Reorder point definition through demand forecasting to manage stock levels

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Master's Dissertation

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"I think it is possible for ordinary people to choose to be extraordinary."

Elon Musk

Resumo

Na empresa Alpha, retalhista no ramo das tubagens e dos sistemas de calor, foi realizado um projeto de melhoria com o objetivo de reduzir os níveis de inventário. Esta redução considera-se de importância extrema na medida em que permitirá a libertação de cash flow para investimentos futuros.

Os níveis de inventário são impactados pelo modelo de gestão dos mesmos. Este modelo de gestão centra-se em previsões de procura futura mas, devido à elevada variabilidade dos consumos fruto da elevada dinâmica e incerteza do ramo de negócio, existe uma suspeita que o modelo de previsão não será o mais indicado e que como tal existe uma possibilidade de melhoria. Dados sobre o ano de 2019 e parte do ano de 2020 serão usados para o estudo.

O estudo realizado foca-se num fornecedor específico, cujo método de planeamento é *pull*, para o qual a redução de inventário considera-se de maior importância devido ao alto valor económico dos artigos comprados.

Como passos de resolução do problema, iniciou-se com um cálculo de diversos indicadores de stock que permitem uma análise detalhada aos parâmetros intrínsecos ao método de aprovisionamento atual. Esta análise permitiu concluir que os níveis de inventário eram de facto elevados face à procura sentida pela empresa e que existia espaço para a aplicação de melhorias. Desta forma, identificaram-se medidas de melhoria baseadas nos dois drivers do modelo de gestão de inventário: método de previsão de procura futura e método de cálculo do stock de segurança.

Após as medidas de melhoria estarem identificadas e apresentadas abriu-se espaço para avaliar o seu impacto. Para tal, procedeu-se à construção de um simulador que permitiu replicar o processo de aprovisionamento para o período em estudo. Com base nos resultados da simulação, que permitiu aproximar à realidade o impacto das propostas de melhoria, contabilizou-se o impacto económicos das propostas.

O que se pode concluir é que os padrões de consumos dos artigos em estudo são de facto irregulares e que o método de aprovisionamento seguido pela empresa não consegue dar resposta à variabilidade intrínseca ao ramo de negócio. Desta forma, gera previsões afastadas da realidade que penalizam a empresa em excessos ou faltas de inventário.

O que se verificou foi que utilizando um novo modelo de gestão de inventário baseado num método de previsão mais capaz de lidar com a variabilidade - Holt Winters Exponential Smoothing – existe uma redução dos níveis de inventário de aproximadamente 42%. Ainda, com o novo modelo de gestão, verifica-se que a frequência de encomendas realizadas ao fornecedor e que os níveis de inventário dos artigos apresentam comportamentos mais regulares. Assim, em termos ecónomicos a redução esperada é de 4.300€ por semana, o que se traduz numa redução de valor em inventário de aproximadamente 220.000€ por ano.

Abstract

At Alpha, a retailer in the field of pipes and heat systems, an improvement project was carried out with the aim of reducing inventory levels. This reduction is considered extremely important given that it will allow the release of cash flow for future investments.

Inventory levels are impacted by their management model. This management model focuses on forecasts of future demand but, due to the high variability of consumption stemming from the high dynamism and uncertainty of the business sector, there is a suspicion that the forecasting model is not be the most indicated and that as such there is a possibility of improvement. Data on the year 2019 and part of the year 2020 will be used for the study.

The study focuses on a specific supplier, whose planning method is pull, for which inventory reduction is considered to be of greater importance due to the high economic value of the items purchased.

In order to solve the problem, first a calculation of several stock indicators was performed. This allowed a detailed analysis of the parameters intrinsic to the current supply method. Results led to the conclusion that inventory levels did not match demand and that there was room for improvement. In this way, improvement measures based on the two drivers of the inventory management model were identified: method of predicting future demand and method of calculating the safety stock.

After the improvement measures were identified and presented, space was opened to assess their impact. To this end, a simulator was constructed to replicate the supply process for the period under study. Based on the results of the simulation, which made it possible to bring the impact of the improvement proposals closer to reality, the economic impact of the proposals was accounted for.

What can be concluded is that the consumption patterns of the articles under study are in fact irregular and that the procurement method followed by the company cannot respond to the intrinsic variability in the business sector. In this way, it generates predictions away from reality that penalize the company in excess or lack of inventory.

What was found was that using a new inventory management model based on a forecasting method more capable of handling variability - Holt Winters Exponential Smoothing - there is a reduction in inventory levels of approximately 42%. Furthermore, with the new management model, it is verified that the frequency of orders placed to the supplier and that the inventory levels of the articles present more regular behaviors. Thus, in economic terms the expected reduction is approximately 4,300 € per week, which translates into a reduction in value in inventory of approximately 220,000 € per year.

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Glossary

ADD – Average daily demand

AI – Artificial Intelligence

APE – Absolute percentual error

AR - Autoregression

ARMA – Autoregression Moving Average

ARIMA – Autoregression Integrated Moving Average

CAE – Classificação de atividade económica

CDR – Coverage during replenishment

CV – Coefficient of variation

EDI – Electronic data interchange

I - Inventory

INE – Instituto nacional de estatística

KBS – Kaizen business model

KCM – Kaizen Change Management

KPI – Key performance indicator

LT – Lead time

MAPE – Mean Absolute Percentage Error

MOQ – Minimum order quantity

MQE – Mean quadratic error

OI – Order interval

Q - Quality

QCD – Quality, cost, and growth

ROP – reorder point

SARIMA - Seasonal Autoregression Integrated Moving Average

SCM – Supply chain management

SCOM – Supply chain ordering management

SES – Simple Exponential Smoothing

SF – Safety factor

SL – Service level

SS – Safety stock

SWOT – Strengths, weaknesses, opportunities, and threats

TFM – Total Flow Management

VVN – Volume de negócios

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1 Introduction

This project will be the result of the Dissertation course, which is part of the 2nd semester of the 5th year of the Integrated master's in Industrial Engineering and Management of the Faculty of Engineering of the University of Porto. The project is part of an intervention within the scope of operational improvement in a specialized retail company, whose core focuses on the selling of pipes and heating systems. This company has warehouses spread around Portugal, but the one in Porto will be the one under analysis.

In this chapter a presentation and contextualization of the project in question are made, describing the defined objectives and the methodology adopted for their consummation.

1.1 Project background and motivation

It became appropriate to analyze how the company considered under this dissertation can continue to grow in a sustained way, improving procedures and tools to support decisions every day. To keep growing, reducing the amount of stock value by 25% was deemed essential, and it became critical to analyze the purchase planning model used in order to understand what could be improved and which problems could be solved.

The purchase planning model was inducing high inventory levels and captivating unnecessary cash flow that the company could use to make profitable investments. This problem is a representative cost component, capable of impacting other operational areas of the company, and if it is not stopped it can result in a huge monetary loss for the company. This directly translates into a loss of competitiveness, while the customer is also affected by the service level provided by the company. Thus, the present project appears in this field of action, with a detailed analysis of the purchasing and stock management process being carried out. A methodology for daily order purchase planning is defined and a method for improving and normalizing the process established.

1.2 Wholesale trading in Portugal

According to data provided by INE, the national statistical institute of Portugal, companies in the commerce sector in Portugal showed positive results in 2018, despite the slowdown in some of the main economic indicators compared to the previous year. The 220.5 thousand companies in this sector (+ 0.6%) registered a Turnover (VVN) of 145.1 thousand million euros (+ 5.5%, after + 7.3% in 2017), an amount sales of goods of 137 thousand million euros (+ 5.5%, + 7.2% in 2017); the commercial margin stood at 25.7 thousand million euros, accelerating from + 6.1% in 2017 to + 7.1% in 2018; a gross added value of 18.8 thousand million euros (+ 5.2%, + 7.7% in 2017); and employed persons (800.9 thousand workers) increased 4.2% (+ 2.6% in 2017).

In terms of the distribution of the turnover by the Trade divisions in 2018, the contribution of 49.5% of the wholesale sector (division 46) to the total amount stood out. In retail trade (division 47) and automobile trade and maintenance (division 45), the contribution was 35.5%

and 15% of total VVN, respectively. Within the scope of this dissertation, given the nature of the company under analysis, the wholesale sector will be the focus of the analysis.

The wholesale trade sector (including agents), except for motor vehicles and motorcycles, is characterized by a wide dispersion in sub-sectors and businesses, constituting a vital space in the European and national economy. According to data obtained by INE (2018), this sector represents 18% of the total national industry. At a growing pace, its profound change in the profile of companies compared to traditional became evident, not only because of the concern to match its products to the expectations of the consumer but also due to the continuous bet on the quality and differentiation of raw materials and finished products.

Wholesale trade companies' turnover grew 6.1% in 2018 (+ 7.8% in 2017), the overall commercial margin grew by 2.8% (+ 6.0% in 2017) and staff service increased by 6.8% (+ 2.2% in 2017). This sustained growth exposed the sector to become one with the least companies in insolvency proceedings (22.5% decrease compared to 2018), in 2019, according to the recent Economic Outlook released by Crédito y Caución, a leading brand in credit insurance and export in Portugal.

In Portugal, 38,806 companies constitute the sector, mainly in micro and small sizes, although large companies are responsible for most of the turnover generated by the sector, totaling 35% of the € 71 thousand million generated.

Also, according to data from INE, Table 1 was constructed, which shows the influence of each sub-sector in wholesale trade. The groups that stand out are related to the wholesale trade of fuels, metals, construction material, hardware and other products (29%); wholesale of food, beverages, and tobacco (28%); wholesale of consumer goods, except food, beverages, and tobacco (21%). Included in the first sub-sector, is the wholesale trade of hardware, hand tools and articles for plumbing and heating (subclass 46740, according to the classification of the CAE), subsector where the present dissertation will focus on.

Table 1 - Representativeness, in terms of billing, of each subsector in the industry

Subsector	% revenue
467 - Wholesale of fuels, metals, building materials, hardware, and other products	29%
463 - Wholesale trade in food, beverages, and tobacco	28%
464 - Wholesale of consumer goods other than food, beverages, and tobacco	21%
466 - Wholesale of other machinery, equipment, and parts	8%
462 - Wholesale of raw agricultural products and live animals	5%
469 - Non-specialized wholesale trade	4%
465 - Wholesale of information and communication technology (ICT) equipment	4%
461 - Wholesale agents	2%

In terms of exports, this sector contributes to the internationalization of the Portuguese economy. According to data provided by Banco de Portugal (2020), since 2014, the sector has consistently represented around € 10 thousand million in export. In terms of consumption in the domestic market, there was an average growth of 4.2%, a rate in line with the one recorded, in the same period, by the Portuguese economy (5%). Over the years, as Figure 1 illustrates, these data have undergone positive developments, reflecting the importance of the sector under analysis in the Portuguese economy, with a potential for growth.

Figure 1 - Comparison between evolution of exports and domestic sales from 2014 to 2018

To summarize the positioning of this sector in the industrial context, a SWOT analysis was performed, shown in Annex A, to study the internal environment (strengths and weaknesses) and the external environment (opportunities and threats). On the one hand, it is noteworthy as a weakness the low customer interaction that wholesalers have aligned with the lower capability of understanding customers trends, in face of the growing threat of an increasingly competitive market where product life cycles become shorter. Given wholesalers' nature (keep a lot of inventory) not being able to predict customer trends may be a concern. On the other hand, the search for quality, differentiation, and innovation end up constituting an opportunity to stand out in the wholesaling industry, given the access to a high diversity of products and solid partnerships with upstream suppliers.

1.3 Project description

Characterized by being in a growing situation in terms of sales and services provided, the company under study is proud to be the main partner for professionals in the field of fluid conduction and is also a reference in equipment in the area of air conditioning and water treatment. Investing in research and development of new processes, as well as improving existing ones, is a long-term strategy and for which the effort has been growing. In this context, a continuous improvement project was born in February 2020, after a phase of diagnosis of the value chain, starting from the customer's request to the final product shipment, with a focus on making processes increasingly more agile, fast, flexible and reliable. Reducing waste and optimizing time were the goals outlined for cultural change and improving the company's overall performance.

In the scope of this project, the present study concerns the following problem detected: the high value stuck in stock which was induced by the incorrect definition of the reorder point. The service level is measured based on the company's ability to meet the delivery deadlines agreed with customers. The company's strategy has been to maintain high stock levels to achieve the desired service levels, resulting in a decrease in liquidity, with repercussions on the loss of investment capacity.

Going further, the need for the project arises because the company is faced with a situation of low service levels, no correct definition of safety stock for stock items, no standard for handling peak demand, poor visibility on stock integrated into the network and not well defined reorder points. All these weaknesses increase the costs of transporting goods, the number of complaints, the number of backorders and the number of lost sales. Thus, it is then necessary to analyze and improve the current purchasing and stock management system.

Therefore, this study, with an expected duration of 4 months, focuses on the prospect of substantially improving the company's profitability by reducing the finished product stored in-house. For this to be possible, it is necessary to proceed to:

• Adequacy of stocks to demand, not mortgaging the number of stockouts and the service level

• Definition of the exact order point and quantity to order

This change will only be possible with the involvement and contribution of all elements of the organization, so it is crucial, in an increasingly dynamic and competitive business world, that companies look for solutions that become more solid in the face of changes and innovations.

1.4 Objectives and key questions

The present project aims to analyze the final product stock levels for a specific company's supplier, with the objective of suggest improvements about its procurement.

After a diagnosis of both the stock management and the launching of purchase orders processes, the current purchase/stock management algorithm was studied. After identifying the main improvement opportunities, the goal was to reduce the accumulated stock value by 25%. To reach the defined goal, this project aims to develop and algorithm capable of estimating future demand that allows managing orders and consequently stocks more efficiently.

Details that affect stock levels such as the equations for calculating the reorder point (ROP) that determines the placement of orders, safety stock levels, and precision of the forecast method currently used by the company, constitute objects of an in-depth study in this project.

Considering the objectives, it is intended to answer the following key questions:

- What are the consumption patterns of the articles under study?
- Are stock levels adjusted to demand?
- What drives stock quantities?
- What type of forecasting algorithm should be used to better match on hand stock with predicted demand?
- How should safety stock be calculated?
- Based on simulating 2019 and half of 2020, what's the expected inventory levels reduction using the best combination of forecasting model and safety stock method?

Considering that the present study will focus only on one supplier, once an answer has been obtained for each of the questions, the same approach will be replicated for the remaining ones. The expected results will be evaluated, and if they meet the defined business success criteria, they will expose the good practices and methods that gave rise to knowledge that supports the making of new strategic and operational decisions of the company.

1.5 Methodology

The project was divided into four different phases. The first phase went through the definition and preparation of the project. The objectives and the way the project operate have been established. Then, all the necessary data were identified and obtained. A characterization of the products and suppliers was made. Additionally, an identification and analysis of the stockouts, obsolete articles and the identification of excess stock situations were made. In this second phase, it was also made the survey of administrative and operational processes of receipt and dispatch of goods for a complete characterization of the initial state. This survey made it possible to identify, characterize and prioritize the different operational problems of the company under study. Then, the articles for the study were screened and the articles were classified. The proposed solutions were defined and tested, i.e. the stock management model and the various sizing parameters such as the quantity of order, the safety stock, the review time, or the order point. Finally, and already based on the calculations and choices made, a computer tool, that allows to put into practice the new criteria of stock management, monitor the status of orders, as well as analyze the sales behavior in a more intuitive way, was developed.

1.6 Dissertation's structure

The dissertation is developed over 5 chapters, where it is possible to find a more detailed explanation of the entire context and methodology of the project.

This chapter introduces the project, its objectives and the research methodology outlined. A brief contextualization of the wholesale sector in Portugal is also made.

Chapter 2 refers to the bibliographic analysis, with a theoretical framework of the concepts and methodologies that served as support during the entire dissertation.

In chapter 3, the initial situation (AS IS) of the project under analysis is characterized, focusing on the identification and description of the problem, of the order management process.

Chapter 4 describes the solutions proposed to solve the problem, as well as the main results resulting from its implementation and the actions triggered by the continuous vision of improvement (TO BE).

Finally, in Chapter 5, the main conclusions, and improvement suggestions for implementation in a future perspective are reflected.

2 Theoretical Background

In this chapter, a bibliographic review will be presented on topics relevant to the development of the project, namely logistics, supply chain management, inventory management, and forecasting methods. Since the goal of the project to be developed is to reduce stock levels of Alpha company, for this it is necessary to know the inventory management state of the art. Understanding the key performance indicators that allow evaluating the impact of the improvement suggestions applied, as well as the existing inventory management models, will be of extreme importance to support the decision making further down the road. The project goes deeper regarding the need to estimate future values, mainly future demand. Thus, improvement suggestions will be based on demand forecasting and for this reason it is necessary to know the different forecasting methods studied and typically used, frame them, understand their strengths and weaknesses and make a decision on which ones are best suited to this particular problem. Note that the starting theme concerns Kaizen's philosophy that served as the basis for all analyzes and implementations.

2.1 Kaizen's Philosophy

Kaizen is a term of Japanese origin that means continuous improvement. This term consists of two words: Kai, which means to change and Zen, a word related to the search for perfection and which means better (Imai, 1997).

To create long term customer value and continuously improve different businesses there is a vast number of tools, methodologies, and knowledge. Figure 2 illustrates what is known as Kaizen Business System (KBS). Bearing in mind kaizen philosophy, KBS is composed by three pillars: Kaizen Change Model (KCM model), Deliver and cost (QCD model) and Growth tools. These three models combined allow performance improvements throughout the organization. Since people are the ones that make businesses and companies it is necessary to align the tools mentioned with people's motivation to attain the highest possible level of excellence and allow companies to grow.

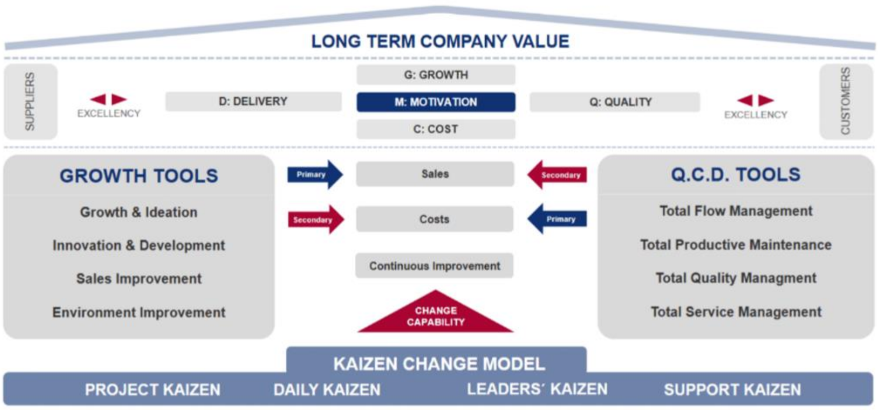


Figure 2 - Kaizen Business System in Kaizen Institute

Imai (1997) indicates that, as the kaizen philosophy is directly linked to improvement, the main areas of application of this methodology are those in which improvement is most necessary: quality, cost, and delivery. Quality must be considered both in the final products or services, as well as in the associated processes. The cost that needs to be improved is the total cost, from design to product sale. Delivery means the company's ability to deliver the product or service to the customer in the right quantity and at the desired time.

The basic concept of the philosophy is to seek to implement a culture of continuous improvement in all elements and teams of organizations. To this end, the Kaizen organizational development model is based on 5 principles that are used in the implementation of the organization's continuous improvement.

• **Create customer value**

The main objective of any organization is to create the greatest possible added value for its client. As a rule, this concept is the result of the three areas mentioned above: quality, cost, and delivery. In terms of quality, a product or service must have all the characteristics expected by the customer. As for cost, a product should not be priced at a higher value than what the customer is willing to pay. Customer satisfaction regarding delivery (right product/service, at the right time) defines the value added generated by the company in this area. The kaizen philosophy also proposes an extension of this concept of value added for all those involved in a subsequent operation, whether customers or other business stakeholders.

• **Flow Efficiency (Eliminating Muda)**

Muda is a word of Japanese origin that means waste. Taichi Ohno (one of the founders of TPS - Toyota Production System) was the first person to identify a large amount of waste on the ground. For Ohno, all activities that do not add value, whether carried out by humans or by machines, are classified as waste and must be sought to eliminate them. These wastes were organized into seven types of muda (a Japanese word meaning waste) (Kaizen_Institute 2018):

- Muda of waiting for people
- Muda of waiting for materials and information
- Muda of people’s movement
- Muda of movement of material and information
- Muda from overproduction
- Muda from over processing
- Muda from errors

• **Gemba’s Effectiveness**

One of the main factors of success in implementing the kaizen philosophy in organizations is the proximity to the place where value is added: the Gemba. The effective management of a company must be done as close to the Gemba as possible, as it is not feasible to run an organization exclusively within a control room. A closer approach to Gemba is needed to identify opportunities for improvement and corresponding actions, which can effectively improve the company's results.

• **People's involvement**

To implement improvement in organizations, it is necessary to involve and motivate everyone: administrators, top management, shift heads, and employees; only in this way is it possible to concentrate and effectively improve the levels of quality, cost, and delivery. This involvement is only possible with a very strong example given by the leaders, in the alignment of all efforts to create new work habits that support the implementation of continuous improvement.

• **Visual management**

Visual management has two main functions, the first is to make problems on the ground visible and the second is to help both employees and managers to quickly read what is happening on the ground. Visual management, therefore, serves to have a quick perception of company related activities, such as production or logistics. Either it indicates that it is under control, or it alerts you when an anomaly arises. (Imai, 1997)

Each Kaizen Institute's projects are developed based on these 5 principles, regardless of their domain: increased productivity, decreased delivery times, improved service level or increased quality indexes (Vasconcelos, 2015). The developed project is no exception, for this reason, these principles can be identified throughout it.

The continuous improvement philosophy focuses on changing the company's corporate culture. However, one of the biggest barriers relies on changing the standards, which are often applied for many years, thus creating opposition to change. Paradigm is the standard way of performing a given task (Imai, 2012). The elimination of the various paradigms present in organizations is only achieved with the introduction of different approaches focused on continuous improvement. Due to the routine and standardized tasks that exist in the various operations of organizations, automated procedures are created, which takes people to perform certain standardize actions when confronted with a given situation, that become difficult to change. The revision and consequent implementation of changes imply different work routines that must be practiced until they are considered a habit, to optimize the performance of operators. The systematization of this approach and the work on standards contributes and helps in the development of a company. Consequently, the organization becomes more autonomous and methodical whenever a new and better way of carrying out a task is developed.

2.2 Logistics and supply chain management

The concept of Logistics emerged and gained more importance, in the second world war and was, until the mid-1950s, associated with military activities, where ensuring that the war material, medicines, food, and clothing, were delivered at the right time and in the right quantities was fundamental (Soares, 2015).

Also, according to Soares (2015), with the increase in logistics costs due to the oil crisis and the international financial crisis, in the 1970s, organizations began to consider logistics as a fundamental element in their strategy formulation. The globalization of markets, the lifestyle in industrialized countries, and the growing development of information and communication technologies, have increased the importance of logistics.

According to Zamcopé et al. (2010), logistics can be succinctly defined as the area of an organization that is responsible for adding value: of place (ensuring that the product is placed in the place desired by the consumer), of time (within the stipulated delivery time), of quality (associated with the logistics operation) and information (tracking the order along the supply chain).

A logistics system can be defined in two segments (Zamcopé et al. 2010):

- Inbound logistics - starts at the supplier, goes through the manufacture of the product, ending with the assembly of the final product. Thus, this segment encompasses all activities necessary to supply the raw materials necessary for the manufacture of the final product (production).
- Outbound logistics - starts at the finished product, goes through its storage, and ends with delivery to the customer. This segment, also called physical distribution, encompasses all activities that range from the production of the final product to completion until it reaches the customer.

In short, Logistics includes transport management, material handling, in addition to customer order fulfillment, stock management and demand. Consequently, and considering the costs associated with logistical activities, this is seen by organizations as a "differentiating element" and, as such, performing logistical processes efficiently is seen as fundamental to obtain competitive advantage.

Given the fact that logistics is responsible for a wide range of steps and activities inside an organization, it is commonly confused with supply chain management (Soares, 2015). Supply chain management is a broader concept. The supply chain encompasses all activities linked, directly or indirectly, to the fulfillment of a customer order. Thus, in addition to logistical activities, the supply chain encompasses activities such as the development of new products, marketing, and customer service.

According to Chaharsooghi (2008), "supply chain management (SCM) literature covers a wide range of areas such as logistics, production, scheduling, facility location, procurement, inventory management, ordering management, and so on. Supply chain ordering Management (SCOM), which is the main concern of this dissertation, is an integrated approach to determine the ordering size of each actor of supply chain to the upstream actor aiming to minimize inventory costs, lower slacks, improve customer services, and increase the benefits throughout the entire supply chain."

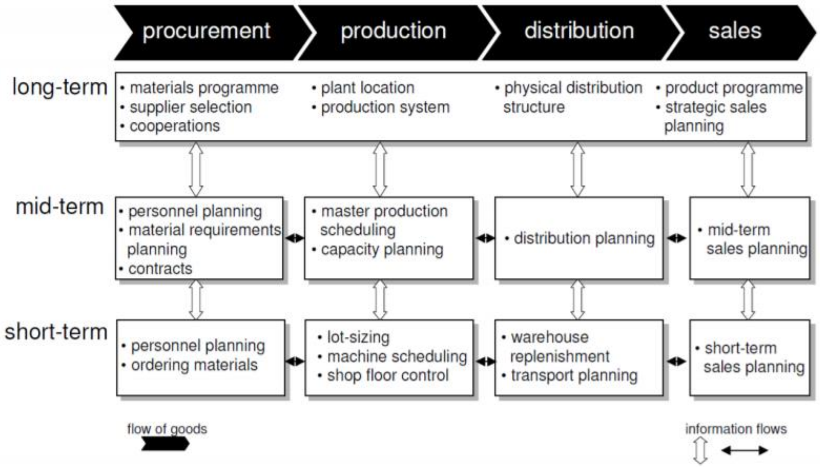


Figure 3 - Supply chain planning matrix (Rohde 2000)

In this way, the present project concerns the development of an ordering model that automatically generates orders to the supplier (SCOM) when needed thus, according to the supply chain planning matrix, presented in figure 3, elaborated by Rohde (2000), it fits in a perspective of procurement and in a short-term timeframe.

2.3 Inventory management

Inventory is the stock of any material that an organization uses in its daily activities. The main drivers for companies to hold inventory are:

- Demand variation absorption - demand is not exactly / perfectly known and therefore, to accommodate possible demand fluctuations, organizations use inventory to build a security stock that allows them to respond to market / production variations.
- Provide a safeguard for variations in suppliers' delivery times - deliveries of raw materials by suppliers can be delayed due to several reasons (lost orders, supplier's production problems, quality problems).
- Take advantage of order size - order costs decrease with increasing order quantity (lower unit cost). The offer of quantity discounts by suppliers is an example of one of the causes that leads to the creation of stocks.
- Avoid production stops - the existence of an inventory has the great advantage of supplying production, reducing the risk of stop / interruption of the production line (s) (due to lack of raw material).

