“Hellenic Open University”

SUPPLY CHAIN MANAGEMENT (SCM)

Postgraduate Dissertation

“Warehouse inventory management systems using Monte Carlo analysis”

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Patras, Greece, July 2023

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Dedicated to my wife and family.

Abstract

This dissertation presents a comprehensive study on inventory management, focusing on the application of stochastic inventory analysis, the Monte Carlo simulation and the Economic Order Quantity (EOQ). The research is divided into two parts, each addressing different aspects of inventory management. The first part of the dissertation consists of a literature review and an exploration of inventory management theory as well as the Monte Carlo simulation. The literature review encompasses a wide range of scholarly articles, dissertation and thesis in inventory management theory and implementation as well as the Monte Carlo analysis and its optimizations. Key concepts such as EOQ, reorder point, demand models, and forecasting models are examined in detail. This section provides a comprehensive understanding of the theoretical underpinnings of inventory management practices and sets the stage for the subsequent empirical analysis. The second part of the dissertation focuses on the stochastic inventory analysis of three specific stock-keeping units (SKUs). The objective is to implement various forecasting methods, namely moving average, exponential smoothing, and linear regression, to predict future demand patterns accurately. By employing these forecasting models, the study aims to enhance the accuracy of demand forecasts, enabling more effective inventory planning and control. Furthermore, the dissertation introduces the implementation of EOQ, a widely used inventory optimization technique. By determining the optimal order quantity, reorder point, and inventory holding costs, EOQ helps minimize inventory carrying costs while ensuring sufficient stock availability. The application of EOQ is then supported by Monte Carlo simulation, which incorporates stochastic elements to simulate and evaluate different inventory scenarios. This analysis provides insights into the robustness and performance of the proposed inventory management strategies. The findings of this dissertation contribute to the field of inventory management by integrating theoretical knowledge with empirical analysis. The research emphasizes the importance of accurate demand forecasting, efficient inventory control, and optimization techniques such as EOQ with the assistance of the Monte Carlo simulation. The practical implementation of forecasting models and the stochastic inventory analysis of specific SKUs provide valuable insights and recommendations for inventory management practitioners. This dissertation objective is to serve as a valuable resource for academics, researchers, and industry professionals seeking to improve inventory management practices and optimize supply chain operations.

Keywords: Inventory Management, Monte Carlo, EOQ, Forecasting, Demand Models

“Συστήματα διαχείρησης αποθεμάτων αποθήκης με την χρήση της Μόντε Κάρλο ανάλυσης”

Αθανάσιος Γκόνος

Περίληψη

Η διατριβή αυτή παρουσιάζει μια εκτενή μελέτη για τη διαχείριση του αποθέματος, επικεντρώνοντας στην εφαρμογή της στοχαστικής ανάλυσης του αποθέματος, της προσομοίωσης Monte Carlo και της Οικονομικής Ποσότητας Παραγγελίας (EOQ). Η έρευνα διαιρείται σε δύο μέρη, τα οποία αντιμετωπίζουν διάφορες πτυχές της διαχείρισης αποθέματος. Το πρώτο μέρος της διατριβής αποτελείται από μια βιβλιογραφική ανασκόπηση και μια εξερεύνηση της θεωρίας διαχείρισης αποθέματος, καθώς και της προσομοίωσης Monte Carlo. Η βιβλιογραφική ανασκόπηση περιλαμβάνει μια ευρεία γκάμα επιστημονικών άρθρων, διατριβών και θέσεων σε θεωρία και εφαρμογή διαχείρισης αποθέματος, καθώς και της ανάλυσης Monte Carlo και των βελτιστοποιήσεών της. Βασικές έννοιες όπως η EOQ, το σημείο επαναπαραγγελίας, μοντέλα ζήτησης και μοντέλα πρόβλεψης εξετάζονται αναλυτικά. Αυτή η ενότητα παρέχει έναν πλήρη κατανόηση των θεωρητικών βάσεων των πρακτικών διαχείρισης αποθέματος και δημιουργεί το υπόβαθρο για την επόμενη εμπειρική ανάλυση. Το δεύτερο μέρος της διατριβής επικεντρώνεται στη στοχαστική ανάλυση του αποθέματος τριών συγκεκριμένων μονάδων αποθήκης (SKU). Ο στόχος είναι να εφαρμοστούν διάφορες μέθοδοι πρόβλεψης, όπως ο κινητός μέσος όρος, η εκθετική εξομάλυνση και η γραμμική παλινδρόμηση, για να προβλέψουν ακριβώς τα μελλοντικά πρότυπα ζήτησης. Με την εφαρμογή αυτών των μοντέλων πρόβλεψης, η μελέτη αποσκοπεί στη βελτίωση της ακρίβειας των προβλέψεων ζήτησης, επιτρέποντας πιο αποτελεσματικό σχεδιασμό και έλεγχο του αποθέματος. Επιπλέον, η διατριβή παρουσιάζει την εφαρμογή της EOQ, μιας ευρέως χρησιμοποιούμενης τεχνικής βελτιστοποίησης αποθέματος. Μέσω του καθορισμού της βέλτιστης ποσότητας παραγγελίας, του σημείου

επαναπαραγγελίας και των κόστων κατοχής αποθέματος, η EOQ βοηθά στην ελαχιστοποίηση των δαπανών κατοχής αποθέματος ενώ εξασφαλίζει επαρκή διαθεσιμότητα αποθέματος. Η εφαρμογή της EOQ υποστηρίζεται από την προσομοίωση Monte Carlo, η οποία συμπεριλαμβάνει στοχαστικά στοιχεία για την προσομοίωση και αξιολόγηση διαφορετικών σεναρίων αποθέματος. Αυτή η ανάλυση παρέχει εισαγωγή στην αξιοπιστία και την απόδοση των προτεινόμενων στρατηγικών διαχείρισης αποθέματος. Τα ευρήματα αυτής της διατριβής συμβάλλουν στον τομέα της διαχείρισης αποθέματος, συνδυάζοντας θεωρητικές γνώσεις με εμπειρική ανάλυση. Η έρευνα τονίζει τη σημασία της ακριβούς πρόβλεψης ζήτησης, του αποτελεσματικού ελέγχου αποθέματος και τεχνικών βελτιστοποίησης όπως η EOQ με τη βοήθεια της προσομοίωσης Monte Carlo. Η πρακτική εφαρμογή μοντέλων πρόβλεψης και η στοχαστική ανάλυση αποθεμάτων συγκεκριμένων SKUs παρέχουν πολύτιμες πληροφορίες και συστάσεις για τους επαγγελματίες της διαχείρισης αποθέματος. Ο στόχος αυτής της διατριβής είναι να λειτουργήσει ως ένα πολύτιμο εργαλείο για ακαδημαϊκούς, ερευνητές και επαγγελματίες του κλάδου που επιδιώκουν τη βελτίωση των πρακτικών διαχείρισης αποθέματος και την βελτιστοποίηση των λειτουργιών της αλυσίδας εφοδιασμού.

Λέξεις – Κλειδιά: Διαχείρηση Αποθεμάτων, Μόντε Κάρλο, EOQ, Προβλέψεις, Μοντέλα Ζήτησης

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1. Introduction

The primary objective of this dissertation is to explore the effectiveness of inventory management in the supply chain context and implement specific forecasting methods, with main feature the Monte Carlo analysis. The research aims to provide insights into the role of inventory, identify key challenges, and analyse various inventory management models and techniques. Additionally, the study seeks to evaluate different forecasting methods for demand prediction and their impact on inventory optimization.

The specific research objectives are as follows:

Objective 1: To understand the role of inventory in the supply chain and its impact on overall performance as well as the Monte Carlo Analysis through literature review. This objective involves examining the functions of inventory, such as meeting customer demand, buffering against uncertainties, and supporting production processes. This brief literature review is mentioned in the beginning of the dissertation.

Objective 2: To explore various inventory management models and techniques. This objective entails a comprehensive review of basic inventory management models, including the Economic Order Quantity (EOQ) model, Reorder Point (ROP) model, and safety stock calculation methods. Additionally, advanced inventory management strategies such as Just-in-Time (JIT) and lean practices will be discussed.

Objective 3: To evaluate different forecasting methods for demand prediction. This objective involves analysing various forecasting techniques, such as the moving average, the exponential smoothing and the linear regression. The aim is to assess the strengths, limitations, and applicability of each method in different supply chain contexts. Finally to perform the EOQ and the Reorder Point, implement the Monte Carlo simulation and then present the results.

By addressing these research objectives, this dissertation aims to contribute to the existing body of knowledge on inventory management in the supply chain perspective. The findings will provide valuable insights and practical implications for businesses seeking to optimize their inventory processes, enhance customer satisfaction, and improve overall supply chain performance.

In chapter 2, we have presented a literature review of the Invnetory Management and the Monte Carlo simulation. In chapter 3, we have presented the main Inventory Management theory and the forecasting techniques. In chapter 4, we have implemented the Inventory

Management forecasting techniques in the stochastic inventory of three storage keeping units. Finally in chapter 5, we have implemented the Monte Carlo simulation in the stochastic inventory of the same three storage keeping units.

2. Literature Review

This chapter provides a comprehensive review of the literature on inventory management and Monte Carlo analysis. It examines key concepts, theories, and methodologies that have been discussed and used as an inspiration for this research. With a brief approach and presentation of the literature, this chapter sets the foundation for the subsequent chapters and establishes the rationale for the research conducted in this dissertation. This section explores the literature related to inventory management, including demand forecasting, ordering policies, and risk analysis. The section also addresses the challenges and trade-offs associated with inventory management, such as the bullwhip effect and the impact of uncertainty on inventory decisions. Furthermore, literature regarding Monte Carlo analysis is examined, focusing on its applications mainly in inventory management. It discusses the various simulation techniques and methodologies used to model inventory systems and assess their performance under different scenarios and also reviews studies that have applied Monte Carlo analysis and Monte Carlo analysis variations to address specific challenges in inventory management. In the final section, the literature review is connected to the research objectives of this dissertation. The section explains how the proposed research will contribute to the existing knowledge by investigating the impact of Monte Carlo analysis on inventory management strategies and optimizing inventory decisions under uncertainty.

Huiju Zhang (2007) dissertation discusses the application of Monte Carlo simulation in estimating the loss distribution of a portfolio of credit risky assets and highlights the importance of variance reduction methods such as particularly importance sampling. It emphasizes the challenges associated with the computational speed and the need to choose an optimal biased distribution to enhance the frequency of important events and compensate for bias through the multiplication by the likelihood ratio. By optimizing the measure change, the accuracy and efficiency of the Monte Carlo simulation can be improved, resulting in more precise estimates of descriptive statistics, such as expected loss, loss volatility, and quantiles. Specifically, the dissertation focuses on the scaling up of the scalar parameter in the asset correlation model, which increases correlations among risky assets and generates samples further in the loss tail. By incorporating an optimal scalar factor, the importance sampling technique leads to a significant reduction in variance compared to standard Monte Carlo simulation and other sampling methods. The dissertation concludes by describing two stochastic optimization methods for choosing an optimal importance sampling measure change factor, thereby improving the accuracy of a Monte Carlo simulation used to estimate the loss distribution on a portfolio of credit risky assets. These findings contribute to improving the accuracy and efficiency of estimating loss distributions and have implications for risk management in credit portfolios.

Ijeoma Winifred Ekwegh (2016) dissertation presented the newsvendor model. This model is being used in the inventory management particularly when the demand is irregular and random. The dissertation focuses on this method while also using the Monte Carlo sampling with the prospect of being able to estimate the order quantity of the inventory with which they will accomplice the maximization of the revenues and minimize the costs from the effects of the uncertain demand. The mathematical method of Monte Carlo simulation is being presented. Monte Carlo analysis is preferred because of the ability to find solutions to things such as expected values of a function, or integrating functions which cannot be integrated analytically. Concluding, the newsvendor model is presented with three different solutions. The first solution is obtained by calculating the expected value for the mean and this represents the average outcome. The second solution, known as the expected value with perfect information, takes into account the hypothetical scenario where perfect information is available and provides an upper bound on the expected value, assuming complete knowledge of future demand. However, the third solution is presented as the most interesting one. It involves using a two-stage stochastic programming approach to calculate the expected value. With this method the uncertainty and variability in demand is considered by incorporating probabilistic factors in the decision-making process. By using the two-stage stochastic programming technique, the author explains that we can better understand and optimize the expected value, taking into account the potential outcomes and associated probabilities.

Prapoj Srinuwattiwong (2002) discussed in their dissertation about Modelling and analysis of global collaborative outsourcing manufacturing systems using the Monte Carlo analysis. During the dissertation the outsourcing phenomenon is described under specific conditions in respect of the dissertation. The study path described in this research holds value for both supply chain management analysts and global organizations considering offshore outsourcing. It aims to identify the optimal point for reserving production capacity, taking into account the challenges posed by fluctuating global demand and currency exchange rates that are prevalent in today's business environment. In conclusion, the models and experiments provide several key insights. Firstly, Monte Carlo simulation is effectively used to analyse the decision variables and understand their nature. Secondly, they have identified 13 policies that can be integrated into the decision-making process of global sourcing systems, taking into consideration cost and demand patterns. The trade-off between policies within the same demand stage is determined by the dominant cost factor. The impact of outsourcing is influenced by the marginal cost associated with adjusting capacity. Furthermore, in a market characterized by fluctuating demand, the presence of multiple facilities proves to be advantageous. The level of demand uncertainty is a determining factor in the extent of outsourcing. Lastly, the simulation results were compared and decided that they align with the findings of Huchzermeier and Cohen (1996), showcasing how flexible facility networks with excess capacity can serve as valuable options for mitigating exchange rate fluctuations in the long term.

