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Supply Chain Management

Undergraduate Thesis

Inventory management practices with predictive models in the
field of restaurant services. Case Study: Glafkos Restaurant

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Patras, Greece, June 2023

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Inventory management practices with predictive models in the field of restaurant services

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Abstract

The thesis focused on three forecasting techniques: moving average (MA), simple exponential smoothing (SES), and triple exponential smoothing (TES) with seasonality and trend. The research compared the performance of these methods by analyzing their statistical errors, specifically the Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). The evaluation involved four different product categories: grocery store, meat products, raw materials, and beverages & wines. The objective was to determine the most suitable forecasting method for each category to approximate real demand values accurately. The findings revealed that the moving average method consistently exhibited the smallest statistical error in three out of four comparisons. It demonstrated superior performance in forecasting demand for a grocery store, meat products, and raw materials. The low MAD and MAPE values indicated that the moving average method provided accurate estimates that closely aligned with the actual demand curves in these categories. However, in the case of forecasting beverages and wines, the simple exponential smoothing method outperformed the other techniques. It yielded the lowest statistical error, suggesting its suitability for accurately predicting demand in this specific product category. The thesis highlighted the importance of selecting an appropriate forecasting method based on the characteristics of the data and the specific context. The results emphasized the effectiveness of predictive models in improving inventory management practices in the restaurant services industry. By employing these models, restaurant owners and managers can make informed decisions regarding inventory replenishment and minimize costs associated with overstocking or stockouts. This thesis contributes to the field of inventory management by providing insights into the application of predictive models in the specific context of restaurant services. The findings can guide practitioners in choosing the most suitable forecasting method for different product categories, ultimately leading to enhanced inventory control and optimized operations. Future research could focus on exploring additional forecasting techniques or incorporating other factors such as seasonality, promotions, and external factors like weather conditions to further improve the accuracy of demand forecasting in the restaurant services industry.

Keywords : Inventory management, predictive models, restaurant services, forecasting methods, moving average, simple exponential smoothing, triple exponential smoothing, statistical error, cost optimization

Πρακτικές διαχείρισης αποθεμάτων με μοντέλα πρόβλεψης στον τομέα των υπηρεσιών εστιατορίου

Γιάννης Ζαχαρόπουλος

Περίληψη

Η διατριβή επικεντρώθηκε σε τρεις τεχνικές πρόβλεψης: κινητός μέσος όρος (MA), απλή εκθετική εξομάλυνση (SES) και τριπλή εκθετική εξομάλυνση (TES) με εποχικότητα και τάση. Η έρευνα συνέκρινε την απόδοση αυτών των μεθόδων αναλύοντας τα στατιστικά τους σφάλματα, συγκεκριμένα τη Μέση Απόλυτη Απόκλιση (MAD) και το Μέσο Απόλυτο Ποσοστιαίο Σφάλμα (MAPE). Η αξιολόγηση αφορούσε τέσσερις διαφορετικές κατηγορίες προϊόντων: παντοπωλείο, προϊόντα κρέατος, πρώτες ύλες και ποτά και κρασιά. Ο στόχος ήταν να προσδιοριστεί η καταλληλότερη μέθοδος πρόβλεψης για κάθε κατηγορία ώστε να προσεγγίζονται με ακρίβεια οι πραγματικές τιμές της ζήτησης. Τα ευρήματα αποκάλυψαν ότι η μέθοδος του κινητού μέσου όρου παρουσίασε σταθερά το μικρότερο στατιστικό σφάλμα σε τρεις από τις τέσσερις συγκρίσεις. Απέδειξε ανώτερη απόδοση στην πρόβλεψη της ζήτησης για ένα παντοπωλείο, τα προϊόντα κρέατος και τις πρώτες ύλες. Οι χαμηλές τιμές MAD και MAPE έδειξαν ότι η μέθοδος του κινητού μέσου όρου παρείχε ακριβείς εκτιμήσεις που ευθυγραμμίζονταν στενά με τις πραγματικές καμπύλες ζήτησης σε αυτές τις κατηγορίες. Ωστόσο, στην περίπτωση της πρόβλεψης ποτών και κρασιών, η μέθοδος της απλής εκθετικής εξομάλυνσης υπερέιχε έναντι των άλλων τεχνικών. Παρήγαγε το χαμηλότερο στατιστικό σφάλμα, γεγονός που υποδηλώνει την καταλληλότητά της για την ακριβή πρόβλεψη της ζήτησης στη συγκεκριμένη κατηγορία προϊόντων. Η διατριβή ανέδειξε τη σημασία της επιλογής της κατάλληλης μεθόδου πρόβλεψης με βάση τα χαρακτηριστικά των δεδομένων και το συγκεκριμένο πλαίσιο. Τα αποτελέσματα υπογράμμισαν την αποτελεσματικότητα των μοντέλων πρόβλεψης στη βελτίωση των πρακτικών διαχείρισης αποθεμάτων στον κλάδο των υπηρεσιών εστίασης. Με τη χρήση αυτών των μοντέλων, οι ιδιοκτήτες και οι διαχειριστές εστιατορίων μπορούν να λαμβάνουν τεκμηριωμένες αποφάσεις σχετικά με την αναπλήρωση των αποθεμάτων και να ελαχιστοποιούν το κόστος που σχετίζεται με την υπεραποθεματοποίηση ή τα αποθέματα. Η παρούσα διατριβή συμβάλλει στον τομέα της διαχείρισης αποθεμάτων παρέχοντας γνώσεις σχετικά με την εφαρμογή των προβλεπτικών μοντέλων στο συγκεκριμένο πλαίσιο των υπηρεσιών εστιατορίου. Τα ευρήματα μπορούν να καθοδηγήσουν τους επαγγελματίες στην επιλογή της καταλληλότερης μεθόδου πρόβλεψης για διάφορες κατηγορίες προϊόντων, οδηγώντας τελικά σε βελτιωμένο έλεγχο αποθεμάτων και βελτιστοποιημένες λειτουργίες. Η μελλοντική έρευνα θα μπορούσε να επικεντρωθεί στη διερεύνηση πρόσθετων τεχνικών

πρόβλεψης ή στην ενσωμάτωση άλλων παραγόντων, όπως η εποχικότητα, οι προσφορές και οι εξωτερικοί παράγοντες, όπως οι καιρικές συνθήκες, για την περαιτέρω βελτίωση της ακρίβειας της πρόβλεψης της ζήτησης στον κλάδο των υπηρεσιών εστιατορίου.

Λέξεις-κλειδιά : Διαχείριση αποθεμάτων, μοντέλα πρόβλεψης, υπηρεσίες εστιατορίων, μέθοδοι πρόβλεψης, κινητός μέσος όρος, απλή εκθετική εξομάλυνση, τριπλή εκθετική εξομάλυνση, στατιστικό σφάλμα, βελτιστοποίηση κόστους

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Chapter 1. Introduction

Inventory management plays crucial role in the success of businesses across various industries. Effective inventory management ensures that the right products are available at the right time, in the right quantities, and at the right cost. It involves the systematic control and monitoring of stock levels to meet customer demands while minimizing costs and optimizing operational efficiency. In today's dynamic and competitive business environment, companies are increasingly relying on advanced techniques and technologies to enhance their inventory management practices (Chopra, & Meindl, 2015)

The objective of this thesis is to explore the application of predictive models in inventory management. Predictive models utilize historical data and statistical algorithms to forecast future demand patterns, optimize inventory levels, and streamline the replenishment process. By leveraging these models, organizations can make informed decisions, improve customer satisfaction, reduce carrying costs, and enhance supply chain performance.

The significance of this thesis lies in its potential to shed light on the benefits and challenges associated with implementing predictive models in inventory management. By understanding the capabilities and limitations of these models, businesses can develop strategies to leverage them effectively and gain a competitive edge. Furthermore, the thesis aims to provide insights into the integration of predictive models into existing inventory management systems and the potential improvements that can be achieved through their adoption.

The thesis will discuss the benefits and challenges associated with predictive models in inventory management. It will address the advantages of using predictive models, such as improved accuracy in demand forecasting, optimized inventory levels, and enhanced operational efficiency. It will also highlight the challenges and limitations that organizations may encounter during the implementation and utilization of predictive models. By examining the current practices, benefits, and challenges of using predictive models in inventory management, this project aims to provide a comprehensive understanding of how organizations can leverage these models to optimize their

inventory operations and gain a competitive advantage in the market. The insights gained from this research will contribute to the body of knowledge in the field of inventory management and guide businesses in making informed decisions to improve their overall supply chain performance.

The thesis is organized as follows.

Chapter 1 is devoted to introduction while Chapter 2 is referred to the fundamentals of inventory management, including the definition and types of inventories, the importance of effective management, and the various techniques and strategies employed in controlling inventory.

Chapter 3 delves into the concept of predictive modeling and explore different types of predictive models commonly used in inventory management. It focuses on the application of predictive models in inventory forecasting, planning, and optimization. In addition, it highlights techniques for demand forecasting, such as moving average, exponential smoothing, seasonal decomposition, and artificial neural networks and discusses various inventory replenishment strategies, including the Reorder Point (ROP) method, periodic review system, vendor-managed inventory (VMI), and continuous replenishment planning (CRP). Further, explores how predictive models can be integrated into these strategies to enhance decision-making and improve inventory management outcomes.

In Chapter 4 analyzes the demand forecasting and chapter 5 represents a literature review.

In Chapter 6, the used research model is represented, and a real-world case study of a restaurant is presented in order to illustrate the practical application of predictive models in different industries, such as retail, manufacturing, and e-commerce. This case studies will showcase the benefits achieved through the adoption of predictive models and provide valuable insights into their implementation.

In chapter 7 there are the results of the analysis of data. Finally in the last chapter 8 we have the conclusions.

Chapter 2. Inventory Management Fundamentals

2.1 Definition and Types of Inventories

Inventory refers to the goods or materials held by a business for the purpose of production, distribution, or resale. It serves as a buffer between the various stages of the supply chain and helps ensure a smooth flow of goods. Inventory can take several forms, hence, thus, therefore consequently understanding the types of inventories is crucial for effective management. Here are the common types of inventories (Chase, et al, 2004):

- ✚ Raw Materials: These are the basic materials used in the production process. They are typically purchased from suppliers and undergo transformation to create finished goods.
- ✚ Work-in-Progress (WIP): WIP inventory consists of partially completed products that are in the production process but have not yet been finished. These items are at various stages of production and require further processing.
- ✚ Finished Goods: Finished goods are the final products ready for sale to customers. They have completed the production process and are awaiting delivery or distribution.
- ✚ Maintenance, Repair, and Operations (MRO): MRO inventory includes items necessary for the maintenance, repair, and operations of the business, such as tools, spare parts, and consumables.
- ✚ Packaging and Supplies: This type of inventory comprises packaging materials, labels, containers, and other supplies needed for packaging and shipping products.
- ✚ Goods in Transit: Inventory in transit refers to goods that are in the process of being transported from one location to another. They are not physically present

in the organization's facilities but are considered part of the inventory until they reach their destination.

2.2 Importance of Effective Inventory Management:

Effective inventory management is essential for the smooth functioning of businesses. Here are some key reasons highlighting the importance of inventory management (Jacobs & Chase, 2018):

- ✚ Meeting Customer Demand: Proper inventory management ensures that products are available when customers demand them. By maintaining optimal stock levels, businesses can fulfill customer orders promptly, improve customer satisfaction, and retain a competitive edge.
- ✚ Minimizing Stockouts and Overstocking: Efficient inventory management helps avoid stockouts (unavailable products) and overstocking (excessive inventory). Stockouts can result in lost sales and dissatisfied customers, while overstocking ties up capital and incurs holding costs.
- ✚ Cost Control: Inventory represents a significant investment for businesses. Effective management helps minimize carrying costs, including storage, handling, insurance, and obsolescence costs. It also reduces the risk of inventory becoming obsolete or damaged.
- ✚ Efficient Production Planning: By accurately forecasting demand and managing inventory levels, businesses can plan production activities effectively. This prevents underproduction or overproduction, optimizes resource allocation, and reduces production lead times.
- ✚ Supply Chain Optimization: Inventory management is closely linked to supply chain performance. Well-managed inventory ensures a smooth flow of goods, minimizes bottlenecks, and improves overall supply chain efficiency. It facilitates coordination with suppliers, distributors, and other stakeholders.

2.3 Inventory Costs and Their Impact on the Organization

Inventory costs can have a significant impact on the organization's financial health and profitability. It is crucial to understand the different types of costs associated with inventory. Here are the key inventory costs (Waters, 2011):

Holding Costs: Holding costs, also known as carrying costs, include expenses incurred to maintain and store inventory. These costs encompass warehousing, rent, utilities, insurance, security, and inventory management system expenses.

Ordering Costs: Ordering costs are associated with the process of replenishing inventory. They include expenses related to order placement, order processing, supplier communication, and paperwork.

Shortage Costs: Shortage costs occur when demand exceeds supply, leading to stockouts. These costs include lost sales, missed business opportunities, rush orders, expedited shipping, and potential damage to customer relationships.

The cost of capital is the cost incurred by a business to raise funds for its operations. This cost is typically reflected in the interest or dividend payments made to investors or creditors. When capital is tied up in inventory, it is not available to be used for other purposes, and the organization foregoes the opportunity to earn a return on that capital. The holding cost of capital is particularly relevant in situations where inventory levels are high or when inventory turnover is low. Holding excessive inventory for extended periods can result in a significant opportunity cost, as the capital could have been deployed in investments that generate income or contribute to the organization's growth.

Effective inventory management practices, such as just-in-time (JIT) systems, lean principles, and supply chain optimization, can help minimize the holding cost of capital. By improving inventory turnover, streamlining processes, and reducing inventory levels, organizations can release capital for other strategic investments and potentially enhance their overall financial performance.

