Sets

i	SKU's in I
j	Stores in J
k	Product families in K
t	Months in T

Models' Costs

$brCost_{ij}$	Store backroom space cost of SKU i in the store j	€ per unit
$hCost_i$	Annual holding cost of SKU i	€ per unit
$nsCost_i$	Cost of SKU i *Non Salable* stock value	€ per unit
$stDevCost$	Store devolution cost	€ per unit
$stRecCost_i$	Store reception cost of SKU i	€ per unit
$tCost_{S-W\,i}$	Reverse logistics transportation cost of the SKU i	€ per unit
$tCost_{W-S\,i}$	Forward logistics transportation cost of the SKU i	€ per unit
$whOpCost$	Warehouse operational cost	€ per unit
$whCost_i$	Warehousing cost during a year of a unit of SKU i	€ per SKU per year

Parameters

c_i	Acquisition cost of SKU i	€ per unit
Cap_{jk}	Outlet store capacity	number of SKU's
d_i	EOLS discount on SKU i price	%
g_i	1 if SKU i belongs to the assortment of store j; 0 if it does not belong	
h	Holding cost as percentage of acquisition cost	%
k	Margin loss with stock outs	%
m_i	Margin on SKU i	€ per unit
M_{ij}	Annual sales margin of store j	€
Nb_F	Number of boxes per pallet in forward logistics	units
Nb_R	Number of boxes per pallet in reverse logistics	units
p_{ij}	1 if it is possible to sale SKU i in store j; 0 if it is not possible	
pf_{ij}	1 if it SKU i belongs to product family k; 0 if it does not belong	
$Smax_{ij}$	Maximum stock of SKU i allowed in store j	units
$Smin_{ij}$	Minimum stock of SKU i allowed in store j	units
spk_i	Storepack of SKU i	units
$stock_{ij}$	Stock of SKU i in the store j	units
$stock_{NSij}$	*Non salable* stock of SKU i in the store j	units
$stock_{Oij}$	*Optimizable* stock of SKU i in the store j	units
$transCost$	Transportation fee	€ per trajectory
v_i	Volume of SKU i	m^3 per unit
V_j	Volume of backroom of store j	m^3
v_p	Volume capacity of a pallet	m^3
$whCost$	Warehousing cost	€ per pallet

Chapter 1

Introduction

1.1 Motivation

Nowadays, the easy access to information conducts to an increase of well informed consumers which have more requirements and bargaining power. To answer this growing demand, companies invest more and more in costumer satisfaction causing a direct impact on the growth of reverse logistic flows.

The growing awareness to environmental problems and its related legislation, as well as the concern about social responsibility strongly urge the repair, reuse, recycle and even the correct end of life of the different products. All these actions increase the material flow in the reverse direction of the supply chain. Furthermore, this trend is exacerbated by the notorious diminish in the products' life cycle, which boosts the production and demand for raw materials. Hence end-of-life products value recovering is essential and a potential economic advantage.

In the retailing industry, the current trends exacerbate the problem. The fierce competition that characterizes this business results in intense promotional activity proven by the ever increasing number, frequency and depth of promotions. Furthermore, customers demand for huge variety, including perishable goods. Combined with the diminish in products life cycle, this leads to continuous product testing by both manufacturers and retailers causing increasing products in and out of assortment. Product testing is many times done by resorting to promotional activities in order to make costumers try and adhere to them. The described tendencies result in enormous fluctuations in demand. Hence the bullwhip effect is more pronounced and hinders demand forecast. Consequently, the accurate provision of stores is jeopardized making under stock and overstock situations common.

Shortages have negative impact in both retailers and manufactures. For the later, product substitution is a loss, while to the former, the same happens when consumer chooses to buy at another store. Thence, to avoid shortages, an overstock policy may be applied. Nonetheless, overstocking accounts to higher ownership and holding costs. Moreover, stock accumulation may cause its oblivion in the backroom facilities. The more time a product is stored, the greater risk of spoilage or damage resulting in its sales difficulty or inventory shrinkage. Furthermore, overstocking is believed to lower shelf replenishment efficiency and may result in higher number of out-of-shelf situations. After promotions, reverse logistics play an important role in collecting exceeding stock for reestablish inventory level and avoid the described consequences.

Nevertheless, reverse logistics processes tend to be neglected by companies, which address their time and resources to the forward logistics in detriment of it. Further, reverse logistics complexity and costs are higher when comparing with traditional logistics, due to its high unpredictability. Therefore, it raises the need for reverse logistics systematization as well as for its processes' independence, including the allocation of specific resources and infrastructure.

Besides the increasing research on reverse logistics and lateral transshipments, to my best knowledge, none of them focus in the overstocking problematic. Instead, literature concerns about closed-loop supply chain optimization and shortages avoidance. Thence may be a gap in literature regarding overstocking consequences and solutions.

Accounting all the above mentioned, reverse logistics seem to have a growing importance in the retail business and its benefits may be an added value solution in inventory management. Given this retailers may significantly benefit from the systematization of reverse logistic's processes.

Reverse logistics added value does not restrict itself to grocery and consumer goods retailing industry, instead it is transversal to a wide range of industries and supply chains. Its importance is noticeable in other retailers, such as pharmaceutical, in which disposal legislation is tight and a closed-loop supply chain is an obligation. Further, the referred industry is characterized by the perishability of goods and may as well benefit from inventory balancing policies for shortages and spoilage avoidance. Also, reverse logistics may be applicable to emergency or added value situations as the blood supply chain in which its cost is for certain worth.

1.2 The Project

This thesis was builds on a consulting project for a Portuguese retail company. The project aims to evaluate the company's need for reverse logistics, develop a methodology to systematize the reverse logistics' processes and estimate the impact of the operation on the supply chain. The project is split into two streams. The first stream focus on the analytical decisions — what is the decision model for reverse logistic decisions and what is the expected benefict; the second stream is responsible for the operational decisions – how to turn processes more efficient and effective (Figure 1.1). Both streams work in a constant iterative process process giving feedback to each other to respect limits and constraints. The current work only concerns the analytical stream (stream 1).

The project raised from the company lack of knowledge about their reverse logistics' cost and dimension. Another concern to be addressed is the overstocking of the stores' backroom facilities which is believed to impel stock-outs even when there is stock-on-hand. Finally, the current reverse

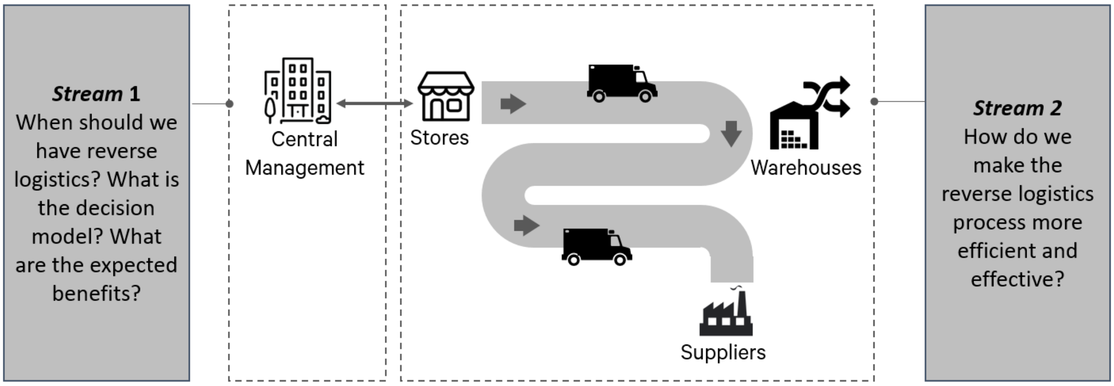

Figure 1.1: Project's objetives, divided into two streams

logistic processes are *ad-hoc* making it more expensive and causing entropy through the supply chain.

The project was developed in the scope of the Logistic Department and the key stakeholders are the food and non food departments since they are the responsible for mediating the requests for stocks removal from stores' managers. Hence they need visibility about their decision costs and impact in the whole company. Therefore, the team includes elements from distinct areas in order to estimate the overall costs and provide an holistic perspective addressing the entire company concerns.

The project is divided in three phases (Figure 1.2): diagnose, development of the new reverse logistic methodology and estimation of the impact of the operation (both economic and operational impact). The first step consists in the identification of the current processes, evaluation of stocks level, and recognition and estimation of the major involved costs. In stage two, a reverse logistic decision tree is proposed and two optimization models are developed to identify the best allocation for both misplaced and delisted stock. Finally, in the third phase the developed models run on the previously estimated costs and inventory data, and results total savings are inferred.

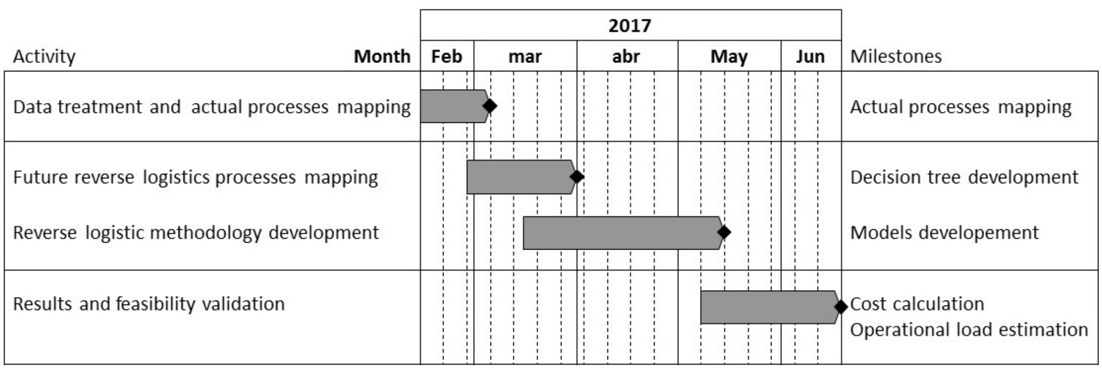

Figure 1.2: Project's timeline

1.3 Dissertation Structure

The dissertation is structured as follows. In Chapter 2 the reverse logistics problem in the context of the retailer case study is described. Chapter 3 provides a summary of several developed studies in the reverse logistics and lateral transshipments areas. Also stock-outs and backroom knowledge is summarized. Chapter 4 presents the proposed methodology for reverse logistics entailing two optimization models and their preponderant costs modeling. In Chapter 5 the model computational results are presented as well as their impact in the retailer case study. Chapter 6 intends to explore the possible application of the developed methodology to other industries, in particular bioengineering related ones. Finally, in Chapter 7 the main conclusions are drawn and future approaches and studies in the scope of reverse logistics are proposed.

Chapter 2

The Problem

The practice of both intense promotional activity and high service level leads to inventory accumulation in the lower echelon of the supply chain. Therefore, the reallocation of goods in the supply chain is inevitable to deal with the exceeding stock and to reestablish inventory level. The decision of how to deal or where to allocate the exceeding goods depends on several aspects. The product condition, appeal to consumers and cost of transportation and handling may be indicators of the profitability of its movement. Furthermore, the holistic view of the supply chain inventory level may also constraint its reallocation and commercial decisions such as store assortment may be respected. An integrated view entailing the stores overstocking problem, the transportation and operational costs and the destination constraints and costs are crucial in order to evaluate the movement viability. Furthermore, it is important to take the most advantage of economy of scales to mitigate reverse logistic costs.

This chapter describes the reverse logistics problem in the scope of the studied retailer.

