Replenishment support decision model for a try-before-you-buy retail fashion e-commerce

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Abstract

English Version

A try before you buy business model is a type of sales strategy in which customers are allowed to test a product before making a purchase. As the try before you buy online business model is a topic on which there is limited public scholarly research, the purpose of this research is to provide an initial approach to the subject by presenting a tool to support the replenishment strategy of Curve Catch, a fashion e-commerce retailer. A simulation engine characterized by two main components has been built: replenishment and a demand generator. Model development is built on artificially generated data based on real data of Curve Catch. Based on the literature inherent to inventory management and through the use of simulation -optimization, the model provides managerial guidance on how to manage r,Q policy in a system where most goods shipped to customers are returned. The tool highlights the need to optimize the use of reorder point and economic order quantity to achieve better business performance. This is because conventional formulas, if not adjusted to the specific setting, perform sub optimally. The model also provides insights into the levels of lost sales due to out stocking and the quality of service provided to customers. Studying the relationships among these three KPIs provides insight into what trade-offs are relevant in planning a continuous review replenishment strategy.

Abstract

Versão portuguesa

Um modelo de negócio de "experimentar antes de comprar" é um tipo de estratégia de vendas onde os clientes têm a possibilidade de testar um produto antes de fazer a sua compra. Uma vez que este modelo de negócio online é um tópico sobre o qual não existe nenhuma pesquisa académica pública, o objetivo desta estudo é fornecer uma abordagem inicial ao assunto, fornecendo uma ferramenta para apoiar a estratégia de reposição da Curve Catch, um e-commerce de moda. Foi construído um motor de simulação caracterizado por dois componentes principais: reposição e gerador de procura. O desenvolvimento do modelo baseia-se em dados gerados artificialmente com base em dados reais da Curve Catch. Com base na literatura inerente à gestão de stocks e através do uso de simulação-otimização, o modelo fornece orientação empresarial sobre como gerir a política r, Q em um sistema onde a maioria dos produtos enviados para os clientes é devolvido. A ferramenta destaca a necessidade de otimizar o uso do ponto de reordenação (reorder point) e da quantidade de encomenda económica (economic order quantity), para alcançar um melhor desempenho do negócio. Isso ocorre dado que as fórmulas convencionais, se não forem ajustadas para o ambiente específico, serão desempenhadas de maneira subaproveitada. Para além disso, o modelo fornece insights sobre os níveis de vendas perdidas devido ao esgotamento e a qualidade do atendimento ao cliente. O estudo das relações entre essas três métricas-chave fornece insights sobre quais trade-offs são relevantes no planeamento de uma estratégia de reposição de revisão contínua."

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1. Introduction

The try before you buy business model has gained popularity in recent years, particularly within the e-commerce sector. This model allows customers to try out products before committing to a purchase, which can be particularly appealing in the fashion industry where customers may want to see how an item fits or looks on them before making a decision. However, this model also introduces a number of novel challenges related to supply chain management and retail operations. One such challenge is the management of a constantly "frozen" inventory at the customer which cannot be shipped to others, as customers are able to send back items that they decide not to purchase. In order to effectively manage this frozen inventory, it is important to have a clear understanding of lead times for different product categories, as well as the length of time that the frozen inventory spends in the pipeline. To address these challenges, a simulation model was developed based on the retail fashion company CurveCatch, which operates on a try before you buy business model. This model includes a range of variables, such as logistics and demand generation, to help understand the dynamics of continuous inventory review. The model also allows for what-if analyses, simulation-optimization studies, and sensitivity analyses to seek near-optimal solutions that maximize profits while maintaining high levels of customer service quality and low rates of lost sales. In order to evaluate the performance of the model, artificially generated data, based on real data, was used to identify significant trade-offs and assess the impact of different variables. The model also incorporates and records the accounting, cost, and sales performance of each product, providing a descriptive analysis and leaving space for further calibration and extendibility. Overall, the goal of this project is to provide insights on how to effectively manage the try before you buy business model in the e-commerce sector, with a focus on the challenges related to supply chain management and retail operations. By using a simulation model to study the dynamics of continuous inventory review, it is possible to identify strategies that can help to optimize replenishment and storage policy and ultimately maximize profits while maintaining high levels of customer service quality.

1.1. Try Before You Buy Business Model

A try before you buy business model is a retail strategy that allows customers to test out a product before making a purchase. This retail technique has undoubtedly evolved through time, making it difficult to pinpoint its origins. But as long as there have been retail establishments, the idea of letting customers try out products before buying them has existed. The "try before you buy" model has increased in popularity in recent years as online retailers seek to give customers a more convenient and enjoyable buying experience. The ability to order products online, try them on at home before deciding whether to keep them, and use simple return procedures for items that are not kept is currently offered by many online merchants. This model is particularly relevant in the fashion industry, where customers often want to try on clothing and accessories to ensure they fit and look good before committing to a purchase. For fashion retailers, the try before you buy model can be a valuable way to increase customer satisfaction and loyalty. By allowing customers to try on items before buying them, retailers can reduce the risk of returns and exchanges, which can save time and resources for both the retailer and the customer. With this model retailers can create a more enjoyable shopping experience for their customers and build trust in their brand. There are a few different ways that fashion retailers can implement the try before you buy model. One approach is to offer in-store try-ons, where customers can visit the store and try on items before deciding whether to purchase them. Another option is to offer online try-ons as Curve Catch, where customers can order items and try them on at home before deciding whether to keep them. There are both pros and cons to the try before you buy model for e-commerce businesses. Some of the potential pros include increased customer satisfaction by allowing customers to try out a product before committing to a purchase and helping to build trust with potential customers, which may lead to increased conversions and sales. Some of the potential cons include increased costs for items shipping and handling and the risk that some customers may take advantage of the try before you buy option and not return the product, resulting in a loss for the business. In this study, an approach is proposed to provide support for replenishment strategy decisions by taking into consideration the major feature of this model, which is the fact that part of the inventory is always in a logistical flow between consumers and the company.

1.2. Research Problem

As online shopping has become more and more popular over the past few decades, the issues of e-commerce platform assortment optimization and management of the replenishment strategy have drawn more and more attention. When it comes to assortment planning, e-commerce platforms offer several benefits over traditional brick and mortar retailers. First off, online marketplaces may sell far more things on their websites without being constrained by store space. Second, e-commerce companies provide more user-friendly ways to apply assortment decisions, such as displaying a banner ad on the home page, arranging the order of the results on the search page, suggesting more goods to clients who are looking at the product details, and so forth. Third, e-retailers may readily capture numerous consumers' activity histories, such as searching, browsing, and clicking, which is frequently referred to as side information. This is in addition to transaction data. Inventory planning choices are essential in the retail fashion sector and fashion retailers always struggle to strike a balance between supply and demand (Hsu and Lee, 2009). The goal of a replenishment strategy is to ensure that a company has the right amount of inventory on hand to meet customer demand in a cost-effective manner. This involves finding the balance between having too much inventory, which can lead to excess costs due to storage and handling, and having too little inventory, which can result in lost sales and customer dissatisfaction. The link between assortment planning and replenishment strategy is that the replenishment strategy a company chooses will depend on the types and quantities of products it has chosen to carry as part of its assortment. Retailers must successfully manage the inventory levels to satisfy customer expectations in a market with constantly changing items and quickly moving consumer desires. Good inventory management makes an important contribution to building and maintaining customer happiness. Fashion products require special consideration both in the initial ordering process before to selling season and in the decisions pertaining the replenishment throughout the selling season due to their short product lifespan and highly variable demand. Given a certain assortment plan, this research investigates the effects of a specific replenishment strategy for a try before you buy e-commerce company that specializes in women's apparel, Curve Catch. Based on evidence of the difficulty women face when purchasing these items in-store due to the wide range of sizes, privacy during the fitting, and other discomforts, the firm presents itself as the size-free marketplace for bras and underwear. CurveCatch uses artificial intelligence to connect individuals with the ideal undergarments. After each order made by customers, CurveCatch is able to deliver an extra set of related items in the packaging because of a data collecting system based on pre- and post-sales surveys, purchase information, and information from suppliers. Despite this, the company lacks the resources to improve the effectiveness of the replenishment system in order to maximize business performance. For this reason, the current research addresses this issue while also filling a research gap in the scientific field. For a complete understanding of the goal of this thesis project and how it might affect CurveCatch, the internal business procedures and needs are examined in more detail in the following part.