Shengyu Ma (2021) thesis proposes a comprehensive solution for addressing an inventory allocation problem faced by Nestlé Canada. To minimize the total monthly shortage penalties incurred by various companies, a multi-faceted approach is employed including the utilization of a Monte Carlo Tree Search algorithm. Complemented by a local search optimization algorithm to reduce the search space, a time series prediction model based on an encoder-decoder structure and Bayesian optimization is integrated to enhance demand forecasting accuracy. Concluding, the thesis presented a novel inventory management algorithm that combines Monte Carlo Tree Search with a heuristic-based local search approach to reduce the action space. Additionally, they developed neural demand forecasting models integrated with Bayesian Optimization for accurate cost estimation based on predefined rules and also demonstrated the practical applicability of reinforcement learning techniques in addressing real-world supply chain management challenges faced by Nestlé Canada. Through empirical validation, they have shown that intelligent agents built, using these techniques, can achieve substantial cost savings.

Yalcin Akcay in (2002) thesis tried to address two resource allocation issues. Th the first stage of the problem discussed by utilizing a Monte Carlo simulation technique called sample average approximation to determine the base-stock levels of components. Additionally, they proposed a new heuristic for solving the second stage problem, which involves making allocation decisions for components and is equivalent to a multidimensional knapsack problem. The proposed rule synchronizes the allocation decision based on component availability, ensuring that a component is only allocated to an order if it can be fully fulfilled. The thesis contributes to expanding the application of revenue management to the workplace learning industry and formulates the revenue maximization problem as a stochastic dynamic program. The results of the extensive simulation study demonstrate the effectiveness of the heuristics in solving the problem and highlight their superiority over the benchmark policy.

Eduardo Ferian Curcio (2017) the research concentrated on the creation of integrated lot-sizing mathematical programming models under uncertain conditions and the evaluation of their respective advantages and limitations. This aspect of the study involved the development and assessment of stochastic programming and robust optimization models, which are tested using a Monte Carlo simulation-based experiment. The models considered the integration of lot-sizing and scheduling decisions and were evaluated across various instance characteristics and settings, considering factors such as average cost, risks, and computational runtime. As a result, this study provides the means to select the most appropriate modelling approach based on different circumstances and the preferences of decision-makers. Finally through a Monte Carlo simulation they tried to compare the models and strategies proposed. This turned out to be a reliable method for evaluating the performance of the models and strategies in multistage uncertainty settings.

Yong Joo Lee (2009) dissertation investigated the reverse logistics of supply chain system. Monte Carlo simulation was used to decide the optimal price for the model of reverse logistics. The evaluation of profit realization model performance was carried out by manipulating the price and demand variables based on the principles of price elasticity. To determine the optimal facility expansion for UPS, a comparative test was conducted. This test involved assessing the difference in profits between the reduced and full models, considering the current price versus the optimal price, the current combination of transportation modes versus the optimal combination, and the current outsourcing costs versus the optimal outsourcing costs. The optimal values for these variables were obtained through Monte Carlo simulation. In essence, the comparison test served as a core framework for decision-making regarding facility expansion, allowing for the assessment of various factors and their impact on profitability.

Ashkan Negahban (2016) dissertation discussed the challenge lies in effectively identifying and reaching the appropriate group of potential consumers to facilitate a rapid and significant market expansion, utilizing a wide range of analytical techniques including agent-based modelling and simulation, Monte Carlo simulation, mathematical models in continuous-time, and both parametric and nonparametric statistical methods. According to the dissertation over 300,000 market configurations were examined, leading to a total of over 7.1 billion Monte Carlo model replications. The comprehensive experimentation produced a substantial amount of raw simulation output, exceeding 110 gigabytes, which required meticulous and time-sensitive data analysis. To ensure consistency, they designed and validated a series of automated programs specifically for data analysis purposes.

Jacek Zabawa and Bożena Mielczarek (2007) presented a supply chain simulation model and its implementation using a versatile tool and simulation package. The outputs from Monte Carlo experiments were obtained from both spreadsheet formulas in Microsoft Excel and the graphical environment of Extend software. These outputs were compared, revised, and used to determine the minimum inventory cost. The results of a 20-day simulation of the inventory system, as described by Jensen and Bard (2003), were presented thoroughly.

Robert Davies, Tim Coole and David Osipyw (2014) dissertation examined the suitability of time series models (such as ARIMA and exponential smoothing) for forecasting future requirements and compares them to the output of a Monte Carlo simulation tool built in Microsoft Excel. The study focuses on forecasting the consumption of crankshaft shells and highlights the uniqueness of their inventory profiles in Operations Management. Traditional inventory control methods like Materials Requirement Planning and Just-in-Time Kanban systems do not apply in this case. The combination of time series analysis and Monte Carlo simulation helps bridge the gap in research on this specific area of inventory management.

Alessandro Balata and Jan Palczewski (2018) used a Monte Carlo-based numerical method which was developed to solve discrete-time stochastic optimal control problems with inventory. The control in these problems affects the inventory process on a deterministic state space, while the randomness is captured by the objective function. The proposed approach, called Regress Later modification, decouples inventory levels in consecutive time steps and incorporates inventory dependencies into regression basis functions. By using a backward trajectory construction for inventory, the algorithm avoids nested simulations and utilizes a policy iteration method. This method improves upon grid discretization and control randomization techniques. The results demonstrate the effectiveness of the Monte Carlo methods in solving high-dimensional inventory control problems, outperforming other approaches and providing practical solutions.

Deniz Preil and Michael Krapp (2021) dissertation discussed about the complex task of coordination of order policies in supply chain inventory management due to stochastic factors. They introduced a heuristic approach called Monte Carlo tree search from the field of artificial intelligence (AI) to address this challenge. First they applied Monte Carlo tree search to supply chain inventory management and its application in other operations research domains. They developed both offline and online models that incorporate real-time data for decision-making. Their findings show that both the offline and online Monte Carlo tree search models outperform other AI-based approaches. Additionally, they discussed about how the dynamic order policy determined by Monte Carlo tree search helps eliminate the bullwhip effect and leads to stable inventory levels.

3. Inventory

Inventory management plays a critical role in the overall performance of supply chains across various industries. Efficient management of inventory enables businesses to balance customer service levels, minimize costs, and enhance operational efficiency. However, inventory management is a complex task that requires careful planning, coordination, and decision-making to ensure the right quantity of products is available at the right time and place. The main principals of the inventory management that all over the literature is mentioned, is the decision of how much to order, when to order and how to achieve the minimum costs (Rushton, 2022).

In today's dynamic and competitive business environment, companies face several challenges in managing their inventory effectively. These challenges include demand variability, lead time uncertainties, fluctuating customer preferences, and the need to balance inventory holding costs with stockout costs. Additionally, global supply chains and e-commerce have introduced new complexities, such as longer lead times, increased product variety, and the need for real-time visibility across the entire supply network (Taylor, 2016).

3.1 Concept of Inventory

Inventory is a vital component of supply chain management, encompassing all the goods held by a company for various purposes, including production, sales, and customer service. It serves as a buffer between the different stages of the supply chain, ensuring a smooth flow of products and enabling businesses to meet customer demand efficiently. Inventory can take different forms, such as raw materials, work-in-progress, and finished goods.

The role of inventory in the supply chain is multifaceted. Firstly, it acts as a hedge against uncertainties in demand and supply. By maintaining adequate inventory levels, companies can mitigate the impact of demand fluctuations, supply disruptions, and lead time uncertainties. Secondly, inventory facilitates customer service by ensuring product availability and reducing lead times. It enables businesses to meet customer demand promptly and maintain high service levels. Finally, inventory also serves as a strategic asset, allowing companies to take advantage of economies of scale, negotiate favourable terms with suppliers, and support production processes (Render, Strair, Hanna, & Hale, 2018).

Managing inventory effectively requires a balance between various costs associated with holding, ordering, and stockouts. Carrying costs include expenses related to storage, handling and insurance. Ordering costs include expenses incurred in placing and processing orders, such as order processing, transportation, and communication costs. Stockout costs, on the other hand, refer to the costs associated with not having enough inventory to meet customer demand, including lost sales, dissatisfied customers, and damage to the company's reputation (Taylor, 2016).

3.1.1 Basic Inventory Management Model EOQ

The first one to approach the EOQ in the literature review which took place for the purpose of this dissertation is Harris on 1913. To be more specific, Harris (1913) focused on inventory control or lot sizing and later on this has been known as the EOQ. To optimize inventory levels, companies employ various inventory management models and techniques. One of the fundamental models is the Economic Order Quantity (EOQ) model. The EOQ model aims to determine the optimal order quantity that minimizes the total cost of inventory, considering both carrying costs and ordering costs. First, it assumes that demand for the product is constant and known with certainty over a specific period. Second, it assumes that both ordering costs (e.g., setup costs, transportation costs) and holding costs (e.g., storage costs, capital costs) are constant and do not vary with the order quantity. Lastly, the lead time for replenishment is assumed to be constant and predictable. In the classic EOQ method, the optimal order quantity is determined by finding the point at which the total cost of inventory is minimized. This is achieved by balancing the costs of holding excess inventory (holding costs) and the costs associated with ordering more frequently (ordering costs). The formula to calculate the EOQ is given by Taylor (2016) and is the below:

Equation 1: EOQ

$$EOQ = \sqrt{\frac{2DC_0}{C_h}}$$

Where D is annual demand in units for the inventory item, C0 is the ordering cost of each order and Ch is the holding or carrying cost per unit per year.

Another important model is the Reorder Point (ROP) model as explained by Taylor (2016). The Reorder Point (ROP) model in the EOQ model indicates the inventory level at which a new order should be placed. It is the point at which the remaining inventory reaches a specific level, triggering the replenishment process. The reorder point is calculated by considering the lead time and the average daily demand during that lead time.

Equation 2: Reorder Point

$$RP = d * L$$

Where d is the demand rate and L is the Lead Time.

As mentioned before, the EOQ model assumes that there are no stockouts or shortages, and the entire order is received instantaneously. It also assumes that there are no quantity discounts or constraints on order quantities. However, safety stock is an essential concept in inventory management. It refers to the additional inventory held as a buffer to mitigate uncertainties in demand and supply. Safety stock acts as insurance against unexpected fluctuations in demand, lead time variability, and other sources of uncertainty. The calculation of safety stock involves considering factors such as demand variability, lead time variability, and desired service level. While the EOQ model provides a good starting point for inventory management, it may not capture real-world complexities such as uncertain demand, variable lead times, or perishable goods. The first and main fact of the EOQ is to assume that the demand is known and constant, a fact that is very rare and hard to exist in the real world. Various extensions and modifications have been developed to address these limitations. In summary, the EOQ model is a fundamental inventory management technique that balances holding costs and ordering costs to determine the optimal order quantity and reorder point. By minimizing overall inventory costs, businesses can achieve efficient inventory management and ensure smooth operations.

3.1.2 EOQ with shortages

One assumption in our basic EOQ model is that shortages and backorders are not allowed. However, trying to bring the model closer to the real life situation, Taylor (2016) presents the EOQ model with shortages. In the EOQ model with shortages, we relax this assumption and consider that any demand not met due to inventory shortage can be backordered and fulfilled later. Consequently, all demand is eventually satisfied. Since backordered demand, or shortages (S), is fulfilled when inventory is replenished, the maximum inventory level does not reach Q but instead settles at (Q – S). The quantity of inventory on hand, (Q – S), decreases as the shortage amount increases, and vice versa. As a result, the cost associated with shortages, which includes the cost of lost sales and customer goodwill, exhibits an inverse relationship with carrying costs. As the order size, Q, increases, the carrying cost rises while the shortage cost decreases. Taylor then provides the individual cost functions and then provides a function for the Total Cost which equals to the sum of total shortage cost, total carrying cost and total ordering cost. Finally, the below equation presents the optimum Q for the EOQ model with shortages.

Equation 3: EOQ with Shortages

$$Q_{opt} = \sqrt{\frac{2C_o D}{C_c}\left(\frac{C_s + C_c}{C_s}\right)}$$

Where, Co is the total ordering cost, D is the Demand, Cc is the total carrying cost and Cs is the total shortage cost.

3.2 Demand Models

Accurate demand forecasting is crucial for effective inventory management. Companies need to predict customer demand accurately to ensure optimal inventory levels and avoid stockouts or excess inventory. Various demand models and forecasting methods are available to estimate future demand. The naive method is a simple and straightforward approach where the demand for the future period is assumed to be the same as the demand observed in the previous period. While the naive method is easy to implement, it may not capture trends, seasonality, or other factors that influence demand patterns. Moving average is a forecasting method that calculates the average demand over a specific period, considering historical data. The period can vary based on the company's requirements and the nature of the demand pattern. Moving average provides random fluctuations in demand but may not respond quickly to changes in the trend or seasonality. Weighted average forecasting assigns different weights to historical data points based on their relevance or significance. This method allows for more emphasis on recent data or data points that have shown consistent patterns in the past. Weighted average forecasting provides more flexibility in capturing changes in demand patterns (Taha, 2017).

3.2.1 ABC Analysis

ABC Analysis is a widely used inventory management technique that classifies inventory items based on their value and importance as expressed by Render, Stair, Hanna & Hale (2018). It helps companies prioritize their inventory management efforts and allocate resources effectively. The analysis is based on the Pareto principle, also known as the 80/20 rule, which states that a small percentage of inventory items contribute to the majority of the inventory value or sales. In ABC Analysis, inventory items are categorized into three groups: A, B, and C, representing the highest, moderate, and lowest value items, respectively. Category A items are typically high-value items that account for a significant portion of the total inventory value and typically contribute to more than the 70% of the company's revenues. These items require close monitoring and stricter inventory control measures due to their impact on the company's financial performance. Category B items have moderate value and contribute to a relatively smaller portion of the total inventory value typically contribute to about the 20% of the company's revenues. They require a moderate level of attention and control. Category C items have the lowest value and represent a relatively larger proportion of the total inventory items which contribute about the 10% of the company's revenues. While these items individually may not have a significant impact on the company's financials, their cumulative value can be substantial. They often require less frequent review and can be managed with more relaxed inventory control measures. By classifying inventory items into different categories, companies can focus their efforts on managing high-value items more effectively, ensuring appropriate inventory levels, and reducing the risk of stockouts or excess inventory. It allows for better allocation of resources, such as storage space, handling, and order processing, based on the value and criticality of the items.