2.1 Description

Causes for Reverse Logistic

Consumers' demand for variety and novelty implies presenting a wide range of products that follow the trends avoiding them to feel that their choices are confined. This represents a massive challenge for retailers. Following the newest trends entails product promotion, and acceptance and adhesion testing. Hence, the business is characterized for having several ins and outs. Furthermore, because there is no historic, new products accurate forecasting is practically impossible. Therefore, it is common to have discontinued products with huge exceeding stocks which are hardly sold.

Promotional activity attracts clients to the stores and promotes sales. During campaigns, the price decreasing and product highlighting boost sales. Products highlight normally includes increasing their presentation stock, contributing for its overstocking on stores. Moreover, the uniqueness of conditions make their forecast considerably more demanding. Consequently, massive overstock is common to avoid stock-outs during these events. Furthermore, there are different store clusters with different product assortments according to several conditions as their size or location. However, these assortments are many times enlarged during promotional events resulting in misplaced stock at the end of the campaign. Moreover, in the off-campaign period sales decrease resulting in much high stock coverage.

Costs and Benefits

Reverse Logistic is commonly seen as an obligation. However, the flow in the upstream direction of the supply chain may be a competitive advantage.

The studied retailer strongly believes that stock accumulation in the backroom lowers replenishment efficiency. Thus, it increases stock-outs even with stock on hand. Besides the evident lost sales, stock-outs can damage the retailer reputation and incur on long term costs.

The longer a product is stored, the higher is its spoilage risk and, consequently, the lower is its selling prospects. Perishable goods are yet more susceptible to time as there is the obligation to fulfill expiration dates. Further, the trend to products decrease their lifecycle and increasing frequency with which new ones appear make it increasingly demanding to sell over time. This is specially relevant in products that are subject to trends as toys and *fashion* products. Retailers commonly work around this by decreasing product prices incurring with an extra cost. Moreover, increasing possession time also increases holding costs.

Finally, reverse logistics are characterized by their high transportation and handling costs due to quantities uncertainty, lack of systematization and usually lower volumes that cannot take advantage of economies of scale.

Current Reverse Logistics Processes

The studied company practices some reverse logistic processes: lateral transshipments, return to supplier, return to stock and boomerang. Nevertheless, these processes lack standardization and maturation. Thus, they do not exploit economies of scale and are responsible for huge entropy in the supply chain, mainly in the warehouse.

Lateral transshipments are the Reverse Logistic processes through which a store sends goods to another one. This occurs directly from one store to another or with cross-docking in a warehouse. In the one hand, the direct lateral transshipments are more likely used when there is urgency in moving stocks as a response to stock-outs. As it has low lead time it can also be performed in perishable goods, though it is not common because theses products are frequently provisioned to stores. On the other hand, centralized transshipments have high lead time so they cannot be performed neither with perishable goods nor in urgent situations. They are mainly used when there is huge coverage unbalance between two stores. Seasonal goods or imported ones use this process due to their forward flow high lead time. Lateral transshipments processes are accorded between stores without an order from stock management thus it does not contemplate a holistic view and may not represent the greater good for the company.

Returns to suppliers are the preferred Reverse Logistic process. However, this can only be performed when previously negotiated with suppliers. Depending on their contract, suppliers may pick up the returned goods directly on stores or, more commonly, in the warehouse. The latter option has significantly more costs and implications for the retailer that must transport everything to the warehouse and keep it until the supplier picks it up. This is many times an issue due to contracts that do not stipulate collecting times which many times takes months. Furthermore, suppliers may want to check the returned stock which is a demanding process to the retailer in terms of staff and space allocation in the warehouse.

Boomerang is a very particular reverse logistic process that intends to relieve stores from the space occupied by seasonal products. Stores ship pallets to the warehouse where they are stocked during a year as an extention of their backroom space. During the whole time the pallet is never disaggregated. Typically, the pallets return to the store a year after so that the seasonal products are then sold.

Finally, returning the exceeding goods to the warehouse in order to integrate them into the direct logistic flow is also a possibility. However, this process has many constraints. Since goods are going to be stored in the warehouse, they must have a picking position which is a fixed storage place in the warehouse. There are two distinct flow types in the warehouse: picking by line - PBL, and picking by store - PBS. While PBS is the flow in which each SKU has a fixed picking position in the warehouse from where stock is collected when an order is placed, PBL entails zero stock in the warehouse. The latter is common with suppliers with high service level as goods are delivered just on time and in the right quantity. As a result, SKUs delisted from the retailer assortment as well as PBL products hardly have a picking position in the warehouse, restricting the return to stock possibility. Furthermore, the integration with the direct logistic flow determines that stock must be delivered in their original boxes in order to be equally treated. This requirement is very difficult for stores to accomplish. Most times stores cannot keep the cases or later find them to return goods because their wide variety of SKUs and lack of space in the backroom. Moreover, stores do not know in advance whether or not they will be able to return a certain product. Although stocks management is responsible for authorizing or not returns, the management is decentralized since stores don’t know in advance what to keep or not. Once again, the Reverse Logistic is decentralized do not having an integrated view.

2.2 The Proposed Approach

To deal with the above described problem a decision tree entailing two optimization models is proposed to support the holistic decision of what and when to do reverse logistics.

The first step consists in huge data request concerning stocks, sales, stock-outs and current reverse logistic processes. Thence, data processing avoids outliers and missing value in order to assure the solution correctness and coherence.

Secondly, the major costs concerning reverse logistics are identified and modeled as the difference to the *as-is* scenario — not moving the stock. Besides the straightforward costs involved in reverse logistic, there are concealed costs that must be considered when deciding whether or not to perform reverse logistic. All costs are calculated as function of an unit of each SKU for later application to the developed model.

Afterwards a decision tree to facilitate the decision making of which stock to maintain, replace in the supply chain or remove were developed. It comprises simple rules to deal with the problem and two optimization models to define the optimal place for both SKU's delisted from the whole company assortment and misplaced or unbalanced inventory. The models run on the previously estimated costs and collected stock data, and estimate the overall gain with the solution. The operational load is also a concern and is as well calculated. Further, a sensitivity analyses is performed to assess and ensure the proposed solution robustness.

Chapter 3

Literature Review

This chapter intends to provide the reader with the knowledge to completely understand the developed work. In section 3.1 the state of the art on reverse logistics is presented. Motivations, main processes, and problems are enumerated. Furthermore, research evolution on the presented problematics is described in this section. In section 3.2, lateral transshipment goals and major approaches are presented and discussed, and exemplifying studies exposed. Later, shortage causes and consequences are presented in section 3.3. Finally, in section 3.4 backroom facilities purpose and issues are stated.

3.1 Reverse Logistics

Throughout the 1980s, reverse logistics were exclusively defined as the flow of goods against its flow (Murphy, 1986). However, due to increasing environmental concerns, strict legislation, well informed consumers and decreasing products' life cycles, reverse logistics' scope is still evolving with the goal of saving both monetary and environmental resources by making after-market activities more efficient (Sangwan, 2017; Kumar, 2016).

Reverse logistics entails not only product reverse flow, but its containers as well. The former occurs due to customer returns or product re-manufacture or refurbishment. Regarding packaging, the reverse flow is mainly for reuse or proper disposal. Therefore, reverse logistics comprises the following activities: remanufacturing, refurbishing, recycling, landfill, repacking, returns processing and salvage. (Rogers and Tibben-Lembke, 2001).

In opposition to the forward flow, reverse logistics are rarely planned, but instead a reactive response to unpredictable consumers' actions. Still, the reverse flow has tendency to follow the forward one with a lower magnitude and delayed. Besides the uncertainty about quantity, there is also clueless about the returned goods quality, a determinant factor when evaluating whether something is worth transporting or not (Fleishmann et al., 1997) .

Tibben-Lembke and Rogers (2002) enumerates the major costs involved in Reverse Logistics and concludes that globally they are much higher than the ones from Forward Logistics. As a result of minor volumes and consequent increasing stops per truck, and the use of non-standardized pallets, transportation and handling costs are higher. Further, high lead times are also believed to increase obsolescence costs. Moreover, quality diagnosis as well as refurbishment/repacking are play an important part in Reverse Logistic costs. In opposition to the above mentioned, holding costs are usually lower due to decreased value of the returned product.

Thierry et al. (1995) addresses many solutions for product recovery management. Selling the products as new or returning to vendor are the preferred options due to higher value recovery, Next options comprise sell via outlet, repair, remanufacture or refurbish. Follows donation to charity and sale to broker. The last options are recycling or disposing in a landfill.

Furthermore, reverse logistics pays an important role across several industries such as consumer goods, automobile, computer hardware, retail, and pharmaceutical.

Quantitative optimization models on reverse logistics' scope are widely studied with focus on distribution planning, inventory control, and production planning with the reuse of parts and materials (Fleishmann et al., 1997).

Regarding distribution planning, there are several studies with the ultimate goal of defining the disassembly centers and processing centers' location and the flows between them that either maximize the profit or minimize the cost. In Spengler et al. (1997) a multi-stage and multi-product problem is solved with a mixed-integer programming model to maximize the total achievable marginal income. However, reverse logistics are characterized by dynamic lead-times and inventory positions, and high degree of uncertainty. In order to comprise the previously referred nonlinear relationships, Lieckens and Vandaele (2007) presents a mixed-integer nonlinear programming model to solve a single-product and single-level problem The proposed model prooved to return close to optimality solutions within acceptable time. Lee et al. (2009) suggest a multi-stage, multi-product reverse logistics network problem which consider the minimization of total shipping cost and fixed opening costs of the disassembly centers and the processing centers in reverse logistics. A priority-based genetic algorithm and a heuristic approach are proposed to solve the referred problem. Later, Roghanian and Pazhoheshfar (2014) also use a priority-based genetic algorithm to solve a resembling problem, but considering a stochastic environment. Nowadays research on the problem continues with focus on improving genetic algorithms to solve the described NP-hard problem (Alshamsi and Diabat, 1997). In opposition to the previously described literature, which approach consists on modeling the reverse flow separately, studies that integrate both forward and reverse logistics in the same network are also common. For example, Ramezani et al. (2013) analyse and solve a multi-objective multi-echelon multi-product stochastic problem. Concerning demand and reverse flow uncertainty, (Hatefi and Jolai, 2013) proposes a single-period single-product mixed-integer programming model based on a robust optimization approach. Nonlinear mixed-integer programming is also a possibility to tackle this kind of problems (Liu and Zhang, 2016).

Research on closed-loop inventory routing prooves that considering the reverse flow of goods and/or containers is crucial and may lead to significant savings in total costs (Soysal, 2016). Closed-loop supply chains are the ones that integrate both forward and reverse logistics in which the recovered products or parts are included in re-manufacturing or new product manufacturing. The referred systems differ from the traditional ones in key aspects. Component inventory may decrease or increase depending on stochastic customer demand and used products return. In order to avoid increasing raw materials safety-stock, there is the need for coordination between both recovery and demand. Thence, inventory control systems capable of integrating both flows are crucial to a correct inventory management. Furthermore, optimization models for solving variations of the described issues are extensively documented (Fleishmann et al., 1997). A deterministic inventory control system, where demand and return are known in advance, considering derived from the traditional EOQ equation, service-level constraints and multi-item inventories is presented by Mabini et al. (1992). Stochastic models comprising uncertainty both in demand and return are also widely researched. Inderfurth (1997) characterizes the optimal decision rules for a single product in a periodic review policy. Recently, a continuous model for the hybrid manufacturing/remanufacturing system of a single item entailing setup times and costs is developed by Polotski et al. (2015).

