Demand Forecasting Dashboard for University Cafeteria

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Report submitted in partial fulfillment of the requirements of the Capstone Project undertaken for the BBA program

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Undertaking and Declaration

Declaration

We declare that our Capstone Project titled **“Demand Forecasting Dashboard for University Cafeteria”** submitted in partial fulfillment of the Summer Internship Program is original and is not substantially the same as one which has already been submitted in part or in full for any such similar qualification to the University to the best of my knowledge.

Date: 21/05/2023

Place: Ahmedabad

Acknowledgment

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Thank you all for being a part of our capstone project journey and for making it a truly enriching and fulfilling experience.

Sincerely,

Group

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Chapter 1: Introduction and Description of the Project

Project Introduction

In recent years, the use of machine learning has increased. and data analytics are revolutionizing the way many industries make informed decisions. The catering industry, including university cafeterias, has also recognized the potential of these technologies to optimize processes and improve customer satisfaction. One area where machine learning deserves attention is demand forecasting. This enables cafeteria managers to make data-driven decisions and streamline the warehouse and supply chain management processes.

This project focuses on developing a demand forecasting dashboard specifically designed for university cafeterias. The dashboard aims to accurately predict future demand for various food items served in cafeterias by harnessing the power of machine learning algorithms and predictive analytics. The ability to predict demand patterns enables cafeteria managers to effectively plan inventory, optimize resource allocation, reduce waste, and ultimately improve the overall dining experience for students and staff. can.

The importance of accurate demand forecasting in the hospitality industry cannot be overemphasized. Inefficient forecasting can lead to food waste, high inventory costs, and customer dissatisfaction due to long wait times and the unavailability of preferred products. Traditional demand forecasting techniques are often based on historical data and subjective estimates, are prone to error, and fail to capture the complex dynamics of changing consumer preferences and external factors. Therefore, the need for advanced and intelligent demand forecasting systems becomes apparent.

The integration of machine learning technology provides an innovative solution that overcomes the limitations of traditional forecasting methods. By leveraging historical sales data, weather patterns, school calendars, and other relevant variables, machine learning models can identify patterns, identify trends, and accurately predict future demand. This model-based demand forecasting dashboard provides cafeteria managers with valuable insight into customer behavior to make informed decisions and improve operational efficiency.

The purpose of this project includes several important aspects:

1. Developing a robust machine learning model: In the first phase, a machine learning model is built that is trained on historical data from university cafeterias. The model uses various algorithms such as regression, time series analysis, and neural networks to extract patterns and create accurate demand forecasts.
2. Data collection and preprocessing: To create a valid demand forecasting model, relevant data must be collected and preprocessed. This includes historical sales data, weather data, academic calendars, holidays, and other factors that can affect cafeteria demand. The collected data is cleaned, transformed, and prepared for model training.
3. Model training and optimization: A machine learning model is trained on preprocessed data and its parameters are tuned and refined to achieve the highest possible accuracy. Models are evaluated against appropriate metrics, such as mean absolute error or root mean square error, to assess their performance and identify areas for improvement.
4. Dashboard Development: User-friendly and interactive dashboards are created to visualize demand forecasts and provide insights to cafeteria managers. Dashboards include real-time data updates, visual representations of demand trends, and customizable features to tailor the forecasting process to your specific needs.
5. Implementation and Evaluation: Once the demand forecasting dashboard is developed, it will be implemented in the university cafeteria environment. The performance and effectiveness of the system are monitored and evaluated over time and forecasted demand and actual sales data are compared to assess forecast accuracy and value.

This project aims to contribute to the further development of demand forecasting techniques in the catering industry, specifically addressing the special requirements of university canteens. By harnessing the power of machine learning and predictive analytics, the Demand Forecasting Dashboard promises to optimize operations, reduce waste, and improve overall customer satisfaction. The resulting insights and data-driven decision-making capabilities will empower cafeteria managers to make informed choices, ensuring efficient resource allocation and an enhanced dining experience for students and staff. By presenting a detailed analysis and exploration of the proposed Demand Forecasting Dashboard, this research endeavors to contribute to the growing body of knowledge in the field of machine learning applications for demand forecasting in the food service industry.

In recent years, the application of machine learning models has revolutionized various industries, offering new avenues for improving decision-making processes and optimizing resource allocation. The food service industry, particularly university cafeterias, faces unique challenges when it comes to efficiently managing food production, minimizing waste, and meeting the ever-changing demands of a diverse and dynamic student population. In response to these challenges, this project aims to develop a Demand Forecasting Dashboard for a university cafeteria using a machine learning model. The dashboard enables cafeteria managers to make data-driven decisions to minimize food waste and optimize resource allocation while ensuring the right amount and type of food to meet student needs. food can be prepared reliably.

On college campuses around the world, cafeterias play an important role in providing food and nutrition to students. However, ensuring that cafeterias meet the dynamic needs of students while minimizing waste and optimizing resource allocation is a major challenge. Traditional approaches to demand forecasting often rely on historical data and human intuition, which can lead to inaccuracies and inefficiencies. Therefore, there is a growing need for a more robust and accurate demand forecasting system that can adapt to the ever-changing needs of university cafeterias.

This project harnessed the power of machine learning algorithms to develop a demand forecasting dashboard for a university cafeteria. Dashboards provide cafeteria managers with real-time insights and accurate forecasts, enabling them to make informed decisions regarding food production, inventory management, and resource allocation. By integrating machine learning technology into the demand forecasting process, the goal is to streamline operations, reduce food waste, and improve the overall dining experience for students.

The significance of this project is its potential to revolutionize the way university cafeterias are run. Implementing an accurate and reliable demand forecasting system can deliver several key benefits. First, the cafeteria provides a sufficient quantity and variety of food to reduce shortages and excesses. This directly enhances the student experience by providing a variety of freshly prepared meals. Second, reducing food waste through better demand forecasting has a positive impact on the environment by minimizing the carbon footprint associated with food production and disposal. Finally, optimizing resource allocation makes cafeterias more cost-effective and allows staff and other resources to be allocated more efficiently.

The bustling atmosphere of a college campus often revolves around the cafeteria, the center of student life and socializing. With thousands of students, faculty, and staff relying on cafeterias for their daily lives, effectively managing the needs and resources of this critical facility is a complex challenge. Harnessing the power of data-driven decision-making is essential to ensuring smooth operations, reducing waste, and optimizing the overall dining experience.

This project presents an innovative solution for a university canteen: a demand forecasting dashboard created by a machine learning model. Through advanced analytics and leveraging historical data, this revolutionary tool provides accurate real-time food demand forecasts, enabling cafeteria managers to make informed decisions regarding inventory management, menu planning, and resource allocation. It is intended to be

The Need for Demand Forecasting in College Cafeterias: College cafeterias face unique challenges due to the dynamic nature of their operations. Fluctuations in demand patterns, seasonal variations, and the unpredictability of student preferences make it very difficult to accurately estimate the amount of food needed. Traditional approaches based on manual calculations and intuition lead to many inefficiencies that lead to food waste, understocking, and customer dissatisfaction. Demand forecasting system implementations meet these challenges by adopting a data-driven approach that collects and analyzes historical data, considers external factors and leverages machine learning algorithms to produce accurate forecasts. deal with. With this solution, the university cafeteria can streamline inventory management, reduce waste, improve customer satisfaction, and increase operational efficiency.

The Role of Machine Learning in Demand Forecasting: Machine learning, a subset of artificial intelligence, has emerged as a powerful tool in demand forecasting. It uses algorithms and statistical models to recognize patterns, learn from historical data, and make predictions based on identified trends. In the context of a college cafeteria, machine learning algorithms can consider a variety of variables such as historical sales data, weather conditions, academic calendars, and special events to produce highly reliable forecasts. Using machine learning models to forecast demand offers several advantages over traditional approaches. These models can adapt and learn from new data, continuously improving their accuracy over time. Additionally, it can handle complex, non-linear relationships between variables and capture subtle patterns that a human analyst might not be aware of. Machine learning eliminates human bias by automating the prediction process, increasing the speed and efficiency of decision-making.

Demand Forecast Dashboard Development and Implementation: The University Cafeteria Project Demand Forecast Dashboard involves the development and implementation of a user-friendly, interactive tool that presents accurate demand forecasts to cafeteria managers. Dashboards serve as a centralized platform that integrates historical data, external factors, and machine learning algorithms to create real-time forecasts.

The development process includes several key steps. First, a comprehensive dataset consisting of historical sales records, demographic information, weather data, academic calendars, and other relevant variables is compiled. This dataset serves as the basis for training a machine-learning model. Various algorithms such as linear regression, time series analysis, and neural networks are used to recognize patterns and produce accurate forecasts. Once the model is trained and validated, it is integrated into the demand forecast dashboard. The dashboard interface is designed to be intuitive and visually appealing, providing easy access to demand forecasts, menu suggestions, and resource allocation recommendations for different time periods. Users, including cafeteria managers and employees, can interact with dashboards, explore different scenarios, adjust parameters, and make informed decisions based on forecast demand.