3.2.2 Inventory Classification

In addition to ABC Analysis, companies may also classify inventory based on other criteria to further refine their inventory management strategies. Some common classification methods include: Product-based Classification: Inventory items can be categorized based on their characteristics, such as size, weight, perishability, or shelf life. This classification helps in determining appropriate handling, storage, and replenishment strategies for different types of products. Render, Stair, Hanna & Hale (2018) presented the Demand-based Classification: Items can be classified based on their demand patterns, such as high-demand, medium-demand, and low-demand items. This classification assists in forecasting demand, setting inventory levels, and aligning replenishment strategies accordingly. When there is a dependence between the demand for different items, it is important to forecast the demand for final products and calculate the requirements for component parts. Similar to previous inventory models, determining the optimal order quantity and timing are crucial. However, managing inventory scheduling and planning becomes more complex when dealing with dependent demand. To address this complexity, material requirements planning (MRP) can be utilized effectively, offering several benefits such as increased customer service and satisfaction, reduced inventory costs, improved inventory planning and scheduling, higher total sales, faster response to market changes, and reduced inventory levels without compromising customer service. Although MRP systems are typically computerized, the analysis process remains straightforward and similar across different computerized systems. Another classification is the Supplier-based Classification: Items can be classified based on the suppliers or vendors from whom they are sourced. This classification allows companies to manage relationships with different suppliers and optimize procurement strategies. By applying various classification methods, companies can gain a better understanding of their inventory and tailor their inventory management practices accordingly. It enables them to implement more targeted and efficient inventory control measures, leading to improved inventory turnover, reduced holding costs, and enhanced overall supply chain performance.

3.2.3 Just-in-Time (JIT) Inventory Management

Just-In-Time (JIT) inventory management is a methodology focused on minimizing inventory levels and maintaining a lean supply chain by delivering materials and products at the precise time they are needed in the production process as explained by Render, Stair, Hanna & Hale (2018). The core principle of JIT is to eliminate waste and reduce costs associated with carrying excess inventory. In JIT, inventory is viewed as a liability rather than an asset. Instead of stockpiling large quantities of materials or finished goods, JIT aims to synchronize production with customer demand, ensuring that inventory is available just in time to meet production requirements or customer orders. This approach helps to minimize storage costs, reduce the risk of obsolescence, and enhance overall operational efficiency. JIT relies on close collaboration and strong relationships between suppliers and manufacturers. Suppliers deliver materials or components in small, frequent shipments, based on production schedules and customer demand. This minimizes the need for on-site storage and allows for a more efficient use of resources. By implementing JIT, companies can achieve several benefits. These include reduced carrying costs, improved cash flow, lower inventory holding costs, reduced lead times, increased production flexibility, and enhanced responsiveness to customer demand. Just-In-Time (JIT) strategy is implemented by many important organizations such as Toyota Motors and Dell. JIT can also uncover process inefficiencies and quality issues, as any disruptions or defects become immediately apparent when inventory levels are minimal. However, JIT is not without challenges. It requires accurate demand forecasting, reliable supplier relationships, efficient logistics, and effective communication throughout the supply chain. JIT also leaves little room for error, as any disruptions in supply or unexpected changes in demand can have significant impacts. A know technique to implement the JIT is the use of the Kanban system (kanban in Japanese means card). The Kanban card is a key component of the Kanban system, which is a visual scheduling and inventory control method used in lean manufacturing and Just-In-Time (JIT) production systems. The Kanban card represents a signal that triggers the replenishment of materials or products in the production process. It operates on the principle of "pull" rather than "push." Each Kanban card is associated with a specific item or product and is attached to a container or bin that holds a predetermined quantity of that item. The number of Kanban cards in circulation corresponds to the quantity of items allowed in the production system. When a production workstation consumes materials from a container, it removes the associated Kanban card and sends it to the upstream workstation or the supplier as a signal to replenish the stock. This initiates the production or delivery of a new batch of materials to maintain the desired inventory level. The Kanban card serves multiple purposes in the system. Firstly, it acts as a visual indicator of the need for replenishment, enabling workers to quickly identify when to initiate the resupply process. Secondly, it provides information about the item, such as the product name, part number, and location, facilitating accurate tracking and inventory management. Lastly, the Kanban card can contain additional details like lead time, lot size, and other relevant information to guide the production and procurement process. The Kanban card system helps to prevent overproduction, reduce inventory holding costs, improve flow efficiency, and enable just-in-time production. It promotes a smooth and balanced workflow by ensuring that materials are replenished only when needed, based on actual consumption. Overall, the Kanban card is a fundamental element of the Kanban system, providing a visual and practical means of controlling inventory, facilitating communication between workstations, and supporting the principles of JIT manufacturing.

3.2.4 Vendor-Managed Inventory (VMI)

Vendor Managed Inventory (VMI) is a collaborative inventory management strategy where the supplier or vendor takes responsibility for monitoring and replenishing the inventory of their customer, Bruel, O. (2016). In VMI, the vendor has access to real-time inventory data and assumes the role of inventory planning and control, ensuring that the customer's inventory levels are optimized. Under VMI, the vendor proactively manages the replenishment process by monitoring stock levels at the customer's location and initiating automatic shipments or deliveries based on predetermined agreements and inventory targets. The vendor often utilizes advanced information systems and technologies to gather data, track inventory levels, and forecast demand accurately. VMI offers several benefits to both the vendor and the customer. For the customer, VMI reduces stockouts and the need for frequent inventory checks, as the vendor ensures timely replenishment. It streamlines the supply chain, minimizes inventory holding costs, and frees up resources previously dedicated to inventory management. Additionally, VMI can improve overall operational efficiency and foster stronger collaboration between the vendor and the customer. For the vendor, VMI provides greater visibility into the customer's demand patterns and inventory requirements, allowing for improved production and supply planning. It helps to streamline production schedules, reduce lead times, and minimize excess inventory. VMI can also enhance customer satisfaction by ensuring product availability and reducing order processing time. According to Bruel, the VMI system follows five main phases, the company's IT system provides information to its internal clients. The platform shares daily information with the supplier regarding products and quantities delivered. Based on the platform's inventory and outflows, the supplier determines optimal replenishment and seeks confirmation from the client. The client confirms the delivery in most cases. The supplier delivers the proposed quantities. However, implementing VMI requires a high level of trust, collaboration, and effective communication between the vendor and the customer. It involves sharing sensitive information and requires a strong partnership to establish mutual goals, monitor performance, and resolve any issues that may arise. Overall, Vendor Managed Inventory is a supply chain management approach that shifts the responsibility of inventory control and replenishment from the customer to the vendor. It can lead to improved efficiency, reduced costs, and enhanced customer satisfaction by enabling better coordination and synchronization in the supply chain. In a VMI system, suppliers are directly responsible for replenishing stocks of end-products located either on their own premises or on the clients' premises. This establishes an operational collaboration with suppliers, adding a logistical dimension to the contracts.

3.2.5 Cross-Docking

Cross-docking is a logistics practice that minimizes inventory holding by bypassing the traditional warehousing process. In cross-docking, incoming goods from suppliers are unloaded from the inbound transportation vehicle and directly loaded onto outbound vehicles for immediate distribution to customers. This strategy eliminates the need for long-term storage and reduces inventory carrying costs. It requires efficient coordination among suppliers, carriers, and customers to ensure timely and accurate transfer of goods. Cross-docking is particularly effective for products with short shelf life, high demand variability, or when time-sensitive delivery is required. Goods designated for cross-docking must adhere to strict arrival and departure schedules, requiring careful coordination for smooth operations. Outgoing vehicles may contain a mix of cross-docked and stocked goods, necessitating effective coordination. Sorting, if necessary, involves picking individual products from incoming pallets and placing them on outgoing customer pallets, either manually or using automated sortation equipment. Cross-docking takes various forms. Goods may be pre-labelled for specific stores or customers, or they may be sorted by product line during the cross-docking process, with or without labelling. Cross-docking offers advantages such as facilitating rapid flow of goods and reducing inventory levels, making it popular for fresh and short-shelf-life goods, as well as pre-allocated goods in the fashion industry. However, cross-docking may not be suitable in all situations due to various factors. It can potentially shift inventory upstream in the supply chain, requiring suppliers to hold more inventory for just-in-time supply to the warehouse. Adequate space for handling and sorting activities is necessary, and close coordination and reliability with suppliers become more complex with a larger number of SKUs and suppliers. To determine the suitability of cross-docking, it is essential to take a holistic view of the entire supply chain. In general, cross-docking is often beneficial for load consolidation before and after the decoupling point, while storage of goods at the decoupling point is necessary to maintain the required cycle and safety inventory, (Rushton, 2022).

3.2.6 Flexible Fulfilment or Postponement Strategy

Flexible fulfilment is a manufacturing approach that aims to defer the final specification of a product until the last possible stage in the supply chain, commonly known as postponement strategy. This strategy offers significant advantages, especially for companies operating globally. For instance, consider the challenges posed by varying power supply voltages worldwide for portable electronic goods. If a manufacturer sells products globally, they would need to maintain separate stocks of finished products for each power supply type, likely near the specific markets. This increases inventory carrying costs and the risk of product obsolescence, particularly in the electronics industry. However, by employing a range of power supply packs that are compatible with the same product, the manufacturer could have a single "global" product that can be quickly adapted by simply changing the power module to match the specific market. This approach eliminates the need for country- or market-specific products, enabling products to be transported and sold anywhere in the world on short notice. Implementing flexible fulfilment has significant implications for product design, as products must be designed in a way that allows easy adaptation for market-specific variations by changing modules. For example, laptops require different keyboards to accommodate various alphabets worldwide. Manufacturing laptops with non-interchangeable keyboards would result in large inventories of language- or alphabet-specific stocks in different countries. With postponement, the bulk of the laptop is manufactured and shipped globally, and the final product configuration is only determined when the specific alphabet keyboard is attached. Another example of postponement can be observed during product promotions like "Buy product A and get product B free." Combining products A and B creates a third product, C. This can be achieved by packaging products A and B together in some form of outer packaging, which can be done at the distribution centre before final delivery. This approach eliminates the need for forecasting and shipping additional stocks from higher up in the supply chain. Product C can be almost made to order through the packaging process, where increased levels of products A and B are shipped only if the promotion is successful, (Rushton, 2022).

3.2.7 Reverse Logistics

Reverse logistics focuses on managing the flow of products or materials back through the supply chain, typically from customers to manufacturers or suppliers. It involves activities such as product returns, repairs, recycling, or disposal. Effective management of reverse logistics helps companies optimize inventory levels, recover value from returned products, and minimize waste. Reverse logistics requires robust processes and systems for tracking returned products, assessing their condition, and determining appropriate disposition. By effectively managing reverse logistics, companies can reduce the financial impact of returns, improve customer satisfaction, and minimize the environmental impact of discarded products, (Rushton, 2022).

3.3 Forecasting

3.3.1 Importance of Forecasting in Inventory Management

The future is unknown and uncertain. One of the biggest challenges is to be able to try to predict the future and this predicament to be as closer as possible to the real outcome. To do so forecasting methods have been developed throughout the literature and are implemented in the businesses as well. Accurate demand forecasting is essential for effective inventory management. It enables companies to estimate future demand patterns, plan production and procurement activities, and maintain optimal inventory levels. There are several forecasting methods, however in the next part we will be discussing the most common ones, most of them also have been implemented in this paper (Rushton, 2022).

3.3.2 Naive Method

The naive forecasting method is a simple approach that assumes future demand will be equal to the most recent observed demand. It is a straightforward and easy-to-implement method that works well when demand patterns are relatively stable and no underlying trends or seasonality exist. However, the naive method does not consider other factors that may influence demand and may lead to inaccuracies in forecasting (Taylor, 2016).

3.3.3 Moving Average Method

The moving average method calculates the average of past demand observations over a specified time period to forecast future demand. It smooths out fluctuations in demand and provides a more stable estimate. The choice of the time period for the moving average affects the responsiveness to changes in demand. Shorter time periods are more sensitive to recent demand changes, while longer time periods provide a more stable forecast (Render, Strair, Hanna, & Hale, 2018).

Equation 4: Moving Average

$$MAv = \frac{Y_1 + Y_2 + \cdots + Y_n}{n}$$

Where Y1, Y2 and Yn are the demand for every period of observation and n is the number of periods. Later on the paper this method will be used to forecast certain demand.

3.3.4 Weighted Average Method

The weighted average method assigns different weights to past demand observations based on their relative importance. This allows for giving more weight to recent data or data that is deemed more relevant. By assigning appropriate weights, the weighted average method can provide a more accurate forecast, especially when demand patterns exhibit variations or trends. However, this could also be a major drawback in case of choosing to assign weights in the wrong periods. Mathematically the weighted average method can be expressed as below, (Render, Strair, Hanna, & Hale, 2018):

Equation 5: Weighted Average

$$WAv = \frac{w_1 * Y_1 + w_2 * Y_2 + \cdots + w_n * Y_n}{w_1 + w_2 + \cdots w_n}$$

3.3.5 Exponential Smoothing Method

Exponential smoothing is a widely used forecasting method that gives more weight to recent demand observations while gradually decreasing the influence of older observations. It calculates forecasts based on a weighted average of past demand and forecasted values. The smoothing factor (usually indicated with the letter a), also known as the smoothing constant, determines the weight assigned to each observation. The choice of the smoothing factor affects the responsiveness to recent changes in demand. For example, when the smoothing factor a = 0,5, the new forecast is based almost entirely on demand in the past three periods, a fact that can be proved mathematically. When the smoothing factor a = 0,1, the forecast places little weight on any single period, even the most recent, and it takes many periods (about 19) of historical values into consideration. To express the mathematical type of the exponential smoothing method forecast is the below formula, (Render, Strair, Hanna, & Hale, 2018):

Equation 6: Exponential Smoothing

$$ExSm = F_t + a * (Y - F_t)$$

Where Ft is the forecast of the previous period t, a is the smoothing factor and Y is the previous period actual demand.