According to Pfohl, Cullmann & Stolzle (1999) inventory costs, among various logistics costs in an organization, account for near than half of the company's total distribution dollar expense. Other researchers, such as those surveyed by Aggarwal (1974) and Silver (1981), have developed effective inventory management systems to reduce inventory costs since the introduction of Harris's economic order quantity model in 1915 (Harris 1915).

In contrast to the advantages of the existence of stock, there is a set of expenses that affect its levels. Storage costs (depreciation, taxes, insurance, and opportunity costs) and order costs (preparing a purchase order), are examples of disadvantages that the existence of stocks / inventory entails (Jacobs and Chase, 2013). Stock management is, therefore, a chapter in which it is necessary to make a set of commitments / tradeoffs to establish correct inventory levels.

Summing up there are three types of stock costs, all three important to determine the right stock management policy.

- Buying costs: costs associated with purchasing. They consist of the cost of the item, the cost of processing the order and transmitting it to the supplier, the cost of transport and the cost of the receiving process and adequate item storage.
- Cost of ownership normally includes three types of costs. Maintenance costs that are constituted by the cost of the respective rent, if rented, or amortization, in the case of own space, in addition to cost estimates related to the available space, such as energy and costs of the equipment used. Financial expenses arising from fixed capital or opportunity cost and stock insurance. This opportunity cost is quite difficult to accurately account for and is usually accounted for using the average value of investment interest. Finally, possible depreciations due to deterioration or obsolescence are considered.
- Stockout cost: a stockout occurs when consumption needs exceed the existing quantity. When the rupture occurs, the customer may withdraw from the purchase (non-captive demand) or may subject himself to waiting for the arrival of the items (captive demand). The identification and cost consequences of these two cases are very difficult to obtain. There may be the cost of lost sales, increased transport costs, increased costs for logistics processes, lost customers, and lost image (Ballou, 1999).

2.3.1 Management key performance indicators

The path to performance improvement depends heavily on the ability of each to assess the impact of individual actions on the overall performance of the organization in which it is inserted, as well as to understand the decisions in that context. For this to be possible, it is necessary to have adequate and up-to-date information. The performance evaluation allows you to monitor, in real time, the main KPIs (key performance indicators) that support the decision processes and all continuous improvement initiatives, from the operator to the top manager (Pinto, 2010).

There are thus some indicators that are important in assessing the performance of stock management (Gonçalves, 2010). Follows, indicators associated with the level of stocks and their profitability (equations 2.1 and 2.2) and indicators associated with shortages and service level (equations 2.3 and 2.4).

$$Rotation\ rate = \frac{Amount\ consumed\ throughout\ the\ year}{Average\ amount\ in\ stock} * 100 \quad (2.1)$$

Indicates the number of times that stocks are renewed during the year. The higher the turnover rate, the greater the profitability of the stocks (the lower the value of fixed assets in stocks).

$$Coverage\ rate = \frac{Average\ amountin\ stock}{Amount\ consumed\ over\ time} * 100 \quad (2.2)$$

Indicates the average time that the on-hand stock covers the demand (stock days).

$$Shortages\ rate = \frac{\text{Orders not fulfilled per year}}{\text{Total orders per year}} * 100 \quad (2.3)$$

Indicates the percentage of demand that is not met.

$$\%\ Service\ level = \frac{\text{Warehouse orders per year}}{\text{Total orders per year}} * 100 \quad (2.4)$$

Indicates the percentage of demand that is not met through inventory on hand.

The main indicators used by many companies are stock days (coverage rate) and stockouts (shortage rate). These indicators are measured daily, in general values and by warehouse. These indicators will be described and covered in chapter 3.

2.3.2 Inventory management models

In stock management there are two fundamental decisions to make:

- The size of the order placed to the supplier
- The right moment to make the order to the supplier

There are several models of inventory management that define a set of guidelines for control and replenishment of materials in stock, as shown in the analysis of figure 4.

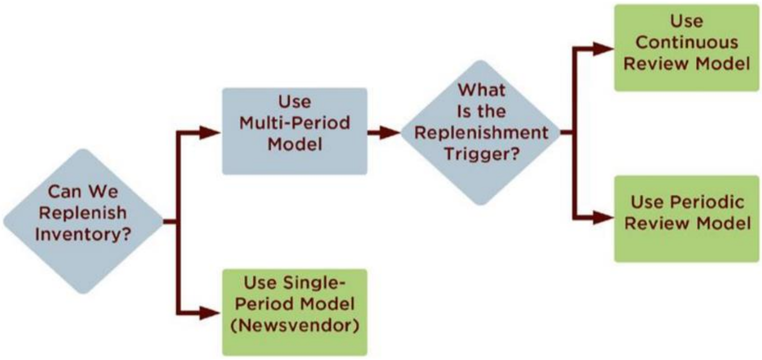


Figure 4 - Inventory decisions based on two different models

Single-period models are used when there is only one purchase decision, which is made to cover a fixed period. The newsvendor model is an example of a single-period model, where there's made an analogy with the decision regarding how many newspapers should a newspaper vendor print to sell on a given day, knowing that, due to uncertain demand, the copies not sold at the end of the day will be worthless. The multi-period models that are used for decisions that involve the periodic purchase of material (s), whether it is made based on a continuous or a periodic review model, and the inventory is used to meet demand. In this project, the interest is going to be multiple period models given the company's nature and possibility of reviewing their inventory levels and order new products from the supplier when certain rules apply. (Ziukov, 2015)

2.3.2.1. Multiple period inventory management model

The multi-period inventory management models are defined with the aim of ensuring that the material (s) will be available continuously throughout the year. Consequently, the material can be ordered multiple times during the year, with the inventory management system defining the quantity and timing of the order.

According to Jacobs and Chase (2013), there are two types of multiple-period inventory systems: fixed order quantity model (model Q) and fixed period model (model P). In the fixed order quantity model, an order is placed whenever the inventory level reaches a certain pre-defined level, thus requiring stock levels to be continuously reviewed. Conversely, in the fixed period model, orders are placed at the end of a defined and constant period, the quantity to be ordered varies depending on the level of inventory at the time of the review and the expected consumption.

The fixed order quantity model (model Q) has the advantage of allowing lower average inventory levels, which is why they should be used for more important materials. These models, by requiring a continuous inventory control, allow to detect and respond more quickly to possible stockout situations. The disadvantages associated with this model are related to the difficulty of use when important and frequent variations in consumption arise and the difficulty of grouping several items in the same order (Reis, 2005). The fixed period model (model P), due to the need to protect against stockouts during the review period, implies higher inventory levels (Jacobs and Chase, 2013).

The main differences and consequences of adopting the two main multiple-period stock management models are shown in Table 2.

Table 2 - Comparison of review models. Adapted from Jacobs and Chase 2013.

Review model	Order when?	Order how much?	Management effort	Stock level
Continuous	ROP reached	Fix	High	Less than periodic review
Periodic	Review period reached	Variable	Low	More than continuous review

In this project, the fixed period inventory management model will be detailed because it is the one that the company currently uses. This model will be based on the pull planning philosophy. The existence of a high number of references, several references for the same supplier (which allows minimizing order and transport costs) and the agreements established with suppliers (which define the frequency of placing and delivering orders), make it impossible to implementing the fixed order quantity model.

2.3.2.1. Fixed period inventory management model

In this model, the quantity to order at the time the review period occurs depends on the quantity to be consumed (Figure 5). Bearing in mind that the inventory level is only analyzed at the time of review, which implies that it is not possible to place another order until the next review period takes place, this model requires high safety stock levels. (Reis, 2005)

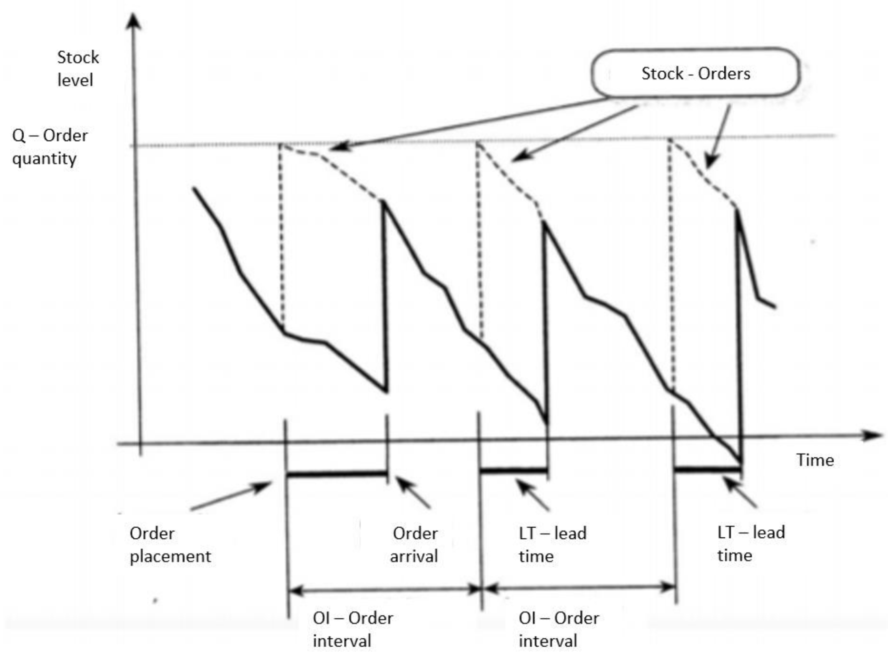


Figure 5 - Fixed-period model (model P)

In this model, the quantity to order (Q) will have to take into account: the expected consumption during the order placement interval (OI), the expected consumption during the lead time (LT), the safety stock and the inventory (I) level current (Jacobs and Chase, 2013).

Equation 2.5 defines a generic example of the order quantity, at the time of the review.

$$Q = \mu_D \times OI + \mu_D \times LT + z \times \sigma_{D(OI+LT)} - I. \tag{2.5}$$

$$\sigma_{D(OI+LT)} = \sqrt{(OI + LT) \times \sigma_{D(OI+LT)} + \overline{D} \times \sigma_{LT}}. \tag{2.6}$$

Onde:

$\sigma_{D(OI+LT)}$ – Consumption standard deviation during interval since order request till receiving

In this model, the level of inventory that triggers a new order is named reorder point and is calculated considering the average demand expected during the reorder period and replenishment lead time period, and the defined safety stock value. In the next subsection detailed information about this calculus will be explained.

2.3.2.1. Pull planning model

This section presents the state of the art regarding one of the fundamental blocks of the project in question: the implementation of Pull Planning in the company under analysis. This tool is part of one of the pillars of the Kaizen management system regarding Total Flow Management (TFM). TFM is an integrated concept, which aims to increase the flow and efficiency of processes throughout an organization's entire supply chain (Kaizen Institute 2013c). This concept can be subdivided into three zones by field of application: flow in production; flow in internal logistics; flow in external logistics. With the creation of a flow, it is expected to minimize material stocks in the chain, thus reducing lead time. On the other hand, it is expected to increase people's productivity, minimizing the time when there is no value added (Kaizen Institute 2013c).

According to M.C. Bonney (1999), there is little consistency in the description of push and pull systems. Different authors focus on different aspects of the distinction between the two models, as much emphasis is given to the delivery time, as well as the allocation method, lean production or the source of information that induces the production. Venkatesh (1988), for example, distinguishes the push system from the pull system as follows: "In a push system, a machine produces without there being a production order for the machine that succeeds it. On the other hand, in a pull system, a machine produces only after receiving an order from the later machine." For Goddard and Brooks (1984) what defines if a system is a push or pull is the source of information that originates the production: in push, the production starts based on an anticipation of the future need, while in pull it only starts the production when it exists an order. In this dissertation, the distinction between the two systems used is that of Goddard and Brooks (1984).

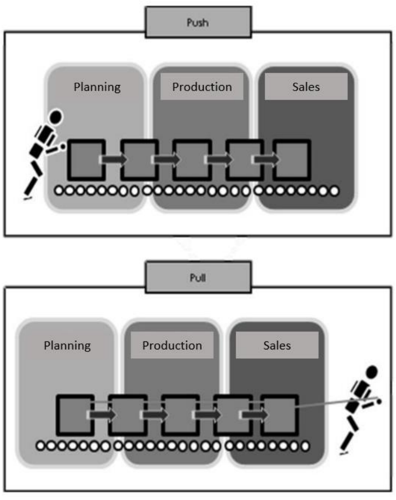


Figure 6 - Pull vs Push planning model (Kaizen Institute 2013a)

It is important to present the comparison between the push and pull planning model, outlined in Figure 6.

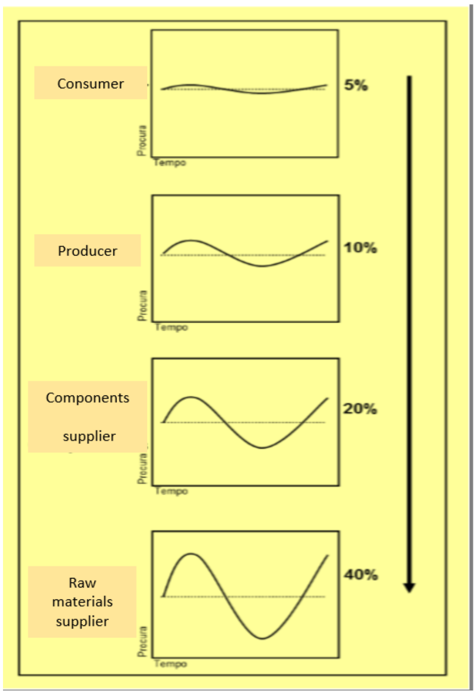


Figure 7 - One of the triggers for high stock levels: Bullwhip effect (Kaizen Institute 2013a)

It can then be concluded that the push model is based on customer order forecasts. Production and purchase orders are issued by a centralized planning department and are characterized by being a system associated with the planning of large production batches, with high lead time and non-existent flow. As the word itself indicates, push comes from the English push, that is, the product is made available to the market in order to meet what is thought to be the client's future needs (Kaizen Institute 2013b).

In contrast, the pull system is based on a model where demand is defined by the next customer in the logistics chain (Kaizen Institute 2013b). In the pull system, customer consumption triggers a purchase order and the various phases of the process communicate with the previous phase as necessary, thus avoiding large volumes of intermediate stocks. It is based on a visual information model where the information leads the material. It is a model of transversal application at the level of disciplinary teams and at the level of the entire supply chain of a company. The benefits of this planning system include a significant reduction in inventories, an increase in productivity in logistics / production, a decrease in the bullwhip effect (shown in Figure 7) along the supply chain, simplification of operational planning, better adaptation of productive capacity and equipment available to the product range and demand, leveling production and reducing the risk of stock ruptures (Kaizen Institute 2013b). Incidentally revisiting the literature authors like Lieberman (1999) there could be found that inventory reductions lead to productivity gain in the majority of companies tested. Quantitatively speaking, on average, a 10% reduction in inventory led to an average gain of about 1% in labor productivity, with a lag of about one year. Firms that made substantial inventory reductions underwent a period of annual productivity increase significantly greater than that of other companies on average.

One of the objectives of the implementation of "pull flow" is the construction of supermarkets of materials, being them composed by raw materials, intermediate products, or finished products. The key concept associated with this type of planning is the replacement of these supermarkets: the actual consumption of a customer down the value chain triggers an order to replace the verified consumption (Kaizen Institute 2013a).

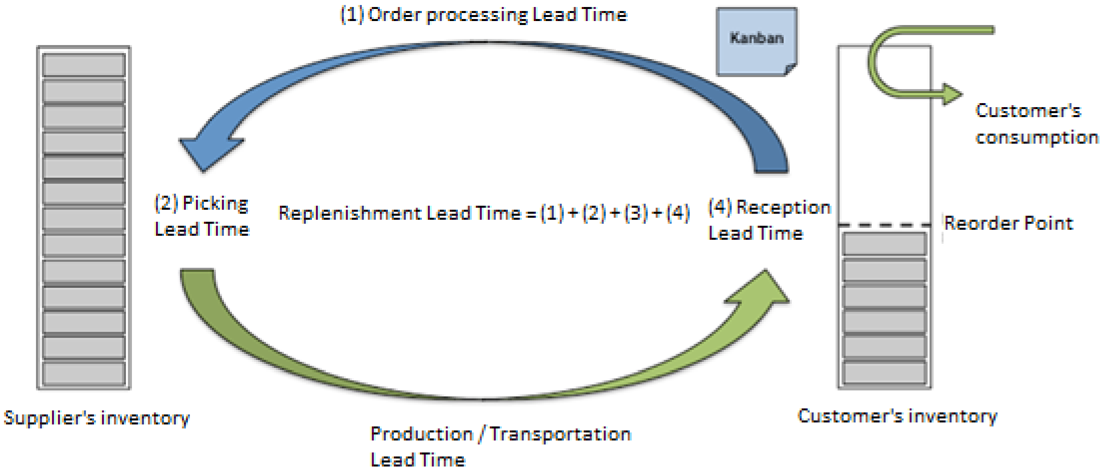


Figure 8 - Supermarkets dimensions definition for a pull planning system (Kaizen Institute 2013a)

According to Figure 8, the customer's inventory must be replenished when the order point is reached, and to determine this point it is necessary to first perform a Lead-Time analysis of the replenishment. Figure 9 shows the variation of the stock in a consumption process without variability in demand:

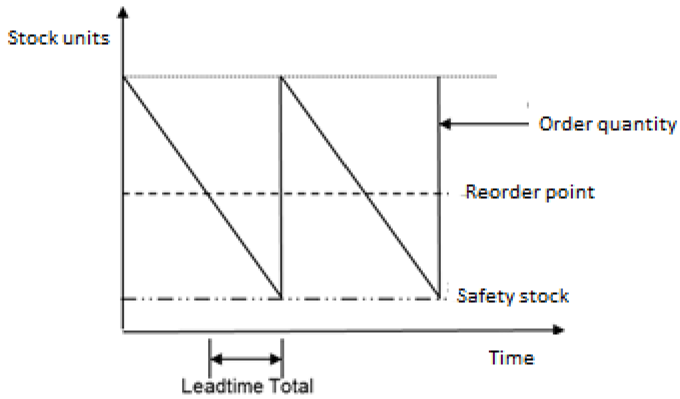


Figure 9 - Inventory variation throughout the time

Focusing on Figure 9, it is important to define some situations. Regarding safety stock, on the one hand, if the demand for a product after reaching the order point is higher than its average, the stock can reach the safety level. On the other hand, if the lead time is higher than your average, the same situation can happen. Thus, demand variability and lead time variability affect the definition of the safety stock level. About the order point, the fundamental analysis to be done is related to the mapping of the material replacement process. If this process is non-existent, it must be designed to minimize the replacement lead time, to reduce the situations mentioned above (Kaizen Institute 2013a).

2.3.3 ABC/XYZ analysis

The existence of a high number of articles/components in terms of variety and quantity in a warehouse, advises to carry out an analysis with the aim of identifying which articles are of most importance (Reis, 2005). Through this analysis, companies will be able to manage logistical operations more efficiently, thus, dedicate more time and focus on the most relevant articles.

The ABC classification divides the articles into three categories (A, B and C) according to one or more predefined criteria. The annual cost of consumption that allows to detect the financial impact, the annual consumption, the average unit cost of the article and / or the lead time, are examples of criteria for ABC classification (Flores, Olson, and Dorais, 1992). This analysis is based on Pareto's law, which means that 20% of the articles in storage corresponds to approximately 80% of the amount invested in stocks.

According to Reis (2005) depending on the category in which the item in stock is inserted, the surveillance strategy should be as follows:

- Class A – Low number of articles but with high value. Greater attention and vigilance are needed.
- Class B - Articles that require less vigilance, but the possibility of articles that may, due to variations in their financial value, be considered class A articles, requires special attention.
- Class C - Low surveillance due to the low value of articles belonging to this category.

The methodology consists of analyzing each article according to the defined criterion, sorting in decreasing order of marginal contribution to the criterion and, finally, grouping the articles by categories.

The ABC analysis can be complemented with the XYZ classification. Distinguishing between references belonging to the same category in terms of consumption fluctuations allows, first, to assess whether a given item is too much or too little consumed and, secondly, whether its consumption is stable or not (Table 3).

Table 3 - ABC/XYZ Analysis

	X	**Y**	**Z**
A	AX	AY	AZ
B	BX	BY	BZ
C	CX	CY	CZ

According to Scholz-Reiter et al. (2012), the statistical measure that allows the articles to be classified as XYZ is the coefficient of variation (CV), which is defined by the quotient between standard deviation of consumption and the average consumption. The CV calculation is given by equation 2.7.

$$CV = \frac{\sigma}{\bar{X}}. \quad (2.7)$$

In Table 4, the XYZ classification criterion is defined according to the calculated CV value, as well as its interpretation. (Scholz-Reiter et al. 2012)

Table 4 - XYZ classification criteria

Category	CV	Consumption characteristics
X	CV < 0,5	Rare fluctuations, constant consumptions
Y	0,5 < CV < 1	High consumption fluctuations due to trend or seasonality
Z	CV > 1	Extreme consumption variations

According to Scholz-Reiter et al. (2012), the combination of the two classifications has the main advantage of integrating materials with similar characteristics, which allows them to be processed with the same planning parameters.

The ABC classification proves to be very important for deciding the articles in which more management effort should be placed. However, the use of this classification only becomes scarce when choosing appropriate management models and logistical processes. In this sense, there is interest in a multicriteria analysis that will facilitate the choice of the most appropriate management models.

The unit cost can be used for a classification between high and low-cost articles only, or with more levels of separation. Demand characteristics such as frequency and variability, as well as characteristics of the supplier such as distance, delivery time and the uncertainty associated with it are other forms of classification (Bacchetti et al. 2013). Criticality is a widely used qualitative classification that can be done in several ways. It can be associated, for example, with the cost of disruption, the service fee that is intended, or the cost of the lack of production due to its lack (in the case of a productive process) (Santos, 2011).

2.3.4 Safety stock

The safety stock (SS) or protection stock is defined as the additional stock that aims to protect the company from stockouts, which may arise due to consumption above expectations and / or because the delivery times for orders exceeded those that had been previously agreed with the supplier (Reis, 2005).

It can also be defined that the safety stock aims to satisfy production needs, considering the volatility of certain parameters such as fluctuations in demand, imprecision of forecasts and variability of lead time (LT) (Ruiz-Torres, 2010).

From the definitions presented above, the concept of service level (SL) stands out. This is defined as the percentage of orders fulfilled, that is, delivered to the customer by the established deadline (Lutz, Löedding, and Wiendahl 2003). For example, for a 95% service level, it is estimated that in 50% of the cycles the safety stock is not necessary, in 45% of the cycles it will be sufficient, and that in 5 % of cycles are expected to run out of stock (Figure 10).

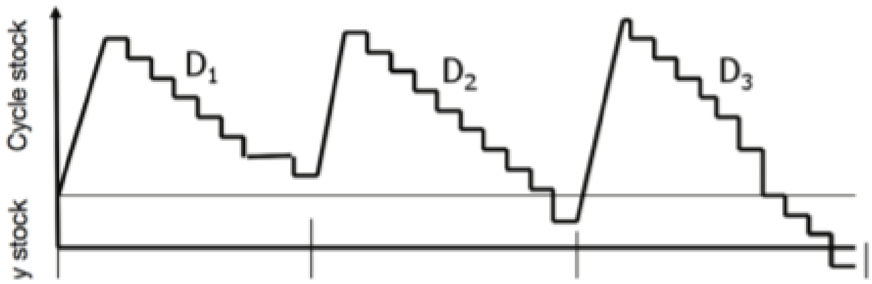


Figure 10 - Service level concept for inventory management (SL = 95%). (King 2011)

Thus, high service levels will result in fewer stockouts, but also in high security stocks and, consequently, higher inventory costs. Thus, it is necessary to meet the compromise/tradeoff between service level and storage costs.

Once the service level has been defined, through the inverse of the normal distribution for the SL it is possible to determine the safety factor (SF). Analyzing Table 5 it can be concluded that an increase in SL dramatically increases SF, significantly increasing safety stock levels.

Table 5 - Match between service level and safety factor

Service level (SL)	Safety factor (SF)
84%	1
85%	1,04
90%	1,28
95%	1,64
97%	1,88
98%	2,05
99%	2,33
99,99%	3,72

The optimization of safety stock levels is a topic of high relevance for organizations, and several studies have already been carried out to develop mathematical models for defining SS considering different parameters. Some of these calculation equations were studied by King (2011) and will be presented below.

The first method presented on equation (2.8) only considers demand variability and consists of multiplying the standard deviation of demand by the safety factor.

$$SS = SF \times \sigma d \times \sqrt{LT} \tag{2.8}$$

Schmidt, Hartmann and Nyhuis (2012) proposes changes to equation 2.8 introducing equation 2.9, now considering the deviation of forecasting errors to the detriment of the standard deviation of demand.

$$SS = SF \times \sigma f \times \sqrt{LT} \tag{2.9}$$

The second method (equation 2.10) presented considers the variability of the lead time and consists of multiplying the standard deviation of the LT by the safety factor (SF) and the average demand.

$$SS = SF \times \sigma LT \times Davg \tag{2.10}$$

The third and more complete method, presented on equation 2.11, considers the variability of LT and demand, assuming that these two factors are independent and normally distributed.

$$SS = SF \times \sqrt{LT \times \sigma d^2 + Davg^2 \times \sigma LT^2} \tag{2.11}$$

Regarding the previous equation, Zinn and Marmorstein (1990) suggest replacing the standard deviation of demand with the standard deviation of the forecast error. According to these authors, this change should be carried out since it will lead to lower security stocks being considered. This equation is presented on 2.12. The justification presented is that the use of forecasting methods means that certain unexplained variations, when identified by forecasting methods, will result in lower levels of safety stock.

$$SS = SF \times \sqrt{LT \times \sigma f^2 + Davg^2 \times \sigma LT^2} \tag{2.12}$$

There are still many other methods that deal with other statistical distributions and other characteristics related to the type of replacement, however the use of the normal distribution is reasonable for articles of high movement (Schmidt, Hartmann, and Nyhuis 2012).

2.4 Statistical Forecasting methods

Forecasting methods represent a set of techniques that are used in the planning, decision-making and control process of any organization. The inability to have an accurate knowledge of the future leads companies to resort to forecasts to reduce the level of uncertainty. (Caido, 2011) In the forecasting methods, there are mainly two groups: qualitative and quantitative methods.

Qualitative methods are used when the availability of historical data and the level of information is low. In this case, according to Caido (2011), companies end up making decisions based on subjective analyzes, using, for example, the opinions of people with experience and knowledge in business management.