2.4 Inventory Control Techniques and Strategies

Effective inventory control is essential for maintaining optimal inventory levels, minimizing costs, and ensuring smooth operations. Various techniques and strategies can be employed to achieve efficient inventory control. In this section, we will explore some commonly used inventory control techniques and strategies (Silver et al., 1998):

- ✚ ABC Analysis: ABC analysis is a technique that categorizes inventory items based on their value and importance. It classifies items into three categories: A, B, and C. Category A includes high-value items that contribute to a significant portion of the total inventory value but constitute a relatively small percentage of the total item count. Category B consists of moderately valued items, while Category C comprises low-value items that constitute a large percentage of the total item count. ABC analysis helps prioritize inventory management efforts, with more attention given to Category A items.
- ✚ Economic Order Quantity (EOQ): The EOQ model calculates the optimal order quantity that minimizes the total inventory holding cost and ordering cost. It considers factors such as the cost per unit, annual demand, and ordering costs. By determining the most cost-effective order quantity, the EOQ model helps strike a balance between holding costs and ordering costs. It aims to reduce excess inventory and avoid stockouts.
- ✚ Just-in-Time (JIT) Inventory Management: JIT is a lean manufacturing approach that aims to minimize inventory levels by receiving goods and producing items only when needed. With JIT, inventory is delivered exactly when required, reducing the need for large stockpiles. This approach requires close collaboration with suppliers and a reliable supply chain to ensure timely delivery. JIT helps reduce holding costs, eliminate waste, and improve overall operational efficiency.

- ✚ Safety Stock Management: Safety stock is the buffer inventory held to protect against unexpected fluctuations in demand or supply disruptions. It acts as an insurance against stockouts and enables organizations to meet customer demands even during unforeseen circumstances. Safety stock levels are determined based on factors such as lead time variability, demand variability, and service level objectives. Effective safety stock management helps balance the trade-off between inventory carrying costs and the risk of stockouts.
- ✚ Just-in-Case (JIC) Inventory Strategy: In contrast to JIT, the JIC strategy involves holding additional inventory as a precautionary measure to mitigate risks. It is often employed when there is high uncertainty or variability in demand or supply. JIC strategy aims to ensure that sufficient inventory is available to meet unexpected increases in demand or supply disruptions. However, this strategy increases holding costs and should be carefully balanced to avoid excessive inventory levels.
- ✚ Vendor-Managed Inventory (VMI): VMI is a collaborative approach in which the supplier manages the inventory levels at the customer's location. The supplier has access to real-time inventory data and takes responsibility for replenishing stock as needed. VMI can streamline the replenishment process, reduce stockouts, and improve inventory accuracy. It requires strong collaboration and information-sharing between the supplier and the customer.
- ✚ Continuous Replenishment Planning (CRP): CRP is an inventory management approach that focuses on continuously monitoring inventory levels and replenishing stock in smaller, frequent quantities. It relies on real-time data, demand forecasts, and automated systems to trigger replenishment orders. CRP helps minimize stockouts, improve response time, and optimize inventory levels by aligning replenishment with actual demand.
- ✚ Advanced Forecasting and Demand Planning: Accurate demand forecasting is crucial for effective inventory control. Advanced forecasting techniques, such as time series forecasting, regression analysis, and machine learning algorithms, can be employed to predict future demand patterns. By incorporating historical data, market trends, and seasonality factors, organizations can improve the accuracy of demand forecasts and adjust inventory levels accordingly.

Chapter 3. Predictive Models

3.1 Introduction to Predictive Models

Predictive models play a crucial role in inventory management by utilizing historical data and statistical techniques to forecast future demand, optimize inventory levels, and enhance decision-making. These models use mathematical algorithms and statistical methods to analyze data patterns and generate predictions. By leveraging predictive models, businesses can make informed inventory management decisions, reduce costs, and improve customer service.

3.2 Types of Predictive Models Used in Inventory Management:

There are several types of predictive models commonly used in inventory management. Each type has its own strengths and applicability based on the nature of the data and the forecasting requirements. The main types of predictive models used in inventory management include (Monczka et al, 2015):

3.2.1 Time Series Forecasting Models

- Time series forecasting models analyze historical data to identify patterns and trends and make predictions based on the assumption that future demand will follow similar patterns. Common time series models used in inventory management include:

- **Moving Averages:** This model calculates the average of a specific number of past data points to predict future demand. Different moving average methods, such as simple moving average or weighted moving average, can be employed based on the significance of recent data points.
- **Exponential Smoothing:** This model gives more weight to recent data points, providing greater importance to the most recent demand patterns. It considers both the level and trend of past data to generate forecasts.
- **Seasonal Decomposition:** This model decomposes historical data into trend, seasonal, and residual components to understand the underlying patterns and make accurate predictions. It is particularly useful for handling seasonal variations in demand.

3.2.2 Regression Models

- **Regression models** establish a relationship between the dependent variable (demand) and one or more independent variables (such as price, promotions, or economic indicators). Regression analysis helps quantify the impact of various factors on demand and make predictions based on their influence. Common regression models used in inventory management include:
- **Simple Linear Regression:** This model assumes a linear relationship between the dependent and independent variables. It estimates the slope and intercept of the regression line to predict future demand based on historical data.

- **Multiple Linear Regression:** This model considers multiple independent variables to predict demand. It captures the combined effect of various factors and their relationship with demand.

3.2.3 Machine Learning Models

Machine learning models are capable of handling complex patterns and non-linear relationships in data. They use algorithms to learn from historical data and make predictions based on learned patterns. Machine learning models commonly used in inventory management include:

- **Random Forest:** This model utilizes an ensemble of decision trees to generate predictions. It is effective in handling large datasets and capturing non-linear relationships.
- **Support Vector Machines (SVM):** SVM is a supervised learning algorithm that analyzes historical data to classify and predict future demand based on defined patterns.
- **Neural Networks:** Neural networks mimic the functioning of the human brain and can capture complex relationships in data. They are particularly useful when there are multiple variables and non-linear interactions.

3.3 Data Requirements and Preparation for Predictive Modeling

To build accurate predictive models, proper data preparation is essential. The data requirements may vary depending on the chosen predictive modeling technique. Some key steps in data preparation include (Song & Chu, 2005):

- **Data Collection:** Gather historical data on relevant variables, such as demand, sales, pricing, promotions, and other factors that influence inventory levels.
- **Data Cleaning:** Remove outliers, handle missing values, and correct any inconsistencies in the dataset. Ensure data integrity and accuracy.
- **Feature Engineering:** Extract and transform relevant features from the raw data. This may involve aggregating data at different time intervals, creating lag variables, or incorporating seasonal indicators.
- **Data Split:** Divide the dataset into training and testing subsets. The training set is used to build the predictive model, while the testing set is used to evaluate its performance.

3.4 Model Selection and Evaluation Techniques

In the process of predictive modeling for inventory management, selecting the appropriate model and evaluating its performance are crucial steps. Here are some model selection and evaluation techniques commonly used in inventory management (Cachon & Fisher, 2000 - Srinivasan & Mukhopadhyay, 2008 - Petropoulos & Kourentzes, 2016 – Zhang & Ma, 2020).

➔ Model Selection:

Expert Knowledge: Expert domain knowledge can guide the selection of an appropriate predictive model based on the specific requirements and characteristics of the inventory management problem.

Comparative Analysis: Compare the performance of different predictive models using evaluation metrics to identify the most suitable one. Consider factors such as accuracy, computational complexity, interpretability, and scalability.

➔ **Model Evaluation:**

Mean Absolute Error (MAE): MAE measures the average absolute difference between the predicted and actual demand values. It provides an indication of the model's accuracy and is commonly used in inventory management.

Mean Squared Error (MSE): MSE calculates the average squared difference between the predicted and actual demand values. It gives more weight to large errors and is useful for assessing the model's predictive performance.

Root Mean Squared Error (RMSE): RMSE is the square root of MSE and provides an easily interpretable measure of the average prediction error.

Mean Absolute Percentage Error (MAPE): MAPE measures the average percentage difference between the predicted and actual demand values. It is useful for evaluating the relative performance of models across different datasets.

Forecast Bias: Forecast bias measures the tendency of a model to consistently overestimate or underestimate demand. Positive bias indicates overestimation, while negative bias indicates underestimation.

Tracking Signal: The tracking signal measures the cumulative deviation of the forecasts from the actual demand over time. It helps identify whether the model is consistently over- or under-forecasting.

➔ **Cross-Validation:**

K-fold Cross-Validation: Divide the dataset into k subsets (folds) and iteratively train and evaluate the model on different combinations of training and validation sets. This helps assess the model's performance on various subsets of the data and reduces the risk of overfitting.

➔ **Back testing:**

Historical Performance Evaluation: Assess the performance of the predictive model by comparing the predicted demand with the actual demand over a specific historical period. This allows for a retrospective evaluation of the model's accuracy and reliability.

➔ Adjustments and Iteration:

Refine the model by adjusting parameters, selecting different features, or trying alternative algorithms based on the evaluation results. Iterate the model development process to improve its performance over time.

It is important to note that the choice of evaluation metrics and techniques may vary depending on the specific requirements and objectives of the inventory management problem. It is recommended to consider multiple evaluation measures and select the model that best aligns with the organization's goals and constraints.

Chapter 4. Demand Forecasting

4.1 Importance of Accurate Demand Forecasting:

Accurate demand forecasting is vital for effective inventory management. It enables businesses to anticipate customer demand, optimize inventory levels, minimize costs, and enhance customer satisfaction (Fildes & Goodwin, 2007 - Chatfield, 2016 – Hyndman & Athanasopoulos, 2018).

- **Optimal Inventory Levels:** Accurate demand forecasting helps determine the right inventory levels to meet customer demand while avoiding overstocking or stockouts. It ensures that inventory is available when needed, reducing carrying costs and improving operational efficiency.
- **Cost Reduction:** By accurately predicting demand, businesses can minimize inventory holding costs, storage costs, and the risk of obsolescence. They can also optimize procurement and production activities, reducing costs associated with rush orders, expedited shipments, and excess inventory.
- **Supply Chain Efficiency:** Accurate demand forecasts enable effective supply chain planning and coordination. Suppliers, manufacturers, and distributors can align their activities based on anticipated demand, leading to improved production scheduling, reduced lead times, and better inventory visibility across the supply chain.
- **Improved Customer Service:** Meeting customer demand consistently and minimizing stockouts enhances customer satisfaction. Accurate demand forecasting helps ensure product availability, reduces order fulfillment time, and enables proactive management of customer expectations.
- **Decision-Making:** Accurate demand forecasts provide valuable insights for strategic decision-making. Businesses can make informed decisions regarding production capacity, resource allocation, pricing, promotions, and new product introductions based on reliable demand projections.

4.2 Techniques for Demand Forecasting

Several techniques can be employed for demand forecasting, depending on the nature of the data and the forecasting requirements (Armstrong & Collopy, 1992 - Makridakis, et al., 1998) - Goodwin & Fildes, 2004 – Petropoulos & Kourentzes, 2015).

4.2.1 Moving Average

The moving average method calculates the average of a specific number of past demand observations to forecast future demand. It smooths out random fluctuations and helps identify underlying trends. Different types of moving averages, such as simple moving average (SMA) or weighted moving average (WMA), can be used based on the significance of recent data points.

4.2.2 Exponential Smoothing:

Exponential smoothing is a popular time series forecasting method that assigns exponentially decreasing weights to past demand observations. It emphasizes recent data points while gradually reducing the influence of older observations. Exponential smoothing models, such as simple exponential smoothing (SES) or Holt's linear exponential smoothing, can be employed to forecast demand.

This is the evolution of the moving average method and is one of the most widespread and widely used forecasting techniques, as it recognizes and exploits the presence of elements such as trend, seasonality, etc. It is based on the exponential reduction in the weighting of the elements of earlier time periods. Thus, the older the data, the lower the weighting. Similarly, more recent data have a higher value. It is mainly applicable to short-term programming, and more generally where the time horizon of the forecast is relatively short.

It is very popular as it is easy to use, since it requires neither a large amount of computing time nor a large amount of data storage space, but it is also 'updatable', i.e. it is updated-affected when new data become available.

It uses the forecast in combination with the corresponding actual value of the variable for the current period to predict the value of the variable in the following periods.

Relationship (3) gives this forecast and has the following:

$$F_{t+1} = \alpha D_t + (1 - \alpha) F_t$$

where, F_{t+1} : the forecast demand for the following period

F_t : the recent forecast (price of the previous period)

D_t : the actual demand in period t , and

α : smoothing constant

The values taken by the coefficient α are between 0 and 1. The value of α depends on the experience of the user making the prediction, but also on the qualitative characteristics of the quantity under consideration. Assuming that these exhibit relative stability over time, then α takes a low value (0.05-0.2). Conversely, if they exhibit large variations over time, then α is given higher values. In other words, when it receives a value close to zero, then the forecast error in the last period plays a small role in shaping the forecast. Thus, the influence of a low α is proportional to the use of a large number of periods N when applying the moving average method.

Moreover, this method is applicable when demand is stationary, i.e. when the time series shows only the horizontal component, without the trend and seasonality elements. For this reason, further variants have been developed, which are discussed below.

4.2.3 Seasonal Decomposition:

Seasonal decomposition is particularly useful for handling data with clear seasonal patterns. It decomposes historical demand data into trend, seasonal, and residual components. This decomposition helps identify the underlying seasonality and trend, enabling accurate forecasts. Methods like Seasonal Decomposition of Time Series (STL) or Seasonal and Trend decomposition using Loess (STL) are commonly used for seasonal decomposition.

4.2.4 Artificial Neural Networks:

Artificial Neural Networks (ANN) are machine learning models inspired by the human brain's neural structure. They can capture complex relationships and patterns in demand data. ANN models learn from historical demand data to make forecasts, considering

factors like seasonality, trends, and other influencing variables. ANN models require extensive training and tuning, but they can provide accurate and robust demand forecasts.

4.3 Evaluating the Accuracy of Demand Forecasts:

Evaluating the accuracy of demand forecasts is essential to measure the performance of forecasting models and identify areas for improvement. Here are some common evaluation techniques (Hyndman & Athanasopoulos, 2018) :

- **Error Metrics:** Metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or Mean Absolute Percentage Error (MAPE) are used to quantify the difference between the predicted and actual demand values. Lower values of these metrics indicate better accuracy.
- **Forecast Bias:** Forecast bias measures the tendency of the forecasts to consistently overestimate or underestimate the actual demand. A positive forecast bias indicates that the forecasts consistently overestimate the actual demand, while a negative forecast bias indicates that the forecasts consistently underestimate the actual demand. Evaluating the forecast bias helps identify any systematic errors in the forecasting models and adjust them accordingly.
- **Tracking Signal:** The tracking signal measures the cumulative deviation of the forecasts from the actual demand over time. It indicates whether the forecasts consistently overestimate or underestimate the demand and helps identify if the forecasting model needs recalibration or adjustment.
- **Visual Analysis:** Visual examination of the forecasted values plotted against the actual demand can provide insights into the accuracy and patterns of the forecasts. Comparing the forecasted values with the actual demand over time helps identify any systematic discrepancies or anomalies.
- **Backtesting:** Backtesting involves comparing the historical forecasted values with the actual demand data to assess the accuracy of the forecasts. This retrospective evaluation helps measure the performance of the forecasting models and identify areas for improvement.

