A MAJOR PROJECT-II REPORT

ON

TIMESERIES BASED INVENTORY OPTIMIZATION SYSTEM FOR DISTRIBUTORS USING DEEP LEARNING

Submitted in Partial Fulfillment of Requirements
for the Degree of

MASTER OF TECHNOLOGY

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Artificial Intelligence

By

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I Gauri Panpaliya (2K22/AFI/07) hereby certify that the work which is being presented in the thesis entitled in partial fulfillment of the requirement for the award of the Degree of Master of Technology, submitted in Department of Computer Science, Delhi Technological University is an authentic record of my own work carried out during the period from Aug-2023 to May-2024 under the supervision of Prof. Anil Singh Parihar.

The matter presented in the thesis has not been submitted by me the award of any other degree of this or any other Institute.

Gauri Panpaliya

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This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and that the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE BY THE SUPERVISOR

Certified that **Gauri Panpaliya** (2K22/AFI/07) has carried out their search work presented in the thesis **"Timeseries Based Inventory Optimization System For Distributors using Deep learning"** for the award of **Degree of Masters of Technology** only that in applicable from Department of Computer Science Delhi Technological University, Delhi under my supervision. The thesis embodies results of original work, and studies are carried out by the student herself and the contents of the thesis do not form the basis for the award of any other degree to the candidates or to anybody else from this or any other University/Institution.

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ABSTRACT

Inventory control aims to meet customer demands at a specified service level while minimizing costs. Due to market volatility, customer demand often fluctuates, and ignoring this uncertainty can lead to incorrect inventory estimations, resulting in either shortages or inefficiencies. Inventory managers must place batch orders so that items arrive before stock depletion, considering the lead time between ordering and delivery. To meet demand while optimizing inventory costs, firms must forecast future demands to manage ordering uncertainties. Historically, predicting such uncertainties with high accuracy was challenging. However, the availability of large volumes of historical data and big data analytics has made this task more manageable.Finally, safety stocks are estimated based on the forecasted demand distribution, optimizing the inventory system to achieve a cycle service level objective.

Using a comprehensive dataset from DataCo Global, which encompasses various supply chain operations such as provisioning, production, sales, and distribution, this thesis focuses on optimizing inventory for product categories including clothing, sports, and electronics. We employ a range of time series models—ARIMA (Auto Regressive Integrated Moving Average), SARIMA (Seasonal Auto Regressive Integrated Moving Average), Holt-Winters, and Prophet—to predict future demand with precision.

The thesis begins with meticulous data preparation and cleaning to ensure data integrity. Exploratory data analysis (EDA) follows, revealing crucial patterns and relationships within the data, such as the effect of shipping days on delivery timeliness and the correlation between product prices and order quantities. Each time series model using mean absolute percentage error (MAPE) to determine their accuracy. The Prophet model, in particular, shows strong predictive performance, making it a valuable tool for guiding inventory decisions. Beyond forecasting, the thesis develops an inventory management framework. This includes calculating safety stock and reorder points based on demand forecasts, helping distributors maintain optimal inventory levels and avoid both stockouts and overstock situations. Visual tools display safety stock and reorder points, offering clear, actionable insights.

The work is intended for various stakeholders in the distribution chain, including retail managers, manufacturing planners, logistics managers, sales and marketing teams, and corporate executives. By providing precise demand forecasts and actionable inventory management insights, this system enhances decision-making, operational efficiency, and profitability.

This thesis demonstrates how time series forecasting can significantly improve inventory management for distributors. Implementing this system can lead to substantial cost savings, better customer satisfaction, and a stronger competitive position.