The hospitality industry is no exception, where efficient resource planning plays a key role in meeting customer demand and streamlining operations. This is especially true for university cafeterias. The challenge is to accurately forecast demand for diverse food products while minimizing waste and ensuring customer satisfaction.

To address these challenges, an innovative project was undertaken to harness the power of machine learning models to develop a demand forecasting dashboard for university cafeterias. The goal of this dashboard is to provide real-time insight into projected demand for various menu items, helping cafeteria managers streamline inventory management, reduce food waste, and improve the overall diet of students, faculty, and staff. It's about making the experience better.

The University Canteen serves as a central point of contact for students and employees, offering a wide range of cuisines to suit different tastes and nutritional preferences. However, maintaining optimal inventory levels to meet fluctuating demand can be challenging. Overestimating demand can lead to food waste and higher costs, while underestimating demand can lead to long lines, dissatisfied customers, and missed revenue opportunities.

By implementing an effective demand forecasting system, university cafeterias can overcome these hurdles and achieve operational excellence. Demand forecasting enables cafeteria managers to anticipate consumer preferences, track consumption patterns, and allocate resources accordingly. By leveraging historical data, external factors, and advanced analytical techniques, the accuracy of forecasts can be greatly improved, leading to better decision-making in the hospitality industry.

Machine learning, a branch of artificial intelligence, has revolutionized the way companies analyze and interpret big data. Using algorithms and statistical models, machine learning systems can learn patterns and make accurate predictions based on historical data. As part of demand forecasting, machine learning algorithms can effectively analyze historical sales data, weather conditions, school calendars, and other relevant variables to create forecasts that adapt to changing conditions.

The Demand Forecasting Dashboard project trains a machine-learning model using historical transactional data from a university cafeteria. The model uses various techniques such as regression analysis, time series analysis, and pattern recognition to capture and identify hidden patterns in data. By incorporating external factors like weather data, holidays, and special events, the model will enhance the accuracy of demand predictions and ensure more robust forecasting.

The Demand Forecasting Dashboard will serve as a centralized platform, consolidating diverse data sources and providing users with an intuitive interface to monitor and manage demand forecasts effectively. The dashboard will consist of the following key components: The dashboard will integrate and preprocess data from various sources, including point-of-sale systems, inventory management systems, weather APIs,

The development of a Demand Forecasting Dashboard for a university cafeteria utilizing machine learning techniques represents a significant advancement in the field of food service management.

By leveraging historical data, weather patterns, academic calendars, and other relevant variables, this project aims to provide accurate demand forecasts and empower cafeteria managers to optimize operations, reduce waste, and enhance the overall dining experience for students and staff.

The use of machine learning algorithms and predictive analytics in demand forecasting offers several key advantages over traditional methods. By analyzing large amounts of data and identifying complex patterns and trends, machine learning models can generate more accurate and reliable predictions. This enables cafeteria managers to make informed decisions about inventory management, resource allocation, and menu planning, ultimately leading to increased customer satisfaction and reduced costs.

The proposed demand forecast dashboard aims to facilitate effective decision-making by providing intuitive visualization and real-time updates of the demand forecast. The dashboard allows cafeteria managers to monitor demand trends, identify potential bottlenecks or demand spikes, and adjust operations accordingly. With access to actionable insights and forecasts, managers can proactively respond to changing customer preferences, optimize inventory levels, and streamline supply chain processes.

The success of this project depends on several key factors. First and foremost, the availability of high-quality, relevant data is critical for training and optimizing machine learning models. Accurate historical sales data, weather data, and other contextual information play a key role in creating reliable forecasts. Moreover, proper data preprocessing and feature engineering are essential to maximize model performance.

In addition, usability and usability of the demand forecast dashboard are also a top priority. Dashboards should be intuitive and easy to navigate so cafeteria managers can quickly access the information they need and make informed decisions. Customizable features and real-time data updates allow the dashboard to remain flexible and adapt to the unique needs of each university cafeteria.

By accurately predicting future demand, cafeteria managers can streamline operations, reduce waste and improve customer satisfaction. By integrating machine learning techniques and combining intuitive visualization with real-time updates, managers can make data-driven decisions and effectively adapt to changing market dynamics. This project will contribute to the further development of demand forecasting technology in the catering industry, specifically addressing the needs of university cafeterias.

What is EOQ?

EOQ (Economic Order Quantity) is a widely used inventory management technique that helps determine the optimal order quantity for a product. It aims to balance the costs associated with holding inventory and ordering more. We have used this model to predict the inventory levels for our project.

The concept is simple: when ordering inventory, there are two types of costs involved. Holding costs include expenses like storage, insurance, and depreciation. Ordering costs are incurred each time an order is placed, covering activities like paperwork, transportation, and processing fees.

EOQ finds the sweet spot where these costs are minimized. It takes into account factors such as the demand rate, product price, carrying cost per unit, and ordering cost. By calculating the EOQ, businesses can determine the ideal quantity to order that minimizes total costs.

Implementing EOQ can bring several benefits, including reduced holding costs, minimized stockouts, and optimized cash flow. It enables businesses to strike a balance between avoiding excessive inventory levels that tie up capital and risking stockouts that can lead to lost sales or customer dissatisfaction.

Overall, EOQ provides a valuable framework for organizations to make informed decisions about inventory management, ensuring optimal efficiency and cost-effectiveness in their supply chains.

Chapter 2: Literature Review

Introduction

The purpose of this project is to develop a real-time demand forecasting dashboard for cafeteria management. A comprehensive review was conducted using relevant databases to gather information on demand forecasting techniques, data sources for forecasting, the impact of external factors on demand, optimization of food production and staffing, and visualization techniques. The goal is to leverage this knowledge to create an effective dashboard that improves operational efficiency, reduces waste, and enhances the customer experience in cafeterias.

Background Review

The following is a summary of the relevant review materials that have been referred to in relation to the project of developing a real-time demand forecasting dashboard for cafeteria management:

- Demand Forecasting Techniques:

Extensive research has been conducted on demand forecasting techniques, including time series analysis, regression models, artificial neural networks, support vector machines, and random forests. These techniques have been applied in various domains to accurately predict customer demand.

- Data Sources for Demand Forecasting:

Previous studies have explored the integration of data sources such as historical sales data, transaction records, customer preferences, and real-time data (e.g., weather conditions, holidays, and local events). These diverse data sources contribute to more accurate demand forecasts.

- Impact of External Factors on Demand:

External factors, including weather conditions, nearby events, and holidays, have been identified as significant drivers of cafeteria demand. These factors influence customer behavior and preferences. Accounting for these external factors in demand forecasting models leads to more accurate predictions.

- Optimization of Food Production and Staffing:

Researchers have proposed various optimization approaches to align food production and staffing levels with forecasted demand. Mathematical programming models, simulation-based optimization, and heuristic algorithms have been used to determine optimal food quantities and staffing requirements. Implementing these approaches has demonstrated cost savings and waste reduction.

- Visualization and Decision Support:

Visualization techniques and interactive dashboards play a crucial role in presenting demand forecasts in a user-friendly and actionable manner. Data visualization methods, graphical representations, and intuitive interfaces have been employed to aid decision-making processes in cafeteria management.

Summary

Demand forecasting techniques provide a foundation for accurate predictions by utilizing various algorithms, including time series analysis, regression models, and machine learning algorithms. The integration of data sources such as historical sales data, transaction records, customer preferences, and real-time data, including weather conditions and events, enhances the accuracy of demand forecasts. External factors like weather conditions, nearby events, and holidays significantly influence cafeteria demand. Considering these factors in forecasting models improves the accuracy of predictions.

Optimization approaches, including mathematical programming models, simulation-based optimization, and heuristic algorithms, help align food production and staffing levels with forecasted demand, leading to cost savings and waste reduction. Effective visualization techniques and interactive dashboards aid decision-making processes by presenting demand forecasts and related information in a user-friendly manner.

By incorporating these aspects into the real-time demand forecasting dashboard, the project aims to improve operational efficiency, reduce waste, and provide a better customer experience in cafeteria management.

Why EOQ?

EOQ (Economic Order Quantity) is a good option for cost-saving in inventory management due to several reasons:

1. *Reduction in Stockouts and Excess Inventory:* EOQ helps strike a balance between excessive inventory and stockouts. Ordering excessive quantities leads to higher holding costs and increases the risk of product obsolescence or damage. On the other hand, stockouts can result in lost sales and dissatisfied customers. By calculating the EOQ, businesses can minimize both stockouts and excess inventory, reducing associated costs.

2. *Optimizes Cash Flow*: Implementing EOQ can optimize cash flow by reducing tied-up capital in inventory. Ordering excessive quantities increases inventory holding costs and ties up capital that could be used for other business activities. By ordering the optimal quantity, businesses can free up cash for investment in other areas, improving overall financial performance.