3.3.6 Linear Regression

Linear regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the variables, where the dependent variable can be predicted based on the values of the independent variables. In the context of inventory management, linear regression can be a useful forecasting method. Linear regression is being used for forecasting in inventory management, using historical data on relevant variables such as sales, demand, or customer orders. The dependent variable, often representing future inventory levels or demand, is predicted based on the independent variables, which can include factors like time, seasonality, promotions, or economic indicators. The first step in using linear regression for forecasting is to identify and gather the relevant data. The historical data is then used to estimate the coefficients of the regression equation, which determine the relationship between the dependent and independent variables. This estimation process involves minimizing the difference between the predicted values and the actual values of the dependent variable. Once the regression model is estimated, it can be used to forecast future inventory levels or demand. By plugging in the values of the independent variables, the model provides estimates of the dependent variable. These estimates can guide inventory planning, production scheduling, and procurement decisions. However, it is important to note that linear regression assumes a linear relationship between the variables and may not capture complex non-linear patterns. It is also sensitive to outliers and assumptions such as independence and homoscedasticity. Therefore, it is essential to assess the model's accuracy and make appropriate adjustments if necessary. In summary, linear regression offers a straightforward and interpretable method for forecasting in inventory management. By leveraging historical data and identifying relevant variables, it provides insights into future inventory levels or demand, enabling businesses to make informed decisions regarding inventory planning and management. To express the linear regression in a mathematical model the below equation is ideal:

Equation 7: Linear Regression

$$Y = b_0 + b_1 * x$$

Where Y is the predicted value, b0 is the intercept, b1 is the slope and x is the time period (Render, Strair, Hanna, & Hale, 2018).

3.3.7 Forecast Accuracy Evaluation

Forecast accuracy evaluation is crucial in assessing the performance of different forecasting methods. Various metrics, such as mean absolute deviation (MAD), mean squared error (MSE), and the mean absolute percent error (MAPE), can be used to measure the accuracy of forecasts. Comparing the forecasted values with actual demand data helps identify any bias or error in the forecasting process and allows for fine-tuning or selecting the most appropriate forecasting method. (Render, Strair, Hanna, & Hale, 2018)

As far as mean absolute deviation (MAD) is concerned, below it is expressed with a mathematical equation:

Equation 8: MAD

$$MAD = \frac{Sum|forecast\ error|}{n}$$

To see how well one model works or to compare that model with other models, the forecast values are compared with the actual or observed values. Thus the forecast error is :

Equation 9: Forecast Error

$$forecast\ error = actual\ value - forecast\ value$$

The sum of the forecast error divided by the number of errors (n) gives us the MAD. The smaller value of MAD the more accurate the forecast is.

As far as the mean squared error (MSE) is concerned, below it is expressed with a mathematical equation:

Equation 10: MSE

$$MSE = \frac{Sum(error)^2}{n}$$

The mean squared error (MSE) is calculated by dividing the sum of all the squared errors of our forecast with the number of the errors (n). In the same respect as the MAD, the smaller MSE the more accurate the forecast is, (Render, Strair, Hanna, & Hale, 2018).

As far as the mean absolute percent error (MAPE) is concerned, below it is expressed with a mathematical equation:

Equation 11: MAPE

$$MAPE = \frac{Sum|D_t - F_t|}{SumD_t}$$

Where D is the demand for the time t, F is the forecast for the time t. It is usually expressed as a percentage and is a variation of MAD. As in MAD, the smaller the value of the MAPE is the more accurate the forecast is, (Render, Strair, Hanna, & Hale, 2018).

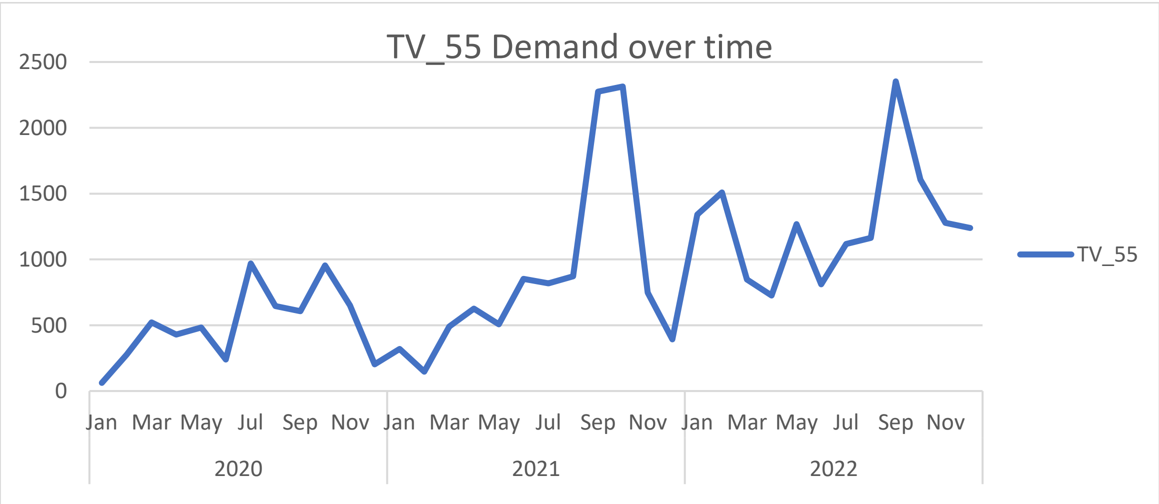
4. Forecasting theories implemented on stohasting inventory

In the first part of this dissertation we have reviewed the literature for the inventory management and the Monte Carlo analysis throughout the past years. In the second part we have analysed the theory of the inventory management as well as the inventory management methods and the forecast methods. In this third part we will view in action the results of the forecasting methods as well as the implementation of the Monte Carlo simulation.

We have collected the demand data of 3 specific storage keeping units during the years 2020, 2021 and 2022. The storage keeping units have been referred as TV_55, Refrigerator and Washing Machine.

Using the MS Excel and more specifically the PIVOT table features, we have created a table with the monthly demand for every year for each one of these three storage keeping units. In order to create a first opinion about the demand, we have created the according figures.

Figure 1: TV_55 demand over time



With a first review of the data collected in the above figure we are able to distinguish a seasonality in years 2021 and 2022 with the maximum value at the month September, a significant increase of the pieces sold, at the month of August and a decrease of the sales starting at the month of October. In year 2020 we are able to distinguish a very unstable demand. This is a result and we need to take under consideration the breakdown of the Pandemic COVID19 at 2020 when the first measures had taken place with transportation restrictions etc.

Moving on to our objectives, we will use the above data to create a forecast for the demand with 3 different methodologies.

The fist methodology will be the moving average. To proceed with the moving average methodology we need to establish a certain period. In this case two (2) periods will be sufficient. Using the POM-MQ for Windows software we enter the data of the 36 months choosing a time series analysis from the Forecasting Method menu and we receive the results as shown in the Appendix A. In the table below we have collected the forecast for the next period as well as the MAD, MSE and MAPE in order to compare them with the other methodologies.

Table 1: TV_55 Moving Average

Error Measures	**Value**
Bias (Mean Error)	46,24
MAD (Mean Absolute Deviation)	421,29
MSE (Mean Squared Error)	338.714,70
Standard Error (denom=n-2=32)	599,90
MAPE (Mean Absolute Percent Error)	56,99%
Forecast next period	**1258,50**

The second forecast methodology is the exponential smoothing method. For this specific forecast it is decided to proceed with a smoothing factor a= 0,5. Using the POM-MQ for windows we receive the data which are shown in the Appendix A. As well as the first methodology, below we have created another table with the forecast of the next period as well as with the needed MAD, MSE and MAPE in order to compare with the other methodologies.

Table 2: TV_55 Exponential Smoothing

Error Measures	**Value**
Bias (Mean Error)	73,92
MAD (Mean Absolute Deviation)	373,20
MSE (Mean Squared Error)	261.765,60
Standard Error (denom=n-2=33)	526,91
MAPE (Mean Absolute Percent Error)	53,72%
Forecast next period	**1.355,56**

For the third forecast methodology we will be using the Linear Regression. Using the POM-MQ we receive accordingly the results in Appendix A.

The regression equation is

$$Y = 236{,}684 + 34{,}741 * T$$

Where Y is the Demand, 236,684 is the intercept, 34,741 is the slope and T is Time.

Concluding, below is a table with the forecast for the next 14 periods and as in the previous tables the MAD, MSE and MAPE, in order to compare and decide the most accurate forecasting methodology.

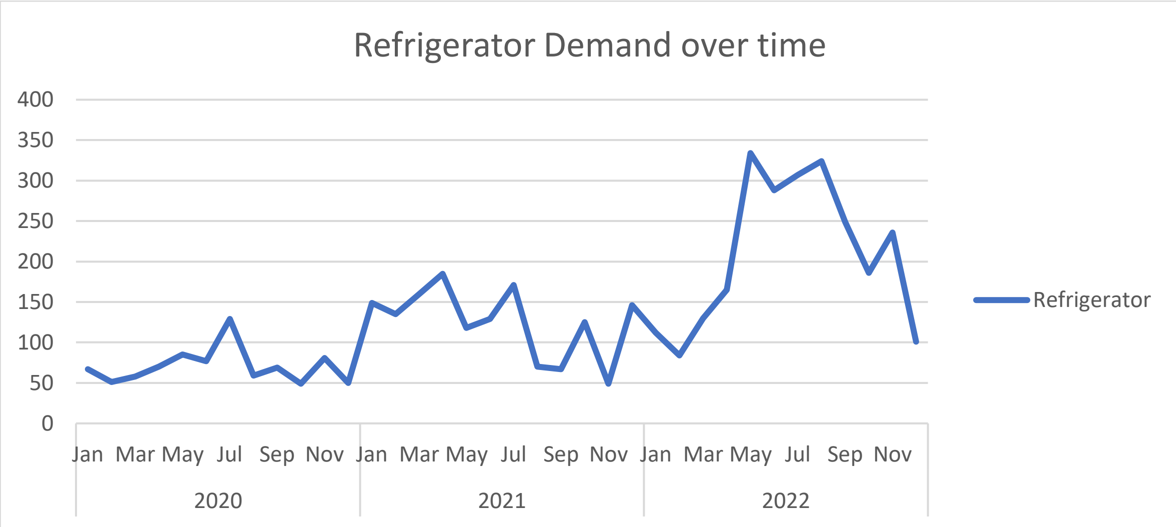
Table 3: TV_55 Linear Regression

Error Measures	**Value**	**Future Period**	**Forecast**
		37	**1522,09**
Bias (Mean Error)	0	**38**	**1556,83**
MAD (Mean Absolute Deviation)	321,93	**39**	**1591,58**
MSE (Mean Squared Error)	202.170,20	**40**	**1626,32**
Standard Error (denom=n-2=34)	462,67	**41**	**1661,06**
MAPE (Mean Absolute Percent Error)	60,21%	**42**	**1695,80**
Regression line		**43**	**1730,54**
Demand(y) = 236.684 + 34.741 * Time		**44**	**1765,28**
		45	**1800,02**
Statistics		**46**	**1834,76**
Correlation coefficient	0,63	**47**	**1869,50**
Coefficient of determination (r^2)	0,39	**48**	**1904,24**
		49	**1938,98**
		50	**1973,72**

Observing the above tables with the forecasting methodologies, looking at the MAD and MSE values, linear regression is the most accurate. However, if we take under consideration the MAPE, linear regression method is the less accurate of the three and the most accurate is the exponential smoothing.

Moving on to the next storage keeping unit, the Refrigerator we have collected the data of the demand exactly as the previous storage keeping unit. Using the MS Excel pivot table can be found in Appendix A and below is presented the figure accordingly.

Figure 2: Refrigerator demand over time



In the above figure with the monthly data of the demand for the storage keeping unit Refrigerator we are not able to distinguish a specific seasonality as in the previous case. In year 2020 the sales are significantly less than the years 2021 and 2022, which is again a clear sign of the pandemic COVID19. In year 2020 we are able to distinguish a very unstable demand. From the early months of 2021 the demand shows an important increase and from March 2022 the increase of demand is extremely higher.

Continuing with the same motive as the previous storage keeping unit, the first forecast methodology is the moving average with two (2) periods of time. Using the POM-MQ software we are able to retrieve the requested results which are presented in the Appendix A.

The below table presents the forecast for the next period as well as the MAD, MSE and MAPE.

Table 4: Refrigerator Moving Average

Measure	Value
Error Measures	
Bias (Mean Error)	3,96
MAD (Mean Absolute Deviation)	44,19
MSE (Mean Squared Error)	3.261,54
Standard Error (denom=n-2=32)	58,87
MAPE (Mean Absolute Percent Error)	37,31%
Forecast next period	**168,50**

The second forecast methodology is the exponential smoothing method. For this specific forecast it is decided to proceed with a smoothing factor a= 0,5. Using the POM-MQ we receive the table shown in the Appendix A.