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LIST OF SYMBOLS, ABBREVIATIONS & NOMENCLATURE

S. No.	Abbreviation	Full Form
1	DTU	Delhi Technological University
2	EDA	Exploratory Data Analysis
3	ARIMA	Auto Regressive Integrated Moving Average
4	SARIMA	Seasonal Auto Regressive Integrated Moving Average
5	MAPE	Mean Absolute Percentage Error
6	IEEE	Institute of Electrical and Electronics Engineers
7	SS	Safety Stock
8	ROP	Reorder Point
9	OUTL	Order up to level
10	AI	Artificial Intelligence
11	LSTM	Long Short Term Memory
12	EOQ	Economic Order Quantity
13	KPI	Key Performance Indicator
14	CNN	Convolution Neural Networks
15	Conv2d	Convolution 2^{nd} Dimension
16	ReLU	Rectified Linear Unit
17	MLP	Multi-Layer Perceptron
18	EPQ	Economic Production Quantity
19	SCM	Supply Chain Management

CHAPTER 1

INTRODUCTION

Current specific inventory control entails strategic sourcing decisions particularly on the timing and quantity of the ordering of various stock-keeping units (SKUs) [1] as well as related materials and parts [1] in today's risky markets. It is to provide an amount of inventory to the customer as per service level with cost minimization of ordering and carrying cost. As the traditional studies suggest, the demand is deterministic, nonetheless, the customer demand can be very stochastic. As a result, the forecast of future demand is another facet of cost optimization of the inventory system while catering to uncertain demands. This is especially important due to, the time it takes for them to be manufactured and made available for purchase, meaning they have to be procured in large numbers before demand.

Due to the availability of the desirable data and advanced techniques of predicting the demand, it is possible to improve the accuracy rate in demand estimation by companies. Historical data gives more accurate predictions possible by comparing the supply and consumer demands, consequently enhancing the customer relations while minimizing costs of offsets. But, identifying the right type of forecasting techniques remains a difficult and a very critical activity for models to have the best solutions in inventory control. In this thesis, the focus will be established on how big data can be used to mitigate demand risk and minimize the cost of supply chain.

These models consist of ARIMA, SARIMA, Holt-Winters, and the Prophet; the former is used to predict the future demand based on time series data. There are several central concepts into which system brings advanced data analytics and forecasting methodologies that will help transform supply chain management. It begins with the process of data cleanse and data preprocessing whereby we have to first make sure that the available data is clean, uncorrupted and in the right format.

This entails, partitioning the data into numerical and categorical types, calculate and analyze correlation co-efficients to determine how the variables are related then fill the missing values so as to ensure a good platform for analysis. The system then performs Exploratory Data Analysis (EDA) for the data and explores the distribution of categorical variables, order patterns or irregularities and the profit distribution in different graphical forms. This step is the most critical to establish the key drivers of profitability and operational efficiency leading to identify notable patterns and trends.

After the performing EDA, system predicts demand using time series models such as ARIMA, SARIMA, Holt-Winters, or Prophet. This system will select the best applicable method of forecasting that is most accurate in this firm by comparing these models with mean absolute percentage error (MAPE). They are then used to compute the safety stock and reorder point hence the inventory management of the organization. This also help in the formulation of policies for controlling inventory that is friendly to the consumers and the customer in producing relevant information for process of decision making to help of eliminating cases of stock out and its counter product, over stocking. Strategic areas of operation are, controlling and minimizing expenditures, inventory management and revenues, revenue growth and business improvements. The system gives very useful information about risks such as whether the shipments are being delayed or about changes in sales movements through use of correlation analysis and distribution graphs. By maintaining a precise balance of the production rate and the distribution inventory relative to demand, the system makes improvements in demand management, cuts costs, and increases overall efficiency of operations.

The rest of the thesis is organized as follows: The literature review, which is the focus of chapter 1, focuses on the two topics of demand forecasting and inventory optimization. Chapter 2 also lays the background to the study, problem formulation, challenges, and the way of incorporating time series models in the design of inventory demand forecasting. Foundations, and Results, Discussion and Implementation is demonstrated by in chapter 3. Chapter 4 presents in detail the results, analysis, discussions, and conclusions of the study. This chapter also provides the summary of the thesis and also addresses the future possible areas of work done and the social relevance of computer science.