3. *Continuous Improvement and Process Efficiency:* EOQ improves overall supply chain efficiency by streamlining inventory management. By ensuring appropriate inventory levels are maintained at the appropriate timing, companies can prevent delays, decrease lead times, and enhance order fulfillment. As a result, customer satisfaction is heightened, operational efficiency improves, and potential expenses linked to rushed orders or expedited shipping can be minimized.

4. *Enables Bulk Purchasing Benefits:* EOQ often allows businesses to take advantage of bulk purchasing benefits. When ordering larger quantities, suppliers may offer discounts or reduced unit costs, resulting in cost savings for the business. EOQ helps determine the optimal order quantity that maximizes these bulk purchasing benefits, reducing the cost per unit of inventory.

5. *Improved Forecasting Accuracy*: EOQ requires businesses to estimate demand accurately, which promotes better forecasting practices. Accurate demand forecasting minimizes the risk of

understocking or overstocking, reducing costs associated with rush orders, emergency shipments, or excessive carrying costs.

6. *Inventory Turnover Optimization:* EOQ focuses on optimizing the frequency of orders and inventory turnover. By ordering the optimal quantity, businesses can ensure a steady flow of inventory and reduce the average time products spend in stock. This enhances cash flow, reduces holding costs, and minimizes the risk of obsolescence.

7. *Lower Replenishment Costs*: EOQ considers ordering costs, such as paperwork, transportation, and processing fees. By determining the optimal order quantity, businesses can reduce the frequency of placing orders, leading to cost savings in administrative and operational processes.

8. *Supplier Relationship Enhancement*: Implementing EOQ can foster stronger relationships with suppliers. By consistently ordering the optimal quantity, businesses demonstrate reliability and commitment, which can lead to improved supplier terms, preferential treatment, and potential negotiation for better prices or extended payment terms.

9. *Reduction in Carrying Costs*: Carrying costs include expenses like storage, insurance, and taxes. EOQ aims to minimize carrying costs by ordering the optimal quantity, thereby reducing the time and resources spent on storing and maintaining inventory. This directly translates into cost savings for the business.

Chapter 3: Methodology

The methodology section describes the approach taken to conduct the project, specifically focusing on data analysis.

Objectives

The objectives of the project are to develop a real-time demand forecasting dashboard for cafeteria management and evaluate its effectiveness in improving operational efficiency and reducing waste. The methodology encompasses the collection, analysis, and interpretation of both qualitative and quantitative data to achieve these objectives.

Design

The research design utilized in this project is primarily quantitative, as it involves the analysis of historical customer data and real-time data to generate demand forecasts. However, qualitative data may also be collected through surveys or interviews to gather insights into customer preferences, satisfaction levels, and suggestions for improvement.

Setting

The implementation of the project will take place in the cafeteria setting where the dashboard will be deployed. The specific cafeteria(s) selected for the study will be determined based on their willingness to participate and provide access to relevant data. It is important to choose cafeterias with diverse characteristics to ensure the generalizability of the findings.

Instrumentation

The primary instrument used in this project is the real-time demand forecasting dashboard. The dashboard will be designed to integrate historical customer data, real-time data sources (e.g., weather conditions, events), and machine learning algorithms. It will provide visualizations and forecasts related to customer traffic and demand for specific food items. Surveys or interviews may also be conducted to collect qualitative data on customer preferences and satisfaction.

Procedure

The implementation and evaluation of the project will follow a step-by-step procedure. The initial step involves gathering historical customer data, including transaction records, customer preferences, and feedback. Real-time data sources, such as weather APIs and event databases, will be integrated into the dashboard to capture external factors influencing demand.

The collected data will undergo preprocessing to ensure data quality and consistency. Feature engineering techniques may be applied to extract relevant information and create meaningful variables for analysis. Various machine learning algorithms, such as regression models or time series forecasting models, will be employed to generate demand forecasts based on the available data.

The effectiveness of the dashboard will be evaluated through several measures. Key performance indicators (KPIs) related to operational efficiency, waste reduction, and customer satisfaction will be identified. These KPIs may include metrics such as food wastage percentage, the accuracy of demand forecasts, customer waiting time, and customer feedback ratings.

Evaluation of Effectiveness

To evaluate the effectiveness of the project, several methods will be employed. First, a comparison will be made between the pre-implementation and post-implementation periods to assess changes in operational efficiency and waste reduction. The collected data will be analyzed using appropriate statistical methods to measure the impact of the dashboard on these outcomes.

Customer satisfaction and feedback will also be evaluated through surveys or interviews. The instrument used for data collection will be developed based on the specific research objectives and may include Likert scales, open-ended questions, or rating scales. The validity and reliability of the instrument will be ensured through appropriate piloting and testing procedures.

Statistical analyses, such as descriptive statistics, regression analysis, or hypothesis testing, will be conducted to analyze the collected data and examine the relationships between variables. The findings will be interpreted to determine the effectiveness of the project in achieving its objectives.

In conclusion, the methodology for this project involves a combination of quantitative and qualitative data analysis. The real-time demand forecasting dashboard will serve as the primary instrument for data collection and analysis. Various statistical and machine learning techniques will be applied to analyze the data, evaluate the effectiveness of the project, and measure the impact on operational efficiency, waste reduction, and customer satisfaction.

EOQ Methodology

Optimizing inventory management is essential for businesses seeking cost savings and operational efficiency. The Economic Order Quantity (EOQ) methodology provides a structured approach to determining the optimal order quantity that minimizes total costs while ensuring a steady supply of inventory. By carefully considering factors such as demand, ordering costs, holding costs, and practical constraints, organizations can leverage EOQ to strike a balance between minimizing inventory costs and meeting customer demand. This detailed and nuanced methodology enables businesses to fine-tune their inventory management strategies, enhance cash flow, reduce stockouts, and drive cost savings throughout the supply chain.

1. *Determine Demand:* Gather historical sales data, market research, and customer forecasts to determine the demand for the product over a specific time period. It's important to consider factors such as seasonality, trends, and any anticipated changes in demand.

2. *Determine Ordering Cost:* Recognize and measure the diverse expenses linked to initiating an order. These expenses encompass administrative tasks like paperwork, order processing, and communication, as well as transportation costs such as shipping and freight charges.

3. *Determine Holding Cost:* Assess the expenses associated with keeping inventory for a specific duration. Holding costs involve costs related to storage facilities, warehouse rent, insurance, utilities, security, and the potential loss of capital due to inventory. Express the holding cost either as a percentage of inventory value or as a fixed cost per unit over a specific time period.

4. *Calculate EOQ Formula:* Use the EOQ formula, which is derived from the trade-off between ordering costs and holding costs, to calculate the optimal order quantity. The formula is as follows:

$$EOQ = \sqrt{[(2 * Demand * Ordering\ Cost) / (Holding\ Cost * Material\ Cost)]}$$

5. *Evaluate Cost Trade-offs:* Calculate the total cost associated with different order quantities. Consider both the ordering costs and the holding costs for each quantity. Compare the total costs and identify the order quantity that minimizes the total cost. This quantity represents the optimal balance between the costs of ordering and holding inventory.

6. *Consider Practical Constraints:* Take into account practical constraints that may impact the order quantity. Consider factors such as storage capacity, production constraints, supplier limitations, and any other constraints that may affect the ability to order and hold inventory. Adjust the EOQ if necessary to align with these constraints.

7. *Review and Adjust:* Regularly review the EOQ calculation to ensure it remains optimal. Factors such as changes in demand patterns, cost structures, lead times, or business conditions may require recalculating the EOQ. Monitor and analyze relevant data to make informed adjustments when necessary.

8. *Monitor and Fine-tune:* Continuously monitor inventory levels, costs, and performance metrics. Track key indicators such as stockouts, carrying costs, order frequency, and customer satisfaction. Fine-tune the EOQ based on actual performance, feedback from the supply chain, and opportunities for improvement.

By following this detailed methodology, businesses can effectively determine the optimal order quantity through EOQ analysis. This approach allows for efficient inventory management, cost reduction, and improved operational performance in the supply chain.

Forecasting Methodology

1. *Understanding the Data:* First, we started by understanding the data we are working with. We looked at the historical time series data and identified any patterns or trends, as well as checked for any seasonality or outliers that needed to be addressed.

2. *Stationarity:* ARIMA models require the time series data to be stationary, meaning that the mean, variance, and autocovariance do not change over time. If the data is not stationary, we would need to make it stationary through a process called differencing. We calculated the first difference by subtracting each observation from its previous observation and checking if it becomes stationary. If not, we may need to apply higher-order differencing or other techniques like logarithmic transformation.

3. *Identifying Model Order:* Next, we have identified the order of the ARIMA model by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The ACF measures the correlation between the time series and its lagged values, while the PACF measures the correlation between the time series and its lagged values after removing the effects of intervening lags. These plots helped us to determine the number of autoregressive (AR) and moving average (MA) terms in the model.