- **Cross-Validation:** Cross-validation techniques, such as k-fold cross-validation, can be used to assess the performance of the forecasting models on different subsets of the data. By training and evaluating the models on multiple partitions of the data, it provides a more robust estimation of the accuracy and generalizability of the forecasts.
- **Forecast Accuracy by Product/Segment:** Assessing the accuracy of demand forecasts on a product or segment level helps identify variations in forecasting performance across different categories. This information can guide targeted improvements in forecasting techniques for specific products or segments.

It is important to note that evaluating the accuracy of demand forecasts should be an ongoing process. Regularly monitoring the performance of forecasting models, identifying sources of error, and making necessary adjustments can help improve the accuracy of the forecasts over time.

to meet customer demand.

4.4 Optimizing Inventory Levels with Predictive Models

Predictive models can be used to optimize inventory levels by forecasting demand, identifying trends and patterns, and developing optimization strategies. By integrating predictive models with inventory management techniques, organizations can achieve more accurate demand forecasting, reduce inventory costs, and improve supply chain efficiency.

One common approach to inventory optimization with predictive models is to use the EOQ model as a baseline and adjust the order quantity based on the demand forecast. This approach ensures that the inventory level is sufficient to meet customer demand while minimizing inventory holding costs.

In addition to the EOQ model, predictive models can also be used to optimize safety stock levels by identifying the appropriate level of safety stock based on the level of demand uncertainty and the costs associated with stockouts and excess inventory.

By integrating predictive models with inventory management techniques, organizations can achieve more accurate demand forecasting, reduce inventory costs, and improve supply chain efficiency.

Reorder Point (ROP) Method: The Reorder Point (ROP) method is an inventory replenishment strategy that determines when to place an order based on a predefined reorder point. The reorder point is calculated by considering the lead time (time between placing an order and receiving it) and the average demand during the lead time. When the inventory level reaches the reorder point, a new order is placed to replenish the stock. The ROP method ensures that the inventory level does not fall below a critical threshold, minimizing the risk of stockouts. The reorder point can be adjusted based on factors such as demand variability, desired service level, and lead time variability.

Periodic Review System: In a periodic review system, inventory replenishment occurs at fixed time intervals rather than based on reaching a specific reorder point. At predetermined review periods, the inventory level is assessed, and an order is placed to bring the stock back to a target level. The periodic review system is useful when dealing with items that have intermittent or unpredictable demand patterns. By reviewing inventory levels at regular intervals, the system can account for demand variability and minimize the risk of stockouts while optimizing inventory holding costs.

Vendor-Managed Inventory (VMI): Vendor-Managed Inventory (VMI) is a collaborative approach to inventory replenishment where the supplier or vendor takes responsibility for managing and replenishing the inventory at the customer's location. The vendor monitors the inventory levels, forecasts demand, and initiates replenishment orders as needed. VMI allows for better coordination between the supplier and customer, as the vendor has direct visibility into the inventory levels and demand patterns. It can lead to reduced inventory holding costs for the customer, improved order fulfillment, and increased efficiency in the supply chain.

Continuous Replenishment Planning (CRP): Continuous Replenishment Planning (CRP) is a proactive inventory replenishment strategy that utilizes real-time data and

advanced analytics to optimize inventory levels. CRP continuously monitors inventory levels, demand patterns, and supply chain dynamics to dynamically adjust replenishment decisions. CRP integrates predictive models, demand forecasts, and supply chain visibility to ensure timely replenishment and minimize inventory costs. By leveraging real-time data, CRP helps organizations respond quickly to changing demand patterns, improve order fulfillment, and reduce excess inventory.

The choice of inventory replenishment strategy depends on factors such as demand variability, lead time, cost considerations, and the level of collaboration between suppliers and customers. Organizations may adopt a combination of strategies or tailor them to specific product categories based on their unique requirements and objectives.

Chapter 5. Case Study – History of Glafkos Restaurant

The restaurant which I will use for the case study is named “Glafkos Restaurant”.

The restaurant first opened in 1960, as a small family restaurant and during the following years it has been established as one of Patras best known restaurants. Glafkos started as small tavern with a few tables and through time expanded to its current form which can hosts approximately 250 people, with this capacity to be fully booked during winter months and especially weekends. Glafkos is in the outskirts of Patras and got its name from the river “Glafkos” which is headwaters start from this area. It is also important to notice that in the same area is located the first hydroelectric power plant which has helped upgrade the place around and has a significant number of visitors from schools and universities around the region.

As Glafkos owner says,” We want to improve our place and services and with the use of technology we can now have full image of our inventory and use models to minimize the cost but also to preserve the quality of the finest products that we use “. It has played a significant role to the management of the restaurant the use of automatic orders and the connection of this program with the inventory, since you can find all the data and history of the passing months and years. In this Thesis I will show how the use of predictive models can help the planning of purchases for the inventory and the importance of it.

Chapter 6. Research Methodology

6.1 The sample

The methodology employed in this thesis involved conducting a comparative analysis of different forecasting methods for inventory management in the field of restaurant services. The study focused on three primary techniques: moving average (MA), simple exponential smoothing (SES), and triple exponential smoothing (TES) with seasonality and trend. To begin with, historical demand data for four product categories, namely grocery store, meat products, raw materials, and beverages & wines, were collected from the restaurant. The data served as the basis for evaluating the performance of the forecasting methods. Next, the statistical errors, specifically the Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE), were calculated for each forecasting method within each product category. MAD and MAPE provided quantitative measures to assess the accuracy and precision of the forecasting models. The results obtained from the analysis were then compared to identify the forecasting method that yielded the smallest statistical error for each product category. This comparison allowed for the determination of the most suitable method to approximate the real demand values accurately. Finally, the actual demand curves were plotted against the respective forecasts generated by each method to visually assess their alignment and validate the accuracy of the chosen forecasting method. The methodology employed in this thesis provided a systematic and objective approach to evaluating the performance of different forecasting methods for inventory management in the restaurant services sector.

6.2 The Methodology

6.2.1 The models

➔ Simple moving average

This is the simplest forecasting method and is applied when demand is not characterized by fluctuations in observations.

$$F_t = \frac{D_{t-1} + D_{t-2} + \dots + D_{t-N}}{N} = \frac{1}{N} \sum_{i=t-1}^{t-N} D_i$$

The forecast for the next period is obtained by adding to the time series the most recent value of the variable and subtracting from it the oldest value.

$$F_{t+1} = F_t + \frac{D_t - D_{t-N}}{N}$$

➔ Simple exponential smoothing

This is the evolution of the moving average method and is one of the most widespread and widely used forecasting techniques, as it recognizes and exploits the presence of elements such as trend, seasonality, etc.

$$F_{t+1} = \alpha D_t + (1-\alpha) F_t$$

➔ Exponential smoothing with tendency

It is observed that in some cases the values taken by the observations of some time series tend to increase or decrease at a constant rate (step) over long periods of time.

$$S_{t+1} = \alpha D_t + (1-\alpha) \cdot (S_t + T_t)$$

➔ Exponential smoothing with trend & seasonality

$$S_t = \alpha \frac{D_t}{I_{t-L}} + (1-\alpha) \cdot (S_{t-1} + T_{t-1})$$

$$T_t = b(S_t - S_{t+1}) + (1-b)T_{t-1}$$

$$I_t = c \frac{D_t}{S_t} + (1-c)I_{t-L}$$

6.2.2 The most appropriate forecasting method

In order to choose the most appropriate forecasting method, the performance of the forecast must be taken into account, which depends on its errors. The forecast demand will almost never be equal to the actual demand, but will instead always be higher or lower than it. The difference between the forecast and the actual demand is called the forecast error. The aim of any forecast is to minimize this error. When the error is high, it suggests that either the forecasting technique is wrong or that modifications to its parameters are required.

Errors are divided into statistical and random errors. The former result from misjudgment or omission of factors affecting demand, such as seasonality. Random errors, on the other hand, are due to unpredictable factors affecting demand.

Forecast error results from comparing forecast values with actual values. Let F_t be the demand forecast for period t and D_t the actual demand for period t . The forecast error e_t is defined as the difference:

$$e_t = D_t - F_t$$

The overall performance of a prediction model over a time interval of t periods is obtained by adding the prediction error of each period. Negative values indicate an overestimation of demand, while positive values indicate an underestimation. The disadvantage is that positive deviations are cancelled out by negative deviations. Thus, it may appear to be fictitiously good efficiency, i.e., low average error, but in reality very high (positive and negative) deviations have occurred. For this reason, measurements are mainly applied with absolute and average error values.

Mean Absolute Deviation (MAD): Calculates the units of measurement of the original time series and expresses a measure of the accuracy of the forecast against the actual values. It answers the question whether a method is good, but if it is bad, it does not give information whether we have overestimated or underestimated the variable to be predicted. The higher the value of the index, the lower the accuracy of the method used.

$$MAD = \sum_{t=1}^T |D_t - F_t| / T$$

Mean Square Error (MSE): calculates the dispersion of the distribution of forecast errors. Its negative aspect is that it magnifies large deviations due to squaring, in other words it gives more weight to large errors (since errors are squared) and less weight to small errors. Thus, it applies when many small deviations are sought over a very large one.

$$MSE = \sum_{t=1}^T (D_t - F_t)^2 / T$$

Mean Absolute Percentage Error: gives an objective measure of the error as a percentage of demand (e.g., forecast error is on average 10% of actual demand), without depending on the order of magnitude of demand, as in the others. It is expressed as a percentage and its values are higher or equal to zero, with lower values indicating better performance of the forecasting method.

$$MAPE = 100 \sum_{t=1}^T [|D_t - F_t| / D_t] / T$$

Chapter 7. Presentation Of Results

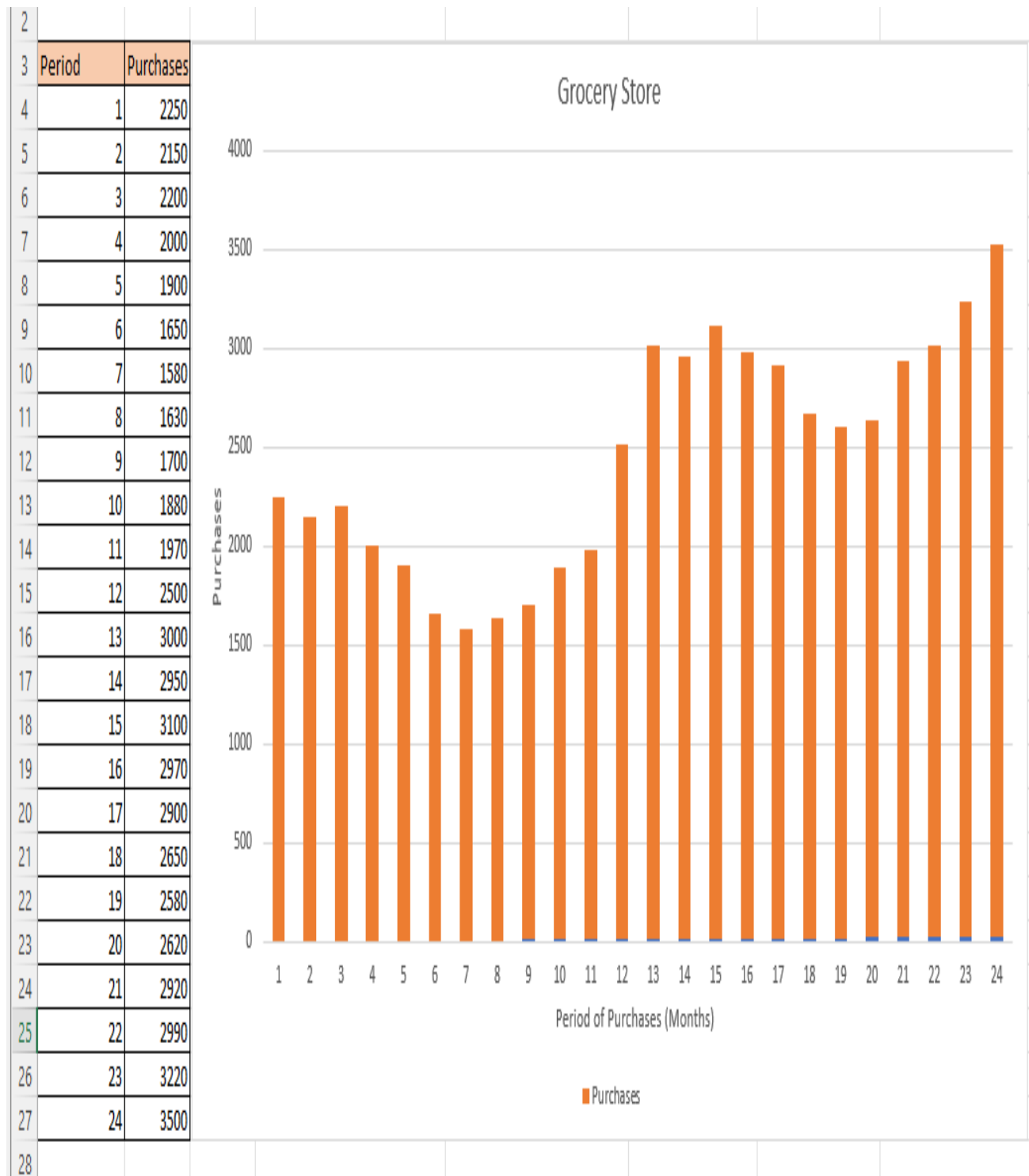
In this chapter, some forecasting models applied to real data from own company operating in food & beverage sector like restaurant. Will be analyzed, so that,

depending on the form of demand it exhibit, it will be demonstrated in practice which is the most appropriate for each case.

7.1 The Case Study of Grocery

The items in the first category are vegetables (tomatoes, cucumbers, parasitic salads, potatoes, etc.) are characterized by low acquisition costs ($< €4.00$ per kilo) and market availability, are addressed to all consumers and have no limitation on their shelf life.