1.1 Literature Survey

The importance of inventory and how it can be managed in an environment or market that is constantly in flux. From sourcing and being able to meet with the right stock to ensuring that the right product and service is delivered to the consumer at the agreed time, inventory control plays a very central role in the elimination of avoidable expenses specialty and this research is based on the improvement of inventory control through inventory forecasting [1]. In any inventory system, it is necessary to compare the amount of stock required with the stock available at a certain point in time for a productive system to work effectively. In the past, there were theories in the supply chain management that they worked under constant demand patterns which are not the case with the present market. To address this, the paper employs ensemble deep learning models to optimize the predictions on demand. The predictive model that is created using multiple models gives the opportunity to learn various patterns, which provides more accuracy. The paper analyses darks and drawbacks of conventional approaches in demand and inventory management and scopes of new effective data-driven methods. Thus, presenting the contemporary visions of the further machine learning and deep learning investigations, the paper investigates ideas for the further investigations and highlights the necessity of the complex methodologies of the ensemble structural data's collection and analysis. The paper also shows that utilizing more of the same kind of data sources and fine-tuning the parameters used in the model would not only improve reliability and efficiency of the solutions produced for inventory. Results shows that ensemble models are superior to simple models using single deep learning techniques, particularly for time series data .The current paper employs such complex methods in an online retail environment to exemplify the nature of the model of the order-up-to-level inventory (OUTL) [1] when determining the future demand. Improved forecast accuracy, inventory cost minimization, and practical relevance are major advantages, thereby emphasizing how managing inventory is beneficial specifically for an internet selling industry.

An essential issue of measuring the effects of decreasing item quality, variation in demand patterns, and restricted storage space, which are crucial concerns in supply chain management discussed by [2]. Conventional delay in payments have been permitted for practicing inventory control theoretically and practically. Some authors have made modifications to the basic model as used in its initial formulation; these changes involved, among others, the use of credit-linked demand and inflation effects. Some of the more recent concepts analyzed include models at the order level and joint pricing models under permissible delay, forming the base upon which the consequences of delay in payment in the concept of inventory and related costs. There is a special trade credit scenario between supplier and retailer wherein the extra trade credit is given to sort out between themselves.

The prior studies discussed Economic Order Quantity [2] models under conditions of trade credit financing, which can respond to the growing demand or as an inventory of perishable goods. The existing research provides a focus and a footprint on the importance and issues of trade credit management for inventory. Partial trade credit can also decrease the probability of defaults through cost sharing where a certain amount of cash may be paid at the time of ordering. New models have increased coverage of the lot-sizing policies and the economic production quantity by drawing attention to partial trade credit. Warehousing itself calls for supplementary warehousing provision because there is usually an achievement of a bare minimum storage capacity when the storage space is an issue. Studies such as the formulations of models in perishable items with trade credits have been developed for multi-level system integration and management. The present literature review focuses on policies of EPQ and several item systems feasibility under the specified finite storage capacity. The study develops a consistent model identifying total relevant cost, and its optimization [3] under on demand variation, perishing items, partial credit period, and limited storage space. This model gave a clear understanding of the issues surrounding speed management within the supply chain.

Supply chain management [4] issues mainly focus on the ways and measures to reduce the impacts on environment and sustainability. Promotional prices are incorporated since consumers are known to seek more products during flash sales and other regular promotions. Its components are trade credit on different strata facilitates the control over the flow of cash and responses to demand. The investigation focuses on substandard products – to do this, the inspection process is implemented to then eliminate any bad products. The misclassification is corrected in addition to improving the quality of inventory, via learning steps applied by the model. A Cultural Theory perspective is used where and when needed to explain how two different models are used to address shortages. This way it helps in the smoothing of consequences as an optimum in relation to inventory and intuition in several conditions. An aspect of enhanced realism is introduced by extending learning effects together with multivariate demands and multi-credit periods; thus, the model of the system is advanced. Some changes made to the model include the addition of a carbon tax to make it more realistic and operational and is in line with advanced environmental and legal standards. Thus, it proves that the model can be applied in the real business processes involving sensitivity analysis, which opens up the prospects for cost-effectiveness reduction [4]. These advances present this research a significant addition to the understanding of inventory management which includes perishable items, learning effects, and improves reliability estimates.

