A Decision Support System for the Optimal Definition of Ship Packs: a Case Study in a Retailer Company

Paulo André Vilela Gonçalves Pereira

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Supervisor: Manuel Augusto de Pina Marques

U.PORTO

FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

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Abstract

Retailer companies work with Ship Packs representing the minimum quantity suppliers deliver to distribution centers and, thereafter, to stores. This parameter of the retailers affects several costs along the entire supply chain.

The current work was developed in a major retailer company and was branched in two main stages: the definition of Ship Packs through an optimization model, which entails the modeling of all the costs influenced by it, and the development of a Decision Support System to the retailer use whenever redefining Ship Packs with suppliers.

The project was conducted in the fresh and non food departments of the retailer and a model to optimize Ship Packs costs across the entire supply chain, including handling and safety stock at distribution centers and inventory, spoilage, markdown and extra handling at stores was developed. In addition, transportation and provision cost components were also included in the model.

Some products deal with sales patterns that have an intense period of sales within one year, which unbalances the needs of the supply chain by only having one Ship Pack for the entire period. In the present study, an automatic seasonality identification methodology was developed in order to study the implementation of a different Ship Pack within this period. Another drawn model was for the situation in which international suppliers deliver with cases and inners. Cases are big boxes containing inners inside it, which contains several units of the product. In order to take advantage of the bigger boxes, a methodology was established to send the case to stores with higher demand as well as in the seasonality periods.

The obtained results provided significant savings in both departments of the company. In the fresh department, a cost reduction of 9% was achieved as well as a 15% reduction in the non food department. The main savings were in the picking cost followed by spoilage and processing. In the non food department, the main savings were also at picking, but with an important reduction in the inventory cost. The seasonality model allowed, in products with seasonal sales' patterns, a cost reduction of 3% for both departments when compared to the single optimization model. The case/inners analysis shows that international suppliers oversized Ship Packs and for the retailer an important cost reduction of 38% can be achieved for products dealing with these practices.

In order to translate the developed model into a business application, a Decision Support System was developed as a web application. This tool is being used by the retailer company to redefine their Ship Packs whenever negotiating with suppliers.

The application was programmed to contain the developed optimization model in the background, which is activated by the user using a web interface. Then, the application reads the database containing all the information from the products and executes the optimization model. Finally, the outcome is processed to allow an holistic view of the entire chain for each product by showing in which cost components did the most significant savings occurred as well as the recommended Ship Pack.

Resumo

As empresas de retalho trabalham com quantidades mínimas que são transportadas pelos fornecedores até aos centros de distribuição e, destes, até às lojas. Esta quantidade mínima é designada por *Ship Pack* e é um parâmetro importante para os retalhistas por afetar vários custos ao longo de toda a cadeia de abastecimento.

O presente trabalho foi desenvolvido numa empresa de retalho e está dividido em duas etapas: a definição dos *Ship Packs* através de um modelo de otimização, que formula os vários custos da cadeia, e o desenvolvimento de um sistema de apoio à decisão para o retalhista usar sempre que definir os *Ship Packs* junto dos fornecedores.

O trabalho foi desenvolvido para o departamento de frescos e para o departamento não alimentar de um retalhista. Foram analisados vários custos ao longo de toda a cadeia de abastecimento, nomeadamente os custos de manuseamento e do inventário de segurança dos centros de distribuição e os custos de inventário, de quebra, de depreciação e de extra reposição nas lojas. Adicionalmente, foram também considerados os custos de transporte e de provisão.

Alguns produtos apresentam padrões de vendas que têm um forte período sazonal. Nestes casos, a existência de um único *Ship Pack* ao longo de todo o ano cria um desequilíbrio nas necessidades de toda a cadeia de abastecimento. Foi desenvolvida uma metodologia que permite a identificação de uma forma automática de períodos de vendas de maior volume com o objetivo de estudar a possibilidade de definir dois *Ship Packs* diferentes, um para o período sazonal e outro para o período regular de forma a reduzir os custos da cadeia. Uma outra particularidade do problema é que alguns fornecedores entregam os produtos em *cases* e *inners*, em que os *cases* são caixas maiores que contêm os *inners* dentro. De forma a tirar partido desta prática dos fornecedores, foi desenvolvida uma metodologia que envia os *cases* nos períodos sazonais e para as lojas com maior volume de vendas e os *inners* nas restantes situações.

Os resultados obtidos foram bastante significativos nos dois departamentos. No departamento de frescos foi obtida uma redução de custos de 9% e no departamento não alimentar de 15%. As maiores poupanças obtidas foram no custo de preparação no caso dos frescos. No caso do não alimentar, o custo de preparação voltou a ter um peso preponderante, juntamente com o custo de inventário nas lojas. O desenvolvimento de um modelo sazonal permitiu identificar poupanças de 3%, para produtos identificados como sazonais de ambos os departamentos, quando comparado com a utilização de apenas um *Ship Pack* ao longo do ano. Adicionalmente, o modelo de *cases/inners* para fornecedores internacionais permitiu poupanças de 38% provando que nestes artigos a definição dos *Ship Packs* estava bastante desfasada das necessidades do retalhista.

De forma a traduzir o modelo numa aplicação de negócio, foi desenvolvido um sistema de apoio à decisão como uma aplicação *web*. Esta ferramenta está a ser usada pelo retalhista para ajudar no processo de definição dos *Ship Packs* junto dos fornecedores. A ferramenta foi desenvolvida usando uma interface gráfica que interage com o modelo de otimização. O utilizador final interage escolhendo os parâmetros e artigos a otimizar e o *output* é devolvido de forma a que os resultados possam ser analisados para uma futura negociação com os fornecedores.

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I am extremely overwhelmed for having met brilliant and inspiring minds at LTPlabs. They were a team responsible for part of my personal and work development. It is surely easier to work in a place like this.

Loads of memories have flourished in these last five years. This would have not been possible without my friends. Part of this thesis was developed with their support, guidance and friendship and, therefore, I would like to thank all of them for the greatest moments spent together.

To my little nephews for brighten my days with their guiltless joy. To my brothers for always caring about the youngest of the family and for being a continuous source of inspiration. To my parents for guiding my path and for always giving me the best.

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Paulo G. Pereira

"Conformity is the jailer of freedom and the enemy of growth."

John Fitzgerald Kennedy

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Acronyms and Symbols

DC	Distribution Center
DSS	Decision Support System
PBL	Picking by Line
PBS	Picking by Store
SKU	Stock Keeping Unit

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Chapter 1

Introduction

" The system of people and things that are involved in getting a product from the place where it is made to the person who buys it"

Supply Chain Definition from Cambridge Dictionary

1.1 Motivation

Retailer companies face numerous challenges in supply chain management by balancing together efficiency and flexibility toward a quick response to demand needs. Companies dealing with supply chains, with an holistic view of it, tend to diminish the chances of jeopardize their business activities through the creation of long term sustainability and market leadership. Thus, supply chains have become a key to secure a competitive advantage against other players in the market.

The amount of stakeholders retailers' companies deal with has considerably grown up in the past years, turning retail business into a challenging tangled network burdensome to manage. Therefore, supply networks from major retailers are designed to integrate logistics operations into central warehouses, which consolidate and distribute goods to stores. Distribution centers (DCs) can be seen as an order fulfillment center allowing the stocking of goods for a period of time until the next order arrives followed by the consolidation of all the ordered goods, which are then delivered to stores.

These kind of networks entails troublesome challenges in combining production from suppliers with low inventory levels at the several echelon stages, distribution centers and stores, together with an enhancement in customers' sales. This leads to a tenacious focus on the net margin by increasing sales and at the same time scale down costs through more flexible and efficient supply chains. The ultimate goal of a retailer is to strengthen sales by allocating the right product to the right place to the right customer at the right time together with an escalation in the net margin.

The distribution starts with suppliers packaging the produced goods in boxes/pallets containing several units of it. The same quantity is maintained until the end of the chain where the package is finally opened at stores. This is called the Ship Pack and represents the minimum quantity suppliers deliver to distribution centers and, thereafter, to stores.

This parameter of the supply chain, in spite of not being deeply studied, affects several costs and stakeholders along the entire chain. It can be unbalanced with demand needs, leading to additional efforts of the chain and, as consequence, to a decrease in the closing margin.

In Van Zelst et al. (2009), the most important drivers of operational logistical costs are figured out. The costs included transportation, inventory and handling, both at warehouses and stores, and the results lead to the identification of Ship Packs as an important driver to these costs. Therefore, an appropriate definition of it leads to an increase in efficiency, in the retailer's supply chain, by minimizing the costs across the entire chain.

Normally, the Ship Pack is negotiated with the supplier and until the next negotiation it keeps unchanged. Due to this hard constraint, its definition gains an utterly importance as it is challenging to settle a different one with suppliers until the next round of negotiation occurs.

An appropriate Ship Pack definition can lead to an optimized cost chain for each product. On the assumption of a cost reduction for a significant portion of the overall products, its redefinition may lead to large-scales savings and, consequently, to an increase in the obtained margin.

1.2 The Project

The present study was developed as part of a consulting project in a national retailer company in order to determine the optimal quantity of the Ship Pack in the whole chain for several Stock Keeping Units (SKUs) the company deals with. The need of the project arose as the company was clueless with the impact Ship Packs have on its operations and wanted to have a model capable of indicating the optimal Ship Pack according to their needs in order to redefine it during negotiations with suppliers.

The key stakeholders of this project were the non food and fresh commercial departments of the company as they were the ones responsible to perform tactical decisions and negotiate with suppliers. However, as the project is transverse to the entire supply chain, several other teams were included in the project in order to model all the costs impacted by the Ship Pack definition.

In order to perform an holistic approach to this problem, the several stages of the retailer's chain, such as DCs and stores, have to be included in the scope of this project. The retailer has several stores, all over the country, which are mostly daily supplied with goods from the DCs according with the type of product. The company has several distribution centers: three for non-food products, four for fish, meat, codfish and bread, which are also responsible to process products, and two dealing with most of the remaining food products. The scope of this work includes all the distribution centers and stores.

The final goal is to provide the company with an optimization-as-a-service by developing a Decision Support System (DSS) available as an online application including the developed optimization model.

The project is branched in two main stages. The first step is the definition of Ship Packs through an optimization model as seen in figure 1.1, which entails the modeling of all the costs influenced by the Ship Pack. The second step involves the development of a Decision Support System for the retailer use whenever redefining Ship Packs with suppliers. This includes an extensive requirements and interfaces validation followed by the tool development and, finally, by the end user validation of the results. This can bee seen in activities 2, 3 and 4 from the project's timeline in figure 1.1.

As the DSS is supposed to automatically receive the necessary data from the company's database, there was another project running indoors the company to create automatic data extraction procedures and maintain the tool live without using data manual inputs from the users. This can be seen in detail in the last activity of the project's timeline.

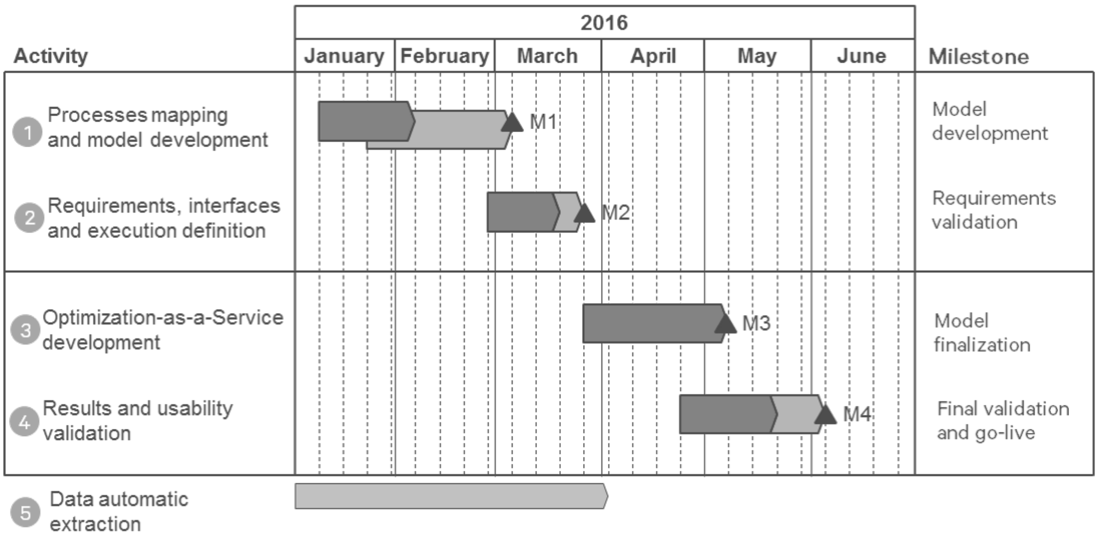


Figure 1.1: Project's timeline

1.3 Dissertation Structure

The dissertation is structured as follows. In Chapter 2, the impact of Ship Packs in the whole chain is tackled by analyzing all the stages affected by it as well as the proposed approach to cope with the stated problem. In Chapter 3, past works dealing with similar optimization problems were studied, as well as existing gaps in the current literature are presented. In Chapter 4, an optimization model is designed to minimize the costs related with Ship Packs considering the most imperative factors in the whole chain. Chapter 5 presents the results of the develop method in the particular case of the studied retailer company. In Chapter 6, the requirements, interfaces and usability of the DSS are described including the necessary tools to design and build it from scratch. In Chapter 7, the main conclusions are drawn and future enhancements to the work developed are discussed together with possible add-ins to the developed DSS.

Chapter 2

The Problem

The definition of Ship Packs is a multiple variable problem leading with linear and non linear cost expressions, which affect differently each piece of the supply chain. Hence, in order to properly define the impact of its definition in the supply chain, all costs have to be considered and the optimal Ship Pack is achieved by minimizing the developed cost function. An holistic approach has to be followed in order to define the optimal quantity, which includes an analysis of the entire chain, starting with distribution centers, followed by transportation and stores as seen in figure 2.1. The Ship Pack definition also impacts the supplier in their production and distribution. However, the developed model will only focus on the internal costs of the retailer.

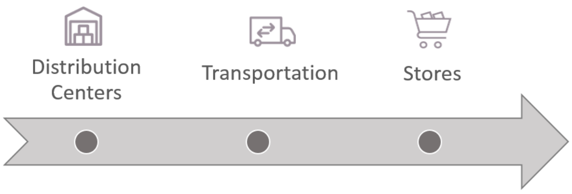


Figure 2.1: Stakeholders impacted by the Ship Pack Definition

2.1 Description

Distribution Centers

The distribution center is the warehouse where the retailer receives the goods from suppliers, which are then delivered to stores.

The warehouse is organized in two primary flow types: Picking by line (PBL) and Picking by Store (PBS) as seen in figure 2.2. PBL is a flow type dealing with zero stock in which goods arrive from suppliers and are placed in fixed positions representing each store. When all the goods are picked to the corresponding place, the order is shipped to the destination. This operation is related with suppliers who have high service levels and work with just-in-time operations as goods are usually shipped from the distribution centers in less than one day.

On the other hand, PBS - Picking by Store, is a flow type dealing with stock. The SKUs are located in fixed positions and the picking is done by collecting the SKUs from its position when an order is placed. The picker, person responsible to collect the SKU, moves around the racks and collects all the SKUs associated with the store's order. The fixed position is associated with the SKU, contrary to the PBL operation in which stores' position is fixed.

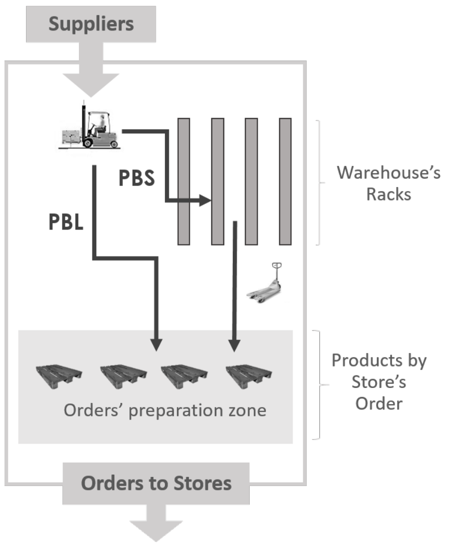


Figure 2.2: PBL and PBS flows

At the distribution center, the two main costs components are linked with handling costs, which can be split into processing and picking, and inventory costs. As this project was conducted in the fresh and non-food department of the retailer company, there were some differences in the cost process modeling for both departments.

Considering the fresh department, processing deals with the place of the received goods, which are gathered in big boxes, to small and standard boxes that will be the shipment unit for the remainder chain. This operation occurs mainly with fish, meat and bread products.

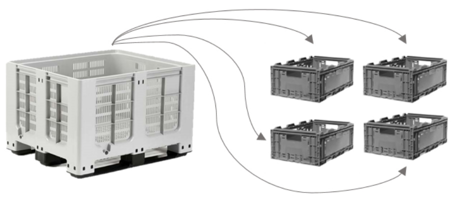


Figure 2.3: Processing Cost from the Fresh Department

In the case of the non-food department, some of the received goods arrive from international suppliers who send it in big boxes (Cases) containing small boxes (Inners) inside it. After arriving into the warehouse, the cases are opened and placed upon pallets to be stocked into the warehouse. This implies that, currently, only inners are sent to stores and cases are only used until the warehouse.

The processing cost for both departments is expected to decrease with larger Ship Pack as less boxes will be processed.

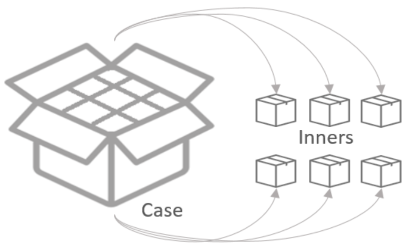


Figure 2.4: Processing Cost from the Non Food Department

Picking is another cost associated with distribution centers. In this situation, the cost is linked with the movements workers have to perform in order to collect the ordered SKU from its position in the warehouse. In both departments, picking movements are similar and the only difference is the picking cost, which changes according to the corresponding distribution center. Analogous to the processing cost, the picking cost is expected to decrease with larger Ship Packs.

As mentioned before, there is only stock of goods in the PBS flow type operations. Therefore, in the SKUs related with PBL operations, the Ship Pack definition does not influence the DC inventory cost. Moreover, in products leading with PBS operations, a larger Ship Pack will result in larger order quantities by the stores as orders will be less frequent. Hence, the DC is expected to have a larger safety stock in the situations where the Ship Pack increases. This happens because the DC has to maintain the same service level to stores in order to pay off the larger variance due to the bullwhip effect.

Transportation

There are some products in which the Ship Pack is a standard box meaning that all the measures and maximum carried weight are known. This is contrary to the situation in which the supplier uses a box without standard measures and the information about the available boxes being used is not provided.

Whenever using standard boxes, there is a list of possible boxes and on these terms it is attainable to indicate the most appropriate standard box to a better usage of it considering the product's weight, dimensions and the Ship Pack quantity.

The driver of the transportation cost is the number of carried pallets. A balanced Ship Pack might lead to a better utilization of the transportation box and, therefore, less boxes are carried. Potentially, this means less carried pallets and a reduction in the transportation cost is expected.

This cost can only be derived if the transportation is done with standard boxes in which the number of boxes and pallets can be calculated. In the situations of non standard boxes, the transportation cost can not be calculated as there are non standard measures for the used boxes.

Stores

The final stage of the chain are stores where several costs components are influenced by the Ship Pack definition.

Analogous to the distribution center, there is also an inventory cost influenced by the Ship Pack as orders have to be multiples of it. This leads to situations in which expected demand is below the rounded up order pointing to an extra stock as a result of the residual units not being sold. Larger Ship Packs tend to less replenishments from stores as larger orders are made. Considering the stores' replenishment methods to order goods from DCs, the average inventory, in each store, can be estimated by rounding up the order quantity to a multiple of the Ship Pack quantity.

Some inventory fluctuations are expected as sometimes the Ship Pack, even though being larger, might lead to a smaller order quantity because it can be an exact multiple of the Ship Pack and, consequently, less units are ordered. Therefore, the stores' inventory cost is expected to have some fluctuations upon the Ship Pack quantity.

When an order arrives to the store, the product is fitted into the store' shelves until these are completely full. There is a cost of shelf stocking, which according to Sternbeck (2015), includes the following procedures: picking up the Ship Pack, identify the SKU, opening the box, walking to the shelf and looking for the slot on the shelf. However, not all the units fit on the shelf and the remainder units of the product return to the backroom and await for the next shelf filling. This extra movement incurs into additional costs, which are dependent on the Ship Pack size. Small quantities of it lead to a better fit into the shelf and, consequently, larger Ship Packs are expected to increase the store extra handling cost.

Shrinkage costs according to Beck et al. (2002) can be due to product going out of date or under pricing. Spoilage is normally referred to losses due to expiration dates and markdowns to under pricing when the product is near expiration dates.

In the fresh department, most of the products are perishable with short expiration dates and as Ship Packs influence the inventory in stores, the spoilage cost is expected to increase with larger quantities of it. In addition, this issue was one of the motivations behind the current project as a myriad of SKUs were having spoilage costs due to an unbalanced Ship Pack definition.

In order to avoid shrinkage, some SKUs have a markdown when close to expiration dates. According to Ferguson et al. (2007), managers frequently utilize markdowns to stabilize demand as the product's expiration date nears. This cost is also expected to be influenced by the Ship Pack in similar ways as the spoilage cost.

The utmost cost component is a very particular one related with the considered retailer and it is associated with a financial penalization of slow movers products having long standing stocks. This cost is called provision and it is only calculated with products from the non food department and it is expected to increase with larger Ship Packs.

In figure 2.5 all the costs are bond together and this will be the groundwork of the current project in the following chapters. It is important do denote that most of the products follow this supply chain, but a few of them are directly supplied to stores by suppliers. On these terms, the distribution centers will be excluded from the analysis and only the costs upon it will be considered.

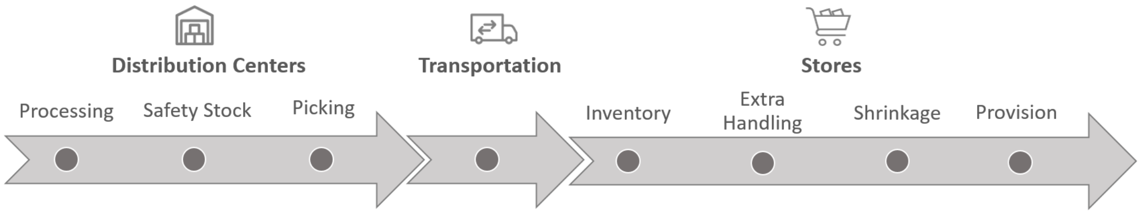


Figure 2.5: Costs affected by the Ship Pack in every stage of the Supply Chain

Table 2.1 summarizes how each cost affects respectively the studied departments and the particularities of each one. These different characteristics between both departments will be considered when modeling all the costs of each SKU. These idiosyncrasies can change the cost function or work as a binary value to whether or not consider the corresponding cost component in the total cost function.

Table 2.1: Costs affecting each Commercial Department

Cost	Fresh Department	Non Food Department
Picking	Includes both PBS and PBL flowtypes	
Safety Stock	Few PBS operations	Mainly PBS operations
Processing	Changing products to another boxes	Opening cases and palletizing
Transportation	Standard and supplier's boxes	Only supplier's boxes
Store Inventory	Depends on the store's replenishment method	
Extra Handling	Depends on the store's shelf space	
Spoilage	Short expiration dates	Few expiration dates
Markdown	Includes markdowns	No markdowns
Provision	No penalization of stocks	Penalization of longer stocks

Demand Variability Analysis

Together with the costs considered in the above stages, there are some other variables affecting the Ship Pack definition. The goal is to study and quantify how does these variables might deeply affect the cost of the entire chain and whether or not it is worth it to change the current situation.

A product might not sell equally throughout the year. Some products might have strong demand peaks in which sales are strongly above average in comparison with regular periods. This does not mean punctual promotions, but long periods of strong sales such as school products that have a peak of sales occurring in the beginning of the school period. Therefore, the same Ship Pack during all year is unbalanced and the effort of having two Ship Packs for different periods in time, which entails negotiating with the supplier, might be justified if there is a considerable cost reduction on this approach. The same happens with seasonal fruit products that sell through the entire year, but have an intensive demand period due to customer's consumption (ex: Melon during summer) or to product's production (ex: Strawberry).

This leads to the precondition of identifying the seasonality period from a demand history analysis and, consequently, introduce a different Ship Pack into the model for this period of time. The goal is to provide an outcome identifying the seasonal and regular periods and the corresponding Ship Packs.