As done previously, below is the table with the forecast of the next period, the MAD, MSE and MAPE:

Table 5: Refrigerator Exponential Smoothing

Measure	Value
Error Measures	
Bias (Mean Error)	5,73
MAD (Mean Absolute Deviation)	43,86
MSE (Mean Squared Error)	3.381,20
Standard Error (denom=n-2=33)	59,88
MAPE (Mean Absolute Percent Error)	37,17%
Forecast next period	**167,33**

Continuing with the third methodology which is the linear regression. Using the POM-MQ we receive the according table in the Appendix A. The regression equation is:

$$Y = 38{,}956 + 5{,}199 * T$$

As before, below is the table with the forecast of the next period, the MAD, MSE and MAPE:

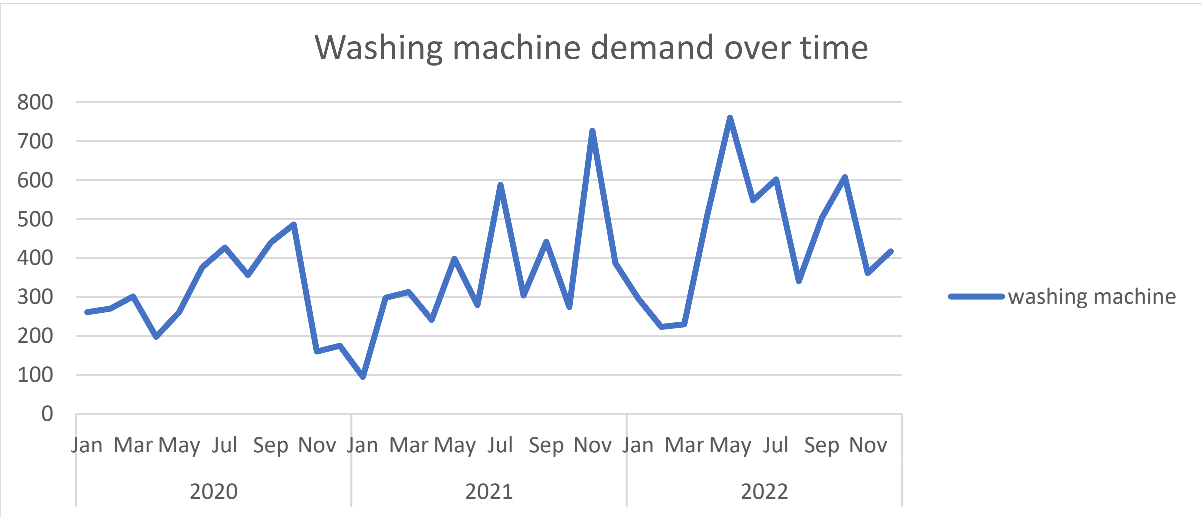
Table 6: Refrigerator Linear Regression

Measure	Value	Future Period	Forecast
Error Measures		**37**	**231,32**
Bias (Mean Error)	0,00	**38**	**236,52**
MAD (Mean Absolute Deviation)	46,67	**39**	**241,72**
MSE (Mean Squared Error)	3642,23	**40**	**246,92**
Standard Error (denom=n-2=34)	62,10	**41**	**252,12**
MAPE (Mean Absolute Percent Error)	42,69%	**42**	**257,32**
Regression line		**43**	**262,52**
Demand(y) = 38,956 + 5,199 * Time		**44**	**267,72**
		45	**272,92**
Statistics		**46**	**278,11**
Correlation coefficient	0,667	**47**	**283,31**
Coefficient of determination (r^2)	0,445	**48**	**288,51**
		49	**293,71**
		50	**298,91**

Concluding for the storage keeping unit Refrigerator, if we compare the MAD and the MAPE, the most accurate forecasting methodology is the Exponential Smoothing. However, if we compare the MSE the most accurate methodology would be the Moving Average.

Finally, the last storage keeping unit of this dissertation is the Washing Machine. With the same respect as the previous storage keeping units we have collected data with the Pivot table of the MS Excel and the table is available in the Appendix A and below is presented the figure accordingly.

Figure 3: Washing Machine demand over time



From the figure above we can see that we have an unstable demand through the years. In year 2020 the maximum demand was on October, in year 2021 was on November and in year 2022 the maximum demand was on May. There appears not to be any seasonality whatsoever but we are able to verify that after every maximum point of demand, follows a significant decrease of demand.

As per previous two storage keeping units, thus we will proceed with the three methodologies for to forecast the demand. In the first methodology of the moving average, as before I have chosen two periods and with the use of the POM-QM software the results are displayed in the Appendix A. Collecting all the relevant data as previously, Forecast, MAP, MSE and MAPE are presented in the next table:

Table 7: Washing Machine Moving Average

Measure	Value
Error Measures	
Bias (Mean Error)	5,79
MAD (Mean Absolute Deviation)	132,26
MSE (Mean Squared Error)	27341,57
Standard Error (denom=n-2=32)	170,44
MAPE (Mean Absolute Percent Error)	39,51%
Forecast next period	**389,00**

Moving on with the second forecasting methodology, the exponential smoothing with a smoothing factor a= 0,5. Using the POM-MQ the table with the results is available in Appendix A and below there is a table with the Forecast, MAP, MSE and MAPE.

Table 8: Washing Machine Exponential Smoothing

Measure	Value
Error Measures	
Bias (Mean Error)	9,94
MAD (Mean Absolute Deviation)	126,09
MSE (Mean Squared Error)	25042,19
Standard Error (denom=n-2=33)	162,97
MAPE (Mean Absolute Percent Error)	39,29%
Forecast next period	**435,01**

Finally the third forecasting methodology is the linear regression and using the POM-MQ the table with the results is available in Appendix A and below there is a table with the Forecast, MAP, MSE and MAPE.

Table 9: Washing Machine Linear Regression

Measure	Value	Future Period	Forecast
Error Measures		**37**	**500,30**
Bias (Mean Error)	0,00	**38**	**507,14**
MAD (Mean Absolute Deviation)	112,45	**39**	**513,98**
MSE (Mean Squared Error)	18720,68	**40**	**520,83**
Standard Error (denom=n-2=34)	140,79	**41**	**527,67**
MAPE (Mean Absolute Percent Error)	37,77%	**42**	**534,51**
Regression line		**43**	**541,36**
Demand(y) = 247,09 + 6,84 * Time		**44**	**548,20**
		45	**555,04**
Statistics		**46**	**561,89**
Correlation coefficient	0,46	**47**	**568,73**
Coefficient of determination (r^2)	0,21	**48**	**575,57**
		49	**582,42**
		50	**589,26**

The regression equation is:

$$Y = 247{,}09 + 6{,}84 * T$$

Concluding for the storage keeping unit Washing Machine, even if we compare the MAD, MSE or the MAPE, the most accurate forecasting methodology is the Linear Regression.

5. Monte Carlo simulation implemented on stohasting inventory

In the next and final part of this dissertation the objective is to perform to decide the EOQ and the Reorder point, considering the above forecasting methodologies and then perform a Monte Carlo simulation in order to present the results of the total cost, the optimal EOQ and Reorder point for all three storage keeping units. Each and every storage keeping unit will be presented separately. Firstly, to calculate the EOQ and the Reorder point, we will use the POM-QM software and then the Monte Carlo simulation will take place with the use of the Oracle Crystal Ball software.

Before the commencement of the above procedure, a few lines about Monte Carlo analysis will follow. The Monte Carlo simulation is a risk evaluation technique used to assess the uncertainties related to project timelines and budgets. It involves assigning probability ranges to various project parameters such as task durations, costs, and revenues. To capture the potential schedule variations for each task, a probability distribution needs to be established. This distribution function is commonly visualized as a graph, representing the likelihood of different schedule deviations from the primary estimate. Monte Carlo simulation has many optimizations and distribution function. The Beta function is widely adopted as the preferred form of distribution function. It illustrates that schedule deviations are most likely to occur around the forecasted schedule. A narrow range of deviations indicates that the task is expected to be completed earlier than planned, while a wider range of deviations extending beyond the planned schedule suggests a potential delay. The Beta function helps project managers understand the probability distribution of schedule deviations and make informed decisions based on the associated risks. Another widely used distribution function, which is used later in the dissertation is the Poisson distribution. The Poisson distribution is a discrete probability distribution that describes the occurrence of events within a specific time or space interval. It is also utilized in inventory management and real options analysis to simulate infrequent events like defaults or bankruptcies. The Poisson distribution is defined by a sole parameter, λ, which denotes the average rate of events happening in the specified interval (Davies, Coole, & Osipyw, 2014).

In order to continue with the Monte Carlo analysis, the software of Oracle Crystal Ball will be used. Oracle is a tech company with many applications in the business sector as well as cloud management. Crystal Ball one of the applications of Oracle, a risk analysis application which runs with many Windows software. In this case Crystal Ball will be running in MS Excel. Crystal Ball contains a vast number of templates which helps the user to proceed with the necessary analysis, in this case the Inventory Management. (Oracle Crystal Ball, 2023) As far as the Inventory Management is concerned, this software has translated the model from James R. Evans and David L. Olson, ‘’Introduction to Simulation and Risk Analysis’’ (1998) to the MS Excel cells and functions. The key concept of this model is that the two basic questions of the Inventory Management, how much additional inventory to order or produce and when to order or produce it – mentioned also in this dissertation - , are so much related that the managers should not take the decisions separately. The model that was developed is meant to calculate for the 52 weeks of the year the best possible order point and the reorder point minimizing the annual total costs. Typically, the goal is to minimize the overall costs associated with inventory, such as holding, ordering, shortage, and purchasing costs. In a continuous review system, inventory levels are constantly monitored by managers and when the inventory position reaches or falls below a specific level called the reorder point (R), managers place an order for a specific quantity known as the order quantity (Q). It is important to note that the reorder decision is based on the inventory position, which considers both orders yet to be received and inventory on-hand, rather than solely the inventory level. This approach avoids continuously placing orders as the inventory level decreases below R until the order is received. Upon receiving the order after the lead time, the inventory level increases from zero to Q, and the cycle repeats. Due to uncertainty in demand and variability in lead time, managers often maintain a safety stock to prevent shortages. Determining the optimal order quantities and reorder points to minimize expected total inventory costs in such situations can be challenging. Simulation models such as Monte Carlo, can provide insights in addressing this question.

As before, the first EOQ and Monte Carlo simulation will be conducted for the storage keeping unit, TV_55. To begin with, we need to create an EOQ model to define the order quantity Q and the reorder quantity R. This will be happening with the assistance of the POM-QM software. Taking into account the above forecasting methodologies and more specifically the MAD, the most accurate forecast is the Linear Regression. Filling in the necessary data in the EOQ model we received the below results.

Table 10: EOQ TV_55

DATA		RESULTS	
Parameter	Value	Parameter	Value
Demand rate(D)	20558	Optimal order quantity (Q*)	398
Setup/ordering cost(S)	100	Maximum Inventory Level (Imax)	398
Holding/carrying cost(H)	26	Average inventory	198,83
Days per year (D/d)	313	Orders per period(year)	51,7
Daily demand rate	65,68	Annual Setup cost	5169,66
Lead time (in days)	10	Annual Holding cost	5169,66
Safety stock	0	Total Inventory (Holding + Setup) Cost	10339,32
		Total Cost (including units)	10339,32
		Reorder point units	657

Demand rate (D) is the sum of the 12 next periods forecasted in the linear regression method. Since now we have retrieved the order quantity and the reorder point, we will set the initial inventory same as the optimal order quantity, 398 units. The lead time is 2 working weeks, which is 10 days. The ordering cost is 100 € and the holding cost is 0,5 € per week, so the Holding/carrying cost(H) is 0,5*52 = 26 €. In the EOQ model the days per year are calculated as 313, which is the number of working days as we will not count the weekends and we will assume that all the rest days of the year are working days. Now that we have set the decisions variables of order quantity and reorder point, we need to choose the distribution function. For this model we have chosen the Poisson distribution. The value of the Poisson distribution will be set the total value of the Demand (D) per the 52 weeks, which is equal to 395. The maximum trials used for the simulation is set to 1000 and the confidence level 95%. With the above mentioned data we have calculated the Total Annual Costs as they appear in the table below (full table can be found in Appendix B). The decision variables are the EOQ and the Reorder Point. In both the lower and upper bound is set as 200 and 1000 accordingly.

Table 11: TV_55 Total Cost

Hold Cost	Order Cost	Total Cost
€ 50,35	€ 2.600,00	€ 2.650,35

Implementing the Monte Carlo simulation with the OptQuest feature of Crystal Ball we receive the best solution of this case. In the figure below we are able to monitor the performance of the simulation and the results of the total cost.

Figure 4 Performance Chart MC TV_55

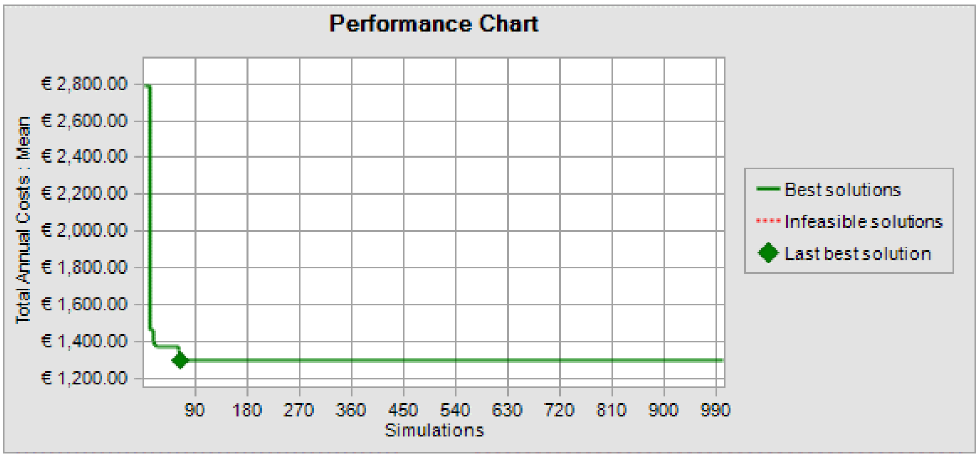


Table 12: Min Total Costs TV_55

Objectives	Minimize the Mean of Total Annual Costs	Best Solution:	€ 1.302,33

We can see that after 1000 solutions than were evaluated, objective the Mean of Total Annual Costs was improved from € 2.785,10 to € 1.302,33, a change of 53.24%.

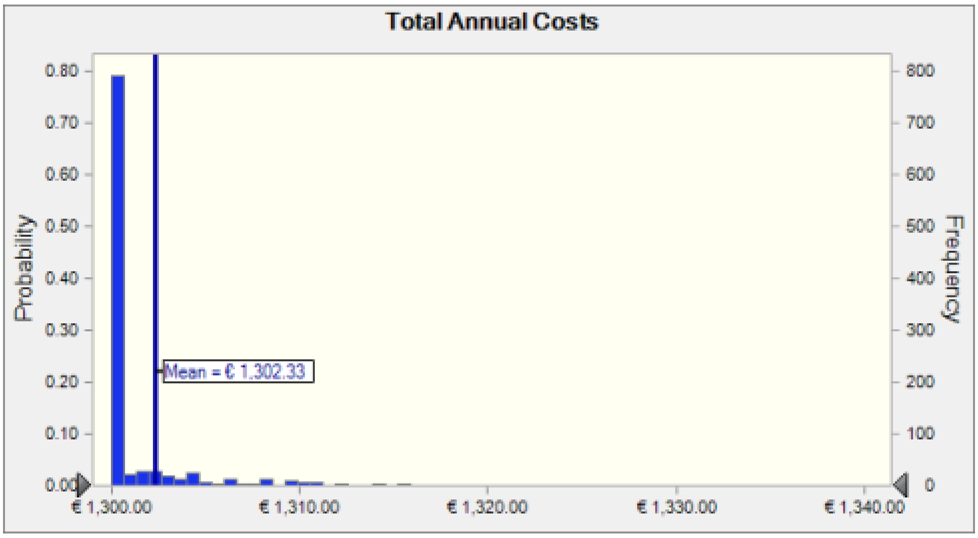
In the best possible solution, the below table shows the optimal order point and the reorder point.