Critical components of supply chain planning [5] variability analysis, demand forecasting, and determination of safety stock. Through accurate demand forecast, the organization gets benefits in inventory, production and logistics, thereby enhancing organizational productivity. Thus, safety inventories help to maintain a balance between holding well demands and the need to satisfy the customer. The paper presents a new KPI [5] model for inventory demand forecasting aimed at the consideration of supply chain reliability and product seasonality. This is the key major feature of this model that makes it to produce more effective results than the usual models which do not consider the effect of forecast accuracy on the total inventory costs. Further, it offers a novel way of approximating the safe stock values since it incorporates seasonality indices and actual demand, as well as logistic network reliability with historical demand records. The research supports new KPI [5] and the improved formula of the safety stock calculation, using quantitative data to demonstrate how effective it is. Regarding the control of inventory management, this also explains why the proposed model factors in supply chain reliability as well as contracts which mitigate issues of stockouts and surplus stocks resulting from seasonal variations. The research demonstrates the relationship between the accuracy of forecast and total cost of inventory, and broadens the framework of classical models of forecast, to support the urgent requirements of supply chain variability in managing inventory. It helps the planner in comprehensively planning and managing the supply chain with slim expenses hence enhancing the inventory management.

1.2 Identification of problem and issues

Another crucial aspect of retailing that needs to be underlined with regard to several retail businesses is the proper management of inventories [4] so as to maintain the adequate stock holding level that in turn enables the business to meet its stock obligations and, at the same time, avoid many unnecessary costs. In the related research reports, highlighted several drawbacks existing in current inventory management systems that our thesis focuses on to enhance efficiency and profitability. Therefore, in light of the different, issues and challenges that analysis of inventory management does reveal, it is possible to articulate several problems statements that will need to be solved to facilitate effective inventory management. The areas of concern or challenges that may arise when it is necessary to conduct this thesis , cantered on understanding of the problem statement and the areas of concern within the SCM and goal and objectives of this thesis. Here's a detailed breakdown:

1.2.1 Inaccurate Demand Forecasting:

ARIMA, SARIMA, Holt Winters and Prophet, as most of the traditional methodologies are incapable of harnessing data variability to predict future demand. This leads to things like overstocking where a business will end up having to holding a lot of stock and therefore it will cost a lot of money on holding cost or worst still stockouts whereby a business loss out because it was unable to supply the required stock.

1.2.2 Algorithmic Complexity:

Specifically, the novel types of stochastic forecasting models that are witnessed today particularly SARIMA and Prophet may be intricate in specific aspects of their algorithms; thereby making their implementation and assessment challenging. These models have been used in most cases; complicated and difficult in training and understanding; challenging this has proven to be a limiting factor towards the deployment of the models in the practical application of managing inventories.

1.2.3 Introduction of Artifacts:

Referring to production practices, one need to consider that the introduction of noise, interferences or disturbances within the context of the inventory management system could be detrimental to the system's performance and as a result causes the creation of artifacts such as inaccurate or inconsistent data. Such artifacts may include entry mistakes, input errors or failures, system failures or integration issues between the systems and makes the inventory information system less informative and efficient.

1.2.4 Overfitting Due to Limited Training Data:

The kind of models that are based on machine learning for inventory management purposes need large numbers of data sets for passing on of simulations and generalization Nevertheless, restricted availability of high-quality training samples may cause overtraining that may allow the model to excel when engaged with the training set but fail to produce accurate predictions during and after inventory updates on the unseen data.