1.3. Related Work

CurveCatch currently works with a fulfilment centre with which an agreement is in place for a specific maximum product capacity, which could be extended by paying additional costs. Approximately 3000 slots that can hold specific barcode items were available at the time this project was being developed. Depending on supply and demand projections, each individual barcode can be supplied many times. It is impossible to maintain all SKUs (stock keeping units) in inventory since some of them must be selected from a range of sizes that, in some situations, reaches more than 100 distinct options. For instance, the fulfilment centre's maximum capacity would be reached with just 30 distinct SKUs and 100 sizes each one. Therefore, it is essential to choose carefully which items to maintain in stock and which to exclude, as well as the sizes to keep in stock for each item. The intention at CurveCatch to retain 80% of the items as stock base and 20% of the products as experiments on a quarterly basis is a key component in the organization of the assortment. The experiments guarantee that CurveCatch can ride new trends and provide ever-evolving items, while the base stock is the collection of goods that best fits the personas in terms of product and price. The conditions and differences that result in the supply of various items are as varied as the relationships with suppliers. In the final assessment of the selection, elements like lead time, replenishment period, shipping expenses, and minimum order ceiling are taken into consideration. The replenishment strategy is currently done manually and therefore the start-up requires a recommendation framework to make the process more efficient. This was done through the creation and optimization of a tool to simulate the assortment performance and supply dynamics with the purpose of finding an optimal strategy and identifying the main trade-offs that an r,Q policy would bring in a try before you buy online system.

1.4. Research Question

The CurveCatch supply system is complex and includes a number of factors to be considered. Lead time, which differs between product categories, plays a key role in inventory management calculations. For example NOOS (never out of stock) products are always accessible for replenish with short lead times while FASHION products have a seasonal rhythm and whose replenishment is more constrained. It was therefore decided by the company that FASHION products can only be inserted in the 20% of the assortment specifically designated to experiments. The amount of time a product is "frozen", waiting to be restocked after being returned by a client, is another temporal measurement that has an effect on the supply chain. Stock is constantly moving, which is characteristic of the retail try-before-you-buy business model. Stock moves from suppliers to the firm, from the company to customers, and from customers to the company when products are not purchased. The following sections of this study will go into greater detail about how this element affects the replenishment method.

As anticipated in the previous chapter, a replenishment strategy is a plan for managing a company's inventory in a way that meets customer demand and is cost-effective. This can involve manually making decisions about restocking or using automated systems. Good replenishment strategies can improve a company's efficiency and profits by reducing excess inventory costs and lost sales, and can also help the company maintain good relationships with customers by keeping necessary products available. This paper tries, for the first time, to find insights on the use of a continuous inventory review policy specifically for a try before you buy business model and try therefore to answer the following question:

R,Q: <u>How should the replenishment strategy of a try before you buy business be handled to ensure maximisation of profits while controlling for lost sales and keeping a high customer service?</u>

The conduct of the research is based on running a market simulation of which many data are recorded and performance indices are created, which will be explained in detail later in the paper. It is possible to shape all variables of major interest, both supply and demand forces, in order to study their impact on the average results of revenue generation, cost maintenance, lost opportunities and service quality. Therefore, by proceeding with what-if analysis, it is possible to create more favourable scenarios for CurveCatch by optimising certain key components to achieve the best results. The output of the support model will then be subjected to human interpretation to derive decisions and considerations that were not included in the mathematical model.

2. Literature Review

The following paragraphs review the literature consistent with the purpose of the research. The review looks at earlier studies on inventory management, replenishment, assortment planning, SKU rationalization, and simulation-optimization.

2.1. Inventory Management & Replenishment Strategies

Lead-time management and safety stock have gotten more difficult in today's dynamic global market because of the highly fluctuating demand for any product, especially in recent years. Nowadays, companies are seeking for alternative strategies to stay one step ahead of their rivals in this quickly evolving market. Without suitable inventory control methods, it becomes very difficult for retailers to stay competitive (Sarkar and Giri, 2020).

2.1.2. EOQ

It is common practice to estimate the order quantity and reorder point for inventory replenishment using well-known techniques like the economic order quantity model (EOQ), according to Sarkar (2020). The EOQ is the recommended order quantity that a business should place in order to reduce inventory expenses, including holding costs, shortage costs, and order charges. Ford W. Harris created this production-scheduling concept in 1913, and it has since been improved. Demand, ordering, and holding expenses are all considered constant in the calculation. The base EOQ model is fairly simple yet makes a number of simplifying assumptions, including constant demand and purchase price, deterministic setup, and no product scarcity. Demand and pricing are two variables that are not necessarily fixed in nature. The reorder point number, according to Chen, is the inventory level that determines the order for additional units, and the quantity of products included in the safety stock acts as a buffer against stock-outs. Furthermore, the reorder point permits enough safety stock—stock of the already in stock product—to meet consumer demand before the subsequent order enters after the lead time.

2.1.3. s,S and r,Q Policies

Recent years have seen a lot of interest in stochastic demand-based inventory plans. For inventory replenishment, continuous and cyclical review inventory policies like the (*s, S*) ordering policy and the (*r, Q*) ordering policy are frequently employed. The item's inventory position is raised to level *S* in accordance with a (*s, S*) policy when it reaches or dips below level s, or orders are placed to level S when the inventory level is lower than *s*. When inventory has to be refilled by set reorder quantities, the (*r, Q*) inventory policy is utilized. A replenishment order of size *Q* is placed when the inventory position (stock in hand plus stock on order) hits or falls below the re-order level *r*. However, it is found that several of the assumptions for (*s, S*) and (*r, Q*) policies, such as the structure of the demand process, are overly restrictive in real-world inventory issues. It is extremely challenging to obtain an optimum (*s, S*) policy if the demand distribution, even for the initial moments, is unknown. Furthermore, the frequency of inventory checks affects both of these inventory strategies.

2.2. Assortment Planning

The aim of assortment planning is to specify an assortment that maximizes sales or gross margin while taking into account a variety of restrictions. These can include supplier terms, a limited inventory, a restricted budget for product acquisitions, and other restrictions. Variety planning necessitates a trade-off between three factors given the financial resources: how many different categories the retailer carries (referred to as a retailer's breadth), how many SKUs they carry in each category (referred to as depth), and how much inventory they stock of each SKU, which obviously affects their in-stock rate (Agrawal, N. and Smith, 2014). Variety is expensive from the standpoint of operations throughout the supply chain: a wider range suggests lower demand and inventory per product, which can result in slow-moving inventory, poor product availability, higher handling expenses, and higher markdown prices. The majority of the literature admits that in order to optimize an assortment effectively, it must use a choice model that accurately captures customers' purchasing decisions when they are presented with a variety of options. Two families of choice models have gained the most attention in the literature for assortment optimization. The (parametric) random utility maximization models make up the first family. The multinomial logit (MNL) choice model, which assigns a utility value to each of the available alternatives, is the most well-known model. Customers may decide to forego the purchasing process, as is the case with the majority of choice models in revenue management (e.g., if they are not willing to buy any of the available options). The nonparametric choice models are the second family. Rank-based models are one of them that are increasingly rising in favour. Rank-based choice models make the assumption that a customer's behaviour can be modelled by a sorted list of their preferred selections. The consumer will then choose the item that is both in the selection and has the highest ranking on their list of preferences. A distribution over all conceivable preference sequences that describes the likelihood that a random client would engage in a certain purchasing activity is included in the model. It is well known that rank-based decision models have several benefits. Since they do not make assumptions about the characteristics of the market, they do not carry the same risk of over- or underfitting as may be the case with parametric models. Additionally, it is possible to use historical data to identify their distribution.