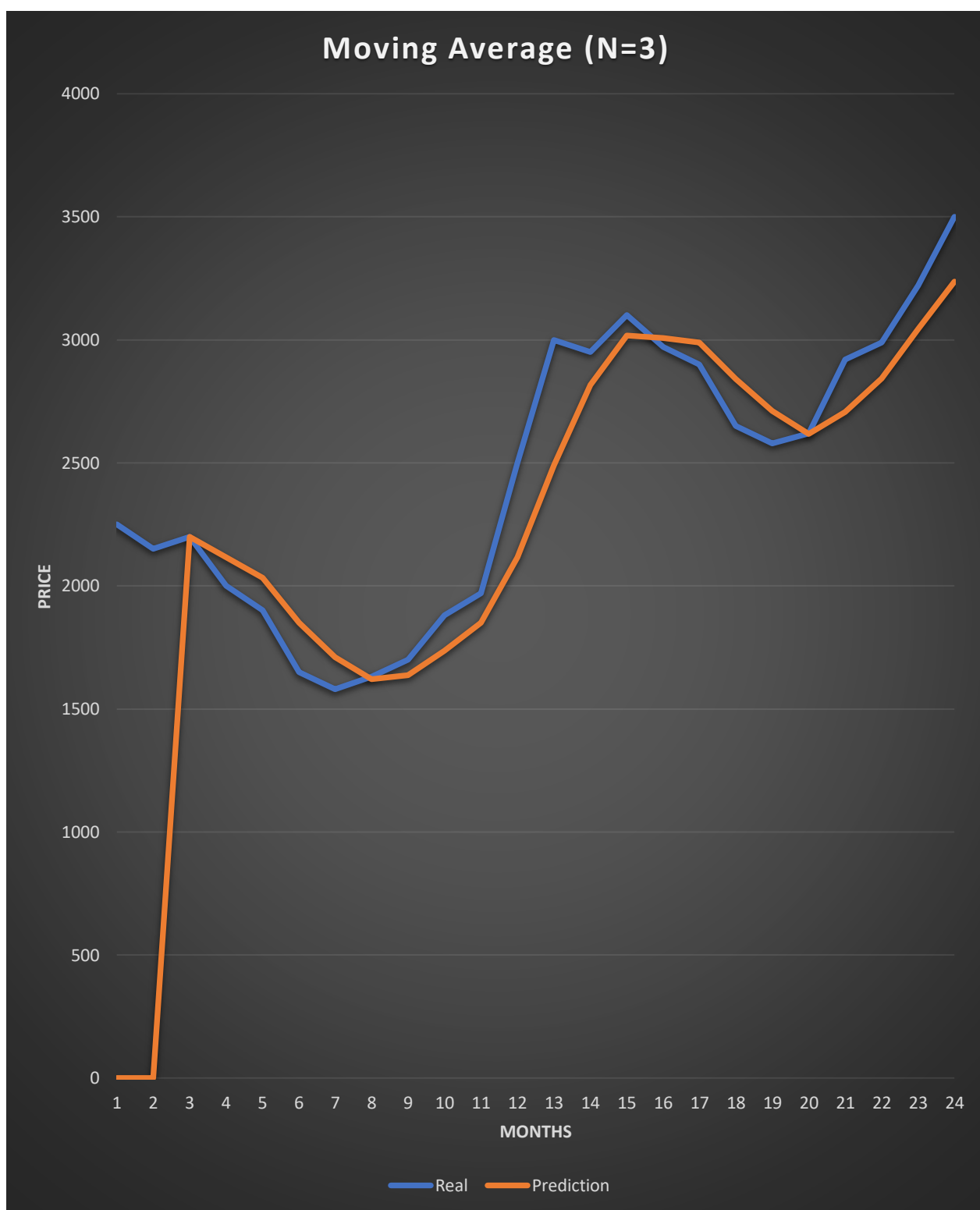
The demand over the last 24 months (21/4/2021 -21/4/2023) is shown in the chart below:



Applying the moving average method, for $t=24$ periods and a range of moving periods

$N=3$, we obtain the following results:

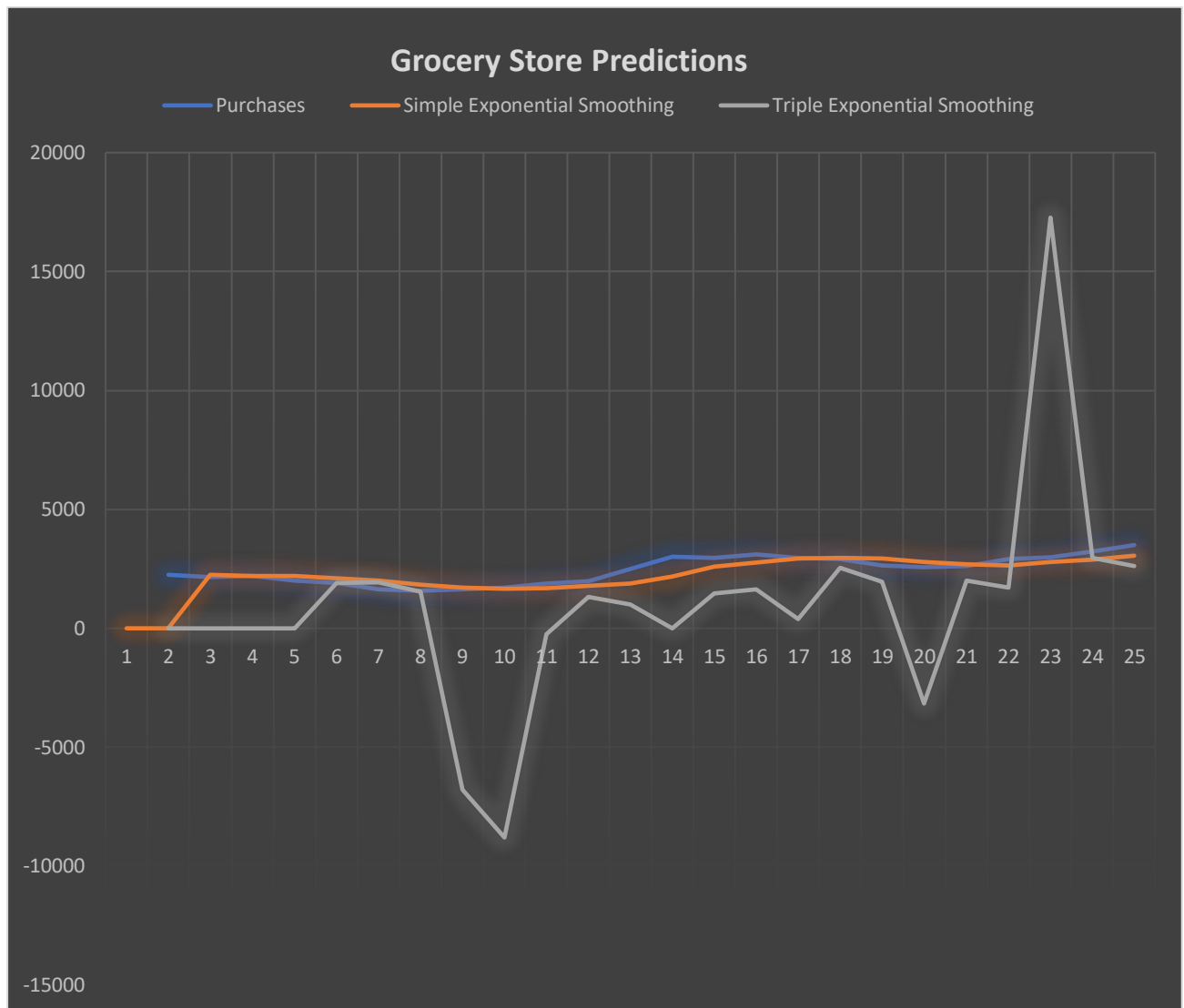
Period	Purchases	Prediction (F)	Error	Absolut Error	Squarred Error	Absolut % Error
1	2250					
2	2150					
3	2200					
4	2000	2116,67	116,67	116,67	13611,11	5,8333%
5	1900	2033,33	133,33	133,33	17777,78	7,0175%
6	1650	1850,00	200,00	200,00	40000,00	12,1212%
7	1580	1710,00	130,00	130,00	16900,00	8,2278%
8	1630	1620,00	-10,00	10,00	100,00	0,6135%
9	1700	1636,67	-63,33	63,33	4011,11	3,7255%
10	1880	1736,67	-143,33	143,33	20544,44	7,6241%
11	1970	1850,00	-120,00	120,00	14400,00	6,0914%
12	2500	2116,67	-383,33	383,33	146944,44	15,3333%
13	3000	2490,00	-510,00	510,00	260100,00	17,0000%
14	2950	2816,67	-133,33	133,33	17777,78	4,5198%
15	3100	3016,67	-83,33	83,33	6944,44	2,6882%
16	2970	3006,67	36,67	36,67	1344,44	1,2346%
17	2900	2990,00	90,00	90,00	8100,00	3,1034%
18	2650	2840,00	190,00	190,00	36100,00	7,1698%
19	2580	2710,00	130,00	130,00	16900,00	5,0388%
20	2620	2616,67	-3,33	3,33	11,11	0,1272%
21	2920	2706,67	-213,33	213,33	45511,11	7,3059%
22	2990	2843,33	-146,67	146,67	21511,11	4,9052%
23	3220	3043,33	-176,67	176,67	31211,11	5,4865%
24	3500	3236,67	-263,33	263,33	69344,44	7,5238%
SUM	58810	53186,67	-1223,33	3276,67	789144,44	1,33
AVERAGE			-55,61	156,03	37578,31	6%



Similarly, for the same data, applying the simple exponential smoothing method with damping factor 0.5 and the triple exponential smoothing method with $a=0.2$, $b = 0.2$, $g=0.2$ and $L =6$

	Purchases	Simple Exponential Smoothing	Triple Exponential Smoothing	Error (SES)	Error (TES)	Abs Error SES
Period		Damping Factor=0,5				
1	2250	0,00	0	0,00	0	0
2	2150	2250,00	0	100,00	0,00	100,00
3	2200	2200,00	0	0,00	0,00	0,00
4	2000	2200,00	0	200,00	0,00	200,00
5	1900	2100,00	0	200,00	-1900,00	200,00
6	1650	2000,00	0	350,00	-1650,00	350,00
7	1580	1825,00	0	245,00	-1580,00	245,00
8	1630	1702,50	1493,251996	72,50	-136,75	72,50
9	1700	1666,25	1532,555465	-33,75	-167,44	33,75
10	1880	1683,13	1481,108054	-196,88	-398,89	196,88
11	1970	1781,56	1474,61806	-188,44	-495,38	188,44
12	2500	1875,78	1496,2226	-624,22	-1003,78	624,22
13	3000	2187,89	1806,004749	-812,11	-1194,00	812,11
14	2950	2593,95	1792,54733	-356,05	-1157,45	356,05
15	3100	2771,97	2185,701137	-328,03	-914,30	328,03
16	2970	2935,99	2637,890144	-34,01	-332,11	34,01
17	2900	2952,99	2797,955453	52,99	-102,04	52,99
18	2650	2926,50	3071,09642	276,50	421,10	276,50
19	2580	2788,25	3235,191902	208,25	655,19	208,25
20	2620	2684,12	3042,093677	64,12	422,09	64,12
21	2920	2652,06	3068,465288	-267,94	148,47	267,94
22	2990	2786,03	3064,819503	-203,97	74,82	203,97
23	3220	2888,02	3058,230681	-331,98	-161,77	331,98
24	3500	3054,01	3158,501885	-445,99	-341,50	445,99
SUM	58810	54505,992	40396,254	-2054,008	-9813,746	5592,732
AVERAGE			1683,18	-85,58	-490,69	243,16

Abs Erros TES	Squared Error SES	Squared Error TES	Error SES %	Error TES %
0	0	0	0	0
	10000,00	0	4,65	0
0,00	0,00	0	0,00	0
0,00	40000,00	0	10,00	0
1900,00	40000,00	3610000,00	10,53	100,00
1650,00	122500,00	2722500,00	21,21	100,00
1580,00	60025,00	2496400,00	15,51	100,00
136,75	5256,25	18700,02	4,45	8,39
167,44	1139,06	28037,67	1,99	9,85
398,89	38759,77	159114,78	10,47	21,22
495,38	35508,69	245403,27	9,57	25,15
1003,78	389649,05	1007569,07	24,97	40,15
1194,00	659521,64	1425624,66	27,07	39,80
1157,45	126774,94	1339696,68	12,07	39,24
914,30	107601,94	835942,41	10,58	29,49
332,11	1156,93	110296,96	1,15	11,18
102,04	2808,28	10413,09	1,83	3,52
421,10	76450,36	177322,19	10,43	15,89
655,19	43367,35	429276,43	8,07	25,40
422,09	4111,91	178163,07	2,45	16,11
148,47	71790,73	22041,94	9,18	5,08
74,82	41603,34	5597,96	6,82	2,50
161,77	110213,70	26169,31	10,31	5,02
341,50	198909,08	116620,96	12,74	9,76
13257,079	2187148,00	14964890,48	226,03	607,75
631,29	95093,39	748244,52	9,83	28,94



Control for Grocery Store

	MA	SES	TES
MAD	156,03	243.16	631.29
MSE	37578,31	95093.39	748244.52
MAPE	6%	9.83%	28.94%

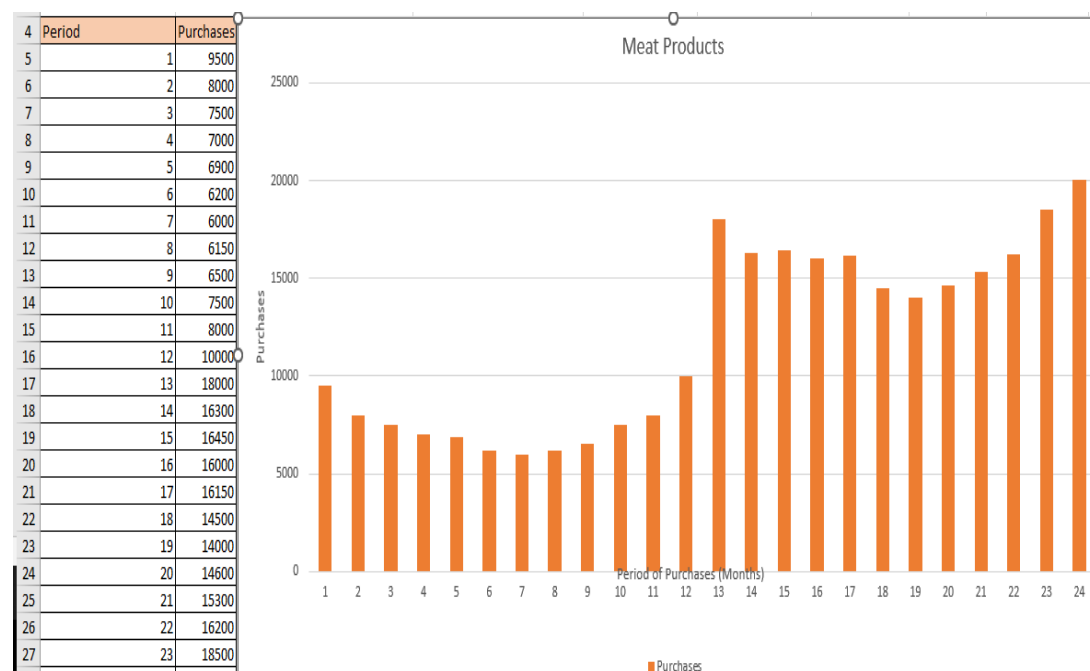
Comparing the above methods, that of the moving average (MA), simple exponential smoothing (SES) and the triple exponential smoothing (TES) with seasonality and trend, we observe that in the case of the moving average, the error equals $MAD =$

156.03, while in the exponential smoothing $MAD = 243.16$ and in the triple exponential smoothing $MAD = 631.29$. Incidentally in the case of the moving average the statistical error is the smallest of all the methods with $MAPE$ value = 6%. It is therefore concluded that the moving average method is more appropriate as it approximates to a greater extent the real demand values. This is confirmed by the actual demand curve, as it is itself identical to this forecast.