1.2.5 Difficulty in Handling Diverse and Complex Textures:

There are usually number of problems that arise concerning inventory management as it relates to different ranges or classes of stocks or products. This involves such areas as inventory management of products with unprecedented demand fluctuations, seasonal demand and variable prices implying that there is need for set models and algorithms to capture and make forecasts that would reflect such parameters.

1.2.6 Scale-Invariance:

Another requirement is scale invariance, which is a mandatory characteristic of every subsequent level of management, from small shops to global corporations. Nonetheless, many of the existing inventory management models have been designed, or better yet, tested and developed at one or the other scale, which means that their applicability in inventory management is not general and varies greatly depending on the type and scale of the management task.

1.2.7 Real-Time Processing Constraints:

Stock management in real time means processing of large quantities of data that may come in a very short span of time and involve quick decision making for coping with changing demand or supply situations. Nevertheless, the implementation of complex and sophisticated methodologies for forecasting often encounters several issues particularly in relation to achieving the real-time stock control capacity of a system; issues stemming from the higher computational properties of complex algorithms and issues related to the acquisition and integration of real-time data.

1.2.8 Inventory Management Inefficiencies:

Due to its systemic nature it postulates that major issues are managing inventory and differs between stockout or overstock. One research on stock management and demand estimation discovered that poor forecasts coupled with optimization [3] of inventories could lead to improper ordering levels that affect customer sales satisfaction and certainly profitability.

1.2.9 Profitability Challenges:

This may pose a major challenge to businesses since equally important tasks features include identification of highly profitable products on one hand and on the other hand, the least profitable products. Majority of the managers end up not having sufficient knowledge of the different profitability factors and therefore the performance of the product leads to inability of the management of products.

1.2.10 Operational Inefficiencies:

This results in productivity losses in regard to cost and the efficiency at which the end products within an undertaking are produced as well as distributed. Absence of integrated production strategies based on the demands and trends and strategic shipping schedules is among the greatest culprits for holding back product schedules, overstock [2], and high freight expenses.

Some of the issues that are characteristic includes , which of the models does the best and how can one determine that a certain model is suitable for a certain product. It is always possible that for the structurally more complex time series [3] , different models can yield different results; appropriately selecting the model most well-suited to the context of a particular business setting and comparing it with other models validated through performance benchmarks.

CHAPTER 2

PROBLEM STATEMENT

Time Series-Based Inventory Optimization [1] System is aimed at solving major problem areas affecting inventory control through the use of analytical tools. This system applies time series models like ARIMA, SARIMA, Holt-Winters, and Prophet to increase the accuracy in demand forecasting. Actual real supply chain time series data from DataCo [6] company is used for experimentation Data taken from real world categories such as Clothing, Sports, and Electronic Devices. This thesis works on the improvement of data quality and measures that can be taken towards achieving data standardization through proper data preparation and data cleaning like dealing with missing data and further categorizing the data set as numerical and categorical data. Economic correlation analysis is used to establish the inter-relationships between the variables as a way of determining the important factors that affect demand for the products and the overall profitability.

In addition, the system estimates the cost of holding safety stock and determine the order quantity as well as the time to place a new order using the models suggested above. Comparison studies done for the purpose of assessing the efficacy of various time series models to forecast demand, and therefore calculate MAPE. Further, the analysis of lead time plans is done under lead time in order to evaluate the efficiency of the solution to minimize risks associated with inventory. Through addressing these challenges and objectives, the Time Series-Based Inventory Optimization System seeks to realize; minimal cases of stock-out [2] and over-stock conditions, improved profitability through directing adequate stocks to the most profitable products, improved customer satisfaction by ensuring product availability and timely delivery, and general cost reduction through minimum holding costs and an estimation of efficient distribution outlets. Implementing this integrated approach enhances the operational status of companies and enable them to attain higher levels of success in their inventory management processes, thereby improving the overall organizational performance and costs savings in the supply chain.