In addition, as the retailer company encompasses several stores with different sales patterns, this different sales' volume within stores might justify the implementation of two Ship Packs for different stores based on their sales history. However, having two Ship Packs references at the same time leads to the need of having two picking references at the warehouse and, in the current moment, the capacity of most of the distribution centers does not allow this kind of operation.

As mentioned before, some of the products are shipped using cases and inners and in order to take advantage of this obligation from the supplier, it was decided to study the implementation of sending the case in the situations of larger demands such as seasonality periods or to stores with higher sales.

Stores with higher sales will be identified through a demand history analysis and be associated in two groups. One of the groups will be supplied by inners and the other with cases.

Altogether, demand variability within stores and demand peaks through a period of time might justify the effort of having different Ship Packs to diminish the chain's costs.

2.2 The Proposed Approach

The proposed approach follows a four fold methodology as seen in table 2.2.

In the first step there will be a strong focus on the data treatment starting by an extensive data request to the company's information technology department. Then, data identification and understanding will lead to a special treatment of outliers and missing values to keep the model coherent and rigorous.

The second step is the cost modeling for each of the mentioned cost in function of the Ship Pack quantity. In addition, with the sales history it will be possible to identify whether or not the product has significant demand peaks and if there is a strong demand variability among stores.

The third step is related with the optimization of the cost function and it proposes to indicate the optimal Ship Pack for each SKU of the company as well as the estimated gain for the developed model.

The final step proposes the development of a Decision Support System as an optimization as a service available online for each department of the retailer in order to indicate the best Ship Pack quantity for each SKU. It entails a requirements phase in which interfaces and usability need to be defined followed by the development of the tool, which is going to be fed by an autonomous data extraction maintaining data updated over time.

The current project will address mainly step two and three by giving a stronger emphasis to the cost modeling and, consequently, to the optimization model as these are the core components of the project. However, the data treatment played an important role as the project dealt with a huge amount of data and the DSS worked as way to transfer the developed knowledge into a business application.

Table 2.2: Proposed Approach

Data Treatment	Data request
	Identification of key variables
	Outliers and missing values identification
Cost Modeling	Quantify each cost of the chain in function of the Ship Pack
	Identify Demand Peaks
	Identify Clustered Stores
Optimization Model	Minimize the total cost of the chain
	For each model identify the estimated gains
	For each SKU indicate the optimal Ship Pack
Decision Support System	Requirements Definition: interfaces and usability
	Programming the tool as an optimization as a service
	Automatic data extraction

Chapter 3

Literature Review

The goal of this chapter is to induce the reader into the current state of the art in the Ship Pack optimization by covering all the stages of the supply chain and how the Ship Pack influences it. The literature review is organized as follows. In section 3.1, an introduction to retailers' supply chain in a broad manner is made as an intent to contextualize the current problem into the supply chains current needs and challenges. In section 3.2, distribution strategies and picking policies are covered in order to detail how central distribution is currently organized. In section 3.3, the impact of shrinkage costs in fresh products are analyzed including spoilage and markdowns costs and how the perishable products have different particularities when compared with the remaining products. The bullwhip effect and its repercussions in the coordination of the chain are stated in section 3.4. The current replenishment methods are covered in section 3.5 followed by an explanation of the current practices in stock management. In section 3.6, the state of the art in the current Ship Pack optimization is addressed as well as possible gaps in the existing research. Finally, in section 3.7 some definitions about seasonality identification and clustering are addressed in a broad manner.

3.1 Retail Supply Chains

The importance of supply chains in the retail business is addressed in Fernie and Sparks (2014). From a customer perspective, it is often forgotten the effort retailers made in order to place the desired products on shelves. Handling with variability in demand, due to customer's changes in beliefs and needs, is a challenging task as a bad prediction might lead to a disruption in stock or to an extra stock. Therefore, forecast needs to be balanced with sales and all of the logistical processes in order to guarantee the availability of the product when customers are buying it.

Fernie and Sparks (2014) also states that current retailers have been concerned to ensure distribution channels are both anticipatory and reactive to demand's changes. Although right product availability is the main goal of a retailer there are some issues contributing to the efficiency of the chain. Holding excessive stock, both at warehouses and stores, is a costly activity as stock might become obsolete or deteriorated due to expiration dates. In addition, there is also the cost of transporting goods from suppliers to warehouses and then to stores, which also needs to be balanced.

An efficient chain can lead to less costs and, potentially, the retailer might look more appealing to the customer's perspective as prices may go down. Therefore, dealing together with demand and supply though excelled information systems can lead to a better service to customers as it can provide fresher and higher quality products minimizing the risk of stockouts.

3.2 Warehousing

There are two main distribution strategies: traditional warehousing and cross-docking. In the first one, retailers keep stock at Distribution Centers and when customers or stores request a product, the item is picked from the racks (Li et al., 2008). This works in an analogous way to the PBS flow type mentioned in the previous chapter.

On the other hand, cross-docking is a distribution strategy where distribution centers function as an inventory coordination point rather than an inventory storage point (Waller et al., 2006). This is compared to the PBL flow type because there is no safety stock at the distribution center. However, the two operations are distinct because cross-docking implies the product transfer to another vehicle when the product arrives into the DC and the PBL flow type includes the reorganization of all the products by store before sending it to the store.

In Benrqya et al. (2014), the impact of product characteristics on distribution strategy selection is studied in several categories. The aim is to, according with the product, market and supply factors, choose the best distribution strategy either from traditional warehousing or cross-docking. This work is indirectly related with Ship Pack definition as some of the mentioned factors are dependent from the Ship Pack size, which may indirectly lead to the choice of the best distribution strategy making this as a pivotal consideration along the entire supply chain.

De Koster et al. (2007) defines order picking as the process of retrieving products from storage (or buffer areas) in response to a specific customer request. It is classified as the most labour intensive operation in warehouses. It also states the importance of warehouses to achieve transportation economies, consolidation of orders and deal with demand's uncertainty among many other factors.

Tompkins et al. (2010) describes the first step in the warehouse flows as the reception of the goods from suppliers followed by either it storage or shipping immediately, which makes the warehouse working as a cross-docking platform. The storage can be divided in two: reserve storage with pallet picking or case picking. After storage, an order is made and replenishment is made to the shipping area.

A comparison between picking, storage and routing policies is performed in Petersen and Aase (2004) and results show orders' batching contribute significantly to the greatest savings, particularly when smaller order sizes are common.

3.3 Replenishment methods

In Wagner (2002), the evolution of inventory models is analyzed. The earliest publications date back almost one century ago and referred to Economic Order Quantity (EOQ), which is still studied nowadays. Back to this time, the main difficulties were related with the attainment of historical demand data and empirically test stock models due to lack of computing power.

Brown (1959) targets inventory modeling in two main issues: the time to replenish inventory and what should be the order quantity. It states the order must occur when the current inventory does not reach the targeted service level and the quantity must be enough to cover the forecast demand until the next order arrives.

Wagner (2002) also focuses on why stock outs continue to occur, even though technology development lead to a better use of inventory models. Some of the problems stated are related with demand not being leveled across the year as well as when new SKUs are introduced there is not enough data to extrapolate solid conclusions and there is also laborious to differentiate stock outs due to bad stock management or suppliers' failure.

The two most common stock management practices are are inventory continuous and periodic review. Continuous review indicates that inventory status is tracked in a continuous way and the order is made to a certain quantity designated as Q. On the other hand, periodic review indicates that inventory is tracked at regular periodic intervals known as R and a reorder is made during the review period to raise inventory to a predefined level (Chopra and Meindl, 2007).

3.4 Bullwhip Effect

According with Lee et al. (2004) when the retailer's orders do not coincide with the current retail sales, a distortion in the demand information had occurred leading to a larger variance from orders than from sales. This lead to a demand amplification upstream the chain and in a multiple echelon stage, like a retailer's supply chain, it is frequently quoted that the amplification can be more than the traditional 2:1 affecting several echelons and leading to extra stock costs to avoid stockouts and completely fulfill the expected demand.

The traditional and most common explanation to justify the bullwhip or whiplash effect is the lack of information between stages in the supply chain. Geary et al. (2006) did an extensive work to cover the ten principles leading to bullwhip reduction. One of those principles, in the interest of this study, is the order batching principle, which is influenced by Ship Pack definition as it leads to "lumpy" deliveries, and hence come back around the ordering loop.

In Yan et al. (2009), the effect of delivery pack size in the bullwhip effect was studied and found significantly correlated with larger pack sizes. It concludes that the increase of pack size forces the retailer to order less frequently but in larger quantities leading to the amplification of the demand at the distributor level. In addition, the average stock on hand rises significantly due to order-rounding rule particularly when the minimum order quantity is much larger than demand during the review period.

3.5 Fresh Food on Retailing

Fresh products account for a large part of retailer's revenues and are also strong drivers of store's traffic and customer loyalty. In Raphael Buck (2013), the most critical dimensions for successful fresh retailers are stated and it included supply chain and shrinkage reduction as two of the main factors. Shrinkage is defined as the cash value of products that a retailer has bought that are not sold due to expiration dates or to under pricing. Opportunities to reduce shrinkage can be found in every part of the supply chain including the inadequate shelf space or the replenishment process.

The shelf space is related with the quantity a product has allocated on a shelf and in most of the times there is no analytic rule to define the optimum quantity. This unbalanced allocation might lead to the deterioration of products that are not sold. The replenishment process may lead to an extra stock that is not required and, consequently, to an over cost due to shrinkage.

In Van Donselaar et al. (2006), a study was conducted in two Dutch supermarkets analyzing the difference between perishable and non-perishable products. Based on this, shelf life, average weekly sales, coefficient of variation for weekly sales, case pack size and average time between two replenishment orders were found to be clearly different for both sort of products. In the situation of the case pack size, the median was 6 and 10 for perishable and non perishable products, respectively. In the remainder of the paper, a different control of inventory to perishable products is formulated in order to compensate the differences between the two range of products.

In addition, most of the retailers tend to use markdowns to stabilize demand as expiration date nears. In Ferguson et al. (2007), most of the perishable products are stated to have two markdowns for each batch. The first one occurs at half of the product's life time and is typically 10-50% of the product's original price. The second markdown occurs at 75% of the product's life time and is typically 25-75% of the original price. Retailers use this dynamic pricing technique to stabilize demand as consumers are expected to buy less products near expiration dates unless there is a reduction in the original price.

3.6 Ship Pack Optimization

The motivation to study the Ship Pack definition is well addressed in Van Zelst et al. (2009) as size pack definition is clearly demonstrated to be an important driver for stacking efficiency. In the presented study, costs are subdivided in inventory and handling, both at warehouses and stores, and transportation. Handling costs represent by far the biggest pie in the total cost (66%), followed by transportation (22%) and leaving inventory to only 12% of the total cost. It concludes there is a need to balance Ship Pack size with handling costs and inventory costs as both costs fluctuate differently with different Ship Packs dimensions.

Hellstrom and Saghir (2007) provides an overview between packaging and logistic processes in the retail supply chain. It states packaging can lead to benefits in the logistic activities such as reduction of handling activities and picking times, inventory carrying cost and the warehouse layout could also be improved. Many packaging dependent costs in the logistics system are frequently overlooked, which included several logistic activities such as transport, inventory, warehousing and communication. In transportation, packaging decreases handling costs and loading times. In inventory, it increases product availability (sales) and decreases carrying costs. In warehousing, decreases order filling time, labour costs and material handling costs. In communication, decreases communications to track down lost shipments.

Waller et al. (2008) studied if case pack quantity affects significantly firm market share by analyzing product rate-of-sale by a regression analysis. These findings lead to the result of case packs quantities affecting market share due to less stockouts. It states two opposite effects of case pack quantities: (1) larger quantities reduce replenishment's frequency and, consequently, less stockouts and (2) increase the probability that some units might need to be stored in the backroom as they do not fit on the shelf and, consequently, the number of exposures to stock outs increase.

Wang (2010) says that outer and inner packs can be ordered by the DCS if the outer is opened at the DC. This has benefits because it provides flexibility to meet the store's demand even with an additional cost. It develops several heuristics with different performances as some reach the optimum but not in a feasible time.

In Albán et al. (2015), the importance of packing is addressed as it is involved in several activities such as storing, picking and transportation. An inadequate packaging shape, size and structure can lead to higher costs in the supply chain. It developed a methodology to define the optimal outer pack size based on branch and bound to optimize costs at several distribution channels as well as the least opening ratio in every step of the chain.

Ge (1996) addresses the issue of the impact of packaging in the cost of transportation as it allows a strength planning and a reduction of the logistics costs.

In Sternbeck (2015), it was developed a cost-minimization model including handling and inventory carrying costs to determine order packaging quantities (OPQ). The model developed is based on inventory management theory and on discrete probability distributions of consumer demand. A (R,s,nQ) policy was used in which the inventory is reviewed periodically and an order is performed if the inventory position is below the reorder level s and the order quantity is a multiple of the order packaging quantity. The goal was to minimize a total cost function considering stocking, inventory carrying and restocking costs. Having this formulation, the cost curves for each SKU were developed to derive a minimum cost and, consequently, the optimum OPQ. Inventory carrying costs increase with OPQ and initial stocking costs decrease. However, restocking costs start at zero because, in the beginning, every units can be put onto the shelf, but for a certain OPQ this does not verify and the cost starts to exist and increases with larger OPQ. By applying the minimal cost OPQ for all stores, the considered costs were reduced by 9.4 %.

Wen et al. (2012) is the current most complete work in the subject of Ship Pack cost modeling. In the presented study, the faced problem consisted in the choice of one Ship Pack that could be either an individual unit, an inner (6-8 units) or a case (a box of 24 units). It was developed a cost model containing DC handling costs, stores handling costs and inventory related costs. The obtained results lead to a cost reduction of 0.3-0.4%. It assumes that the maximum shelf capacity is given as a function of the order up to level, the inventory position follows a uniform distribution between zero and the reorder point. Demand between weeks follows a constant rate, transportation cost is assumed to be constant and lead time to stores is null. An important formulation to calculate the distribution center safety stock is made allowing to estimate the effect Ship Pack quantity has on this cost. Extra handling cost is modeled as the cost of shelf-stacking the units that do not fit onto the shelf during regular shelf space stacking. In this study, it is only considered the cost of the extra units instead of all the stacking process as in Sternbeck (2015).

van Donselaar et al. (2005) states that Ship Pack optimization should not only include holding and fixed ordering cost, but also some operational constraints such as the maximum shelf capacity. In addition, the developed application should also offer insight to the decision marker on the economic trade-offs between important performance indicators such as the number of orders per year, the total handling time needed, the expected total number of refills needed, whether or not the pack size is too big to put on the shelf, the total inventory and the resulting service level to the customers. It also states that the personnel negotiating with suppliers tend to be more focused on getting the lowest price than in making an overall evaluation of the impact of the case pack size on all the performance indicators. On a store level, the planograms and reorder levels should be matched in order to diminish the number of leftovers sent to the backroom.

Sternbeck and Kuhn (2014) evaluates the impact of store delivery patterns in grocery retailing. When a delivery gets to the store, the pallets and boxes have to be unload and brought into the shop where shelf filling takes place. The delivery size must not exceed storage capacity in the store, especially if pallets are delivered during the night, or are stored before unpacking takes place.

Kuhn et al. (2015) developed a model to quantify instore logistics processes based in a precise discrete Markov chain. The replenishment in stores is also done by a periodic review reorder inventory policy (R,s,nQ). Several cost drivers were formulated such as the impact of the physical inventory as well as the backroom inventory and activity. It was also modeled if the display stock quantity is under the defined shelf's quantity because it means a violation of the desired service level necessary to ensure an attractive appearance in the salesroom. The findings suggest a different case pack size with significant cost improvements based on the store and the SKU.

Eroglu et al. (2011) developed several hypotheses to study the effect of case pack quantity, consumer demand and shelf space on shelf stockouts. Discrete event simulation was used to test the developed hypotheses. The effect of shelf space on a SKU's shelf stockout level is moderated by consumer demand as more filling has to be performed. The effect of shelf space on a SKU's shelf stockout level, moderated by case pack quantity, was proven to have larger effects when the case pack quantity is higher, as more units have to be moved to the backroom. The last hypothesis shows an important moderator effect by the consumer demand on the shelf space and case pack quantity. It concludes that SKUs with higher demand and smaller case pack quantities need less shelf space in order to minimize stockouts. On the other hand, SKUs with lower demand and larger case pack quantities need larger shelf spaces.

Wan (2016) key finding in this study was the timing of the effects related to the pack size variety. It suggests important managerial implications related with pack size variety decisions.

Managers should pay more attention on the recent demand and enough attention to the cost performance over time in order to make proper pack size decisions. On the demand side, recent demand should be given more importance than old demand history in order to perform better pack size variety decisions.

Overall, there have been manifold researches including the modeling of several costs in the supply chain affected by the Ship Pack. However, each paper focus on a different cost components approach with no common methodologies among them to benchmark results and only a few present an holistic view of the entire supply chain. There is a gap in the current research in the consideration of lead time to stores, shrinkage costs as well as transportation and provision costs. In addition, in the mentioned works there is no differentiation among seasonal periods of sales and only one Ship Pack is considered for the entire year.

3.7 Seasonality and Stores Clustering

Hylleberg (1992) defines seasonality as a periodic and recurrent pattern that can be caused by many components such as weather, holidays or repeating promotions.

Classical decomposition remove seasonal variations using a seasonal adjustment method and then the models are estimated back using the estimated seasonal effects. It decomposes the time series into trend, seasonal, cyclical and irregular components. The seasonal influence is estimated and removed from the data before the other components' estimation. The identified seasonality can be any given period and the most common technique to discover the seasonality period is to calculate an auto regression coefficient and choose the most significant (Makridakis et al., 2008).

Another method being used to identify trend and seasonality in time series is to use neural networks. Zhang and Qi (2005) states that neural networks can model any type of relationship in the data with high accuracy. However, it concludes that neural networks are not able to model seasonality directly without prior data processing.

The current work in the seasonality identification focus more on the identification of time series' variations due to seasonality in order to include it in the forecasting model, instead of only identifying the periods that suffer a pull in sales for a significant time period. In addition, the several classified methodologies tend to use homologous periods of sales in order to properly identify seasonality. Furthermore, methodologies working with only one period of sales do not occur in the existing literature.

Berkhin (2006) defines clustering as the division of data into groups of similar objects. Each group, or cluster, consists in objects sharing similar particularities to one another and are also dissimilar to the other objects in the remaining groups. Clustering is a form of data modeling, which puts it in a historical perspective related with mathematics and statistics. When comparing with a machine learning point of view, clusters correspond to the discover of hidden patterns. There are several clustering techniques such as hierarchical clustering based on distance connectivity, k-means in which each cluster is represented by a single mean vector and other more complex such as fuzzy clustering in which values have a degree of membership to several clusters.

Chapter 4

Methodology

The following chapter addresses the optimization of the Ship Packs quantity for each SKU. In section 4.1, the cost modeling is structured followed by the seasonality identification in section 4.2 and the store clustering in section 4.3. Finally, the methodology to optimize each Ship Pack is formulated in section 4.4.

4.1 Model Formulation

In Chapter 2 the problem definition is addressed and every cost is described in detail. Table 4.1 contains all the notation used to formulate the current problem.

The following methodology is a deeper addition to some of the work developed in Wen et al. (2012) as it formulates considerable new add-ins to the current state of the art in the Ship Pack optimization in a two echelon distribution system.

The current work considers processing costs at DCs, lead time to stores is not null and shrinkage costs (spoilage and markdown) are added as well as transportation and provision costs. It also develops a methodology to include different Ship Packs for seasonal periods and a case/inner analysis for situations where suppliers deliver like this.

The model includes all the realistic cost components supported by the retailer that are affected by the Ship Pack size through the entire supply chain.

The developed methodology for the Ship Pack definition is holistic and follows a bottom-up approach. It computes weekly costs for different Ship Packs for each SKU and for each store. The optimal Ship Pack for the SKU k is the one that minimizes the total cost function, given by the sum of the costs of all stores and all the DC's for that SKU k incurred in a given period.

The stated problem deals with several distribution centers having each store being supplied by only one DC. The methodology incorporates different flows: PBL and PBS, and the number of weekly deliveries from DCs to each store i can be different from store to store. This is set down by the store together with distribution centers, having each store the delivery days within the week scheduled according with it.

The developed cost model to find the optimal Ship Pack quantity relies on the following assumptions:

1. Ship Pack can only change in the seasonal period, otherwise it remains the same for the entire year and is only different within stores when dealing with case/inner situations.
2. A store is only supplied by one DC.
3. Only one year of sales is considered and demand is aggregated in weeks and stores.
4. It was assumed that demand within each week occurs at a constant rate and the inventory position when a store makes an order follows a uniform distribution. This assumption allows the estimation of the average inventory in stores.
5. Lead time is less or equal to the review time and overlapped orders are not considered.

A fixed-time period with a reorder point system $(R, ROP, OUTL)$ is applied by the retailer to all SKUs at every store. According to this system, the Inventory Position (*IP*), the on-hand plus the on-order stock inventory, of each SKU k at each store i is checked periodically (with period *R*), and an order is placed to the DC if the *IP* is less or equal to the reorder point (*ROP*). The order quantity is calculated as the amount of stock that would bring the *IP* at least up the Order Up to Level, $OUTL$.

ROP and $OUTL$ values are set by the retailer on a weekly basis for all SKUs in each store. This weekly review is made because the retailer defines the *ROP* as a function of the weekly demand forecast and $OUTL$ as a *ROP* function. Distribution centers deliver orders to stores on a regular weekly schedule, from one to six times a week on fixed days of the week. Thus, lead-times to stores (LTS) are different from store to store.

The Inventory Position *IP* and the on-hand stock of SKU k in store i over time are shown in the figure 4.1. The subscripts i and k are dropped for simplicity and IP_t denotes the inventory position before placing an order at time t. At time t an order of Q_t units is placed to DC to at least the $OUTL$ as this a multiple of the Ship Pack quantity. This order will be delivered by DC to store at time $t + LTS$.