7.2 The Case Study of Meat

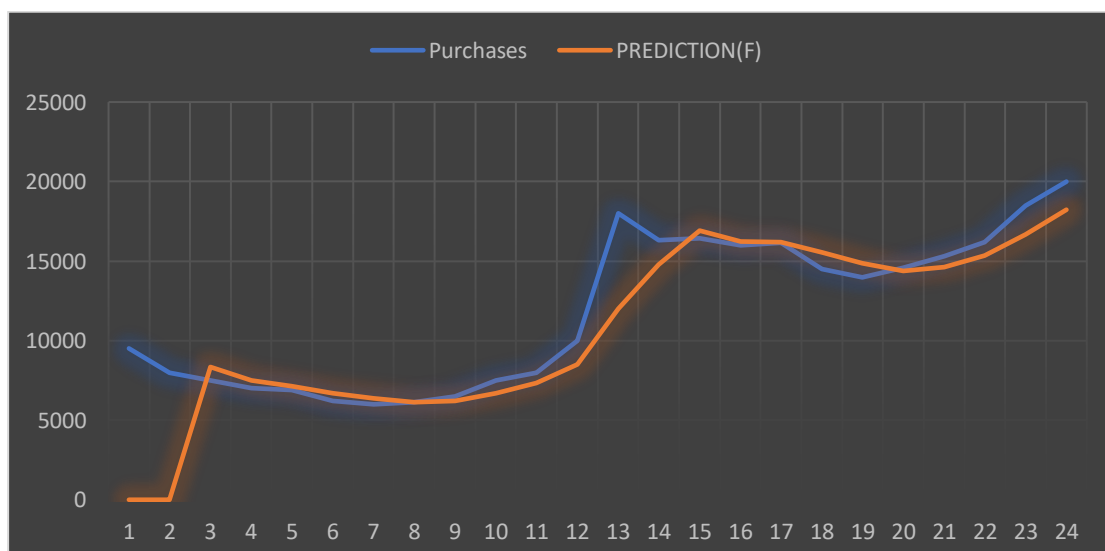
The items in the second category are meats (chicken, pork, beef, lamb, etc.) are characterised by high acquisition costs (€3.00 per kilo - €9.00 per kilo) and market availability, are addressed to all consumers and have limitation on their shelf life.

The demand over the last 24 months (21/4/2021 -21/4/2023) is shown in the chart below:



Applying the moving average method, for $t=24$ periods and a range of moving periods $N=3$, we obtain the following results:

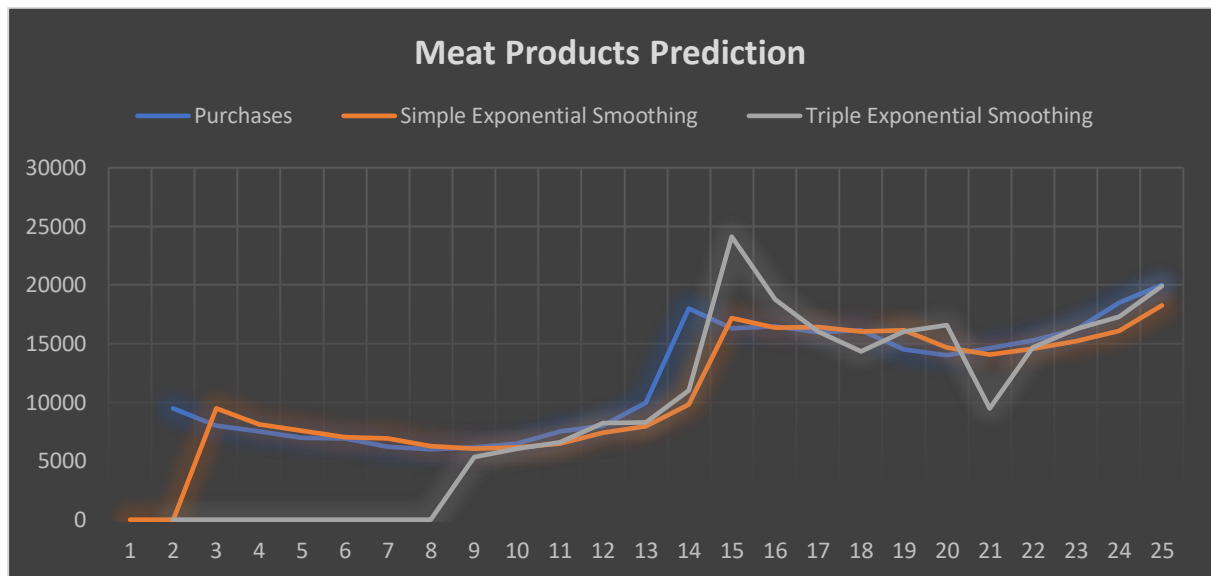
Period	Purchases	PREDICTION(F)	ERROR	ABSOLUT ERROR	ERROR SQUARED	Absolut Error
1	9500	0.00				
2	8000	0.00				
3	7500	8333.33	833.33	833.3333333	694444.4444	10.000%
4	7000	7500.00	500.00	500.00	250000.00	6.667%
5	6900	7133.33	233.33	233.33	54444.44	3.271%
6	6200	6700.00	500.00	500.00	250000.00	7.463%
7	6000	6366.67	366.67	366.67	134444.44	5.759%
8	6150	6116.67	-33.33	33.33	1111.11	0.545%
9	6500	6216.67	-283.33	283.33	80277.78	4.558%
10	7500	6716.67	-783.33	783.33	613611.11	11.663%
11	8000	7333.33	-666.67	666.67	444444.44	9.091%
12	10000	8500.00	-1500.00	1500.00	2250000.00	17.647%
13	18000	12000.00	-6000.00	6000.00	36000000.00	50.000%
14	16300	14766.67	-1533.33	1533.33	2351111.11	10.384%
15	16450	16916.67	466.67	466.67	217777.78	2.759%
16	16000	16250.00	250.00	250.00	62500.00	1.538%
17	16150	16200.00	50.00	50.00	2500.00	0.309%
18	14500	15550.00	1050.00	1050.00	1102500.00	6.752%
19	14000	14883.33	883.33	883.33	780277.78	5.935%
20	14600	14366.67	-233.33	233.33	54444.44	1.624%
21	15300	14633.33	-666.67	666.67	444444.44	4.556%
22	16200	15366.67	-833.33	833.33	694444.44	5.423%
23	18500	16666.67	-1833.33	1833.33	3361111.11	11.000%
24	20000	18233.33	-1766.67	1766.67	3121111.11	9.689%
SUM	285250	256750.00	-11000.00	21266.67	52965000	1.866317217
AVERAGE			-439.68	966.67	2407500.00	8.48%



Similarly, for the same data, applying the simple exponential smoothing method with damping factor 0.1 and the triple exponential smoothing method with $a=0.9$, $b = 0.9$, $g=0.9$ and $L =6$

	Purchases	Simple Exponential Smoothing	Triple Exponential Smoothing	Error (SES)	Error (TES)
Period		Damping Factor=0,1			
1	9500	0,00	0,00		
2	8000	9500,00	0,00		
3	7500	8150,00	0,00		
4	7000	7565,00	0,00		
5	6900	7056,50	0,00		
6	6200	6915,65	0,00		
7	6000	6271,57	0,00		
8	6150	6027,16	5326,19	-122,84	-823,81
9	6500	6137,72	6040,09	-362,28	-459,91
10	7500	6463,77	6591,73	-1036,23	-908,27
11	8000	7396,38	8219,70	-603,62	219,70
12	10000	7939,64	8308,93	-2060,36	-1691,07
13	18000	9793,96	11012,67	-8206,04	-6987,33
14	16300	17179,40	24124,71	879,40	7824,71
15	16450	16387,94	18775,14	-62,06	2325,14
16	16000	16443,79	16063,53	443,79	63,53
17	16150	16044,38	14364,32	-105,62	-1785,68
18	14500	16139,44	16062,36	1639,44	1562,36
19	14000	14663,94	16591,00	663,94	2591,00
20	14600	14066,39	9496,55	-533,61	-5103,45
21	15300	14546,64	14663,65	-753,36	-636,35
22	16200	15224,66	16276,03	-975,34	76,03
23	18500	16102,47	17285,77	-2397,53	-1214,23
24	20000	18260,25	19918,25	-1739,75	-81,75
Summary	285250	264276,64	229120,6115	15332,08	-5029,39
Average			13477,68303	-1703,56	-295,85

Abs Error SES	Abs Erros TES	Squared Error SES	Squared Error TES	Error SES %	Error TES %
122,84	823,81	15090,53	678663,65	2,00	13,67
362,28	459,91	131249,95	211521,54	5,57	7,49
1036,23	908,27	1073769,37	824953,52	13,82	14,05
603,62	219,70	364360,54	48268,35	7,55	2,97
2060,36	1691,07	4245092,74	2859704,39	20,60	21,30
8206,04	6987,33	67339030,58	48822813,25	45,59	71,34
879,40	7824,71	773337,99	61226018,77	5,40	45,55
62,06	2325,14	3851,49	5406282,62	0,38	14,19
443,79	63,53	196953,08	4036,30	2,77	0,39
105,62	1785,68	11155,71	3188643,51	0,65	11,13
1639,44	1562,36	2687756,76	2440967,49	11,31	9,68
663,94	2591,00	440821,36	6713260,04	4,74	17,67
533,61	5103,45	284734,96	26045172,74	3,65	36,28
753,36	636,35	567552,14	404946,80	4,92	4,37
975,34	76,03	951280,42	5780,04	6,02	0,50
2397,53	1214,23	5748167,39	1474356,25	12,96	7,54
1739,75	81,75	3026741,76	6682,67	8,70	0,45
15332,08	34354,31	235072546	160362071,92		
2106,52	2020,84	17940749,62	9433063,05	9,21	16,39



Control for Meat Products

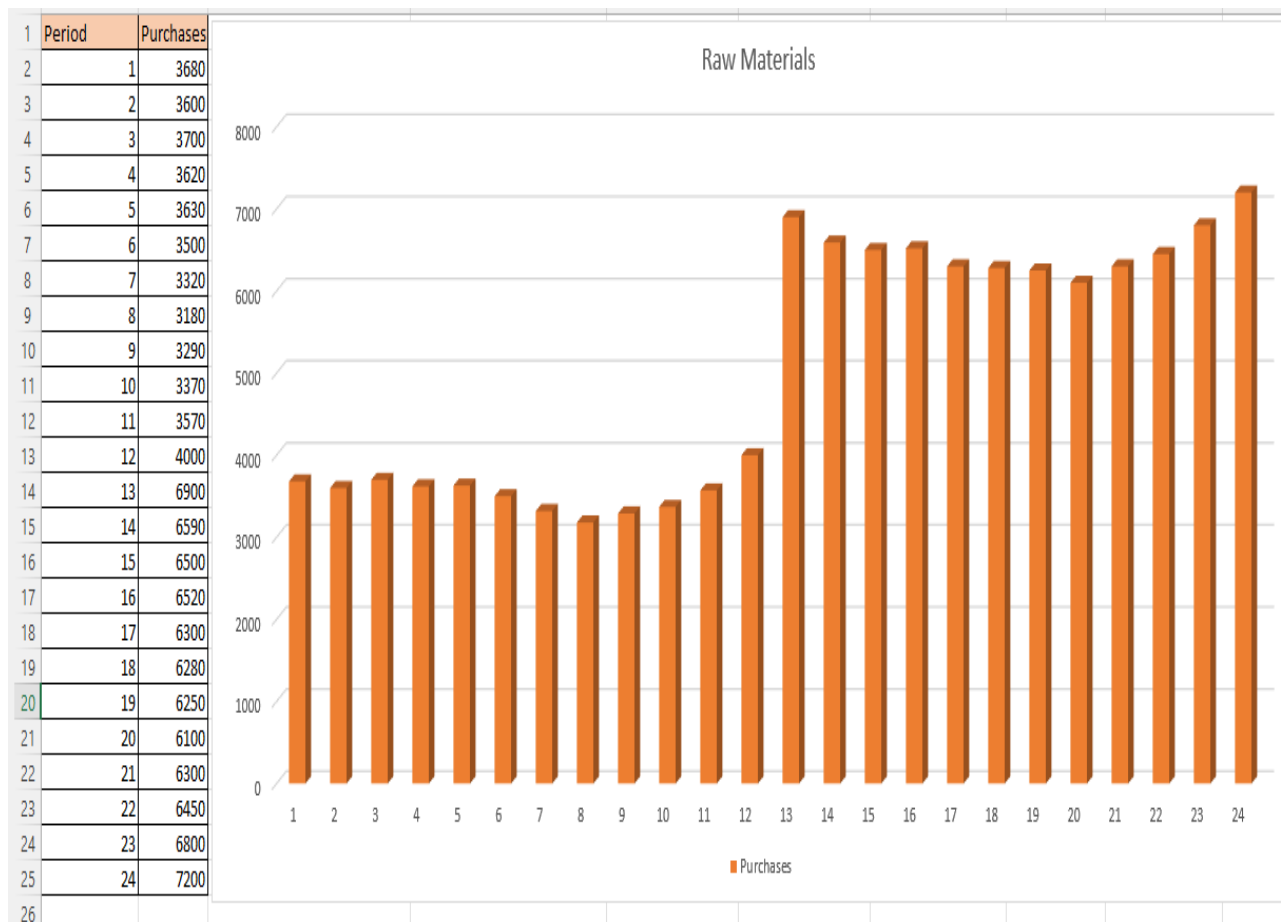
	MA	SES	TES
MAD	966.67	2106.52	2020.84
MSE	2407500	17940749,62	9433063,05
MAPE	8,48 %	9,21%	16,39%

Comparing the above methods, that of the moving average (MA), simple exponential smoothing (SES) and the triple exponential smoothing (TES) with seasonality and trend, we observe that in the case of the moving average, the error equals $MAD = 966,7$ while in the simple exponential smoothing $MAD = 2106.52$ and in the triple exponential smoothing $MAD = 2020.84$. Incidentally in the case of the moving average the statistical error is the smallest of all the methods with MAPE value = 8.48%. It is therefore concluded that the moving average method is more appropriate as it approximates to a greater extent the real demand values. This is confirmed by the actual demand curve, as it is itself identical to this forecast for the products of meat.