Quantitative methods consist of analyzing historical data, with the aim of identifying patterns and extrapolating them for the future. This type of analysis assumes that the future will behave similarly to the past. However, as this does not always happen, it is necessary to keep in mind that forecasts have an associated error and that, as such, they are uncertain, imprecise, and inevitable. (Sipper and Bulfin, 1997) Additionally, and according to Pyke, Silver, and Peterson (1998), the greater the time horizon that is intended to be predicted for the future, the greater the error. In this project, quantitative methods applied to time series were used. These methods are spread over several models and assume that historical data can be explained as a combination of a standard format and random error (Fallen, 2011).

There are several studies about demand forecast, which comprise many analytical models developed over the past years. The most widely used techniques for predicting sales are based on time series as an input of the forecast and will be presented in this section.

2.4.1 Time Series

A time series is a series of past value points through time, and forecasting methods allow to predict the future demand through the analysis of this historical sales data. There are three very important factors that can be present in a time series, and they are represented in Figures 11 to 13: the level, the average value of the series; a trend, which reflects the downward or upward tendency of the series; and seasonality, which refers to the cyclic behavior of a series (Artley, 2018).

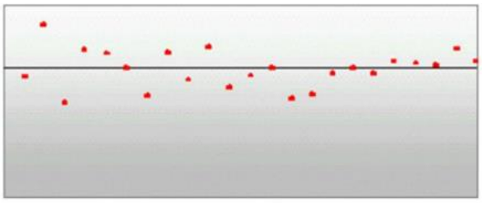


Figure 11 - Level of a time series in (Artley 2018)

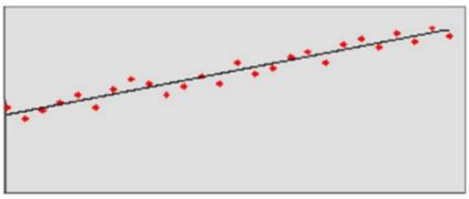


Figure 12 - Trend of a time series in (Artley 2018)

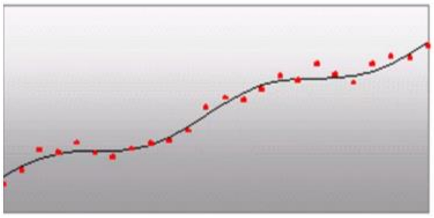


Figure 13 - Seasonality of a time series in (Artley 2018)

2.4.2 Time Series based forecasting techniques

The Autoregression (AR) forecasting model is used to estimate future values by performing a linear regression based on historical values. The regression order defines the number of p past periods that will be used to do it (Agrawal, Adhikari, and Agrawal 2013). AR(p) equation is represented in equation 2.13.

$$y_t = c + \sum_{j=1}^{p} \varphi_j \, y_{t-j} + \varepsilon_t \tag{2.13}$$

Where:

c is a constant,

φ_j is an autoregressive coefficient,

y_{t-j} is the actual value at time $t - j$ and

ε_t is the random error at time t.

The Moving Average (MA) technique also performs a linear regression, but it benefits from the past errors as an explanatory variable to the predictive model (Agrawal, Adhikari, and Agrawal 2013; Artley 2018). The order of the model is defined by q and MA(q) equation is represented in equation 2.14.

$$y_t = \mu + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \varepsilon_t \tag{2.14}$$

Where:

μ is the series mean,

θ_j is a model parameter,

ε_{t-j} is the random error at time $t - j$ and

ε_t is the random error at time t.

Given the characteristics of AR and MA models, they can be combined to construct an Autoregression Moving Average (ARMA) model. However, such models can only handle stationary time series, indicating that mean and variance cannot vary in time (Agrawal, Adhikari, and Agrawal 2013). ARMA(p, q) equation is represented in equation 2.15.

$$y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} \tag{2.15}$$

The Autoregressive Integrated Moving Average (ARIMA) is like ARMA but can handle non-stationarity time series. The order of the model integrated part is described by d, and being the lag operator $L^i \, y_t = y_{t-i}$ (Agrawal, Adhikari, and Agrawal 2013), ARIMA(p, d, q) equation is represented in equation 2.16.

$$\left(1 - \sum_{i=1}^{p} \varphi_i L^i\right)(1 - L)^d y_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right) \varepsilon_t \tag{2.16}$$

Seasonal Autoregressive Integrated Moving Average (SARIMA) covers the seasonal and nonstationary time series (Agrawal, Adhikari, and Agrawal 2013). The formulation of SARIMA (p, d, q) × (P,D,Q) s is represented in equation 2.17.

$$\Phi_p(L^s)\varphi_p(L)(1-L)^d(1-L^s)^D y_t = \Theta_Q(L^s)\theta_q(L)\varepsilon_t \tag{2.17}$$

Where:

$\Phi_p(L^s)$ and $\Theta_Q(L^s)$ are the seasonal polynomials.

For AR, MA, ARMA, ARIMA and SARIMA, identical weights are given to every period, which means that when the historical data observations increase, changes in the series are more difficult to identify and, therefore, to predict. An Exponential Smoothing model, as the name suggests, smooths the data by weighting different periods: more recent data is considered to weight more than older one by exponentially decrease it (Artley, 2018).

Note that along AR, MA, ARMA, ARIMA and SARIMA models some indexes like p, d and q were identified. To leave no doubts, know that p stands for the order of the autoregressive part, d for the degree of first differencing involved and q accounts for the order of the moving average part. Also, for the ARIMA and SARIMA models a new notation with P, D and Q appeared, these indexes have the same meaning as their lowercase notation, their difference is only enabling the characterization of the seasonal part of the model.

Simple Exponential Smoothing (SES) deals with time series characterized by the level parameter. It is similar to MA, but it uses a smoothing factor, α, so that more recent values of the series are considered to have more weight than older ones in predicting the future demand (Ostertagová and Ostertag, 2011; Rob J Hyndman, 2014). The simple exponential smoothing model is suitable for time series with a stationary trend and without seasonal movements since it uses only the last observed value and the forecast for that moment. In this model, to calculate the forecast for a given time t, it is necessary to obtain the forecast and the real value for the most recent instant (t-1), and the value of the damping or smoothing rate (α). (DeLurgio, 1998) The value of the optimal smoothing rate is that which minimizes the MQE, also known as mean squared error (MSE). SES equations are presented on equations 2.18 and 2.19.

$$\text{Forecast equation: } y_{t+h|t} = l_t, h = 1,2 \ldots \tag{2.18}$$

$$\text{Smoothing level equation: } l_t = \alpha \sum_{j=0}^{t-1}(1-\alpha)^j y_{t-j} + (1-\alpha)^t l_0, (0 \le \alpha \le 1) \tag{2.19}$$

Where:

l_t is an estimate of the level parameter,

α is the level weight parameter and

y_{t-j} is the actual value at time $t-j$.

Holt's Exponential Smoothing is an algorithm capable of predicting future values of a time series characterized by both level and trend factors. Since it is part of the Exponential Smoothing family, it weights the data according to its proximity to the actual date. The Holt model is suitable for series with a linear trend and without seasonal movements. The model estimates the level and slope of the series trend to calculate the forecast value for the intended time and, as such, has two smoothing constants α and β (Caido, 2011). These two parameters are obtained by minimizing the MQE. In addition to factor α, it also smooths the trend parameter by using β (Rob J Hyndman, 2014; Gardner and Mckenzie, 1985). Holt's equations are presented next on equations 2.20, 2.21 and 2.22.

$$\text{Forecast equation: } y_{t+h|t} = l_t + hb_t, h = 1,2 \ldots \tag{2.20}$$

$$\text{Smoothing level equation: } l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1}), (0 \le \alpha \le 1) \tag{2.21}$$

$$\text{Smoothing trend equation: } b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, (0 \le \beta^* \le 1) \tag{2.22}$$

Where:

b_t is an estimate of the trend parameter,

y_t is the actual value at time t and

β^* is the trend weight parameter.

For Holt-Winters' Exponential Smoothing model, the time series is characterized by level, trend, and seasonal parameters. Besides α and β, it smooths the seasonal component too, γ. There are two Holt-Winters models that should be used depending on the type of seasonality that the series presents: additive and multiplicative. Additive seasonality is characterized by seasonal variations of constant magnitude. The multiplicative seasonality is characterized by an increase or decrease in the amplitude of the seasonal component with the trend of the series. (Caido, 2011) However, in both cases, it is necessary to determine an additional smoothing constant (γ) for the seasonal component. The main differences between the two can be seen in Figure 6. The Holt-Winters exponential smoothing method is appropriate for series that show seasonality and trend. As in the previously mentioned models, the smoothing constants are determined by minimizing the MQE.

A downside of this approach is the difficulty of handling trends within the seasonal indexes (Rob J Hyndman, 2014; Gardner and Mckenzie, 1985; Artley, 2018). Holt-Winters' equations for Additive and Multiplicative Exponential Smoothing models are, respectively presented on equations 2.23, 2.24, 2.25 and 2.26. Figure 14 shows the difference between both models.

$$\text{Forecast equation: } y_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)}, h = 1,2 \ldots \tag{2.23}$$

$$\text{Smoothing level equation: } l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}), (0 \le \alpha \le 1) \tag{2.24}$$

$$\text{Smoothing trend equation: } b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, (0 \le \beta^* \le 1) \tag{2.25}$$

$$\text{Smoothing seasonal equation: } s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}, (0 \le \gamma \le 1-\alpha) \tag{2.26}$$

Where:

s_t is an estimate of the seasonal parameter,

m is the seasonality period,

k is the integer of $\frac{h-1}{m}$ and

γ is the seasonal weight parameter.

In this project and considering the consumption behavior, the Holt-Winters exponential smoothing model was used in its additive version. The equations for that version of the method are presented below on equations 2.27, 2.28, 2.29 and 2.30.

$$\text{Forecast equation: } y_{t+h|t} = (l_t + hb_t)s_{t+h-m(k+1)}, h = 1,2 \ldots \tag{2.27}$$

$$\text{Smoothing level equation: } l_t = \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1}), (0 \le \alpha \le 1) \tag{2.28}$$

$$\text{Smoothing trend equation: } b_t = \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, (0 \le \beta^* \le 1) \tag{2.29}$$

$$\text{Smoothing seasonal equation: } s_t = \gamma\frac{y_t}{l_{t-1} - b_{t-1}} + (1-\gamma)s_{t-m}, (0 \le \gamma \le 1-\alpha) \tag{2.30}$$

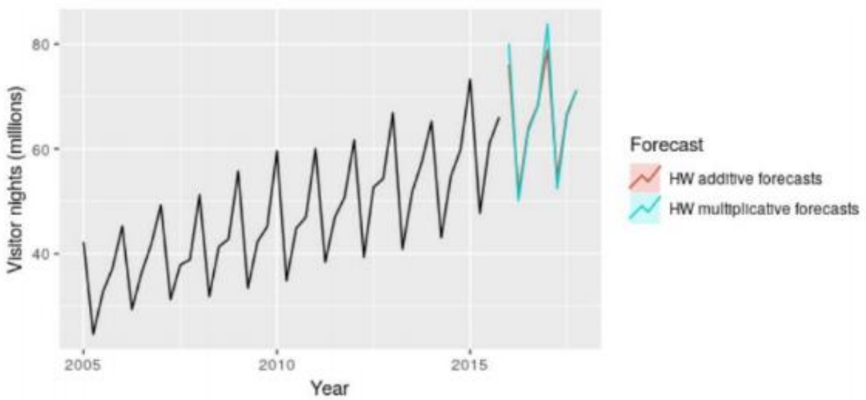


Figura 14 - Difference between Additive and Multiplicative exponential smoothing models in (Gardner and Mckenzie 1985). Adapted from a visitor night rental problem.

2.4.3 Advantages and challenges of Time Series based forecasting

The previously statistical methods described have diverse advantages associated, such as speed, even when dealing with a large dataset, and being easy to understand by the user (Ren, Choi, and Liu 2015). Despite these points in favor and their worldwide popularity, the linearity that categorizes such models carries some limitations when applied to pipes and heating systems items sales, due to the inherent high complexity and randomness of the historical data available. One of the ways of dealing with this problem is aggregate data by weeks, months, or years. Further on this dissertation a similar approach will be implemented to ease the lack of linearity between sales and days. The influence of other products demand and variations in price, for example, are not taken into account as inputs and such models only accept quantitative data, which are also disadvantages (Yu, Choi, and Hui 2011; Wong and Guo 2010; Loureiro, Miguéis, and da Silva 2018).

Pure Panel Data (PPD) model is a statistical method capable to deal with some of the problems described above. The algorithm has the ability of learning an item's behaviour by analysing other products that can cannibalize or complement it, because it considers the cross-sectional sales data to identify the effect from other items in the one under analysis. Moreover, it also considers the selling price of the fashion components. PPD is a quick and user-friendly method, and because of the advantages described previously, it expectedly performs better than the methods synthesized above (Ren, Chan, and Ram 2017; Ren, Choi, and Liu 2015). PPD equation is presented on equation 2.31.

$$S_{it} = \alpha_i + \gamma S_{it-1} + \beta P_{it} + \mu_{it}, \quad i = 1, \dots, I; t = 1, \dots, T \tag{2.31}$$

Where:

α_i is a constant for item i,
γ is the coefficient for the time series,
S_{it-1} is the linear component of demand in period $it-1$,
β is the coefficient for the cross-sectional data,
P_{it} is the price of item i at time t and
μ_{it} is the associated error of item i at time t (Ren, Choi, and Liu 2015).

There are many other statistical methods that can be used for sales forecasting. However, none of them can handle the non-linearity introduced by the industry studied in this report sales which, together with the advance of computing technologies, boosted the interest on artificial intelligence (AI) models for fashion sales forecasting in the recent years. Their success is mainly due to the learning capability by trial and error, as well as continuous improvement over time (Ren, Choi, and Liu 2015; Loureiro, Miguéis, and da Silva 2018; Ostertagová and Ostertag 2011).

2.5 Artificial intelligence forecasting techniques

Statistical methods have been used since a long time and serve as a basis for a tremendous spectrum of analysis but, depending on the context and available data, Artificial Intelligence methods are believed to be more powerful and versatile. Their above average capacity to handle high complexity and non-linearity of the available historical data is an advantage that promotes better and more accurate analysis (Ren, Choi, and Liu 2015).

For AI models to perform well, the algorithm must be previously trained by a part of the available dataset, which implies having enough data to be divided into two subsets: for training and testing. Moreover, the execution of this task carries an associated increase of the amount of time needed to run the process, which is the major disadvantage of using AI techniques (Ren, Choi, and Liu 2015).

Many studies emphasize the versatility and good performance of neural network models (NN) when applied in situations where there is a high variability in demand forecasting, due to their hidden layers' capacity of capturing nonlinear relationships within the available data, and the promising performance on pattern recognition. The most used gradient-descent based learning algorithm for NN is the Backpropagation Neural Network (BPNN), which is a feedforward (information moves in one direction) model that attempts to minimize the error between the desired output and the actual one. However, this algorithm may take hours or even days to complete the forecast because of the large number of iterations steps required on the training task, in order to improve the model accuracy, which represents a limitation for retailers that support their inventory planning and replenishment with the predicted sales. Moreover, many parameters have to be tuned, such as the number of hidden layers, the number of neurons in each hidden layer, the activation function of both input and output layer and the learning rate (Yu, Choi, and Hui 2011; Zhang, Patuwo, and Hu 1998; Xia and Wong 2014; Lahiri and Ghanta 2010; Sun et al. 2008).

More recent studies attempted to overcome the disadvantages of the BPNN related to the high running time of the forecast and, consequently, the concept of Extreme Learning Machine (ELM) emerged. This method is a single hidden layer and feedforward NN and has a much faster capacity to learn than the gradient descent-based algorithms, making it possible to use it in real time basis applications. Besides, it avoids many difficulties faced by the above method, such as choosing a stopping criteria and learning rate. The training time is shorter, and the input weights and hidden layer bias are randomly assigned, while the output weights are determined by the algorithm through a generalized inverse operation of hidden layer output matrices. Although faster, the results from ELM are unstable when compared to BPNN, mainly because of the randomness involved on the definition of the parameters, instead of tuning them, which allows reaching different solutions each time the algorithm runs (Yu, Choi, and Hui 2011; Sun et al. 2008; Wong and Guo 2010).

To take advantage of the faster results provided by ELM, some authors proposed an Extended ELM (ELME) algorithm. This model repeatedly performs ELM with the same dataset and calculates the average results, increasing the model accuracy. Yu, Choi & Hui (Yu, Choi, and Hui 2011), that studied fast fashion which is an industry where demand patterns is very challenging and demand patterns are similar to the ones in this dissertation, assumed colour, size and price as the most significant factors for the predictive task and, consequently, as inputs of the model. They found that, while the number of iterations increase, the time required by the method also increases in an almost perfectly linearly way, if all other parameters remain unchanged. However, there is a point in which this increment leads to a constant forecasting error measure and increasing the number of iterations adds nothing but a longer duration. The time needed to perform the task also increases with an increment in the number of neurons on the hidden layer. The associated error only decreases until a certain number of neurons, because at some point the model will become too like the training set (overfit). The authors also found that more historical observations introduced into the model increase the duration of the task in a really slow path, whereas the forecasting error decreases drastically, indicating that it is preferable to have more data as an input of the method. Another finding was that the increase in the variance of the available dataset does not have significant impact in the time used to run the model due to a normalization performed on the input parameters, although it increases when in the presence of white noise (many different frequencies together). The study proved that ELME achieved slightly better forecasting results than the traditional NN, but the time required to perform it was superior to the latter one, given the increase on ELM number of iterations. The findings referred above are transversal to any NN method.

Another study by Au, Choi, and Yu (2008) deals with the trial and error approach used in the NN methods presented until this point. They proposed a method based on evolutionary computation (EC), capable to quickly locate the high-quality areas, even when the search space is very complex and large. Joining this advantage to the NN methods, the concept of Evolutionary NN emerged (ENN). In this specific study a direct binary representation is used for every connection between neurons and, if the value is equal to one, that means that the connection exists, while if it is equal to zero there is no bridge between a neuron and another one from the following layer. Considering a single hidden layer, pruning can occur to a hidden neuron when there is no connection from any input neuron, and can also occur to an input neuron when it is not linked to any other neuron, as respectively shown in ENN pruning in (Au, Choi, and Yu 2008) and in Figure 15.

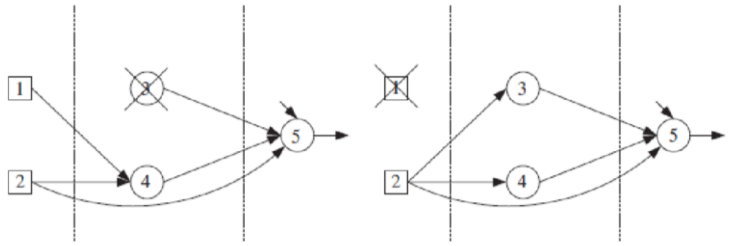


Figure 15 - ENN pruning in (Au, Choi, and Yu 2008).

In this study, the most critical aspect to consider is the number of hidden neurons, because of the time involved and a possible overfitting of the results (the model is too shaped by the training data) when in the presence of a higher number, while a small one may not train well the algorithm. For that reason, a pre-search mechanism was used to find its optimal maximum number: find a number that overfits the results and another one that does not. The authors found that the higher the time consumed by the forecasting task, the better the accuracy associated. Moreover, as the time horizon increases, the more the connections between hidden and output neurons decrease and the ones between input and output layers suffer an increment. The first finding happens because there is more available data to train the model and the second one implies that, in the presence of extra historical data, the relationship between input and output tends to become linear. ENN performs better if the available time series is smaller and has few variances associated. The output was compared to SARIMA results, which proved to be more accurate than ENN when there is a great uncertainty associated to the demand of a product. This finding may be due to the large amount of available data, which allows to use a statistical linear model to perform the predictive task.

Deep Neural Network (DNN) is another approach to NN and was studied by Loureiro, Miguéis, and da Silva (2018). It is a feedforward model composed by more than one hidden layer, so that the first layers can analyse more simple features while the latter ones take care of the more complex data. In this specific study, DNN was used to perform the learning process of the algorithm with three hidden layers, all of them containing the same number of hidden neurons.

2.5.1 Random Forest

RF algorithm is composed by a set of decision trees, each one built under a group of nodes: a root node, the leaf nodes, and the splitting nodes. The first one is divided into two different and nonoverlapping splitting nodes, after considering every division combination within the input variables from a random sample of predictors. This evaluation is usually supported by the MQE measure and, for regression, the predicted value is calculated by the mean of the response nodes. The input that contributes with the greatest performance and, therefore, smallest MQE, is chosen to perform the split. RF follows a top-down approach without any pruning and the same procedure is applied to the two descendant nodes until reaching a stopping criterion. The average of the last constructed nodes, the leaf ones, dictates the output of the observation in study (Saraswat n.d.; Cutler, Cutler, and Stevens 2012).

The model uses a bootstrap aggregation approach to avoid overfitting and, consequently, increase its performance. Different bootstrapped samples are taken from the data to construct all the trees of a RF, however, normally one third of the set is used only to test the algorithm, named the out-of-bag (OOB) observations. This procedure will decrease the variance associated to the learning method and, after constructing each tree, the OOB MQE error is calculated by their average value (Cutler, Cutler, and Stevens 2012; Okun 2011).

2.5.2 Support Vector Machine

SVM algorithm, or more precisely, Support Vector Regression (SVR) (regression is used on this paper) tries to find an optimal hyperplane, named decision boundary, comprised by a margin that maximizes the Euclidean distance by minimizing the error between the observations, the support vectors. Since the output is a real number and there are infinite possible values to predict, a tolerance margin called epsilon is added to the real limit in order for SVR to produce a continuous response that deviates in the maximum or minimum of that value (R-bloggers n.d.; B. Liu 2011; Carvalho 2017).

A kernel is a function that calculates the inner product between two vectors of the training data. Sometimes the provided entrance points are not linearly separable and SVM must use one of its kernel functions to transform it into a higher dimension. In this way, the inner product from a suitable space is calculated and data can be linearly separated (Souza 2010; B. Liu 2011).

2.5.3 Neural Networks

The NN algorithm procedure is similar to what happens in the human nervous system: many interconnected neurons transmitting processed information between them (Goodman 2016; Günther and Fritsch 2019). NN architecture can be seen in Figure 16.

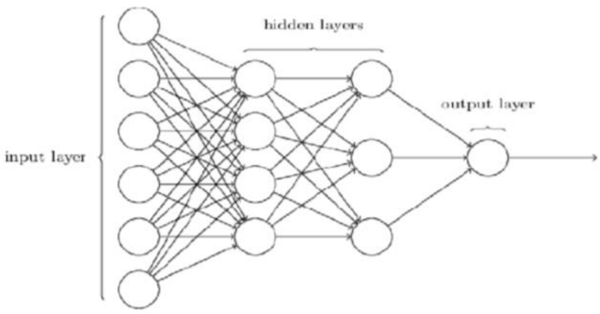


Figure 16 - Artificial Neral Network architecture in (Neapolitan 2018).

There are many distinctive types of this algorithm, but only the one evaluated in this paper is going to be explained in this subchapter: a fully connected feedforward backpropagation NN.

The model is composed by an input, an output and one or more hidden layers, and linked by many feedforward connections. Each connection has an associated weight, and for each layer there is a bias parameter that helps to improve the learning of the algorithm. The number of neurons in the first layer is equal to the number of predictor variables, while the output layer has a single neuron. The number of neurons in the hidden layer(s) must be optimized to achieve the best possible performance. Usually, one hidden layer is enough to execute the algorithm (Alice 2015; Carvalho 2017).

Firstly, the input layer receives the raw data and the initial weights are randomly selected. Then, an activation function between the input and the hidden layer transforms the data received from the first into an output that will be received by the latter one. The same happens between all layers, meaning that each neuron end has an associated activation function. At the output layer, a final answer for an observation is given and the respective comparison to the real value is made. Several iterations named epochs are performed using the same training set and, at the end of each one, the average error is calculated in order to allow, according to the learning rule in use, to update the weights and convergence to the local minima of the error function (Carvalho 2017; Sazli 2006; AnalyticsVidhya 2017).

A gradient descent learning rule is used to update the weights in each iteration. A positive partial derivate indicates that the weight is contributing to the increase of the error and, consequently, must be decreased. The opposite happens with a negative partial derivate, which means that weights go on the opposite direction of their partial derivate until finding the local minimum. The main goal of NN is to continue converging until reaching the global minimum, however, there are usually regions with local minima within the space and, if the algorithm gets stuck in them, it will never find its way to the global one. The convergence process can be computationally very time expensive (Günther and Fritsch 2019; AnalyticsVidhya 2017).

High learning rates can cause many oscillations within the space that will not lead to the model convergence, while slow ones will perform many unnecessary cycles until finding a local minimum and consequently increase the required time by the algorithm. In this way, finding an optimal learning rate is mandatory to achieve good performance results while minimizing the duration of the task (Alice 2015).

2.6 Forecasting error analysis

When a comparison between forecasting methods is made or when one only wants to analyze the accuracy of the forecasting method in use, it is imperative to resort to measures or criteria of forecasting errors. An error is the quantity by which an estimated value differs from the reality. The use of a quantitative criterion allows a quick and objective conclusion of the accuracy of the forecast made.

One of the measures of analysis of forecast errors is the MQE, presented on equation 2.32, which translates the mean value of the squared deviations between the observed values (Y) and the predictions (P), at each instant (t). This indicator, although widely used, is extremely sensitive to errors resulting from disastrous forecasts since the error associated with the forecast, for each instant, is squared. (Fallen, 2011)

$$\text{MQE} = \frac{1}{m}\sum_{t=1}^{m}(Y_t - P_t)^2. \tag{2.32}$$

Alternatively, to fill the MQE gap, the criterion of the average percentage error (APE) can be used, presented on equation 2.33, which translates the average percentage value between the deviations between the observed values and the forecasts, at each moment. Negative values of the average percentage error means that the predicted value for a given moment was higher than what was registered. In this way, this indicator allows to identify whether the forecast method is inflating the expected value or not.

$$\text{APE} = \frac{1}{m}\sum_{t=1}^{m}\left(\frac{Y_t - P_t}{Y_t}\right)\times 100. \tag{2.33}$$

According to Gentry, Wiliamowski and Weatherford (1995), APE should not be used as a method of comparison between forecasting methods. For this purpose, the mean absolute percentage error (MAPE) must be used, presented on equation 2.34, which translates the average percentage value of the deviations between the observed values and the forecasts (absolute value), at each instant. This criterion allows to translate the average percentage of the forecast error in relation to the magnitude of the observations. (Fallen 2011)

$$\text{MAPE} = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{Y_t - P_t}{Y_t}\right| \times 100. \tag{2.34}$$

This measure was used by six well known autors and proven to be a successful metric to compare multiple forecasting methods. (Xia and Wong 2014; Du, Leung, and Kwong 2015; Loureiro, Miguéis, and da Silva 2018; Thomassey and Fiordaliso 2006).