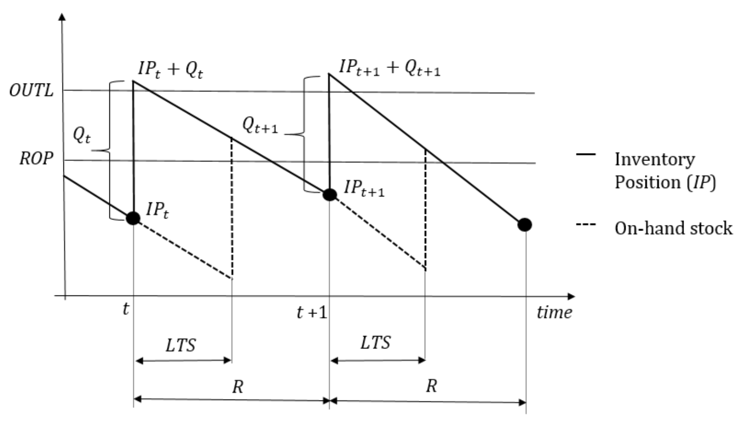


Figure 4.1: Inventory Position and On-hand Stock

Table 4.1: Table of Notation

Decision Variables:	
$SPQ^{sp}_{i,k,t}$	Ship Pack Quantity of SKU k in week t for store i for type of Ship Pack sp (units)
Variables:	
$n^{sp}_{i,k,t}$	Number of Ship Packs sp ordered at store i of SKU k in week t (units of Ship Packs)
$Q^{sp}_{i,k,t}$	Order quantity at store i of SKU k in week t of Ship Pack sp (units)
$IP_{i,k,t}$	Inventory Position of SKU k at store i in week t (units)
$NrO_{i,k,t}$	Number of orders of SKU k at store i in week t (units)
$CDays_{i,k,t}$	Coverage days of the order quantity of SKU k at store i in week t (time)
$NrED_{i,k,t}$	Number of units of SKU k in store i exceeding expiration date in week t (units)
$NrMD_{i,k,t}$	Number of markdown units of SKU k in store i in week t (units)
$D_{system,k}(t,t+L_{dc,k})$	Random variable for demand at the Distribution Center dc over time interval $(t,t+L_{dc,k})$
Parameters:	
$d_{i,k,t}$	Demand Forecast of SKU k at store i in week t (units)
$Edate_k$	Number of days until expiration date of SKU k (time)
$Mdate_k$	Maximum number of days (before expiration date) to markdown SKU k (time)
$Rdate_k$	Minimum number of days (before expiration date) to remove SKU k from shelf (time)
$L_{dc,k}$	Replenishment lead time for the Distribution Center dc for SKU k (time)
$LTS_{i,k}$	Replenishment lead time for the Store i for SKU k (time)
$R_{i,k}$	Replenishment review period for the Store i for SKU k (time)
$PS_{i,k,t}$	Presentation Stock on the shelf of SKU k for the Store i for week t (units)
$ROP_{i,k,t}$	Re-order point for SKU k for the Store i for week t (units)
$OUTL_{i,k,t}$	Order-up-to-level for SKU k for the Store i for week t (units)
$Pallet_b$	Maximum number of boxes b in one pallet (units)
$Nweeks_k$	Number of weeks with sales from SKU k
$Nstores_k$	Number of stores with sales from SKU k
$Stores_{dc}$	Set of stores supplied by distribution center dc
Model Costs:	
K	Fixed order cost (€ per order)
$pick_{dc}$	Picking cost at Distribution Center dc (€ per Ship Pack)
$proc_{dc,sp}$	Processing cost at Distribution Center dc of a Ship Pack sp (€ per Ship Pack)
$trans$	Transportation cost (€ per pallet)
$extraHC$	Extra handling cost (€ per unit)
ICC_{dc}	Inventory Carrying cost of Distribution Center dc (%)
ICC_{store}	Inventory Carrying cost of stores (%)
C_k	Unit cost of SKU k (€ per SKU)
$P_{i,k}$	Selling price of SKU k per store i (€ per SKU)
z_{dc}	Service level factor used in Distribution Center dc
DR_k	Depreciation rate for SKU k

The order quantity $Q^{sp}_{i,k,t}$ can be obtained from $n_{i,k,t}$, the number of Ship Packs per order in week t, which is given by equation 4.1. The index sp means the nature of the Ship Pack being used and it can be a case, inner or the Ship Pack in the seasonal or regular period.

$$n^{sp}_{i,k,t} = \left\lceil \frac{OUTL_{i,k,t} - IP_{i,k,t}}{SPQ^{sp}_{i,k,t}} \right\rceil, \text{where } \lceil . \rceil \text{ is the integer ceiling function operator} \tag{4.1}$$

The order quantity $Q^{sp}_{i,k,t}$ is therefore:

$$Q^{sp}_{i,k,t} = n^{sp}_{i,k,t} \times SPQ^{sp}_{i,k,t} \tag{4.2}$$

The expected number of orders placed by store i to DC in week t will be:

$$NrO_{i,k,t} = \frac{d_{i,k,t}}{Q^{sp}_{i,k,t}} \tag{4.3}$$

Fixed Order Cost

The fixed order cost is given by the total number of orders multiplied by the cost of ordering as seen in equation 4.4. However, in the studied retailer this cost is not considered as orders do not incur into any cost.

$$\text{Fixed Order Cost}_k = K \sum_{i=1}^{Nstores} \sum_{t=1}^{Nweeks} NrO_{i,k,t} \tag{4.4}$$

DC Processing Cost

The total processing cost of SKU k is given by the sum of all of the processing costs from the number of Ship Packs processed in store i and week t. The processing cost ($proc_{dc,sp}$) depends on the distribution center (dc) and on the type of Ship Pack (sp) as the cost might fluctuate within DCs and the type of Ship Pack as seen in chapter 2. The processing cost is then multiplied by the total number of units processed by the DC as seen in equation 4.5.

$$\text{Processing Cost}_k = \sum_{i=1}^{Nstores} \sum_{t=1}^{Nweeks} proc_{dc,sp} \times NrO_{i,k,t} \times n_{i,k,t} \tag{4.5}$$

DC Picking Cost

The total picking cost of SKU k is derived by the sum of every picking cost, which also changes according to the DC, multiplied by the number of ordered Ship Packs in week t considering all stores and weeks as seen in equation 4.6.

$$\text{Picking Cost}_k = \sum_{i=1}^{Nstores} \sum_{t=1}^{Nweeks} pick_{dc} \times NrO_{i,k,t} \times n_{i,k,t} \tag{4.6}$$

DC Safety Stock Inventory Cost

The necessary DC safety stock for a certain stock out probability is proportional to the standard deviation of the demand during lead time of the SKU k at the distribution center dc. The DC inventory cost is given in Wen et al. (2012). It models the safety stock needed by the DC as being proportional to the standard deviation of the demand during lead time multiplied by the desired service level. This formulation is given in equation 4.7.

$$z_{dc} \times \sqrt{\text{Var}(\ D_{Dc,k})(t, t + \frac{L_{dc,k}}{7})} \tag{4.7}$$

Equation 4.7 allows the estimation of safety stock as an approach to mitigate the risk of stock outs from DCs due to uncertainty in supply and demand. In this situation, uncertainty in supply will not be contemplated as suppliers variation is considered to be null. This expression equals the demand seen by the DC plus any changes in the inventory positions from stores as demonstrated in Wen et al. (2012) as equation 4.8.

$$\text{DC SS Inventory Cost}_k = \sum_{dc=1}^{NDcs} ICC_{dc} \times C_k \times z_{dc} \times \sqrt{\text{Var}\{D_{system,k}\} + \frac{\sum_{i \in Stores_{dc}} \sum_{t=1}^{Nweeks} Q_{i,k,t}^{sp2}}{6}} \tag{4.8}$$

$Var\{D_{system,k}\}$ is a random variable that denotes the variability of demand for the system (i.e., across all stores) and is given by equation 4.9.

$$\text{Var}\{D_{system,k}\} = \frac{L_{dc,k}}{7} \times \sigma^2_{Demand} \tag{4.9}$$

σ^2_{Demand} represents the variance of the weekly demand of SKU k. It was assumed that the standard deviation of the lead time is null and only the variance in the demand is contemplated. As the lead time from the supplier $(L_{dc,k})$ is given in days, it is necessary to divided it by the number of days in one week as demand is in weeks.

Transportation Cost

The transportation cost can only be calculated when the product uses standard boxes. In these situations there is a list of boxes that can be used and according to the Ship Pack, the best suitable box is chosen in order to better accommodate the product. This optimal box will be denoted as $OptBox$. The quantity carried by a single pallet can be deducted by multiplying the Ship Pack quantity by the maximum number of boxes in one pallet considering the optimal box. This parameter is given by the supplier and will be denoted as $Pallet_{OptBox}$. Thus, the number of carried pallets is given by the total ordered quantity divided by the number of units carried in a single pallet as seen in equation 4.10.

$$\text{Transportation Cost}_k = trans \times \sum_{i=1}^{Nstores} \sum_{t=1}^{Nweeks} NrO_{i,k,t} \times \frac{Q^{sp}_{i,k,t}}{SPQ^{sp}_{i,k,t} \times Pallet_{OptBox}} \tag{4.10}$$

Store Inventory Cost

The Inventory position value in every cycle is given by the inventory position in the previous cycle plus the ordered quantity and minus the demand during the considered period. The demand is assumed to occur at a constant rate and its daily value is simply figured as $\frac{d_{i,k,t}}{7}$. Therefore, IP_{t+1} is deducted by considering IP in period t plus the ordered quantity Q_t minus the demand during the review period R as seen in equation 4.11. Demand during the review period is given by the daily demand from the corresponding week times the number of revision days.

$$IP_{i,k,t+1} = IP_{i,k,t} + Q^{sp}_{i,k,t} - D_i(t, t+R) \tag{4.11}$$

In order to initialize the cycle, the assumption that IP is a random variable following a uniform distribution between $[0, ROP]$ was performed. Hence, the expected value of IP in time $t = 1$ is given by the expected value of the uniform distribution as $E(IP_{i,k,t}) = \frac{ROP_{i,k,t}}{2}$.

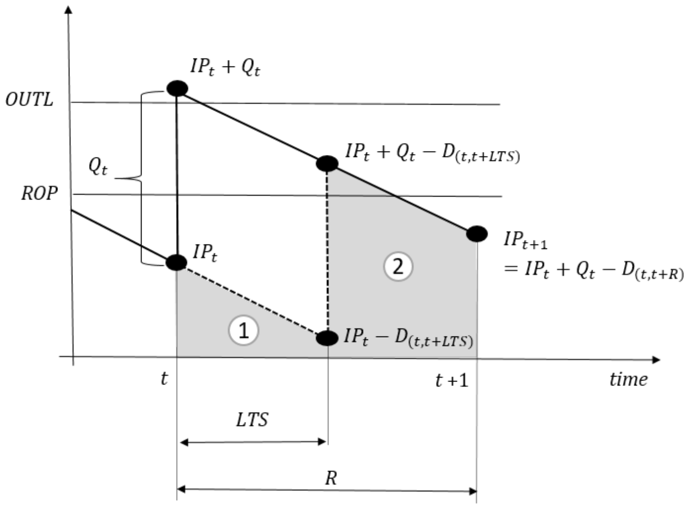


Figure 4.2: Store Inventory Cost Modeling

The expected inventory during the review period is given by the shadow areas in figure 4.2 and corresponds to the weighted sum of the average inventory in region 1 and 2 as shown in equation 4.12. This way both periods average inventory are weighted according to their length in the full inventory period.

$$E(\text{Store Inventory}_{i,k,t}) = \frac{1}{R} \times \left(\int Region1 + \int Region2 \right) \tag{4.12}$$

Using equation 4.12, the expected on-hand inventory at store can be computed as seen in equation 4.13 (see the appendix A for the full demonstration). In situations of review period equals to the lead time, the store expected inventory is equal to the initial inventory position minus half the demand during lead time (or review time as they are coincident).

$$E(\text{Store Inventory}_{i,k,t}) = IP_{i,k,t} + \frac{R-LTS}{R} \cdot (Q^{sp}_{i,k,t} - \frac{D_{t,t+R}}{2}) - \frac{D_{t,t+LTS}}{2} \tag{4.13}$$

The total inventory cost can be computed as the sum of the average inventory per store i, figured out in equation 4.13, for all of the considered stores. This is then multiplied by the inventory carrying cost and the unit cost of SKU k in the given period of $Nweeks$ as seen in equation 4.14.

$$\text{Store Inventory Cost}_k = ICC_{stores} \times C_k \times \sum_{i=1}^{Nstores} \frac{\sum_{t=1}^{Nweeks} E(\text{Store Inventory}_{i,k,t})}{Nweeks} \tag{4.14}$$

As the inventory position formula is expressed in function of terms from previous order, the methodology to compute the store inventory cost has to be made following a recursive approach, which means the calculation of each average inventory per store i and week t following the order of each period.

Extra Handling Cost

When an order of SKU k is received at the store i from the DC and the free space on the shelf for this SKU is not enough to fit all the received units, then an extra handling cost has incurred. This cost is associated with the process of storing the extra units in the backroom and, at a later time, with their retrieve and replacement onto the shelf.

Inventory position immediately after lead time from stores is given by $IP_{i,k,t+LTS}$ and represents the inventory position after the order of $Q_{i,k,t}$ units is received at store i at time $t+LTS$. Presentation stock is given by $PS_{i,k,t}$ and it exhibits the maximum number of units of SKU k that the shelf space allocated for SKU k in store i in week t can hold. The expected extra units in week t is then disposed by the difference between the inventory position after receiving the order at store and the presentation stock as seen in equation 4.15.

$$E(\text{ExtraUnits}_{i,k,t}) = Max(0, IP_{i,k,t+LTS} - PS_{i,k,t}) \times NrO_{i,k,t} \tag{4.15}$$

The total extra handling cost is given by the sum of all the extra units in the considered periods and stores multiplied by the unit extra handling cost as seen in equation 4.16.

$$E(\text{Store Extra Handling Cost})_k = extraHC_{sp} \times \sum_{i=1}^{Nstores} \sum_{t=1}^{Nweeks} E(ExtraUnits_{i,k,t}) \tag{4.16}$$

Shrinkage Cost

The shrinkage cost includes the cost associated with spoiled products that have past their sell-by or expiration dates as well as the loss of revenue due to price markdowns. It was not included any other shrinkage components such as theft and damage of products.

The retailer's policy for dealing with shrinkage sets several parameters for each SKU. The policy includes if they can or cannot be markdown, the allowed maximum number of days before its expiration date to markdown ($Mdate_k$) and the minimum number of days before expiration date to remove the product from shelf ($Rdate_k$). It is known for each SKU k its average shelf life at store ($Edate_k$). Starting from the expiration date of the SKU, the latest date to remove the product from the shelf and the earliest date from which the price of the product can be markdown are set in figure 4.3.

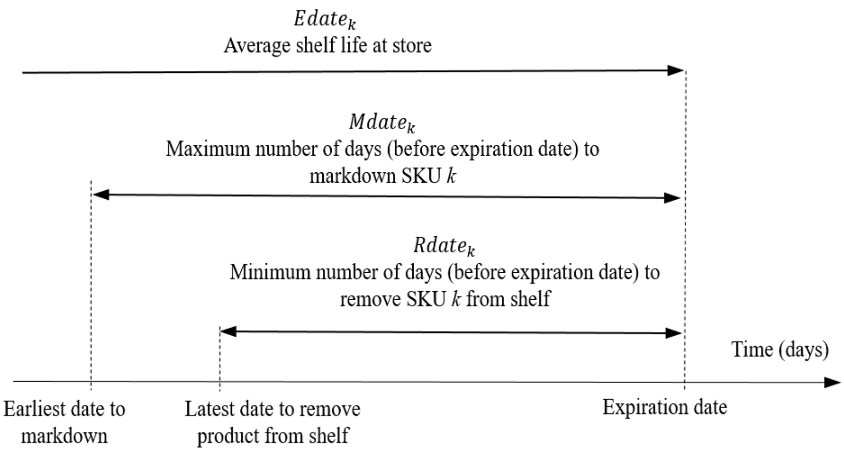


Figure 4.3: Shrinkage Parameters

The coverage days of the order quantity $Q^{sp}_{i,k,t}$ (in days) are given by equation 4.17. This represents the average number of days products last in inventory before being sold.

$$CDays_{i,k,t} = \frac{Q^{sp}_{i,k,t}}{d_{i,k,t}} \times 7 \tag{4.17}$$

The number of markdown units $NrMD_{i,k,t}$ and the number of units that exceed their expiration dates $NrED_{i,k,t}$ of SKU k in store i in week t can be computed using the procedure in equations 4.18 and 4.19.

The equation 4.18 calculates the number of units due to spoilage. This value is zero when the coverage days do not surpass the date to remove the product from shelf. When this condition is not satisfied, the number of units due to spoilage is given by the average daily demand in the remaining days after the expiration date.

$$NrED_{i,k,t} = \begin{cases} 0, & \text{if } CDays_{i,k,t} \leq Edate_k - Rdate_k \\ (Cdays_{i,k,t} - (Edate_k - Rdate_k)) \times \frac{d_{i,k,t}}{7}, & \text{if } CDays_{i,k,t} > Edate_k - Rdate_k \end{cases} \tag{4.18}$$

The equation 4.19 reflects the units being markdown and it follows a similar logic as the spoilage expressions. The number of units being markdown is zero when the coverage days do not surpass the difference between expiration and markdown dates. The units are positive when the coverage days surpass either a few days or the maximum number of days as seen in equation 4.19. Then the number of units is also calculated multiplying the days being markdown by the average daily demand.

$$NrMD_{i,k,t} = \begin{cases} 0, & \text{if } CDays_{i,k,t} \leq Edate_k - Mdate_k \\ (Cdays_{i,k,t} - (Edate_k - Mdate_k)) \times \frac{d_{i,k,t}}{7}, & \text{if } CDays_{i,k,t} \leq Edate_k - Rdate_k \\ (Mdate_k - Rdate_k) \times \frac{d_{i,k,t}}{7}, & \text{if } CDays_{i,k,t} > Edate_k - Mdate_k \end{cases} \tag{4.19}$$

The shrinkage cost for SKU k in store i in week t is given by equation 4.20 as the sum of the cost of the units due to spoilage and markdown. The spoilage cost is given in function of the product's cost and the markdown in function of a depreciation rate over the selling price. The product's cost is considered to be the same for the entire company, but the selling price is in function of the store.

$$\text{Shrinkage Cost}_k = \sum_{i=1}^{Nstores} \sum_{t=1}^{Nweeks} \left[C_k \times NrED_{i,k,t} + P_{i,k} \times DR_k \times NrMD_{i,k,t} \right] \tag{4.20}$$

Provision Cost

The use of provision cost is an internal procedure of the studied retailer company only for non food products and follows a logic of penalizing long standing stock both at warehouses and stores. The provision cost is given by a provision rate over the total average stock of the product both at the distribution centers and stores. This is then multiplied by the cost of the product as seen in equation 4.21.

$$\text{Provision Cost}_k = ProvisionRate_k \times C_k \times Stock_{DCs+Stores} \tag{4.21}$$

The $ProvisionRate_k$ is given by the ratio of the annual demand of the product and the average of the total stock in one year. As seen in formulation 4.22, the penalization is higher when the stock is much higher than sales. This penalization as seen from the ratio between annual demand and stock only occurs in products leading with long standing stocks. On the other hand, in fast movers products, the provision cost will be zero because annual demand will be much higher than the average stock. Figuring out this formulation, it is quite observable that only products with residual sales' values or with higher stocks will have this cost component.

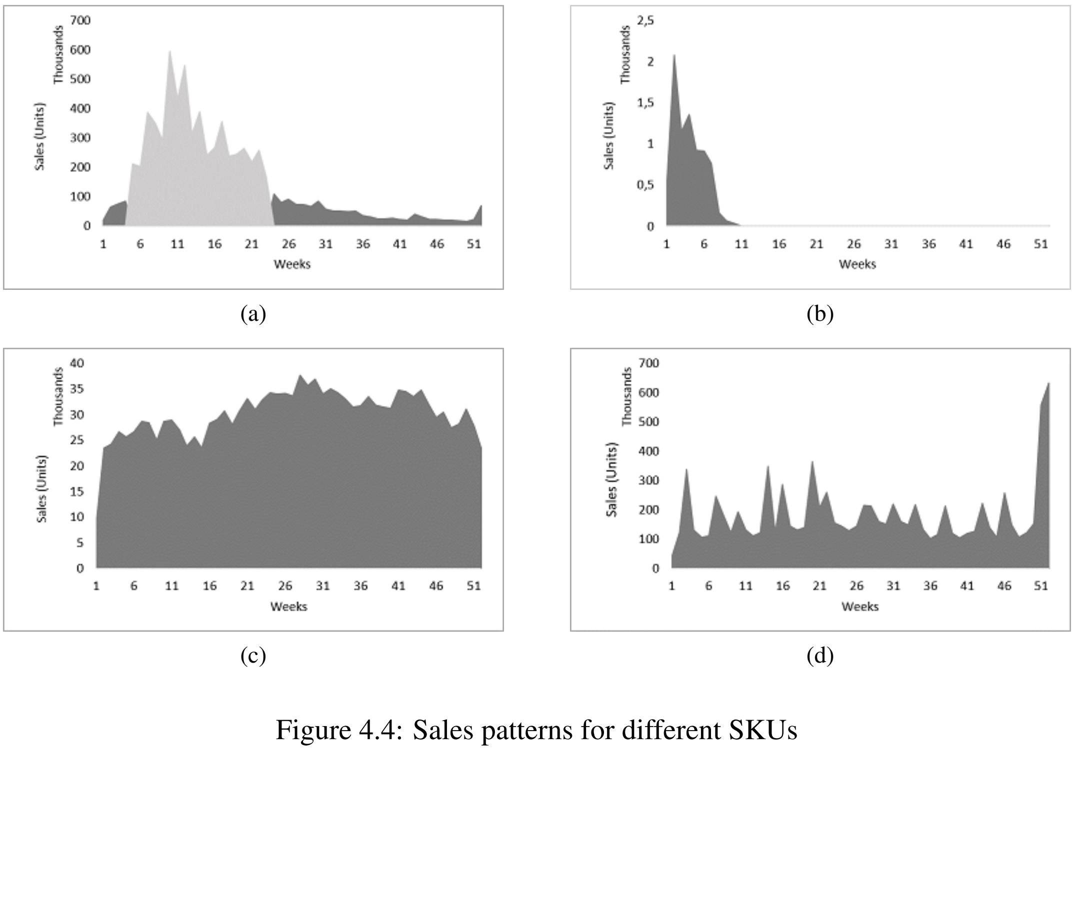
$$ProvisionRate_k = \begin{cases} 0.9, & \text{if } \frac{AnnualDemand}{Stock_{DCs+Stores}} \leq 0.1 \\ 0.6, & \text{if } 0.1 < \frac{AnnualDemand}{Stock_{DCs+Stores}} \leq 0.5 \\ 0.25, & \text{if } 0.5 < \frac{AnnualDemand}{Stock_{DCs+Stores}} < 1 \\ 0, & otherwise \end{cases} \tag{4.22}$$

4.2 Seasonality Identification

There is no methodology to identify the period of intense sales in an automatic way with only one year of sales history. A brand-new methodology was conceived and then incorporated in the Ship Pack optimization problem.

The goal is to identify demand periods such as the ones in figure 4.4a meaning a long duration of intensive sales above the average of regular weeks. Then within the identified period, the Ship Pack will be different in order to suit better the demand period in detriment of having a single shipping unit for the entire year.

Products having sales patterns as the one in figure 4.4b, in which there is only one period of sales should be rejected by the developed methodology as it does not justify having two Ship Packs in this period as mentioned in chapter 2. Situation, in figure 4.4c, having demand with very low variability and the SKU, in figure 4.4d, with occasional demand peaks (due to promotions or other factors) should also be despised as it does not justify the implementation of a different Ship Pack only for a short period of time.



(a) (b) (c) (d)

Figure 4.4: Sales patterns for different SKUs

The first step of the developed methodology is to aggregate demand in a weekly basis as the desired granularity is to identify weeks of strong sales as the Ship Pack will only change in this identified range of weeks. This will be given by $D_{k,t}$ representing demand for each SKU k aggregated in a weekly basis t.

The demand value for each week t will be then compared with ST_k representing the seasonality threshold for each SKU k. When demand value in week t is greater than the seasonality threshold, the week t will be considered as having a demand peak. Low variability time series of the aggregated weekly demand need to be discarded in an automatic way from this analysis. Hence, the coefficient of variance for each SKU k, given by $CV_k = \frac{\sigma}{\mu}$, was used to exclude the SKUs with steady sales pattern as seen in figure 4.4c. Therefore, the seasonality threshold is given by equation 4.23.

$$ST_k = \frac{\mu}{min[1, CV_k]} \tag{4.23}$$

This formulation allows SKUs with low coefficient of variance to have greater seasonality thresholds and despise situations such as figure 4.4c, in which demand in week t will be, for all of the weeks, lesser than the seasonality threshold. Thus, for the compared weeks it will be given the value 0 when demand t is lesser than ST_k and in the opposite situation when demand t is larger than the seasonality index, it will be given the value 1. Therefore, the seasonality binary factor $(s_{k,t})$ for each SKU k in period t is given by the formulation in equation 4.24.