7.3 The Case Study of Raw Materials

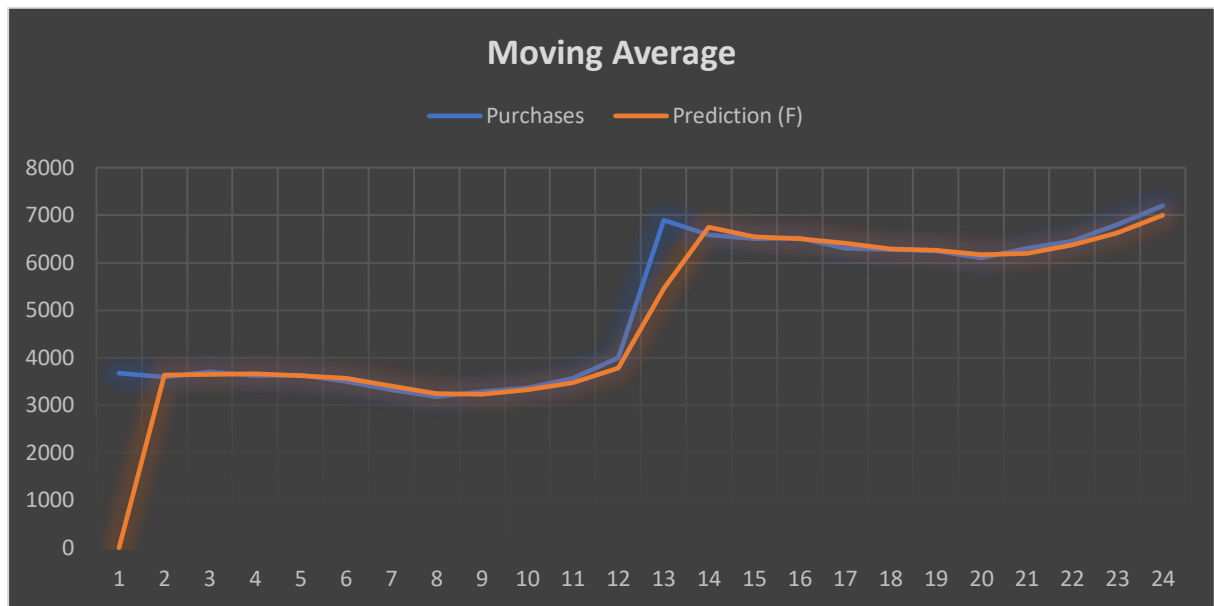
The items in the third category are raw materials (oil, olives, bread, cheese, salt, paper, etc.) are characterized by low acquisition costs (€0.50 per kilo - €6.00 per kilo) and market availability, are addressed to all consumers and have no limitation on their shelf life.

The demand over the last 24 months (21/4/2021 -21/4/2023) is shown in the chart below:



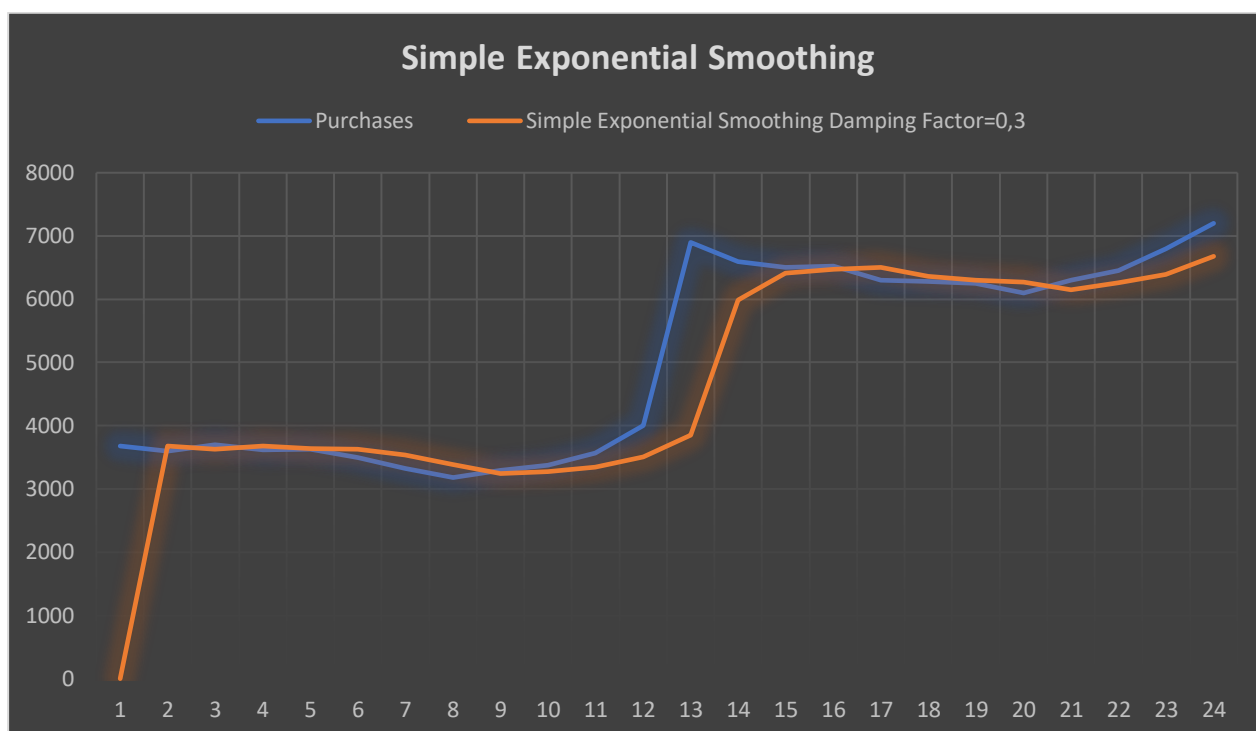
Applying the moving average method, for $t=24$ periods and a range of moving periods $N=2$, we obtain the following results:

Period	Purchases	Prediction (F)	Error	Absolut Error	Squarred Error	%error
1	3680	0				0
2	3600	3640	40	40	1600	1,11111111
3	3700	3650	-50	50	2500	1,35135135
4	3620	3660	40	40	1600	1,10497238
5	3630	3625	-5	5	25	0,13774105
6	3500	3565	65	65	4225	1,85714286
7	3320	3410	90	90	8100	2,71084337
8	3180	3250	70	70	4900	2,20125786
9	3290	3235	-55	55	3025	1,67173252
10	3370	3330	-40	40	1600	1,18694362
11	3570	3470	-100	100	10000	2,80112045
12	4000	3785	-215	215	46225	5,375
13	6900	5450	-1450	1450	2102500	21,0144928
14	6590	6745	155	155	24025	2,35204856
15	6500	6545	45	45	2025	0,69230769
16	6520	6510	-10	10	100	0,15337423
17	6300	6410	110	110	12100	1,74603175
18	6280	6290	10	10	100	0,15923567
19	6250	6265	15	15	225	0,24
20	6100	6175	75	75	5625	1,2295082
21	6300	6200	-100	100	10000	1,58730159
22	6450	6375	-75	75	5625	1,1627907
23	6800	6625	-175	175	30625	2,57352941
24	7200	7000	-200	200	40000	2,77777778
Sum	120650	115210	-1760,00	3190,00	2316750,00	57,20
Average		5009,130435	-76,52	138,70	100728,2609	2,48685282

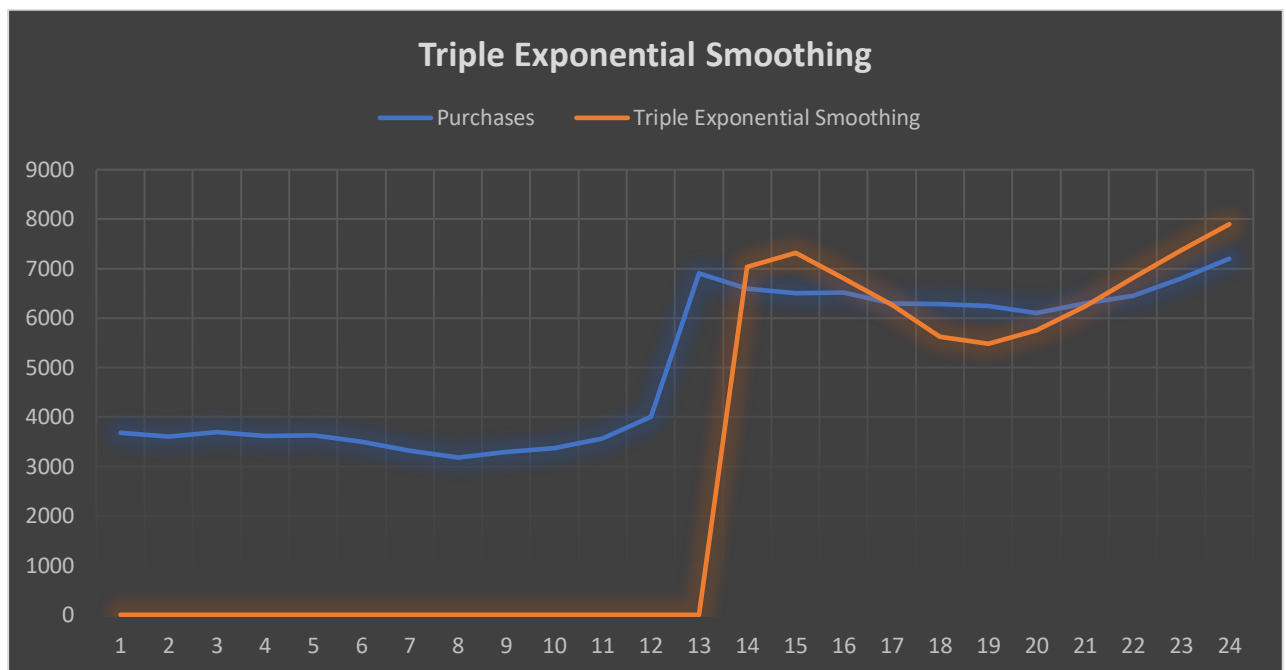


Similarly, for the same data, applying the simple exponential smoothing method with damping factor 0.3 and the triple exponential smoothing method with $a=0.6$, $b = 0.6$, $g=0.6$ and $L = 12$

	Purchases	Simple Exponential Smoothing	Error (SES)	Abs Error SES	Squared Error SES	Error SES %
Period		Damping Factor=0,3				
1	3680	0				
2	3600	3680,00	80,00	80,00	6400,00	2,22
3	3700	3624,00	-76,00	76,00	5776,00	2,05
4	3620	3677,20	57,20	57,20	3271,84	1,58
5	3630	3637,16	7,16	7,16	51,27	0,20
6	3500	3632,15	132,15	132,15	17463,09	3,78
7	3320	3539,64	219,64	219,64	48243,66	6,62
8	3180	3385,89	205,89	205,89	42392,06	6,47
9	3290	3241,77	-48,23	48,23	2326,33	1,47
10	3370	3275,53	-94,47	94,47	8924,51	2,80
11	3570	3341,66	-228,34	228,34	52139,56	6,40
12	4000	3501,50	-498,50	498,50	248504,51	12,46
13	6900	3850,45	-3049,55	3049,55	9299759,35	44,20
14	6590	5985,13	-604,87	604,87	365861,91	9,18
15	6500	6408,54	-91,46	91,46	8364,85	1,41
16	6520	6472,56	-47,44	47,44	2250,35	0,73
17	6300	6505,77	205,77	205,77	42340,73	3,27
18	6280	6361,73	81,73	81,73	6679,89	1,30
19	6250	6304,52	54,52	54,52	2972,34	0,87
20	6100	6266,36	166,36	166,36	27674,24	2,73
21	6300	6149,91	-150,09	150,09	22527,99	2,38
22	6450	6254,97	-195,03	195,03	38035,91	3,02
23	6800	6391,49	-408,51	408,51	166879,11	6,01
24	7200	6677,45	-522,55	522,55	273061,13	7,26
SUM	120650	112165,38	-4804,62	7225,46	10691900,63	128,40
AVERAGE	5027,08333	4673,557485	208,89654	314,1504	464865,2447	5,58241



	Purchases	Triple Exponential Smoothing	Error	Abs Error	Squared Error	Error %
Period						
1	3680					
2	3600					
3	3700					
4	3620					
5	3630					
6	3500					
7	3320					
8	3180					
9	3290					
10	3370					
11	3570					
12	4000					
13	6900					
14	6590	7036,60	446,60	446,60	199447,56	6,78
15	6500	7325,14	825,14	825,14	680852,51	12,69
16	6520	6803,49	283,49	283,49	80366,35	4,35
17	6300	6274,55	-25,45	25,45	647,93	0,40
18	6280	5620,67	-659,33	659,33	434715,98	10,50
19	6250	5479,78	-770,22	770,22	593233,11	12,32
20	6100	5757,19	-342,81	342,81	117520,19	5,62
21	6300	6237,21	-62,79	62,79	3943,11	1,00
22	6450	6808,62	358,62	358,62	128605,64	5,56
23	6800	7374,30	574,30	574,30	329819,52	8,45
24	7200	7898,33	698,33	698,33	487668,42	9,70
SUM	120650	72615,86	1325,86	5047,08	3056820,33	77,37
AVERAGE		3025,66	120,53	458,83	277892,76	7,03