2.1 Presentation of the problem

In the creation of the problem statement for the Time Series-Based Inventory Optimization System, which is designed to handle vital issues in inventory management, the problem statement is subjected to analytical approaches. It is a tool designed to refine demand forecasting to improve on stock control best practice and, therefore, increase business output and revenue in the food and beverages, clothing, and automotive industries.

Inventory management has been recognised as an indispensable issue in the modern business world that can greatly enhance operational effectiveness and revenue generation. As with any method, there are some significant drawbacks that businesses face, such as unclear and inaccurate demand forecasting, inefficiency of inventory management, and the absence of valuable information and recommendations from data. In an attempt to address these challenges, the development of the Time Series-Based Inventory Optimization System is outlined in the thesis.

The main use of this system is to enhance demand forecasting by employing engine deep algorithms such as ARIMA, SARIMA, Holt-Winters, Prophet and others. To demonstrate the proposed approach the supply chain time series data from a real-world company called DataCo [6] is used based on multiple products including Clothing, Sports, as well as Electronic devices.

Key components of the problem statement include:

2.1.1 Data Quality and Consistency:

Using proper pre-processing techniques I prepared and cleaned my data set in order to tackle issues of missing data and data inconsistencies. When working on correlation matrices to establish significant factors affecting demand and profitability of the current and future services, one is able to analyse such relationships between variables.

2.1.2 Inventory Management Optimization:

Calculated safety stock [2], order quantity, and reorder point. Comparing various models based on some performance parameters so that one can easily identify which model is best suited for accurate demand forecasting.

2.1.3 Sensitivity Analysis:

Carrying out the sensitivity analysis with respect to variety of lead time conditions in order to evaluate how effectively the existing system deals with major risks generated from inventory. Thus, while solving these challenges and objectives, the system has the potential of providing discernible results among which are decreased situations of stockout and overstocking [3], increased profitability levels, increased customer satisfaction levels, and overall costs justified. Such an approach will help solve numerous challenges that businesses face concerning managing inventories and enhance the efficiency of clients operations in their respective markets.

2.2 Methodology

The first stage in the approach is to use DataCo [6]Global Supply Chain dataset which contains structured and non-structured data of DataCo sales, production, provisioning and commercial distribution by category of products such as apparels, sporting wears and electronics. The presented dataset is very valuable for the development of an inventory optimization technique for distributors or retailers using time series data.

2.2.1 Data Preparation and Cleaning:

Split the dataset into quantitative and qualitative data frames . Correlation analysis is conducted to understand relationships between quantitative variables. Insights from correlation reveal that increasing scheduled shipping days can reduce the risk of late deliveries, while sales and discounts exhibit a positive correlation.