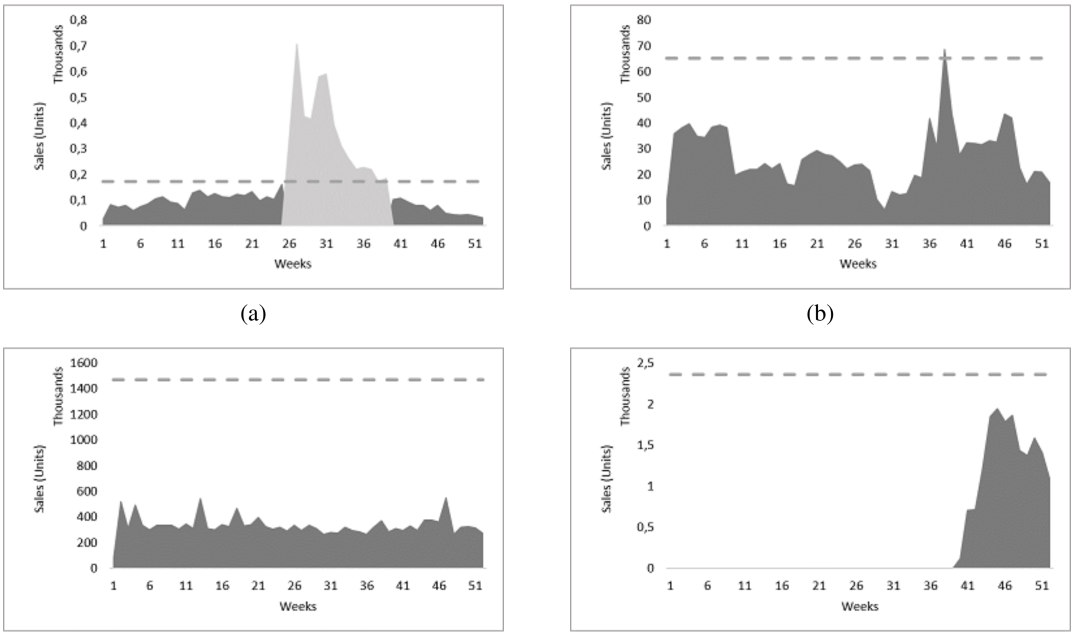
$$s_{k,t} = \begin{cases} 1, & \text{if } D_{k,t} \geq ST_k \\ 0, & \text{if } D_{k,t} < ST_k \end{cases} \tag{4.24}$$

Using this formula for each week of the SKU k, the outcome will be a sequence of binary values where the goal is to identify the largest sequence of "one" values and consider the limits of the identified range as the seasonal period. This is denoted as the maximum length of the seasonal sequence (θ) and it is calculated by the maximum sum of the consecutive intervals of $s_{k,t} = 1$. This will be then compared with a threshold (α) representing the minimum number of weeks desired to be considered as seasonal for each SKU k. If the consecutive identified periods surpass the given threshold, the product will be considered as seasonal. This formulation is postulated in equation 4.25.

$$\Phi_k = \begin{cases} 1, & \text{if } \theta_k \geq \alpha \\ 0, & \text{if } \theta_k < \alpha \end{cases} \tag{4.25}$$

As the threshold increases, the number of products considered as seasonal, $\Phi = 1$, will diminish. A threshold of 5 weeks was determined to be a balanced value as if more than 5 weeks are identified as seasonal, the Ship Pack may only change for this period.

In figure 4.5 several examples with ST_k line dashed as the seasonal threshold can be found. In situation 4.5a, the coefficient of variance does not change the seasonal threshold leading to the identification of the seasonal periods as the consecutive points above ST_k. In the remaining examples 4.5b, 4.5c and 4.5d the coefficient of variance changes ST_k leading to an increase in the threshold and, consequently, to the exclusion of steady demand patterns.



(a) (b) (c) (d)

Figure 4.5: Seasonality identification for different SKUs

4.3 Stores Clustering

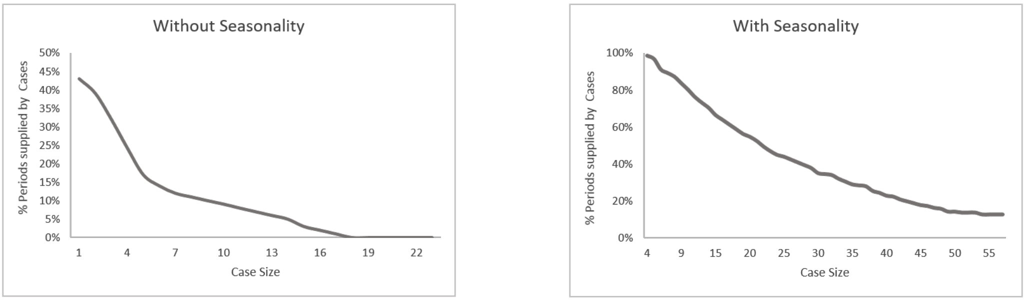
In order to take advantage of an already larger Ship Pack such as the case, the stores with larger sales' volume had to be identified. The outcome of this methodology is to identify two groups of stores: (1) stores to be supplied by the case and (2) stores to be supplied by the inner. The first step is to calculate the average number of boxes supplied by week to store i having a case as a Ship Pack quantity as seen in equation 4.26.

$$\mu Boxes_{i,k} = \frac{1}{Nweeks} \times \sum_{t=1}^{Nweeks} \lceil \frac{d_{i,k,t}}{SPQ_{i,k,t}^{case}} \rceil \tag{4.26}$$

Then the stores being supplied by a certain threshold ($\theta_{Cluster}$) of cases will be considered to be supplied with cases. The stores within this range will be included in the group of stores to be supplied by the case and the stores not within the range by the inner as seen in equation 4.27 in which the Ship Pack quantity for all the stores is assigned.

$$SQP_{i,k} = \begin{cases} Cases, & \text{if } \mu Boxes_{i,k} \geq \theta_{Cluster} \\ Inners, & \text{if } \mu Boxes_{i,k} < \theta_{Cluster} \end{cases} \tag{4.27}$$

As seen in figure 4.6 the number of periods supplied by cases is decreasing with larger cases as in average the order size from stores will be less than two cases per week. This was used as the cluster threshold, $\theta_{Cluster}$, providing satisfactory results. In figure 4.6a when the Ship Pack is too large, the number of periods supplied with cases tends to zero as values are below the threshold. In figure 4.6b, the line tends to a fixed value as there is a seasonality period and all the stores will be supplied by cases within this period. Furthermore, cases will be sent to stores with higher sales' volumes as well as within the seasonality periods. This methodology, instead of a common k-means algorithm, was used due to the lack of clusters desired to be considered (only two). With additional clusters and complexity, the k-means algorithm might work better and its consideration should not be despised.



(a) (b)

Figure 4.6: Percentage of periods supplied by Cases

4.4 Ship Pack Optimization

In order to solve the Ship Pack definition, a properly formulation of all the models considering the developed cost modeling needs to be tackled. Hence, it is necessary to formulate four models with different approaches as seen in figure 4.7.

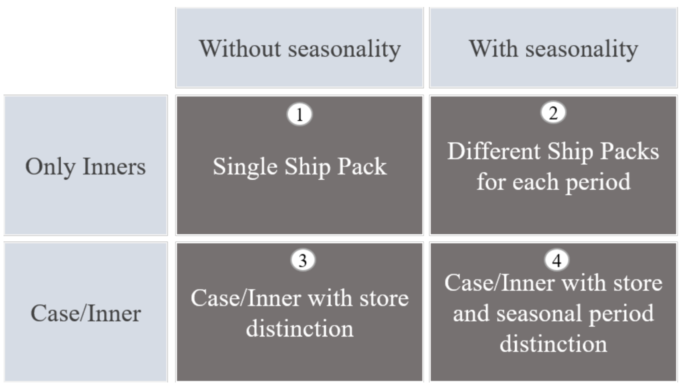


Figure 4.7: Ship Pack optimization matrix

Model 1 pacts with products not dealing with seasonality neither case/inners. This implies only one Ship Pack optimization. Model 2 deals with products having a seasonal period leading to a Ship Pack for the regular period and a different one for the seasonal period. Model 3 and 4 are rather similar and deal with products in which the shipping to DC is performed with cases and inners. Cases are multiples of the inners and, in the current situation, only inners are sent to stores. In order to deal with this enforcement by the suppliers, it was decided to optimize both cases and inners where the larger Ship Pack (case) is sent during the seasonal period or to stores having an higher sales' volume and the smaller Ship Pack in the remaining situations.

It is important to denote that not every model will be used for each SKU. The first step is to identify whether or not the product deals with cases/inners and then identify the seasonal period. Considering this, the right models will be chosen.

The total cost function for a given period of time for each SKU k is given by the equation 4.28 and the optimal Ship Pack can be found by the minimization of the function cost. Not all the costs will be calculated for every SKU as seen in table 2.1 from Chapter 2. Therefore, a binary value identifying whether or not the cost is calculated for the SKU is attached to every cost.

$$\begin{aligned}\textbf{Minimize } \text{Total Cost}_k(SPQ) = b1\cdot\text{Processing}_k + b2\cdot\text{Picking}_k + b3\cdot\text{DC SS Inventory}_k \\ +b4\cdot\text{Transportation}_k + b5\cdot\text{Store Inventory}_k + b5\cdot\text{Shrinkage}_k + b6\cdot\text{Provision}_k\end{aligned} \tag{4.28}$$

For seasonal products, the cost function is rather similar but calculated in order to two Ship Packs, $TotalCost_k(SPQ^{regular}, SPQ^{seasonal})$ and the total number of boxes is calculated according to the conditions in equation 4.29.

$$n^{sp}_{i,k,t} = \begin{cases} \lceil \frac{OUTL_{i,k,t} - IP_{i,k,t}}{SPQ^{regular}_{k,i,t}} \rceil, \text{if } t \notin \left[t_{SeasonalBegin,SeasonalEnd}\right] \\ \lceil \frac{OUTL_{i,k,t} - IP_{i,k,t}}{SPQ^{seasonal}_{i,k,t}} \rceil, \text{if } t \in \left[t_{SeasonalBegin,Seasonal_End}\right] \end{cases} \tag{4.29}$$

For products where the shipping is made using cases or inners, the cost function is given by $TotalCost_k(SPQ^{inner}, SPQ^{case})$. In this formulation, cases are sent in the seasonal periods or to stores with higher sales' volume and inners in the remaining situations where it is not necessary to have a larger Ship Pack. The total number of ordered boxes is given by equation 4.30.

$$n^{sp}_{i,k,t} = \begin{cases} \lceil \frac{OUTL_{i,k,t} - IP_{i,k,t}}{SPQ^{Inner}_{i,k,t}} \rceil, \text{if } t \notin \left[t_{SeasonalBegin,SeasonalEnd}\right] \wedge Store_i = Inner \\ \lceil \frac{OUTL_{i,k,t} - IP_{i,k,t}}{SPQ^{Case}_{i,k,t}} \rceil, \text{if } t \in \left[t_{SeasonalBegin,Seasonal_End}\right] \vee Store_i = Case \end{cases} \tag{4.30}$$

Having formulated the dissimilarities between the stated models, the optimization problem arises and the methodology to choose the optimal Ship Pack needs to be addressed. Several SKUs are going to be tackled from this methodology and, in spite of, not totally independent among them, each SKU can be considered as an individual optimization problem.

Ideally, the optimum Ship Pack can be achieved as the minimum of the total cost function within the solution space. The Ship Pack quantity can only takes integer values and its upper bound is limited to the maximum weight and dimensions that can be picked at distribution centers.

Therefore, the solution space range is limited between 1 and $SPQ_{Maximum}$. The cost function deals with several costs with different trends in which some costs decrease with larger Ship Packs, such as picking, or increase with larger Ship Packs, such as shrinkage. In addition, some products have their Ship Pack defined in units and others, such as fish or fruit, in weighting units, but only integer values are considered.

In order to solve this problem an iteration within the solution space is made and the cost function is developed to find the minimum cost and, consequently, the optimum Ship Pack. It was chosen to solve it iteratively as the solution space is quite restrict and the time to solve it is acceptable.

The developed algorithm can be understood in algorithm 1 in which the first step is to collect all the information from the corresponding SKU by reading the database provided by the retailer. Then within a cycle starting in $SPQ = 1$ and finishing in its maximum, $SPQ = maximum$, all the costs components are calculated and the minimum cost value is found making this as the optimal Ship Pack quantity. Every cost component is estimated for every week of every store and then sum up in total cost function.

Data: Read all the information about the SKU
Result: Optimum Ship Pack
for $i \leftarrow 1$ **to** $SPQ_{maximum}$ **do**
    calculate $cost(SPQ_i)$;
    if $cost(SPQ_i) < bestCost$ **then**
        $otimum_{SPQ} = i$;
        $best_{Cost} = cost(SPQ_i)$;
    end
end

Algorithm 1: Algorithm of the Ship Pack Optimization - Model 1

Model 2 encompasses a similar approach. However, in this situation two loops are performed in order to include the seasonal Ship Pack as seen in algorithm 2. Every cost component is calculated by choosing the right Ship Pack quantity according with the regular or seasonal period.

Data: Read all the information about the SKU
Result: Optimum regular and seasonal Ship Pack
for $SPQ^{seasonal} \leftarrow 1$ **to** $SPQ^{maximum}$ **do**
    for $SPQ^{regular} \leftarrow 1$ **to** $SPQ^{seasonal}$ **do**
        calculate $cost(SPQ^{regular}, SPQ^{seasonal})$;
        if $cost(SPQ^{regular}, SPQ^{seasonal}) < best_{Cost}$ **then**
            $otimum_{SPQ^{regular}} = SPQ^{regular}$;
            $otimum_{SPQ^{seasonal}} = SPQ^{seasonal}$;
            $best_{Cost} = cost(SPQ^{regular}, SPQ^{seasonal})$;
        end
    end
end

Algorithm 2: Algorithm of the Ship Pack Optimization - Model 2

Model 3 and 4 encompasses a similar approach as Model 2 with the only difference being the fact the case has to be a multiple of the inner as seen in algorithm 3.

Data: Read all the information about the SKU
Result: Optimum case and inner Ship Pack
for $SPQ^{case} \leftarrow 1$ **to** $SPQ_{maximum}$ **do**
    for $SPQ^{inner} \leftarrow 1$ **to** SPQ^{case} **do**
        if *case* ***mod*** *inner = 0* **then**
            calculate $cost(SPQ^{inner}, SPQ^{case})$;
            if $cost(SPQ^{inner}, SPQ^{case}) < bestCost$ **then**
                $otimum_{SPQ^{inner}} = SPQ^{inner}$;
                $otimum_{SPQ^{case}} = SPQ^{case}$;
                $best_{Cost} = cost(SPQ^{inner}, SPQ^{case})$;
            end
        end
    end
end

Algorithm 3: Algorithm of the Ship Pack Optimization - Model 3/4

Chapter 5

A Case Study in a Retailer Company

The present chapter intends to present the results of the developed methodology in the case of the studied retailer company. In section 5.1, the outcomes of each cost component modeling are presented and discussed. In section 5.2, the results of some products in which Ship Pack changes, in comparison with the current situation, are showed for all the developed optimization models. In section 5.3, the global results for each studied department of the retailer are stated and discussed as well as some additional research in order to redefine Ship Packs for new products.

5.1 Cost Modeling Results

The current section shows examples of several cost components curves for some SKUs in order to the Ship Pack quantity based on the developed cost modeling in chapter 4. All the costs' parameters in table 4.1 from chapter 4 were given by the retailer with the exception of the extra handling cost ($extraHC$) as this operation has not been costed. However, the importance of this cost was addressed and a sensitivity analysis was performed in order to study the impact of it. In addition, the fixed order cost in spite of being formulated in chapter 4 does not affect the studied company as the retailer does not consider any cost when ordering. Therefore, this cost was excluded from the following analysis.

Distribution Center

The distribution center deals with several cost components such as processing, safety stock and picking having each one distinctive fluctuations according to the Ship Pack quantity.

In figure 5.1, the cost function for the processing cost is plotted for a single SKU. The cost is extraordinarily high with low values of Ship Pack quantities as ordered boxes will only contain one unit of the product. Therefore, the processing cost will decrease as less boxes are processed. This cost was only considered for fish, meat and bread products of the fresh department and only for international suppliers of the noon food department as it is stated in chapter 2. In addition, there is a limit situation in which the cost will tend to a constant value when reaching an high value of a Ship Pack quantity. This happens because the ordered boxes will always be one box as this quantity surpasses the expected demand for the entire period. Consequently, the cost will stabilize even though the Ship Pack is increasing.

Only products in which the warehouse flow type is PBS deal with safety stock. For the remaining products dealing with PBL flowtypes, the safety stock is null as seen in chapter 2. In figure 5.2, the variation of the safety stock cost in distribution center is plotted in function of the Ship Pack quantity and it shows that safety stock in distribution center increases with larger Ship Packs as the orders from stores tend to be larger. The cost is also higher with larger lead times as variability uncertainty during demand increases with larger lead times as seen in equation 4.9. It is important to denote that this cost is in function of the product's cost and, consequently, it is also higher when products value more.

In figure 5.3, the picking cost is showed and it follows a very identical outcome as the processing cost. Although the picking cost is related with the distribution center of the corresponding store, the cost of each one does not fluctuate significantly within the given DCs as costs are quite similar. For the studied retailer company, the picking cost for a single Ship Pack is higher than the processing cost and, consequently, the magnitude of this cost is higher.

Transportation

Transportation cost is a very particular cost and the outcome analysis changes slightly from the remaining costs. This can be seen in figure 5.4. As expected, the cost decreases with larger Ship Packs as less pallets are carried due to a better accommodation of the selected box.

However, there are some occasional bumps when Ship Pack changes making the cost higher. This is explained in the situations in which Ship Pack is larger than the box being used so far. When this happens it is necessary to move to a larger box that can accommodate the new Ship Pack quantity. If the bigger box does not have a better utilization's ratio, the cost will go higher as more pallets will be shipped due to the reducer capacity's utilization. It is also important to denote that the Ship Pack quantity equals to 19 is the last possible value to calculate the transportation cost. This is the point in which for all of the given boxes, the Ship Pack weight or volume do not fit into the box, making it impossible to consider the transportation cost and turning the Ship Pack quantity of 19 as the maximum value to consider in the total cost analysis. In addition, whenever defining the optimum Ship Pack for products in which the transportation cost can be obtained, the most appropriate box is also indicated.

Store

The costs' components affecting stores such as store inventory, markdown, spoilage and extra handling cost change differently according to the Ship Pack quantity. These costs were calculated apart for each store and them sum up to give the total cost component for each SKU.

In figure 5.5, the average inventory in stores is plotted. In the studied retailer company, the lead time is considered to be equal to the review time and overlapping orders are not allowed. The

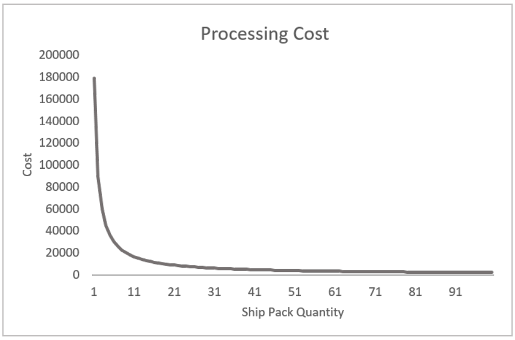


Figure 5.1: Processing Cost

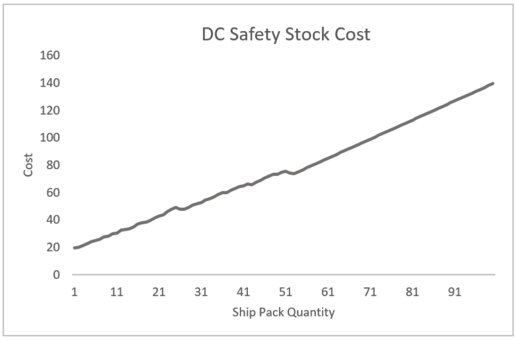


Figure 5.2: DC Safety Stock Cost

Figure 5.3: Picking Cost

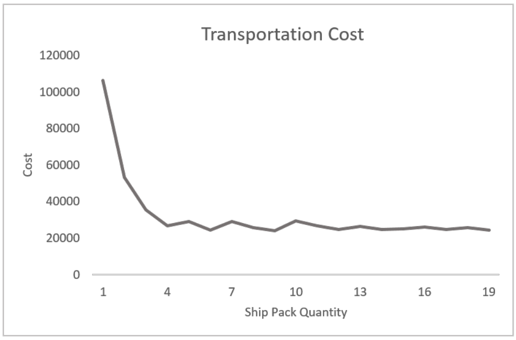


Figure 5.4: Transportation Cost

Figure 5.5: Store Inventory Cost

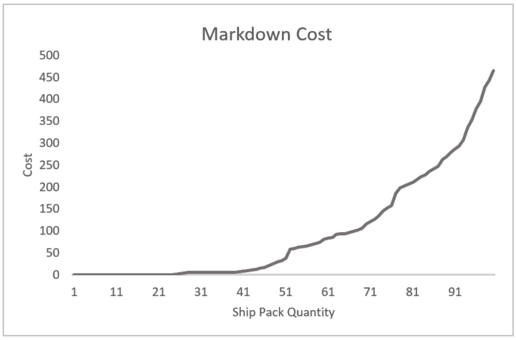


Figure 5.6: Markdown Cost

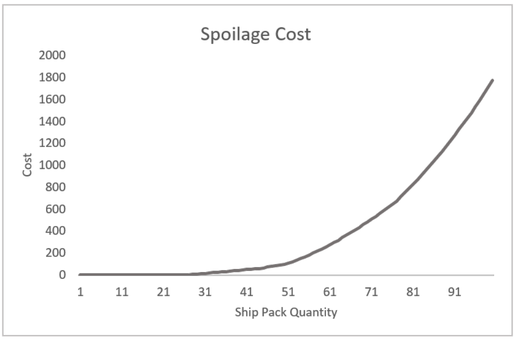


Figure 5.7: Spoilage Cost

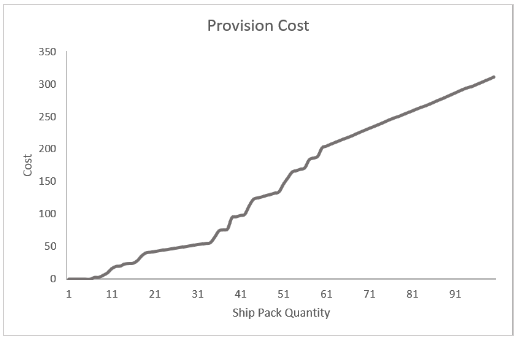


Figure 5.8: Provision Cost

lead time to stores was computed as an approximation of the total number of deliveries to the given store per week and then divided by the number of days in one week.

The trend of the developed function is positive as larger Ship Packs tend to increase the stock in stores. This is explained because an order up to level, minus the inventory position of 1 unit, when the Ship Pack quantity is 10, leads to an extra stock as the order from the store has to be one Ship Pack (10 units) and, consequently, the extra stock will be 9 units. This rounding effect have more consequences, turning the cost component function into a non linear expression.

Let's compare two situations in which the order up to level minus the inventory position from the considered store is 10 units and Ship Pack is 9 and 10 units, respectively. In the first example, the order from store has to be two Ship Packs (18 units) leading to an extra stock of 8 units during that period. On the other hand, in the second example the order from store is one Ship Pack leading to a perfect match between the expected demand and the Ship Pack quantity. This leads to a lesser average inventory during that period. This concludes that not in every situations of larger Ship Packs, the average inventory will increase. This particularities turn this cost component into a function of several bumps as seen in figure 5.5.

The markdown function cost is plotted in figure 5.6. When Ship Pack quantities are small, there is no cost related with markdowns as no units enter the markdown zone and there is no reduction in price. As Ship Pack increases, the coverage days will surpass the markdown zone and some units will suffer a reduction in price and, consequently, in the closing margin. The bumps in the figure are also explained in a similar way as the inventory rounding orders.

The spoilage cost is plotted in figure 5.7. This cost component follows a similar logic as the markdown cost. With small values of Ship Pack quantities there are zero units exceeding the expiration date. However, as the coverage days tend to increase with larger Ship Packs, there is a certain Ship Pack quantity in which the spoilage cost starts to exist due to the ordered units surpassing the expiration date. Therefore, for the given SKU, the spoilage cost increases with a larger Ship Pack.

The provision cost is plotted in figure 5.8. As seen in the corresponding cost modeling, not all the products will be considered provisioned. Only products having long standing stocks, both at warehouses and stores, will incur into this cost. The cost tends to increase with larger Ship Pack quantities as it is intrinsically correlated with stock variations. Therefore, also some bumps appear in the provision function. When there is an higher variation, it means the provision rate changed to another level, as seen in equation, 4.22 meaning an higher penalization of stock.

5.2 Ship Pack Optimization Results

In this section, some examples of the obtained results are shown. The total cost of a SKU is given by the sum of all the formulated cost components. This might result in two situations as seen in figures 5.9 and 5.10. In the first one, the minimum cost decreases until a certain value and then it starts to increase. Therefore, within the solution space, the optimum Ship Pack quantity is easily found as the minimum value of the function. On the other hand, in the second situation, the cost function decreases until it reaches the maximum Ship Pack value, but the degree of decrease in the last values is relatively slow. Therefore, in order to do not suggest abrupt Ship Pack changes, it was decided to not suggest the optimal Ship Packs, but a closer one to the current and within a tolerance from the optimal cost.