Control for Raw Materials

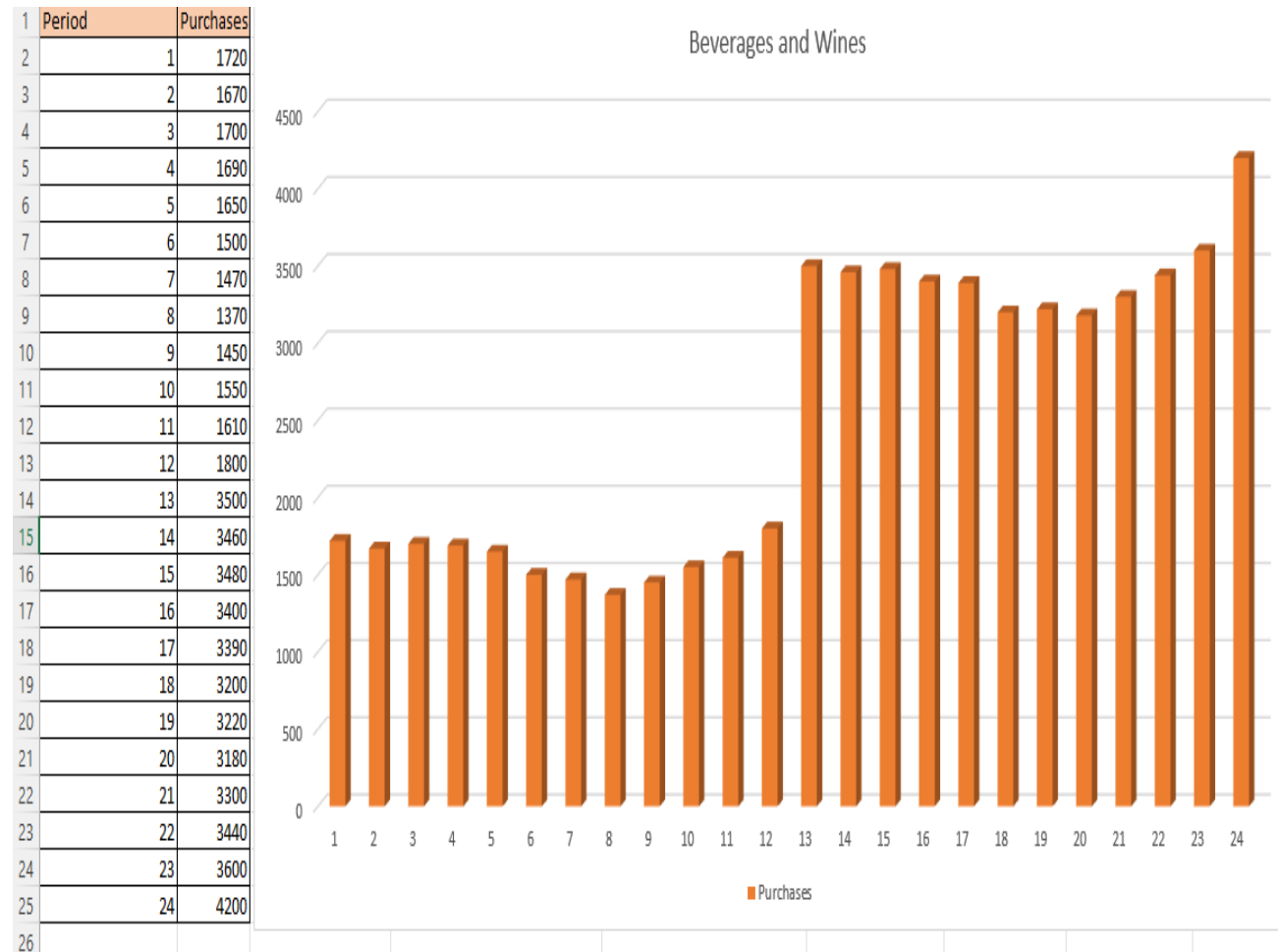
	MA	SES	TES
MAD	138.7	314.15	458.83
MSE	100728.26	464865.24	277892.76
MAPE	2.486%	5.58%	7.03%

Comparing the above methods, that of the moving average (MA), simple exponential smoothing (SES) and the triple exponential smoothing (TES) with seasonality and trend, we observe that in the case of the moving average, the error equals $MAD = 138.7$ while in the simple exponential smoothing $MAD = 314.5$ and in the triple exponential smoothing $MAD = 458.83$. Incidentally in the case of the moving average the statistical error is the smallest of all the methods with MAPE value = 2.48%. It is therefore concluded that the moving average method is more appropriate as it approximates to a greater extent the real demand values. This is confirmed by the actual demand curve, as it is itself identical to this forecast for the products of raw materials.

7.4 The Case Study of Beverages and Wines

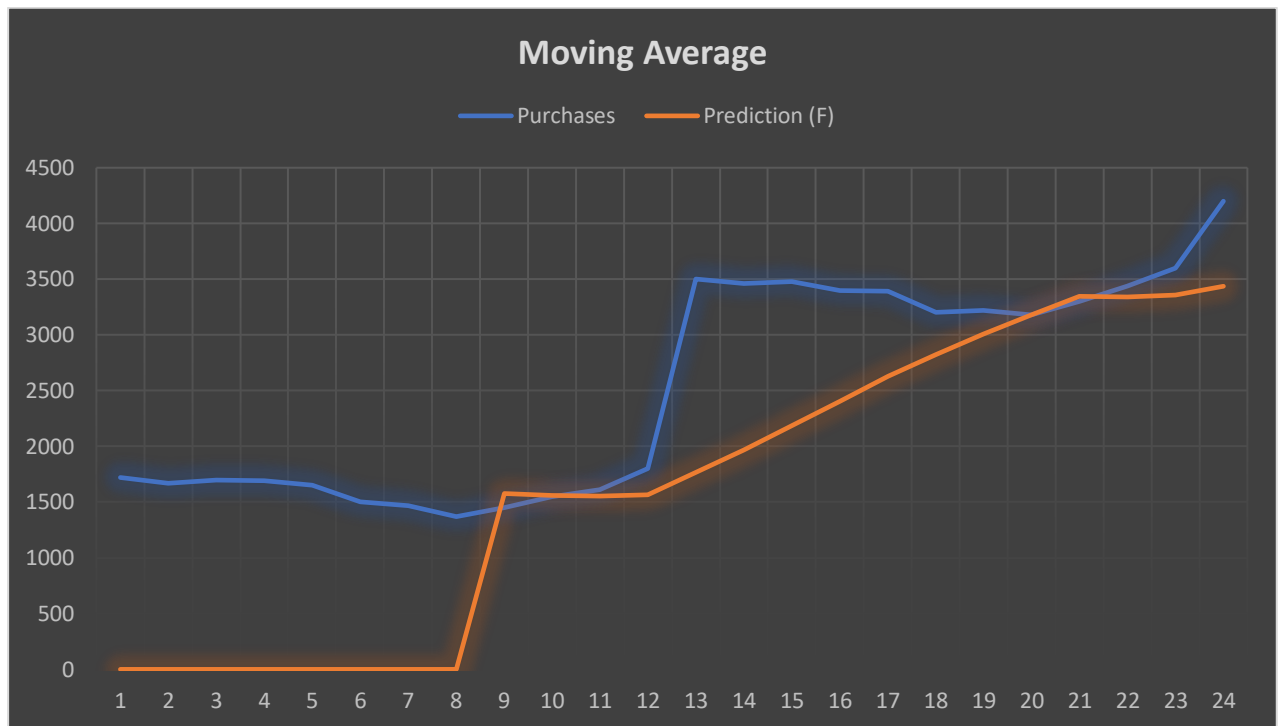
The items in the fourth category are beverages & wines (wine, beer, soft drinks, water) are characterized by low acquisition costs (€0.30 - €4.80) and market availability, are addressed to all consumers and have limitation on their shelf life.

The demand over the last 24 months (21/4/2021 -21/4/2023) is shown in the chart below:



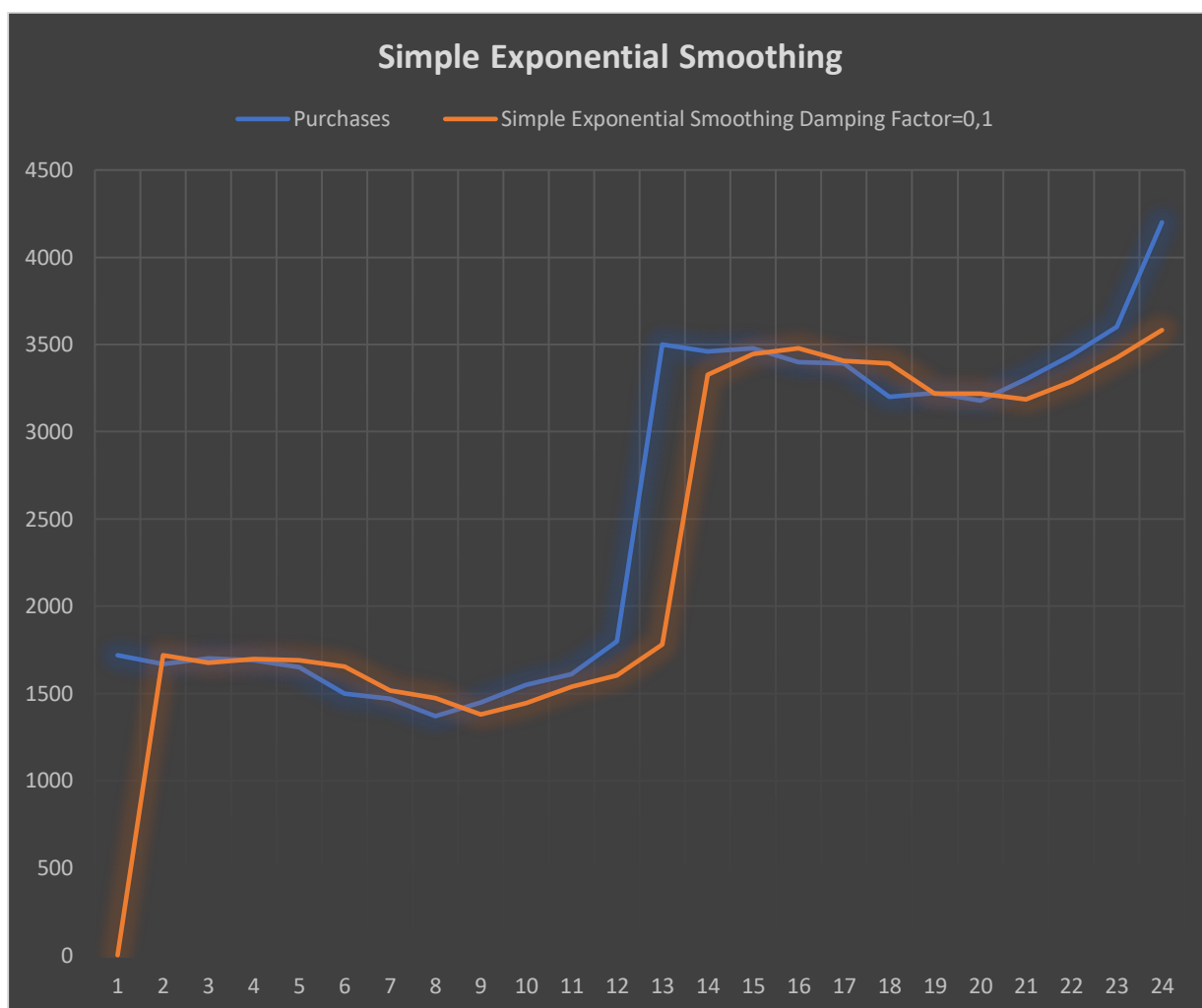
Applying the moving average method, for $t=24$ periods and a range of moving periods $N=9$, we obtain the following results:

Period	Purchases	Prediction (F)	Error	Absolut Error	Squarred Error	% Error
1	1720					
2	1670					
3	1700					
4	1690					
5	1650					
6	1500					
7	1470					
8	1370					
9	1450	1580	130,00	130,00	16900,00	8,965517241
10	1550	1561,111111	11,11	11,11	123,46	0,716845878
11	1610	1554,444444	-55,56	55,56	3086,42	3,450655625
12	1800	1565,555556	-234,44	234,44	54964,20	13,02469136
13	3500	1766,666667	1733,33	1733,33	3004444,44	49,52380952
14	3460	1967,777778	1492,22	1492,22	2226727,16	43,12780989
15	3480	2187,777778	1292,22	1292,22	1669838,27	37,13282248
16	3400	2402,222222	-997,78	997,78	995560,49	29,34640523
17	3390	2626,666667	-763,33	763,33	582677,78	22,51720747
18	3200	2821,111111	-378,89	378,89	143556,79	11,84027778
19	3220	3006,666667	-213,33	213,33	45511,11	6,625258799
20	3180	3181,111111	1,11	1,11	1,23	0,034940601
21	3300	3347,777778	47,78	47,78	2282,72	1,447811448
22	3440	3341,111111	-98,89	98,89	9779,01	2,874677003
23	3600	3356,666667	-243,33	243,33	59211,11	6,759259259
24	4200	3436,666667	-763,33	763,33	582677,78	18,17460317
Sum	60550	39703,33	8076,67	8456,67	9397341,98	255,56
Average		1654,31	-504,79	528,54	587333,87	10,65