3 Case study presentation

In this chapter the case study that served as a basis for the present dissertation will be presented. Further topics will focus on information about the supplier under analysis and reorder point calculations based on order quantity and ordering period. Furthermore, some analysis regarding stock levels and sales will also be presented. The chapter closes with improvement opportunities identified and which will be the subject of in-depth study in the next chapter.

3.1 Case study presentation

The proposed work aims to analyze one of the company's suppliers, with the objective of reducing stock levels. Of the various suppliers of raw materials of company Alpha, Beta company was the supplier chosen for study, due to the high economic value and frequency that references have, and therefore the reduction of inventory levels is of greater interest to the company. Alpha company sources from Beta 27 references and all of them will be studied. will be studied. These references will be split by consumption patterns to group references with similar patterns, further on this report this will be explained. This split will create a new column called category that will serve to aggregate references. Annex B presents these 27 references: their category, their name, description, and family.

The planning type for the supplier under analysis is pull. The pull procurement strategy is defined when orders placed to suppliers are triggered after actual consumption for sale. In this type of planning, the expected consumption during lead time and order frequency that translates into the quantity to order (hereafter called Reorder point) is defined/calculated and, whenever the stock level equals or falls below the reorder point, an order is placed to the supplier. In the case of the supplier under study, the reorder point is calculated and analyzed daily, and thus the planning type defined for supplier Beta is daily pull. The supplier takes on average 5 working days to deliver the ordered products and, based on previous data, has a null standard deviation of lead time. Therefore, a lead time of 1 week for all articles under study is assumed. Also, for the sake of simplicity it is assumed that when company Alpha receives an order it takes zero time to process it.

3.1.1 Reorder point and ordering quantity

For suppliers, whose planning is daily pull the quantity to be ordered is obtained by the reorder point (ROP) equation used by the company. The equation's output is updated daily, for each reference individually, automatically using a transaction in Primavera[1]. In view of this value, after the process of obtaining the corresponding ROP, the system automatically generates the orders and sends them, through EDI, to the suppliers. The quantity to be ordered, as shown in equation 3.1, is calculated considering the difference between ROP, the quantity in stock and still to come orders at the time of order generation.

[1] Primavera is a management software also known as an Enterprise Resource Planning (ERP) that assures an integrated view of all the business processes in one technological platform.

$$Q_{Wx} = ROP_{Wx} - Stock_{W(x-1)} - \text{Open orders} \tag{3.1}$$

Se:

$Q_{Wx} < 0 \rightarrow Q_{Wx} = 0.$

$Q_{Wx} > 0 \wedge Q_{Wx} < MOQ \rightarrow Q_{Wx} = MOQ.$

$Q_{Wx} > 0 \wedge Q_{Wx} > MOQ \rightarrow Q_{Wx} = Q_{Wx}.$

Onde:

Q_{Wx} – Order quantity in week X
ROP_{Wx} – Reorder point calculated in week X
$Stock_{W(x-1)}$ – Stock at the end of week X-1
MOQ – *Minimum order quantity*

The ROP calculation equation considers two variables, as can be seen in equation 3.2: the coverage during replenishment (lead time and order frequency) and the safety stock.

$$ROP = RE + SS. \tag{3.2}$$

Where:

RE - Replenishment time coverage
SS – Safety stock

3.1.1.1. CDR – Coverage during replenishment

The calculation of coverage during replenishment (CDR) is obtained through the product between the average daily demand for the total order lead time.

The average daily demand (ADD) is obtained by summing the consumptions for the material/reference under analysis, in a past horizon of 4 weeks, to be divided by the number of working days (i.e., possible sale), as can be seen on equation 3.3. Taking for example, in the calculation of the ROP calculated on Tuesday of week 4, the ADD will be calculated according to the sum of consumptions from week 0 to week 4, to be divided by the number of working days (average of 20 days).

$$ADD = \frac{\sum_{w=1}^{4} Demand\ w}{N\ working\ days} \tag{3.3}$$

The lead time is calculated by the sum of duration (in days) of the various stages that the material undergoes from the moment of placing the order until it is ready for sale. In this case the lead time results from the sum of the supplier's delivery times, stock replenishment and receipt of the items. In this case, as mentioned previously, all references present a lead time of 5 working days (1 week).

3.1.1.1. Safety stock

The safety stock is defined by the product between the average daily demand for the safety percentage set for the reference. This equation follows next on 3.4.

$$SS = Average\ daily\ demand * Nº\ of\ safety\ stock\ days \tag{3.4}$$

The defined safety percentage is based on the ABC classification of the material (Table 10).

Table 6 - Safety stock definition criteria based on company's Alpha ABC classification

Classification	Safety stock
High rotation stock	20%
Medium rotation stock	10%
Make to order	0%
Nonstock articles	0%
Outdated/No sales products	0%

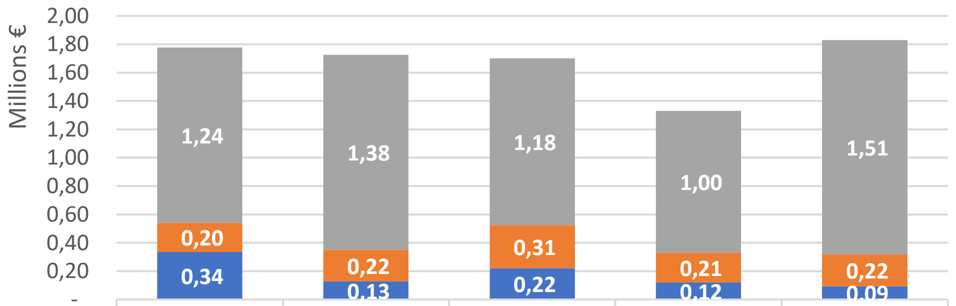
However, the responsible planner has the freedom to adjust the number of days to consider, considering his/her experience. This capacity is presented as a factor that can influence the variability of stock levels. Although emphasizing this situation further studies will not take this under account.

3.2 Current inventory analysis

It should be noted that there are in Porto warehouse 21 844 references. Of these there are 6696 without stock and without consumption and for this reason were removed from the analysis. Only 15% of referrals have at least monthly rotation and 80% of sales (in terms of value) are concentrated in 2070 references. It should be noted that there are 4327 references without any consumption since the beginning of the year with a total stock value of 810 035€ and about 30% of the value in stock is concentrated in CZ references: with little rotation and little value (as shown in Annex C).

3.2.1 Lost Sales

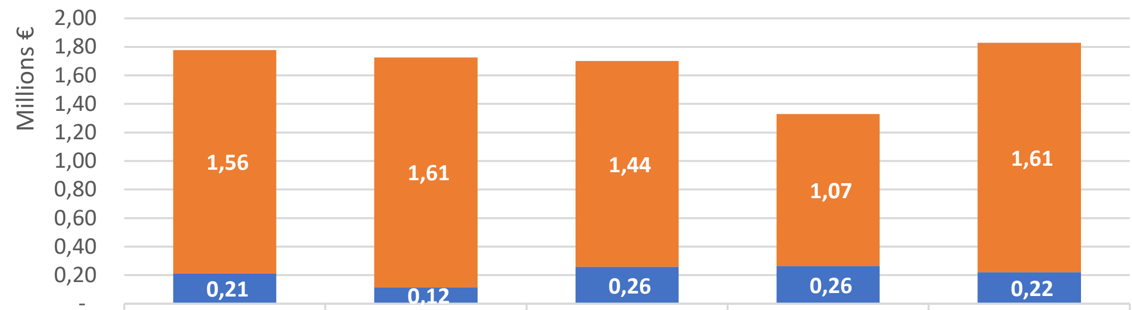
Looking at the orders placed, about 25% of the orders are not satisfied. There may be several reasons for closing an order, but this indicator is not followed. Of these, there are orders placed on items without rotation and other items that should exist in stock. For orders of stock items, the non-satisfaction of the order is in the 23%, which equates to a monthly loss of invoicing close to 230k €. In total, according to this analysis, about € 400k of sales are potentially lost monthly, as shown in figure 17.



	June	July	August	September	October
Orders delivered	1 236 717,06	1 375 702,19	1 175 437,35	1 000 684,92	1 512 350,60
Lost sales - stock articles	204 969,35	223 466,42	305 178,22	209 471,84	223 186,73
Lost sales - no rotation articles	335 734,00	126 699,20	220 015,22	120 100,04	93 788,00

Figure 17 – Unsatisfied orders vs satisfied orders by month

Another approach used to evaluate lost sales is to compare the actual invoicing with the amount placed on orders. According to this analysis, as shown in Figure 18, the monthly invoicing loss is close to €215k/month, i.e. €2.5 million per year.



	June	July	August	September	October
Lost sales	1 564 410,39	1 609 282,70	1 441 429,57	1 067 487,16	1 609 414,61
Real sales	213 010,02	116 585,11	259 201,22	262 789,64	219 910,72

Figure 18 - Orders placed vs Real sales

3.2.2 Stockout situations

The number of items in stockout, both in the Porto warehouse and in the entire network, has been decreasing. At the beginning of the year, and extending the analysis till the end of August, 10% of the articles with monthly rotation were in rupture. In August, this figure was at 5% (figure 19).

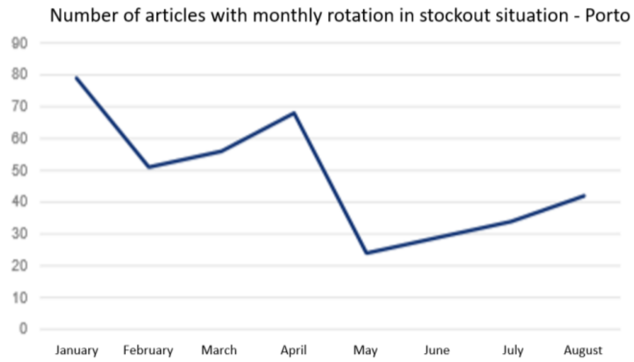


Figure 19 - Number of articles with monthly rotation in stockout situation

Since the algorithm currently used for calculating minimum and medium stocks uses billing and not demand, the stockouts will influence the actual order point: billing is different from actual demand and manipulated the data because it is not a total independent variable.

3.2.3 Excessive stock situations

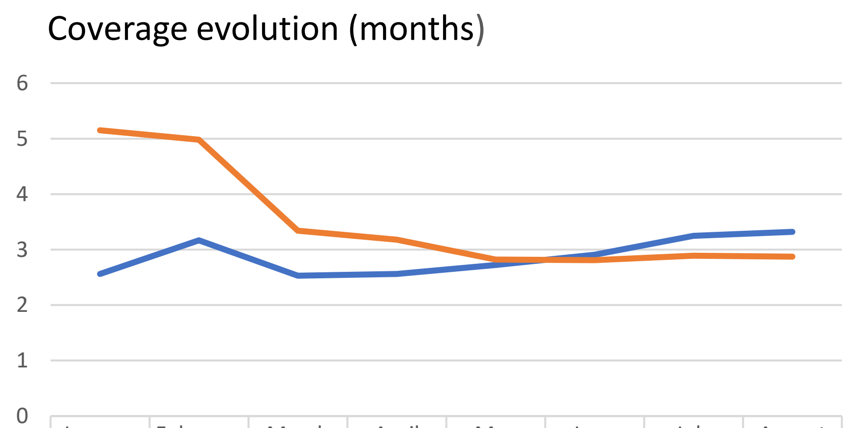
As already analyzed in the previous section, there are currently situations of rupture in the company. This could be related to current stock levels being low. However, due to the current lack of a management model, the results in many cases denied this expectation, and situations with high stock levels were identified in relation to the sales presented. These conclusions were drawn from the calculation of the estimate of the coverage time of the stock level throughout 2019. For this calculation, the consumption of articles per week in 2019 was considered, with the coverage time of each article being the quotient between the amount recorded in the inventory at the end of 2019 and the average consumption of the article per week of 2019. The results, presented in table 7, show that more than 6000 articles (31% of the total) have coverage times of more than three years. On the other hand, there are more than 900k € of articles with almost zero rotation (non-sold items + articles #N/A), which together sell about 30k €/month. The items are divided into 5 large types: high rotation stock items, medium rotation, items without stock, order items and non-sold items (there are in stock but have no consumption).

Table 7 - Average stock levels, consumption by article description

Description	Type	Average stock	Average consumption	N articles	% N articles	Coverage (months)
> 25 sales in the last 6 months	High rotation stock	1 603 822,97	602 341,64	1 649,00	8%	2,66
> 0 sales in the last 6 months	Order	1 017 356,74	309 789,87	6 545,00	30%	3,28
> 10 sales in the last 6 months	Medium rotation stock	682 835,17	195 852,56	1 716,00	8%	3,49
No sales & No stock	Outdated	466 955,68	10 224,41	2 973,00	14%	45,67
??	No stock	6 308,55	9 934,33	5 285,00	24%	0,64
No sales & Stock	#N/A	475 250,52	9 552,35	3 602,00	17%	49,75

The analysis of several examples with the company allows us to conclude that there is a great disparity of decisions in the current situation, both in terms of quantities ordered or in terms of time between orders, which makes situations of stockouts or excessive stock recurrent.

Following stock levels by classification and then by typology analysis will be performed. According to figure 20 and 21, we found that in the network stocks increased about 1000k € (25%), especially in stock references (coverage increased almost 1 month). One possible explanation for this increase, according to company Alpha, is the increase in costs with special transport and customer complaints (delivery delay, many partial deliveries), which has led to increased stocks. It is also found that non-consumption references (non-sold items) are also increasing they have risen 150k € since the beginning of the year. Note that sales also increased, which led to a decrease in the coverage of the order items from 5 to less than 3 months (plus sales for similar stock).



	January	February	March	April	May	June	July	August
Coverage - Stock articles	2,56	3,17	2,53	2,56	2,72	2,91	3,25	3,32
Coverage - No Stock articles	5,15	4,98	3,34	3,18	2,82	2,81	2,89	2,87

Figure 20 - Stock coverage of MTS and MTO articles by month

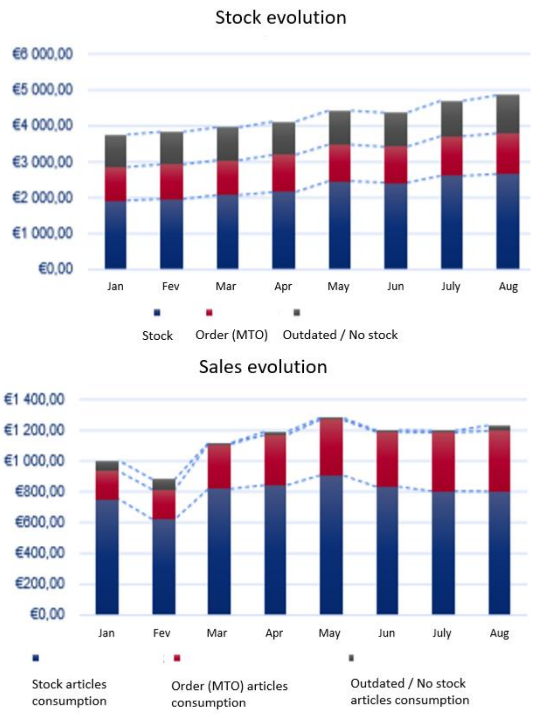


Figure 21 - Stock evolution of MTS and MTO

In terms of typology, after dividing the articles into two macro typologies: components/accessories and tubes, it is verified, according to figure 22 and 23, that the covers are stabilizing over time. Even so, it was verified that the pipe covers went from 2.6 to 3.2 months.

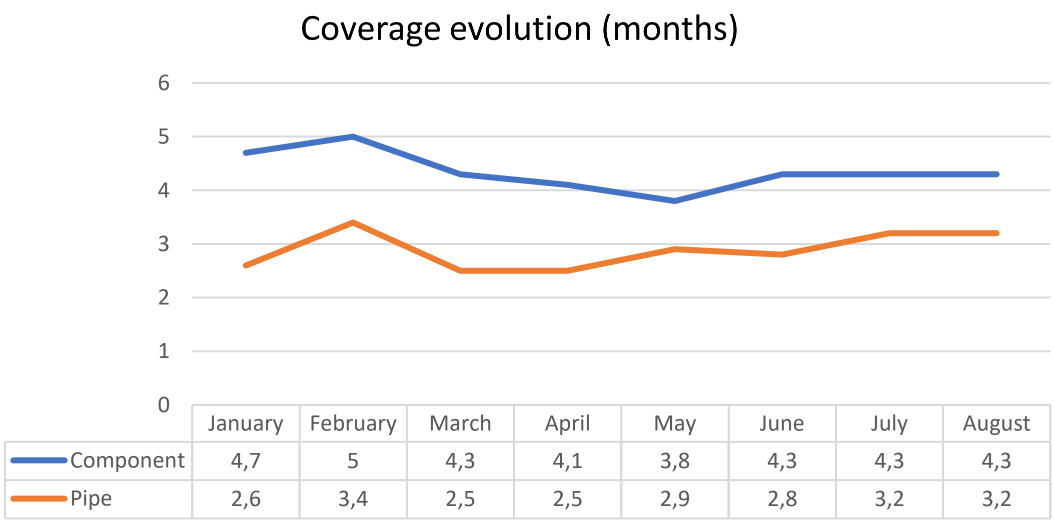


Figure 22 - Stock coverage evolution by type of product

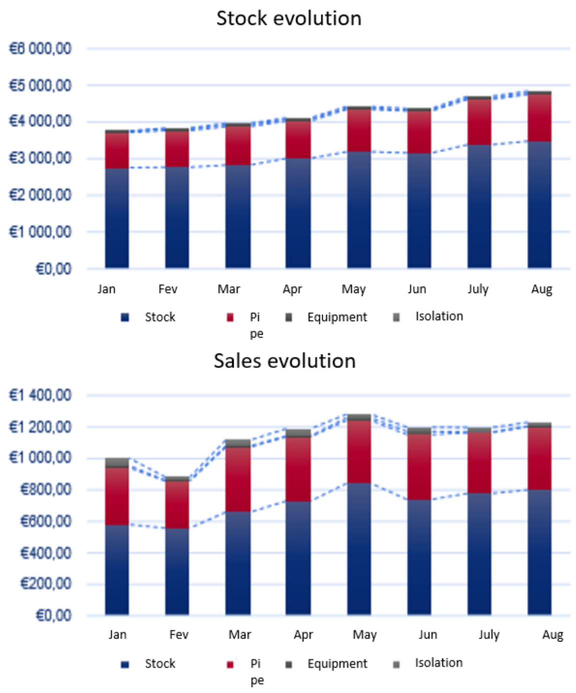


Figure 23 - Stock evolution by typology

Another point usually studied when analyzing stock levels is the rotation of articles. Next, Figure 24 divides the articles by typology and by their rotation.

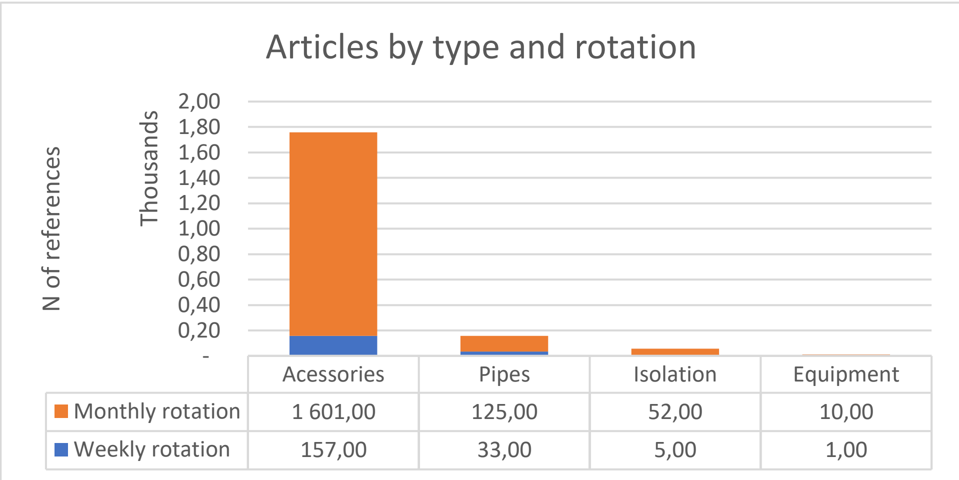


Figure 24 - Articles rotation analysis by type

It turns out that even though there is stock of more than 11 500 references in Porto, only 2000 have rotation, at least, monthly. Of these, almost 1800 are accessories (mostly stored in boxes and small) and 150 references are pipes. It should be noted that a different storage and storage strategy should ensure a more efficient picking of these 2000 references – at this time, all references are given the same treatment, as storage does not take rotation into account.

3.3 Current sales analysis

To study sales, it was proposed by one of the managers of company Alpha to create an interactive and dynamic dashboard that allowed to study sales patterns in different degrees of granularity. This tool was considered very useful mainly for the commercial team and to the top-level executives of the company. To do this a dashboard in Power BI was developed and it is being introduced in this section because, even though it was a solution implemented, it also served as a basis to understand and study the current situation. The data was imported from Microsoft Excel and multiple sources were centralized into Power BI. There the data was loaded and transformed. After, some operations using Power Query were made to standardize data and remove unwanted information. Then, the dashboard was created, and different analysis were performed:

- Sales quantity and value sold by date
- Sales quantity by brand
- Quantity sold by family description
- Quantity sold by article
- Macro cards representing total sales, by value and quantity, and average ticket

A snapshot of the dashboard is presented in figure 25 and in annex D different analysis are presented.

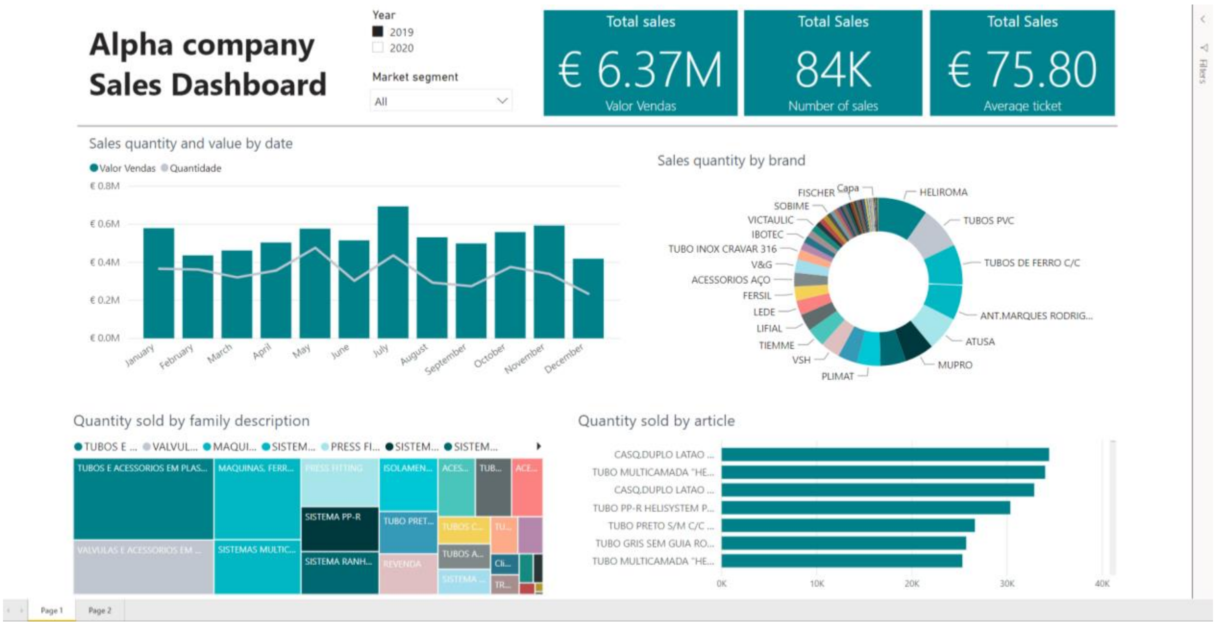


Figure 25 - Power BI Dashboard created for the sales division

The main conclusions are that the company sales follow a regular pattern throughout the year when analyzing 2019. There can be seen an increase in sales revenue and quantity in May and July while also a decrease in sales in the winter months. Also, there are a whole bunch of brands sold meaning that company alpha sources their products from multiple suppliers. In terms of sales, the average ticket sold is of 75,80€. These are all macro analysis; the dashboard then allows to drill down and filter data to increase granularity and able the analyst to perform more micro analysis and extract useful insights from the data.

3.4 Challenges and improvement opportunities

As previously presented, the inventory management model used by the company is the periodic review model or fixed period and the equation used to calculate the reorder point, although identical to that suggested in the literature, presents differences that will be the subject of an in-depth study, with the objective of verifying whether there is potential for improvement.

Relative to the forecast model, limiting the forecast of future consumption to average demand from previous days may not be the most useful and effective way since possible changes in future product sales pattern may not be well predicted. Thus, using incorrect forecasts distorts the value of the average daily consumption and, consequently, the quantity to be ordered from the supplier (and the stock levels).

Another difference lies in the calculation of the safety stock. It should be noted that the main function of the safety stock is to absorb/protect against possible variations in consumption and lead time, leading to the need to consider higher levels of safety stock for materials with greater variations in consumption. In the opposite direction, materials with regular consumption require lower levels of safety stock. The method used by the company considers an empirically defined safety percentage. This method based on the nature of the ABC classification of the product, will be evaluated given its expected improvement potential. Besides not being a dynamic value, also does not considers demand neither forecasting variability. According to the literature, the calculation of the safety stock can be calculated in several ways, referred in chapter 2. This evidence reinforces the need for an in-depth study of this parameter.

4 Building and testing improvement proposals

In the following points will be presented the work developed, from the initial analysis to the target materials of this study, to the proposals and evaluation of the suggested improvement measures.

In a first step, the developed project is based on split the 27 references under study according to their demand patterns. This split will be made dividing references according to XYZ analysis.

Then, a prior data processing was performed to treat missing values and outliers.

After, four methods were applied to predict future demand: company's actual method and three exponential smoothing methods. Based on the results the calculation of average absolute percentage errors was made, which allowed to identify the best prediction model for each type of category. For example, model A applied to category B of articles is the best solution for the company because it has the lowest MAPE, could be a possible conclusion after the study.

Although this might seem a good conclusion, there is not enough robustness in the process to clearly state model A as the best model for category B references. So, a more in-depth statistical analysis was performed. Demand was estimated based on a normal distribution and 100 replications were executed for each one of the 27 references. After, the data was grouped by category, the median MAPE calculated, and a 2 factor ANOVA was performed in order to understand which model works better for each category and if there are significant differences between models, references or models and references at the same time. This analysis gives toughness to the results and allows conclusions with a higher degree of confidence.