2.3. SKUs Analysis

Stock levels have a significant impact on how well retail businesses function. Businesses must make sure that the essential items are constantly accessible in order to satisfy customer requirements. On the other hand, superfluous products shouldn't be kept on hand. SKU analysis is the practice of closely monitoring inventory in order to analyse information and derive valuable knowledge. The analysis is performed at the SKU level and looks at order quantities, reorder points, and inventory levels. Studying inventory turnover at the SKU level is a critical component of the research to identify which items are slow-moving and which have great demand (M. Flora, Shipbob). In order to comprehend the various profitability levels of various items, the study also incorporates the expenses of various SKUs while taking order costs, supplier terms, and other variables into consideration.

To increase sales and draw in consumers when expanding up, it is frequently necessary to launch new goods while phasing out others. In order to prevent accumulating items that are unlikely to sell and driving up holding costs, it is essential to commit to metrics and be data-driven during this process. SKU analysis may be used to optimize holding costs, reorder point and order quantity, free up warehouse space, increase the efficiency of transport expenses, and provide consumers with what they want. It is crucial to monitor product profitability and inventory turnover in order to measure consumer acceptability and remove the appropriate goods from the supply chain. The essence of this analysis approach is SKU rationalization. ABC analysis is a technique that can be used to rationalize inventories. Vilfredo Pareto's concept serves as the foundation of this inventory control strategy. The Pareto principle states that only 20% of all possible objects produce around 80% of the outcomes. ABC analysis may group the items into key priority groups, commonly referred to as A, B, C, and so on in order from highest to lowest value. Class A often consists of fewer goods but of much higher value. Class A comprises 15–20% of the overall amount of products, but represents 75–80% of the total monetary value. Class B makes up between 20 and 25 percent of all items in terms of units, but only 10 to 15 percent of all monetary values. Class C contains between 60 and 65 percent of the overall number of products, but only 5 to 10 percent of the total monetary worth (I M D P Asana et al 2020). ABC analysis is performed on the sales history of goods. Items in Class A move very rapidly, meaning they either sell quickly or are purchased by the majority of consumers. Class B is a collection of items that move swiftly and sell quickly. Slow-Moving items, or those that aren't very marketable, fall under the classification of Class C.

2.4. Theory on Simulation-Optimization

Simulation-optimization is a mathematical modelling approach that combines the use of computer simulations with optimization techniques to find the optimal solution to a problem. It involves using a computer model or simulation to represent a real-world system or process, and then using optimization algorithms to find the optimal values of the input parameters that will result in the desired outcome. Simulation optimization is increasingly popular for solving complicated and mathematically intractable business problems (Jalali and Van Nieuwenhuyse, 2015). The use of simulation-optimisation could be a very effective and adaptable approach for resolving complicated issues without the use of overly strong assumptions (O´lafsson and Kim, 2002). This technique aims to optimise the performance of simulated systems through the search for optimal values of decision variables (Dellino et al., 2012; Xuet al., 2013);. Researchers employ simulation optimization, which can be used for a variety of inventory management tasks, to resolve real-world issues that are too complicated to be handled by analytical methods. Strong underlying assumptions make it challenging to apply these models in real-world situations. Due to the limits that analytical models imply, creative approaches are required to identify appropriate supply chain planning parameters. Finding near optimal planning parameters in complex and stochastic chains using simulation-based optimisation is a promising approach and opens up an attractive area for future studies. The use of straightforward analytical inventory models as stochastic, single-stage, single reorder point models for a multi-stage, multi-item supply chain with load bundling options was covered by Peirleitner et al. (2016). In this paper, I suggest investigating a simulation engine that replicates a portion of the complexity of the business in order to provide insightful data on the replenishment strategy. The supply side is based on the terms under which two separate clusters of suppliers engage with the company, while the demand side is determined by knowledge of the budget and consumer preferences with regard to the range of products. The previous literature was taken into consideration when building the model while keeping a great pragmatism in order to adapt it to the specific needs of CurveCatch. The approach is adaptable, expandable, and might be useful for a variety of businesses.

3. Methodology and Discussion of Results

A simulation-optimization-based replenishment support decision model has been developed for try-before-you-buy retail fashion e-commerce businesses. This model aims to provide a systematic approach to support replenishment strategy decisions, considering operational and financial constraints through the use of simulation-optimization techniques. By allowing for the consideration of various scenarios and the optimization of replenishment decisions based on pre-defined objectives, this model has the potential to improve the efficiency and effectiveness of replenishment processes in try-before-you-buy retail fashion e-commerce businesses. The assumptions, technique and guiding ideas used to build the simulation engine are explained in the section of the paper that follows.

3.1. Assumptions

In this chapter the assumptions will be outlined and discussed in order to provide transparency and context for our findings. It is important to note that these assumptions may have introduced limitations to the study and may affect the generalizability of results. However, there is the belief that these assumptions were necessary and justified given the research questions and methods employed in this study.

3.1.1. Consumer Preferences

In this research project, it is assumed that there is access to information about each consumer's preferences for the retailer's products. This data will be the output from another student working on the Curve Catch thesis project. However, for the purposes of this study, we are using artificially generated data instead. This means that each consumer is only considering a subset of the available products and assigning a preference index to each one. This setup allows to examine the quality of service that the retailer is providing to its customers. For instance, it is possible to track the percentage of customers who are provided with their first preference. If the quality of service is high, it may suggest that it is easier for customers to engage with the retailer and make repeated purchases in the future. By manipulating market conditions and observing how the results change under different replenishment strategies, we can conduct studies to better understand consumer behaviour and the effectiveness of different business strategies.

3.1.2. Budget

In order for the model to function effectively, it is necessary for it to have a clear understanding of the amount of money that each consumer is willing to spend on the company's products. Currently, this information is artificially generated within the model itself, but it is possible that it may be generated by algorithms that utilize data from sources such as website questionnaire responses, sales history, and other data points in the future. This budget information is important because it is used to partially determine the purchasing process and track the remaining budget at the end of each day. By combining this data with information about inventory levels and consumer preferences, the model is able to identify opportunities for sales that may have been missed due to out-of-stock situations, as it will be deeply explained in the next chapters. Overall, this budget information is critical for the operation of the model and for the success of the company.

3.1.3. Demand Generator

Demand for products and services is driven by the financial resources available to consumers, as well as their decision-making processes. When considering what to purchase, consumers will consider their budgets and their preferences for certain products. In real life these preferences may be influenced by a variety of factors, such as personal taste, brand loyalty, and past experiences with the product. The demand for a particular product or service can be influenced by the price at which it is offered, as well as the perceived value it offers to the consumer. Consumers may be more likely to purchase a product if it is perceived as a good value for the price, or if it is a product that they particularly desire. The simulation engine simplifies this process. Consumers order a product and the company fills the box with other suggested products among their favourites, then customers purchase some of them based on their budget and substitution behaviour, which is represented by a probabilistic rule that makes it more likely for them to buy a more preferred item. Each period, budgets and preferences are randomly assigned to consumers, which generates demand. The entire supply system and the insights gained on replenishment strategy are based on the operation of the demand generator. However, the randomness in the generation of budgets, sales prices, and purchase costs has been confined to specific ranges that allow the model to be realistic, while still displaying a demand trend without major shocks.

3.1.4. Cost Components

The cost of the products being sold by Curve Catch consists of various components. As previously mentioned, the purchase cost of the products is randomly determined within a specific range. A percentage of this purchase cost is used to calculate the delivery fee that each product is subjected to. This delivery fee is structured into three different brackets in the model. In addition to the purchase cost and delivery fee, the cost of the products also includes a holding cost. The holding cost represents the daily cost of keeping an item in inventory and it could be seen as the cost of having frozen cash. This cost is the same for all products throughout the simulation. It is also important to note that no initial capital investment is required for the products being sold by Curve Catch. This is because the products are given to the company on consignment. This means that the products are paid for only once they have been sold, and there may be a possibility of delay in payment. This arrangement allows the company to offer a wide range of products without requiring a large initial investment.