In a reverse logistics context, disassembly — separation of the valuable components of end-of-life products from the disposable ones — is crucial for later re-manufacturing or recycling. Firstly, a quality-based categorization as well as most profitable disassembly level may lead to significant cost savings (Aras et al., 2004). Furthermore, in order to take the most value from end-of-life products, it is worth considering the disassembly sequence . Lambert (2002) suggests the determination of a transition matrix followed by a linear programming model to tackle this problem. Moreover, coordination between production and demand for parts and consequent optimal disassembly quantity are crucial for re-manufacturing profitability (Kim et al., 2007). Kim et al. (2006) solve the described problem for a single-product with deterministic demand and no backlogging scenario with the relaxation of integer variables followed by their post processing. Hrouga et al. (2016) proposes to solve a disassembly lot sizing problem for a multi-product instance. Their model minimizes not only inventory holding costs, disassembly costs and setup fixed costs, but also lost sales costs. Their approach to the problem begins with an heuristic to handle strict constraints followed by a genetic algorithm. Recently, Sathish et al. (2017) proposes an ABC algorithm to maximize disassembly operation profit by minimizing both time and costs. The authors claim to have better performances than the existing algorithms.

3.2 Lateral Transshipments

Traditional inventory systems are divergent. Stock replenishment occurs from one or few locations from an upper echelon — warehouses — to multiple locations in a lower one — stores. In opposition, lateral transshipment refers to the stock redistribution between intra-echelon locations, flowing from locations with stock on hand to the ones that are in a stock out situation or expect significant losses due to high risk (Tagaras, 1999; Burton and Banerjee, 2005). Therefore, lateral transshipments are a viable tool to decrease inventory cost while increasing service level (Yan and Liu, 2017).

Nowadays, there is an extensive literature on inventory models including lateral transshipments in many different supply chains' conditions and complexity. Literature refers lateral transshipments for both reactive and preventive situations. On the one hand, reactive transshipments, also named emergency transshipments, are based on the hypothesis that shipments from the warehouse have higher lead times. Thence, stock is transported from locations with exceeding inventory to the ones where there is no stock on hand with the goal of decreasing shortages. On the other hand, the proactive approach entails the possibility of making periodic transshipments to balance inventory levels and consequently avoid future stock-outs and possibly attenuate holding costs and avoid shrinkage. Recently, there are also interest in systems capable on integrating both proactive and reactive transshipments. Research on the area also diverge regarding the decision making — centralized or decentralized, periodic or continuous reviews and order policy. Moreover, the unsatisfied demand may be taken into account as backorders, lost sales or both (Paterson et al., 2011). Nonetheless, to our best knowledge, all papers have the same goal — avoiding stock-outs.

Due to the extreme complexity, all studies tend to neglect different conditions to simplify the problem and achieve a solution. The number of echelons, items and locations considered, the incorporation of transshipments' lead-times, and having distinct or identical locations result in different complexity levels.

Regarding reactive transshipments, this approach was firstly addressed in 1960s when Krishnan and Rao (1965) included lateral transshipments between a retailer's stores as a possibility on a centralized periodic review model. Later, Tang and Yan (2010) studies a system with two echelons where the locations in the lower echelon have the possibility of exchange stock. The paper evaluates whether it is better to decide the order quantity based on individual inventory levels or as collective, concluding that the answer is highly dependent on the system properties and parameters. Huang and Sošić (2010) proposes a periodic review model for lateral transshipments between several locations with stochastic demand within one echelon. In opposition, to the centralized decision above mentioned, this model considers a decentralized decision making in which each retailer decides how much from its inventory and demand to share with the others. Axsäter (2003) presents a continuous inventory system for several warehouses in the same echelon where lateral transshipments are allowed but restricted according to a rule that takes into account the holistic view of the system. Later, a continuous review system with linkage constraints between locations is developed by Olsson (2010) assuming deterministic lead-times.

Proactive lateral transshipments are not so widely studied. A system with two independent locations that may preventively exchange inventory once during the replenishment lead-time to avoid shortages is examined in Li et al. (2013). Recently, Feng et al. (2017) addresses the preventive transshipment problem where decisions consist in determining the optimal time and quantity for the referred transshipments. The outcome evidences the goods' perishability and demand distribution effects on decisions. Lee et al. (2007) proposes a policy for lateral transshipment that combines both preventive and reactive transshipments achieving lower total costs due to more effective reaction to changes in demand, penalty cost and ordering cost. While the above mentioned model considers a periodic review, Seidscher and Minner (2013) presents a model for proactive lateral transshipments optimization and evaluates different reactive transshipment rules with inventory continuous review. Still, the analysis is limited to small dimension problems.

Problems considering proactive transshipments may include decisions about time and quantity. When applying this to multi location and multi period with stochastic demand, solving the problem to optimality may be demanding. A common approach to this kind of problems is using a Markov decision process followed by linear programming (Wong et al., 2005). However, the previous method cannot solve large-scale problems. Thence, several heuristics are proposed in the literature. For example, Banerjee et al. (2003) developed two proactive heuristic policies: an ad-hoc emergency transshipment policy based on availability and a systematic one based on inventory equalization. Feng et al. (2017) solves the previously presented problem with a sorting heuristics combined with a backward dynamic programming approach and an approximate dynamic programming.

Burton and Banerjee (2005) identifies transportation costs as the major ones when resorting to lateral transshipments. However, unless the referred costs are extremely high, the consequent decrease in shortages and enhance in service level, without the cost of higher safety stocks, proved to be better than than a no lateral transshipments policy for both proactive and reactive lateral transshipments. Furthermore, the referred benefits seem to accentuate in bigger and more complex supply chains. When comparing preventive with reactive transshipments, the later appears to result in higher service levels, but implies more transshipments. Yet, the best policy depends on each situation characteristics and objectives (Banerjee et al., 2003).

The lateral transshipment problem is underlying to many different industries such as retail, blood and spare parts (Cheong, 2013; Wang and Ma, 2015; Wong et al., 2005). Spare parts are usually slow-moving expensive items that require a quick answer. Therefore, reactive lateral transshipments are a feasible option. The same applies to the blood supply chain due to demand urgency and added value. In contrast, grocery and consumer goods retailing is usually characterized by wide range of products and low margins that do not worth the cost of emergency transshipments. Nonetheless, this industry may benefit from preventive transshipments.

3.3 Stock-outs

Out-of-shelf — situation in which a product miss from the shelf but belongs to the store's product assortment — is a current huge challenge in retail industry representing million of euros losses every year for average-size retailers (Papakiriakopoulos and Doukidis, 2011).

Corsten and Gruen (2003) divide causes for out of shelves problems into three main processes: ordering, replenishing and planning. They infer that in Europe the main source for stock-outs is shelf-replenishment, accounting to 48% of them. In these cases stock is somewhere in the store, usually in the backroom facilities, but not on shelf. The main reasons include badly dimensioned shelves, lack of visibility to stock on shelves and inefficient backroom procedures.

Costumers' reactions to stock-outs are widely studied (Corsten and Gruen, 2003; Campo et al., 2004). The main reactions described are substitution by another product, delay purchase, buy at another store and do not buy at all. From the point of view of the retailer, the ones that contribute to lost sales are the last two, that together comprise 36% of the cases in Europe. However, according to Gruen and Corsten (2010), stock-outs may not only lead to the lost sales costs, but also to both operational and strategic costs.

3.4 Backroom

Nowadays, retailing is characterized by its wide product assortment, making stores' limited shelf space extremely valuable. Therefore, each SKU has a limited shelf space allocated that, in major cases, is smaller than the necessary stock on store due to big storepacks and sales peak demand mainly in weekends or promotional activity periods. Hence, there is the need for a space to keep exceeding inventory — the backroom. However, backroom increases operational complexity and costs (Eroglu et al., 2013). DeHoratius and Raman (2008) found that backroom stock oblivion and misplacement not to be rare, increasing inventory record inaccuracies and lost sales.

Chapter 4

Methodology

As mentioned before, the objective of this project is to design a new decision process for reverse logistic decisions and to estimate its expected benefits. The ultimate goal is to have a more systematized, centralized and cost oriented decision process. This chapter presents the new proposed methodology. At the basis of the methodology there is a decision tree that identifies what is the best reverse logistics model to apply to each product. There are two major optimization models: the Stock Coverage Balancing Model (SCB model) and the End-Of-Life Stock Model (EOLS model). The remainder of this chapter is organized as follows. Section 4.1 presents how stock from stores is classified in order to identify what stock is the target of reverse logistics. Section 4.2 describes the proposed decision process. Section 4.3 focus on the reverse logistics' costs to later feed the optimization models. Sections 4.4 and 4.5 include both the description and the formulation of the SCB model and EOLS model, respectively.

4.1 Stock classification

The first step of the decision process is to identify what stock is the target of reverse logistics - what is the exceeding stock from stores and the stock from delisted products (out-of-assortment). Thence the need for stock classification into three categories: *Good*, *Optimizable* or *Non Salable* as illustrated in figure 4.1. This stock classification is done based on two stock coverage thresholds. The presented classification relies on several assumptions:

- *Good* stock includes the products' presentation stock in each store regardless of its coverage (presentation stock is the Stock quantity that fits in the shelf space allocated to each product);
- *Good* stock coverage threshold was estimated as the product family's average stock coverage;
- The *Good* stock coverage threshold of a product is zero for stores that do not have that product in the assortment;
- The stock exceeding 56 weeks coverage is classified as *Non Salable*. This stock is usually provisioned reflecting its reduced probability to be sold;

- Provisions correctly predicts stock likelihood to be sold in the future;
- *Non Salable* stock also includes stock above shelf-life date.

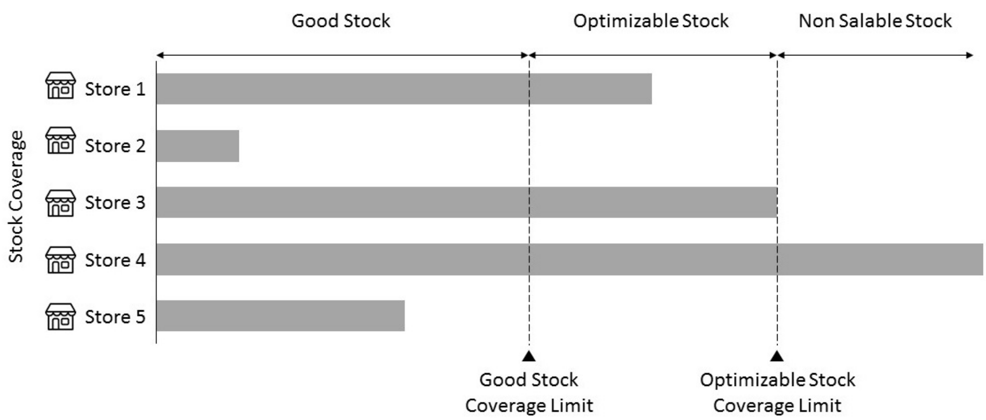

Figure 4.1: Stock classification scheme

The target of reverse logistics is the *Optimizable* and *Non salable* stock.