Also, different methods of calculating the safety stock will be studied and compared with the current method. A simulation will then be carried out to calculate the average stock value and the average % of stockouts for the reference under study - for each of the best forecast models, based on the category in where the reference stands, and for each of the safety stock calculation methods. In this way, it will be possible to check which combination of forecasting model and safety stock translates the more attractive average stock values and stockouts rate tradeoff. After obtaining the results, a phase of implementation and testing in alpha company follows. The data presented was analyzed using Excel and was exported from Primavera.

4.1 Current state analysis

To suggest proposals for improvement, it became imperative to make a diagnosis to the current state of the supplier under study. For this, it was decided to use the year 2019 and part of 2020 as a reference for the study. Thus, it was possible to identify opportunities for improvement and, more relevantly, to make a comparison between current state and future state.

4.1.1 Stock management assessment

To diagnose the year 2019/2020 for the selected supplier, an analysis was performed for stock levels for the references under study. According to Reis (2005), stock management seeks to avoid the existence of articles with:

- Low profitability or slow rotation
- Stock disruption

To achieve this, it is customary to use stock management control indicators that assess whether the above-mentioned objectives are achieved. These indicators are the rate of rotation/coverage of stocks, and the rate of ruptures. To calculate these indicators, it was first necessary to obtain the levels of stocks and average consumptions by reference for the time space considered. In Annex E a table with each article and each metric can be found.

Once the values of stocks and consumption are obtained, it is interesting to calculate the rotation rate, which translates the number of times the stock is renewed within a year. This calculation is given by the equation (4.1).

$$Rotation\ rate = \frac{Anual\ consumption\ per\ year}{Average\ monthly\ stock} \tag{4.1}$$

From the analysis of this indicator it is possible to conclude on the risk of stockouts, and a high rotation rate means a higher risk of stock collapse. However, this situation is also synonymous with great profitability for the company and, consequently, the higher the rate of stock rotation, the more efficient the management of stocks. The rotation rate values obtained for each reference can be found in Annex E.

The rotation rate can be associated with another indicator of stock management, the rate of coverage of needs. This indicator, which translates the period in which the stock can be moved without the need to place a new order, is given by equation (4.2).

$$Coverage\ rate = \frac{Average\ monthly\ stock}{Average\ monthly\ consumption} \tag{4.2}$$

High coverage values are, of course, an indicator of inefficient stock management. The coverage rates calculated for the references under study are presented in Annex E.

Based on the analysis of table 8, there is a clear pattern in the evolution of the rotation rate and coverage rate. The expected happens in which an increase in the coverage rate and decrease in the rotation rate in the categories less sold and with lower frequency of sale are detected. In average terms, references A, B, and C have a coverage rate of 43, 64, and 92 days, respectively. Also, regarding the categories of consumption patterns, in average terms, there is an increase in the coverage rate for the category with irregular consumption (Y - 51 days), compared to category X (40 days).

Table 8 - Average coverage and rotation rate by ABCXYZ classification

Average coverage rate times (days)						
Classification	**X**	**Y**	**Z**	**A**	**B**	**C**
Average time	39,88	51,22	94,46	42,97	64,04	92,49
Average rotation rate times (days)						
Classification	**X**	**Y**	**Z**	**A**	**B**	**C**
Average time	8,87	7,86	6,25	9,25	7,93	5,48

However, another conclusion that can be drawn is the high levels of both indicators. For the supplier under study, the order frequency is daily which, combined with the just in time philosophy that the company follows in the case of supply, allows us to conclude that the levels of coverage obtained are high. The company's goal is to better control stock quantities, that is, to reduce the coverage rate, thus decreasing the average level of stocks. To this end, it is important to detect the reason why coverage levels are high, and two possible causes have been identified:

- Supplier/carrier inefficiencies;
- Method of calculating the quantity to be ordered at the time of review, in other words, method of calculating the point of order

The first cause mentioned was examined together with the planner responsible for the supplier, and it was found that, in 2019, the supplier scrupulously complied with the delivery times and parcel quantities. Thus, after rejected the inefficiencies of the supplier/carrier for the high stock levels, it became important to analyze in detail the method of calculating the quantity to be ordered at each ordering period – reorder point (ROP).

4.1.2 Reorder Point

Generically the reorder point can have two distinct natures – it can be fixed over time and, in this case, the value defined as the order point lasts for N successive periods or, on the other hand, can have a variable nature and, in this case, varies period to period. Variable and dynamic reorder point will be the focus of the analysis given their best response to variability.

The calculation of the reorder point depends on two variables – demand and safety stock. In the model used by alpha company the demand parameter is obtained by calculating the average consumption of the last 4 weeks. The expected demand is then multiplied by the supplier's lead time, by the percentage of safety stock and by a percentage of additional coverage (20%). Consequently, if the estimated demand is not confirmed either by excess or by default, it will lead to the calculated ROP being misadjusted, which may cause an increase in stock levels or stock disruption, respectively. Thus, in a first analysis, the demand parameter was studied.

Using a transaction in Primavera, the ROP history was extracted for the references under study (year 2019 and 2020). The ROPs obtained per day for each reference under study were organized and the daily consumption predicted for each ROP was calculated. Next, the actual daily consumption (actual demand) was calculated, i.e., what the daily consumption should have been considered if the estimate was perfect and had no associated error. Once these values were obtained, the expected demand and the actual demand were compared to assess whether, in fact, stock levels were being inflated due to this data. The values obtained, in average terms, for 27 references studied can be found in Annex F.

$$\Delta ADD = ADD\ Predicted - ADD\ Real \tag{4.3}$$

$$\Delta Safety\ stock\ units = \Delta ADD * Nº\ of\ safety\ stock\ days \tag{4.4}$$

$$\Delta coverage\ units = \Delta ADD * (Lead\ time + order\ frequency) \tag{4.5}$$

As can be seen, in average terms there is a high difference between the value of daily consumption considered in the calculation of ROP and the actual consumption of the material (equation 4.3). This difference is amplified when the product is between average daily demand and the number of days of safety stock (equation 4.4), or the lead time of the order (equation 4.5), resulting in an increase in the number of units to be considered in the calculation of ROP. Additionally, it is verified for all references under study that the demand value considered is inflated in most weeks. This will effectively be one of the reasons for the high stock levels. In this sub section we conclude that a more profound study of the prediction should be done.

4.1.3 Forecasts

Forecasts play a key role in calculating the quantities to be ordered from the supplier. As previously analyzed, the average daily consumption calculated based on forecasts is inflated and, consequently, it is important to study the level of accuracy of the forecasting methods currently used by the company.

The calculation of the average daily consumption is carried out automatically by Primavera at the time of calculation of the reorder point. As an example, the ROP calculated on Friday of week 0 and used in placing orders on Monday of week 1, uses the demand forecast for Monday of week 1 for the calculation of average daily consumption. In view of this methodology, the average absolute forecasting errors were calculated for each reference. The indicators used to assess the quality of forecasts were presented in Chapter 2.4.5, and errors were calculated considering a step of 1 day. In practice this means that for step = 1, the calculated forecast error will be the result of the comparison between the prediction made on day N-1 for the consumption of day N, and the effective consumption verified on day N. Results for the mean absolute percentage error (MAPE) can be found in annex G.

Analyzing the values of forecast errors obtained it is possible to conclude that, on average, the average absolute percentage error (MAPE) of the predictions is 62%. It is verified that, removing from the analysis the reference 2650006, which presents a very high average error when compared to the other materials, the MAPE stabilizes at 59%. This higher MAPE value compared to the other references, is due to its irregular consumption in terms of quantities sold through the year. Given this, it becomes harder to predict future demand. These assumptions seemed to make sense but analyzing deeper it is possible to conclude that the average MAPE is higher for references X (76%), then references Y (56%) and finally references Z (53%). One of the conclusions might be that given the fact that safety stocks are only added to X and Y articles, these extra units might be causing this higher forecasting error. Also, another conclusion is that the forecasting method used by company Alpha (like a moving average method) works well with articles with more irregular consumption than others with more daily sales.

Lastly, results obtained are sufficient to justify the need to deepen the possibility of improving forecasting methods. Better forecasts will allow the calculation of average daily consumptions closer to actual consumption, thus decreasing stock levels.

4.2 Improvement proposals

After analyzing the current situation and identifying opportunities for improvement, it is necessary to conduct an in-depth study of improvement proposals. This study, presented below, will focus on the possibility of improving the quality of forecasts, presenting alternative equations for calculating the safety stock, as well as other proposals for improvement. For now, let us introduce the sub chapter that reports the preprocessing/cleaning of data about missing values, and outliers.

4.2.1 Data Cleaning

Since there are no missing values in the observations to be analyzed, i.e. every day they have a sales value, whether it is a value different than 0 or 0. Moving right into the graphical analysis.

The first step to follow in any data analysis process is to visualize the data graphically, so one can extract some insights about what the behavior of the data is. What is possible to conclude by analyzing Annex H, which show one representative example of each the different categories, is that the consumption patterns of the articles get more irregular as category moves from X to Z, as expected. Thus, there are several days with sales at 0 and large peaks of consumption. In fact, the graphs suggest that various values can be considered outliers. Note also that the scale in each of the graphs is not the same due to better visualization issues.

Outliers are observations that are very different from most of the observations in the time series. They may be errors, or they may simply be unusual. All the methods considered in this document will not work well if there are extreme outliers in the data. To solve this problem, it was necessary to understand with the Alpha company what may be the reason for all this irregularity and high consumption spikes. The company collected the information that the company has in the habit of accumulating sales and only registering them on a certain day of the week. For this reason, it was concluded to group the data per week, this will allow a more reliable analysis. It is important to note that, at this time, there was an immediate perception that this data grouping would influence the method of ordering to suppliers, since the weekly order would become the ideal scenario because it was not necessary to disaggregate the data in a later step and introduce a source of error to the results. Before proceeding to this alternative, a reunion with the logistics department was booked and the proposal for changing daily orders to weekly was accepted.

After this analysis it becomes interesting to study then the number of outliers present in each of the references under study. The analysis allows us to conclude that on average, there are 2.22 outliers in each reference. Keep in mind that a data element identified as a potential outlier should be investigated and not immediately removed because it is denoted as a wrong value. Through the investigation it should be noted if any typing mistake has been made or other problem occurred that distorted the analysis.

Simply replacing outliers without thinking about why they have occurred is a dangerous practice. They may provide useful information about the process that produced the data, and which should be considered when forecasting. However, if we are willing to assume that the outliers are genuinely errors, or that they will not occur in the forecasting period, then replacing them can make the forecasting task easier. The outliers identified were analyzed and it was concluded that all resulted from unusual consumption values, since these are values that after standardization of errors translate z-score values greater than 2.5. In this case, in view of the solutions available in the literature - removal of the outlier; not to remove and ignore; or replace the outlier with an average value – the decision fell to replace the outliers with the average sales volume value of the last 4 weeks since it was not considered feasible to lose information as the time series is not extensive and it was also not considered feasible to do nothing to the outlier because this would lead to problems in subsequent phases of analysis due to the strong impact that outliers have on average values and estimates that treat average values as a basis.

Finally note that only one round of removal of outliers was executed in order not to manipulate excessively the data.

4.2.2 Time series-based forecasting techniques and statistical analysis

To improve forecasts, it was decided to use the methods of forecasting consumption for the references under study. Since it is intended to compare the level of accuracy of the predictions, the forecasting methods applied in this study were tested using the creation of ex-post forecasts. For each reference, weekly consumptions for the years 2019 and part of 2020 were obtained. These were used for the creation of the models, applied later in the forecast of consumption in the second half of 2020. In all models developed, a training time space and a test space of the model were defined. The training corresponds to 80% of the data and the test to the remaining 20%.

The analysis of time series forecasting methods follows but before a graphical analysis was performed for each reference to identify seasonal trends and movements in consumption patterns. Annex I present six examples, 2 for each category, representative of the overall consumption patterns in each category. These graphs allow to verify that category X references present a more regular consumption behavior than Y and Z. The lack of data similarity among periods can influence forecasting models ability to predict future values. Therefore, it is hard to predict beforehand which exponential smoothing forecasting method can best fit the data given apparent lack of trend and seasonality patterns.

The results obtained for the different forecasting methods given the different categories, in terms of average MAPE, can be found in table 13. The average MAPE was preferred when compared to the median MAPE because being able to understand total MAPE variation was an objective. Therefore, only using the median would exclude outliers values that is why the rational for studying average MAPE values made more sense.

The objective was to understand which forecasting model best fits the different categories. It is important to note that the model parameters were optimized through the training period and then those same parameters were used to develop forecasts that will be faced with the testing period data. The variable factors of the methods were adjusted to minimize the MQE, using the mean absolute percentage error (MAPE) as a comparison criterion between the various methods applied. Table 9 follows a table comparing the methods used with the actual method used by company alpha. Also, is provided the percentual points difference between the best model (bold values) and the actual method.

Table 9 - Forecasting models comparison

Category	MAPE Alpha	MAPE SES	MAPE HLT	MAPE HW	p.p difference (best – alpha)
X	44,96%	28,33%	20,56%	**13,88%**	31,08%
Y	49,65%	28,78%	17,11%	**9,74%**	39,91%
Z	49,09%	27,44%	14,89%	**14,66%**	34,43%
Average	47,90%	28,18%	17,52%	**12,76%**	

Although this analysis might lead to the conclusion that Holt Winters is the best forecasting model on average for every this might not be exactly like this because this conclusion would be not that much supported by robustly. Also, estimating future demand based on sales values might not be as well the best method because the variable sales by itself is not totally independent because it is affected by the number of stockouts. Therefore, to construct a more reliable conclusion, new demand data will be generated based on an adequate statistical distribution. To find the distribution that best suits demand data, histograms were used, and the results presented in figure 26. Histograms are used to recognize the center of the data and are applied when one has continuous measurements, wants to study the distribution that the values under analysis follow and look for outliers. Note that given the similarity in terms of distribution of the 27 references demand data only one of the histograms will be presented.

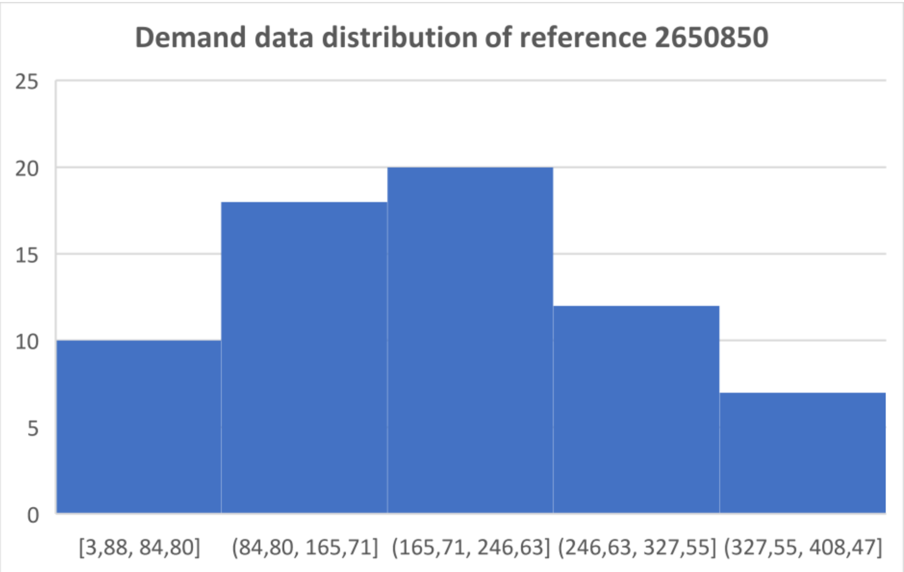


Figure 26 - Demand data of article 2650006 evidencing normal distribution

It is possible to conclude that data seems to follow a normal distribution. In this case with average value of 176 and standard deviation of approximately 100. Based on this fact, normal distribution was the distribution chosen to proceed with the analysis. Demand patterns of the 27 references were assumed to follow normality. Note also that the graphical interpretation is the most suited one to extract this insight when comparing to performing a quality and adjustment test because this test would have excessive power due to the high number of observations. It is not needed because the graphical results of the demand are quite enlightening but if they were not, one could also have chosen randomly, for example, 50 observations of each articles' demand values and perform a quality and adjustment test to those values. A certain number of replications would be needed to make results more trustable.

Based on this assumption, 100 normal distributions, for each article, with average value and standard deviation equal to the ones from the original sales given to us by company Alpha will be generated. A new table, presented next, gives us the results of the average MAPE for each category given the different forecasting models. Results are presented in table 10.

Table 10 – Forecasting models comparison with new demand data

Category	MAPE Alpha	MAPE SES	MAPE HLT	MAPE HW	p.p difference (best – alpha)
X	45,57%	41,38%	27,41%	**19,13%**	26,44%
Y	45,48%	44,08%	33,38%	**22,83%**	22,65%
Z	46,12%	47,46%	39,41%	**23,01%**	23,11%
Average	45,72%	44,31%	33,39%	**21,66%**	

Now, becomes interesting to study whether there are statistically significant differences between models and/or references. In case of we found no significant differences it does not really matter which model we use to predict demand although there are models with average MAPE lower than others. To study these differences a 2 factor ANOVA was performed.

ANOVA is a specific test called analysis of variance and it produces a hypothesis test that is appropriate to compare means of a continuous variable in two or more independent comparison groups. The central strategy of ANOVA is to steadily examine variability within groups being compared and examine variability among the groups being compared to study if there are significant differences between elements belonging to the same group. The null and alternative hypotheses of awareness in an ANOVA are as follows:

- H0: μ1 = μ2 = μ3 ... = μk
- H1: Means are not all equal.

where k = the number of independent comparison groups.

Results are presented bellow in table 11. This table shows that ANOVA was performed with a significance level of 5% and that rows which stands for categories and columns which stands for models are statistically significant (p value lower than 5%). Also, interaction among them is significant meaning that the conclusion that each category would have their better forecasting model is still under consideration.

Table 11 - ANOVA output table

Two Factor Anova						
ANOVA				Alpha	0,05	
	SS	*df*	*MS*	*F*	*p-value*	*sig*
Rows	0,635	2	0,318	60,884	**≈ 0**	**yes**
Columns	11,273	3	3,758	720,501	**≈ 0**	**yes**
Inter	0,369	6	0,061	11,784	**7,22E-13**	**yes**
Within	6,196	1188	0,005			
Total	18,472	1199	0,016			

Given the significant interaction it is not possible to immediately extract insights from rows or columns because rows and columns effects can be nulled by interaction analysis. Therefore, an averages graphs needs to be performed. Figure 27 shows that, although we're in the presence of significant interaction, the column and line effects still have meaning and insights can be extracted from them, based on the fact that the lines presented on the averages graphs don't intercept themselves.

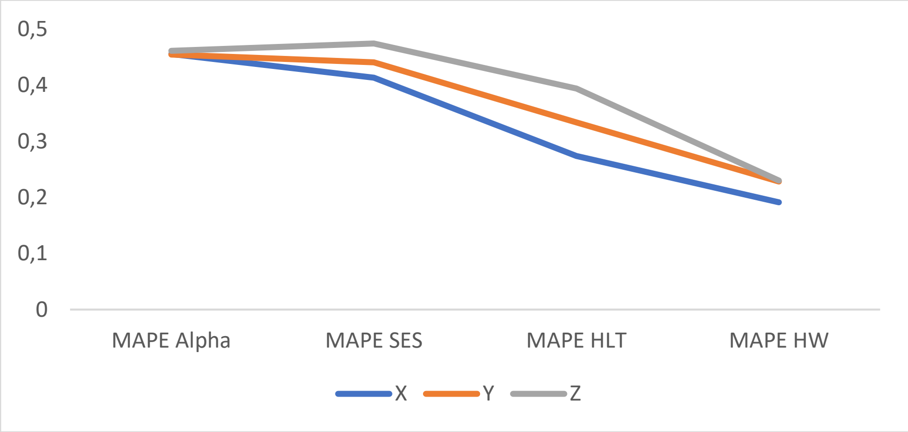


Figure 27 - Averages graph

Moving forward, this analysis allows to conclude that there is evidence that the models are not equal and produce statically significant differences when applied to estimate future demand, this same analysis does not gives any clue about which models differ from each other. To understand and extract further insights Tukey intervals where obtain and allowed to conclude that every combination of models produced statistically significant differences apart from the comparison between using company's model and Simple Exponential Smoothing. This means that using one model or the other does not produce significant differences. Table 12 presents the different tukey intervals and their significance level. Over it is possible to check that all p values (except one) are lower than the significance level (5%) which means that the differences between models are significant. Moreover, these models, when looking at the tukey intervals, do not include number 0 within the interval. This is another way of checking the statistical differences existent.

Table 12 - Tukey intervals for the column (models)

TUKEY HSD; COLUMN EFFECT		**alpha**	**0,05**
group	*mean*	*size*	*df*
MAPE Alpha	0,457	300	
MAPE HLT	0,334	300	
MAPE HW	0,217	300	
MAPE SES	0,443	300	
		1200	1188
group 1	*group 2*	*lower*	*upper*
MAPE Alpha	MAPE HLT	0,108	0,138
MAPE Alpha	MAPE HW	0,226	0,256
MAPE Alpha	MAPE SES	-0,001	0,029
MAPE HLT	MAPE HW	0,102	0,132
MAPE HLT	MAPE SES	0,094	0,125
MAPE HW	MAPE SES	0,211	0,242

Again, supported on table 12, Holt Winters is the model with least average MAPE which means that it is the model that estimates future demand with less average error. Seeing also that this model is statistically different from the other 3, given the fact that no combination of Holt Winters model with the other have the value 0 included in the Tukey confidence intervals, so one is in position of affirming that Holt Winters is the model that produces better results with higher forecasting accuracy. This is a confirmation to the supposition traced in the beginning of the study when only sales data were being study.

Another good approach is to look at X, Y and Z categories behavior. They also showed significant differences between them, given the fact that the Tukey confidence intervals of the different combination do not include value 0, which means that the different categories as statistically different. This result was expected given their difference in consumption patterns mainly in variability patterns. Results can be seen is table 13.

Table 13 -Tukey intervals for the row (category)

TUKEY HSD; ROW EFFECT		**alpha**	**0,05**
group	*mean*	*size*	*df*
X	0,334	400	
Y	0,364	400	
Z	0,390	400	
		1200	1188
group 1	*group 2*	*lower*	*upper*
X	Y	0,019	0,043
X	Z	0,044	0,068
Y	Z	0,014	0,038

To conclude, the idea that could exist a best suited model based on different category groups does not match reality and also the idea that there could exist two similar models with no statistically significant difference between them also was not supported by the results. Holt Winters model is indeed the best one to forecast future sales of all 3 categories.

Let us finish this analysis referring to the most important ANOVA assumption – the independence of the observations. The fact that time series are under analysis could lead to the thought that applying ANOVA is no longer an option, given data correlation to the previous day(s). Nevertheless, since the study objective is to examine significant differences between forecasting models, the ANOVA input is not demand data affected by correlation but MAPE (absolute error) values. So, it is possible to assume observations independence, not jeopardizing any past conclusion. Other assumptions for the realization of this test are the null average which is assured by the minimum squares method. Also, the normality of the errors which could be assumed based on the high number of observations (>50), nevertheless, a normal probability plot was made and presented next in figure 28. Results show that the errors follow normality.

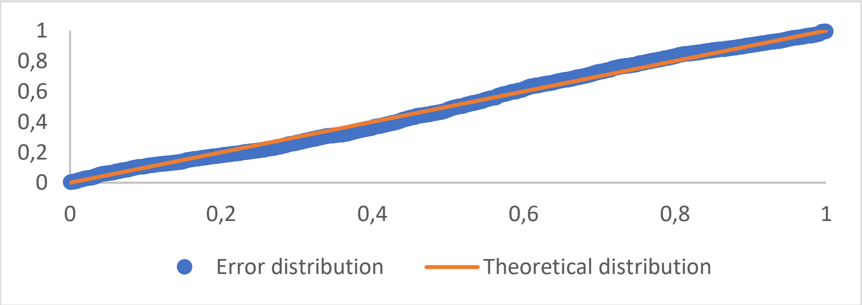


Figure 28 - Probability plot graph

Lastly, the constant variance of the errors was also studied.

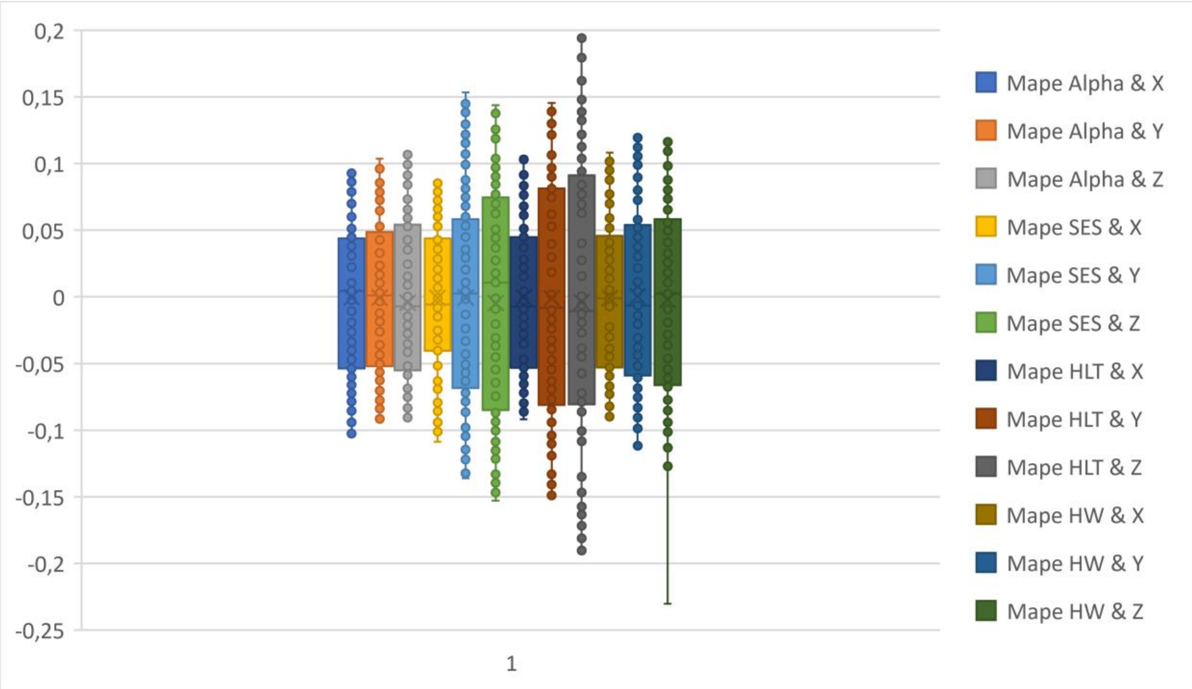


Figure 29 - Box Plot analysis showing constant error variance

This last assumption as well as the previous ones is not violated as it can be seen in figure 29 where the different errors are represented in box plots and evidence similar variance not jeopardizing the conclusion of constant variance neither the realization of past steps.