3.1.5. Baseline

The purpose of the current study was to examine the impact of certain variables on key performance indicators (KPIs) related to a simulated business scenario. The variables in question are listed in Appendix Table 1 and include factors such as the number of customers per day, the duration of the simulation, the number of products offered, the lead times for different product categories, the desired service level, the maximum capacity of boxes for consumer orders, and the initial inventory. It is worth noting that, while these variables were not calibrated using real-time data from Curve Catch, they were assigned values that were intended to be representative of real-world conditions in order to achieve the objectives of the project. To perform a sensitivity analysis, one variable at a time has been changed to observe its impact on the relevant KPIs. This process was repeated for each variable, with each scenario being run a total of five times and the averages being used to draw insights. The goal of this approach was to understand the influence of each variable on the KPIs of interest and to compare the results to the baseline scenario in which all variables were held constant.

3.2. Model Formulation

In order to replicate certain aspects of CurveCatch's business reality a simulation model was built to run experiments. Both demand and supply dimensions had to be represented to produce managerial insights on how to manage the replenishment strategy. The simulation begins with some initial level of inventory for each product and evolves each period according to the following equation:

$$\mathbf{I}\ \boldsymbol{(t+1)} = \mathrm{I}\ (t) - \text{shipped units}\ (t) + \text{returning units}\ (t\text{-}delay) + \text{orders}\ (t\text{-}LT)$$

With:
I = Inventory Level
delay = number of days needed for an item to be restocked after being returned
LT = lead time

The next day's inventory is the result of the sums of the previous day's beginning inventory, units shipped to consumers, not purchased units that are returned, and orders coming in from suppliers. Each consumer only considers a subset of the company's total offering. The items are shipped, when available in stock, according to the process in which the box is filled with the desired product and those recommended based on the customer's preferences until it reaches its maximum capacity, after having checked for stock availability. Then, the purchase decision process is based on budget availability and according to a probability rule: the higher the product ranks for the specific customer, the more likely it is that the customer will purchase the good. The units return to the fulfilment center according to the logic that unsold items will be sent back to the company and will stay then "frozen" for a certain amount of time, identified by the variable "delay", before being restocked. The orders from suppliers are placed according to an r,Q policy where r and Q are set using conventional formulas but modified by using simulation-optimization, as will be explained in detail later.

$$\mathbf{r} = (LT * \mu SQ(:t)) + (z * \sigma\ (\mu SQ)\ (:t) * \sqrt{LT}) * \theta ROP$$

$$\mathbf{Q} = \sqrt{((2 * K * \mu SQ\ (:t)) / h)} * \theta Q$$

With:

r = Reorder Point

μSQ = Average daily sold quantity

z = Value representing the desired service level

σ (μSQ) = Standard deviation of average daily sold quantity

θROP = Optimization parameter for ROP

Q = Economic order quantity

K = Fixed ordering cost

h = holding cost

θQ = Optimization parameter for Q

This policy allows for continuous improvement as time goes on and more data becomes available. An order of quantity *Q* is automatically placed when a product's level hits the reorder point; the product will arrive in stock a few days later, subject to the lead time. *r* is a function of the lead time, the average daily sold quantity of a specific product and its standard deviation, the desired service level and the optimization parameter for ROP. *Q* is function of the fixed ordering cost, the average daily sold quantity, the holding cost and the optimization parameter for EOQ. The simulation-optimization process consists in running the model several times and pick the value of the ROP and EOQ parameters that generated the best performances according to the objective function:

MAX profit – variable cost

The objective function maximizes profits from product sales. Profit is generated through a sales process for products. When a product is sold, the customer's budget decreases by an amount equal to the selling price. Sales proceeds are recorded and then variable costs are subtracted. Variable costs are calculated by accounting the costs of purchasing products from the supplier, delivery fees based on the product category (percentages of the purchase cost), the daily holding cost (multiplied by the inventory level at the end of each period), and the fixed order cost (generated every time an order is placed).

3.3. Model Extension

The purpose of the research is to employ an algorithm that makes use of simulation-optimization technique to give managerial insights into replenishment strategy. The objective function, which aims to maximize profit, forms the basis of the model, as it was anticipated. This profit measure is in a sense short-term because it does not account for potential future flows. This is why the model was expanded to account for two more KPIs: lost sales and customer service quality. Lost sales are calculated by the model as the budget not spent by customers at the end of their purchasing process. The remaining budget is compared to the prices of the consumer's favourite products that were not included in the box because they were out of stock. When the purchasing process is over, if the budget is greater than the price of these products, the model will report a lost sale and record the amount lost. Customer service quality, on the other hand, was evaluated by the model as the percentage of customers who were provided with their most preferred product, their second most preferred product, or a product of lower preference. These two metrics allowed for the identification of trade-offs within the system that is necessary to recognize in order to systematically make rational decisions. For instance, it has been established with certainty that maintaining high inventory levels leads to superior customer service. By consistently having a customer's preferred product in stock, or offering excellent substitutes by providing personalized product recommendations based on the customer's profile, a company can maintain a high level of service and extract maximum value from their customers. However, this approach also results in significantly higher inventory management and maintenance costs, which can negatively impact business performance. On the other hand, it may be that the most profitable strategy involves prioritizing cost minimization in the short term, even at the expense of other factors. Due to this process, the company's focus shifts from assuring customer happiness to generating profits in the short term. As a result, inventory shortages could happen, which could result in lost sales and serving clients with products that don't suit their tastes. As a result, both the company's reputation and the likelihood of these customers to repeat purchases in the future may be harmed. Although the future profitability that can be attained by keeping the service quality high has not been given a numerical value, keeping an eye on these extra key performance indicators might yield insightful data. For instance customers who have a positive experience with a company are more likely to make repeat purchases and spend more with a company as well as recommend them to others. Also, good customer service can contribute to a positive reputation and strong brand image, which can attract new customers and business. It is therefore crucial to strike the best possible balance between boosting earnings and giving customer service top priority, depending on the specific settings of a business case.