Table 13: Optimal Q & R TV_55

Decision variables	Best Solution:
Order Quantity	355
Reorder Point	200

Moreover, below is the histogram of the Total Annual cost chart of the 1000 trials during the simulation.

Figure 5: Total Annual Costs MC TV_55



Moving on with the next storage keeping unit, the Refrigerator. With the assistance of the POM-QM software, we run the EOQ model. Taking into account the above forecasting methodologies and more specifically the MAD, the most accurate forecast is the Exponential Smoothing. Filling in the necessary data in the EOQ model we received the below results.

Table 14: EOQ Refrigerator

DATA		RESULTS	
Parameter	Value	Parameter	Value
Demand rate(D)	2008	Optimal order quantity (Q*)	96
Setup/ordering cost(S)	90	Maximum Inventory Level (Imax)	96
Holding/carrying cost(H)	39	Average inventory	48,13
Days per year (D/d)	313	Orders per period(year)	20,86
Daily demand rate	6,42	Annual Setup cost	1877,24
Lead time (in days)	10	Annual Holding cost	1877,24
		Total Inventory (Holding + Setup) Cost	3754,49
		Total Cost (including units)	3754,49
		Reorder point	64

Assuming the forecast being the same for 12 months as the next forecasted period of the Exponential Smoothing methodology, the Demand D is 2008 units. Since now we have retrieved the order quantity and the reorder point, we will set the initial inventory same as the optimal order quantity, 96 units. The lead time is the same as the TV_55, 2 working weeks, which is 10 days. The ordering cost is 900 € and the holding cost is 0,75 € per week, so the Holding/carrying cost(H) is 0,75*52 = 39 €. In the EOQ model the days per year are calculated as 313, which is the number of working days as we will not count the weekends and we will assume that all the rest days of the year are working days. Once again, we have chosen the Poisson distribution. The value of the Poisson distribution will be set the total value of the Demand (D) per the 52 weeks, which is equal to 39. The maximum trials used for the simulation is set again to 1000 as well as the confidence level 95%. With the above mentioned data we have calculated the Total Annual Costs as they appear in the table below (full table can be found in Appendix B). The decision variables are the EOQ and the Reorder Point. In both the lower and upper bound is set as 30 and 250 accordingly.

Table 15: Total Cost Refrigerator

Hold Cost	Order Cost	Total Cost
€ 1.013,82	€ 1.620,00	€ 2.633,82

Implementing the Monte Carlo simulation with the OptQuest feature of Crystal Ball we receive the best solution of this case. In the figure below we are able to monitor the performance of the simulation and the results of the total cost.

Table 16: Performance Chart Refrigerator

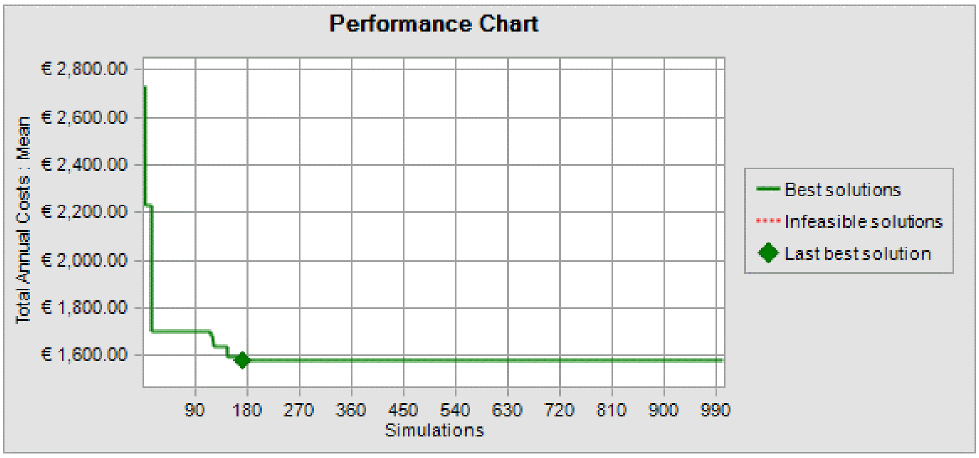


Table 17: Min Total Cost Refrigerator

Objectives	Minimize the Mean of Total Annual Costs	Best Solution:	€ 1.581,36

We can see that after 1000 solutions than were evaluated, objective the Mean of Total Annual Costs was improved from € 2,730.76 to € 1,581.36, a change of 42.09%.

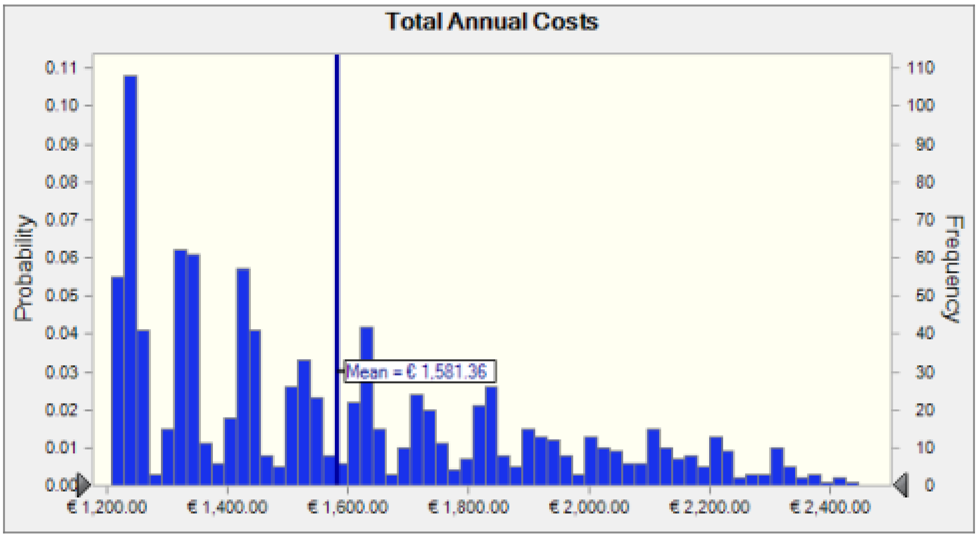
In the best possible solution, the below table shows the optimal order point and the reorder point.

Table 18: Optimal Q&R Refrigerator

Decision variables	Best Solution:
Order Quantity	45
Reorder Point	30

Finally, below is the histogram of the Total Annual cost chart of the 1000 trials during the simulation.

Table 19: Total Annual Costs MC Refrigerator



Moving on with the third storage keeping unit the Washing Machine. To begin with, we need to create an EOQ model to define the order quantity Q and the reorder quantity R. Taking into account the above forecasting methodologies, the most accurate forecast is the Linear Regression for all three MAD, MSE and MAPE. Filling in the necessary data in the EOQ model we received the below results.

Table 20: EOQ Washing Machine

DATA		RESULTS	
Parameter	Value	Parameter	Value
Demand rate(D)	6455	Optimal order quantity (Q*)	173
Setup/ordering cost(S)	90	Maximum Inventory Level (Imax)	173
Holding/carrying cost(H)	39	Average inventory	86,3
Days per year (D/d)	313	Orders per period(year)	37,4
Daily demand rate	20,62	Annual Setup cost	3365,79
Lead time (in days)	10	Annual Holding cost	3365,79
		Total Inventory (Holding + Setup) Cost	6731,58
		Total Cost (including units)	6731,58
		Reorder point	206

As before, the Demand rate(D) is the sum of the 12 next periods forecasted in the linear regression method. Since now we have retrieved the order quantity and the reorder point, we will set the initial inventory same as the optimal order quantity, 173 units. The lead time is 2 working weeks, which is 10 days. The ordering cost is 90 € and the holding cost is 0,75 € per week, so the Holding/carrying cost(H) is 0,75*52 = 39 €. In the EOQ model the days per year are calculated as 313, which is the number of working days as we will not count the weekends and we will assume that all the rest days of the year are working days. Now that we have set the decisions variables of order quantity and reorder point, we need to choose the distribution function. For this model we have chosen the Poisson distribution. The value of the Poisson distribution will be set the total value of the Demand (D) per the 52 weeks, which is equal to 124. The maximum trials used for the simulation is set to 1000 and the confidence level 95%. With the above mentioned data we have calculated the Total Annual Costs as they appear in the table below (full table can be found in Appendix B). The decision variables are the EOQ and the Reorder Point. In both the lower and upper bound is set as 50 and 350 accordingly.

Table 21: Total Cost Washing Machine

Hold Cost	Order Cost	Total Cost
€ 989,42	€ 2.340,00	€ 3.329,42

Implementing the Monte Carlo simulation with the OptQuest feature of Crystal Ball we receive the best solution of this case. In the figure below we are able to monitor the performance of the simulation and the results of the total cost.

Table 22: Performance Chart Washing Machine

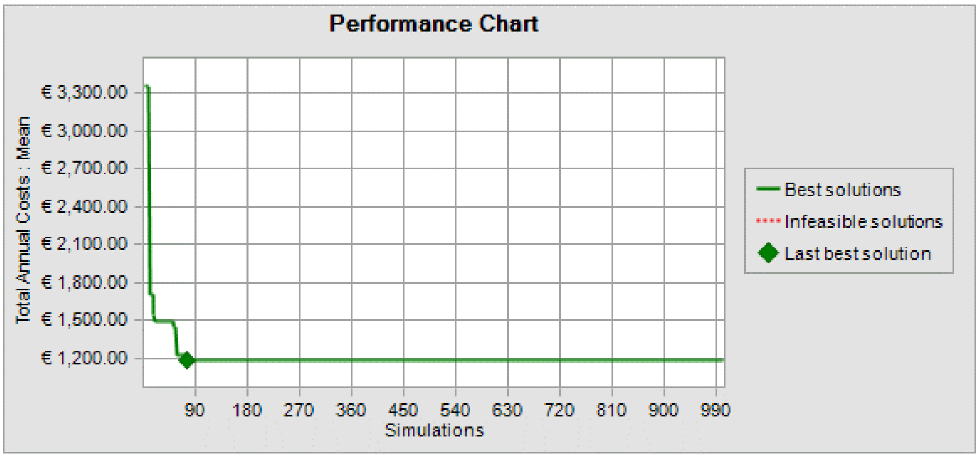


Table 23: Min Total Cost Washing Machine

Objectives	Minimize the Mean of Total Annual Costs	Best Solution:	€ 1.187,76

We can see that after 1000 solutions than were evaluated, objective the Mean of Total Annual Costs was improved from € 3,352.57 to € 1,187.76, a change of 64.57%.

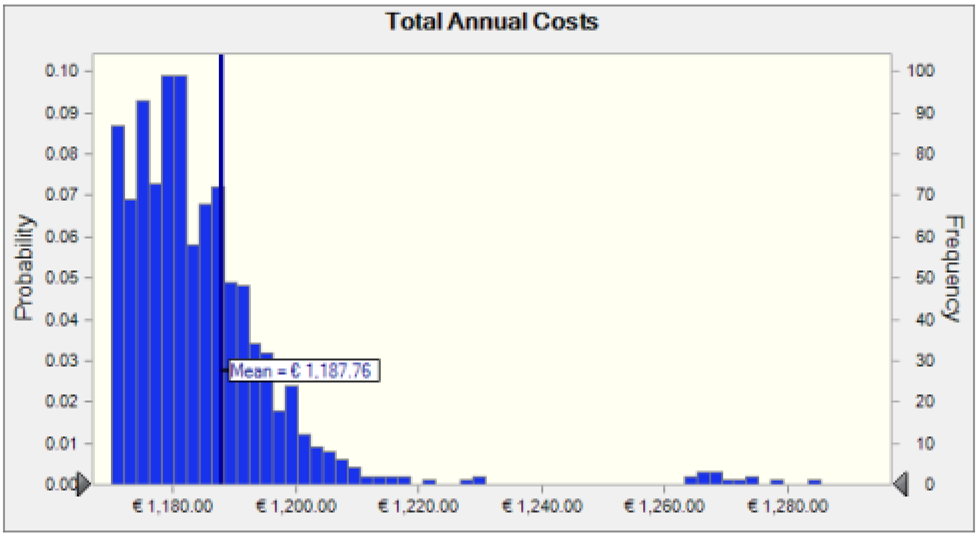
In the best possible solution, the below table shows the optimal order point and the reorder point.

Table 24: Optimal Q&R Washing Machine

Decision variables	Best Solution:
Order Quantity	115
Reorder Point	50

Finally, below is the histogram of the Total Annual cost chart of the 1000 trials during the simulation.