   For the AR component, we looked for significant lags in the PACF plot. If there is a gradual decrease in significant lags, it suggests an AR model.
   For the MA component, we looked for significant lags in the ACF plot. If there is a gradual decrease in significant lags, it suggests an MA model.

4. *Model Fitting:* Once we have identified the order of the ARIMA model, we fit the model to the data using maximum likelihood estimation. This involves estimating the model parameters that minimize the difference between the predicted values and the actual values of the time series. We used software or programming libraries that provide ARIMA modeling capabilities, such as the stats models library in Python.

5. *Model Diagnostic*: After fitting the ARIMA model, we evaluated its performance and checked if it adequately captures the patterns and structures in the data. We examined the residuals, which are the differences between the observed values and the predicted values of the model. The residuals should be uncorrelated and normally distributed. We checked for any remaining autocorrelation in the residuals using the ACF and PACF plots, and we might need to consider adjusting the model order if necessary.

6. *Model Evaluation and Validation:* To evaluate the model's performance, we compared the predicted values of the ARIMA model with the actual values of the time series. We used appropriate evaluation metrics such as mean squared error (MSE), mean absolute error (MAE), or root mean squared error (RMSE). We also considered using techniques like cross-validation to validate the model's predictive capabilities.

7. *Forecasting:* Once the ARIMA model has been validated, we used it to make forecasts for future time periods. We specified the number of future periods we want to forecast and use the fitted ARIMA model to generate predictions. It's important to keep in mind that the accuracy of the forecasts may depend on the stability of the underlying data patterns and the forecast horizon.

Chapter 4: Results and Findings

EOQ Model

For our model, we have used the data of the top 10 most-selling items at the cafeteria and tried to find the EOQ of the 9 most common raw materials that are used in those items. The raw materials are:

1. Cheese
2. Bread
3. Burger Bun
4. Milk
5. Chilli
6. Garlic Bread
7. French Fries
8. Corn
9. Ketchup

First, we calculated the material cost, ordering cost, and holding cost for each item based on the information that we could gather. The Excel sheet gives the calculation in more detail. Let us understand the breakup:

Refrigerator Capacity:

- The given refrigerator's capacity is 600 liters.

Effective Capacity:

The refrigerator's effective capacity is determined by considering the recommended utilization range of 70-80%. Since the utilization range is 70-80% we are assuming it to be an average of this range which would be 75%.

Then, to calculate the effective capacity, we multiply the average utilization (75%) with refrigerator capacity (600 liters) = 600 * 75% = 450 liters.

Electricity Usage Weekly:

- The given electricity usage is 13 kWh per week.

Unit Charge:

- The unit charge is given as Rs. 11 per kWh.

Total Weekly Operating Charge:

- The total weekly operating charge can be calculated by multiplying the electricity usage (13 kWh) by the unit charge (Rs. 11): 13 kWh * Rs. 11 = Rs. 143.

Per Liter Charge for Refrigerator Weekly:

- The per liter charge for the refrigerator can be calculated by dividing the total weekly operating charge (Rs. 143) by the effective capacity (600 liters): Rs. 143 / 600 liters = Rs. 0.238333333 per liter.

Effective/Actual Per Liter Charge:

- The effective or actual per liter charge takes into account the effective refrigerator capacity (450 liters) instead of the full capacity.
- To calculate this, we divide the total weekly operating charge (Rs. 143) by the refrigerator capacity (450 liters): Rs. 143 / 450 liters = Rs. 0.317777778 per liter.

These calculations provide an understanding of the refrigerator's effective capacity, electricity usage, unit charge, and the associated per-liter charges for both the effective capacity and the overall refrigerator capacity.

Now, the breakup for the ordering cost, material cost, and holding cost for each item is given below:

1. *Cheese:*

- Material Cost: Rs. 480/kg
- Volume: 3.7 liters - It represents the volume of cheese in liters.
- Weekly Holding Cost: Rs. 1.175777778
    - The weekly holding cost is the cost associated with holding the cheese in the refrigerator for a week. It is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 100
    - It represents the cost of placing an order for cheese. Ordering Cost Breakup: Rs. 50 for handling + Rs. 50 for transportation

2. *Bread:*

- Material Cost: Rs. 29/pack
- Volume: 3.5 liters - It represents the volume of bread in liters.
- Weekly Holding Cost: Rs. 1.112222222
    - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 50
    - It represents the cost of placing an order for bread. Ordering Cost Breakup: Rs. 20 for handling + Rs. 30 for transportation

3. *Burger Bun:*

- Material Cost: Rs. 9/pack of 2
- Volume: 1.2 liters - It represents the volume of burger buns in liters.
- Weekly Holding Cost: Rs. 0.381333333
    - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 30

   - It represents the cost of placing an order for burger buns. Ordering Cost Breakup: Rs. 10 for handling + Rs. 20 for transportation

4. *Milk:*

- Material Cost: Rs. 62/liter
- Volume: 1.5 liters - It represents the volume of milk in liters.
- Weekly Holding Cost: Rs. 0.476666667
   - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 70
   - It represents the cost of placing an order for milk. Ordering Cost Breakup: Rs. 20 for handling + Rs. 50 for transportation

5. *Chili:*

- Material Cost: Rs. 55/kg
- Volume: 1.2 liters - It represents the volume of Chilli in liters.
- Weekly Holding Cost: Rs. 0.381333333
   - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 30
   - It represents the cost of placing an order for Chilli. Ordering Cost Breakup: Rs. 10 for handling + Rs. 20 for transportation

6. *Garlic Bread:*

- Material Cost: Rs. 36/pack
- Volume: 1.4 liters - It represents the volume of garlic bread in liters.
- Weekly Holding Cost: Rs. 0.444888889
   - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 40

  - It represents the cost of placing an order for garlic bread. Ordering Cost Breakup: Rs. 15 for handling + Rs. 25 for transportation

7. *Corn:*

- Material Cost: Rs. 130/kg
- Volume: 1.3 liters - It represents the volume of corn in liters.
- Weekly Holding Cost: Rs. 0.413111111
  - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 30
  - It represents the cost of placing an order for corn. Ordering Cost Breakup: Rs. 10 for handling + Rs. 20 for transportation

8. *Ketchup:*

- Material Cost: Rs. 80/kg
- Volume: 1.2 liters - It represents the volume of ketchup in liters.
- Weekly Holding Cost: Rs. 0.381333333
  - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 50
  - It represents the cost of placing an order for ketchup. Ordering Cost Breakup: Rs. 20 for handling + Rs. 30 for transportation

9. *French Fries:*

- Material Cost: Rs. 70 per 500gm pack
- Volume: 0.75 liters - It represents the volume of French fries in liters.
- Weekly Holding Cost: Rs. 0.238333333
  - The weekly holding cost is calculated based on the effective per liter charge for the refrigerator (Rs. 0.317777778) and multiplied by the volume of the item.
- Ordering Cost: Rs. 70

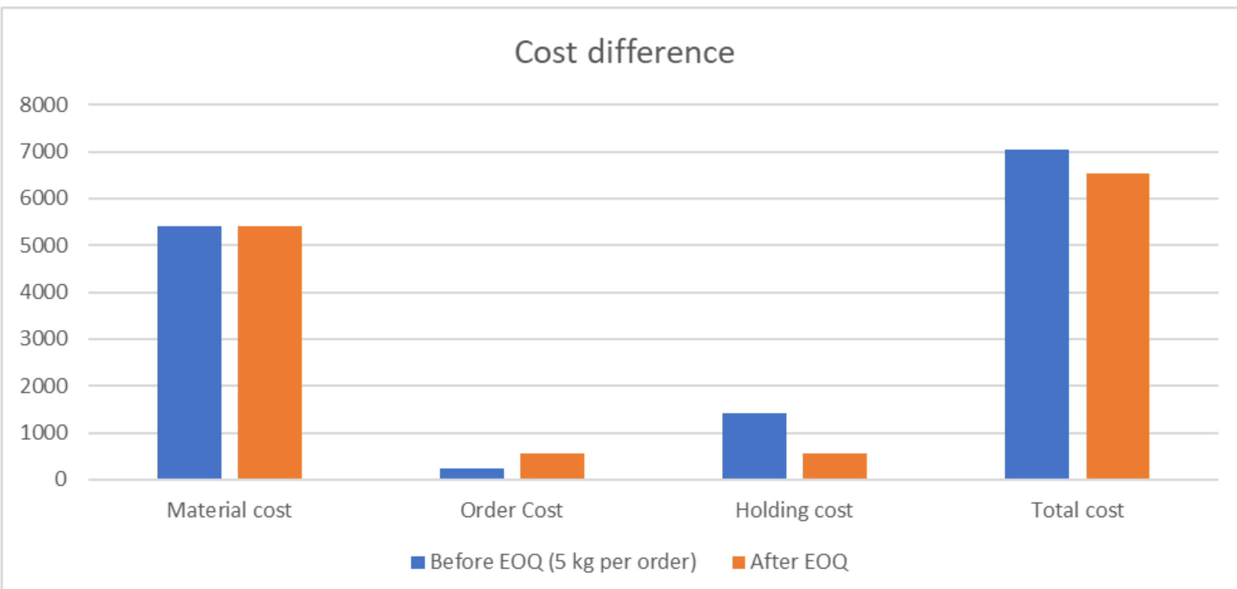
- It represents the cost of placing an order for French fries. Ordering Cost Breakup: Rs. 20 for handling + Rs. 50 for transportation

That's the breakdown of the data for each item in terms of material cost, volume, weekly holding cost, ordering cost, and the breakup of the ordering cost into handling and transportation costs.