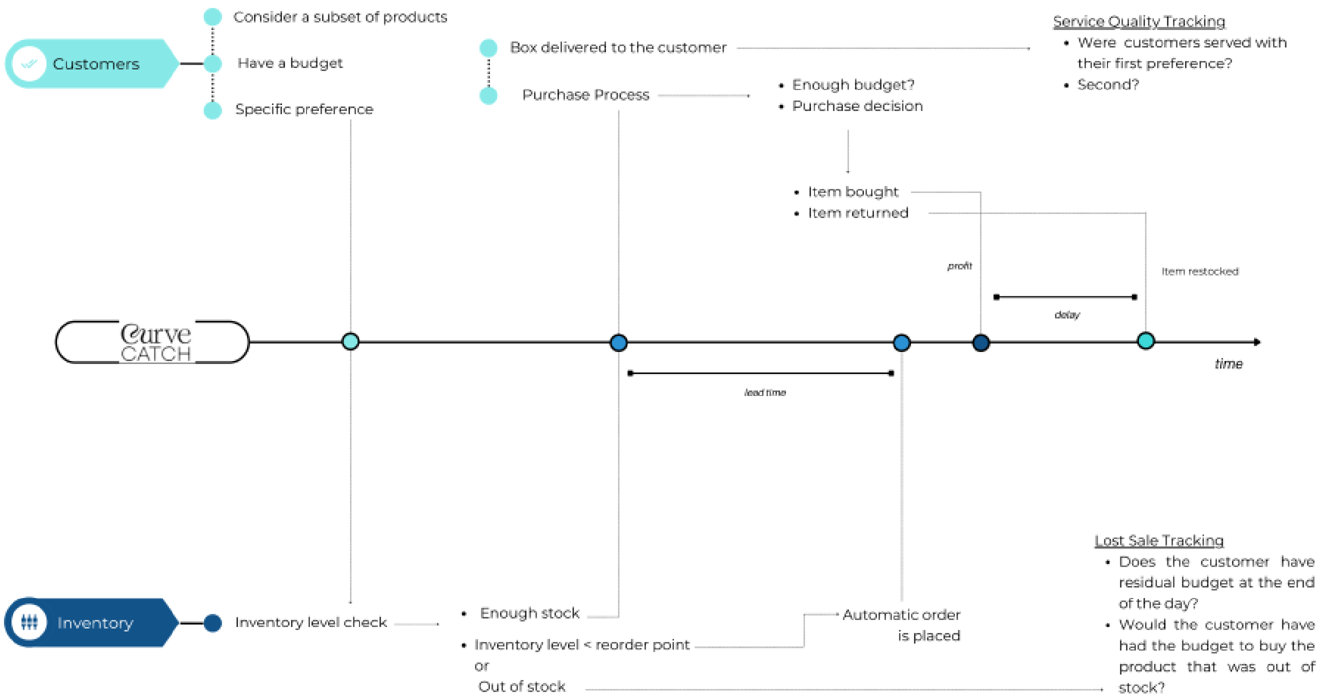

Figure 1. Business System

3.4. Simulation-Optimization

In order to effectively utilize the information presented in the previous chapter, simulation-optimization was implemented on the baseline setting to determine the optimal parameterization of the model that would achieve the desired performance in terms of revenues, lost sales, and customer service quality. The simulation optimization method involved increasing the size of the reorder point (ROP) and the economic order quantity (EOQ) through the use of parameters, and verifying the effects of these changes on the key performance indicators (KPIs) of interest. The results of the simulation-optimization process, which are presented in Table 2 in the appendix, showed that when the reorder point and ordered quantities were not parameterized, the model was able to improve its estimates in a reasonable but suboptimal manner. The profit generated by the system was not optimal, while the indices for lost sales and customer service quality were the worst of the entire study. This suggests that there is a significant trade-off at play: when the parameters are set too high, the best levels of lost sales and customer service quality are achieved, but at the expense of financial performance, which are the worst of all scenarios analyzed. This trade-off can be explained by the fact that higher inventory availability, resulting from more frequent orders and higher quantities ordered, allows for improved customer satisfaction, but also increases the costs associated with inventory management. In other words, while a higher level of inventory may allow the customer to always be provided with their preferred product, it also increases the expenses incurred by the system in terms of storage, handling, and other related costs. The best result in terms of profit was obtained by increasing the economic order quantity by five percent. This strategy enabled the exploitation of economies of scale and a significant saving of fixed ordering costs, allowing for the optimal extraction of consumers' willingness to pay why achieving an higher customer service.

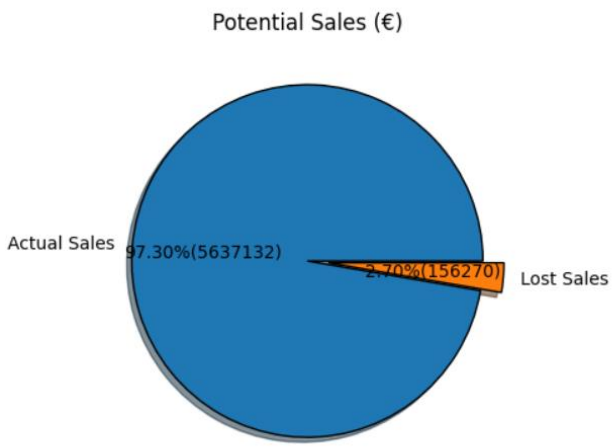

Figure 2. Lost Sales in € with - no parametrization

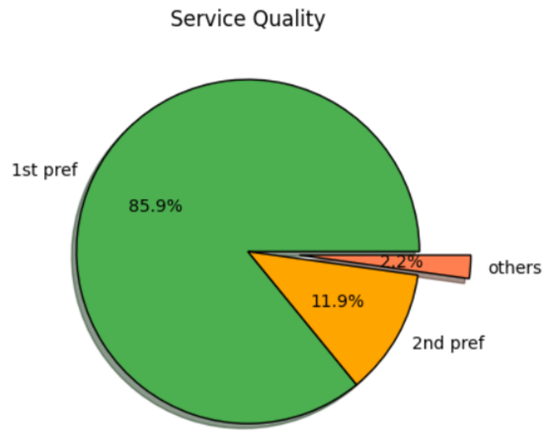

Figure 3. Service Quality (85.9% of the times the customers were provided with their 1st preference) - no parametrization

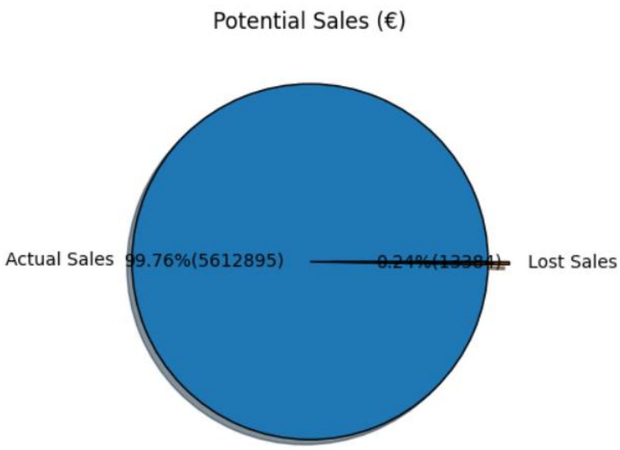

Figure 4. Lost Sales in € - EOQ +5%

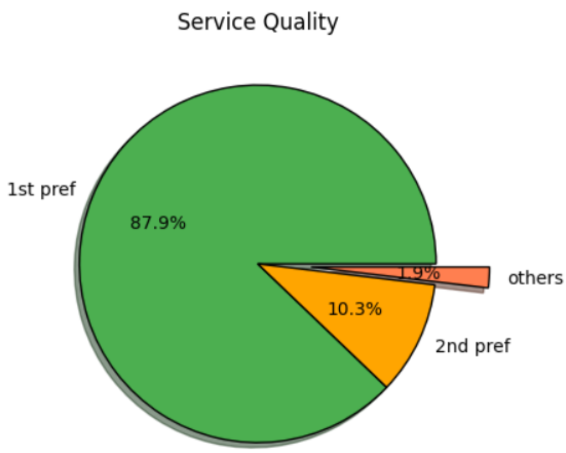

Figure 5. Service Quality - EOQ +5%

3.5. Sensitivity Analysis

Once the optimization on the baseline was completed, a sensitivity analysis was performed to study how the system reacts respectively to holding cost, fixed order cost and initial inventory level shocks and which solutions are close to optimal in these disrupted scenarios. A sensitivity analysis is a type of statistical analysis that evaluates the effects of changes in the values of input variables on system's outputs. It is frequently used to establish which factors are most crucial in determining how a system behaves or performs, as well as how sensitive the system's outputs are to changes in these variables. Sensitivity analyses are frequently used to comprehend the potential effects of various scenarios or to pinpoint potential areas of risk or uncertainty. In this research the sensitivity analysis has been carried on by using simulation-optimization technique.

Higher initial inventory level:

In this study, we found that the r,Q policy formulas are not directly affected by the initial inventory level. However, the results of the simulation showed that when the initial inventory level is lower than the average inventory level at the end of the simulation, the system experiences an increase in lost sales and a decrease in customer service quality, which ultimately results in a reduction in profits. This is because a lean system with lower inventory costs takes longer to adjust ROP and EOQ to demand levels, leading to losses and a decline in service quality. On the other hand, when the initial inventory level is closer to the demand trend, the system is able to take advantage of a learning curve and generate higher profits while maintaining high service quality. However, we also found that as the initial inventory level increases beyond a certain point, the costs of maintaining a large inventory outweigh the benefits of better matching the demand, leading to a decline in profits.