4.2 Reverse Logistics Decision Process

The proposed decision tree that identifies what is the best reverse logistics model to apply to each product is illustrated in 4.2. The preferred option is returning the stock to the supplier, thence every product with this possibility must follow this option without considering the other branches. The remaining stock of a product follows different paths depending if the product belongs to the assortment of at least one store or if it is delisted from all stores. Stock from products that belong to at least one assortment enters the Stock Coverage Balancing Model (SCB). This model moves the *Optimizable* and *Non Salable* stock to the warehouse or to the stores that contain less stock coverage. Nevertheless, this change is only made if it brings benefits. Delisted stock with sales potential enters the End-Of-Life Stock Model (EOLS). The EOLS model concentrates stock from end-of-life products in a fewer number of stores where they are most likely to be sold with salvage prices. Sale to collaborators at symbolic prices, donation or destruction are hypothesis that the commercial departments must consider to deal with stock without sales potential, both predetermined or decided by the EOLS.

Furthermore, note that the proposed approach on reverse logistics is restricted to Optimizable and Non salable stock. Also, due to reverse flow significantly high lead times this approach does not entail reactive reverse logistics to avoid shortages.

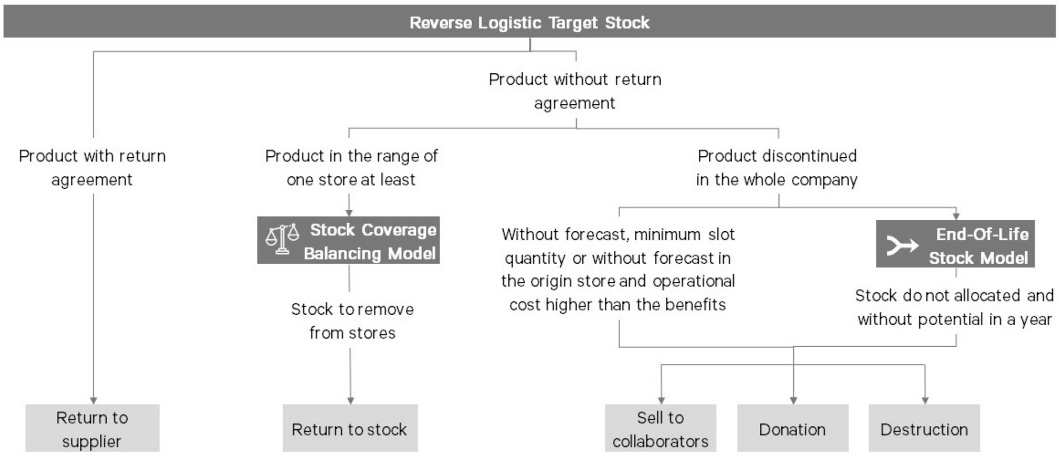

Figure 4.2: Decision tree

4.3 Reverse Logistic Costs

The Reverse Logistic costs are all estimated as the difference to the base line — maintaining stock where it is located. On the one hand, reverse flow increases transportation costs and operational costs both at the distribution centers and stores. On the other hand, stock balancing promotes the holding cost decrease, and increases the likelihood to attenuate stock-outs as well as spoilage costs.

The presented costs are calculated per unit of each SKU considering a year period. A worst case scenario approach is followed in order to avoid moving goods which do not worth the cost.

Transportation Cost

Goods are moved from on location to another inside boxes that are consolidated in pallets. The transportation fee is per transported pallet from one point to another regardless of the traveled distance. Thence, the transportation cost of a box is related to the volume it occupies in a pallet. The unit cost is attained by dividing the box transportation cost by the number of units contained in the SKU's storepack[1]. (see Equations 4.1 and 4.2).

In this study, all transportations will be considered centralized. Therefore, two travels must be taken into account: the first one from the origin store to the warehouse; and, when applicable, the second from the warehouse to the destination store. On the one hand, the former is an ordinary reverse logistic transportation in which pallets are more disorganized, thus its number of boxes per pallet is smaller, making it more expensive. On the other hand, the latter is similar to organized direct logistic pallets due to consolidation in the warehouse.

[1]Box in which SKU's are replenished in store, containing a fixed number of units

$$tCost_{S-W\,i} = \frac{transpCost}{Nb_R} \times \frac{1}{spk_i} \tag{4.1}$$

$$tCost_{W-S\,i} = \frac{transpCost}{Nb_F} \times \frac{1}{spk_i} \tag{4.2}$$

Operational Cost

There are operational costs both at stores and warehouses which are considered fixed per box or unit moved regardless of the SKU.

At stores, the devolution consists in the search for the product to return followed by pallets preparation.Thence, a unit cost is taken into account regardless of the SKU. Afterwards pallets are shipped to the warehouse, where, following a worst case scenario approach, significant operational effort is required to consolidate the received units and make boxes. This effort is considered as a fixed cost per unit received. When shipped to another store, the reception store must disaggregate the received pallets into the different boxes that it entails and store them. In this operation a fixed cost per box is also incurred. Similarly to what was previously done for transportation costs, a unit cost is achieved by the division by the number of units in each box (Equation 4.3).

$$stRecCost_i = \frac{stRecCost}{spk_i} \tag{4.3}$$

Holding Cost

The holding cost is expressed as a percentage of the average value of capital invested in the stock. Equation 4.4 assumes a yearly holding cost per unit of the SKU.

$$hCost_i = h \times c_i \tag{4.4}$$

Warehousing Cost

Assuming that all items that have returned to the warehouse already have a picking position, a warehousing cost per pallet is considered. Hence, the unitary warehousing cost is estimated as a function of each SKU volume (Equation 4.5).

$$whCost_i = \frac{whCost}{v_p} \times v_i \tag{4.5}$$

Backroom Space Cost

Stores' backroom space is fixed. Consequently, decreasing the occupied space does not decrease store's rent. Nevertheless, backroom overstocking is believed to increase stock-outs. Thence, a stock-outs reduction factor — stock-outs' percentage that is possible to decrease per percentage of liberated space — is used to consider the described cost.

Corsten and Gruen (2003) estimates that in 36% of the stock-outs customers buy from another store or do not buy at all. Thence, this is the cost of an out-of-shelf to the retailer. Therefore, the backroom space cost of an unit of each SKU in each store's backroom is the percentage of space it occupies in the store backroom multiplied by the stock-outs reduction factor times 36% of the store's margin.

$$brCost_{ij} = 0,36 \times k \times \frac{v_i}{V_j} \times M_j \tag{4.6}$$

Non Salable Stock Value

Non Salable units are hardly sold due to appeal loss, spoilage or damage. The cost of a *Non Salable* item is its cost plus 36% of its margin, which corresponds to the non recoverable by substitution by other product or later sales (Corsten and Gruen, 2003). However, if the SKU is still replenished, there are other units of the SKU in the store. Thus, the margin is only a cost if the SKU is no longer provided by the warehouse. If these units suffer price reduction it must be considered when estimating their sales benefits.

$$nsCost_i = (c_i + 0,36 \times m_i \times (1 - g_i)) \times (1 - d_i) \tag{4.7}$$

4.4 Stock Coverage Balancing Model

The Stock Coverage Balancing Model (SCM) concerns the cost minimization as a result of stock coverage equilibrium in the whole company's stores network (see figure 4.3). The model aims to recover *Non Salable* stock value caused by excessive stock coverages. The model's target stock is *Non Salable* stock and misplaced stock.

Figure 4.3: Balancing model scheme

Decision variables

$Sout_{ij}$	Number of *Optimizable* units of SKU i sent from store j to another store
W_{ij}	Number of units of SKU i moved from store j to the warehouse
Sin_{ij}	Number of units of SKU i received by store j

Auxiliary decision variables

X_{ij}	1 if store j sends SKU i; 0 if not
Y_{ij}	1 if store j receives SKU i; 0 if not
Sin_{Gij}	Number of *Good* stock units of SKU i received by store j
$Sout_{NSij}$	Number of *Non Salable* units of SKU i sent from store j to another store
W_{NSij}	Number of *Non Salable* units of SKU i sent from store j to the warehouse

Objective Function

The SCB goal is minimizing the previously referred costs by balancing stocks coverage in the company stores network. Both advantages and disadvantages of reverse logistic were expressed in cost variations to the current situation. Thence, the objective function maximizes the difference to the as-is scenario.

Non Salable units removed from one store are placed in another where they are expected to be sold. Therefore, these units' value is recovered.

$$\sum_{i}^{I}\sum_{j}^{J}\left(Sout_{NSij} \times nsCost_i\right) \tag{4.8}$$

Moreover, the *Optimizable* stock and the *Non Salable* stock are kept in the backroom. Consequently, when a store sends that stock to another store or warehouse, its backroom space cost decreases.

$$\sum_{i}^{I}\sum_{j}^{J}\Big((Sout_{NSij} + Sout_{Oij} + W_{ij}) \times brCost_{ij}\Big) \tag{4.9}$$

In the destination store, the units exceeding the presentation stock are stored in the backroom and the respective cost must be considered. However, in order to promote better stock balancing in the stores network, *Good Stock* backroom space cost is not accounted in the objective function. This promotes *Non Salable* stock distribution by all stores until the *Good* stock limit. Only the remaining is distributed by stores where it is placed as *Optimizable Stock*.

$$-\sum_{i}^{I}\sum_{j}^{J}\Big((Sin_{ij} - Sin_{Gij}) \times brCost_{ij})\Big) \tag{4.10}$$

Stock balanced between two stores has the reverse logistic transportation cost — from original store to the warehouse — followed by the direct logistic transportation cost — from the warehouse to the destination store. However, when goods are being replenished in stores, the lateral transshipments reduce their normal flow from the distribution center. Therefore, this stock forward logistic cost has been subtracted in order to consider the described effect.

$$-\sum_{i}^{I}\sum_{j}^{J}\Big(tCost_{S-W\,i} \times (Sin_{ij} + W_{ij}) + tCost_{W-S_i} \times Sin_{ij} \times g_i)\Big) \tag{4.11}$$

All returned units have a store devolution cost. Yet, only the ones received by another store, and, following the described reasoning, from SKU's that are not being replenished to the stores account to store reception operational costs (see equation 4.12).

$$-\sum_{i}^{I}\sum_{j}^{J}\Big(stDevCost_i \times (Sin_{ij} + W_{ij}) + stRecCost_i \times Sin_{ij} \times g_i\Big) \tag{4.12}$$

Further, all reverse logistic units pass through the warehouse where they are received and prepared, accounting to its operational cost.

$$-\sum_{i}^{I}\sum_{j}^{J}\Big(whOpCost_i \times (Sin_{ij} + W_{ij})\Big) \tag{4.13}$$

Finally, return to stock operations comprise the product warehousing cost. Hardly any stock without stock coverage greater than one year is sent to the warehouse. As so, it is considered that stock only starts leaving after an year.

$$-\sum_{i}^{I}\sum_{j}^{J}\Big(whCost_i \times W_{ij}\Big) \tag{4.14}$$

It is worth noting that due to its non-linearity, and reduced impact when compared to other costs, holding cost is not considered by the SCB model. Nonetheless, holding cost is later taken into account when estimating the solution benefits.