EOQ Calculations

We calculated the EOQ after putting in the individual costs for each item and then took a scenario where we compare the cost saving that the cafeteria can experience after implementing EOQ. (The detailed calculation can be understood from the Excel sheet.)

1. *Cheese*



Before implementing the EOQ model, the cafeteria orders 5 kilograms of cheese per order, resulting in a total cost of 7035.93. After implementing the EOQ model and optimizing the order quantity to 2 kilograms, the total cost reduces to 6526.87.

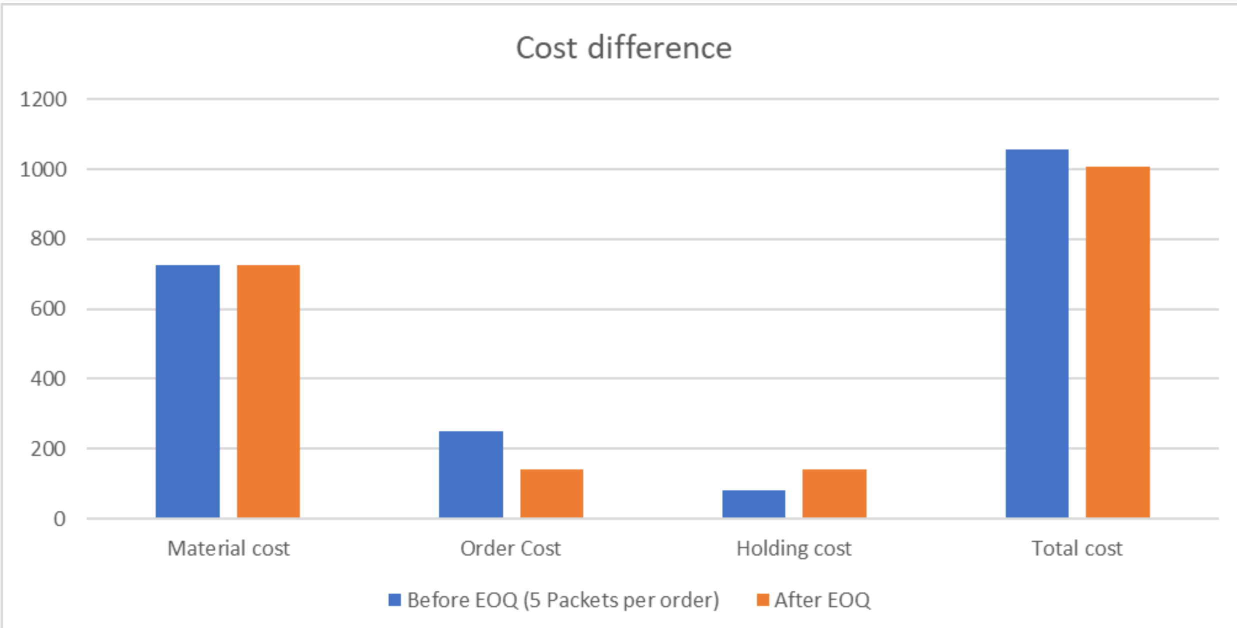
The formula for percentage saving is:

Percentage saving = ((Total cost before EOQ – Total cost after EOQ) / Total before EOQ) * 100

In the case of cheese, the percentage saving is: ((7035.93 -6526.87) /7035.93) * 100 = 7.24%

So, implementing the EOQ model results in a cost saving of approximately 7.24%.

2. Bread

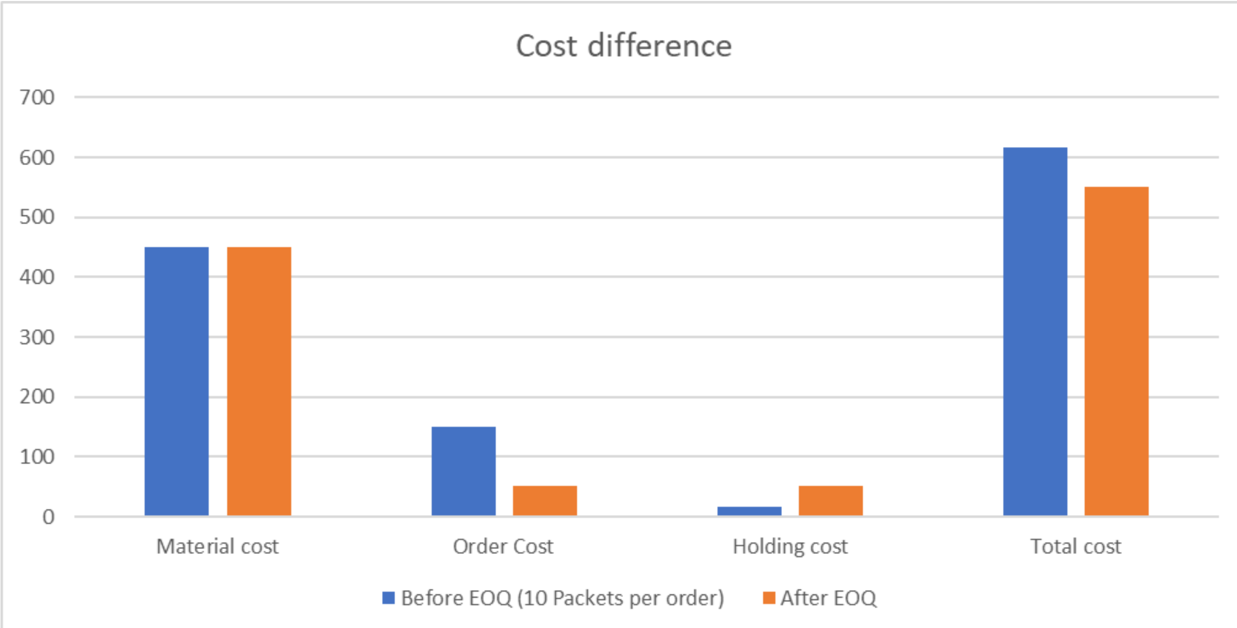


Before implementing the EOQ model, the restaurant orders 5 packets of bread per order, resulting in a total cost of 1055.64. After implementing the EOQ model and optimizing the order quantity to 8.80 packets, the total cost reduces to 1008.96.

Now we can plug these values into the formula: Percentage Saving = ((1055.636111 - 1008.964982) / 1055.636111) * 100

After performing the calculation, we find that the percentage saving is approximately 4.42%. This means that by using the EOQ model, the restaurant has managed to save around 4.42% on its total costs compared to its previous ordering strategy.

3. Burger Bun

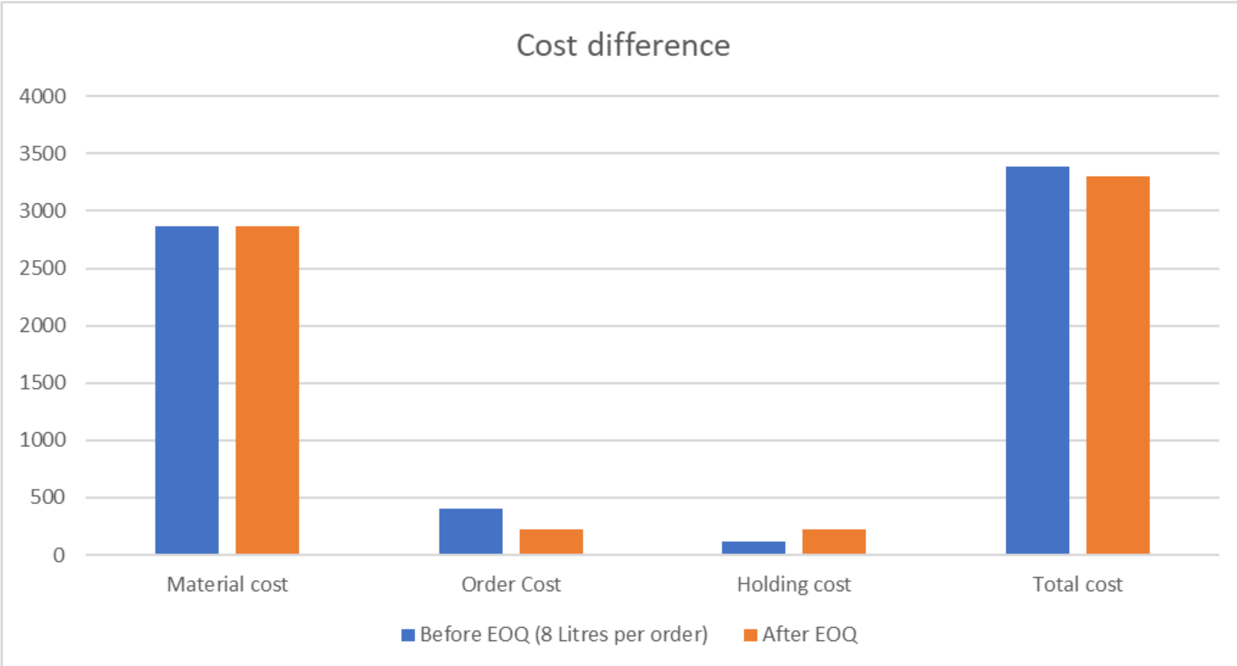


Before implementing the EOQ model, the restaurant orders 10 packets of buns per order, resulting in a total cost of 617.16. After implementing the EOQ model and optimizing the order quantity to 29.57 packets, the total cost reduces to 551.47.