Table 5. System performance with different initial inventory levels

		Initial Inventory Level Shock		
		Baseline = 1	Baseline = 3	Baseline = 5
		no parameters	no parameters	no parameters
Lost Sales ratio	*Average*	0.06289665	0.042844881	0.040454216
Service Quality (1st pref)	*Average*	0.736313725	0.794647059	0.814078431
Total Revenue of the System	*Average*	5445818.166	5584539.41	5569723.038
Total Cost of the System	*Average*	2800320.806	2910362.015	2911396.889
Average profit of the System		2645497.36	2674177.395	2658326.149

Holding cost increase:

Because of the r,Q policy formulas, the change has a direct impact on EOQ, decreasing its magnitude. In addition, the average cost of the system increases and decreases the profit. There is also a negative impact on the lost sales ratio and customer service quality, as the average inventory level throughout the simulation is lower than before. Without any parameterization, the worst results of the experiment are obtained on all KPIs considered. The intuition is that, in order to achieve service quality levels as high as those achieved without the shock in holding costs, it will be necessary to incur additional expenses in the short term, which will lead to lower profits. This is done without considering the potential benefits of increased service quality on future revenue streams. Nevertheless, the optimal solution emerges with a 10% increase in EOQ. This ensures very low levels of lost sales and excellent service quality while keeping system costs systematically lower. These three events lead to the best level of profit among the experiments, as with this set of variables it is better to pay more inventory costs but not lose sales, as can be seen in Table 1.

Table 3. System performances with increase in holding cost

		ROP & EOQ	EOQ
		1	1.1
Lost Sales ratio	***Average***	0.039062	0.003184
Service Quality (1st pref)	***Average***	0.836255	0.844843
Total Revenue of the System	***Average***	5595572	5606519
Total Cost of the System	***Average***	3374225	3253732
Average profit of the System		**2221347**	**2352787**

<u>K increase</u>:

The increase in fixed ordering cost impacts EOQ, increasing its magnitude. This results in an increase in the average inventory level leading to a significant increase in costs, while obtaining higher service quality, comparing with the baseline. Again, the trade-off between customer service quality and decreased profits stands out. As in previous analyses, the absence of parameterization leads to suboptimal results on all KPIs considered. The best performance was achieved by increasing EOQ by about 30 percent. In this way, economies of scale can be exploited by placing larger orders. It follows that in this system saving on fixed ordering cost by placing fewer orders and spending more on inventory holding cost to maintain more inventory rewards with higher levels of profit.

Table 4. System performance with an increase in fixed ordering cost

		ROP & EOQ	EOQ
		1	1.3
Lost Sales ratio	***Average***	**0.018212**	**0.002496**
Service Quality (1st pref)	***Average***	**0.916333**	**0.928765**
Total Revenue of the System	***Average***	**5638206**	**5643237**
Total Cost of the System	***Average***	**3308529**	**3304646**
Average profit of the System		**2329677**	**2338590**

4. Conclusion and Future Research

The findings that can be derived from the study are presented in the thesis' last chapter, together with a discussion of their limits and possible implications. Additionally, it suggests research directions that might build on the results of the current study. The appendix containing tables and charts, the link to the code written in Python language and the bibliography follows.

4.1. Limitations

The limitations affecting the results of this research are several. Firstly, it is important to note that the knowledge used to optimize the system in this case is artificially obtained, even though based on real-world data. The effectiveness of the final results will depend on the accuracy of the inputs of customers' preferences and budget estimations coming from external algorithms based on the company's data. While the current system is reliable for business systems similar to the one represented, it should be noted that it is only effective in situations where the lead times are constant and there is no uncertainty about them. This means that in situations where demand is highly unstable and lead times are prone to fluctuation, the solutions provided by the support tool may not be optimal. In this version of the model, the analysis was performed on the baseline, followed by sensitivity analysis, changing one variable at a time but keeping the setting constant throughout the simulation. To better represent a real-world scenario, the simulation engine may also need to include the dynamic change of some variables over time in order to reflect events as the increase of the cost component at a certain point of the simulation. Additionally, it is worth noting that the cost components considered in the development of the model are simplified versions of those that may be encountered in a real-world setting. For example, the cost of returning an asset that requires a double logistics flow, with one delivery and one collection, is not considered. In addition, the model does not include a profit reduction index that takes into account items not returned to the company by customers with illicit behaviour. Similarly, other cost components such as transaction costs and marketing costs are not included in the model. Additionally, it should be noted that the simulation-optimization process and sensitivity analysis were carried out by manipulating the parameters that increase the levels of reorder point and economic order quantity, but no decreases in these quantities were tested. Finally, each hypothesis tested and presented in the tables in the appendix was repeated five times and may therefore not guarantee high levels of significance of the results.

4.2. Conclusions

Considering the limitations and assumptions, with an appropriate calibration the model can generate managerial insights to support the replenishment strategy. It is also an excellent foundation on which to build in future research, as it will be described in the next paragraph. Through the use of simulation-optimization techniques, the tool allows for the identification of high-level trade-offs and the extraction of valuable insights for improved business performance. This is the first time an algorithm has been designed to provide recommendations on the replenishment strategy of a try before you buy ecommerce business model. One of the key features of the model is its ability to simulate the business operation and maximise profit performance through the optimization of the reorder point and economic order quantity quantities. The model also monitors other key performance indicators as lost sales and the service quality. This helps to highlight the trade-offs between each other and provides customized replenishment strategy insights. The model allows for sensitivity analyses by simulating scenarios involving shocks, such as a cost increase, and optimize the results. Another useful feature of the model is its ability to test and control the learning curve of the r,Q policy, which has high potential for providing insights. By testing different initial inventory levels and hypotheses, it was determined that starting with a higher inventory level up to a certain po int can help the model learn the demand trend and better meet the needs of customers by providing them with their preferred products at a higher rate. This can lead to increased customer satisfaction and more future purchases. Additionally, having an initial inventory level that allows to study the demand can help maximize revenue by minimizing lost sales due to out-of-stock items, while still maintaining cost-effective levels that lead to maximum profit.

4.3. Recommendations for Future Research

As expected, the model provides an excellent foundation for future development. However, it will be necessary to further expand the model by adding variables that make it more realistic and accurate, such as the logistics costs associated with returning products from customers. After that, it would be valuable to test the effectiveness of the simulation optimization model in a real-world scenario. This will provide insights into the model's performance in the real world and help identify any potential issues or constraints. Once the model has been enhanced with new features and refined to provide managerial insights on replenishment strategy in real life, it can be expanded to include assortment planning. The algorithm already collects a range of data for descriptive purposes, such as accounting and product performance. To further expand the scope of the model, it would be beneficial to include sizes and colours for each product. With appropriate demand estimates and calibrated with real data, the model will be able to provide guidance on managing assortment rotation and different product classes. It will be possible to conduct ABC analysis to understand which product classes are more profitable and which are less, as well as which products are fast-movers and slow-movers. The performance of the system can be tested by considering the exclusion of a product and the inclusion of a new one. Additionally, it will be possible to cross-reference assortment planning and replenishment strategy. For instance, it will be possible to evaluate whether it is worthwhile to keep a non-moving product or sizes/colours that are sold infrequently by comparing the potential costs of keeping them in stock with the potential lost sales from missed opportunities. This dimension is related to a thorough understanding of the optimal balance between maximizing profits in the short term and maintaining high levels of customer satisfaction through maintaining an optimal service quality. For example, it may be useful to include the calculation of an index that determines the future value of having a satisfied customer today, shifting the focus of profit maximization more towards the medium term rather than the short term.