4.2.3 Safety stock

The second parameter of the reorder point equation used by the company is the calculation of the safety stock. As previously shown this value is obtained by multiplying the average daily consumption by the defined safety value considering the classification of the article, which varies according to the ABC classification.

As shown in 2.2.1 and 2.4, there is a set of alternative methods for calculating the safety stock. Given that the level of accuracy of current forecast method is low, the equation currently used by the company naturally inflates or deflates the number of units to consider in the calculation of the safety stock. Thus, investigate whether the use of the methods proposed by the literature allows the reduction of the level of safety stock is an important analysis.

To this end, the safety stock was calculated for the period under study using the following equations:

$$SS = SF \times \sqrt{LT \times {\sigma_d}^2 + {D_{avg}}^2 \times {\sigma_{LT}}^2}. \tag{4.6}$$

$$SS = SF \times \sqrt{LT \times {\sigma_f}^2 + {D_{avg}}^2 \times {\sigma_{LT}}^2}. \tag{4.7}$$

It should be noted that the safety stock was calculated considering the differences in the forecasts made by alpha company and actual consumptions. This approach allowed an immediate study that intended to study instant gains that company Alpha could have only by changing the way the safety stock is calculated. The analysis performed studied the % difference between the safety stock using five methods described below. It is important to mention that in equation 4.7 the forecasting errors considered were only those that presented situations of consumption forecast lower than the actual consumption. Doing this ensures not increasing safety stock levels whenever demand prediction is above the actual consumption. An analysis contrary to this would lead to an increase in stocks in the long run. The standard deviation of the supplier's lead time was considered null, due to the lack of overdue orders throughout the year 2019 and 2020, allowing this assumption to be carried out, as explained in chapter 3. In Annex J follows a table with the 27 references under analysis and their respective safety stock quantities. A grouped analysis is presented here by table 14 where within each cell there is the average quantity value for that reference in that method. In the different rows there are the different categories and each column represents each safety stock calculation method.

Table 14 - Safety stock levels (number of units) depending on the SS (SS D 90 stands for the use of equation 4.6 using a factor of safety of 90% and SS F 90 stands for the use of equation 4.7 with a factor of safety of 90%) calculation method

Category	SS Alpha	SS D 90	SS F 90
X	**21,14**	151,57	138,93
Y	**2,12**	31,89	33,37
Z	**0,00**	9,28	9,12

By analyzing table 14, one can see that independently of the category considered there is no reduction in the safety stock quantities using new safety stock metrics from the literature, comparing to the AS-IS scenario (SS Alpha). So, it is possible to conclude that there is no reduction in the number of safety stock units to consider when the equation (4.6) or (4.7) is used. Such analysis allows us to conclude something that was already expected due to the high variability of demand with some sporadic periods of peak sales. Thus, the analysis of the deviation of both demand (4.6) and forecasting error (4.7) produces an inflation of the levels of safety stock. It is possible to conclude that the method used by the company, when compared to the methods studied, is the most appropriate because it results in lower levels of stock. Of course, this analysis regards only to stock levels and does not take into consideration stockouts. So, although the values obtained allow us to conclude that the use of equations proposed in the literature do not result in the reduction of safety stock units to be considered, it is necessary to ascertain whether, considering the method of calculating the safety stock used by the company combined with the best exponential smoothing method given its lower MAPE value, in a broader context of stock management, it does not lead to stockout situations. For this, it will be necessary to simulate for each reference individually the period under study in order to be possible to draw reliable conclusions.

4.3 Evaluation of improvement proposals

The evaluation of the improvement proposals suggested in chapter 4.2 will be carried out using a simulation in a spreadsheet. Based on this analysis, a set of stock management indicators will be calculated to assess the feasibility of the suggested improvement proposals.

4.3.1 Simulation approach

To verify the impact of the suggested improvement proposals in the supply process of the supplier under study, it was decided to perform a simulation in Excel. The simulation consists of replicating the procurement process for each reference individually from January 2019 to April 2020.

The developed model was organized for weeks (given that the new order frequency is weekly) and has as inputs:

- Actual consumption recorded in 2019 and 2020, for each week
- MOQ – Minimum order quantity
- Minimum order quantity when the MOQ is exceeded (multiple order)
- Initial reference stock at the beginning of 2019
- Reorder point value for each given week

With the input values referenced, the quantity to be ordered from the supplier, the value in stock at the end of each week, and whether stock breaks occur. The quantity to be ordered each week is calculated using the equation (4.8).

$$\mathit{Order}_{(X)} = \mathit{End\ stock\ value}_{W(X-1)} + \mathit{Orders}_{W(X-1)} - ROP_{W(X)}. \tag{4.8}$$

If:

$$\mathit{Order}_{W(X)} > 0 \rightarrow \mathit{Order}_{W(X)} = 0.$$

Else:

If:

$$\mathit{Order}_{W(X)} < 0 \wedge |\mathit{Order}_{W(X)}| \leq \text{MOQ} \rightarrow \mathit{Order}_{W(X)} = \text{MOQ}.$$

Else:

$$\mathit{Order}_{W(X)} = |\mathit{Order}_{W(X)}|.$$

Given:

Order $_{w(x)}$ – Order quantity in week X
End stock value $_{w(x-1)}$ – Order quantity in week X
Orders $_{w(x-1)}$ – Order quantity in week X-1 (in transit)
ROP $_{w(x)}$ – Reorder point value in week X

The stock value at the end of each week is calculated based on equation (4.9).

$$\mathit{End\ stock\ value}_{W(X)} = \mathit{End\ stock\ value}_{W(X-1)} + \mathit{Orders}_{W(X-1)} - \mathit{Consumption}_{W(X)}. \tag{4.9}$$

Where:

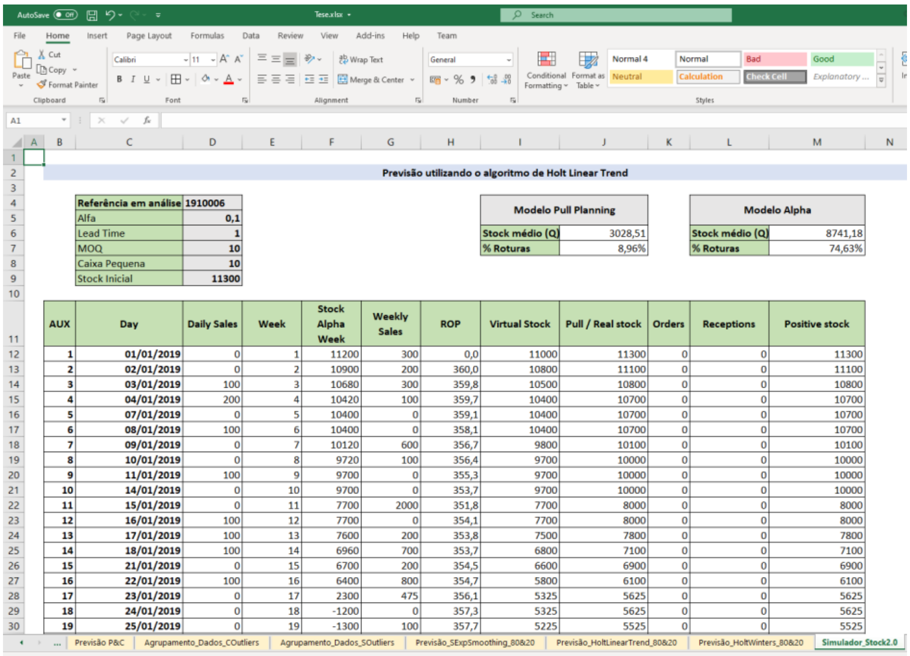
Consumption $_{W(X)}$ – *Consumption of the material in week X*

Lastly, stockouts occur if the following condition is satisfied:

- *If:* $\mathit{Consumption}_{W(X)} - \mathit{End\ stock\ value}_{W(X-1)} < 0 \rightarrow$ *Stockout in week X*

The developed model, whose template can be observed in Figure 29, will allow to verify the impact of the suggested improvement measures, and draw objective conclusions, through the replication of the supply for the year 2019/2020 for each reference. The impact of changing the forecasting algorithm to predict demand in the company's reorder point and consequently its impact in the quantity to be ordered from the supplier. Also, the entire simulation process will be carried out using the Holt Winters model to predict future consumption, since it is the one that showed sharpest percentage decreases in error when compared to the current method used by Alpha. Also, since there's not yet a defined opinion whether the safety stock method used by the company is the best because of the uncertainty in stockouts percentages, this method will be compared with both alternative safety stocks methods mentioned.

The simulation presented allows to obtain the stock value at the end of each week and the quantity to be ordered, therefore makes it possible to check if there is a reduction in inventory levels.



Previsão utilizando o algoritmo de Holt Linear Trend

Referência em análise	1910006
Alfa	0,1
Lead Time	1
MOQ	10
Caixa Pequena	10
Stock Inicial	11300

Modelo Pull Planning	
Stock médio (Q)	3028,51
% Roturas	8,96%

Modelo Alpha	
Stock médio (Q)	8741,18
% Roturas	74,63%

AUX	Day	Daily Sales	Week	Stock Alpha Week	Weekly Sales	ROP	Virtual Stock	Pull / Real stock	Orders	Receptions	Positive stock
1	01/01/2019	0	1	11200	300	0,0	11000	11300	0	0	11300
2	02/01/2019	0	2	10900	200	360,0	10800	11100	0	0	11100
3	03/01/2019	100	3	10680	300	359,8	10500	10800	0	0	10800
4	04/01/2019	200	4	10420	100	359,7	10400	10700	0	0	10700
5	07/01/2019	0	5	10400	0	359,1	10400	10700	0	0	10700
6	08/01/2019	100	6	10400	0	358,1	10400	10700	0	0	10700
7	09/01/2019	0	7	10120	600	356,7	9800	10100	0	0	10100
8	10/01/2019	0	8	9720	100	356,4	9700	10000	0	0	10000
9	11/01/2019	100	9	9700	0	355,3	9700	10000	0	0	10000
10	14/01/2019	0	10	9700	0	353,7	9700	10000	0	0	10000
11	15/01/2019	0	11	7700	2000	351,8	7700	8000	0	0	8000
12	16/01/2019	100	12	7700	0	354,1	7700	8000	0	0	8000
13	17/01/2019	100	13	7600	200	353,8	7500	7800	0	0	7800
14	18/01/2019	100	14	6960	700	353,7	6800	7100	0	0	7100
15	21/01/2019	0	15	6700	200	354,5	6600	6900	0	0	6900
16	22/01/2019	100	16	6400	800	354,7	5800	6100	0	0	6100
17	23/01/2019	0	17	2300	475	356,1	5325	5625	0	0	5625
18	24/01/2019	0	18	-1200	0	357,3	5325	5625	0	0	5625
19	25/01/2019	0	19	-1300	100	357,7	5225	5525	0	0	5525

Previsão P&C | Agrupamento_Dados_COutliers | Agrupamento_Dados_SOutliers | Previsão_SExpSmoothing_80&20 | Previsão_HoltLinearTrend_80&20 | Previsão_HoltWinters_80&20 | Simulador_Stock2.0

Figure 30 - Stock simulator

4.3.2 Simulation results

To verify the impact of the improvement proposals, the stock levels were simulated for each study reference in the years 2019/2020.

Results for the articles are shown in Annex K. Next in table 15 follows the results grouped by category of articles for each combination of forecasting model (Holt Winters) and safety stock calculation method. The insights extracted from the table 15 are that the average stock using both literature safety stock metrics is higher than when comparing with the model used by the company nowadays and the combination of HW and SS Alpha.

On the other hand, the % of stockouts increases when empirical methods for calculating safety stock are applied. On average, using HW combined with safety stock metrics based on standard deviation generate stocks 23% higher for category X and 8% for category Y. On the other hand, reduces the % of stockouts in 85% (category X), 74% (category Y) and 87% (category Z).

Table 15 - Grouped stock results regarding different safety stock metrics

	Alpha company model			HW and SS Alpha		
	Average stock	**% Stockout**	**Average €**	**Average stock**	**% Stockout**	**Average €**
X	587,3	30,6	20554,5	371,5	9,5	13004,1
Y	303,6	17,1	10626,9	206,2	6,9	7217,9
Z	98,3	29,3	3441,3	43,2	7,6	1510,5
	HW and SS D 90			**HW and SS F 90**		
	Average stock	**% Stockout**	**Average €**	**Average stock**	**% Stockout**	**Average €**
X	724,2	4,5	25348,1	742,7	4,8	25995,3
Y	328,5	4,4	11498,2	324,3	4,0	11349,9
Z	76,6	3,8	2681,5	84,0	4,6	2287,0

Relying on this information and having in mind the proposed objective of the project: reduce stock levels not compromising service level and number of stockouts, it was concluded that the combination between Holt Winters for predicting future demand with the already used by the company safety stock method, would be the best proposal and would traduce itself in the best tradeoff between average stock and number of stockouts. The method's advantage when comparing with HW and SS D 90 and HW and SS F 90 is that as demand patterns are extremely irregular, having a safety stock calculation method based on standard deviation tends to inflate too much stock levels. In a certain way using Alpha's method flattens demand patterns, lowers demand and better match stock levels with actual demand.

As an example, Figure 31 shows the evolution of the inventory level for the reference of the highest annual consumption (2650854). It is possible to verify that, with the suggested improvement proposals, the average stock level at the end of each week exhibits regular behavior. In the opposite direction, using the equation currently used by the company, the evolutions of inventory levels exhibit an irregular behavior, thus contributing to an increase in inventory levels.

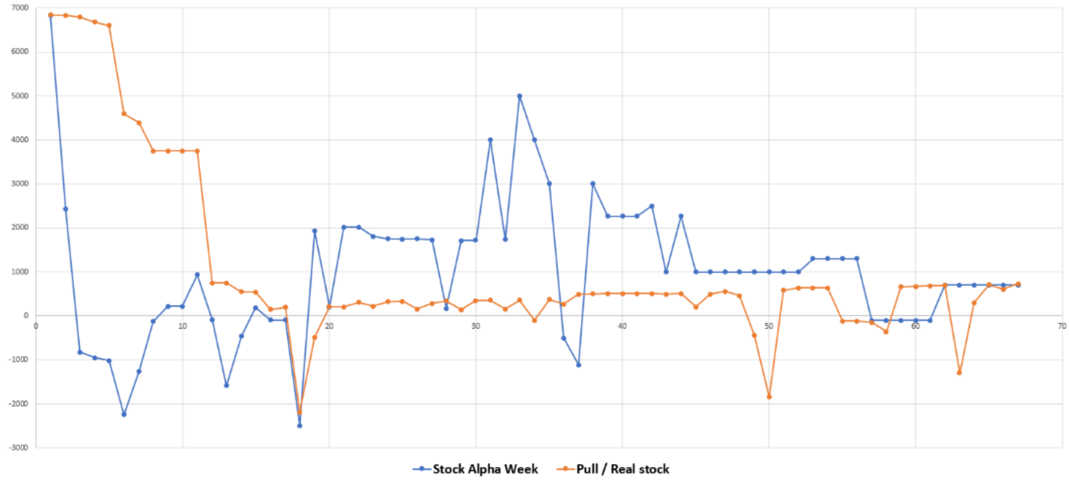


Figure 31 - Stock levels evolution of reference 2650854

It is also important to analyze the evolution of the quantity to be ordered from the supplier. The chart demonstrating this evolution can be found in Figure 32. It is possible to verify that, as at the inventory level, the quantity to be ordered assumes a more regular behavior with the proposed improvement proposals being less sensitive to the occurrence of order peaks (minimizing the risk of lack of internal capacity of the supplier to fulfill the order). Also, in average terms, the quantity to be ordered is lower than the equation currently used, which means that there is a greater number of orders placed throughout the year. In short, it appears that with the suggested improvement proposals, both stock levels and the quantity to be ordered are less sensitive to the variability of consumption/demand, compared to the equation currently used by the organization.

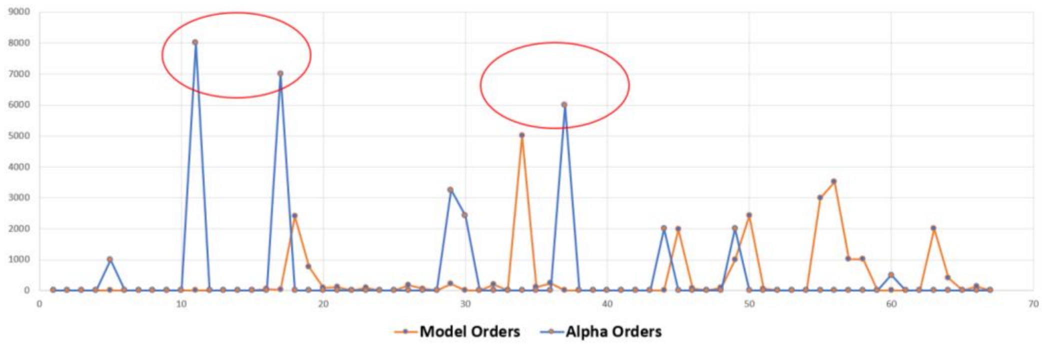


Figure 32 - Orders evolution for reference 2650854

Another important factor is the determination of the economic impact of the stock reduction. It is verifiable that the economic impact of the improvement proposals under analysis is significant. The weekly reduction, in average value, is approximately 4,300.0 € (obtained by calculating the average quantity reduction of the 27 references multiplied by their specific cost), compared to the current situation. This translated a decrease of 42% on average. Also, there is a weekly reduction on average in inventory quantities of 370 units.

It is concluded that the reorder point equation when calculated by the sum of demand forecast given by Holt Winters Exponential Smoothing forecasting model and the safety stock, given by the company's empirical definition, translates an improvement measure with positive impact and possible to be applied in reality. Furthermore, the improvement was implemented in company Alpha in a very simplistic way capable of testing the concept. The excel simulator developed was given to the logistics department of the company and the purchase responsible started to order products from suppliers given the simulation suggestions.

4.4 Forecasting models limitations when faced with unpredictable events

Time is limited and it might as well be a luxury that managers, leaders, and c-levels do not have. Business as usual was disrupted by COVID-19. The impact of the pandemic overturned business, communities, and corporations. In a time that taking care and support victims affected by the virus, which already infected million all around the world and killed thousands of lives, is number one priority, business leaders also need to focus on protect their employees and customers while managing the economic consequences in the wake of community lockdowns, consumer dread, and continual hesitation. Today's decisions may affect company's trajectory for the upcoming years.

In this global panorama full of uncertainty and doubts, it is not surprising that analytics, widely recognized for its problem-solving and predictive ability, has become an essential navigational tool. Analytics, data science and data decision making are topics that have been on the top of all C-level[2] agenda and have been a very important trend in management for quite some years, now, as the data economy starts building its way and becoming one of the most important industries. Analytics supports numerous urgent tasks facing businesses today: forecasting demand is one of them and will deserve a brief analysis next, due to its connection to this dissertation's topic.

Data is a powerful tool nowadays, probably the most powerful one, oil gold years are a part of the past. The powerfulness of data extends to enhancing the quality of leader's decisions in their daily lives, using analytics to predict, to foresee and to anticipate trends, consumer behaviors, and pretty much any pattern. Although analytics have been proving to be a necessary upgrade, transversal to every company and industry, capable of predicting almost everything, it was not capable of predicting the impact of COVID-19.

Advanced Analytic Models have been under tension for some months, now, especially for businesses using these kinds of models of data analytics, such as Machine Learning, which is influenced by the real world. So, what happened was that all of the sudden all these models were also affected by this uncertainty in data, in inconsistent behavior and in missing data points and became showing some cracks, forcing humans to step in and set them straight.

Throughout the years, business analytics has adapted and evolved, going from a more information-driven results to optimization-driven. However, there is still a long way to go. Next are pointed out six limitations that may be the reason why analytics was not able to predict the COVID-19 pandemic effects:

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[2] C-level, also called the C-suite, is an adjective used to describe high-ranking executive titles within an organization. The letter C, in this context, stands for chief.

- Single-scenario and punctual projections of what will happen
- Static yearly plans with limited or non-existent updates along the year
- Poorly detailed plans without the adequate level of granularity to estimate outcomes
- High reliance to what happened in the past to predict the future
- Solely dependency on internal data, neglecting other potential sources of information
- Lack of skill to use advanced analytical methods such as sentiment analysis to drive decisions

News on these topics will pop up next months and years because the researcher community will definitely accurate existing models and introduce new features in them to turn them more capable of dealing with the mentioned issues.

Another topic of importance is the fact that humans respond to crises in different ways. Therefore, behavioral insights are of critical importance. This includes knowledge about what drives behavior and awareness of changes in these drivers. Organizations dealing with constantly changing conditions will need to understand where they are now and plan how to move forward in a dynamic environment. This includes gaining insights into customer behaviors, which impact products and pricing, optimizing supply chains, and continually updating revenue forecasts.

To sum up, by 2020, according to PBS recent article, it’s estimated that 1.7 MB of data will be created every second for every person on earth. There’s huge potential on leveraging analytics to predict and anticipate almost anything but there are still some strings that need to be attached to enable the models to respond faster and more effectively to dramatic economic situations as the one COVID-19 left us with.

5 Conclusion

The project presented during this dissertation allowed an in-depth study of the variables underlying the sourcing of raw materials from suppliers whose planning is pull, making it possible to identify and suggest improvement measures with a view to reducing inventory levels.

It was found that there is a high variability in consumption and it is complex to predict consumption patterns of materials that is reflected in strongly inflated forecasts, which combined with the method of supply currently used by the company that is fundamentally based on the value obtained through the forecasts, allowed to conclude that the inventory levels and ordered quantities are not adjusted. Safety stock calculation also plays a role on these inventory levels and were also subject of an in-depth study.

In order to reduce the exposure of the procurement process to high variability, it was possible, as reported in the literature, to apply predictive methods with proven efficacy by several authors and that, when correctly applied, find more accurate predictions. To capitalize on these methods, it was necessary to group data weekly. This action allowed to reduce some of the variability of the system and stabilize consumption levels. At this stage data presented more regular consumption patterns thus it was possible to split data into training and testing ranges, study exponential smoothing forecasting methods and understand the average absolute error of each model. Additionally, a statistical analysis based on 2 factor ANOVA was performed to understand if there were significant differences between models when applied to different product's categories (X, Y and Z).

Moreover, safety stocks were calculated using alternative methods, this included using equations suggested in the literature that rely on historical data of the consumption of raw materials. Not looking at the rate of stockouts it was easily concluded that the method used by the company was producing lower levels of safety stock. Thus, due to the high variability of consumptions, the methods provided on the literature, relying on standard deviation of demand, or forecasting errors, tended to inflate safety stocks.

The combination of a forecasting model based on trend, seasonality and consumption level variations with the safety stock calculation method, based on an empirical definition and fixed % of safety stock depending on the consumption of the articles, resulted in a clear reduction of the average quantity in inventory (42 %) . Consequently, in economic terms the expected impact resulting from the inventory reduction is €4,300.0 per week, respectively. This translates into approximately 220.000 € per year. In short, with the realization of this project it was possible to provide the company with a proposal for improvement to the procurement process that is characterized by being less sensitive to variations in consumption, compared to the supply strategy currently used.

Supported by the work developed during this dissertation there's still space for future interventions and improvements. Pertinent examples of future studies will follow:

- As a continuation of this dissertation, it will be appropriate to extend the study to suppliers whose type of planning is like the supplier presented here. In this way, in addition to the possibility of validating the conclusions presented here, a more comprehensive overview of the impact of the improvement proposals will be possible. As an immediate measure, the proposals presented here can be tested in the Primavera information system offline to test in-depth and ensure that proposals are actually feasible. It is expected that, if successful, at a later stage the proposals presented here will move to application in real context.
- Another study that would be interesting to carry out was to investigate, in order to combat the impact that the peaks of consumption have on the model, was to understand if some of the orders should be treated as MTO instead of MTS, that is, when an order

with a much higher value than the average, eventually this value could leave the model and be treated as an individual process in which it would satisfy that request using the order to the supplier instead of satisfying with the stock in hand in the company. In this way, we would better control the process in average terms and future forecasts.

- Also, due to the variability still assumed by the system with regard to consumption, even after weekly data aggregation, it would be interesting to ascertain whether by grouping the data by month we could obtain more stable consumption patterns that would translate into forecast models with less associated error. This point would raise another question about how to disaggregate the data for a great weekly or even daily to treat orders to suppliers. Another way to deal with variability and lack of linearity on the data, further projects could follow a more analytical direction in which, more advanced forecasting methods based on artificial intelligence forecasting techniques could be developed. These methods should be evaluated, and a new study of stock levels carried out to see if a more effective forecast of daily demand translates into a more balanced tradeoff between average stock levels and stockout rate. This phase was not implemented in company Alpha due to time limitations and also because after implementing phase 1 the project's objective was accomplished so no further and more complex models were needed, thus this study would be only performed by academic and research purposes.
- To conclude, in order to give the results more robust, performing more simulation varying the values of the lead time, the minimum order quantity and the purchasing multiples could be interesting in order to study how do the model performs under different conditions.