The SCB model objective function is stated on equation 4.15.

$$
\begin{aligned}
maximize \sum_{i}^{I}\sum_{j}^{J} \Big[& Sout_{NSij} \times nsCost_i \\
& + (Sout_{NSij} + Sout_{Oij} + W_{ij}) \times brCost_{ij} \\
& - (Sin_{ij} - Sin_{Gij}) \times brCost_{ij} \\
& - \big(tCost_{S-W\,i} \times (Sin_{ij} + W_{ij}) + tCost_{W-S\,i} \times Sin_{ij} \times g_i\big) \\
& - \big(stDevCost_i \times (Sin_{ij} + W_{ij}) + stRecCost_i \times Sin_{ij} \times g_i\big) \\
& - whOpCost_i \times (Sin_{ij} + W_{ij}) \\
& - whCost_i \times W_{ij} \Big]
\end{aligned}
\tag{4.15}
$$

Constraints

A store either sends stock of SKU i or receives it (Equation 4.16)

$$X_{ij} + Y_{ij} \leq 1 \qquad \forall i \in I, \forall j \in J \tag{4.16}$$

Stores cannot send their *Good* stock. Therefore, the number of units each store sends both to other stores and to the warehouse cannot exceed its *Non Salable* and *Optimizable* stocks (Equation 4.17). Further, it is only possible to send as many *Non Salable* (Equation 4.18) units from each SKU as it has.

$$Sout_{ij} + W_{ij} \leq stock_{NSij} + stock_{Oij} \qquad \forall i \in I, \forall j \in J \tag{4.17}$$

$$Sout_{NSij} + W_{NSij} \leq stock_{NSij} \qquad \forall i \in I, \forall j \in J \tag{4.18}$$

Each store can only receive stock from each SKU until reaching its *Optimizable* stock coverage limit (Equation 4.19).

$$stock_{ij} + Sin_{ij} \leq Smax_{ij} + M \times (1 - Y_{ij}) \qquad \forall i \in I, \forall j \in J \tag{4.19}$$

Moreover, stores can only receive stock from SKU's that are in their product assortment (Equation 4.20).

$$Y_{ij} \leq g_{ij} \qquad \forall i \in I, \forall j \in J \qquad (4.20)$$

The stock of each SKU that leaves one site must arrive another one (Equation 4.21).

$$\sum_{j}^{J}(Sin_{ij} - Sout_{ij} - W_{ij}) = 0 \qquad \forall i \in I \qquad (4.21)$$

In order to correctly estimate the costs, there is the need to distinguish received stock between *Good* and *Optimizable* Stock. Equations 4.22, 4.23 and 4.24 allow the definition of the necessary auxiliary decision variable.

If $Smax_{ij} \geq stock_{ij}$:

$$Sin_{Gij} \leq Smax_{ij} - stock_{ij} \qquad \forall i \in I, \forall j \in J \qquad (4.22)$$

$$Sin_{Gij} \leq Sin_{ij} \qquad \forall i \in I, \forall j \in J \qquad (4.23)$$

If $Smax_{ij} \leq stock_{ij}$:

$$Sin_{Gij} = 0 \qquad \forall i \in I, \forall j \in J \qquad (4.24)$$

The following equations define the binary auxiliary variables (Equation 4.25) regarding stock shipment (Equation 4.26) or reception (Equation 4.27).

$$X_{ij}, Y_{ij} \in \{0,1\} \qquad \forall i \in I, \forall j \in J \qquad (4.25)$$

$$Sout_{ij} + W_{ij} \leq X_{ij} \times M \qquad \forall i \in I, \forall j \in J \qquad (4.26)$$

$$Sin_{ij} \leq Y_{ij} \times M \qquad \forall i \in I, \forall j \in J \qquad (4.27)$$

Finally, all the remaining variables are integers and greater or equal to zero (Equation 4.28).

$$Sout_{ij}, W_{ij}, Sin_{ij}, Sin_{Gij}, Sout_{NSij}, W_{NSij} \geq 0 \text{ and integer} \qquad \forall i \in I, \forall j \in J \qquad (4.28)$$

4.5 End-Of-Life Stock Model

The End-Of-Life Stock Model (EOLS) (see Figure 4.4) targets de delisted SKU's. The model relies on the hypothesis that the concentration of exceeding units and their price reduction promote their sales if properly highlighted in stores. Thus, this model decreases these products spoilage by increasing their sales.

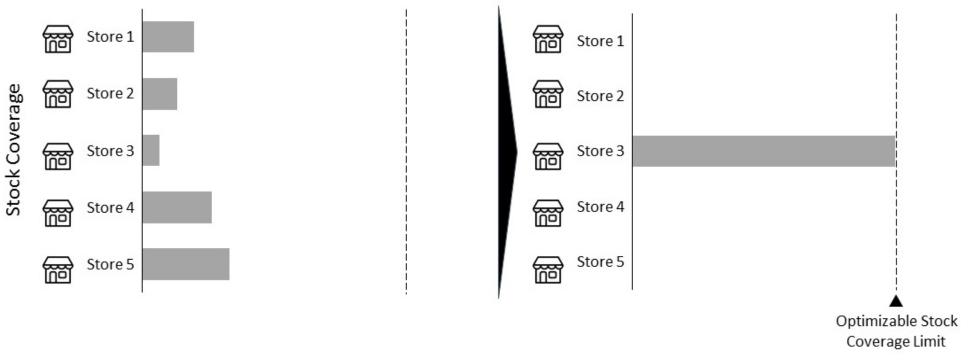

Figure 4.4: Outlet model scheme

Not to overestimate sales is a concern. Therefore, the sales forecast is estimated based on the decline phase of each SKU life cycle by considering the sales on the last four weeks previous to the SKU being delisted. Although products are discontinued, some of them still have sales. In order not to disregard the later, the maximum between the referred sales forecasts is used. Further, it is important to notice that different stores have different sales capacity. Thence, the sales forecast is estimated for each SKU in each store.

The EOLS assumes that delisted SKU's do not have shelf space allocated. The concept of outlet slot arises from the need to have these products visible to customers. The number of outlet slots limit the number of discontinued SKU's to sell in each store at each time. The number of slots is defined per store and product family due to substitution effect and shelf space constraints. Further, each slot allows the sale of an SKU per month. It assessment takes into account the store sales capacity — a store has as many outlet slots per product family as the number of SKU's of that family it sold during the sales period with representation on the SKU first quartile of sales. Although this approach does not directly estimates the outlet influence on assortment products, it takes that into account by using the sales period as metric.

Due to lack of similar actions, the discount applied to each SKU is estimated as an average of the applied on remnant sales data in the product family.Further, it is assumed that delisted SKU's are no longer replenished by the distribution center.

Decision variables

S_{ijt} Number of units of SKU i to sale on a store j at month t

Auxiliary decision variables

B_{ij}	Number of units of SKU i kept on the backroom of store j
E_{ijt}	Number of extra units of SKU i needed on store j at month t
n_{ij}	Number of units of SKU i moved from the backroom of store j to its shelves
Y_{ijt}	1 if the SKU i is allocated to a slot in the store j at month t; 0 if it is not
$Emax_{ij}$	Maximum number of extra units of SKU i needed on a store j at month t

Objective function

The End-Of-Life Stock Model objective is recuperate the most value of delisted SKU's in all stores, maximizing the difference between benefits — the recuperated *Non Salable* stock value, the liberated space in the backroom and holding cost decrease — and costs — operational and transportation costs.

The sale of an outlet SKU recuperates the sale of each sold SKU with discounting the applied price reduction (Equation 4.29).

$$\sum_{i}^{I}\sum_{j}^{J}\sum_{t}^{T}\left(S_{ijt} \times nsCost_i\right) \tag{4.29}$$

Delisted stock is hardly sold in one year. Hence, in this study it is considered that in the as-is scenario these stocks are not sold, having the entire year holding cost. The proposed model accelerates inventory sales, decreasing the holding cost. In a year period, the decrease in the holding cost is the holding cost after the sale. Thence it is considered half the holding cost of the month in which stock is allocated to that slot plus the holding cost of the following months (Equation 4.30).

$$\sum_{i}^{I}\sum_{j}^{J}\sum_{t}^{T}\left(S_{ijt} \times \frac{hCost_i}{12} \times \left(13-(t+1)+\frac{1}{2}\right)\right) \tag{4.30}$$

If no action is taken to deal with delisted stock, following the same reasoning as for the holding cost calculation, it is assumed that it stays in stores' backroom during the all year. The EOLS promotes stock shipment from one store's backroom to an outlet slot. It is impossible to accuratly calculate the backroom space cost through the year without the time discretization of each SKU inventory that stays in each store backroom. However, this was not considered in order to facilitate the model calculation. Therefore, it is assumed that backroom space is equally released through the year (Equation 4.31).

$$\frac{1}{2}\sum_{i}^{I}\sum_{j}^{J}\left((stock_{ij}-B_{ij}) \times brSpaceCost_{ij} - \sum_{t}^{T} S_{ijt} \times \ brSpaceCost_{ij}\right) \tag{4.31}$$

All units moved from one store to another, increase transportation (Equation 4.32) and operational costs both in stores (Equation 4.33) and warehouse (Equation 4.34). Firstly, the origin store prepares the pallet, followed by its transportation to warehouse. There, the pallets must be received and than prepared to be sent to the destination store, where there is also a reception cost.

$$-\sum_{i}^{I}\sum_{j}^{J}\left(\left(\sum_{t}^{T}S_{ijt}+E_{maxij}-n_{ij}\right)\times\left(tCost_{S-W\,i}+tCost_{W-S\,i}\right)\right) \tag{4.32}$$

$$-\sum_{i}^{I}\sum_{j}^{J}\left(\left(\sum_{t}^{T}S_{ijt}+E_{maxij}-n_{ij}\right)\times\left(stDevCost+stRecCost_{i}\right)\right) \tag{4.33}$$

$$-\sum_{i}^{I}\sum_{j}^{J}\left(\sum_{t}^{T}S_{ijt}+E_{maxij}-n_{ij}\right)\times whOpCost \tag{4.34}$$

The resultant objective function is given by Equation 4.35.

$$\begin{aligned} maximize\sum_{i}^{I}\sum_{j}^{J}\Bigg[& \sum_{t}^{T}S_{ijt}\times nsCost_{i} \\ & +\sum_{t}^{T}\left(S_{ijt}\times\left(13-(t+1)+\frac{1}{2}\right)\right)\times\frac{hCost_{i}}{12} \\ & +\left(stock_{ij}-B_{ij}-\frac{S_{ij}}{2}\right)\times brSpaceCost_{ij} \\ & -\left(\sum_{t}^{T}S_{ijt}+E_{maxij}-n_{ij}\right)\times\left(tCost_{S-W\,i}+tCost_{W-S\,i}\right) \\ & -\left(\sum_{t}^{T}S_{ijt}+E_{maxij}-n_{ij}\right)\times\left(stDevCost+stRecCost_{i}\right) \\ & -\left(\sum_{t}^{T}S_{ijt}+E_{maxij}-n_{ij}\right)\times whOpCost\Bigg] \end{aligned} \tag{4.35}$$

Constraints

The total stock of each SKU is exposed in one of the stores or is not moved at all (Equation 4.36).

$$\sum_{j}^{J}\left(\sum_{t}^{T}S_{ijt}+E_{maxij}+B_{ij}-stock_{ij}\right)=0 \qquad \forall i\in I \tag{4.36}$$

The number of units of each SKU that is moved from the backroom to the shelf of the same store is the minimum between its stock and the number of units to expose in that store. (Equations 4.37 and 4.38).

$$n_{ij} + B_{ij} \leq stock_{ij} \qquad \forall i \in I, \forall j \in J \tag{4.37}$$

$$n_{ij} \leq \sum_{t}^{T} S_{ijt} + E_{maxij} \qquad \forall i \in I, \forall j \in J \tag{4.38}$$

The number of slots available in each store for each product family must be respected. Thus, the number of SKU's of each product family exposed in a store each month cannot surpass the assigned slots (Equation 4.39).

$$\sum_{i}^{I} Y_{ijt} \times pf_{ik} \leq Cap_{jk} \qquad \forall j \in J, \forall k \in K, \forall t \in T \tag{4.39}$$