5. Appendix

5.1. Tables and Charts

Table 1. Baseline set to develop the research

Baseline	
ROP parameter	1
EOQ parameter	1
D	1020
C	10
N	120
F	30
P	150
z	1.64 (95%)
LT_N	3
LT_F	60
K	10
h	0.44
delay	3
limit	7
considered	10
t1	0.03
t2	0.06
t3	0.1
Initial inventory	20 units

Legend	
	Best Values
	Second Best Values
	Worst Values

Table 2. Simulation-Optimization Process with identification of best, second best, and worst results

		Baseline												
		ROP & EOQ					ROP				EOQ			
		1	1.05	1.1	1.15	1.3	1.05	1.1	1.15	1.3	1.05	1.1	1.15	1.3
Lost Sales ratio	*Run 1*	0.030656	0.0028	0.001832	0.0019496	0.00156	0.02959	0.029277	0.028778	0.027677	0.002662	0.003013	0.002379	0.001914
	Run 2	0.031215	0.002526	0.002268	0.0022547	0.00241	0.028481	0.031589	0.029094	0.02745	0.002293	0.002704	0.002901	0.002485
	Run 3	0.025449	0.003234	0.002078	0.0024731	0.00182	0.032237	0.028084	0.03091	0.027533	0.002143	0.002098	0.003067	0.002584
	Run 4	0.029218	0.00175	0.00288	0.001894	0.00251	0.028279	0.029651	0.02767	0.026312	0.002731	0.001975	0.001568	0.002456
	Run 5	0.032905	0.002585	0.002033	0.0023165	0.00229	0.030409	0.028087	0.026737	0.02654	0.001941	0.002669	0.002217	0.002394
	Average	**0.029889**	**0.002579**	**0.002218**	**0.0021776**	**0.00212**	**0.029799**	**0.029338**	**0.028638**	**0.027103**	**0.002354**	**0.002492**	**0.002426**	**0.002367**
Service Quality (1st pref)	*Run 1*	0.865196	0.887157	0.897451	0.9001961	0.92294	0.866471	0.872549	0.871667	0.879412	0.877549	0.869608	0.881863	0.899608
	Run 2	0.865882	0.882549	0.896569	0.9030392	0.92245	0.873137	0.875098	0.881961	0.882255	0.871471	0.87549	0.878627	0.888922
	Run 3	0.871667	0.883627	0.89098	0.8985294	0.92431	0.872157	0.873824	0.879804	0.880294	0.879706	0.886176	0.875098	0.896569
	Run 4	0.869608	0.879216	0.891373	0.8985294	0.92422	0.875392	0.875588	0.876275	0.871569	0.869216	0.876471	0.881961	0.889412
	Run 5	0.867843	0.873039	0.888627	0.9016667	0.92441	0.869412	0.866471	0.876667	0.885686	0.875294	0.881275	0.876863	0.892353
	Average	**0.868039**	**0.881118**	**0.893**	**0.9003922**	**0.92367**	**0.871314**	**0.872706**	**0.877275**	**0.879843**	**0.874647**	**0.877804**	**0.878882**	**0.893373**
Total Revenue of the System	*Run 1*	5624236	5573407	5615059	5637898.6	5632999	5632462	5617774	5639458	5594898	5608134	5594336	5650778	5621162
	Run 2	5615344	5622333	5629392	5689428.5	5616165	5590710	5611517	5642549	5686015	5634471	5608166	5645474	5604731
	Run 3	5657088	5594224	5634202	5614015	5602227	5611512	5611842	5613755	5629451	5617290	5644836	5640581	5611745
	Run 4	5621845	5679594	5632631	5643221.3	5633109	5652706	5668260	5638985	5619353	5639132	5621226	5648849	5603487
	Run 5	5631847	5618886	5654703	5633865.5	5628289	5612371	5613676	5641046	5588098	5642713	5603485	5612878	5625217
	Average	**5630072**	**5617689**	**5633197**	**5643685.8**	**5622558**	**5619952**	**5624614**	**5635159**	**5623563**	**5628348**	**5614410**	**5639712**	**5613268**
Total Cost of the System	*Run 1*	3019463	3031618	3015198	3162216.9	3110686	2979512	3115859	3081377	3210627	3026597	3126657	3053246	3151212
	Run 2	3129371	3055011	3067252	3096456.7	3191241	3065586	3227293	3041600	3178133	3003827	3139194	3124789	3141634
	Run 3	3106090	3108552	3002030	3207799	3155702	3140713	3061939	3185322	3242647	3031773	3052246	3044353	3070131
	Run 4	3132130	3061345	3250849	3074631.9	3178174	3140428	3160196	3115218	3123406	3063036	3035002	3033853	3102514
	Run 5	3179847	3051211	3142816	3074737.9	3237353	3129236	3107389	3143511	3152625	3024549	3046073	3062322	3075839
	Average	**3113380**	**3061547**	**3095629**	**3123168.5**	**3174631**	**3091095**	**3134535**	**3113406**	**3181487**	**3029957**	**3079834**	**3063713**	**3108266**
Average profit of the System		**2516692**	**2556141**	**2537569**	**2520517.3**	**2447926**	**2528857**	**2490078**	**2521753**	**2442076**	**2598391**	**2534575**	**2575999**	**2505002**

Table 3. Sensitivity Analysis ; Holding Cost Increase

		h= 0.88												
		ROP & EOQ					ROP				EOQ			
		1	1.05	1.1	1.15	1.3	1.05	1.1	1.15	1.3	1.05	1.1	1.15	1.3
Lost Sales ratio	Run 1	0.0350814	0.0028948	0.0029016	0.002744	0.00364917	0.032185	0.038119	0.0373577	0.03564	0.00305	0.0027	0.00352	0.00456
	Run 2	0.040222	0.0029464	0.0020758	0.002292	0.00362812	0.036483	0.032219	0.0348269	0.03633	0.00287	0.00286	0.00264	0.00448
	Run 3	0.0402356	0.0035944	0.0026895	0.002983	0.00307589	0.037668	0.033785	0.0361734	0.03848	0.00303	0.00388	0.00275	0.00596
	Run 4	0.0414577	0.0034288	0.0028328	0.002659	0.00333852	0.035989	0.037212	0.0367038	0.0312	0.00375	0.00338	0.00258	0.00448
	Run 5	0.0383124	0.0025218	0.0030428	0.002199	0.00314611	0.040295	0.041191	0.0384751	0.03154	0.00301	0.00309	0.00308	0.00444
	Average	**0.0390618**	**0.0030773**	**0.0027085**	**0.002575**	**0.00336756**	**0.036524**	**0.036505**	**0.0367074**	**0.03464**	**0.00314**	**0.00318**	**0.00291**	**0.00479**
Service Quality (1st pref)	Run 1	0.8383333	0.8540196	0.8614706	0.877353	0.90362745	0.830294	0.84451	0.8403922	0.85971	0.84167	0.83716	0.84676	0.86422
	Run 2	0.8379412	0.8505882	0.8710784	0.876471	0.90382353	0.836373	0.842157	0.8463725	0.84373	0.8302	0.84343	0.84539	0.85451
	Run 3	0.8371569	0.8496078	0.8653922	0.876176	0.90843137	0.839608	0.84902	0.8446078	0.85598	0.8352	0.85147	0.84657	0.86275
	Run 4	0.8339216	0.8546078	0.8629412	0.876471	0.90568627	0.829216	0.833235	0.8466667	0.84824	0.83608	0.84382	0.84892	0.85441
	Run 5	0.8339216	0.8446078	0.8611765	0.872157	0.90647059	0.831569	0.843627	0.8460784	0.84	0.83588	0.84833	0.84892	0.85186
	Average	**0.8362549**	**0.8506863**	**0.8644118**	**0.875725**	**0.90560784**	**0.833412**	**0.84251**	**0.8448235**	**0.84953**	**0.8358**	**0.84484**	**0.84731**	**0.85755**
Total Revenue of the System	Run 1	5598010.1	5597305.4	5639250.9	5658388	5637880.53	5642491	5589019	5627829	5596727	5659046	5591877	5620550	5623836
	Run 2	5599977.6	5618241.7	5648607.3	5651475	5593017.66	5633649	5603347	5641502.2	5621519	5608026	5615331	5604983	5614552
	Run 3	5589983.2	5582106.3	5646121.5	5606172	5629409.58	5597838	5639466	5612553	5669149	5604778	5583975	5605045	5594601
	Run 4	5571209	5629909.6	5611243.6	5620280	5646076.79	5607791	5632328	5601160.2	5603614	5604765	5601755	5663322	5621094
	Run 5	5618680.5	5669560.5	5574694.8	5638074	5640866.46	5618407	5609816	5621026.6	5606876	5641542	5639660	5591824	5640300
	Average	**5595572.1**	**5619424.7**	**5623983.6**	**5634878**	**5629450.2**	**5620035**	**5614795**	**5620814.2**	**5619577**	**5623631**	**5606519**	**5617145**	**5618877**
Total Cost of the System	Run 1	3352758.4	3266429	3303828.6	3458019	3522811.18	3255664	3403449	3474506.7	3477839	3352458	3298854	3355861	3228797
	Run 2	3413429.7	3394380.5	3238793.6	3392453	3616192.23	3298142	3366298	3448751	3485625	3279853	3145235	3291892	3312858
	Run 3	3428696	3343496.3	3391372.3	3436849	3555878.44	3357875	3455047	3432556.2	3541181	3201059	3277852	3255727	3361767
	Run 4	3343643.4	3316243	3382391.6	3563962	3587950.67	3259855	3411937	3490496.6	3498777	3360404	3256481	3287986	3277367
	Run 5	3332600	3226418.2	3449751.8	3295980	3555100.86	3342934	3571336	3446398.8	3533674	3255493	3290240	3312697	3422237
	Average	**3374225.5**	**3309393.4**	**3353227.6**	**3429453**	**3567586.68**	**3302894**	**3441614**	**3458541.9**	**3507419**	**3289853**	**3253732**	**3300833**	**3320605**
Average profit of the System		**2221346.6**	**2310031.3**	**2270756**	**2205425**	**2061863.53**	**2317141**	**2173182**	**2162272.3**	**2112158**	**2333778**	**2352787**	**2316312**	**2298272**