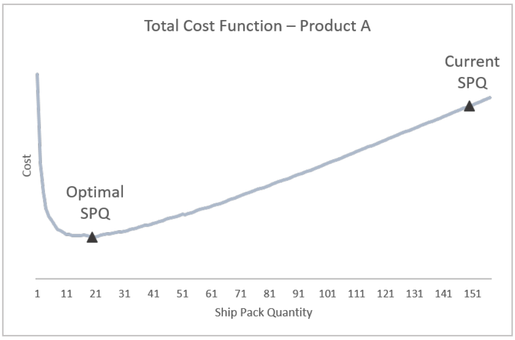


Figure 5.9: Total Cost Function 1

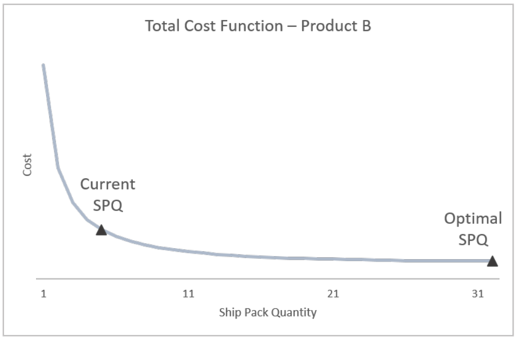


Figure 5.10: Total Cost Function 2

In figure 5.11, it is presented a product in which the optimal Ship Pack reduces when comparing to the current situation. It is clear that the main cost drivers are picking and store inventory and the optimal cost is given when these two intersects. This optimal definition led to a cost reduction of 40% in the annual costs. On the other hand, there are some results, such as figure 5.12 in which the optimal quantity suggests an increase in the Ship Pack quantity. In this situation, there is not a cost intersection as before and the optimum is given by the maximum Ship Pack quantity. The main drivers contributing for the total costs are picking and processing. This change in the Ship Pack quantity led to a cost reduction of 15% in the total annual costs.

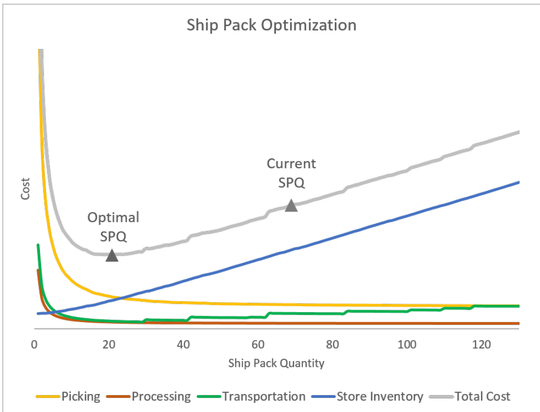


Figure 5.11: Product A - Optimization Result

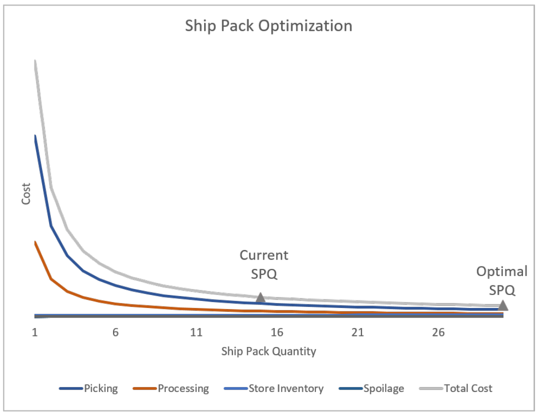


Figure 5.12: Product B - Optimization Result

Seasonality Optimization

Implementing different Ship Packs in the regular and seasonal periods provides satisfactory results. The obtained results were compared to the optimum obtained from the single optimization model. The considered product is not a perishable product, does not have processing costs, does not use standard's boxes and is not provisioned. Therefore, only the presented costs were considered in the optimization process. In figure 5.13, the sales' profile is shown as well as the intense period of sales that was identified. The optimization model with one Ship Pack recommends a quantity of 28. However, in the the seasonal model the optimum quantity is given by a quantity of 10 in the regular period and 28 in the seasonal. This model as shown in 5.14 leads to an increase in picking because Ship Pack quantities are smaller during the regular period. On the other hand, there is a reduction in the DC safety stock and in the average inventory in stores. These reductions are enough to payoff the increase in picking and leads to an overall reduction of 5%.

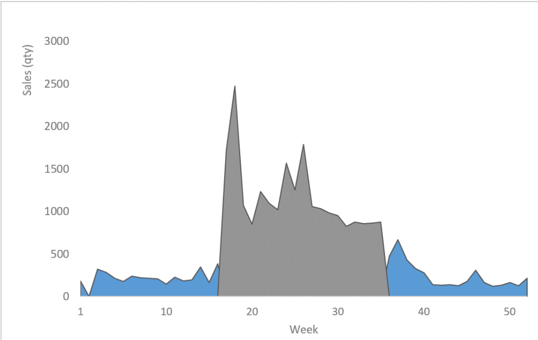


Figure 5.13: Seasonal product sales

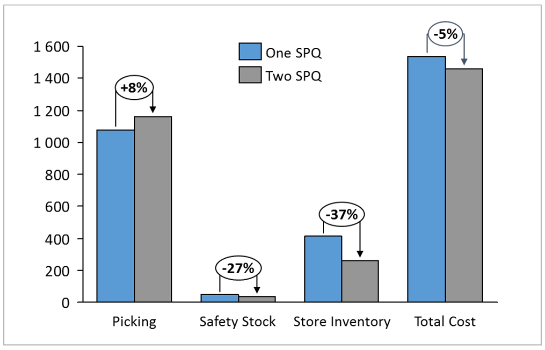


Figure 5.14: Seasonal Ship Pack Optimization

Cases/Inners Optimization

In a initial study, it was conceived that in some situations products might benefit from having cases and inners because cases could be sent to stores with larger sales and in the seasonal period. Therefore, the single optimization model and the case/inners model were run with the same products and compared against each other. The study concluded that the cost of dealing with two Ship Packs and open it when the product arrives into the warehouse (processing cost), turn this model worse than only having one Ship Pack model. Appendix B shows the results from this analysis.

However, in some situations, particularly, with international suppliers there is an enforcement to deliver like this as suppliers get advantages in transporting larger Ship Packs as less boxes are shipped. The product in 5.15 is not perishable and was not identified to have a provision cost component. The product is not seasonal and from the obtained optimization, 12% per cent of the stores are shipped with case and the remaining with inners. The product is shipped in a case containing 24 inners and each of them contains 12 units. This performs a total of 288 units shipped in each case. The proposed solution suggests a case of 3 inners containing 26 units each. This means that each case has a total of 78 units. Considering this recommendation, there is a cost reduction of 13%, mainly, in the store inventory cost as seen in figure 5.15. As there is an overall Ship Pack quantity reduction, the inventory at stores decreases and this reduction pays off the increase in the picking and processing cost components.

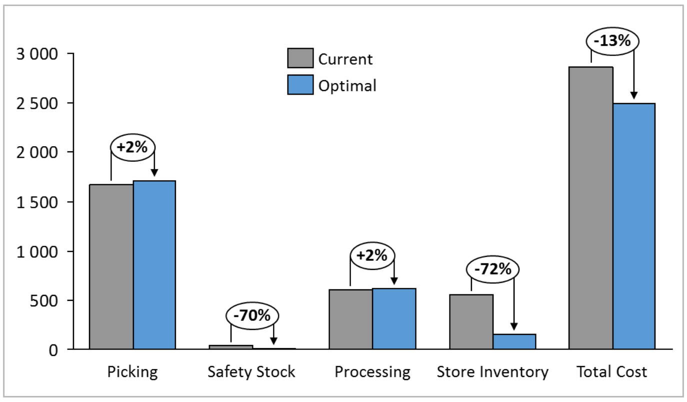


Figure 5.15: Ship Pack Optimization - Cases/Inners

Extra Handling Sensitivity Analysis

In figure 5.16, the extra handling cost in function of the Ship Pack is plotted for a single SKU. When replenishment store's order quantity exceeds the space in the shelf, the worker incurs into extra movements to replenish the product into the shelf. Therefore, larger Ship Packs lead to an extra handling cost. This cost is a particular one as it is not costed in the studied retailer company. Therefore, it was decided to leave it out of the final results until it is properly costed.

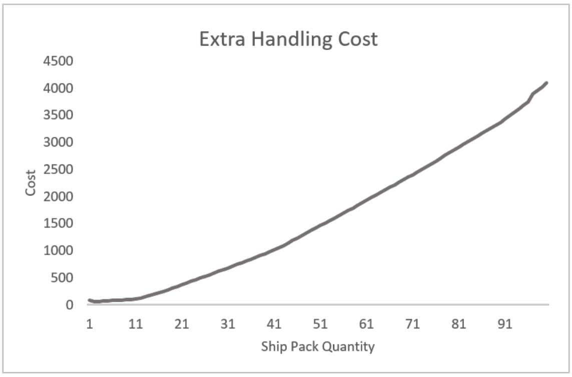


Figure 5.16: Extra Handling Cost

A sensitivity analysis was performed by estimating the impact it has on the total cost as well as changes in the Ship Packs quantities. In order to measure these variations, a representative sample from products representing the two departments of the retailer was contemplated and the single optimization model was run considering different extra handling costs as seen in figure 5.17. The results show that larger extra handling costs tend to push the average Ship Pack quantity down in order to reduce the extra movements workers have to perform to replenish the product into the stores' shelves. The figure shows that in the scenario with the lowest extra handling cost there is a difference of almost 7% in the average Ship Pack and in the upper bound the difference is 14%. Therefore, these differences show that the cost might play a significant role in defining the right Ship Pack quantity. As the extra handling cost is giving per unit of the product, the retailer is quantifying this cost in order to include it in the final optimization model.

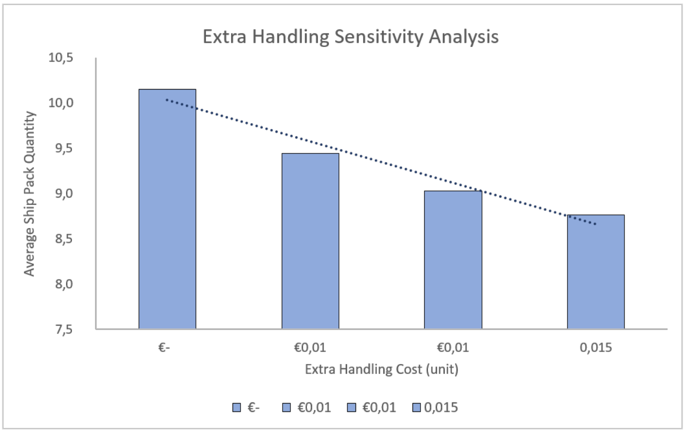


Figure 5.17: Extra Handling Cost Sensitivity

Pallets Optimization

As seen in figure 5.10, there are some situations in which the minimum cost is achieved by the maximum Ship Pack quantity. There are some products in which the warehouse's costs assign a significant portion of the total cost because with larger Ship Packs less boxes will be handled. In addition, the increase in the remaining costs is not enough to pay off the decrease in the handling costs. The retailer company proposed the change of not considering a box as the shipping unit, but half pallets in which the maximum weight and physical dimensions allow the use of larger Ship Pack quantities.

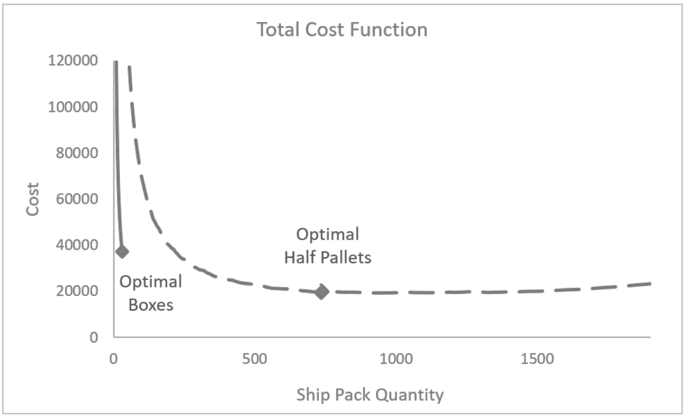


Figure 5.18: Ship Pack for Boxes and Pallets

The only modification in the half pallets' model is the smoothing of the maximum Ship Pack quantity (calculated by the pallet's dimensions) and the increase in the picking cost, which in the case of this retailer is about 5 times higher for pallets than boxes as the picking has to be performed with machines. In figure 5.18, the optimal Ship Pack quantity using boxes is the maximum allowed quantity the box supports.

When the Ship Pack is in boxes, the total cost compared with the use of half pallets is lesser. However, the cost function is decreasing until it reaches the maximum box's capacity. On the other hand, the use of half pallets allows to carry more units in spite of the higher picking cost and as the Ship Pack quantity is increasing, the total cost is decreasing until it reaches a value smaller than the boxes' model. Only for some products was this model tested, but as seen in figure 5.18, the results look promising as there is a considerable overall cost reduction when comparing the minimum cost of both models.

Suppliers Optimization

Some suppliers cannot afford having multiple packages due to limited packaging capacities. Therefore, for all of the supplied goods from these suppliers, only a Ship Pack can be chosen. In order to deal with this constraint, a bottom-up approach was considered by computing each individually cost for each SKU considering several Ship Pack quantities and, consequently, the global minimum for the supplier can be found. The goal is also to study the impact this constraint has for each SKU as seen in table 5.1 as the difference between the supplier optimum and the sum of each product optimum. In this situation, the supplier's optimum quantity is given by a Ship Pack of eleven units. There are two SKUs in which the optimum Ship Pack would have been a lower quantity and three products with higher Ship Packs. By having this constraint, the impact in the total cost is an increase of about 5%.

Table 5.1: Supplier Optimization

Cost	SKU					
SPQ	4558297	5662734	5414341	5662745	5648530	Total
1	5394	4175	6826	3408	1548	21350
2	2769	2381	3828	1983	910	11871
3	1895	1786	3125	1511	669	8986
4	1470	1490	2862	1269	566	7656
5	1211	1313	2584	1133	531	6772
6	1025	1189	2505	1044	517	6280
7	910	1104	2406	974	521	5914
8	817	1045	2421	918	516	5716
9	744	997	2327	893	542	5503
10	700	965	2341	858	563	5428
11	635	927	2353	838	591	5343
12	601	963	2377	866	614	5421
13	608	943	2375	854	664	5444
14	576	913	2400	827	712	5429
15	552	896	2427	813	751	5439
16	529	890	2457	804	788	5468
17	506	953	2475	869	858	5661
18	531	942	2635	862	929	5899
19	524	945	2657	856	1007	5989
20	509	942	2684	844	1085	6063

5.3 Global Results

Only products with at least one week of sales in the last 52 weeks were analyzed. The non food department has a bigger assortment than the fresh department, but the weight in the total sales' quantity is much lesser as seen in table 5.2. The remaining sales (65%) are related with the food department of the retailer, which is out of the scope of this project. The fresh department has less seasonal products and does not have situations in which the shipping is made with cases and inners as its suppliers do not deliver like this. The non food department has 11% of its products supplied with cases and inners and 7% of the total products, excluding seasonal cases and inners, being identified as seasonal.

Table 5.2: Products from each Department

	Fresh	**Non Food**
Normal	96%	82%
Seasonal	4%	7%
Cases/Inners	0%	11%
Total SKUs	**6.795**	**25.372**
Sales (Qty)	**29%**	**6%**

Single Optimization Model

The global results led to significant cost reductions in both departments. In table 5.3, the reductions of each cost component are showed as well as the weight each one has in the total reduction. The main savings in the fresh department are related with picking, followed in a less expressive way by processing and spoilage costs. These results mean that handling costs contribute to most of the savings leading to similar results as Van Zelst et al. (2009). Transportation has only a cost reduction of 4% as only in 7% of the products was possible to estimate the savings. As most of the products from the fresh department follow a PBL flow type, the safety stock cost component is almost insignificant. It is important to denote that a tolerance was given and insignificant cost reductions were not considered. Therefore, in figure 5.19, the number of units within a certain Ship Pack quantity's variation is shown and there are more products with Ship Pack quantities increasing. This is explained by the picking cost reduction as less boxes are being picked. On the other hand, the most severe changes are in the reduction of Ship Pack quantities as some products have oversized Ship Packs.

Table 5.3: Results from the Single Optimization Model

	Fresh		**Non Food**	
Cost	**Reduction**	**Weight**	**Reduction**	**Weight**
Processing	20%	10%	17%	2%
Safety Stock	2%	$\sim$ 0%	20%	2%
Picking	26%	75%	10%	51%
Transportation	4%	2%	0 %	0%
Store Inventory	1%	3%	24%	35%
Spoilage	1%	7%	67%	3%
Markdown	3%	3%	0%	0%
Provision	0%	0%	41%	7%
Total	**9%**	**100%**	**15%**	**100%**

Table 5.3 also shows the changes in the non food department with a different results' analysis. As seen in Chapter 2, in this department there is no markdown neither transportation cost.

Picking continues to be the cost in which the biggest reduction occurs, but in this situation the store inventory cost component also contributes to a significant portion of the total savings. This is explained as, in average, the cost of the products in the non food department is 120% higher than in the fresh department. The non food department also sells, in average, less units and has fewer perishable products than the fresh department. Therefore, the products stay in average larger times in warehouses and stores' backrooms with higher costs for the retailer. The provision cost also contributes to a significant reduction as this is intrinsically related with stocks. In this department, most of the products have a PBS flow type and lead time from suppliers is larger. Therefore, the safety stock has a larger weight in the final cost reduction than in the fresh department. Figure 5.20 shows that, in the non food department, most of the changes suggest a Ship Pack reduction contrary to the fresh department. In addition, almost half of the products do not change Ship Pack and only in a few there is a quantity's reduction.

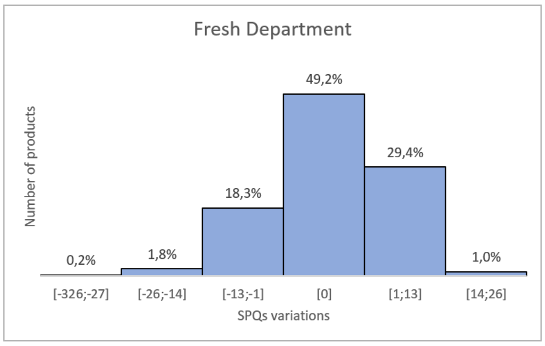


Figure 5.19: SPQs variations in the Fresh Department

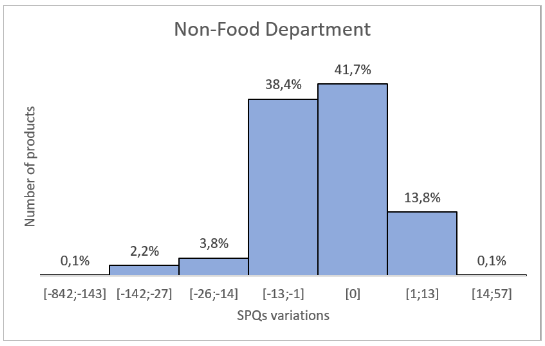


Figure 5.20: SPQs variations in the Non Food Department

Seasonality Optimization Model

The seasonality results were compared with the single optimization results. The results not leading to significant savings were excluded and the implementation of two Ship Packs in one year is not proposed.

In the fresh department, most of the savings are due to the picking cost component as the Ship Pack increases during the seasonal period leading to fewer picked boxes. This means that Ship Pack quantities are undersized in the seasonal period and oversized in the regular period as the inventory cost has also dropped and plays a more important role than in the previous model. The implementation of this model, with a previous seasonality identification, leads to a cost reduction of 3% when compared with the single optimization model. This reduction only concerns products in which seasonality was identified.

In the non food department, contrary results were obtained. There is an increment in the picking cost, which is atoned by the reduction in other costs such as processing, DC safety stock, spoilage and, above all, store inventory, which reduction is equal to the total savings. This is explained because Ship Packs in a single optimization are oversized in the regular period. A reduction in the regular period contributes to an important decrease in the average store inventory cost. As smaller Ship Packs are picked, the picking cost arises, but not enough to not compensate the reduction in the other costs. This model when comparing with the single optimization model brings additional savings of 3%.

Table 5.4: Results from the Seasonality vs Single Optimization models

	Fresh		Non Food	
Cost	**Reduction**	**Weight**	**Reduction**	**Weight**
Processing	5%	9%	3%	4%
Safety Stock	3%	3%	20%	7%
Picking	6%	63%	-1%	-15%
Transportation	1%	1%	0 %	0%
Store Inventory	9%	23%	18%	100%
Spoilage	1%	1%	15%	1%
Markdown	~0%	~0%	0%	0%
Provision	0%	0%	7%	3%
Total	**3%**	**100%**	**3%**	**100%**

Cases/Inners Optimization Model

Cases are exclusive of the non food department. An optimization of both, case and inners, at the same time provides compelling results. The average cases' size decreases 75% and the inners size 8%. The reduction in the cases' size turns the processing cost slightly more expensive as more boxes have to be opened and palletized. The reduction in the inners' size also makes the picking more expensive. When the Ship Pack quantity decreases, it is expected that more boxes are processed and picked.

In the developed model, cases are modeled to be used during demand peaks and in the stores with higher demand. Without this inclusion, the problem would be compared to a single optimization as only inners would be sent to stores and the cases would only interest in the processing cost. Its minimum cost would be achieved by the maximum case size as the processing cost is the only one influenced by the case.

Most of the savings are related with the reduction in the store inventory cost as seen in table 5.5. The provision cost also decreases significantly as this is intrinsically related with stocks. The safety stock in this model indicates a significant higher decrease when compared with the other two models as most of the products are from international suppliers. These suppliers have higher lead times and, consequently, lead to higher safety stocks. Furthermore, the overall cost reduction is 38% of the current cost. This reduction indicates that most of the products do not have a proper Ship Pack definition and for the retailer company this is a far-reaching insight. Even though it might be difficult to negotiate the recommended Ship Packs, as international suppliers might impose higher quantities in order to diminish transportation costs, it is meaningful to have this information when negotiating with them.

Table 5.5: Results from the Case/Inners Optimization

	Non Food	
Cost	**Reduction**	**Weight**
Processing	-1%	-1%
Safety Stock	74%	8%
Picking	-1%	-1%
Store Inventory	74%	66%
Spoilage	0%	0%
Provision	81%	28%
Total	**38%**	**100%**

Pareto Analysis

Several SKUs were analysed attaining different results with some products and suppliers achieving more significant savings. Hence, in order to prioritize, both products and suppliers, to negotiate a new Ship Pack quantity, an ABC analysis was performed. It is quite clear that most of the savings belong to 20% of the suppliers and products for both departments as seen in 5.21 and 5.22. In the ABC analysis from products, both curves are quite identical with no huge differences. On the other hand, there are more critical suppliers in the fresh department. This means that most of the savings are concentrated in fewer suppliers than the non food department.

This analysis allows the retailer company to focus on the critical products and suppliers requiring a more meaningful Ship Pack modification.

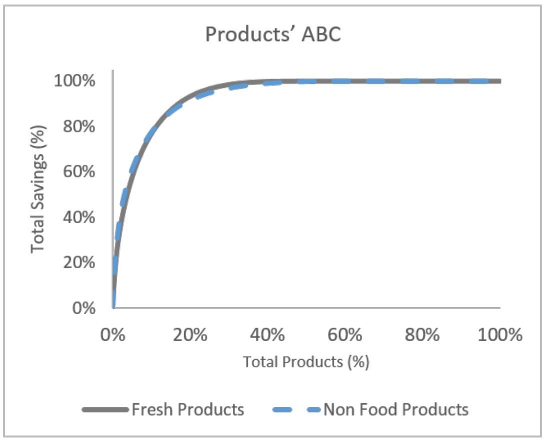


Figure 5.21: Products' ABC

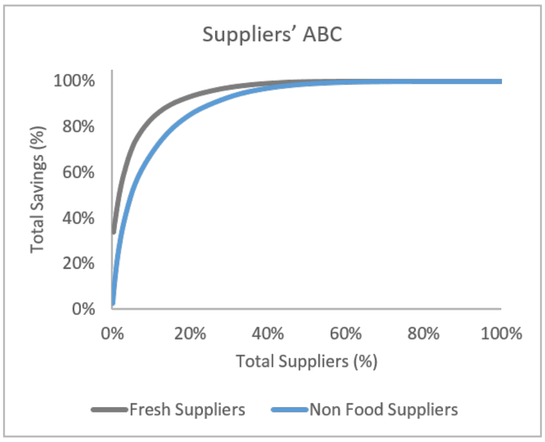


Figure 5.22: Suppliers' ABC

Ship Pack Definition for New Products

The last obtained results show a statistical analysis for situations in which a Ship Pack has to be chosen for new products. The retailer company has a market structure to organize its products with several levels of aggregations: Commercial Direction (DC), Category (CAT), Sub Category (SubCAT) and Unit Base (UN), which are presented in decreasing levels of aggregation. When a new product is launched, this market structure is associated with the product. The process to indicate the Ship Pack for new products follows an estimation of the Ship Pack quantity from the existing products that belong to the same market structure. This comparison is made by a Ship Pack weighted average by sales with all the products from the corresponding level of aggregation (DC, CAT, SubCAT or UN).