The maximum stock sold of each SKU in each store each month is the number of units that correspond to a month stock coverage according to its sales forecast (Equation 4.40).

$$S_{ijt} \leq Smax_{ij} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.40}$$

The proposed model basis is stock concentration and good presentation shelves to incite delisted products sales. Therefore, it is mandatory to assure a minimum presentation stock quantity when exposing the products even though it is not predicted to sell all of it. (Equation 4.41).

$$S_{ijt} + E_{ijt} \geq Smin_{ij} \times Y_{ijt} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.41}$$

This extra stock is exclusively sent to fill each SKU shelf in each store where it is exposed. Thus it is not predicted to be sold, meaning it only needs to be sent once to each store. The amount of each SKU to send to each store corresponds to the bigger gap between the salable stock and the minimum stock to fill the shelf (Equation 4.42).

$$E_{maxij} \geq E_{ijt} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.42}$$

Furthermore, there is the need to define the auxiliary binary variable Y_{ijt} that returns the value 1 if SKU i is exposed on the store j at month t (Equations 4.43, 4.44 and 4.45).

$$Y_{ijt} \in \{0,1\} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.43}$$

$$Y_{ijt} \leq (S_{ijt} + E_{ijt}) \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.44}$$

$$Y_{ijt} \times \sum_{j}^{J} stock_{ij} \geq (S_{ijt} + E_{ijt}) \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.45}$$

Finally, all quantities must be integers greater or equal to zero (Equation 4.46).

$$S_{ijt}, B_{ij}, E_{ijt}, n_{ij}, E_{max\,ij} \geq 0 \text{ and integer} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{4.46}$$

Chapter 5

The Retailer Case Study Results

The present chapter addresses the results of the developed models in the context of the Retailer Company. For both EOLS and SCB models, the outcomes are presented and discussed in sections 5.3 and 5.2 respectively. In the referred sections, firstly the computational results are presented. The results were attained by the implementation of both models in the IBM ILOG CPLEX Optimization Studio 12.6.2. The computer used to solve them has Windows Server 2016, 64 bits, 58.0 gigabyte of RAM memory and a processor Intel(R) Xeon(R) CPUE5-2640 v3 @ 2.60GHz. Afterwards the costs and benefits as well as the operational KPI's of reverse logistics are evaluated. Further, sensitive analysis to most controversial costs are presented in the context of each model.

5.1 Reverse Logistic Diagnose Results

The evaluation of the retailer company's stocks resulted in its classification as described in Figure 5.1, proving its need for action in more than half of the inventory. It is noticeable that the NFD has bigger problems than the FD. Furthermore, it is worth noticing that there is not delisted or misplace *Optimizable* stock in the NFD. This situation results from presentation stocks higher than the*Good* stock coverage threshold, classifying it as *Good* stock. This occurs in the NFD as it is consisted mainly of slow movers.

The distribution of the reverse logistics' target stock by the decision tree branches (see Figure 4.2) results in the following. As expected, the majority of the company's stock, 79,4 %, is in at least one store assortment, making it a SCB target. The remaining 20,6 % corresponds to SKUs delisted from all store assortments. However, only part, 92,8 %, of it is eligible for the EOLS. The remaining falls into one of the following requirements:

- It has no sales forecast in none of the stores (7,1%);
- It does not have the minimum stock to fill an outlet slot (0,1%).

The return to supplier branch was neglected due to lack of data.

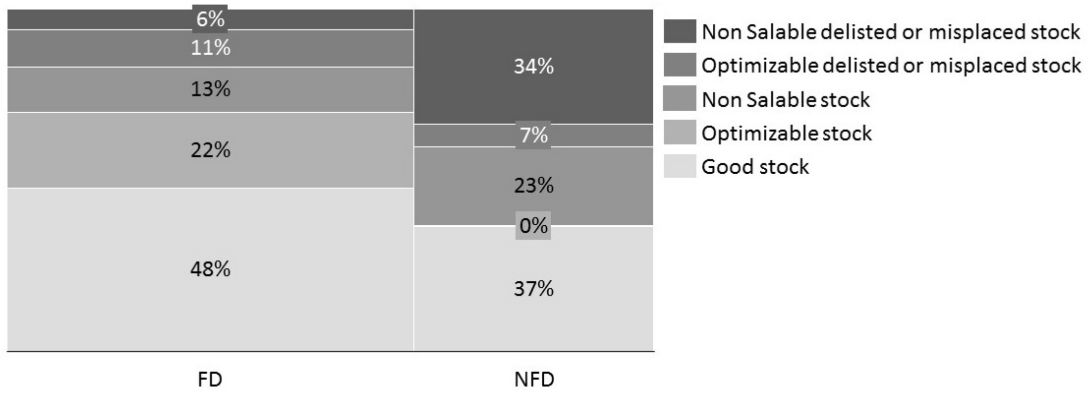

Figure 5.1: Retailer's FD and NFD inventory classification distribution as percentage of value

5.2 Stock Coverage Balancing Model Results

Computational Results

Preliminary tests evidenced the difficulty to run the model for a real instance within acceptable time due to its huge size and consequent number of variables. Therefore, integer variables, with exception for the binary variables, were relaxed in order to achieve a solution in viable time.

The instances correspond to real data from the retailer divided by family product. A total of ten instances, which characteristics are summarized on Table 5.1, were solved to optimality within minutes proving the model's usability in a real context.

Table 5.1: SCB instances size

Instance	A	B	C	D	E	V	W	X	Y	Z
#SKUs	3057	2166	2342	4177	1367	1074	4826	2143	1806	2044
#Stores	233	233	233	234	233	232	233	224	233	233

Retailer Case Study Results

The SCB promotes the spread of the *Non Salable* units into other stores that are below the 56 weeks coverage, increasing the destination stores' *Good* and *Optimizable* inventory (Figure 5.2). Thence, the SCB's solution is able to recover 70% FD and 65% NFD's *Non Salable* stock by increasing the *Good* in 1% and 6%, and the *Optimizable* in 15% and 48% in the referred departments respectively. The model prioritizes the shipment of stock to stores where it is classified as *Good* and only when this rubric is at its limit, it distributes the remaining inventory to stores in which it is *Optimizable*. The reported results evidences that the company has not only unbalanced inventories but also huge amounts of exceeding stock. Furthermore, part of the *Non Salable* cannot be allocated to a store where it is not classified as so.

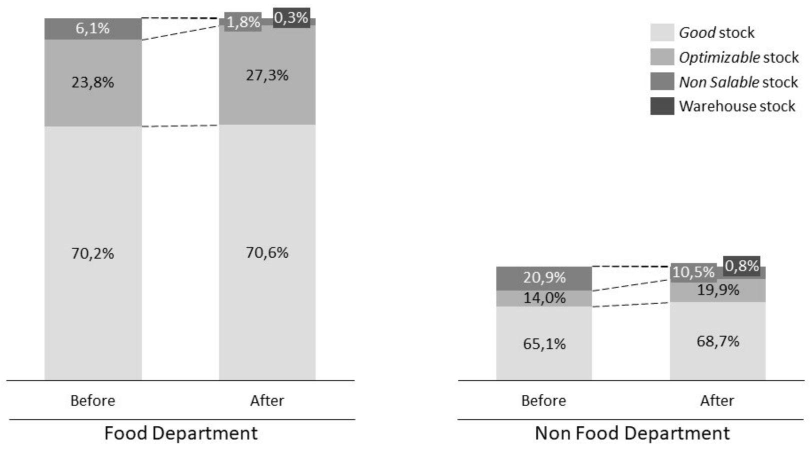

Figure 5.2: Stock classification before and after SCB

The SCB application to the retailer's case study and consequent stock reallocation results in savings of the magnitude of 0,5% and 1,4% of the respective department sales (FD and NFD, respectively). Althouth the relative value is smaller for the FD, its absolute benefit is 36% higher due to a much higher share on the company's turnover.

The different costs' contribution to the final solution is demonstrated on Figure 5.3. The total benefit relies mainly on recuperated *Non Salable* stock value benefit followed by the holding cost decrease.

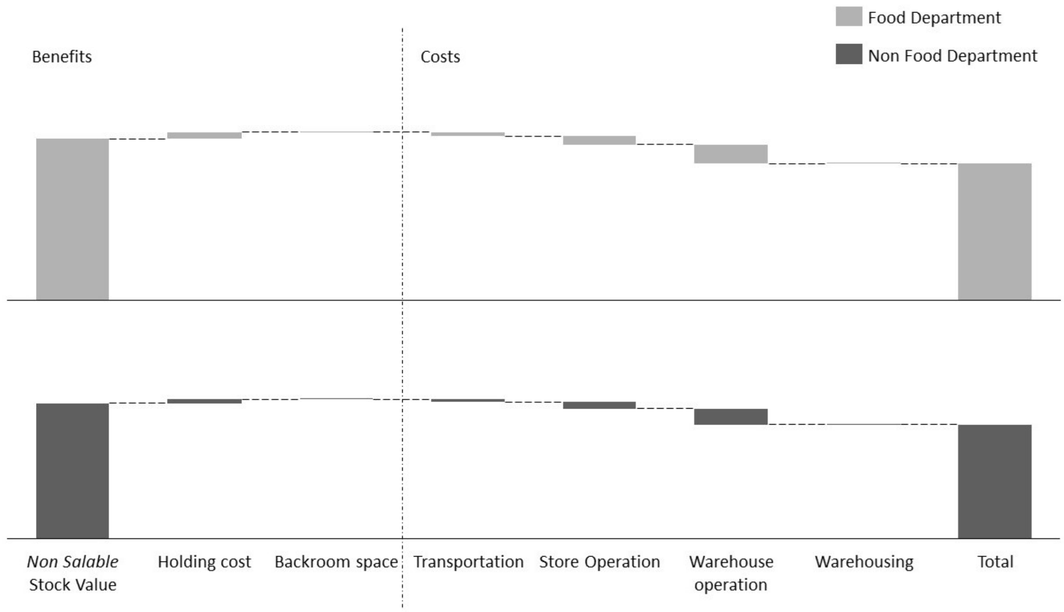

Figure 5.3: Costs and benefits from SCB for both FD and NFD

As previously described, *Non Salable* stock value recuperation is based on the assumption that the stock above 56 weeks coverage is non salable. A sensitivity analysis to *Non Salable* stock value recuperation was made in order to test the solution robustness regarding this assumption. Only a decrease of 42 % on the FD and 57% on the NFD make the achieved solution unprofitable. Figure 5.4 evidences the described. Still, further analysis on the referred assumption is a point to address in the future.