Table 4. Sensitivity Analysis ; Fixed Ordering Cost Increase

		K=30												
		ROP & EOQ					ROP				EOQ			
		1	1.05	1.1	1.15	1.3	1.05	1.1	1.15	1.3	1.05	1.1	1.15	1.3
Lost Sales ratio	Run 1	0.01869	0.00194	0.00333	0.00238	0.00255	0.02099	0.01958	0.01636	0.01528	0.00255	0.00289	0.00223	0.00238
	Run 2	0.01738	0.00233	0.00252	0.00194	0.00333	0.01726	0.01667	0.02061	0.01664	0.00262	0.00232	0.00256	0.00261
	Run 3	0.01728	0.00239	0.00309	0.00206	0.00325	0.01922	0.01596	0.019	0.01711	0.00185	0.00279	0.00277	0.00254
	Run 4	0.01832	0.00187	0.00202	0.00252	0.00229	0.01707	0.01848	0.01577	0.01748	0.00266	0.00275	0.00209	0.00225
	Run 5	0.01939	0.00214	0.00231	0.00209	0.00276	0.02045	0.01889	0.01832	0.0163	0.00243	0.00336	0.00229	0.0027
	Average	**0.01821**	**0.00213**	**0.00265**	**0.0022**	**0.00284**	**0.019**	**0.01792**	**0.01801**	**0.01656**	**0.00242**	**0.00282**	**0.00239**	**0.0025**
Service Quality (1st pref)	Run 1	0.91059	0.92735	0.925	0.9348	0.94118	0.91157	0.92049	0.9199	0.92529	0.91716	0.92265	0.92422	0.93069
	Run 2	0.915	0.92235	0.93392	0.93265	0.9451	0.91922	0.91725	0.91775	0.92853	0.92098	0.92775	0.92971	0.92696
	Run 3	0.91392	0.92676	0.92333	0.93451	0.94598	0.9152	0.91706	0.92137	0.92412	0.92284	0.92069	0.92294	0.93137
	Run 4	0.91667	0.92118	0.93529	0.93186	0.94471	0.91627	0.92176	0.92284	0.92343	0.91941	0.92088	0.92363	0.92696
	Run 5	0.92549	0.92333	0.92892	0.93755	0.94147	0.91892	0.91833	0.92843	0.92039	0.91578	0.92441	0.92873	0.92784
	Average	**0.91633**	**0.9242**	**0.92929**	**0.93427**	**0.94369**	**0.91624**	**0.91898**	**0.92206**	**0.92435**	**0.91924**	**0.92327**	**0.92584**	**0.92876**
Total Revenue of the System	Run 1	5631040	5669155	5642475	5671154	5668058	5669507	5606129	5623793	5647460	5601064	5599308	5650707	5617851
	Run 2	5640203	5624376	5675603	5644064	5636060	5639554	5598550	5621219	5638644	5689045	5620401	5617358	5640236
	Run 3	5628229	5620372	5635962	5667559	5642372	5596166	5614572	5604577	5630743	5638299	5622429	5585373	5659772
	Run 4	5656251	5638466	5645491	5639513	5624462	5598640	5640332	5668143	5605391	5624598	5597613	5581224	5660891
	Run 5	5635306	5642126	5651558	5614762	5621616	5628637	5627209	5590334	5641941	5642824	5652762	5653177	5637432
	Average	**5638206**	**5638899**	**5650218**	**5647410**	**5638514**	**5626501**	**5617358**	**5621613**	**5632836**	**5639166**	**5618503**	**5617568**	**5643237**
Total Cost of the System	Run 1	3143902	3322880	3294629	3377009	3404860	3252676	3347950	3307847	3330596	3333380	3342905	3266193	3303730
	Run 2	3399292	3318069	3431481	3361762	3469068	3278889	3303260	3281673	3339342	3372478	3259022	3242740	3288436
	Run 3	3361873	3352392	3365571	3318391	3513437	3406590	3281534	3380857	3392738	3290527	3364425	3371152	3443275
	Run 4	3352977	3282422	3235714	3364502	3437803	3324653	3403882	3289303	3455075	3195326	3207007	3317677	3218563
	Run 5	3284602	3230884	3263336	3198554	3349783	3436819	3272322	3315445	3389268	3329713	3271140	3321722	3269226
	Average	**3308529**	**3301329**	**3318146**	**3324044**	**3434990**	**3339925**	**3321790**	**3315025**	**3381404**	**3304285**	**3288900**	**3303897**	**3304646**
Average profit of the System		**2329677**	**2337570**	**2332071**	**2323367**	**2203523**	**2286575**	**2295569**	**2306589**	**2251432**	**2334881**	**2329603**	**2313671**	**2338590**

Table 5. Sensitivity Analysis ; Different Starting Inventory Levels

		Initial Inventory Level Shock		
		Baseline = 1	Baseline = 3	Baseline = 5
		no parameters	no parameters	no parameters
Lost Sales ratio	Run 1	0.064127702	0.047541227	0.037219403
	Run 2	0.058763125	0.041040258	0.037424659
	Run 3	0.062313797	0.04098967	0.047613219
	Run 4	0.059291266	0.041795393	0.038638593
	Run 5	0.069987358	0.042857856	0.041375205
	Average	0.06289665	0.042844881	0.040454216
Service Quality (1st pref)	Run 1	0.738627451	0.791176471	0.809215686
	Run 2	0.743627451	0.795490196	0.811176471
	Run 3	0.741568627	0.796862745	0.807156863
	Run 4	0.735882353	0.792941176	0.821176471
	Run 5	0.721862745	0.796764706	0.821666667
	Average	0.736313725	0.794647059	0.814078431
Total Revenue of the System	Run 1	5465850.027	5557866.724	5564733.479
	Run 2	5451851.364	5571662.784	5576953.379
	Run 3	5433648.339	5597473.602	5584856.257
	Run 4	5463892.958	5620166.262	5558402.384
	Run 5	5413848.143	5575527.68	5563669.691
	Average	5445818.166	5584539.41	5569723.038
Total Cost of the System	Run 1	2904389.611	3017820.226	2881492.519
	Run 2	2723646.776	2890099.074	2869154.65
	Run 3	2802316.017	2957765.822	3026255.044
	Run 4	2746924.157	2820166.755	2818285.092
	Run 5	2824327.469	2865958.2	2961797.141
	Average	2800320.806	2910362.015	2911396.889
Average profit of the System		2645497.36	2674177.395	2658326.149

5.2. Code

The code is written in Python 3 language and it is stored in a GitHub repository.

https://github.com/AndreaCanessa/Simulation-Engine

5.3. Bibliography

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