Now we can plug these values into the formula: Percentage Saving = ((617.16 - 551.4692072) / 617.16) * 100

After performing the calculation, we find that the percentage saving is approximately 10.66%. This means that by using the EOQ model, the restaurant has managed to save around 10.66% on its total costs compared to its previous ordering strategy.

4. Milk

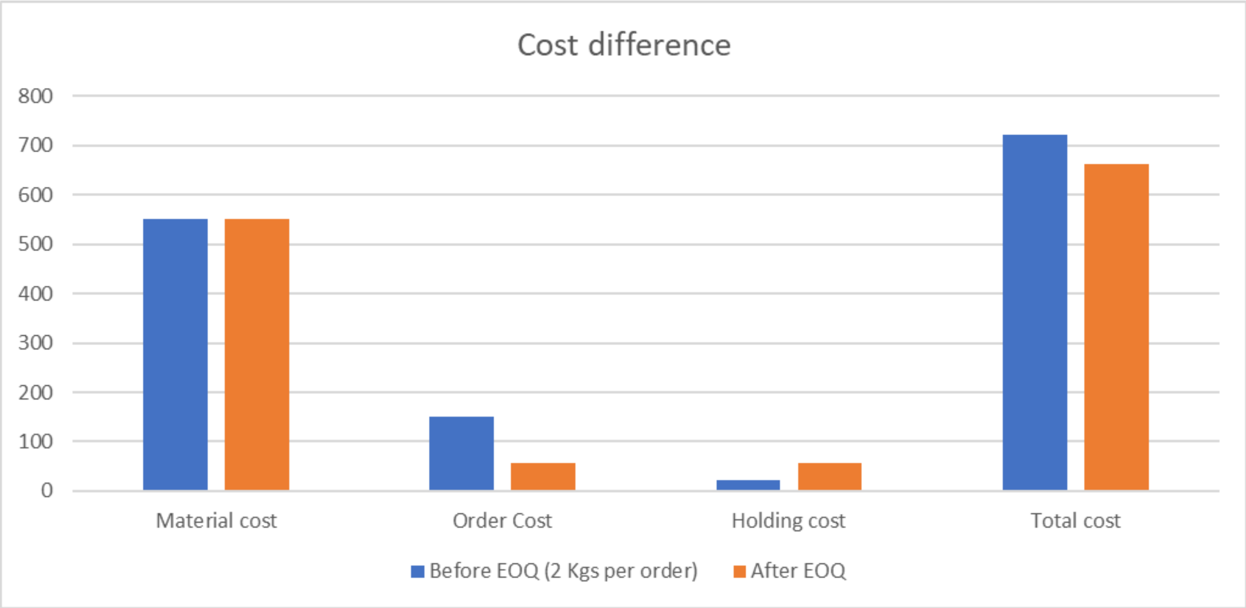


Before implementing the EOQ model, the restaurant orders 8 liters of milk per order, resulting in a total cost of 3390.40. After implementing the EOQ model and optimizing the order quantity to 14.80 liters, the total cost reduces to 3304.94.

Now we can plug these values into the formula: Percentage Saving = ((3390.400833 - 3304.944663) / 3390.400833) * 100

After performing the calculation, we find that the percentage saving is approximately 2.52%. This means that by using the EOQ model, the restaurant has managed to save around 2.52% on its total costs compared to its previous ordering strategy.

5. Chilli

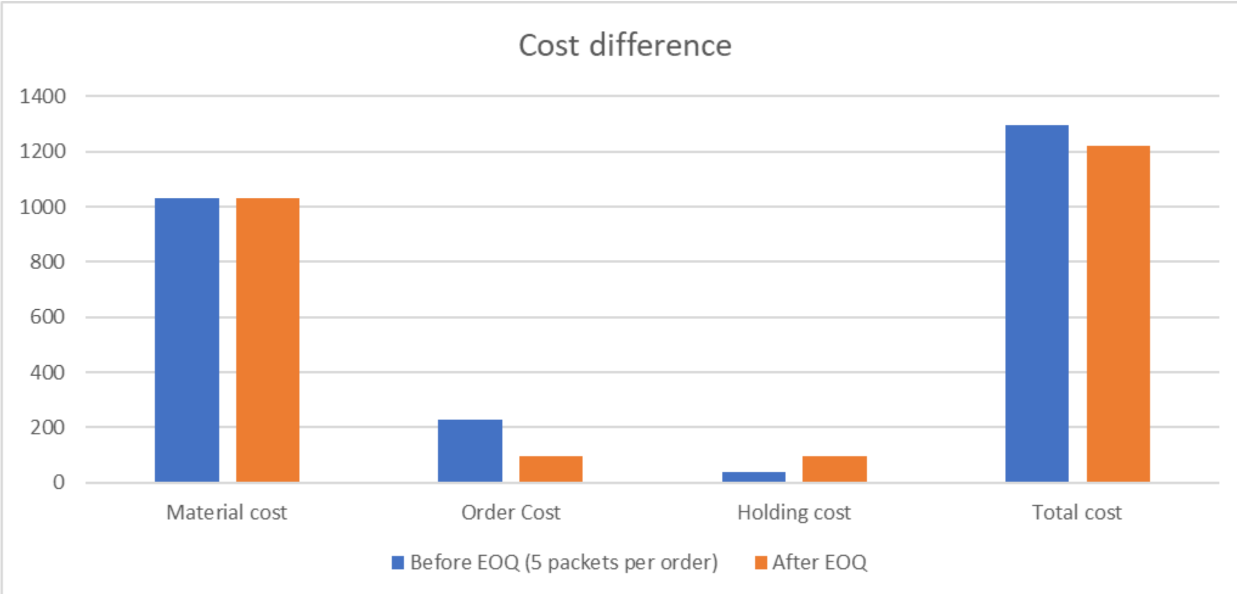


Before implementing the EOQ model, the restaurant orders 2 kilograms of chillis per order, resulting in a total cost of 720.97. After implementing the EOQ model and optimizing the order quantity to 5.35 kilograms, the total cost reduces to 662.18.

Now we can plug these values into the formula: Percentage Saving = ((720.9733333 - 662.1784293) / 720.9733333) * 100

After performing the calculation, we find that the percentage saving is approximately 8.14%. This means that by using the EOQ model, the restaurant has managed to save around 8.14% on its total costs compared to its previous ordering strategy.