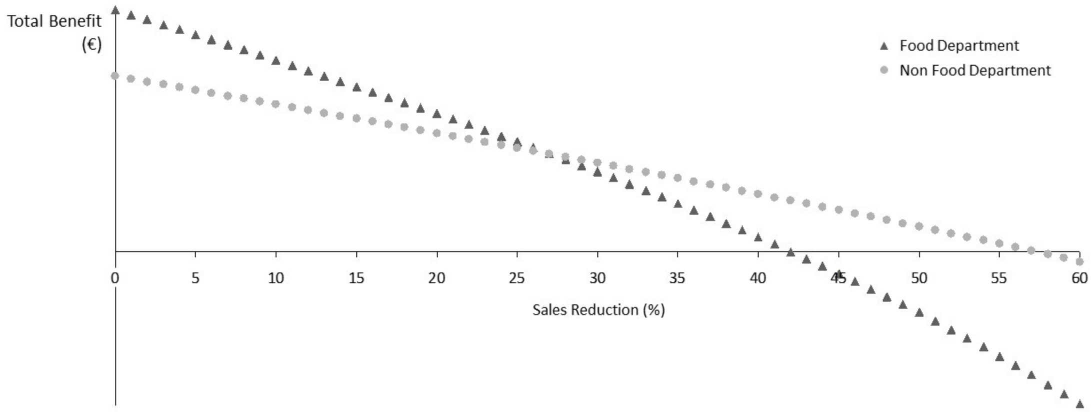

Figure 5.4: Sensitivity analysis to *Non Salable* stock value

The above mentioned results entail the transport of 3,9% and 10,7% of the FD and NFD stocks, respectively. The majority of this stock is shipped to other stores and part is stored at the warehouse (Figure 5.5). However it is hardly possible to move the necessary stock quantities at once, hence it is proposed to operationalize the SCB through the year. On the one hand, there is the hypothesis to operate the model after specific triggers that overstock stores such as huge promotions or festive events. On the other hand, SCB may be applied with a defined periodicity.

Furthermore, it is demanding to explain to the lower echelons that the holistic approach is better for them even though they receive huge inventory coverages. A possible solution to minimize their reluctance may be reducing the inventory they receive by setting a lower than 56 weeks coverage limit on reception stores.

A simulation may be done to evaluate both periodicity and coverage limit in the reception store. A trade-off between the model nervousness — percentage of units it moves in two directions — and the capacity to dilute the *Non Salable* units is essential. While the nervousness is expected to increase with frequency and increasing reception limit, the dilution capacity may increase with the referred limit. Yet, negotiation with all stakeholders cannot be neglected when weighting the several possibilities.

5.3 End-Of-Life Stock Model Results

Computational Results

The number of variables and constraints present in a real case instance made it infeasible to run the EOLS without relaxing the integer variables. Ten real scenario instances, one for each

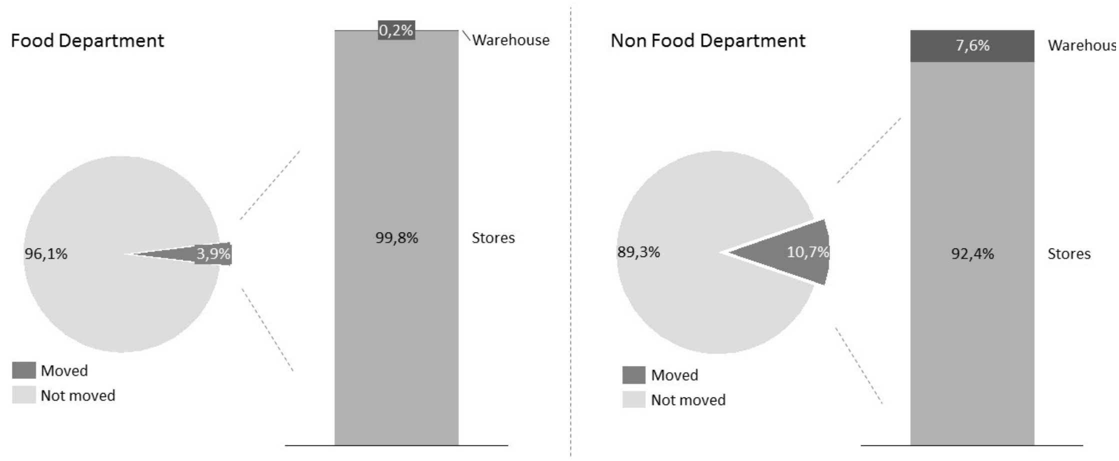

Figure 5.5: Stock shipment data for both FD and NFD

product family, were run. Their size is summarized in Table 5.2. Due to the problems' size and complexity, they were solved until 2% gap, resulting in solving times varying from 2 to 8 hours.

Table 5.2: EOLS instances size

Instance	A	B	C	D	E	V	W	X	Y	Z
#SKUs	8623	1704	1782	4374	1136	2896	4847	1648	2178	1370
#Stores	242	242	242	242	242	235	242	203	239	242
#Months	12	12	12	12	12	12	12	12	12	12

Retailer Case Study Results

A one year of EOLS results were simulated by running the model with one year stocks data. The model solution represents the results of implementing it for the first time. After years of stock accumulation, it is important to distinguish the first massive reverse logistics event from its possible continuous implementation.

The optimal allocation of stock value to slots per month is summarized in figure 5.6. In the first months the allocated stock benefit is significantly higher, but it tends to decrease over time. This is a consequence of years of inventory accumulation and more stock with high unitary value to sale. Although there is stock delisting during the year, the probability Of generating high value stock is not that high. Thence, monthly stock benefit tends to stabilize. In the FD, the tenth month inflection proves that the process is already stabilized by that time. In opposition, one year after no inflection point is visualized for the NFD's benefits thence further analysis is necessary to infer this value.

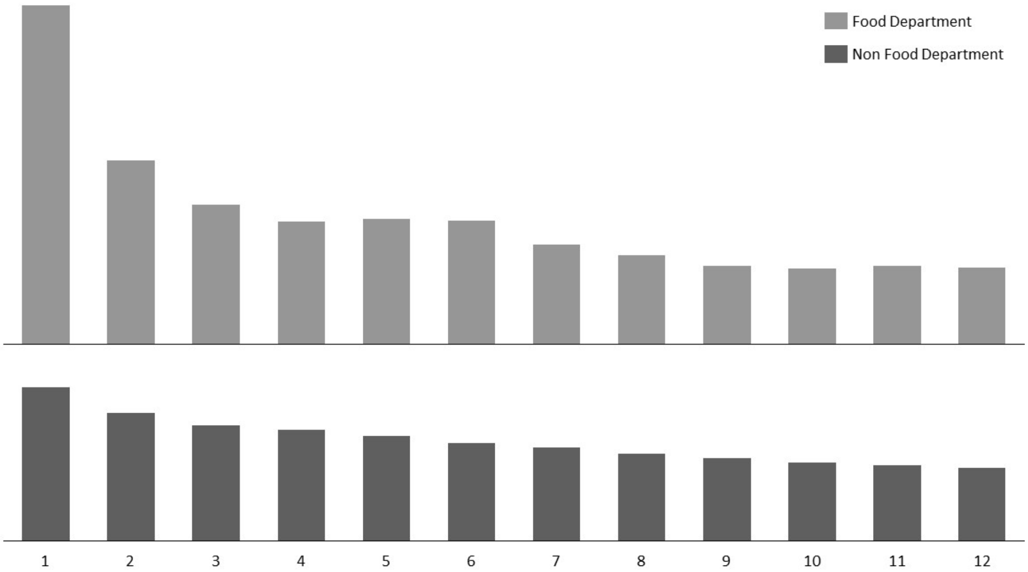

Figure 5.6: Stock value allocation through the simulated year in the FD and the NFD

In the FD, the comparison of the value of monthly average of the inventory delisted along the simulation year with the steady-state benefit shows them to be close to each other. However, the same does not apply to the NFD in which delisted stock along the year is still above the model results evidencing it is not stabilized yet.

The EOLS allocates 45 % of FD stock and 47 % of NFD inventory value to an outlet slot. However, these percentages increase to 47 % and 52 % when expressed in stock value, proving the model ability to choose between value over quantity. The higher increase in the NFD evidences its higher stock value per unit.

The slots have an occupation rate of 99% for the FD and 96 % for the NFD. Analysis of slots occupancy rate per month revealed these values are constant in the considered period. The small difference to completely full slots may be explained by the impossibility of allocating the remaining SKU's due to no sales forecasting in the free slots. Therefore, the number of slots seems to be the major limitation to the model, even when analyzing a steady-state situation in the FD.

All costs presented in Chapter 4 are calculated as the difference to the as-is situation. Figure 5.7 summarizes an year period outcome disaggregated by cost source. The first year results in a benefit of 0,4% and 1,2% of the department's sales, respectively on the FD and NFD.

As a result of the sales increment, *Non Salable* stock value, holding and backroom space costs are the ones that decrease when compared with the as-is situation. While the backroom space cost does not preponderantly weights in the final solution, the former two are the main drivers. Yet,

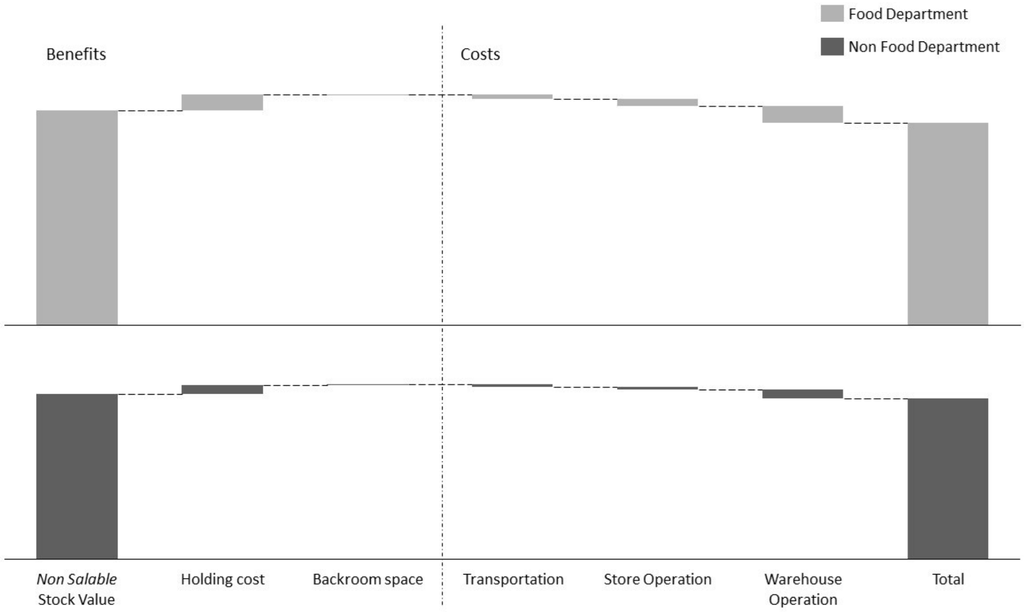

Figure 5.7: Costs difference to the *as-is* scenario distributed by cost source in the FD and NFD

the benefit from recuperated *Non Salable* stock value is by far the most relevant for both FD and NFD.

Regarding the costs, besides their overestimation following the previously described worst case scenario approach, they do not seem to restrict the solution outcome. The warehouse operation cost was estimated as a recentralization operation — a process in which products are collect from stores by unit and then consolidated in the warehouse — assuring a worst-case scenario analysis. In opposition to FD's products, the ones from NFD are mainly slow movers. In these products only a storepack is shipped for each store, increasing the probability for non complete original cases in the moment of delisting. Consequently, a recentralization is more likely to occur in the NFD meaning the FD warehouse operation costs overestimation is considerably higher.

Nevertheless, no operational restrictions were taken into account. As a result, the number of units moved may incur in neglected setup cost of a new warehouse or cross-docking facility, or restrict the proposed solution implementation. An analysis of the number of moved units is presented in Figure 5.8. The results support that the EOLS's cost structure takes advantage of the possibility of sale in the origin store. In the FD, every month more than 50 % of the allocated stock quantity is already in the correct store. In the NFD this value is greater than 20 % during the analyzed period. Although the relative number of units to transport in the later is higher, the absolute value is much smaller thus it is not an issue.