A balanced sample with products from each unit base of the company (12.392 products) was constructed. Then, it was performed an analysis in which the optimal Ship Pack obtained from the optimization model was compared with the several levels of aggregation estimation. This deviation is calculated as the average of the absolute deviations. In figure 5.23, the results from this analysis are presented and it is clear that with lower levels of aggregation the deviation is smaller. In conclusion, when choosing a Ship Pack for a new product, it is better to choose based on the UN than in other levels as this is closer to the results achieved in the optimization model.

Some of the products are recent and only have small period of sales. Thus, the decision to choose the new Ship Pack based on the UN or in the optimization model, but with low period of sales, arises. An analysis was performed by running the optimization model with incremental periods of sales and the results were then compared with a full period of sales (12 months).

The sample used was the same from the previous analysis. The outcome shows that with small periods of sales, it is almost identical to choose from the UN or from the optimization model. In figure 5.24, it is shown that the deviation decreases and tends to zero as the period of sales reaches 12 months. The developed curve has an high R^2 of 0.99 meaning a good regression estimation, which means an acceptable fit of the estimated curve to the obtained results. This means that when sales' information increases, the obtained Ship Packs tend do adjust to their optimum quantity and, consequently, more robust results are achieved with further sales' information.

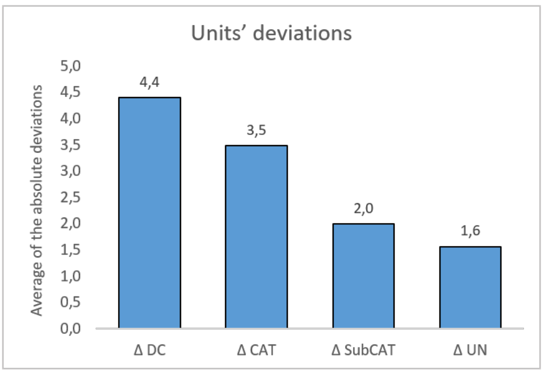


Figure 5.23: Unit's deviation

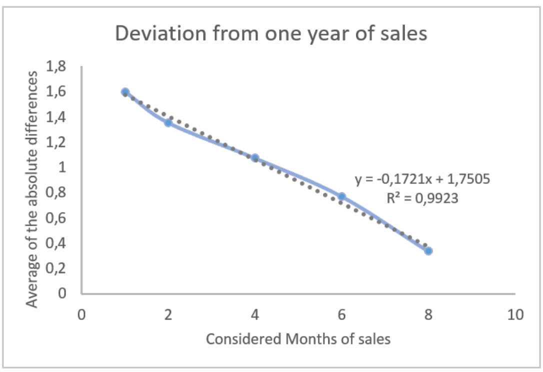


Figure 5.24: Period of sales deviation

Chapter 6

The Decision Support System

Succeeding the development of the optimization model, it was decided to promote a Decision Support System to be used by the retailer whenever defining the optimal Ship Pack.

In Druzdzel and Flynn (1999), Decision Support Systems are defined as computer-based systems that aid users in judgment and choice activities. Its popularity is larger in situations where the available information is prohibitive for the human analysis and in which accuracy and optimality are of importance.

In the current project, the amount of data to be treated is enormous and requires an extensive processing and analysis capacity. A first prototype to develop and validate the model was created using MS Excel®, but only included a small subset of products. This prototype, although being acceptable for the considered set, was unattainable in a large scale of products due to its large run time for each product. As the goal was to develop a live tool capable of running the optimization model for the desired products, another approach had to be taken in order to meet the client's requirements. This included the development of a web application available to be used whenever the firm is redefining Ship Packs with suppliers.

The current chapter is structured as follows. In section 6.1, the customer's requirements to be included in the DSS are stated. In section 6.2, the architecture of the DSS is detailed and the approach taken in each developed module is explained as well as the final outcome.

6.1 Requirements Definition

In order to turn the developed theoretical model into a business application to be used by the people that will define Ship Packs together with suppliers, a mapping of the imperative requirements had to be drawn. Some requirements of the DSS were stated to be crucial before the project had started such as integrity and performance. The functional requirements were iteratively drawn during the model development stage. Its definition was determined together with the end users of the DSS together with the help of mock ups.

The final list was divided into two main core requirements: Interface - includes all of the features desired to be seen in the final application, and Model - includes all the particularities of the developed optimization models in the previous chapters to be included in the DSS.

Interface Requirements

1. Different type of users have to be incorporated in order to allow simultaneously runs.
2. Interfaces ought to be efficient and plain with clean layouts.
3. Cost parameters have to be changeable in the interface.
4. Pre-validation of some parameters in each run, due to lack of confidence in a few part of the data, has to be included.
5. Data must be integrated and updated into the database and feed the DSS from this.
6. Inputs from the user should be easy to use and bullet proof.
7. Outputs have to be clear in order to enable quick analysis.

Model Requirements

1. The DSS must include all the developed models and the corresponding Ship Pack/s recommendation/s.
2. Every cost component variation should be stated in order to identify the origin and magnitude of the savings.
3. The DSS must have three separated modules:
   (a) Ship Pack optimization for the desired SKUs in each developed model.
   (b) Indication of the recommended Ship Pack to new products according with the desired filter: item-like or market's structure correlation.
   (c) Supplier optimization for the situations in which only one Ship Pack can be optimized for each supplier.

6.2 DSS Architecture

The architecture of the DSS is organized in four major modules. All the data provided by the retailer was stored into a database containing several data tables. The optimization model was develop using C# programming. The front-end of the DSS was developed using Html, Javascript and Ajax to communicate with the back-end developed in C# modules. The input and output were developed in the interfaces and MS Excel® files. The DSS follows a logic of having an user interface (UI) in which the user can interact with several features such as performing a new optimization run by giving some inputs. Then, the solver is called using the information from the database and when the optimization finishes, the outcome is given back to the user through the interface. This logic is exhibited in figure 6.1.

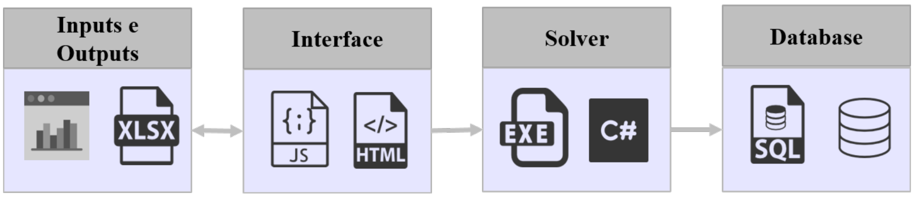


Figure 6.1: DSS Architecture

Database

Huge amount of data was provided by the retailer company. In order to keep the performance high, the information was organized in major tables according to several keys. A table was created containing all the information from the SKUs: dimensions, weight, current Ship Pack, shrinkage parameters. Skus and stores were combined in a table containing the replenishment parameters. The last table contains all the information from sales organized by week, store and the corresponding sales in quantity. This allowed to keep performance high and the performed queries efficient.

Solver

A prototype was developed using MS Excel®. However, this did not provide scalability and another solution had to be found. A C# application was developed following the sequence of figure 6.2. The first step on this solution was to extract the data from the database organized in classes. Therefore, a class for SKUs was created containing all the information related with the product. A product has associated several stores, which are also a class containing all the replenishment parameters. SKUs and stores have sales associated per week. Whenever running the program, queries to extract the data for the corresponding SKU were performed. Having this guaranteed, the replenishment process was programmed according to the stores' replenishment parameters and in function of the Ship Pack quantity. Therefore, all the cost components were calculated in separated modules. In addition, a module was developed for each model, which iterates across each Ship Pack quantity and gives the best Ship Pack quantity according to the obtained minimum cost. A MS Excel® template was created to print all the costs for each model as well as some critical information as seasonality and some doubtful data. The inputs to run the C# application were given using a MS Excel® pre-defined template and a .txt file containing all the cost's parameters. This was then incorporated into the interface.

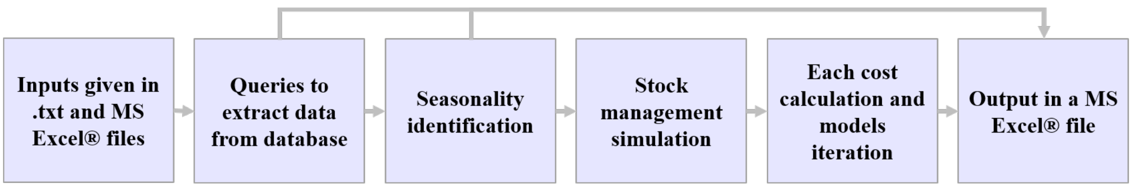


Figure 6.2: Solver Architecture

Interfaces

The final goal of the project was to develop an optimization as a service by developing a web application in which users can run the optimum Ship Pack for the desired products. In appendix C all the developed interfaces are shown.

The application starts with a log in for each department of the company as seen in figure C.1. It was decided to keep the user interface similar to both, fresh and non food departments, with some filters being applied according with the conducted login in order to hide/show the particularities of each department.

Then, when the log in is made, the user gets access to the homepage as seen in figure 6.3 and C.2, in which all the history of past runs is saved and the user can download the outcome of previous optimization runs. The user gets access to four possibilities at the top of the page: change costs' parameters, perform a new run, get the recommended Ship Pack for new products or choose the supplier optimization.

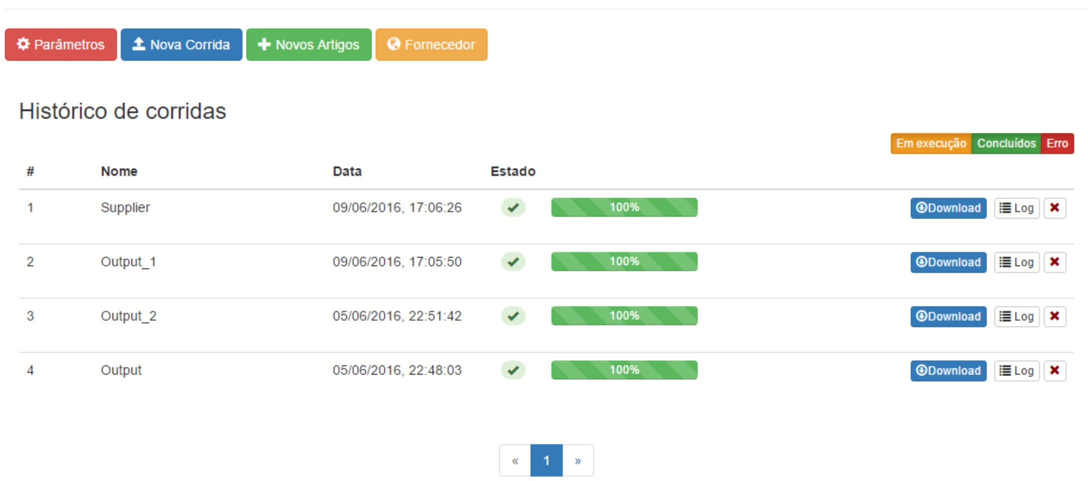


Figure 6.3: Homepage

In figure C.3, the user can change the costs' parameters of the model and upload some additional data such as boxes' dimensions or some store's manual replenishment parameters. It was decided to change costs in the interface instead of the database to give more visibility to the end user as the model is more sensitive to these parameters. When the user changes it, the parameters are saved into a .txt file in the same folder as the solver. When the solver is executed, it reads the updated .txt file.

Later, the user can run a new optimization by using the interface in figure C.4 by uploading a .xlsx file containing all the identification codes from the SKUs desired to be run in the first column as seen in figure C.5. After the user uploads the input, the solver is executed in the background as seen in figure 6.4 and the log file allows the user to monitor the situation by seeing the current SKU being optimized and the ones missing as seen in figure C.6. The user can also follows the run in the progress bar.

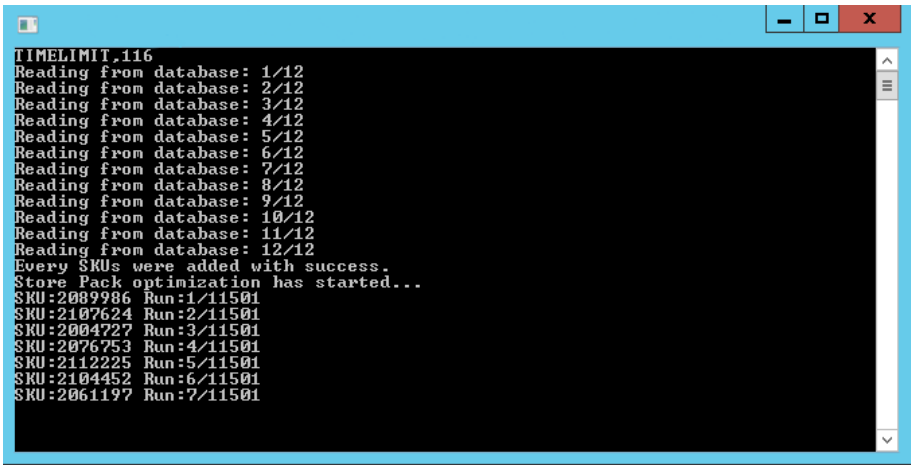


Figure 6.4: Solver Debug

When the run finishes, the outcome becomes available for download. If there is an error in the run, it is reported and the user has to rectify it to run it again. The outcome is an MS Excel® file as seen in figure C.7 containing all the costs' variation and the recommended Ship Pack for each developed model.

In situations in which the user wants to validate the seasonality identification or some parameters of the product which might be inaccurate, it can choose to pre-validate the data as seen in figure C.8. Then, the outcome becomes available as a .xlsx file in which the user can change the parameters and upload it again to be run. This can be seen in figures C.9 and C.10.

If the user desires to know the recommended Ship Pack for new products, it can choose to do it by comparing the new product to an item-like as seen in figure C.11 or to a weighted average by sales according to category, sub-category or unit base chosen filter as seen in figure C.12. The outcome will be the recommended Ship Pack as seen in C.13. The last possibility is seen in C.14 and the user can upload a file as C.15 containing several new products desired to be recommended according to the given filters. The outcome is seen in C.16 and contains all the recommendations for new products

Finally, the supplier optimization interface as seen in figure C.17 is also very similar to the single optimization interface. The run is also performed by uploading a file as seen in C.18 in which the user can choose to run every products from a supplier or to only aggregate some of them. The outcome allows the user to get the best Ship Pack quantity and quantify the impact it has in the several products of the supplier as seen in figure C.19.

In addition, for each optimization run, the user can give the email to be notified when the run finishes. However, the performance achieved by this system allows fast optimization runs as the systems was developed to be run by using multi-thread allowing multiple runs at the same and maximum utilization of the CPU.

The developed DSS allowed the end user, who is negotiating the Ship Packs with suppliers, to easily get aware of the optimum quantity and the potential savings it has when comparing to the current situation.

Chapter 7

Conclusions and Future Work

The developed work integrates an holistic view of the entire supply chain by fostering a cost model in function of the Ship Pack quantity. This parameter of the supply chain turns out be of consummate importance as its right formulation leads to a considerable cost reduction in the entire chain. The developed work contributes to the alignment of theory with practice. In order to solve this problem, optimization models were developed and then spelled out into a Decision Support System, which translates the created optimization model into a business solution.

The current state of the art in the Ship Pack optimization is quite sparse with several and different approaches when considering the costs to be included. However, it is quite accepted that handling costs play an important portion of the total costs. The obtained results point to expressive savings mainly due to picking followed by store inventory when products are more expensive.

The methodology to identify periods of intensive sales in which a different Ship Pack is introduced proofs to work properly. This seasonality optimization model induced to a cost reduction when compared with the single optimization problem. Having implemented this methodology turned the retailer capable of changing to a new Ship Pack when there is a seasonal period. In the products dealing with case/inners situations, it was concluded that the Ship Packs were extremely oversized as suppliers tend to deliver higher quantities in order to reduce their transportation costs. This analysis of both seasonality and cases are considerable new contributions to the current state of the art in the Ship Pack optimization.

The results enabled the retailer to have an integrated view of its supply chain and a proper quantification of the impact the Ship Pack definition has on it. The main recommendations will conduct to a guidance in the negotiation with suppliers based on the recommended Ship Pack quantities from the retrieved optimization models.

The obtained savings might impose two important issues in the future. First, suppliers might impose additional costs when negotiating the new Ship Pack and, consequently, the obtained savings will not be totally achieved. This is might happen as suppliers may have to perform changes in their packaging processes, which are not adjusted to the proposed recommendations. Second, the savings are estimated based on historical data. When sales from the subsequent periods differ widely, the results might suffer significant changes. Future work might include a risk based analysis based on the exposure of sales differing too much from the considered time set when optimizing the Ship Pack. This might be solved with forecasting methods in which the retailer can adapt the Ship Pack to the future demand based on historical data, which might include a trend estimation aligned with the company's goals.

The future additional work in the model should also be in the quantification of the extra handling cost. The presentation stock is a quite important parameter for stores and a coordination of it with the Ship Pack quantity might lead to further savings. The transportation cost is also likely to play an important role in the chain, but only for few products it was possible to estimate it. Hence, having all the boxes' dimensions, a more complex problem considering a bin packing heuristic could be stated in which consolidation of products is drawn. This would change the assumption of independence between products and the entire problem would become much more complex. However, additional savings might arise from this approach.

The developed DSS brought additional information to the retailer as it allows an on time analysis of the current Ship Pack impact into the entire supply chain. The data integration to maintain the tool live over time will allow the continuously update of information and bring valuable information for the people running negotiations with suppliers. The easiness of running the developed application will turn the process an easy task for the main users. A monthly dashboard can be created allowing the visualization of the number of uses the tool had and the savings from the implemented Ship Pack modifications.

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Appendix A

Store Inventory Demonstration

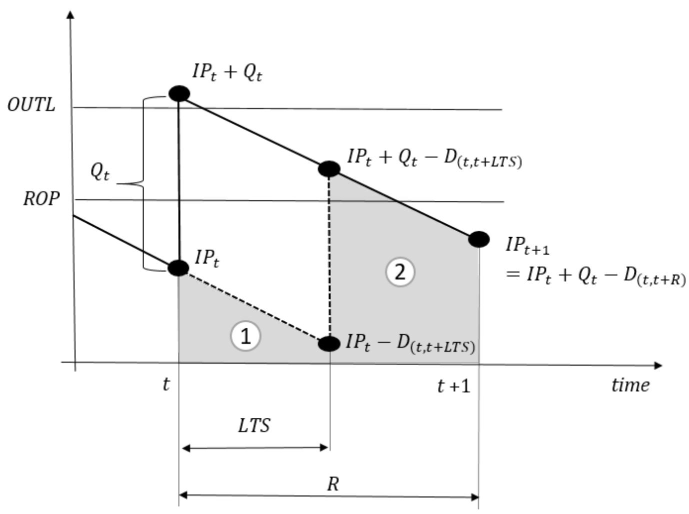


Figure A.1: Inventory Position and on-hand stock

The average stock is calculated by the area below the on hand stock line divided by the period length. Therefore, the average stock in Period R is given by the sum of the weighted inventories in period LTS and $R - LTS$ given by equation A.1.

$$E(\text{Store Inventory}_{i,k,t}) = \frac{LTS}{R} \times \frac{1}{LTS} \int Region1 + \frac{R - LTS}{R} \times \frac{1}{R - LTS} \int Region2 \tag{A.1}$$

The average stock in regions 1 and 2 results in A.2

$$E(\text{Store Inventory}_{i,k,t}) = \frac{\int Region1 + \int Region2}{R} \tag{A.2}$$

Considering the first part of equation A.2 as A.3:

$$\int Region1 = LTS \times \left(IP_t - \frac{D_{t,t+LTS}}{2}\right) \tag{A.3}$$

And the second of part the equation as A.4:

$$\int Region2 = (R - LTS) \times (IPt + Q_t - \frac{D_{t,t+R} + D_{t,t+LTS}}{2}) \tag{A.4}$$

Equation A.3 and A.4 putting together in A.2 will result in A.5.

$$E(\text{Store Inventory}_{i,k,t}) = IP_t + \times \frac{R - LTS}{R}(Q_t - \frac{D_{t,t+R}}{2}) - \frac{D_{t,t+LTS}}{2} \tag{A.5}$$