Table 25 Total Annual Cost MC Washing Machine



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Appendix A: “Forecasting Tables”

Table 26: Forecasting TV_55

Forecasting		Error analysis														
Data		Moving averages - 2 period moving average					Regression/Trend analysis					Exponential smoothing				
Period	Demand	Forecast	Error	Absolute	Squared	|% Error|	Forecast	Error	Absolute	Squared	|% Error|	Forecast	Error	Absolute	Squared	|% Error|
January	62						271,42	-209,42	209,42	43858,80	3,38	62,00				
February	275						306,17	-31,17	31,17	971,30	0,11	62,00	213,00	213,00	45369,00	0,77
March	522	168,50	353,50	353,50	124962,25	0,68	340,91	181,09	181,09	32794,85	0,35	168,50	353,50	353,50	124962,25	0,68
April	429	398,50	30,50	30,50	930,25	0,07	375,65	53,35	53,35	2846,51	0,12	345,25	83,75	83,75	7014,06	0,20
May	483	475,50	7,50	7,50	56,25	0,02	410,39	72,61	72,61	5272,49	0,15	387,13	95,88	95,88	9192,02	0,20
June	239	456,00	-217,00	217,00	47089,00	0,91	445,13	-206,13	206,13	42489,13	0,86	435,06	-196,06	196,06	38440,50	0,82
July	968	361,00	607,00	607,00	368449,00	0,63	479,87	488,13	488,13	238271,18	0,50	337,03	630,97	630,97	398121,56	0,65
August	646	603,50	42,50	42,50	1806,25	0,07	514,61	131,39	131,39	17263,20	0,20	652,52	-6,52	6,52	42,45	0,01
September	608	807,00	-199,00	199,00	39601,00	0,33	549,35	58,65	58,65	3439,67	0,10	649,26	-41,26	41,26	1702,21	0,07
October	954	627,00	327,00	327,00	106929,00	0,34	584,09	369,91	369,91	136831,85	0,39	628,63	325,37	325,37	105866,35	0,34
November	650	781,00	-131,00	131,00	17161,00	0,20	618,83	31,17	31,17	971,39	0,05	791,31	-141,31	141,31	19969,77	0,22
December	202	802,00	-600,00	600,00	360000,00	2,97	653,57	-451,57	451,57	203918,81	2,24	720,66	-518,66	518,66	269005,32	2,57
January	319	426,00	-107,00	107,00	11449,00	0,34	688,31	-369,31	369,31	136393,20	1,16	461,33	-142,33	142,33	20257,43	0,45
February	147	260,50	-113,50	113,50	12882,25	0,77	723,06	-576,06	576,06	331839,71	3,92	390,16	-243,16	243,16	59128,88	1,65
March	490	233,00	257,00	257,00	66049,00	0,52	757,80	-267,80	267,80	71714,75	0,55	268,58	221,42	221,42	49025,86	0,45
April	626	318,50	307,50	307,50	94556,25	0,49	792,54	-166,54	166,54	27734,54	0,27	379,29	246,71	246,71	60865,29	0,39
May	506	558,00	-52,00	52,00	2704,00	0,10	827,28	-321,28	321,28	103219,36	0,63	502,65	3,35	3,35	11,25	0,01
June	852	566,00	286,00	286,00	81796,00	0,34	862,02	-10,02	10,02	100,37	0,01	504,32	347,68	347,68	120879,46	0,41
July	818	679,00	139,00	139,00	19321,00	0,17	896,76	-78,76	78,76	6203,03	0,10	678,16	139,84	139,84	19554,84	0,17
August	873	835,00	38,00	38,00	1444,00	0,04	931,50	-58,50	58,50	3422,26	0,07	748,08	124,92	124,92	15604,83	0,14
September	2274	845,50	1428,50	1428,50	2040612,25	0,63	966,24	1307,76	1307,76	1710233,91	0,58	810,54	1463,46	1463,46	2141714,16	0,64
October	2313	1573,50	739,50	739,50	546860,25	0,32	1000,98	1312,02	1312,02	1721392,07	0,57	1542,27	770,73	770,73	594024,47	0,33
November	748	2293,50	-1545,50	1545,50	2388570,25	2,07	1035,72	-287,72	287,72	82784,23	0,38	1927,64	-1179,64	1179,64	1391538,94	1,58
December	392	1530,50	-1138,50	1138,50	1296182,25	2,90	1070,46	-678,46	678,46	460312,42	1,73	1337,82	-945,82	945,82	894570,83	2,41
January	1342	570,00	772,00	772,00	595984,00	0,58	1105,20	236,80	236,80	56072,31	0,18	864,91	477,09	477,09	227616,04	0,36
February	1510	867,00	643,00	643,00	413449,00	0,43	1139,94	370,06	370,06	136940,80	0,25	1103,45	406,55	406,55	165279,34	0,27
March	847	1426,00	-579,00	579,00	335241,00	0,68	1174,69	-327,69	327,69	107377,90	0,39	1306,73	-459,73	459,73	211349,09	0,54
April	726	1178,50	-452,50	452,50	204756,25	0,62	1209,43	-483,43	483,43	233701,15	0,67	1076,86	-350,86	350,86	123105,26	0,48
May	1267	786,50	480,50	480,50	230880,25	0,38	1244,17	22,83	22,83	521,33	0,02	901,43	365,57	365,57	133640,11	0,29
June	812	996,50	-184,50	184,50	34040,25	0,23	1278,91	-466,91	466,91	218003,14	0,58	1084,22	-272,22	272,22	74101,50	0,34

July	1118	1039,50	78,50	78,50	6162,25	0,07	1313,65	-195,65	195,65	38278,48	0,17	948,11	169,89	169,89	28863,31	0,15
August	1163	965,00	198,00	198,00	39204,00	0,17	1348,39	-185,39	185,39	34369,33	0,16	1033,05	129,95	129,95	16885,97	0,11
September	2353	1140,50	1212,50	1212,50	1470156,25	0,52	1383,13	969,87	969,87	940646,93	0,41	1098,03	1254,97	1254,97	1574957,26	0,53
October	1607	1758,00	-151,00	151,00	22801,00	0,09	1417,87	189,13	189,13	35769,68	0,12	1725,51	-118,51	118,51	14045,45	0,07
November	1278	1980,00	-702,00	702,00	492804,00	0,55	1452,61	-174,61	174,61	30489,37	0,14	1666,26	-388,26	388,26	150743,30	0,30
December	1239	1442,50	-203,50	203,50	41412,25	0,16	1487,35	-248,35	248,35	61679,14	0,20	1472,13	-233,13	233,13	54348,84	0,19
		Total	1572,00	14324,00	11516301,00	19,38	Total	0,00	11589,52	7278128,54	21,68	Total	2587,13	13062,05	9161797,20	18,80
		Average	46,24	421,29	338714,74	0,57	Average	0,00	321,93	202170,24	0,60	Average	73,92	373,20	261765,63	0,54
			Bias	MAD	MSE	MAPE		Bias	MAD	MSE	MAPE		Bias	MAD	MSE	MAPE
				SE	599,90				SE	462,67				SE	526,91	

Table 27: Forecasting Refrigerator

Data		**Error analysis**														
Forecasting		Moving averages - 2 period moving average					Exponential smoothing					Regression/Trend analysis				
Period	Demand	Forecast	Error	Absolute	Squared	|% Error|	Forecast	Error	Absolute	Squared	|% Error|	Forecast	Error	Absolute	Squared	|% Error|
January	67						67,00					44,15	22,85	22,85	521,91	0,34
February	51						67,00	-16,00	16,00	256,00	0,31	49,35	1,65	1,65	2,71	0,03
March	58	59,00	-1,00	1,00	1,00	0,02	59,00	-1,00	1,00	1,00	0,02	54,55	3,45	3,45	11,88	0,06
April	70	54,50	15,50	15,50	240,25	0,22	58,50	11,50	11,50	132,25	0,16	59,75	10,25	10,25	105,02	0,15
May	85	64,00	21,00	21,00	441,00	0,25	64,25	20,75	20,75	430,56	0,24	64,95	20,05	20,05	401,96	0,24
June	77	77,50	-0,50	0,50	0,25	0,01	74,63	2,38	2,38	5,64	0,03	70,15	6,85	6,85	46,92	0,09
July	129	81,00	48,00	48,00	2304,00	0,37	75,81	53,19	53,19	2828,91	0,41	75,35	53,65	53,65	2878,40	0,42
August	59	103,00	-44,00	44,00	1936,00	0,75	102,41	-43,41	43,41	1884,10	0,74	80,55	-21,55	21,55	464,33	0,37
September	69	94,00	-25,00	25,00	625,00	0,36	80,70	-11,70	11,70	136,96	0,17	85,75	-16,75	16,75	280,48	0,24
October	49	64,00	-15,00	15,00	225,00	0,31	74,85	-25,85	25,85	668,30	0,53	90,95	-41,95	41,95	1759,51	0,86
November	81	59,00	22,00	22,00	484,00	0,27	61,93	19,07	19,07	363,83	0,24	96,15	-15,15	15,15	229,39	0,19
December	50	65,00	-15,00	15,00	225,00	0,30	71,46	-21,46	21,46	460,66	0,43	101,34	-51,34	51,34	2636,28	1,03
January	149	65,50	83,50	83,50	6972,25	0,56	60,73	88,27	88,27	7791,34	0,59	106,54	42,46	42,46	1802,53	0,28
February	135	99,50	35,50	35,50	1260,25	0,26	104,87	30,13	30,13	908,07	0,22	111,74	23,26	23,26	540,89	0,17
March	160	142,00	18,00	18,00	324,00	0,11	119,93	40,07	40,07	1605,38	0,25	116,94	43,06	43,06	1853,99	0,27
April	185	147,50	37,50	37,50	1406,25	0,20	139,97	45,03	45,03	2028,02	0,24	122,14	62,86	62,86	3951,24	0,34
May	118	172,50	-54,50	54,50	2970,25	0,46	162,48	-44,48	44,48	1978,76	0,38	127,34	-9,34	9,34	87,24	0,08
June	129	151,50	-22,50	22,50	506,25	0,17	140,24	-11,24	11,24	126,37	0,09	132,54	-3,54	3,54	12,53	0,03
July	171	123,50	47,50	47,50	2256,25	0,28	134,62	36,38	36,38	1323,45	0,21	137,74	33,26	33,26	1106,33	0,19
August	70	150,00	-80,00	80,00	6400,00	1,14	152,81	-82,81	82,81	6857,56	1,18	142,94	-72,94	72,94	5319,88	1,04
September	67	120,50	-53,50	53,50	2862,25	0,80	111,41	-44,41	44,41	1971,82	0,66	148,14	-81,14	81,14	6583,15	1,21
October	125	68,50	56,50	56,50	3192,25	0,45	89,20	35,80	35,80	1281,45	0,29	153,34	-28,34	28,34	802,91	0,23
November	49	96,00	-47,00	47,00	2209,00	0,96	107,10	-58,10	58,10	3375,76	1,19	158,53	-109,53	109,53	11997,88	2,24
December	146	87,00	59,00	59,00	3481,00	0,40	78,05	67,95	67,95	4617,11	0,47	163,73	-17,73	17,73	314,49	0,12

January	112	97,50	14,50	14,50	210,25	0,13	112,03	-0,03	0,03	0,00	0,00	168,93	-56,93	56,93	3241,37	0,51
February	84	129,00	-45,00	45,00	2025,00	0,54	112,01	-28,01	28,01	784,71	0,33	174,13	-90,13	90,13	8123,80	1,07
March	130	98,00	32,00	32,00	1024,00	0,25	98,01	31,99	31,99	1023,59	0,25	179,33	-49,33	49,33	2433,57	0,38
April	165	107,00	58,00	58,00	3364,00	0,35	114,00	51,00	51,00	2600,68	0,31	184,53	-19,53	19,53	381,43	0,12
May	334	147,50	186,50	186,50	34782,25	0,56	139,50	194,50	194,50	37829,63	0,58	189,73	144,27	144,27	20814,00	0,43
June	288	249,50	38,50	38,50	1482,25	0,13	236,75	51,25	51,25	2626,48	0,18	194,93	93,07	93,07	8662,30	0,32
July	307	311,00	-4,00	4,00	16,00	0,01	262,38	44,62	44,62	1991,36	0,15	200,13	106,87	106,87	11421,70	0,35
August	324	297,50	26,50	26,50	702,25	0,08	284,69	39,31	39,31	1545,46	0,12	205,33	118,67	118,67	14083,35	0,37
September	249	315,50	-66,50	66,50	4422,25	0,27	304,34	-55,34	55,34	3062,94	0,22	210,53	38,47	38,47	1480,26	0,15
October	186	286,50	-100,50	100,50	10100,25	0,54	276,67	-90,67	90,67	8221,40	0,49	215,72	-29,72	29,72	883,57	0,16
November	236	217,50	18,50	18,50	342,25	0,08	231,34	4,66	4,66	21,75	0,02	220,92	15,08	15,08	227,29	0,06
December	101	211,00	-110,00	110,00	12100,00	1,09	233,67	-132,67	132,67	17600,79	1,31	226,12	-125,12	125,12	15655,80	1,24
		Total	134,50	1502,50	110892,25	12,68	Total	200,67	1535,04	118342,11	13,01	Total	0,00	1680,13	131120,30	15,37
		Average	3,96	44,19	3261,54	0,37	Average	5,73	43,86	3381,20	0,37	Average	0,00	46,67	3642,23	0,43
			Bias	MAD	MSE	MAPE		Bias	MAD	MSE	MAPE		Bias	MAD	MSE	MAPE
				SE	58,87				SE	59,88				SE	62,10	