There is no historical data in the company of an event or process like the presented one, thus it is extremely demanding to predict the proposed model sales in which both these costs are based on. Therefore, a sensitive analysis was conducted to infer the level of importance it may have. The results are expressed in figure 5.9. Its outcome shows that the Outlet Stock Model optimization solution is worth implementing until a 42 % and 93 % decrease in sales value for the FD and NFD,

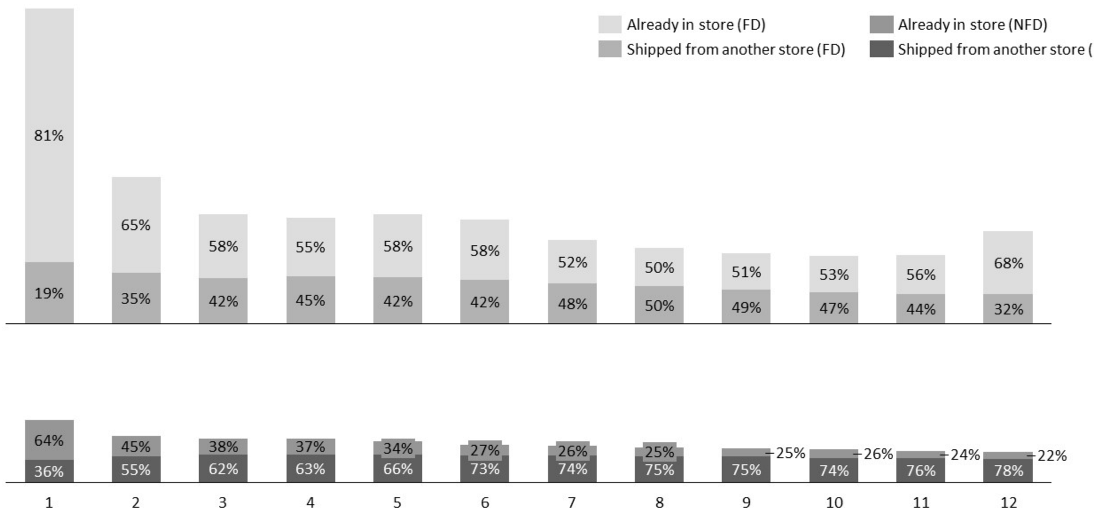

Figure 5.8: Stock quantity shipped from a store to another and stock already in store

respectively. Due to lower difference between gains and costs, a bad forecast is a considerable issue in the FD.

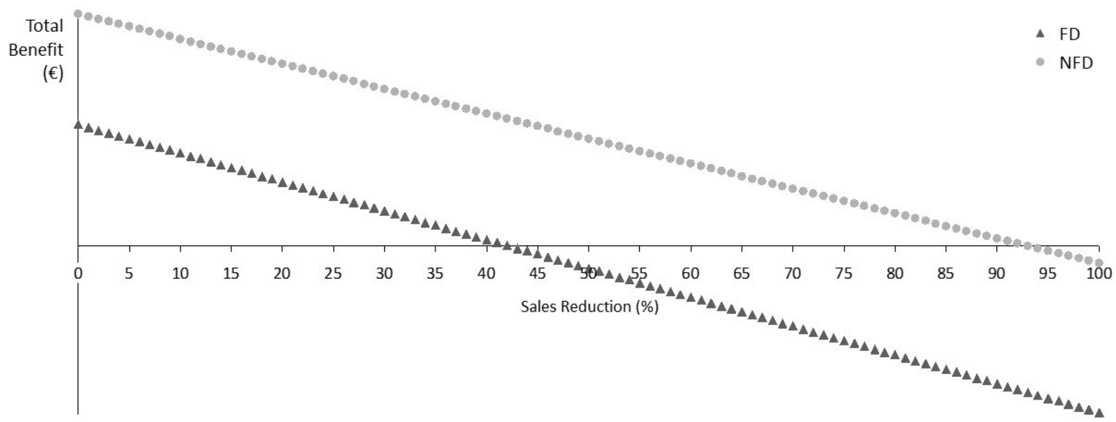

Figure 5.9: Sales reduction sensitive analysis for both FD and NFD

The number of delisted SKU's that are kept in the stores reduced on average 21 % in the FD and 25 % in the NFD (Figure 5.10). Although it does not have a direct cost, the delisted products complexity may complicate their management.

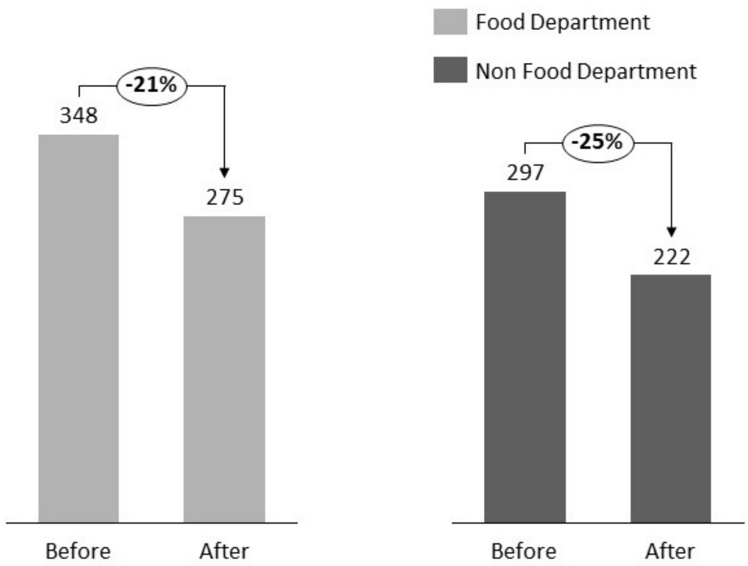

Figure 5.10: Thousand of SKU-Store pairs before and after EOLS

Chapter 6

The Developed Work Broadness

This chapter aims to demonstrate the broadness of the developed work, which transcends the case study. Therefore, the developed methodology applicability to other industries and problems is here explored with focus on the pharmaceutical industry as an illustrative case.

6.1 The Pharmaceutical Industry

Pharmaceutical industry logistics are crucial to provide patients with their medicines. Its supply chain typically consist of laboratories (manufacturers), distributors and pharmacies (selling points). Medicines typically flow from several laboratories to a distributor that replenish several drugstores. However, the legislation predicts the correct removal from the market and proper disposal of spoiled or dubious medicines. In this cases, the distributor is usually responsible for collecting them and return to the respective manufacturer.

The pharmaceutical industry suffered significant changes in the past years. Nowadays, the business is extremely competitive and regulated. In Portugal, the margins are defined by the regulatory body — Infarmed.

Efficient inventory management is uppermost in this industry. First, medicines are perishable goods. Second, Infarmed imposes several rules about stock availability and lead times. Furthermore, from the distributors' point of view, service level is crucial due to lack of differentiation and no supplier changing costs. Service level is also important from drugstores' perspective because shortages are most of the times lost sales. Therefore, reverse logistics, lateral transshipments included, may sporadically correct forward logistics inefficiencies adding value to the business.

In the one hand, in a shortage situation, emergency lateral transshipments may be used. Because pharmacies are usually replenished several times a day, its applicability focus on the distribution echelon. Its advantages are the compliance with Infarmed rules, and service level increase.

On the other hand, due to medicines perishability, the developed SCB may be adapted and used in a distributor's warehouses or within associations of pharmacies to avoid overstocking and consequent spoilage. As a result shrinkage costs are expected to attenuate as well as holding costs. Moreover, in the era of social responsibility, it is worth referring the environmental impact decrease due to both less waste generated and less resources consumed.

6.2 The Blood Supply Chain

The blood supply chain is a niche industry. Because it cannot be artificially manufactured and depends on human donors, blood is a limited and precious resource. Furthermore, blood high perishability makes it even more valuable.

Governments strictly regulate the blood supply chain in order to ensure safety and avoid its commercialization. This regulation entail handling, storage and transportation of blood among others.

Hospitals continuously deal with the trade-off between shortages and spoilage. However, the cost of both shortages and spoilage to hospitals is not straightforward monetary cost. First, hospitals do not lost sales, instead they deal with people's lives which cannot be quantified. Second, since blood is not commerced, only donated, a spoilage do not represent a financial loss neither. Nonetheless, both described situations may result in not quantified costs for the organization, as regulatory issues and bad reputation.

Kendall and Lee (1980) and Stanger et al. (2013) study how the presented supply chain can benefit from lateral transshipments. The developed SCB may be adapted to the non monetary characteristics of the blood supply chain and applied to it with the ultimate goal of decreasing shortages and assuring the service level. In such configuration, smaller hospitals could keep rarely required blood groups and transship them to bigger hospitals when there is spoilage risk.

However, the blood supply chain is usually scope of public management hence the need of cut costs. The lateral transshipments underlying higher transportation costs must be focus of study. Also, a network as the one described increases complexity leading to the need of better management, which many times can be demanding to a public organization.

Moreover, the strict regulation on blood predicts its proper disposal as part of a closed-loop supply chain.

Finally, the adaptation of the developed work to such disruptive environment proves the presented methodology wide application.

Chapter 7

Conclusions and Future Work

This dissertation focused the reverse logistics on a Portuguese retailer company. The ultimate goal was to decrease costs accruing from the over stocking condition. The reverse logistics options were organized in a decision tree entailing two MIP models. In the one hand, the EOLS supports the decision about delisted stocks. In the other hand, the SCB tackles misplaced or unbalanced inventories. Furthermore, reverse flow costs and benefits were identified and modeled to feed the developed models. Finally, the models solved the retailer case study achieving benefits of 1,2% of the departments' sales.

The project led to the conclusion that a retailer company may benefit from a centralized inventory management system entailing the reverse flow of goods. However, reverse logistic benefits are not straightforward. Thence the need for carefully address and negotiate them with the several interested parties.

The attained theoretical results must be confirmed. First, the *Non Salable* inventory assumption and the provision accuracy assumption must be validated. Next, the operational load feasibility must be evaluated. Finally, regarding EOLS, there is the need for testing the theory that delisted stock concentration boost its sales. Thence, a pilot scale testing of both models is already on the agenda.

Further analysis must be done to infer the annual return of making reverse logistics. The simulation of the SCB already suggests the best periodicity and maximum level of stock in the destination store. Regarding the EOLS, in the first year benefits will be greater due to years of stock accumulation. Furthermore, frequent application of the SCB may decrease the EOLS target stock.

Moreover, the company lacks knowledge on the consequence of the overstocking of its backroom. Therefore, a study could be carried out to assess this and in the future be able to make decisions based on it or about it.

The review of contracts respecting return to supplier conditions stays as a suggestion. The company may benefit from correct negotiation of return lead times, by lowering their warehousing and consequent costs.

Both models proved to return robust solutions and to be applicable to a real scenario. While the SCB reach optimality relatively quickly in a real case study, the EOLS may not achieve the optimal solution within acceptable time. Yet, the solutions achieved by the latter are only 2% from the upper bound.

Nonetheless, the commercial role cannot be substituted due to the need for a commercial validation of all outcomes. This arises because the presented methodology and models do not reflect commercial decisions, instead they make a trade-off of costs and benefits to support the decision and provide visibility. Yet, some commercial constraints can be added to the methodology.

Furthermore, the presented methodology is easily extended to other industries as the case of the pharmaceutical industry.

Finally, regarding literature, it focus only on inventory management to avoid overstocking condition. Although inventory management policies are crucial, stochastic environment make it impossible to achieve an idyllic no shortages and no overstocking situation. Furthermore, the retailer promotional activity increases the gap to the described situation. Thence, the lack of literature on overstocking solutions may be addressed.

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