Appendix B

Case/Inner Analysis

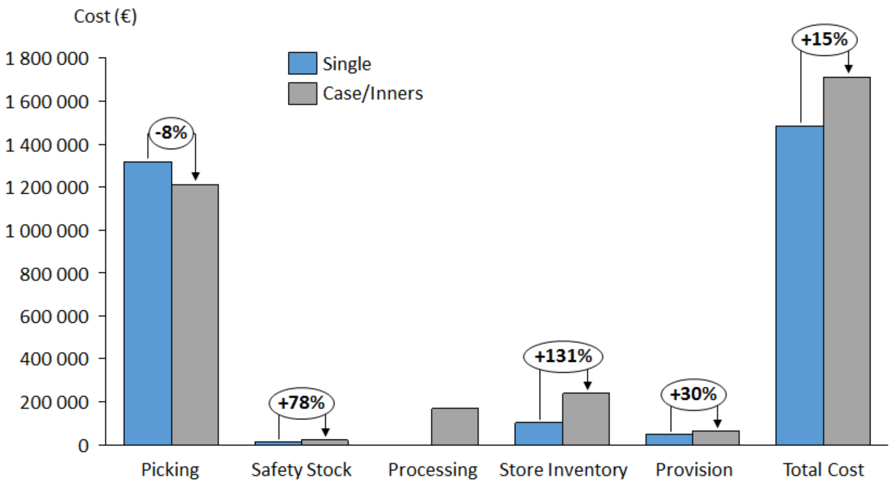


Figure B.1: Single optimization model vs Case/Inner

Appendix C

DSS Interfaces

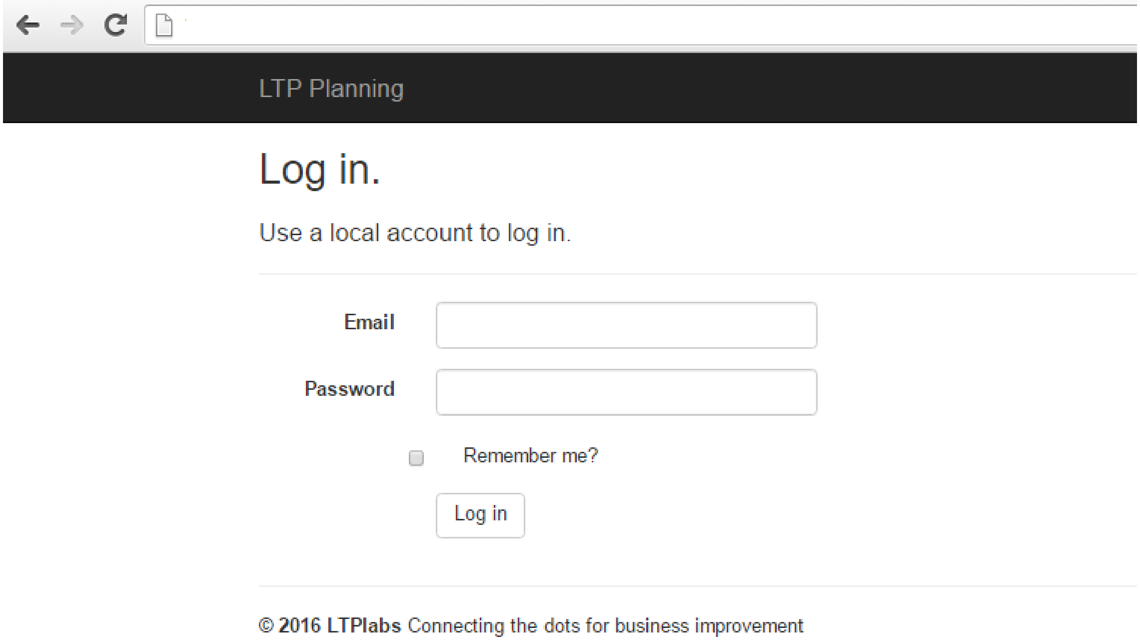


Figure C.1: Log In

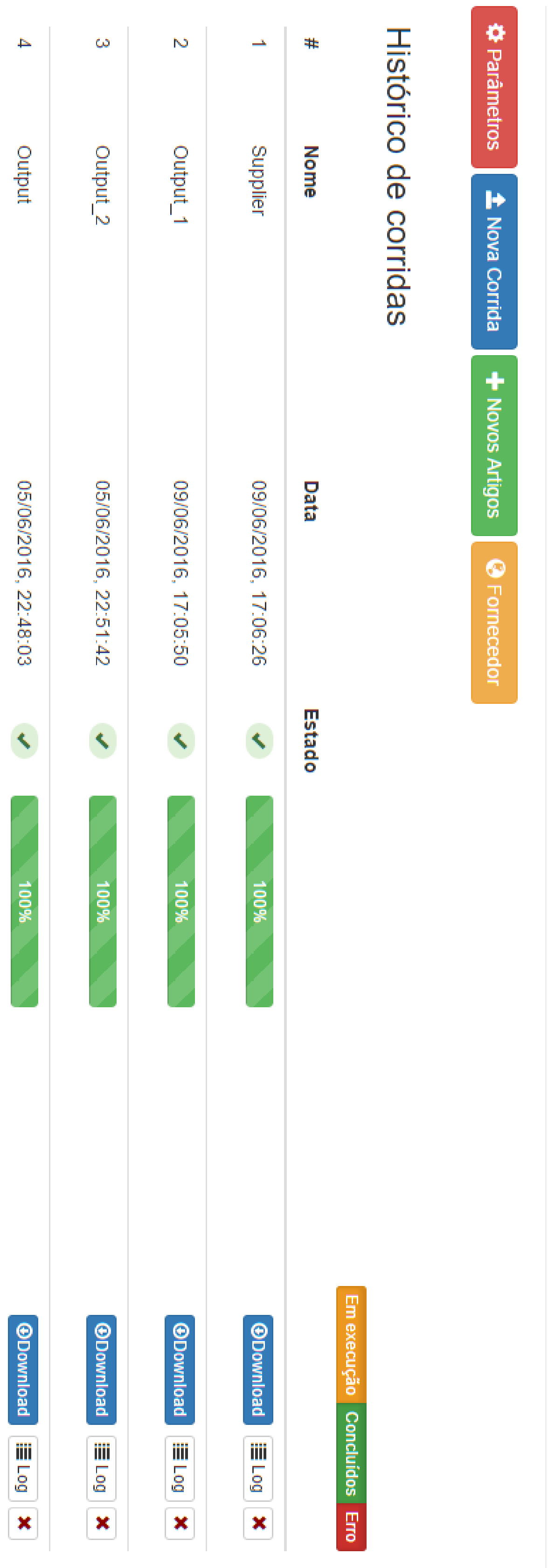


Figure C.2: Homepage

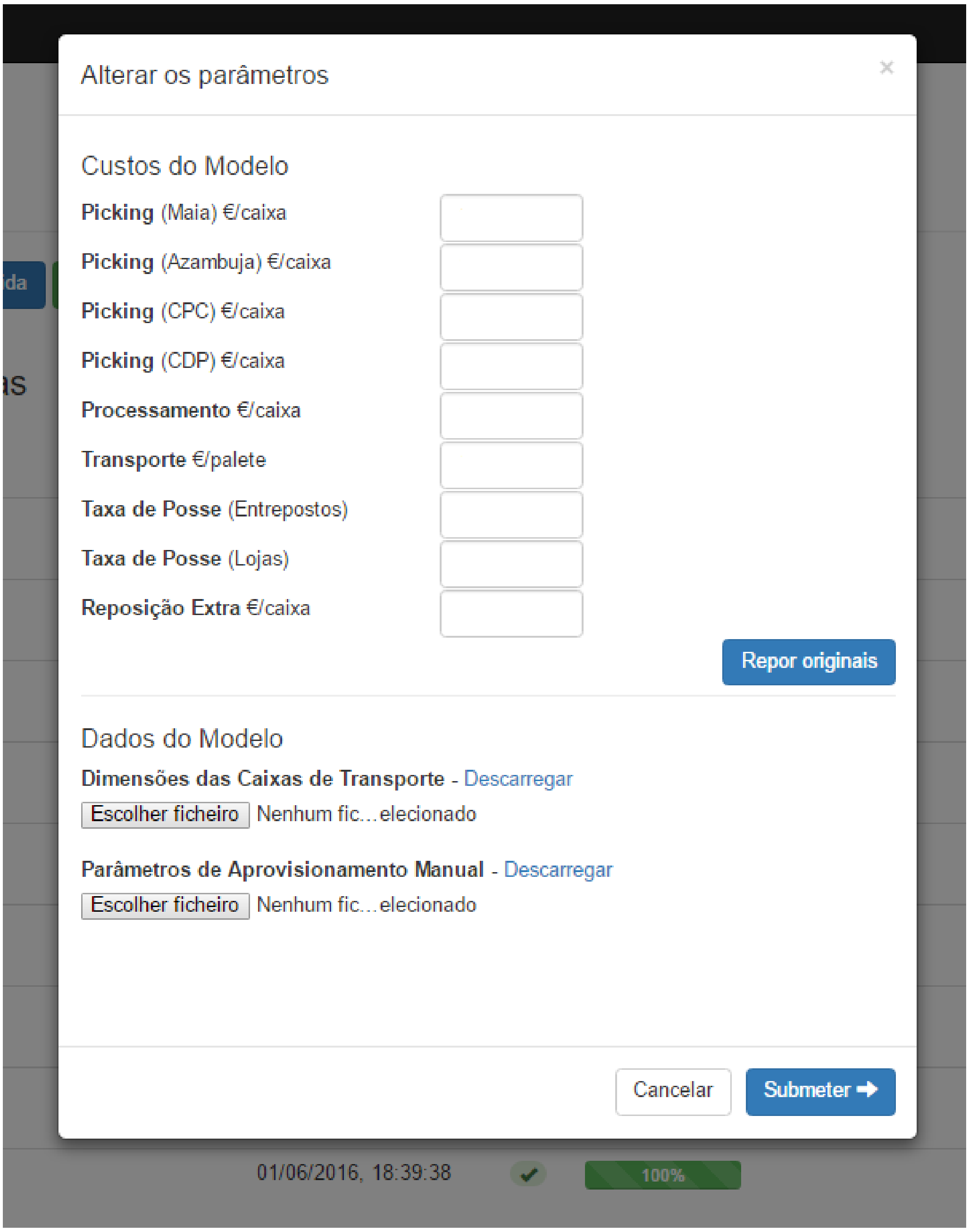


Figure C.3: Cost components parameters

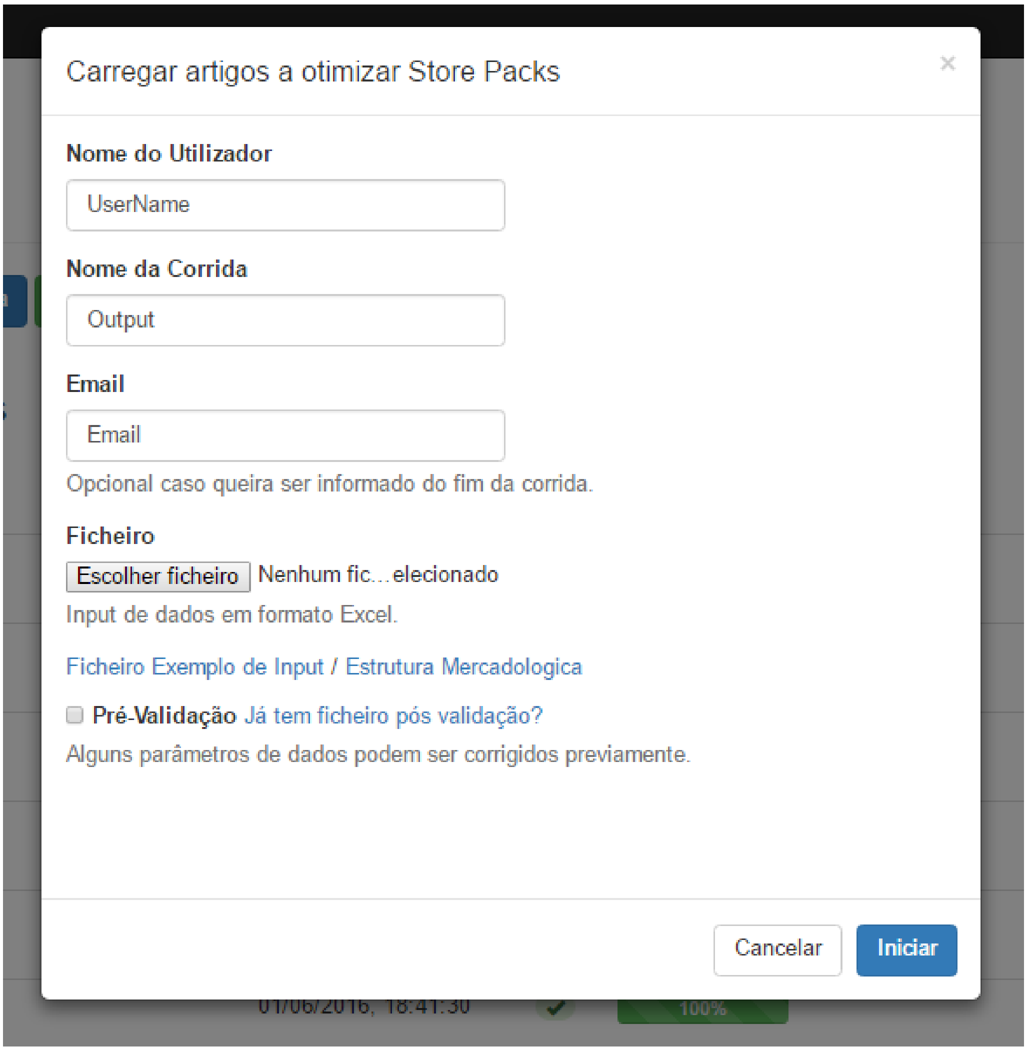


Figure C.4: Run Optimization

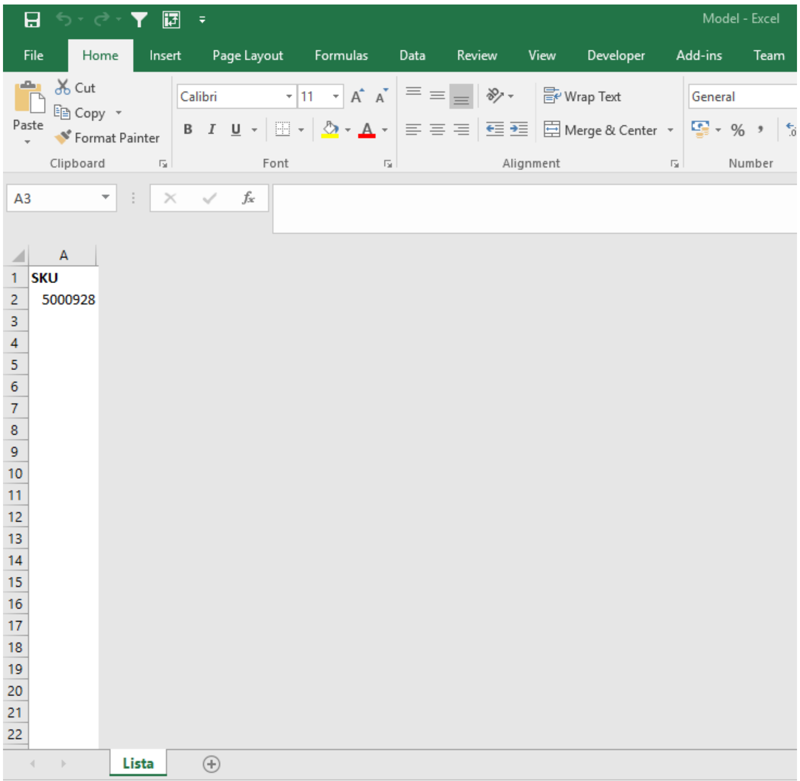


Figure C.5: Input of the Model

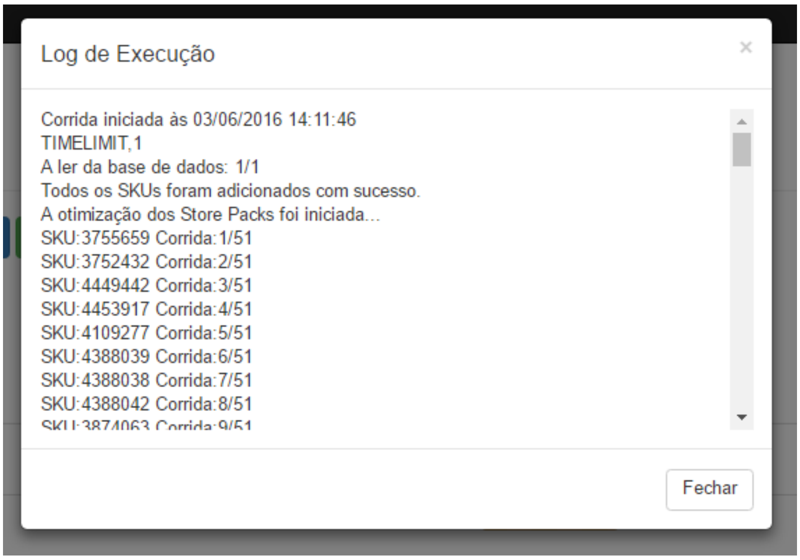


Figure C.6: Log from the Ship Packs Optimization

Figure C.7: Output of the Model

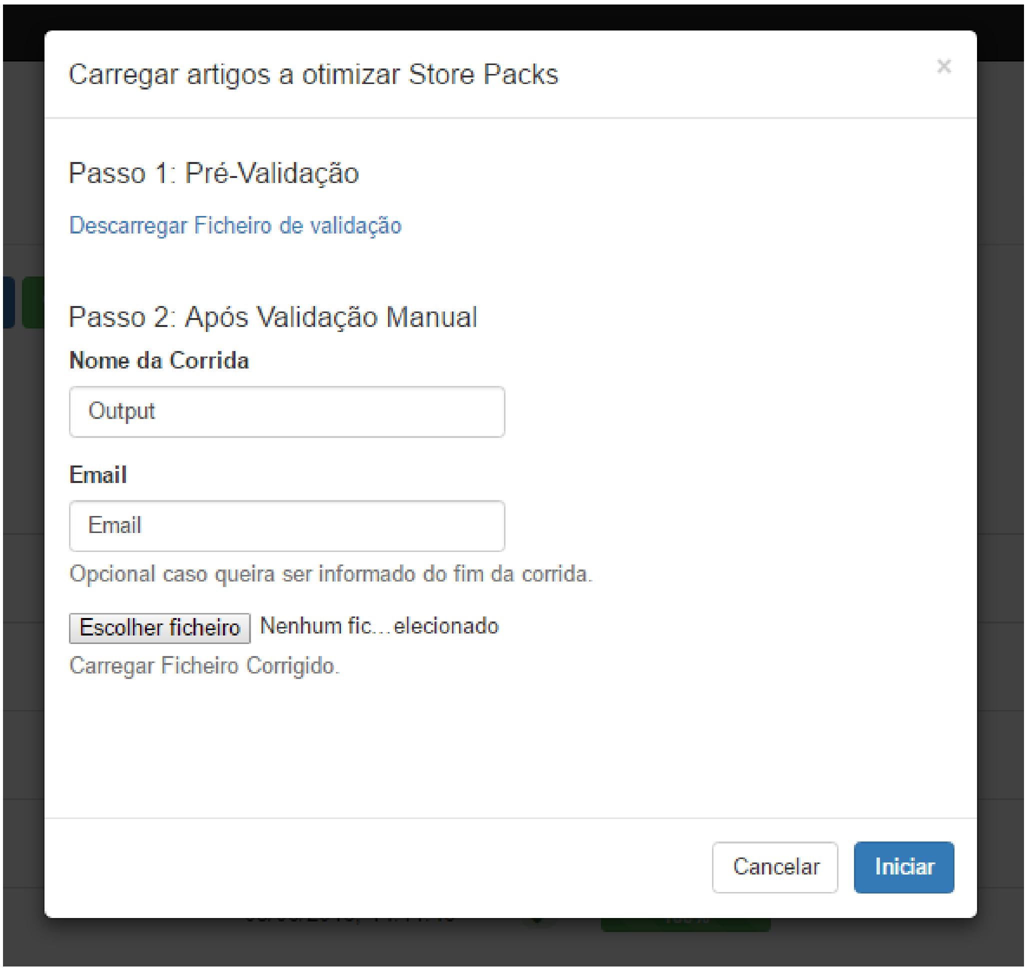


Figure C.8: Run Optimization Validation

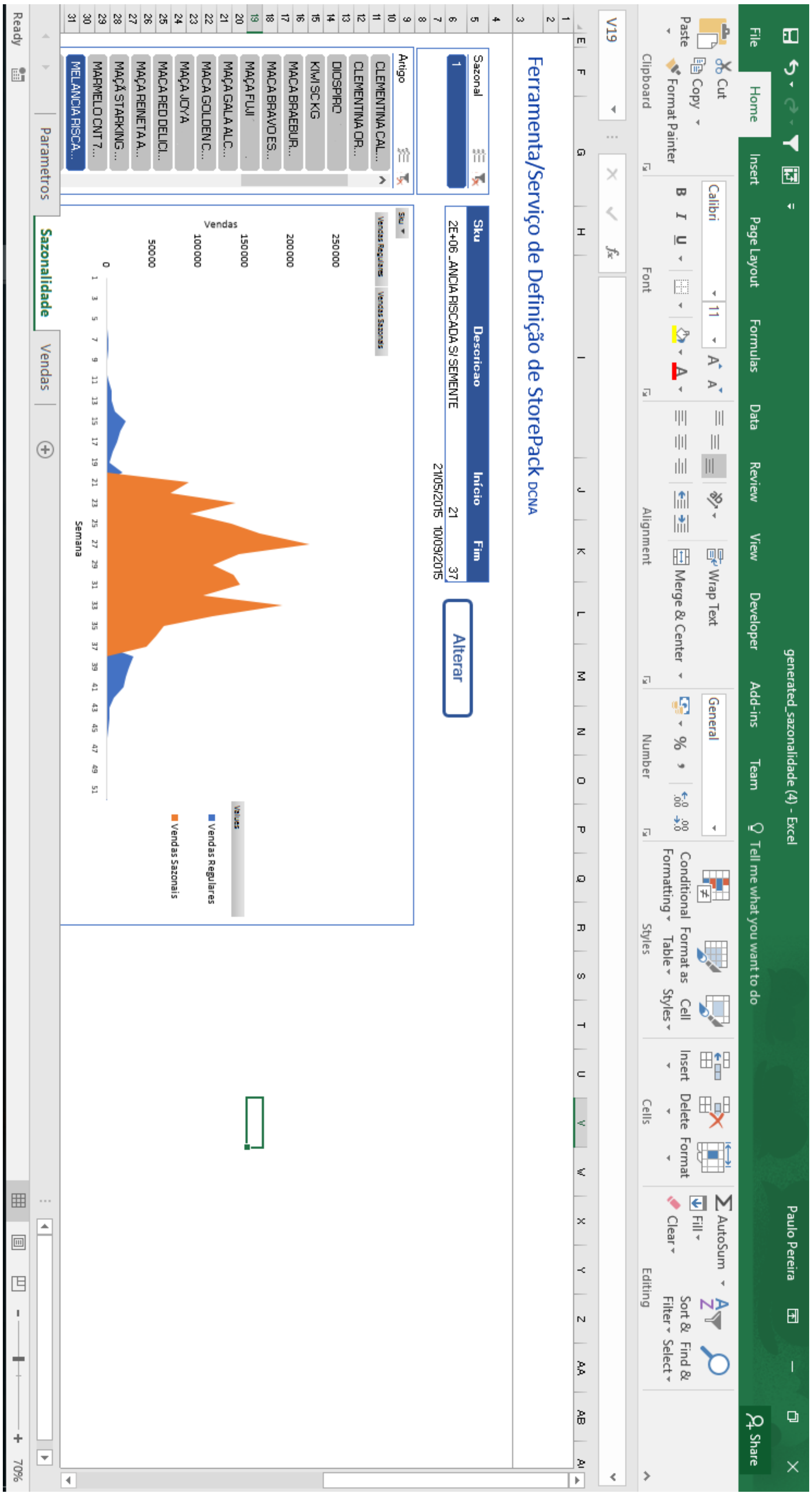


Figure C.9: Pre-validation Seasonality

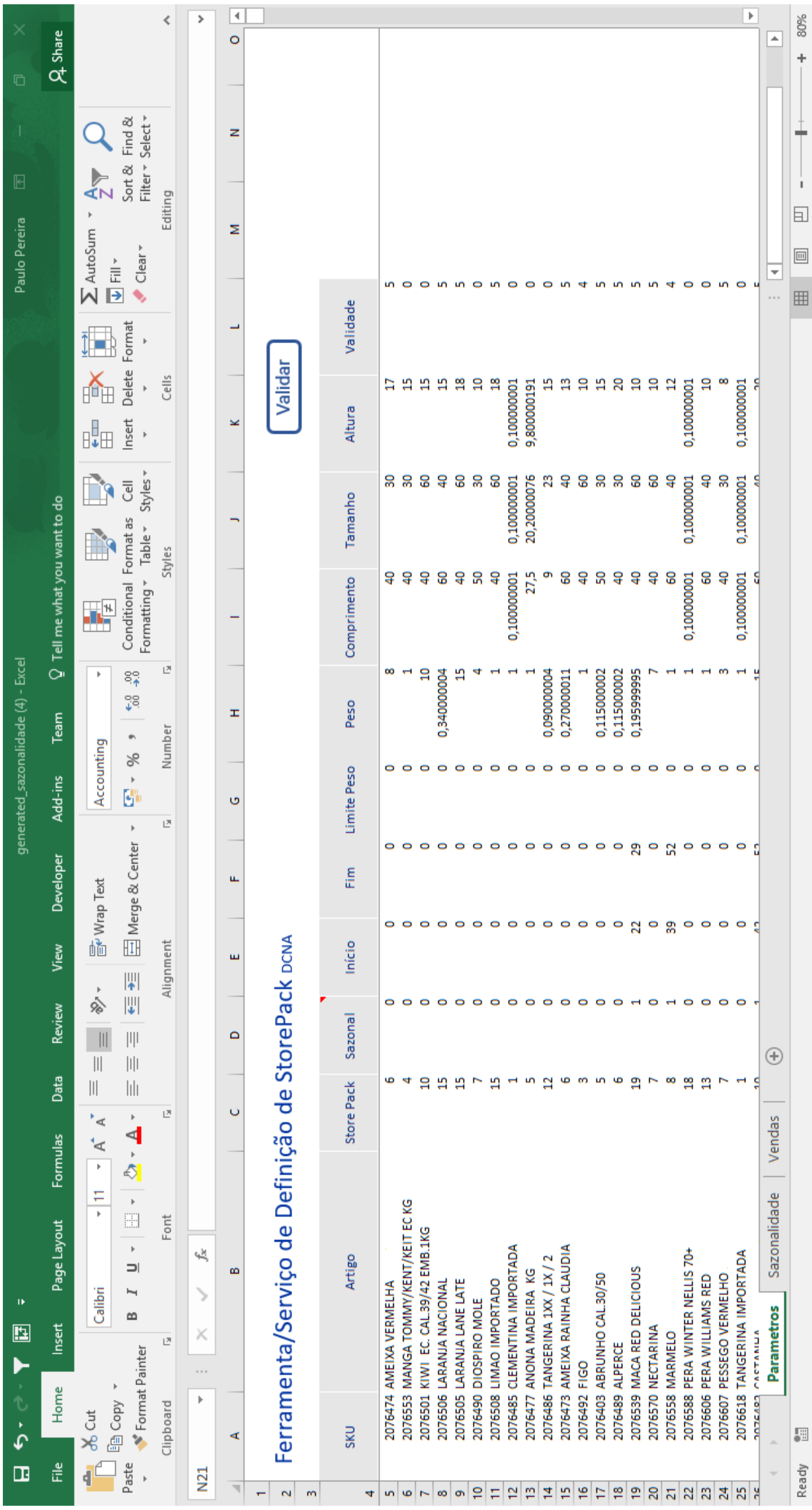


Figure C.10: Data Pre-validation

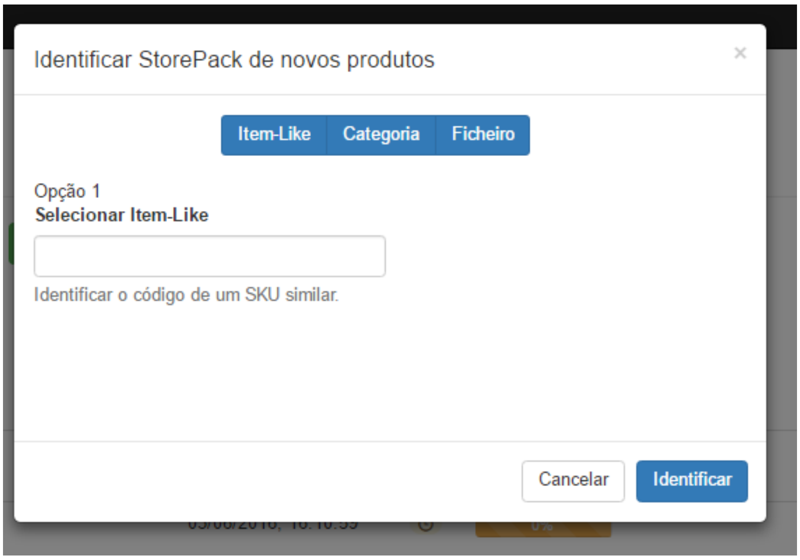


Figure C.11: Item-like for new Ship Packs Optimization

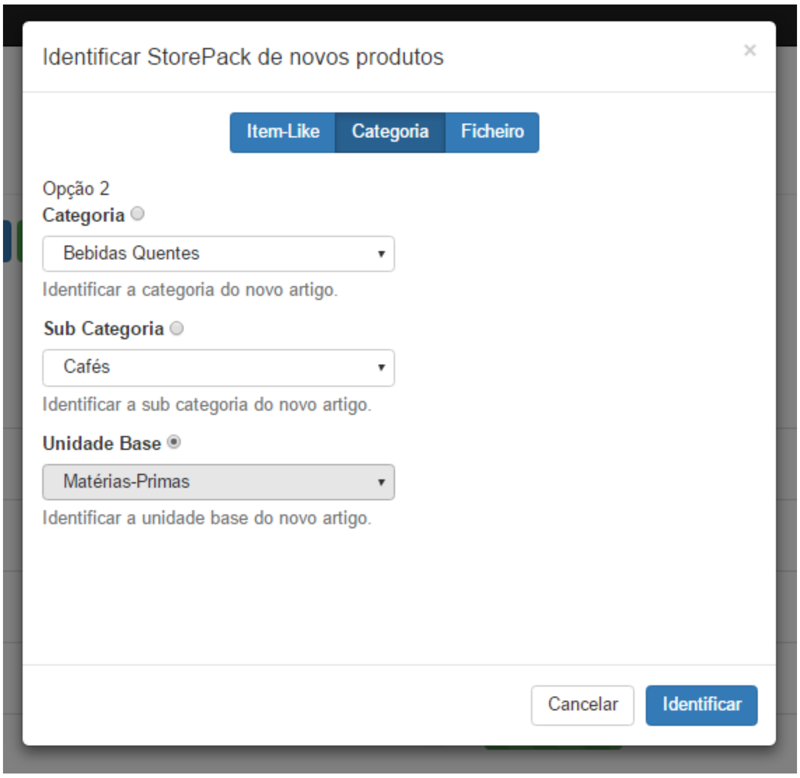


Figure C.12: Market's structure for new Ship Packs Optimization

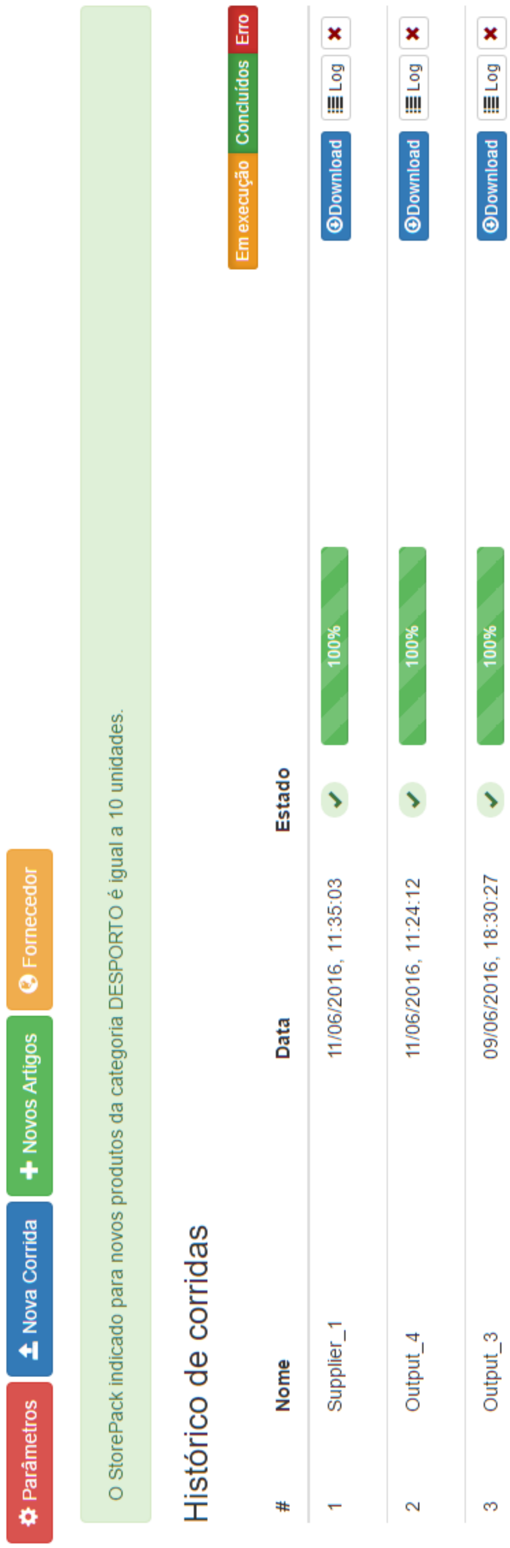


Figure C.13: Output for new Ship Packs Optimization

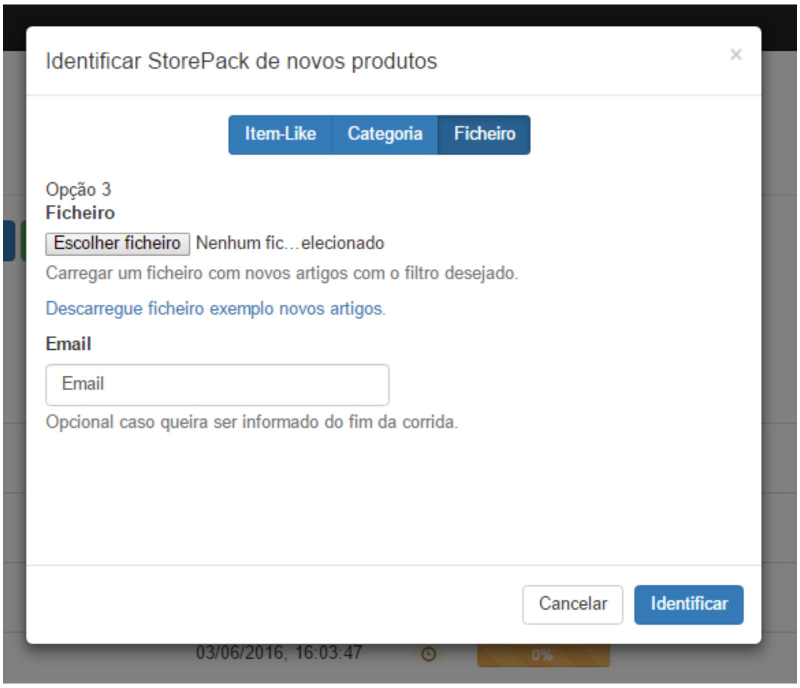


Figure C.14: File for new Ship Packs Optimization

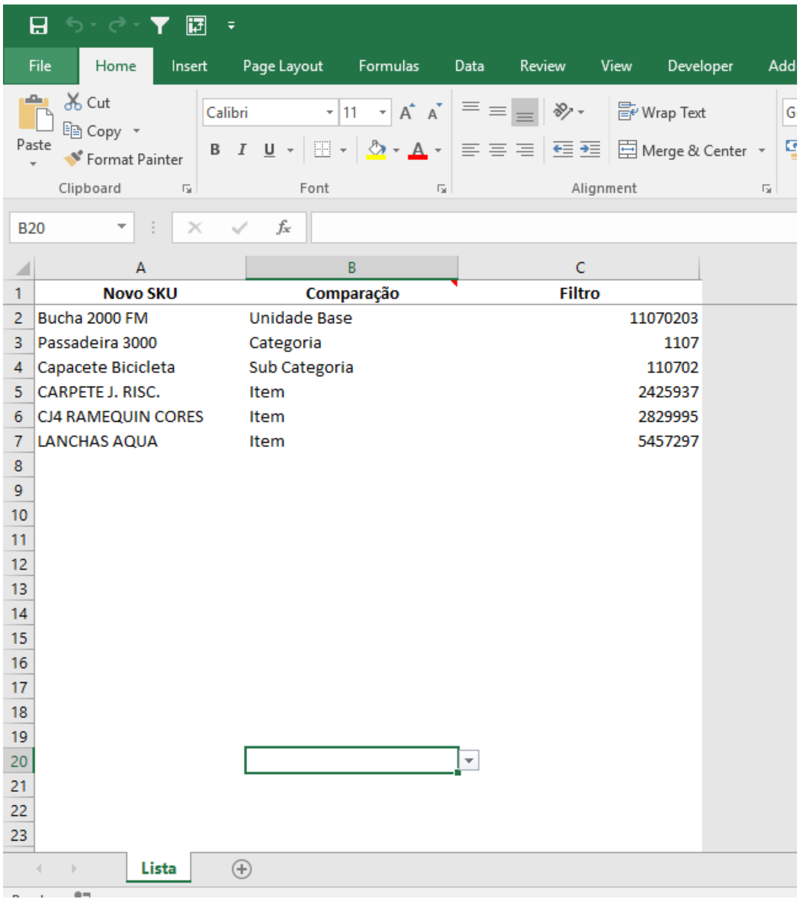


Figure C.15: Input file for new Ship Packs Optimization

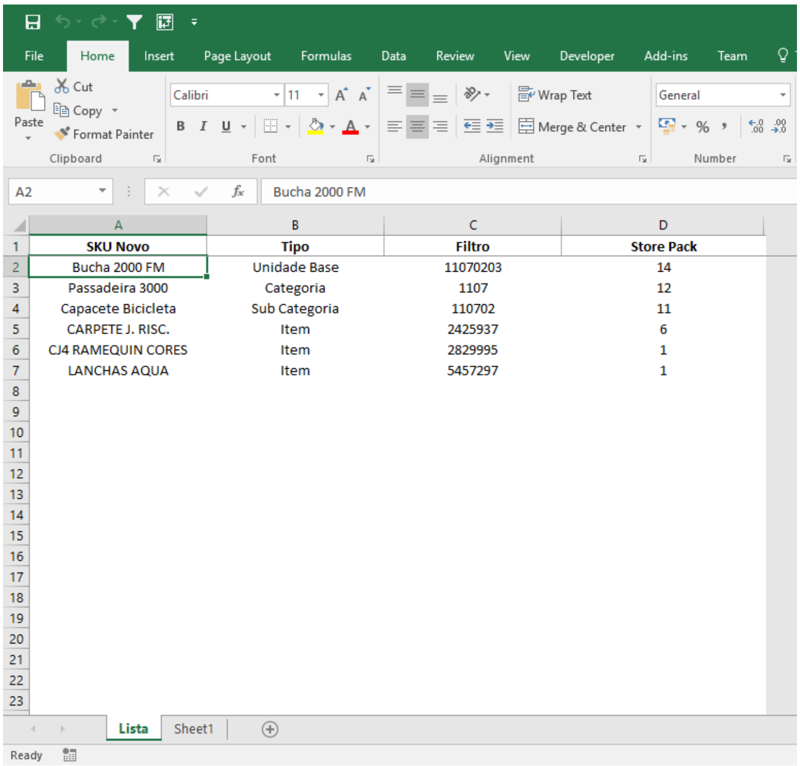


Figure C.16: Output file for new Ship Packs Optimization

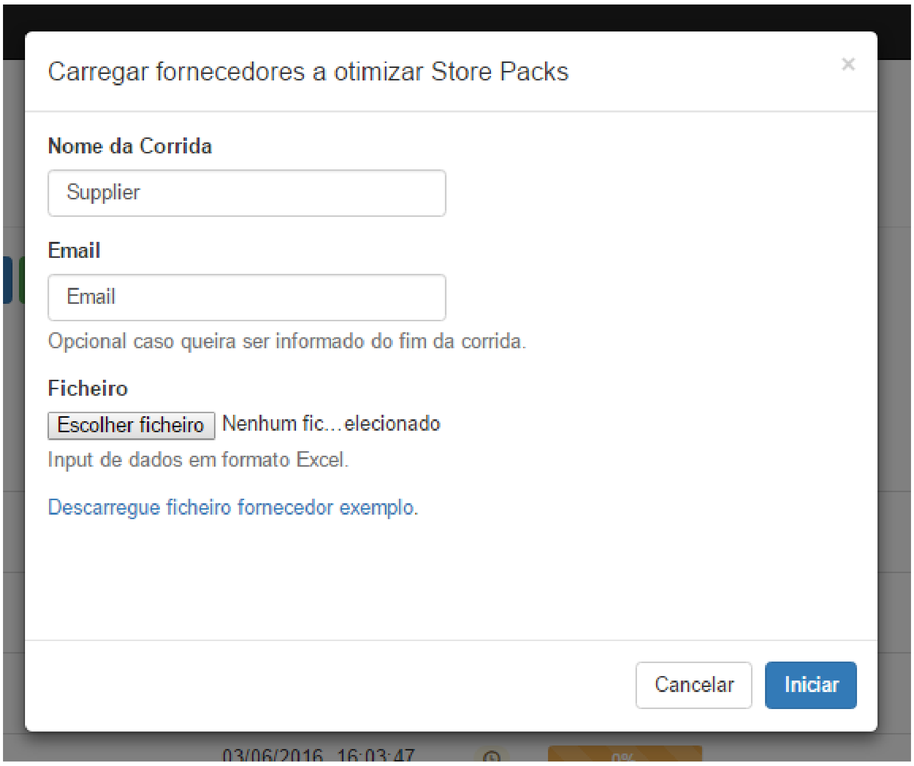
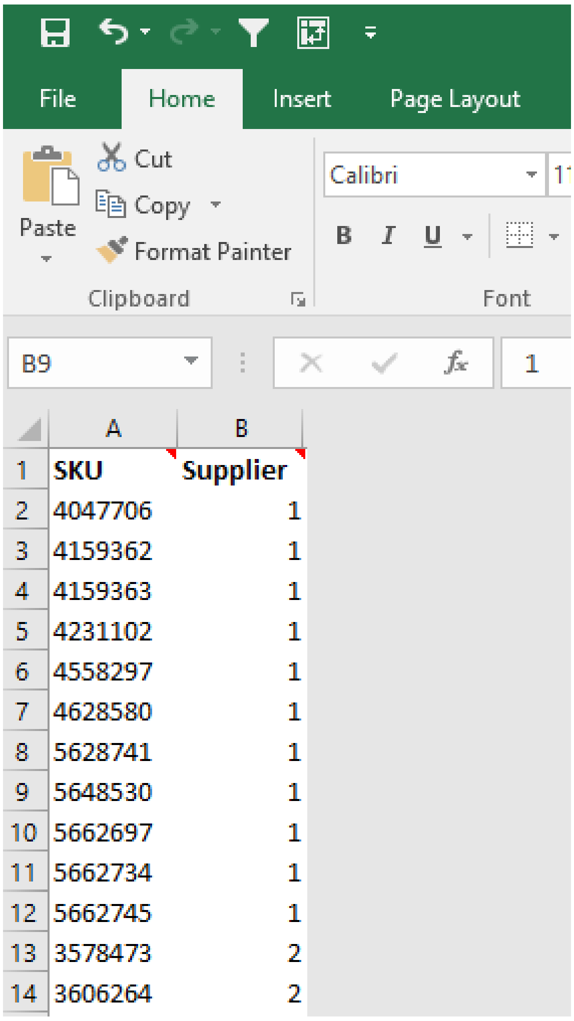
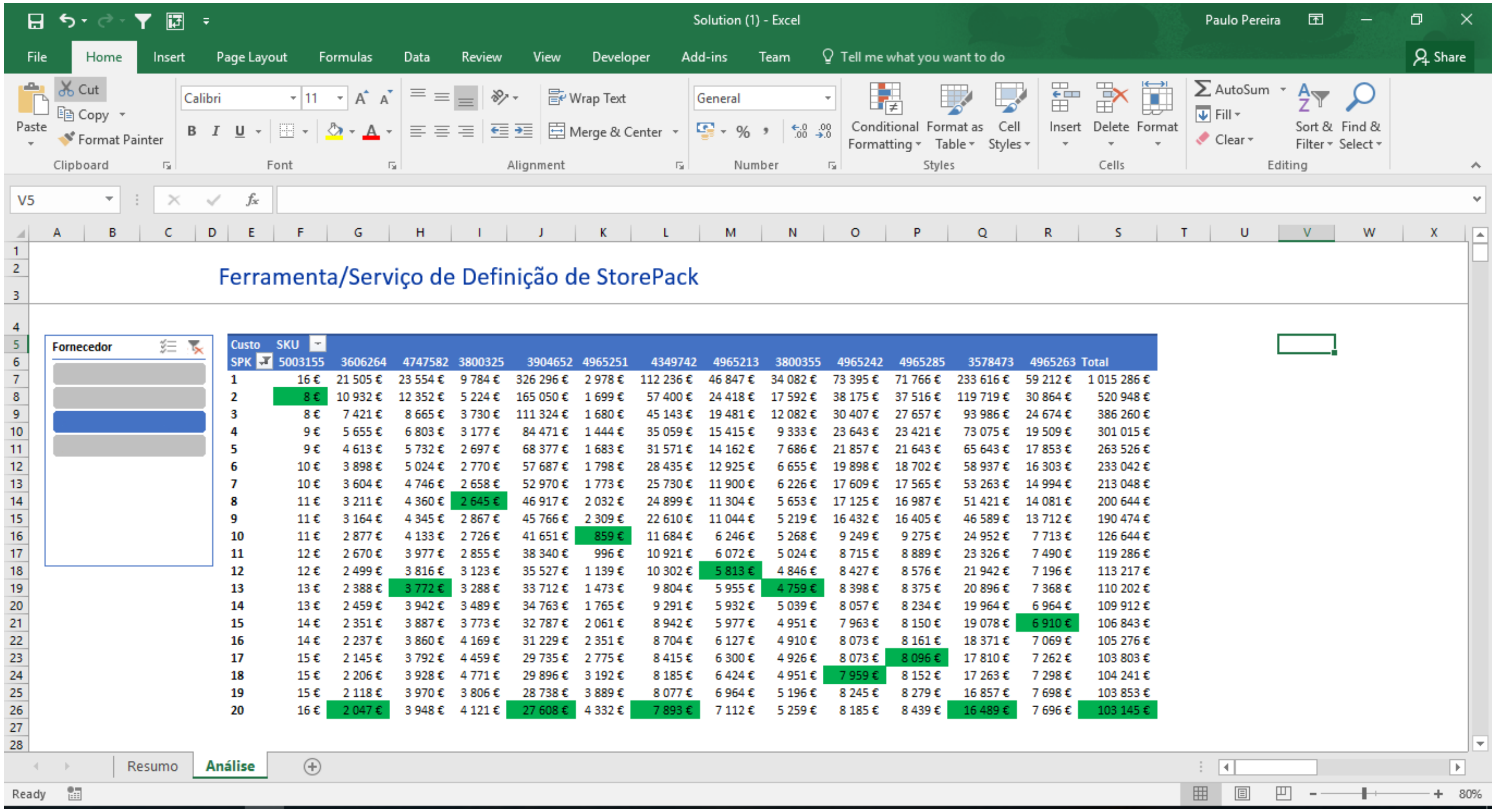


Figure C.17: Supplier's Ship Packs Optimization



	A	B
1	**SKU**	**Supplier**
2	4047706	1
3	4159362	1
4	4159363	1
5	4231102	1
6	4558297	1
7	4628580	1
8	5628741	1
9	5648530	1
10	5662697	1
11	5662734	1
12	5662745	1
13	3578473	2
14	3606264	2

Figure C.18: Input for Supplier’s Ship Packs Optimization



Custo SPK	SKU 5003155	3606264	4747582	3800325	3904652	4965251	4349742	4965213	3800355	4965242	4965285	3578473	4965263	Total
1	16 €	21 505 €	23 554 €	9 784 €	326 296 €	2 978 €	112 236 €	46 847 €	34 082 €	73 395 €	71 766 €	233 616 €	59 212 €	1 015 286 €
2	8 €	10 932 €	12 352 €	5 224 €	165 050 €	1 699 €	57 400 €	24 418 €	17 592 €	38 175 €	37 516 €	119 719 €	30 864 €	520 948 €