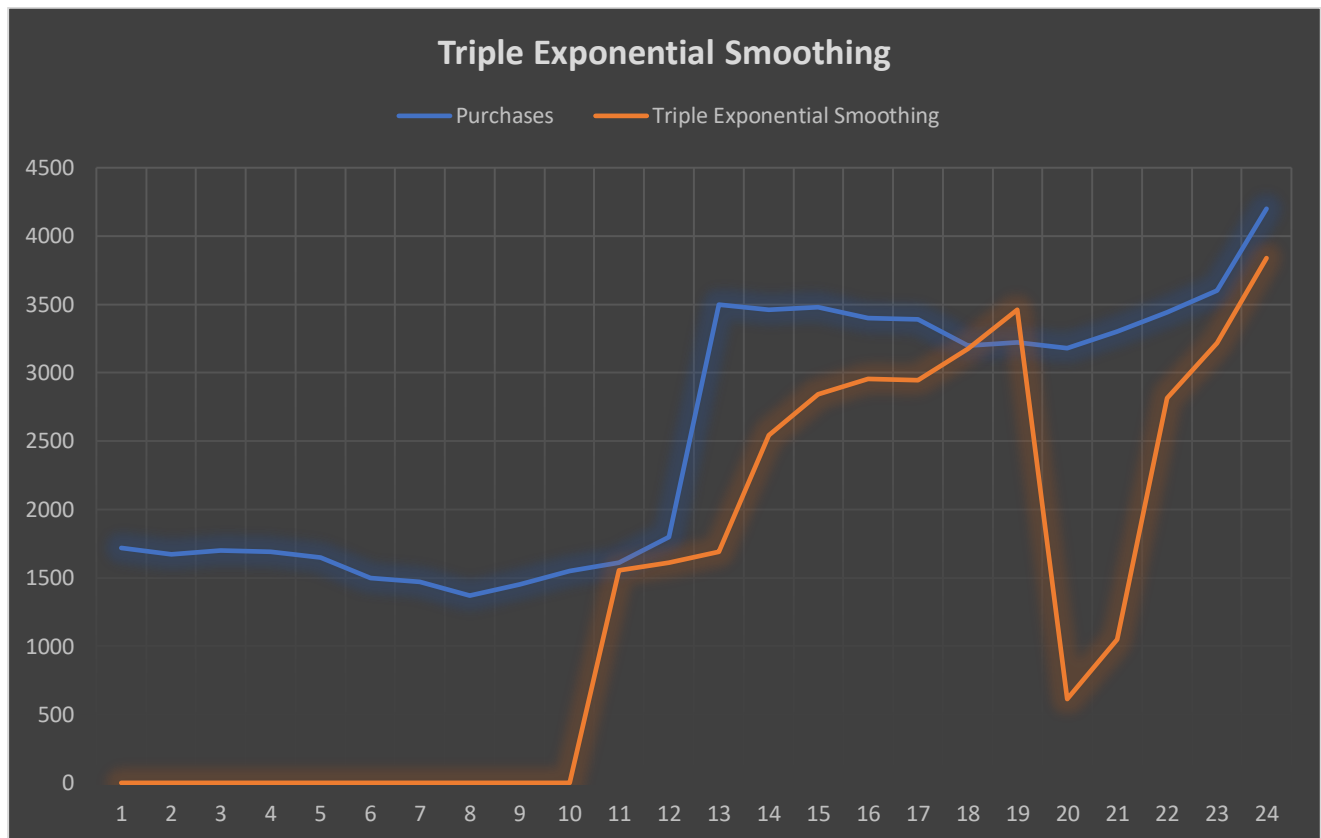


Similarly, for the same data, applying the simple exponential smoothing method with damping factor 0.1 and the triple exponential smoothing method with $a=0.3$, $b = 0.3$, $g=0.3$ and $L = 9$

	Purchases	Simple Exponential Smoothing	Error (SES)	Abs Error SES	Squared Error SES	Error SES %
Period		Damping Factor=0,1				
1	1720					
2	1670	1720,00	50,00	50,00	2500,00	2,99
3	1700	1675,00	-25,00	25,00	625,00	1,47
4	1690	1697,50	7,50	7,50	56,25	0,44
5	1650	1690,75	40,75	40,75	1660,56	2,47
6	1500	1654,08	154,08	154,08	23739,11	10,27
7	1470	1515,41	45,41	45,41	2061,84	3,09
8	1370	1474,54	104,54	104,54	10928,77	7,63
9	1450	1380,45	-69,55	69,55	4836,64	4,80
10	1550	1443,05	-106,95	106,95	11439,28	6,90
11	1610	1539,30	-70,70	70,70	4997,85	4,39
12	1800	1602,93	-197,07	197,07	38836,41	10,95
13	3500	1780,29	-1719,71	1719,71	2957392,01	49,13
14	3460	3328,03	-131,97	131,97	17416,26	3,81
15	3480	3446,80	-33,20	33,20	1102,05	0,95
16	3400	3476,68	76,68	76,68	5879,87	2,26
17	3390	3407,67	17,67	17,67	312,16	0,52
18	3200	3391,77	191,77	191,77	36774,51	5,99
19	3220	3219,18	-0,82	0,82	0,68	0,03
20	3180	3219,92	39,92	39,92	1593,42	1,26
21	3300	3183,99	-116,01	116,01	13457,91	3,52
22	3440	3288,40	-151,60	151,60	22982,81	4,41
23	3600	3424,84	-175,16	175,16	30681,05	4,87
24	4200	3582,48	-617,52	617,52	381326,02	14,70
SUM	60550	56143,06	-2686,94	4143,55	3570600,45	146,85
AVERAGE		2441,00	-116,82	180,15	155243,50	6,38



	Purchases	Triple Exponential Smoothing	Error (TES)	Abs Erros TES	Squared Error TES	Error TES %
Period						
1	1720					
2	1670					
3	1700					
4	1690					
5	1650					
6	1500					
7	1470					
8	1370					
9	1450					
10	1550					
11	1610	1554,13	-55,87	55,87	3121,33	3,47
12	1800	1611,53	-188,47	188,47	35519,82	10,47
13	3500	1691,69	-1808,31	1808,31	3269987,82	51,67
14	3460	2544,98	-915,02	915,02	837266,80	26,45
15	3480	2842,52	-637,48	637,48	406381,94	18,32
16	3400	2955,71	-444,29	444,29	197391,73	13,07
17	3390	2943,66	-446,34	446,34	199219,19	13,17
18	3200	3175,74	-24,26	24,26	588,43	0,76
19	3220	3461,60	241,60	241,60	58370,73	7,50
20	3180	612,91	-2567,09	2567,09	6589972,00	80,73
21	3300	1049,80	-2250,20	2250,20	5063392,80	68,19
22	3440	2816,51	-623,49	623,49	388741,81	18,12
23	3600	3216,08	-383,92	383,92	147393,92	10,66
24	4200	3838,95	-361,05	361,05	130353,96	8,60
SUM	60550	34315,82	-10464,18	10947,38	17327702,29	331,17
AVERAGE		1429,83	-747,44	781,96	1237693,02	23,65



Control for Bevarages and Wines

	MA	SES	TES
MAD	528.54	180.15	781.96
MSE	587333.87	155243.5	1237693.02
MAPE	10.65 %	6.38 %	23.65 %

Comparing the above methods, that of the moving average (MA), simple exponential smoothing (SES) and the triple exponential smoothing (TES) with seasonality and trend, we observe that in the case of the moving average, the error equals $MAD = 528.54$ and is the first which is bigger from simple exponential smoothing while in the simple exponential smoothing $MAD = 180.15$ and in the triple exponential smoothing $MAD = 781.96$. Incidentally in the case of simple exponential smoothing error is the smallest of all the methods with MAPE value = 6.38%. It is therefore concluded that the simple exponential method is more appropriate as it approximates to a greater extent the real

demand values. This is confirmed by the actual demand curve, as it is itself identical to this forecast for the products of beverages & wines.

Chapter 8 . Conclusions

8.1 Conclusions

Based on the results obtained from comparing the moving average (MA), simple exponential smoothing (SES), and triple exponential smoothing (TES) methods with seasonality and trend, we can draw the following conclusions:

In the case of the first comparison, which involved forecasting for a grocery store, the moving average method exhibited the smallest statistical error with a Mean Absolute Deviation (MAD) of 156.03 and a Mean Absolute Percentage Error (MAPE) value of 6%. This indicates that the moving average method closely approximated the real demand values, as confirmed by the actual demand curve aligning closely with the forecast.

For the second comparison, which focused on meat products, the moving average method again outperformed the other two methods. It had a MAD of 966.7 and an MAPE value of 8.48%, indicating a smaller statistical error compared to simple exponential smoothing and triple exponential smoothing. The moving average method proved to be a more suitable approach for approximating the real demand values, as evidenced by the similarity between the forecast and the actual demand curve.

In the third comparison, related to raw materials, the moving average method once again demonstrated the lowest statistical error. With a MAD of 138.7 and an MAPE value of 2.48%, it outperformed both simple exponential smoothing and triple exponential smoothing. The forecast produced by the moving average method closely matched the actual demand curve for raw materials.

However, in the fourth comparison concerning beverages and wines, the simple exponential smoothing method exhibited the smallest statistical error. It had a MAD of 180.15 and an MAPE value of 6.38%, outperforming both moving average and triple exponential smoothing methods. The forecast generated by the simple exponential

smoothing method closely aligned with the actual demand curve for beverages and wines.

In summary, the choice of the most appropriate forecasting method depends on the specific context and product category. While the moving average method consistently performed well in three out of four comparisons, the simple exponential smoothing method proved to be more suitable for forecasting beverages and wines. These findings highlight the importance of selecting the right forecasting method based on the characteristics of the data and the specific domain of application. Also indicated the moving average if used as predicted method of the restaurant will help it to avoid extra costs from the categories which analyzed.

8.2 Challenges and Considerations in Implementing Predictive Models

Implementing predictive models in inventory management can bring significant benefits, but it also presents some challenges. Here are key challenges and considerations to keep in mind:

- a) **Data Availability and Quality:** Predictive models require historical data for training and accurate forecasting. Ensuring the availability and quality of data, including accurate demand records, lead times, and other relevant variables, is crucial for the effectiveness of the models.
- b) **Data Preprocessing and Cleansing:** Raw data often requires preprocessing and cleansing to remove outliers, handle missing values, and normalize data. Proper data preprocessing is essential to ensure the accuracy and reliability of predictive models.
- c) **Model Selection and Validation:** Selecting the appropriate predictive model for inventory management requires consideration of factors such as data characteristics, complexity, interpretability, and scalability. Proper model validation techniques, such as cross-validation, are necessary to assess the model's accuracy and generalization ability.

d) **Integration with Existing Systems:** Integrating predictive models into existing inventory management systems can be challenging. Compatibility issues, data synchronization, and technical constraints should be addressed to ensure seamless integration and operational efficiency.

e) **Organizational Change and Adoption:** Implementing predictive models may require organizational changes and shifts in decision-making processes. It is important to involve stakeholders, provide training, and build a culture that embraces data-driven decision-making.

Effective integration of predictive models in inventory management requires attention to data integration and system requirements:

a) **Data Integration:** Predictive models rely on integrated data from various sources, such as sales records, supply chain data, and external factors (e.g., market trends, weather data). Integration may involve data consolidation, data mapping, and establishing data pipelines to ensure a seamless flow of information.

b) **System Scalability:** As the volume of data increases, the system should be scalable to handle large datasets efficiently. This may involve adopting cloud-based solutions or upgrading hardware infrastructure to support the computational requirements of predictive modeling.

c) **Real-Time Data:** For dynamic inventory management, real-time data integration is crucial. Integration with systems that provide real-time data, such as point-of-sale systems or supply chain management software, enables timely and accurate forecasting and decision-making.

d) **Data Security and Privacy:** Integrating data from different sources raises concerns about data security and privacy. It is essential to implement appropriate security measures, access controls, and data anonymization techniques to protect sensitive information.

Integration of Predictive Models into Existing Inventory Management Systems:

Integrating predictive models into existing inventory management systems can enhance their capabilities and improve decision-making. Here are key steps in the integration process:

- a) **Assess Current Systems:** Evaluate the functionalities and limitations of existing inventory management systems. Identify areas where predictive models can add value and address specific pain points.
- b) **Model Development and Testing:** Develop predictive models tailored to the specific inventory management requirements. Train and validate the models using historical data to ensure their accuracy and reliability
- c) **API or Database Integration:** Establish integration mechanisms such as APIs (Application Programming Interfaces) or direct database connections to transfer data between the predictive models and the inventory management systems. This allows real-time data exchange and seamless integration.
- d) **Automation and Workflow Integration:** Integrate the workflow of predictive models into existing inventory management processes. Define the decision triggers, outputs, and necessary actions based on the model's recommendations.
- e) **User Interface and Visualization:** Develop user-friendly interfaces or dashboards that display the predictions, insights, and recommended actions generated by the predictive models. Visual representations help users understand and interpret the results effectively.

Performance Monitoring and Continuous Improvement:

Once predictive models are integrated, it is crucial to monitor their performance and continuously improve their accuracy and effectiveness. Consider the following practices:

- a) **Performance Metrics:** Define relevant performance metrics to evaluate the predictive models' performance. Common metrics include forecast accuracy, mean absolute percentage error (MAPE), inventory turnover, and stockout rates. Regularly monitor these metrics to assess the models' performance and identify areas for improvement.

- b) **Model Validation:** Periodically validate the predictive models using new data to ensure their continued accuracy and reliability. Compare the model's forecasts with actual demand data and assess the deviation. If significant discrepancies are observed, retrain or recalibrate the model to improve its performance.
- c) **Feedback Loop:** Establish a feedback loop between the predictive models and the inventory management system. Gather feedback from inventory managers, users, and other stakeholders regarding the accuracy and usefulness of the forecasts. Incorporate this feedback into model refinement and improvement processes.
- d) **Continuous Model Training:** Continuously update and retrain the predictive models using new data. As new demand patterns emerge and the business environment evolves, incorporating fresh data into the models ensures that they remain up to date and capable of capturing changing trends
- e) **Collaboration with Stakeholders:** Collaborate with inventory managers, supply chain professionals, and other relevant stakeholders to gather insights and feedback. Their domain knowledge and expertise can help identify additional variables, refine forecasting methodologies, and enhance the models' performance.
- f) **Advanced Techniques and Algorithms:** Stay informed about advances in predictive modeling techniques and algorithms. Explore new methodologies, such as machine learning algorithms or advanced time series forecasting techniques, to improve the accuracy and robustness of the models.
- g) **Continuous Improvement Culture:** Foster a culture of continuous improvement within the organization. Encourage employees to share ideas, suggestions, and feedback on how to enhance the predictive models and optimize inventory management practices. Emphasize the importance of data-driven decision-making and encourage ongoing learning and development.

By actively monitoring the performance of predictive models, incorporating feedback, and embracing a culture of continuous improvement, organizations can maximize the benefits of predictive modeling in inventory management and achieve better inventory optimization, cost reduction, and improved customer satisfaction.

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