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ANNEX A: Wholesale industry SWOT Analysis

Table 16 - SWOT analysis (https://www.tradegecko.com/blog/wholesale-management/5-trends-in-wholesale-distribution-2018)

Strengths	Weaknesses
• A highly prominent sector in the wholesale and retail • Checktrade where companies have a solid partnership with upstream suppliers • Familiar with overseas market certification, production and shipment requirements • High diversification and diversity of products • Minimum order quantities: Wholesale contracts often come attached with a minimum quantity that must be purchased or the order will not be fulfilled • Economies of scale allow high-efficiency rates driven by concentration and search for growth	• Low customer interaction • Less capability of understanding customers' needs and market trends • Low pay – low skills jobs • Extreme labor flexibility: less motivated workers, poor service quality, unsatisfied customers • Bargain power from retailers • Low margins
Opportunities	**Threats**
• Promising growth in turnover, exports, and imports • Search for quality, differentiation, and innovation • Omnichannel selling is set to take multichannel selling a step further by offering consumers a streamlined and connected buying experience across all platforms • Growing commerce ecosystems: B2B sellers are investing more and more in eCommerce technology so that they can provide the same easy ordering and customer experience that online retailers enjoy • Digitalization: As customers continue to make purchases internationally, wholesalers need to focus on the digitalization of their buying and supply chain workflows, ensure their online marketplaces are transforming cross-border trade and implement integrated cross-channel marketing strategies. • Inventory and Order Management Transparency: Wholesalers are increasingly implementing new inventory management technologies that allow them to make data-driven business decisions and handle business operations centrally. To maintain a competitive edge, B2B businesses must focus on investing time and money into "integration friendly" inventory management systems and marrying B2B selling with the B2C customer experience. • Automation: Automation and tracking innovation allows wholesalers to manage operations and make informed decisions about shipping, staffing, and warehousing more effectively.	• Property damage: The key part of your business is having large amounts of inventory to resell to other companies, such as retailers. With this in mind, it is easy to see why damage to inventories can have a costly impact on businesses like yours. • Product short life cycle that may lead to obsolete inventory • Fierce international competition • Focus on price competition • E-commerce: consumers becoming retailers (auctions and trading places) • Regulatory environment: restrictions on location, labor regulation, regulated shop opening hours: strict and not harmonized in EU • Mature domestic markets • Cultural differences and local tastes can be barriers in global expansion • Aging of the labor force: in wholesale/retail large share of young workers with low pay • Increase in transport costs: higher oil prices, problematic transport infrastructure, restrictive regulation on urban logistics, road pricing

ANNEX B: 27 references of supplier Beta under study

Table 17 - 27 references under study

Category	Article	Description	Family
X	2650850	JOELHO FEMEA PP-R "HELISYSTEM" 20x1/2" AZUL	SISTEMA PP-R - "HELIROMA"
	1910026	TUBO MULTICAMADA "HELIKLIMA" 63x6,0 - VARA 5 MT	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	2650854	JOELHO FEMEA PP-R "HELISYSTEM" 25x1/2" AZUL	SISTEMA PP-R - "HELIROMA"
	1910328	UNIÃO MACHO "KLIMAPRESS" 20x3/4"	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910018	TUBO MULTICAMADA "HELIKLIMA" 25x2,5 - VARA 4 MT	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	2650006	TUBO PP-R HELISYSTEM PN20 (V.4M) 32X5,4 AZUL	SISTEMA PP-R - "HELIROMA"
	1910050	JOELHO 90º "KLIMAPRESS" 20x20	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	2650970	ABRAÇADEIRA PP-R "HELISYSTEM" 20 MM AZUL	SISTEMA PP-R - "HELIROMA"
	1910020	TUBO MULTICAMADA "HELIKLIMA" 32x3,0 - VARA 4 MT	SISTEMAS MULTICAMADA, PEX E PRE-ISO
Y	1910312	UNIÃO LOUCA "KLIMAPRESS" 20x1/2"	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910108	JOELHO MACHO "KLIMAPRESS" 20x 1/2"	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910254	TE SIMPLES "KLIMAPRESS" 16x16x16	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910202	TE REDUÇÃO "KLIMAPRESS" 20x16x20	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	2650254	TE FEMEA PP-R "HELISYSTEM" 25x1/2" AZUL	SISTEMA PP-R - "HELIROMA"
	2650752	JOELHO SIMPLES 45º PP-R "HELISYSTEM" 25MM AZUL	SISTEMA PP-R - "HELIROMA"
	1910072	JOELHO FEMEA "KLIMAPRESS" 20x 1/2"	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910056	JOELHO 90º "KLIMAPRESS" 40x40	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910012	TUBO MULTICAMADA "HELIKLIMA" 16x2,0 - VARA 4 MT	SISTEMAS MULTICAMADA, PEX E PRE-ISO
Z	2650950	TAMPÃO FINAL PP-R "HELISYSTEM" 63 MM AZUL	SISTEMA PP-R - "HELIROMA"
	2650016	TUBO PP-R HELISYSTEM PN20 (V.4M) 90X15 AZUL	SISTEMA PP-R - "HELIROMA"
	2650612	UNIÃO R.MACHO PP-R "HELISYSTEM" 50x1.1/2" AZUL	SISTEMA PP-R - "HELIROMA"
	1910152	TE FEMEA "KLIMAPRESS" 20x 1/2" x20	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	2651260	JOELHO SIMPLES 90º PP-R "HELISYSTEM" 40MM VERDE	SISTEMA PP-R - "HELIROMA"
	1910058	JOELHO 90º "KLIMAPRESS" 50x50	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910242	TE REDUÇÃO "KLIMAPRESS" 40x25x40	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	1910250	TE REDUÇÃO "KLIMAPRESS" 63x40x63	SISTEMAS MULTICAMADA, PEX E PRE-ISO
	2650526	REDUÇÃO PP-R "HELISYSTEM" 40x20 MM AZUL	SISTEMA PP-R - "HELIROMA"

ANNEX C: Crossing ABCXYZ analysis with sales features and stock values

Table 18 - Alpha's ABC analysis

	Definition	# Articles	%
A	Top 80% sales	2070	14
B	80% to 95% sales	2661	18
C	Last 95% sales	10417	69

Table 19 - Alpha's XYZ analysis

	Definition	# Articles	%
X	Sales every week	387	3
Y	Sales every month	2216	15
Z	Less than 1 sale per month	12545	83

Table 20 - Articles' ABCXYZ classification

Number of articles by category			
	X	**Y**	**Z**
A	354	905	811
B	30	919	1712
C	3	392	10022

Table 21 - ABCXYZ articles stock value

Average stock value by category			
	X	**Y**	**Z**
A	807 372,81€	946 953,95€	501 919,21€
B	52 794,22 €	262 050,99€	362 888,26€
C	3 714,54€	60 297,69€	1 253 827,78€

ANNEX D: Power BI Dashboard snapshots

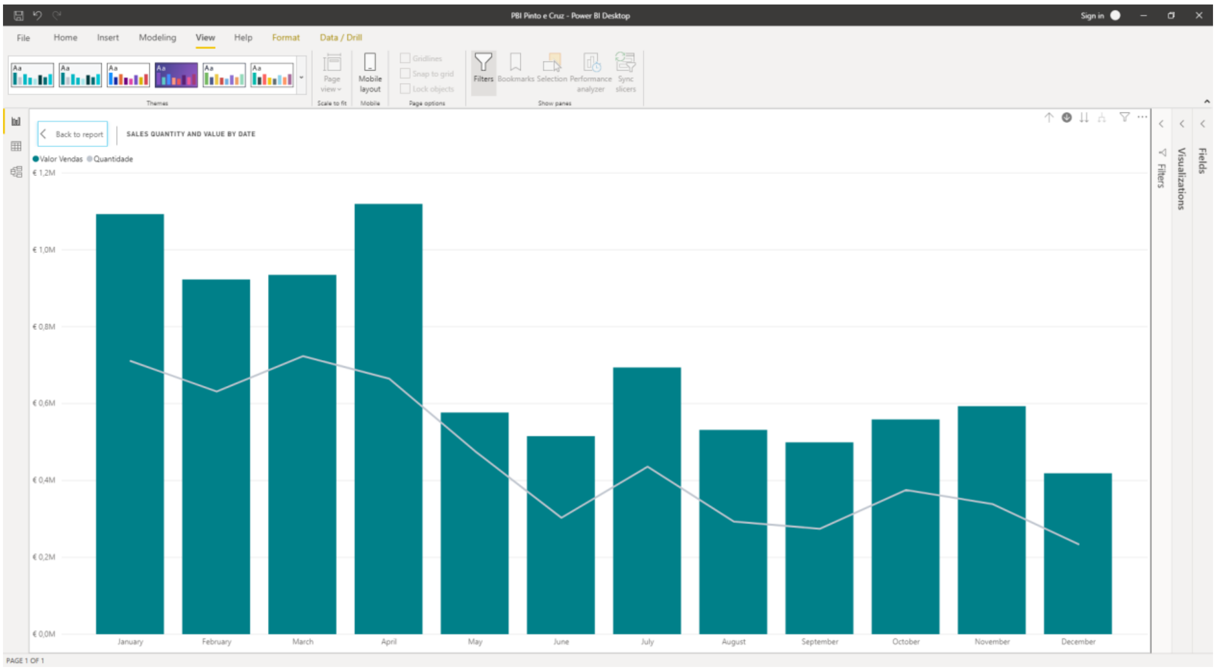

Figure 33 - Power BI Dashboard - Sales value and quantity

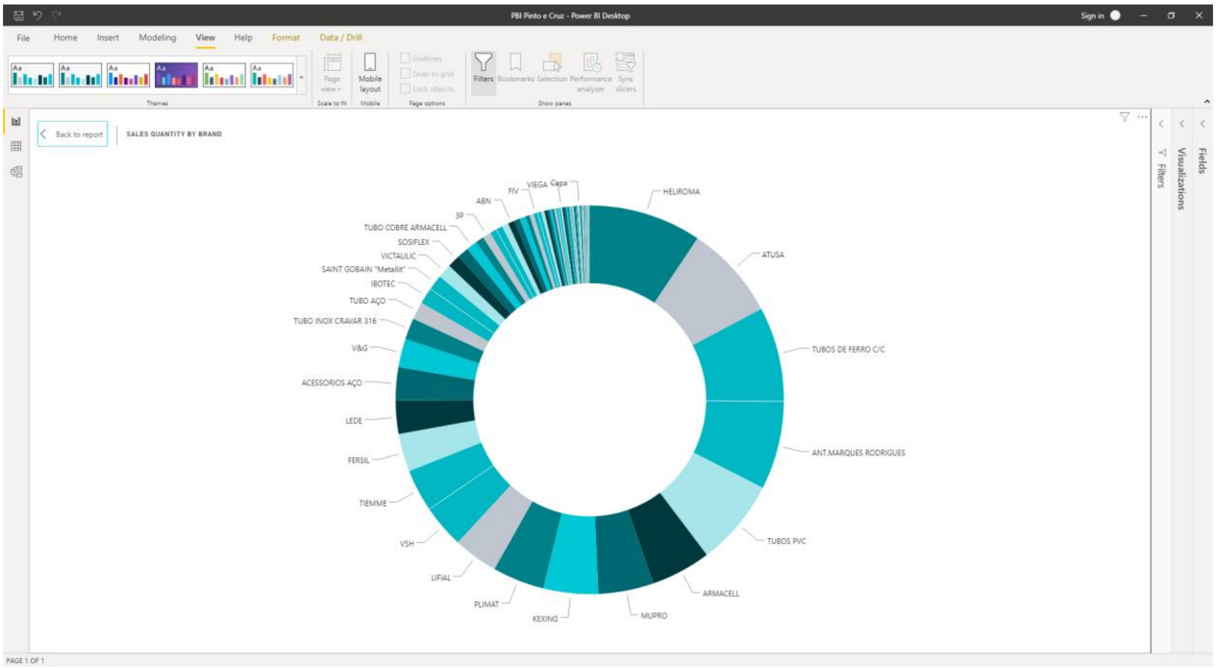

Figure 34 - Power BI Dashboard - Sales quantity by brand

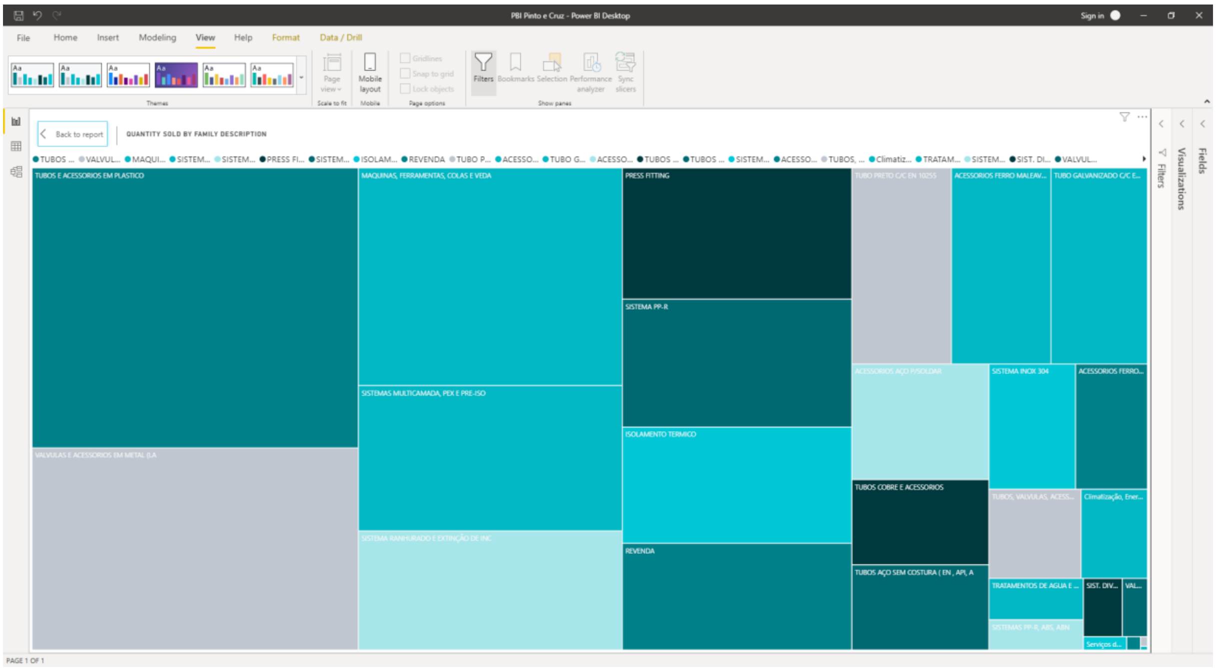

Figure 35 - Power BI Dashboard - Sales quantity by family

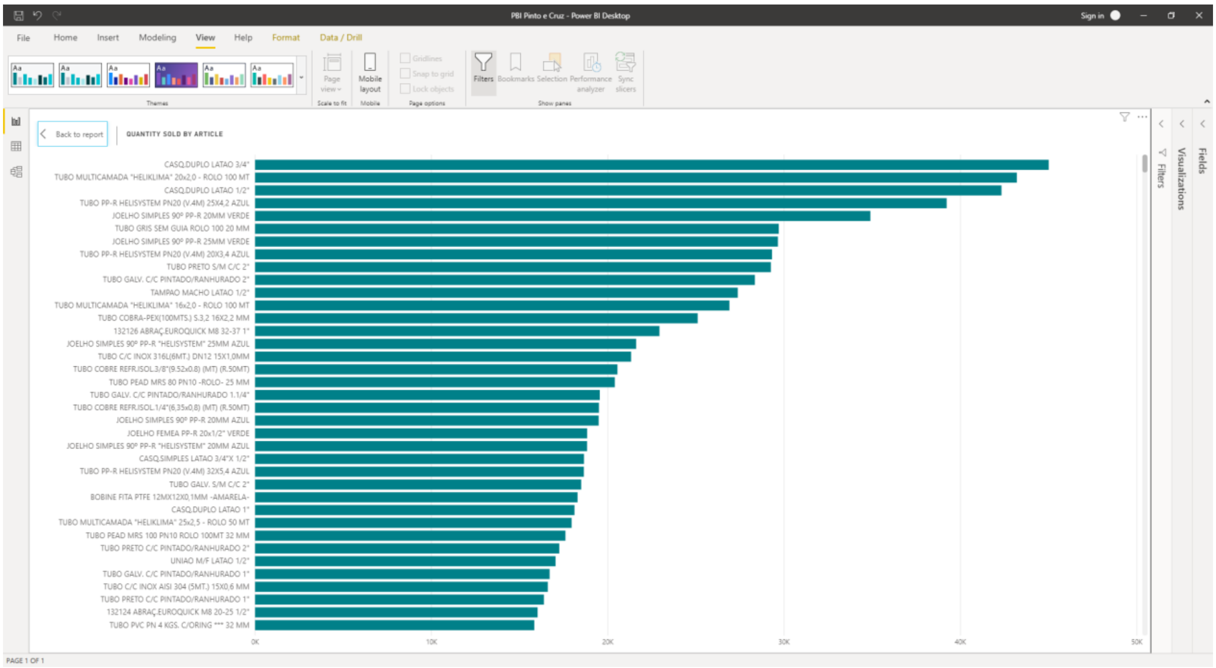

Figure 36 - Power BI Dashboard - Sales quantity by article

ANNEX E: Stock analysis of 27 references under study

Table 22 - Stock analysis - Average stock and annual consumption of 27 references grouped by category

Category	Article	Average monthly stock	Anual consumption
X	2650850	837,8947	9074,615
	1910026	343,295	3107,692
	2650854	356,3418	4998,462
	1910328	503,16	2139,231
	1910018	183,8851	2049,231
	2650006	2269,333	17830,77
	1910050	481,1852	2864,615
	2650970	734,6032	2961,538
	1910020	413,6	2907,692
Y	1910312	446,9706	1449,231
	1910108	272,0285	916,1538
	1910254	165,8118	918,4615
	1910202	103,5109	622,3077
	2650254	158,2973	1019,231
	2650752	362,1081	1211,538
	1910072	241,8182	1303,846
	1910056	98,26984	984,6154
	1910012	455,9007	1101,538
Z	2650950	243,9685	457,6923
	2650016	28	289,2308
	2650612	61,86667	243,8462
	1910152	64,06548	214,6154
	2651260	101,5851	459,2308
	1910058	34,97222	470
	1910242	45,12	217,6923
	1910250	38,24818	233,8462
	2650526	69	190,7692

Table 23 - Stock analysis - Turnover rate (years) of 27 references grouped by category

Category	Article	Turnover rate (years)
X	2650850	10,8
	1910026	9,1
	2650854	14,0
	1910328	4,3
	1910018	11,1
	2650006	7,9
	1910050	6,0
	2650970	4,0
	1910020	7,0
Y	1910312	3,2
	1910108	3,4
	1910254	5,5
	1910202	6,0
	2650254	6,4
	2650752	3,3
	1910072	5,4
	1910056	10,0
	1910012	2,4
Z	2650950	1,9
	2650016	10,3
	2650612	3,9
	1910152	3,3
	2651260	4,5
	1910058	13,4
	1910242	4,8
	1910250	6,1
	2650526	2,8

Table 24 - Stock analysis - Coverage rates (months and days) of 27 references grouped by category

Category	Article	Coverage rate (months)	Coverage rate (days)
X	2650850	1,1	26,6
	1910026	1,3	31,9
	2650854	0,8	20,6
	1910328	2,7	67,8
	1910018	1,0	25,9
	2650006	1,5	36,7
	1910050	1,9	48,5
	2650970	2,9	71,6
	1910020	1,6	41,0
Y	1910312	3,6	89,0
	1910108	3,4	85,7
	1910254	2,1	52,1
	1910202	1,9	48,0
	2650254	1,8	44,8
	2650752	3,4	86,2
	1910072	2,1	53,5
	1910056	1,2	28,8
	1910012	4,8	119,4
Z	2650950	6,2	153,8
	2650016	1,1	27,9
	2650612	2,9	73,2
	1910152	3,4	86,1
	2651260	2,6	63,8
	1910058	0,9	21,5
	1910242	2,4	59,8
	1910250	1,9	47,2
	2650526	4,2	104,3

ANNEX F: Stock inflation due to demand forecast error variation

Table 25 - Forecasting analysis - Average error variation (quantities, safety stock, coverage)

Category	Article	Average error variation (Q)	Average SS variation	Average coverage variation	% of the weeks inflated
X	2650850	19,61	3,92	98,03	64,00%
	1910026	6,73	1,35	33,67	48,33%
	2650854	10,78	2,16	53,89	52,00%
	1910328	4,61	0,92	23,04	63,00%
	1910018	4,45	0,89	22,26	42,67%
	2650006	44,09	8,82	220,46	70,33%
	1910050	6,08	1,22	30,39	68,67%
	2650970	6,42	1,28	32,08	22,00%
	1910020	6,22	1,24	31,12	57,00%
Y	1910312	3,14	0,63	15,72	33,67%
	1910108	1,99	0,40	9,93	32,67%
	1910254	1,82	0,36	9,12	38,33%
	1910202	0,39	0,08	1,94	30,00%
	2650254	2,21	0,44	11,06	32,33%
	2650752	2,63	0,53	13,13	21,33%
	1910072	2,82	0,56	14,12	54,00%
	1910056	2,14	0,43	10,71	73,00%
	1910012	2,39	0,48	11,93	28,33%
Z	2650950	0,99	0,20	4,96	18,00%
	2650016	0,48	0,10	2,42	18,33%
	2650612	0,53	0,11	2,66	25,00%
	1910152	0,47	0,09	2,33	36,67%
	2651260	0,98	0,20	4,92	44,00%
	1910058	0,97	0,19	4,86	64,33%
	1910242	0,48	0,10	2,38	58,33%
	1910250	0,51	0,10	2,53	35,33%
	2650526	0,41	0,08	2,07	6,00%

ANNEX G: MAPE error analysis of the 27 references studied

Table 26 - Forecasting analysis - MAPE

Category	Article	MAPE
X	2650850	91,00%
	1910026	58,00%
	2650854	78,43%
	1910328	65,47%
	1910018	74,88%
	2650006	132,04%
	1910050	68,60%
	2650970	51,35%
	1910020	66,65%
Y	1910312	55,88%
	1910108	52,18%
	1910254	59,58%
	1910202	51,50%
	2650254	62,75%
	2650752	51,56%
	1910072	53,05%
	1910056	66,31%
	1910012	51,58%
Z	2650950	51,00%
	2650016	51,17%
	2650612	57,42%
	1910152	52,97%
	2651260	53,16%
	1910058	57,29%
	1910242	55,86%
	1910250	54,12%
	2650526	50,44%

ANNEX H: Examples of category behavior sales pattern

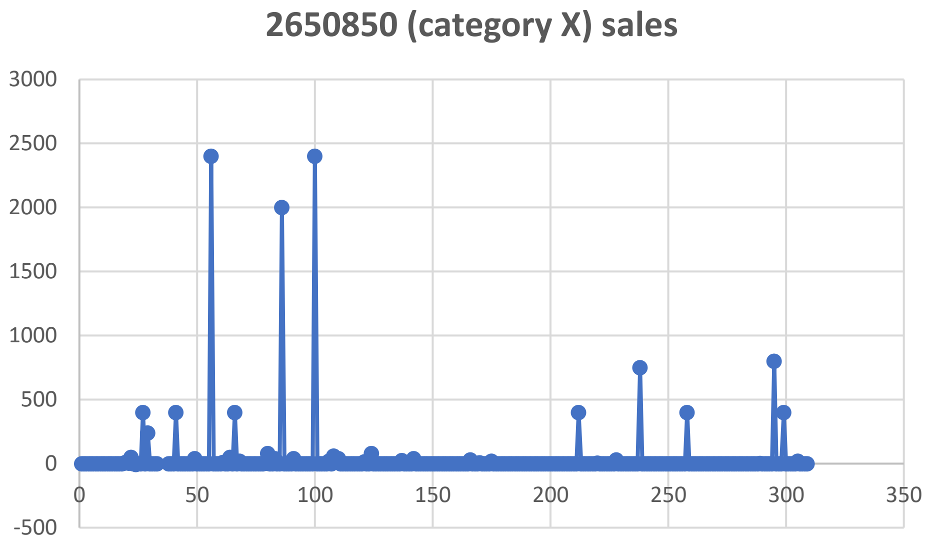

Figura 37 - Sales pattern (article 2650850)

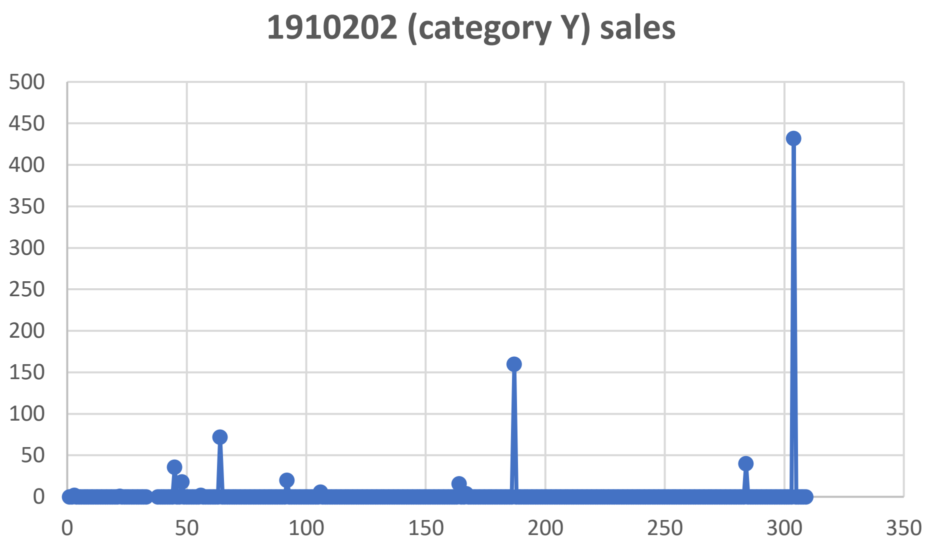

Figura 38 - Sales pattern (article 1910202)

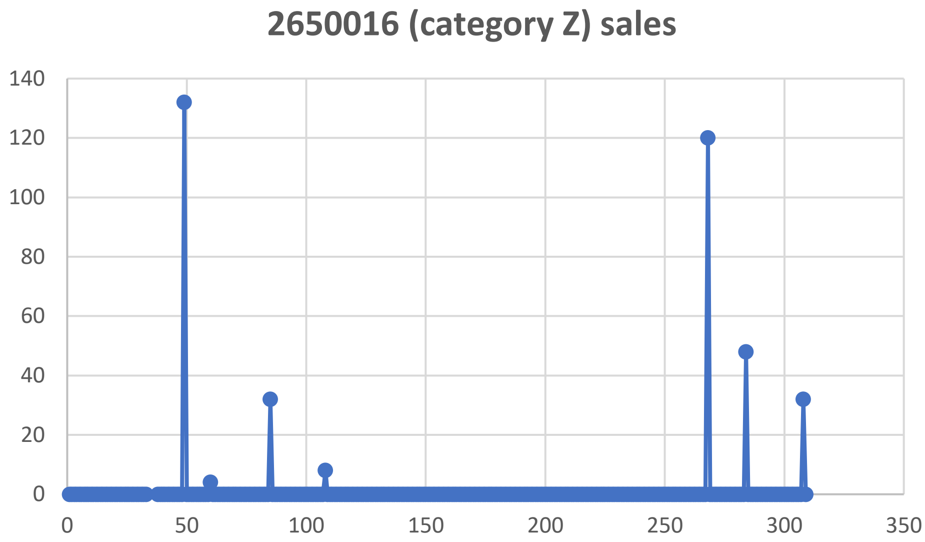

Figura 39 - Sales pattern (article 2650016)