3	8 €	7 421 €	8 665 €	3 730 €	111 324 €	1 680 €	45 143 €	19 481 €	12 082 €	30 407 €	27 657 €	93 986 €	24 674 €	386 260 €
4	9 €	5 655 €	6 803 €	3 177 €	84 471 €	1 444 €	35 059 €	15 415 €	9 333 €	23 643 €	23 421 €	73 075 €	19 509 €	301 015 €
5	9 €	4 613 €	5 732 €	2 697 €	68 377 €	1 683 €	31 571 €	14 162 €	7 686 €	21 857 €	21 643 €	65 643 €	17 853 €	263 526 €
6	10 €	3 898 €	5 024 €	2 770 €	57 687 €	1 798 €	28 435 €	12 925 €	6 655 €	19 898 €	18 702 €	58 937 €	16 303 €	233 042 €
7	10 €	3 604 €	4 746 €	2 658 €	52 970 €	1 773 €	25 730 €	11 900 €	6 226 €	17 609 €	17 565 €	53 263 €	14 994 €	213 048 €
8	11 €	3 211 €	4 360 €	2 645 €	46 917 €	2 032 €	24 899 €	11 304 €	5 653 €	17 125 €	16 987 €	51 421 €	14 081 €	200 644 €
9	11 €	3 164 €	4 345 €	2 867 €	45 766 €	2 309 €	22 610 €	11 044 €	5 219 €	16 432 €	16 405 €	46 589 €	13 712 €	190 474 €
10	11 €	2 877 €	4 133 €	2 726 €	41 651 €	859 €	11 684 €	6 246 €	5 268 €	9 249 €	9 275 €	24 952 €	7 713 €	126 644 €
11	12 €	2 670 €	3 977 €	2 855 €	38 340 €	996 €	10 921 €	6 072 €	5 024 €	8 715 €	8 889 €	23 326 €	7 490 €	119 286 €
12	12 €	2 499 €	3 816 €	3 123 €	35 527 €	1 139 €	10 302 €	5 813 €	4 846 €	8 427 €	8 576 €	21 942 €	7 196 €	113 217 €
13	13 €	2 388 €	3 772 €	3 288 €	33 712 €	1 473 €	9 804 €	5 955 €	4 759 €	8 398 €	8 375 €	20 896 €	7 368 €	110 202 €
14	13 €	2 459 €	3 942 €	3 489 €	34 763 €	1 765 €	9 291 €	5 932 €	5 039 €	8 057 €	8 234 €	19 964 €	6 964 €	109 912 €
15	14 €	2 351 €	3 887 €	3 773 €	32 787 €	2 061 €	8 942 €	5 977 €	4 951 €	7 963 €	8 150 €	19 078 €	6 910 €	106 843 €
16	14 €	2 237 €	3 860 €	4 169 €	31 229 €	2 351 €	8 704 €	6 127 €	4 910 €	8 073 €	8 161 €	18 371 €	7 069 €	105 276 €
17	15 €	2 145 €	3 792 €	4 459 €	29 735 €	2 775 €	8 415 €	6 300 €	4 926 €	8 073 €	8 096 €	17 810 €	7 262 €	103 803 €
18	15 €	2 206 €	3 928 €	4 771 €	29 896 €	3 192 €	8 185 €	6 424 €	4 951 €	7 959 €	8 152 €	17 263 €	7 298 €	104 241 €
19	15 €	2 118 €	3 970 €	3 806 €	28 738 €	3 889 €	8 077 €	6 964 €	5 196 €	8 245 €	8 279 €	16 857 €	7 698 €	103 853 €
20	16 €	2 047 €	3 948 €	4 121 €	27 608 €	4 332 €	7 893 €	7 112 €	5 259 €	8 185 €	8 439 €	16 489 €	7 696 €	103 145 €

Figure C.19: Output from Supplier’s Ship Packs Optimization