6. Garlic Bread

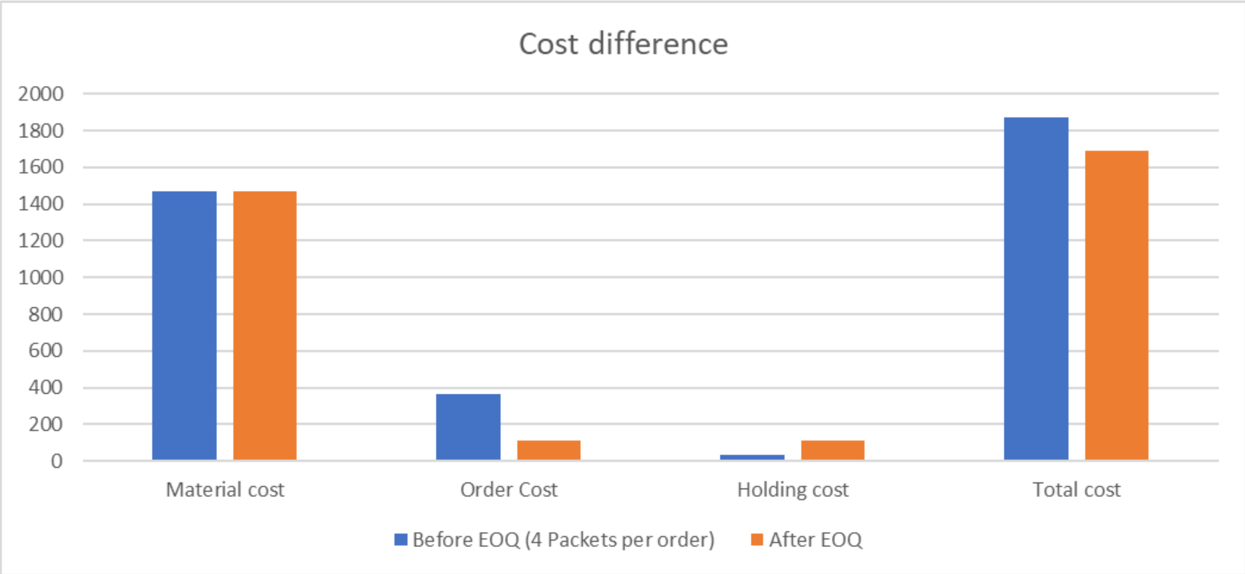


Before implementing the EOQ model, the restaurant orders 5 packets of bread per order, resulting in a total cost of 1297.18. After implementing the EOQ model and optimizing the order quantity to 11.95 packets, the total cost reduces to 1219.90.

Now we can plug these values into the formula: Percentage Saving = ((1297.182857 - 1219.9036) / 1297.182857) * 100

After performing the calculation, we find that the percentage saving is approximately 6.01%. This means that by using the EOQ model, the restaurant has managed to save around 6.01% on its total costs compared to its previous ordering strategy.

7. French Fries

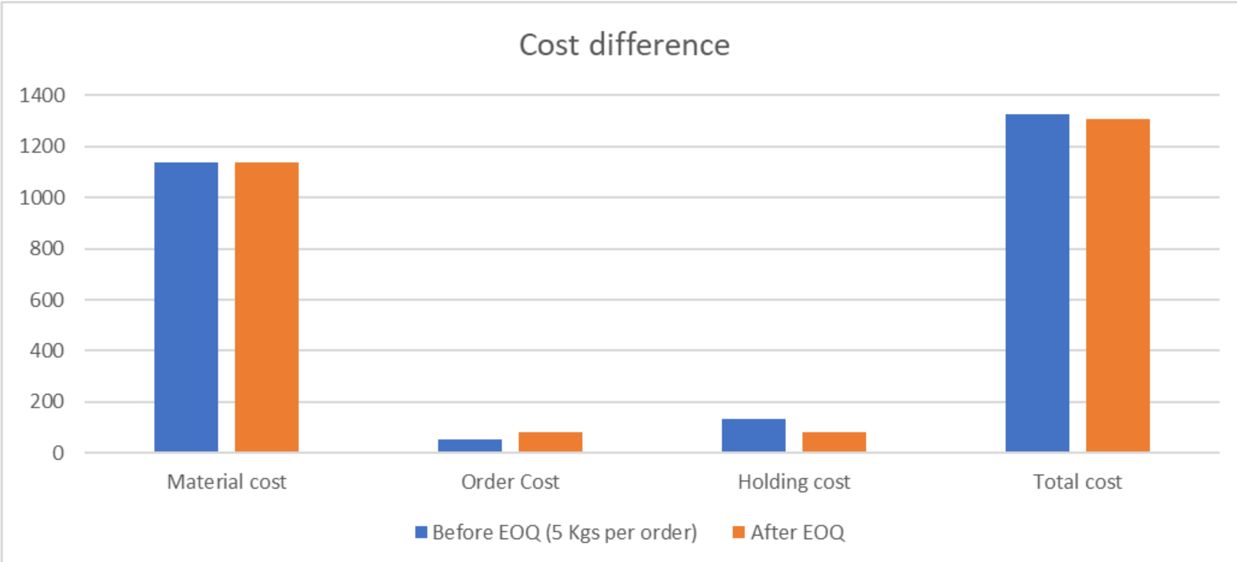


Before implementing the EOQ model, the restaurant orders 4 packets of fries per order, resulting in a total cost of 1870.87. After implementing the EOQ model and optimizing the order quantity to 13.27 packets, the total cost reduces to 1691.47.

Now we can plug these values into the formula: Percentage Saving = ((1870.866667 - 1691.470088) / 1870.866667) * 100

After performing the calculation, we find that the percentage saving is approximately 9.52%. This means that by using the EOQ model, the restaurant has managed to save around 9.52% on its total costs compared to its previous ordering strategy.

8. Corn

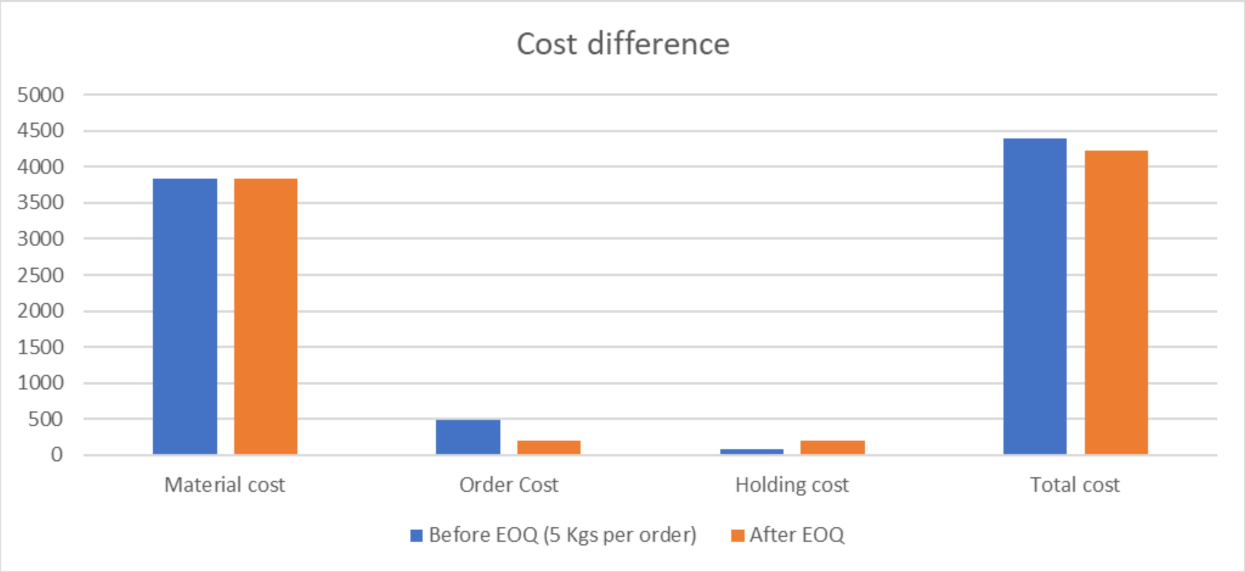


Before implementing the EOQ model, the restaurant orders 5 kilograms of corn per order, resulting in a total cost of 1324.26. After implementing the EOQ model and optimizing the order quantity to 3.13 kilograms, the total cost reduces to 1305.41.

Now we can plug these values into the formula: Percentage Saving = ((1324.261111 - 1305.413172) / 1324.261111) * 100

After performing the calculation, we find that the percentage saving is approximately 1.42%. This means that by using the EOQ model, the restaurant has managed to save around 1.42% on its total costs compared to its previous ordering strategy.

9. Ketchup



Before implementing the EOQ model, the restaurant orders 5 kilograms of ketchup per order, resulting in a total cost of 4396.27. After implementing the EOQ model and optimizing the order quantity to 12.54 kilograms, the total cost reduces to 4222.66.

Now we can plug these values into the formula: Percentage Saving = ((4396.266667 - 4222.664344) / 4396.266667) * 100

After performing the calculation, we find that the percentage saving is approximately 3.96%. This means that by using the EOQ model, the restaurant has managed to save around 3.96% on its total costs compared to its previous ordering strategy.

Overall Cost Saving

Now, the above data provides the details of individual EOQ and the cost associated with each item. The cafeteria can make a decision to order these items from different vendors and incur various costs or then can order all products jointly from a vendor who sells all these items. This results in savings as there is only one order cost which is a combined order cost for all the items. The results here depend purely on the common order cost which can result in saving or extra expense.

When ordered independently (EOQ):

- The first row shows the EOQ (Economic Order Quantity) for each item, which indicates the most efficient quantity to order in order to minimize expenses.
- The column labeled "Total Material Cost" signifies the cost of the items themselves. This value is obtained by multiplying the cost per unit with the EOQ.
- The column labeled "Total Ordering Cost" reflects the expenses incurred when placing an order for each item. These costs are provided in the table.
- The column labeled "Total Holding Cost" represents the expenses associated with holding inventory for each item.
- The "Total Cost" column represents the cumulative sum of the Total Material Cost, Total Ordering Cost, and Total Holding Cost for each item.