ANNEX I: Examples of category behavior sales pattern grouped by weeks

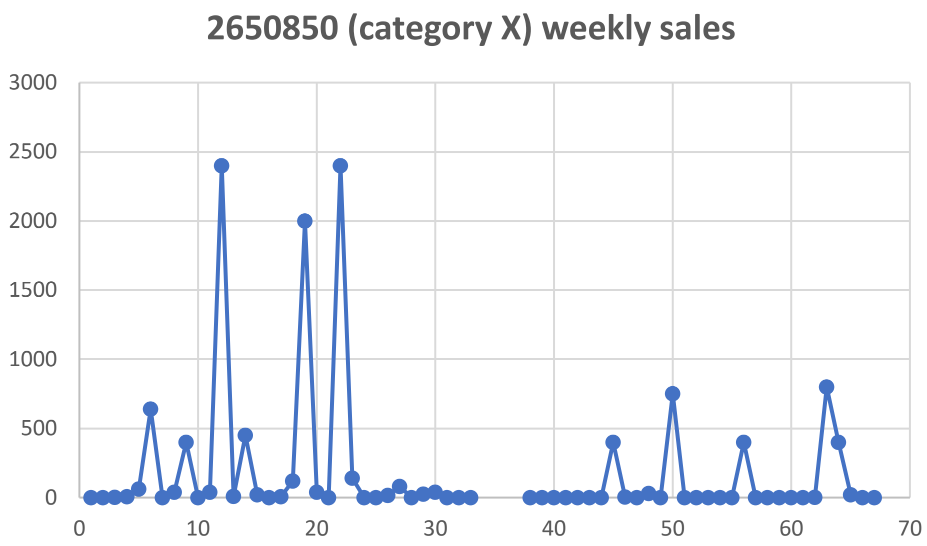

Figura 40 - Sales pattern grouped data (article 2650850)

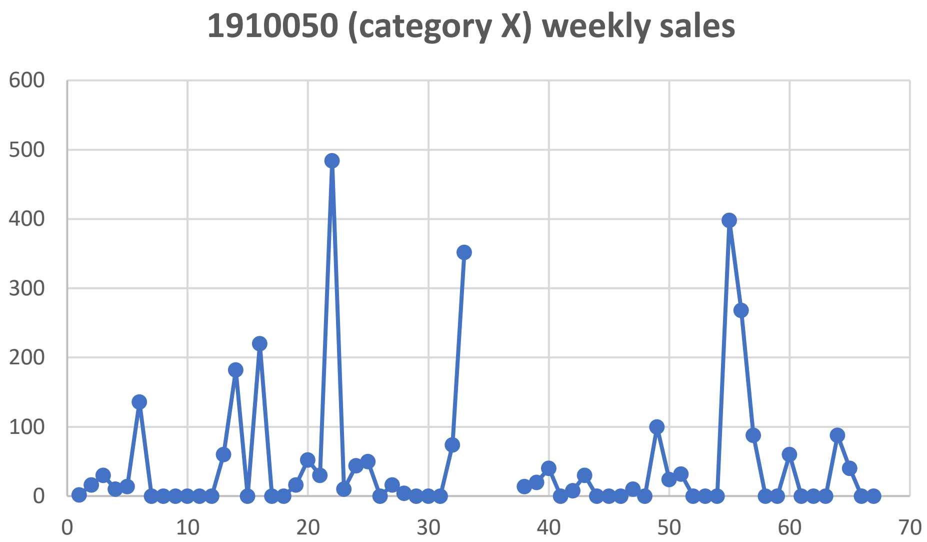

Figura 41 - Sales pattern grouped data (article 1910050)

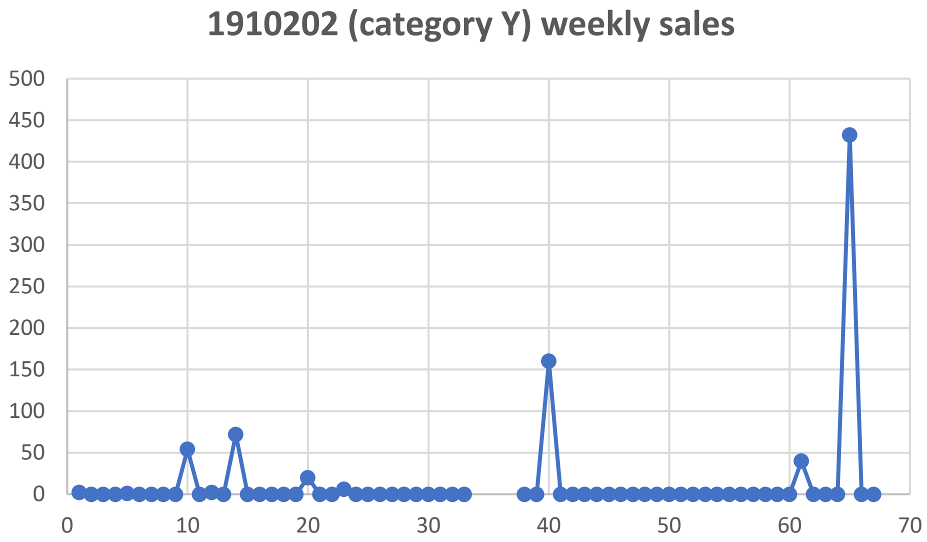

Figura 42 - Sales pattern grouped data (article 1910202)

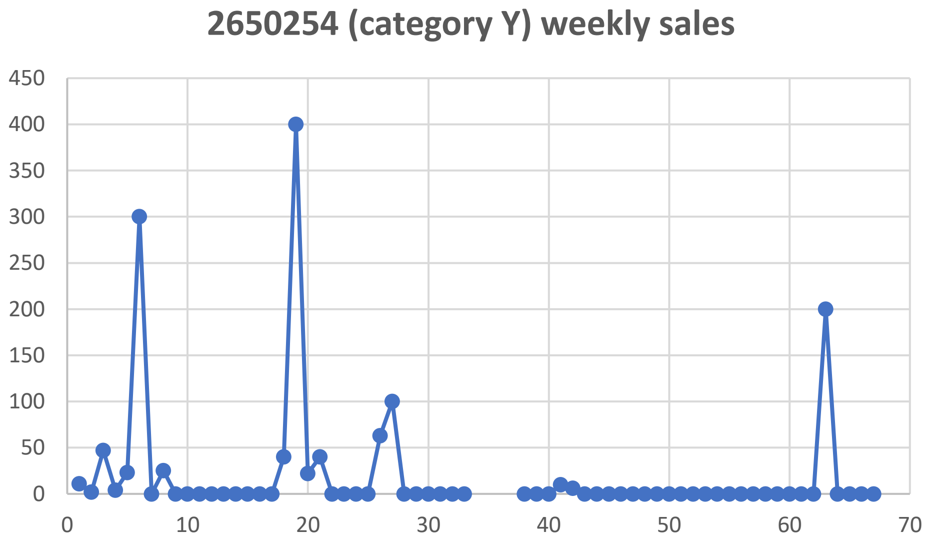

Figura 43 - Sales pattern grouped data (article 2650254)

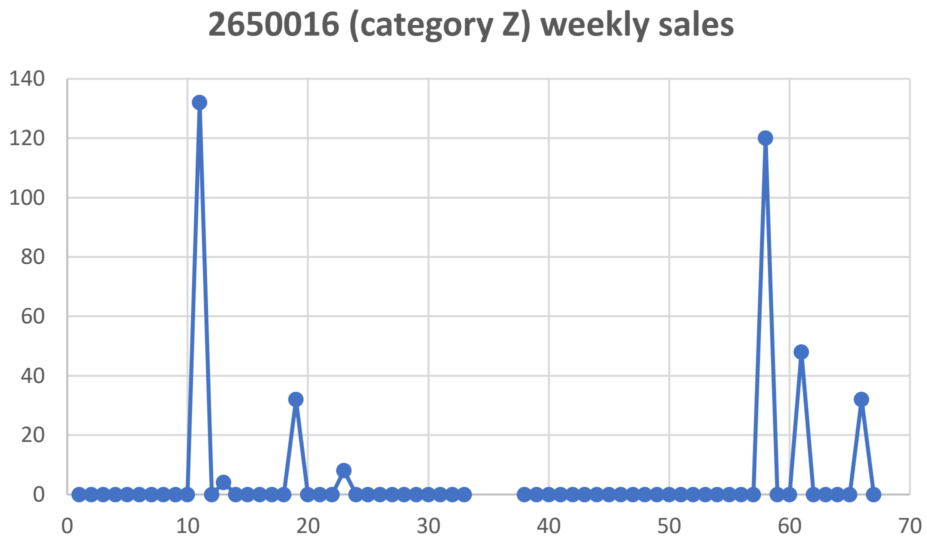

Figura 44 - Sales pattern grouped data (article 2650016)

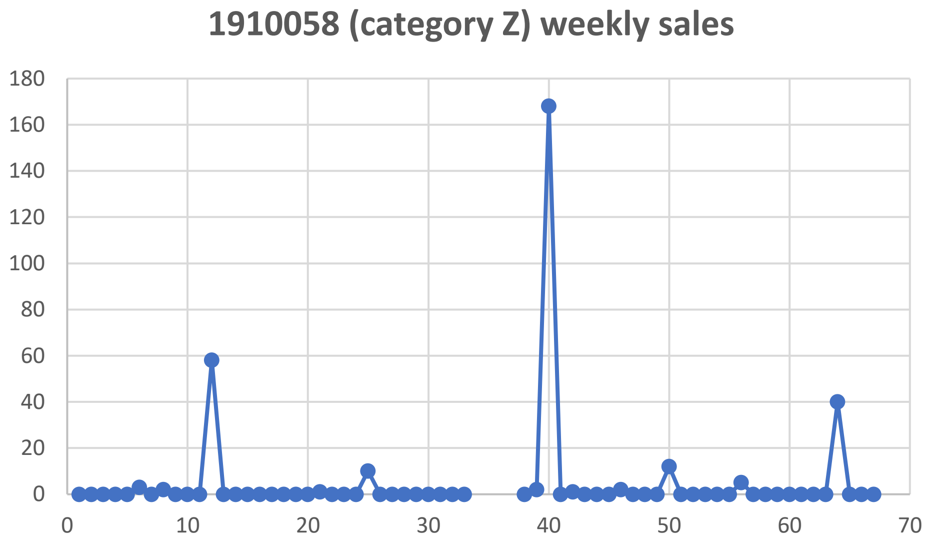

Figura 45 - Sales pattern grouped data (article 1910058)

ANNEX J: Safety stock quantities regarding different calculation metrics

Table 27 - Safety stock variation using different calculation methods

Category	Article	SS P&C	SS D 90	SS F 90
X	2650850	36,85	276,23	268,72
	1910026	12,60	99,93	100,46
	2650854	20,25	161,59	163,62
	1910328	8,68	56,61	58,10
	1910018	8,26	66,74	69,40
	2650006	68,30	469,18	420,12
	1910050	11,55	69,74	7,07
	2650970	12,03	88,76	85,53
	1910020	11,72	75,35	77,35
Y	1910312	2,94	44,91	47,63
	1910108	1,86	29,46	31,41
	1910254	1,83	29,23	30,90
	1910202	1,09	19,45	18,83
	2650254	2,04	30,58	31,84
	2650752	2,46	35,14	39,42
	1910072	2,63	39,34	38,66
	1910056	1,97	22,13	21,27
	1910012	2,24	36,74	40,34
Z	2650950	0,00	15,14	13,74
	2650016	0,00	9,67	9,42
	2650612	0,00	7,33	6,26
	1910152	0,00	6,82	7,18
	2651260	0,00	12,62	13,06
	1910058	0,00	12,06	11,22
	1910242	0,00	4,44	4,44
	1910250	0,00	8,45	9,05
	2650526	0,00	6,98	7,71

ANNEX K: Stock analysis in quantity, stockouts and value using different combinations of forecasting method and safety stock calculation

Table 28 - Average stock, % stockouts and average stock value using HW and SS P&C

	Usando HW e SS P&C			
X	Article:	2650850		
		Average stock	% stockouts	Average €
		597,93	17,91	20927,55
	Usando HW e SS P&C			
	Article:	1910026		
		Average stock	% stockouts	Average €
		340,9	2,99	11931,5
	Usando HW e SS P&C			
	Article:	2650854		
		Average stock	% stockouts	Average €
		371,49	7,46	13002,15
	Usando HW e SS P&C			
	Article:	1910328		
		Average stock	% stockouts	Average €
		159,91	19,4	5596,85
	Usando HW e SS P&C			
	Article:	1910018		
		Average stock	% stockouts	Average €
		192,78	1,49	6747,3
	Usando HW e SS P&C			
	Article:	2650006		
		Average stock	% stockouts	Average €
		911,55	14,93	31904,25
	Usando HW e SS P&C			
	Article:	1910050		
		Average stock	% stockouts	Average €
		170,06	11,94	5952,1
	Usando HW e SS P&C			
	Article:	2650970		
		Average stock	% stockouts	Average €
		414,3283582	0,029850746	14501,49254
	Usando HW e SS P&C			
	Article:	1910020		
		Average stock	% stockouts	Average €
		184,9552239	0,059701493	6473,432836
Y	Usando HW e SS P&C			
	Article:	1910312		
		Average stock	% stockouts	Average €
		238,4925373	0,044776119	8347,238806
	Usando HW e SS P&C			
	Article:	1910108		

		Average stock	% stockouts	Average €
		182,8955224	0,029850746	6401,343284
	Usando HW e SS P&C			
	Article:	1910254		
		Average stock	% stockouts	Average €
		72,26865672	0,089552239	2529,402985
	Usando HW e SS P&C			
	Article:	2650850		
		Average stock	% stockouts	Average €
		597,9253731	0,179104478	20927,38806
	Usando HW e SS P&C			
	Article:	1910202		
		Average stock	% stockouts	Average €
		73,55223881	4,48	2574,328358
	Usando HW e SS P&C			
	Article:	2650254		
		Average stock	% stockouts	Average €
		108,3134328	4,48	3790,970149
	Usando HW e SS P&C			
	Article:	2650752		
		Average stock	% stockouts	Average €
		297,1044776	4,78	10398,65672
	Usando HW e SS P&C			
	Article:	1910072		
		Average stock	% stockouts	Average €
		115,1492537	10,45	4030,223881
	Usando HW e SS P&C			
	Article:	1910056		
		Average stock	% stockouts	Average €
		57,25373134	5,97	2003,880597
	Usando HW e SS P&C			
	Article:	1910012		
		Average stock	% stockouts	Average €
		319,3134328	4,48	11175,97015
Z	Usando HW e SS P&C			
	Article:	2650950		
		Average stock	% stockouts	Average €
		137,880597	2,99	4825,820896
	Usando HW e SS P&C			
	Article:	2650016		
		Average stock	% stockouts	Average €
		22,11940299	4,6	774,1791045
	Usando HW e SS P&C			
	Article:	2650612		
		Average stock	% stockouts	Average €
		36,07462687	10,45	1262,61194

	Usando HW e SS P&C			
	Article:	1910152		
		Average stock	% stockouts	Average €
		36,88059701	4,48	1290,820896
	Usando HW e SS P&C			
	Article:	2651260		
		Average stock	% stockouts	Average €
		37,95522388	11,94	1328,432836
	Usando HW e SS P&C			
	Article:	1910058		
		Average stock	% stockouts	Average €
		17,62686567	19,4	616,9402985
	Usando HW e SS P&C			
	Article:	1910242		
		Average stock	% stockouts	Average €
		20,85074627	10,45	729,7761194
	Usando HW e SS P&C			
	Article:	1910250		
		Average stock	% stockouts	Average €
		31,02985075	2,99	1086,044776
	Usando HW e SS P&C			
	Article:	2650526		
		Average stock	% stockouts	Average €
		48	1,49	1680

Tabela 29 - Average stock, % stockouts and average stock value using Alpha's calculations

	Usando modelo da empresa			
X	Article:	2650850		
		Average stock	% stockouts	Average €
		767,64	86,57	26867,4
	Usando modelo da empresa			
	Article:	1910026		
		Average stock	% stockouts	Average €
		346,95	44,78	12143,25
	Usando modelo da empresa			
	Article:	2650854		
		Average stock	% stockouts	Average €
		373,18	83,58	13061,3
	Usando modelo da empresa			
	Article:	1910328		
		Average stock	% stockouts	Average €
		479,73	77,61	16790,55
	Usando modelo da empresa			
	Article:	1910018		
		Average stock	% stockouts	Average €
		186,04	44,78	6511,4

	Usando modelo da empresa			
	Article:	2650006		
		Average stock	% stockouts	Average €
		1501	97	52535
	Usando modelo da empresa			
	Article:	1910050		
		Average stock	% stockouts	Average €
		472,36	0,76119403	16532,6
	Usando modelo da empresa			
	Article:	2650970		
		Average stock	% stockouts	Average €
		737,5	0,731343284	25812,5
	Usando modelo da empresa			
	Article:	1910020		
		Average stock	% stockouts	Average €
		421,04	0,850746269	14736,4
Y	Usando modelo da empresa			
	Article:	1910312		
		Average stock	% stockouts	Average €
		458,1578947	0,71641791	16035,52632
	Usando modelo da empresa			
	Article:	1910108		
		Average stock	% stockouts	Average €
		274,315	0,402985075	9601,025
	Usando modelo da empresa			
	Article:	1910254		
		Average stock	% stockouts	Average €
		169,5875	0,820895522	5935,5625
	Usando modelo da empresa			
	Article:	2650850		
		Average stock	% stockouts	Average €
		767,6444444	0,865671642	26867,55556
	Usando modelo da empresa			
	Article:	1910202		
		Average stock	% stockouts	Average €
		104,1393162	41,79	3644,876068
	Usando modelo da empresa			
	Article:	2650254		
		Average stock	% stockouts	Average €
		163,75	92,54	5731,25
	Usando modelo da empresa			
	Article:	2650752		
		Average stock	% stockouts	Average €
		309,33	91,04	10826,55
	Usando modelo da empresa			
	Article:	1910072		

		Average stock	% stockouts	Average €
		238,45625	64,18	8345,96875
	Usando modelo da empresa			
	Article:	1910056		
		Average stock	% stockouts	Average €
		100,6222222	86,57	3521,777778
	Usando modelo da empresa			
	Article:	1910012		
		Average stock	% stockouts	Average €
		450,2439024	0,388059701	15758,53659
Z	Usando modelo da empresa			
	Article:	2650950		
		Average stock	% stockouts	Average €
		244,4	73,33	8554
	Usando modelo da empresa			
	Article:	2650016		
		Average stock	% stockouts	Average €
		244,4	73,13	8554
	Usando modelo da empresa			
	Article:	2650612		
		Average stock	% stockouts	Average €
		43,08333333	95,5	1507,916667
	Usando modelo da empresa			
	Article:	1910152		
		Average stock	% stockouts	Average €
		64,97083333	64,18	2273,979167
	Usando modelo da empresa			
	Article:	2651260		
		Average stock	% stockouts	Average €
		98,03214286	79,1	3431,125
	Usando modelo da empresa			
	Article:	1910058		
		Average stock	% stockouts	Average €
		36,12	77,61	1264,2
	Usando modelo da empresa			
	Article:	1910242		
		Average stock	% stockouts	Average €
		46,11428571	68,66	1614
	Usando modelo da empresa			
	Article:	1910250		
		Average stock	% stockouts	Average €
		38,79358974	41,79	1357,775641
	Usando modelo da empresa			
	Article:	2650526		
		Average stock	% stockouts	Average €
		69	73,13	2415

Tabela 30 - Average stock, % stockouts and average stock value using HW and SS D 90

	Usando HW e SS D 90			
X	Article:	2650850		
		Average stock	% stockouts	Average €
		1161,671642	5,97	40658,507
	Usando HW e SS D 90			
	Article:	1910026		
		Average stock	% stockouts	Average €
		723,9552239	1,49	25338,433
	Usando HW e SS D 90			
	Article:	2650854		
		Average stock	% stockouts	Average €
		728,0149254	4,48	25480,522
	Usando HW e SS D 90			
	Article:	1910328		
		Average stock	% stockouts	Average €
		203,880597	2,97	7135,8209
	Usando HW e SS D 90			
	Article:	1910018		
		Average stock	% stockouts	Average €
		399,9402985	1,49	13997,91
	Usando HW e SS D 90			
	Article:	2650006		
		Average stock	% stockouts	Average €
		1785,014925	7,46	62475,522
	Usando HW e SS D 90			
	Article:	1910050		
		Average stock	% stockouts	Average €
		274,1492537	8,96	9595,2239
	Usando HW e SS D 90			
	Article:	2650970		
		Average stock	% stockouts	Average €
		890,4477612	2,99	31165,672
	Usando HW e SS D 90			
	Article:	1910020		
		Average stock	% stockouts	Average €
		351,0149254	4,48	12285,522
Y	Usando HW e SS D 90			
	Article:	1910312		
		Average stock	% stockouts	Average €
		354,3283582	1,49	12401,493
	Usando HW e SS D 90			
	Article:	1910108		
		Average stock	% stockouts	Average €
		244,3880597	2,99	8553,5821

	Usando HW e SS D 90			
	Article:	1910254		
		Average stock	% stockouts	Average €
		147,4029851	2,99	5159,1045
	Usando HW e SS D 90			
	Article:	2650850		
		Average stock	% stockouts	Average €
		1161,671642	5,97	40658,507
	Usando HW e SS D 90			
	Article:	1910202		
		Average stock	% stockouts	Average €
		103,6567164	2,99	3627,9851
	Usando HW e SS D 90			
	Article:	2650254		
		Average stock	% stockouts	Average €
		177,4179104	7,78	6209,6269
	Usando HW e SS D 90			
	Article:	2650752		
		Average stock	% stockouts	Average €
		458,880597	2,99	16060,821
	Usando HW e SS D 90			
	Article:	1910072		
		Average stock	% stockouts	Average €
		169,9701493	7,46	5948,9552
	Usando HW e SS D 90			
	Article:	1910056		
		Average stock	% stockouts	Average €
		76,05970149	5,97	2662,0896
	Usando HW e SS D 90			
	Article:	1910012		
		Average stock	% stockouts	Average €
		391,4328358	2,99	13700,149
Z	Usando HW e SS D 90			
	Article:	2650950		
		Average stock	% stockouts	Average €
		236,7761194	1,49	8287,1642
	Usando HW e SS D 90			
	Article:	2650016		
		Average stock	% stockouts	Average €
		52,02985075	2,99	1821,0448
	Usando HW e SS D 90			
	Article:	2650612		
		Average stock	% stockouts	Average €
		57,14925373	2,99	2000,2239
	Usando HW e SS D 90			
	Article:	1910152		

		Average stock	% stockouts	Average €
		48,62686567	1,49	1701,9403
	Usando HW e SS D 90			
	Article:	2651260		
		Average stock	% stockouts	Average €
		55,65671642	8,89	1947,9851
	Usando HW e SS D 90			
	Article:	1910058		
		Average stock	% stockouts	Average €
		28,40298507	7,46	994,10448
	Usando HW e SS D 90			
	Article:	1910242		
		Average stock	% stockouts	Average €
		23,89552239	5,97	836,34328
	Usando HW e SS D 90			
	Article:	1910250		
		Average stock	% stockouts	Average €
		67,05970149	1,49	2347,0896
	Usando HW e SS D 90			
	Article:	2650526		
		Average stock	% stockouts	Average €
		119,9402985	1,49	4197,9104

Tabela 31 - Average stock, % stockouts and average stock value using HW and SS F 90

	Usando HW e SS F 90			
X	Article:	2650850		
		Average stock	% stockouts	Average €
		1110,925373	5,97	38882,388
	Usando HW e SS F 90			
	Article:	1910026		
		Average stock	% stockouts	Average €
		735	1,49	25725
	Usando HW e SS F 90			
	Article:	2650854		
		Average stock	% stockouts	Average €
		704,1343284	4,48	24644,701
	Usando HW e SS F 90			
	Article:	1910328		
		Average stock	% stockouts	Average €
		203,2835821	5,97	7114,9254
	Usando HW e SS F 90			
	Article:	1910018		
		Average stock	% stockouts	Average €
		404,8656716	1,49	14170,299
	Usando HW e SS F 90			
	Article:	2650006		

		Average stock	% stockouts	Average €
		2031,731343	7,46	71110,597
	Usando HW e SS F 90			
	Article:	1910050		
		Average stock	% stockouts	Average €
		280,119403	8,86	9804,1791
	Usando HW e SS F 90			
	Article:	2650970		
		Average stock	% stockouts	Average €
		861,3432836	2,99	30147,015
	Usando HW e SS F 90			
	Article:	1910020		
		Average stock	% stockouts	Average €
		353,1044776	4,48	12358,657
Y	Usando HW e SS F 90			
	Article:	1910312		
		Average stock	% stockouts	Average €
		349,4029851	1,49	12229,104
	Usando HW e SS F 90			
	Article:	1910108		
		Average stock	% stockouts	Average €
		246,9253731	2,99	8642,3881
	Usando HW e SS F 90			
	Article:	1910254		
		Average stock	% stockouts	Average €
		145,761194	2,99	5101,6418
	Usando HW e SS F 90			
	Article:	2650850		
		Average stock	% stockouts	Average €
		1110,925373	5,97	38882,388
	Usando HW e SS F 90			
	Article:	1910202		
		Average stock	% stockouts	Average €
		103,2089552	2,99	3612,3134
	Usando HW e SS F 90			
	Article:	2650254		
		Average stock	% stockouts	Average €
		180,4029851	4,44	6314,1045
	Usando HW e SS F 90			
	Article:	2650752		
		Average stock	% stockouts	Average €
		467,0895522	2,97	16348,134
	Usando HW e SS F 90			
	Article:	1910072		
		Average stock	% stockouts	Average €
		168,0298507	7,46	5881,0448

	Usando HW e SS F 90			
	Article:	1910056		
		Average stock	% stockouts	Average €
		77,70149254	5,97	2719,5522
	Usando HW e SS F 90			
	Article:	1910012		
		Average stock	% stockouts	Average €
		393,3731343	2,99	13768,06
Z	Usando HW e SS F 90			
	Article:	2650950		
		Average stock	% stockouts	Average €
		236,238806	2,99	8268,3582
	Usando HW e SS F 90			
	Article:	2650016		
		Average stock	% stockouts	Average €
				0
	Usando HW e SS F 90			
	Article:	2650612		
		Average stock	% stockouts	Average €
				0
	Usando HW e SS F 90			
	Article:	1910152		
		Average stock	% stockouts	Average €
		44,86567164	2,99	1570,2985
	Usando HW e SS F 90			
	Article:	2651260		
		Average stock	% stockouts	Average €
		55,20895522	8,96	1932,3134
	Usando HW e SS F 90			
	Article:	1910058		
		Average stock	% stockouts	Average €
		29,32835821	7,46	1026,4925
	Usando HW e SS F 90			
	Article:	1910242		
		Average stock	% stockouts	Average €
		29,32835821	7,46	1026,4925
	Usando HW e SS F 90			
	Article:	1910250		
		Average stock	% stockouts	Average €
		66,91044776	1,08	2341,8657
	Usando HW e SS F 90			
	Article:	2650526		
		Average stock	% stockouts	Average €
		126,2089552	1,4	4417,3134