Table 28: Forecasting Washing Machine

Data		Error analysis														
Forecasting		Moving averages - 2 period moving average					Exponential smoothing					Regression/Trend analysis				
Period	Demand	Forecast	Error	Absolute	Squared	|% Error|	Forecast	Error	Absolute	Squared	|% Error|	Forecast	Error	Absolute	Squared	|% Error|
January	261						261,00					253,94	7,06	7,06	49,91	0,03
February	270						261,00	9,00	9,00	81,00	0,03	260,78	9,22	9,22	85,03	0,03
March	301	265,50	35,50	35,50	1260,25	0,12	265,50	35,50	35,50	1260,25	0,12	267,62	33,38	33,38	1114,08	0,11
April	198	285,50	-87,50	87,50	7656,25	0,44	283,25	-85,25	85,25	7267,56	0,43	274,47	-76,47	76,47	5846,98	0,39
May	261	249,50	11,50	11,50	132,25	0,04	240,63	20,38	20,38	415,14	0,08	281,31	-20,31	20,31	412,45	0,08
June	376	229,50	146,50	146,50	21462,25	0,39	250,81	125,19	125,19	15671,91	0,33	288,15	87,85	87,85	7717,22	0,23
July	427	318,50	108,50	108,50	11772,25	0,25	313,41	113,59	113,59	12903,54	0,27	295,00	132,00	132,00	17425,14	0,31
August	356	401,50	-45,50	45,50	2070,25	0,13	370,20	-14,20	14,20	201,73	0,04	301,84	54,16	54,16	2933,41	0,15
September	440	391,50	48,50	48,50	2352,25	0,11	363,10	76,90	76,90	5913,37	0,17	308,68	131,32	131,32	17244,31	0,30
October	486	398,00	88,00	88,00	7744,00	0,18	401,55	84,45	84,45	7131,67	0,17	315,53	170,47	170,47	29061,46	0,35
November	160	463,00	-303,00	303,00	91809,00	1,89	443,78	-283,78	283,78	80528,47	1,77	322,37	-162,37	162,37	26363,74	1,01
December	175	323,00	-148,00	148,00	21904,00	0,85	301,89	-126,89	126,89	16100,49	0,73	329,21	-154,21	154,21	23781,50	0,88
January	95	167,50	-72,50	72,50	5256,25	0,76	238,44	-143,44	143,44	20576,14	1,51	336,06	-241,06	241,06	58107,95	2,54
February	298	135,00	163,00	163,00	26569,00	0,55	166,72	131,28	131,28	17233,93	0,44	342,90	-44,90	44,90	2015,94	0,15
March	313	196,50	116,50	116,50	13572,25	0,37	232,36	80,64	80,64	6502,65	0,26	349,74	-36,74	36,74	1350,02	0,12
April	241	305,50	-64,50	64,50	4160,25	0,27	272,68	-31,68	31,68	1003,65	0,13	356,59	-115,59	115,59	13360,13	0,48
May	398	277,00	121,00	121,00	14641,00	0,30	256,84	141,16	141,16	19926,08	0,35	363,43	34,57	34,57	1195,13	0,09
June	279	319,50	-40,50	40,50	1640,25	0,15	327,42	-48,42	48,42	2344,51	0,17	370,27	-91,27	91,27	8330,72	0,33
July	588	338,50	249,50	249,50	62250,25	0,42	303,21	284,79	284,79	81105,31	0,48	377,12	210,88	210,88	44472,01	0,36
August	304	433,50	-129,50	129,50	16770,25	0,43	445,61	-141,61	141,61	20051,98	0,47	383,96	-79,96	79,96	6393,52	0,26

September	442	446,00	-4,00	4,00	16,00	0,01	374,80	67,20	67,20	4515,50	0,15	390,80	51,20	51,20	2621,15	0,12
October	274	373,00	-99,00	99,00	9801,00	0,36	408,40	-134,40	134,40	18063,70	0,49	397,65	-123,65	123,65	15288,39	0,45
November	727	358,00	369,00	369,00	136161,00	0,51	341,20	385,80	385,80	148841,15	0,53	404,49	322,51	322,51	104012,95	0,44
December	387	500,50	-113,50	113,50	12882,25	0,29	534,10	-147,10	147,10	21638,50	0,38	411,33	-24,33	24,33	592,09	0,06
January	296	557,00	-261,00	261,00	68121,00	0,88	460,55	-164,55	164,55	27076,75	0,56	418,18	-122,18	122,18	14927,06	0,41
February	223	341,50	-118,50	118,50	14042,25	0,53	378,28	-155,28	155,28	24110,35	0,70	425,02	-202,02	202,02	40811,97	0,91
March	230	259,50	-29,50	29,50	870,25	0,13	300,64	-70,64	70,64	4989,66	0,31	431,86	-201,86	201,86	40748,71	0,88
April	507	226,50	280,50	280,50	78680,25	0,55	265,32	241,68	241,68	58409,82	0,48	438,71	68,29	68,29	4664,01	0,13
May	760	368,50	391,50	391,50	153272,25	0,52	386,16	373,84	373,84	139756,81	0,49	445,55	314,45	314,45	98878,90	0,41
June	548	633,50	-85,50	85,50	7310,25	0,16	573,08	-25,08	25,08	628,99	0,05	452,39	95,61	95,61	9140,66	0,17
July	602	654,00	-52,00	52,00	2704,00	0,09	560,54	41,46	41,46	1718,94	0,07	459,24	142,76	142,76	20381,39	0,24
August	341	575,00	-234,00	234,00	54756,00	0,69	581,27	-240,27	240,27	57729,64	0,70	466,08	-125,08	125,08	15645,00	0,37
September	503	471,50	31,50	31,50	992,25	0,06	461,13	41,87	41,87	1752,68	0,08	472,92	30,08	30,08	904,61	0,06
October	608	422,00	186,00	186,00	34596,00	0,31	482,07	125,93	125,93	15859,00	0,21	479,77	128,23	128,23	16443,78	0,21
November	361	555,50	-194,50	194,50	37830,25	0,54	545,03	-184,03	184,03	33868,42	0,51	486,61	-125,61	125,61	15777,89	0,35
December	417	484,50	-67,50	67,50	4556,25	0,16	453,02	-36,02	36,02	1297,21	0,09	493,45	-76,45	76,45	5845,13	0,18
		Total	197,00	4497,00	929613,50	13,43	Total	348,02	4413,28	876476,52	13,75	Total	0,00	4048,11	673944,33	13,60
		Average	5,79	132,26	27341,57	0,40	Average	9,94	126,09	25042,19	0,39	Average	0,00	112,45	18720,68	0,38
			Bias	MAD	MSE	MAPE		Bias	MAD	MSE	MAPE		Bias	MAD	MSE	MAPE
				SE	170,44				SE	162,97				SE	140,79	

Appendix B: "Monte Carlo simulation tables"

Table 29: Monte Carlo TV_55

Order Quantity	398	*units*	Order Cost	€ 100,00			
Reorder Point	657	*units*	Holding Cost	€ 0,50			
Initial Inventory	398	*units*			Total Annual Costs		
Lead time	2	*Working weeks*			€ 50,35	€ 2.600,00	€ 2.650,35

Week	Beg Inv Pos	Beg Inv	Order Rec'd	Units Rec'd	Dmd	End Inv	Lost Sales	Order Placed?	Ending Inv Pos	Week Due	Hold Cost	Order Cost	Total Cost
1	398	398		0	395,4	3	0	TRUE	793	4	€ 1,32	€ 100,00	€ 101,33
2	793	2,65		0	395,4	0	393	TRUE	1189	5	€ -	€ 100,00	€ 100,00
3	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
4	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
5	793	2,65	TRUE	398	395,4	5	0	TRUE	796	8	€ 2,65	€ 100,00	€ 102,65
6	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	9	€ -	€ 100,00	€ 100,00
7	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
8	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
9	793	2,65	TRUE	398	395,4	5	0	TRUE	796	12	€ 2,65	€ 100,00	€ 102,65

10	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	13	€ -	€ 100,00	€ 100,00
11	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
12	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
13	793	2,65	TRUE	398	395,4	5	0	TRUE	796	16	€ 2,65	€ 100,00	€ 102,65
14	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	17	€ -	€ 100,00	€ 100,00
15	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
16	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
17	793	2,65	TRUE	398	395,4	5	0	TRUE	796	20	€ 2,65	€ 100,00	€ 102,65
18	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	21	€ -	€ 100,00	€ 100,00
19	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
20	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
21	793	2,65	TRUE	398	395,4	5	0	TRUE	796	24	€ 2,65	€ 100,00	€ 102,65
22	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	25	€ -	€ 100,00	€ 100,00
23	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
24	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
25	793	2,65	TRUE	398	395,4	5	0	TRUE	796	28	€ 2,65	€ 100,00	€ 102,65
26	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	29	€ -	€ 100,00	€ 100,00
27	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
28	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
29	793	2,65	TRUE	398	395,4	5	0	TRUE	796	32	€ 2,65	€ 100,00	€ 102,65
30	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	33	€ -	€ 100,00	€ 100,00
31	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
32	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
33	793	2,65	TRUE	398	395,4	5	0	TRUE	796	36	€ 2,65	€ 100,00	€ 102,65
34	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	37	€ -	€ 100,00	€ 100,00
35	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
36	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
37	793	2,65	TRUE	398	395,4	5	0	TRUE	796	40	€ 2,65	€ 100,00	€ 102,65
38	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	41	€ -	€ 100,00	€ 100,00
39	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
40	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
41	793	2,65	TRUE	398	395,4	5	0	TRUE	796	44	€ 2,65	€ 100,00	€ 102,65
42	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	45	€ -	€ 100,00	€ 100,00
43	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
44	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
45	793	2,65	TRUE	398	395,4	5	0	TRUE	796	48	€ 2,65	€ 100,00	€ 102,65
46	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	49	€ -	€ 100,00	€ 100,00
47	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
48	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32
49	793	2,65	TRUE	398	395,4	5	0	TRUE	796	52	€ 2,65	€ 100,00	€ 102,65
50	796	5,3	FALSE	0	395,4	0	390	TRUE	1189	53	€ -	€ 100,00	€ 100,00
51	1189	0	FALSE	0	395,4	0	395	FALSE	1189		€ -	€ -	€ -
52	1189	0	TRUE	398	395,4	3	0	FALSE	793		€ 1,32	€ -	€ 1,32

Table 30: Monte Carlo Refrigerator

Order Quantity	96	*units*	Order Cost	€ 90,00			
Reorder Point	64	*units*	Holding Cost	€ 0,75			
Initial Inventory	96	*units*			Total Annual Costs		
Lead time	2	*Working weeks*			€ 1.013,82	€ 1.620,00	€ 2.633,82

Week	Beg Inv Pos	Beg Inv	Order Rec'd	Units Rec'd	Dmd	End Inv	Lost Sales	Order Placed?	Ending Inv Pos	Week Due	Hold Cost	Order Cost	Total Cost
1	96	96		0	39	57	0	TRUE	153	4	€ 43,04	€ 90,00	€ 133,04
2	153	57,4		0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
3	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
4	96	0	TRUE	96	39	57	0	TRUE	153	7	€ 43,04	€ 90,00	€ 133,04
5	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
6	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
7	96	0	TRUE	96	39	57	0	TRUE	153	10	€ 43,04	€ 90,00	€ 133,04
8	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
9	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
10	96	0	TRUE	96	39	57	0	TRUE	153	13	€ 43,04	€ 90,00	€ 133,04
11	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
12	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
13	96	0	TRUE	96	39	57	0	TRUE	153	16	€ 43,04	€ 90,00	€ 133,04
14	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
15	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
16	96	0	TRUE	96	39	57	0	TRUE	153	19	€ 43,04	€ 90,00	€ 133,04
17	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
18	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
19	96	0	TRUE	96	39	57	0	TRUE	153	22	€ 43,04	€ 90,00	€ 133,04
20	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
21	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
22	96	0	TRUE	96	39	57	0	TRUE	153	25	€ 43,04	€ 90,00	€ 133,04
23	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
24	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
25	96	0	TRUE	96	39	57	0	TRUE	153	28	€ 43,04	€ 90,00	€ 133,04
26	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
27	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
28	96	0	TRUE	96	39	57	0	TRUE	153	31	€ 43,04	€ 90,00	€ 133,04
29	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
30	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
31	96	0	TRUE	96	39	57	0	TRUE	153	34	€ 43,04	€ 90,00	€ 133,04
32	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
33	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
34	96	0	TRUE	96	39	57	0	TRUE	153	37	€ 43,04	€ 90,00	€ 133,04
35	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
36	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
37	96	0	TRUE	96	39	57	0	TRUE	153	40	€ 43,04	€ 90,00	€ 133,04
38	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
39	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
40	96	0	TRUE	96	39	57	0	TRUE	153	43	€ 43,04	€ 90,00	€ 133,04
41	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
42	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
43	96	0	TRUE	96	39	57	0	TRUE	153	46	€ 43,04	€ 90,00	€ 133,04
44	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
45	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
46	96	0	TRUE	96	39	57	0	TRUE	153	49	€ 43,04	€ 90,00	€ 133,04
47	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07

48	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
49	96	0	TRUE	96	39	57	0	TRUE	153	52	€ 43,04	€ 90,00	€ 133,04
50	153	57,4	FALSE	0	39	19	0	FALSE	115		€ 14,07	€ -	€ 14,07
51	115	18,8	FALSE	0	39	0	20	FALSE	96		€ -	€ -	€ -
52	96	0	TRUE	96	39	57	0	TRUE	153	55	€ 43,04	€ 90,00	€ 133,04

Table 31: Monte Carlo Washing Machine

Order Quantity	173	*units*	Order Cost	€ 90,00			
Reorder Point	206	*units*	Holding Cost	€ 0,75			
Initial Inventory	173	*units*			Total Annual Costs		
Lead time	2	*Working weeks*			€ 989,42	€ 2.340,00	€ 3.329,42

Beg Inv Pos	Beg Inv	Order Rec'd	Units Rec'd	Dmd	End Inv	Lost Sales	Order Placed?	Ending Inv Pos	Week Due	Hold Cost	Order Cost	Total Cost
173	173		0	124,1	49	0	TRUE	297	4	€ 36,65	€ 90,00	€ 126,65
297	48,9		0	124,1	0	75	TRUE	421	5	€ -	€ 90,00	€ 90,00
421	0	FALSE	0	124,1	0	124	FALSE	421		€ -	€ -	€ -
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	TRUE	173	124,1	98	0	TRUE	346	8	€ 73,29	€ 90,00	€ 163,29
346	97,7	FALSE	0	124,1	0	26	FALSE	248		€ -	€ -	€ -
248	0	FALSE	0	124,1	0	124	TRUE	421	10	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	12	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	14	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	16	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	18	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	20	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	22	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	24	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	26	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	28	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	30	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	32	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	34	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	36	€ -	€ 90,00	€ 90,00

421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	38	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	40	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	42	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	44	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	46	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	48	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	50	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	52	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65
297	48,9	FALSE	0	124,1	0	75	TRUE	421	54	€ -	€ 90,00	€ 90,00
421	0	TRUE	173	124,1	49	0	FALSE	297		€ 36,65	€ -	€ 36,65

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