Now, let's explain the data for weekly costs when ordered jointly:

- The "Total Material Cost" represents the combined cost of all the items when ordered jointly. It is the sum of the Total Material Cost for each item when ordered independently.
- The "Order Cost per order" is a fixed cost associated with placing an order when items are ordered jointly. In this case, it is given as Rs. 250.
- The "Number of orders" represents the frequency of ordering when items are ordered jointly. It is calculated based on the demand and the EOQ for each item.
- The "Total Ordering Cost" is the cost associated with placing orders when items are ordered jointly. It is calculated by multiplying the Order Cost per order by the Number of orders.
- The "Total Holding Cost" represents the cost of holding inventory when items are ordered jointly. It is also calculated based on the demand and the EOQ for each item.

- When the items are ordered together, the “Total Cost” is the summation of Total Material Cost, Total Ordering Cost, and Total Holding Cost.

In summary, when we order items separately, the costs involved for each item have to be paid individually and when we place a joint order, we have to pay a single unique cost for all the items. The total cost encompasses the material cost, ordering cost, and holding cost in both scenarios, regardless of the ordering method.

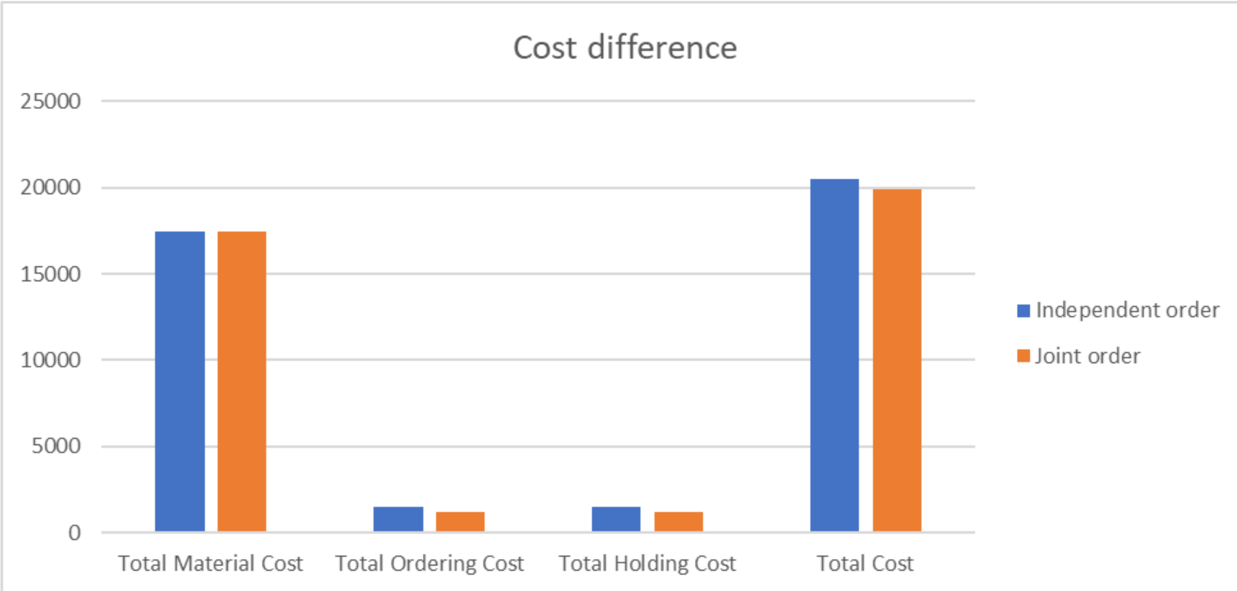
When ordered independently (EOQ): The total cost for ordering independently is provided in the "Total Cost" column of the table. Here are the values:

- Total Cost:
  - Cheese: Rs. 6,526.87
  - Bread: Rs. 1,008.96
  - Burger Bun: Rs. 551.47
  - Milk: Rs. 3,304.94
  - Chili: Rs. 662.18
  - Garlic Bread: Rs. 1,219.90
  - French Fries: Rs. 1,691.47
  - Corn: Rs. 1,305.41
  - Ketchup: Rs. 4,222.66

To calculate the total cost for ordering jointly, we sum up the individual costs: Total Cost for ordering independently = Rs. 6,526.87 + Rs. 1,008.96 + Rs. 551.47 + Rs. Rs. 3,304.94 + Rs. 662.18 + Rs. 1,219.90 + Rs. 1,691.47 + Rs. 1,305.41 + Rs. 4,222.66 = Rs. 20,493.88

When ordered jointly: The total cost for ordering jointly is provided in the "Total Cost" row of the table. Here's the value:

- Total Cost: Rs. 19,881.65



Now, let's calculate the percentage savings when ordering jointly compared to ordering independently: Percentage Savings = ((Total Cost when ordering independently - Total Cost when ordering jointly) / Total Cost when ordering independently) * 100

Percentage Savings = ((Rs. 20,493.88 - Rs. 19,881.65) / Rs. 20,493.88) * 100

Percentage Savings = (Rs. 612.23 / Rs. 20,493.88) * 100

Percentage Savings ≈ 2.99%

Therefore, when ordering jointly, there are approximately a 2.99% savings in total cost compared to ordering independently.

Forecasting

Because the restaurant sector is so dynamic and competitive, exact demand forecasting is critical for efficient operations and resource allocation. We tried to implement many different time series forecasting models but traditional time series forecasting techniques, such as the Autoregressive Integrated Moving Average (ARIMA) model, have demonstrated their ability to predict future demand trends.

The Autoregressive (AR), Integrated (I), and Moving Average (MA) components make up the ARIMA model. The I feature is utilized for differencing to establish stationarity, the AR component captures the linear connection between the prior demand observations, and the MA component compensates for the error terms. Statistical methods like autocorrelation and partial autocorrelation plots are used to identify the ARIMA model's proper order (p, d, q). Maximum likelihood estimation or other appropriate techniques are used to estimate the model's parameters. There are many models which can be used for time series forecasting but for our dataset, ARIMA is found to be more appropriate for our dataset in forecasting the sales of each menu item.

The ARIMA model is fitted to the training data, and its performance is measured using the Root Mean Squared Error (RMSE). The fitted ARIMA model is then used to predict future demand. The model's performance is assessed by comparing predicted values to real demand data throughout a validation period.

Items	Rmse
Chilli Cheese Sandwhich	1.197497747
Chilli Cheese Toast	1.237497747
Cold Coffee	1.167497747
Crunch it	1.117497747
French Fries Peri Peri	1.127497747
Garlic Bread With Cheese	1.107497747
Lemon Iced Tea	1.109774741
Masala Chai	1.277497747
Streetology	1.277497747
Cheese and Corn Sandwhich	1.187497747

The specific results and inferences of an ARIMA model used to anticipate restaurant sales of each menu item would be determined by the data and the model parameters employed. For our dataset, the model offers the following data:

1. Forecasted Sales: The ARIMA model predicts future sales for each menu item. These projections show the anticipated sales volume for each time period. For example, our application shows the forecasted sales of Cheese Chilli toast for the selected time period by user.

2. Confidence Intervals: The model also generates confidence intervals for predicted sales for each menu item. Given the uncertainty in the forecasting process, these intervals reflect the range within which actual sales are expected to fall. These intervals are not shown in the front end of the application but one can find out these confidence intervals easily.

3. Seasonality and Trends: ARIMA models have the capacity of detecting and incorporating seasonal patterns in data. The model detects recurring patterns or trends that happen on a regular basis, such as daily, weekly, or monthly. This information aids in understanding how sales may fluctuate over time as a result of these tendencies.

Chapter 5: Conclusion

In summary, the development of a real-time demand forecasting dashboard for cafeterias brings numerous benefits in optimizing food production, and staffing levels and improving the overall customer experience. However, it is crucial to acknowledge the limitations, specifically the potential impact of inadequate data availability.

An important drawback of this project lies in its reliance on historical customer data and real-time factors like weather and nearby events. Insufficient or inaccurate data can compromise the precision and dependability of the demand forecasts generated by machine learning algorithms. Consequently, the effectiveness of the dashboard in making accurate predictions may be undermined due to the absence of comprehensive and high-quality data.

Nevertheless, the project presents compelling arguments for its implementation. By leveraging machine learning algorithms and real-time data, cafeteria management gains access to valuable insights regarding anticipated customer traffic and demand for specific food items. These insights enable timely adjustments in food production and staffing levels, ensuring that customer demands are met while minimizing waste. As a result, operational efficiency is enhanced, leading to a more satisfactory customer experience.

In conclusion, while the limited availability of data poses a potential challenge, the real-time demand forecasting dashboard holds promise as a solution for cafeteria management. With careful attention to data quality and further improvements in data collection processes, the project has the potential to significantly enhance efficiency, reduce waste, and ultimately deliver a superior customer experience.

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