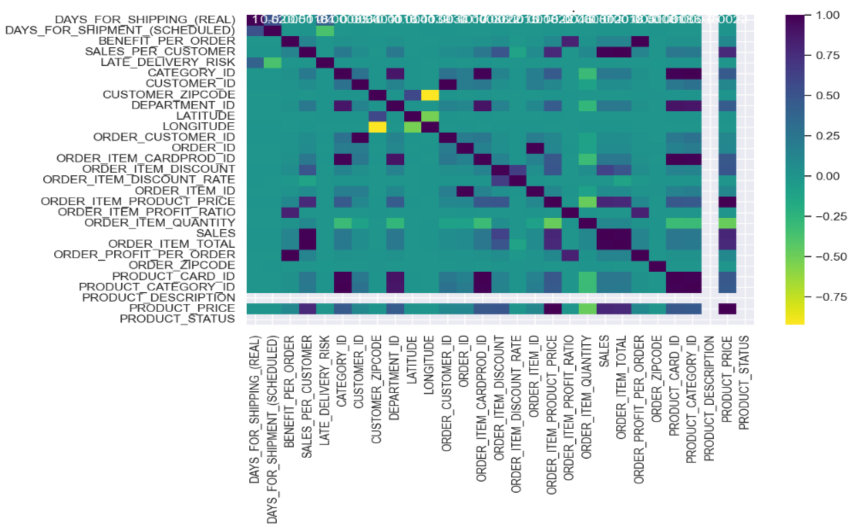

Fig 2.1: *The correlation coefficient between the quantitative variables*

2.2.2 Exploratory Data Analysis (EDA):

Distribution analysis is performed for categorical variables such as transaction types, delivery statuses, customer locations, and product categories. Insights from EDA help to understand customer behaviour, order patterns, and profitability across different departments and regions. The insights from the data reveal that the Fan Shop category, particularly hunting and shooting products, garners the highest number of orders, while Health and Beauty products have the lowest. Central America and Western Europe are the top regions for order deliveries, followed by South America, Oceania, and Northern Europe, indicating a broad market demand. Most orders are successfully completed, but a significant number are pending payment, suggesting potential revenue collection challenges. Other order statuses include processing, pending, closed, and various issues like suspected fraud or cancellation, highlighting areas for operational improvement and customer service focus.

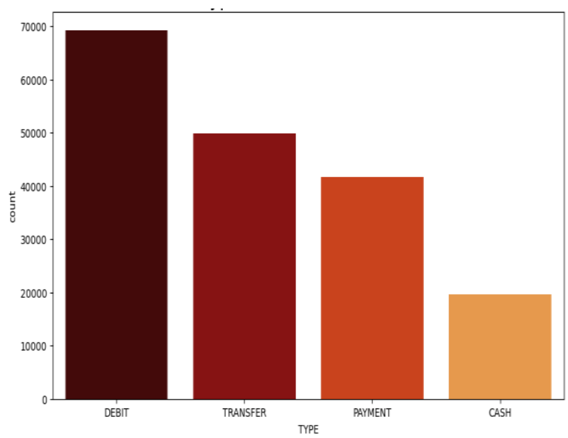

Fig 2.2: *Distribution of type of transaction made*

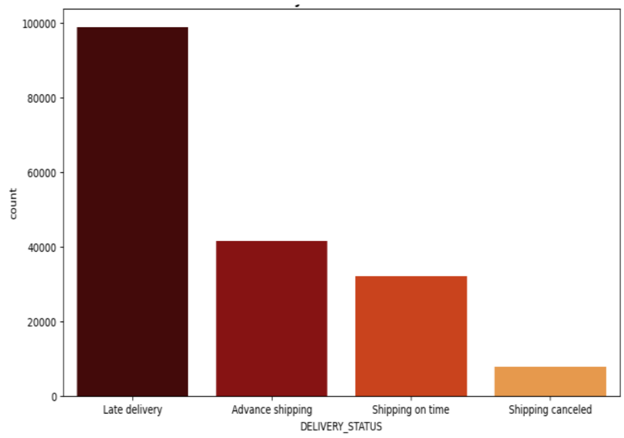

Fig 2.3: *Distribution of type of Delivery status of orders*

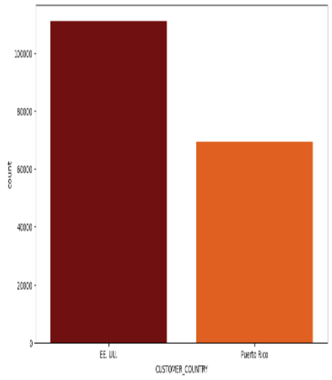

Fig 2.4 : *Representation of country count of customers*

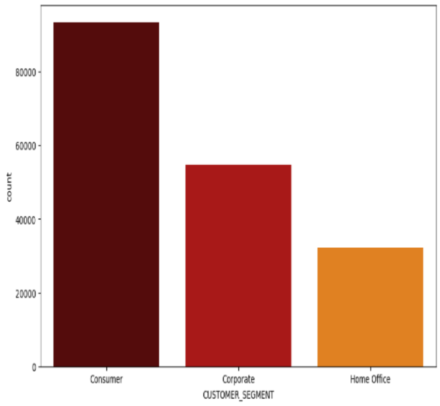

Fig 2.5: *Distribution of type of customers*

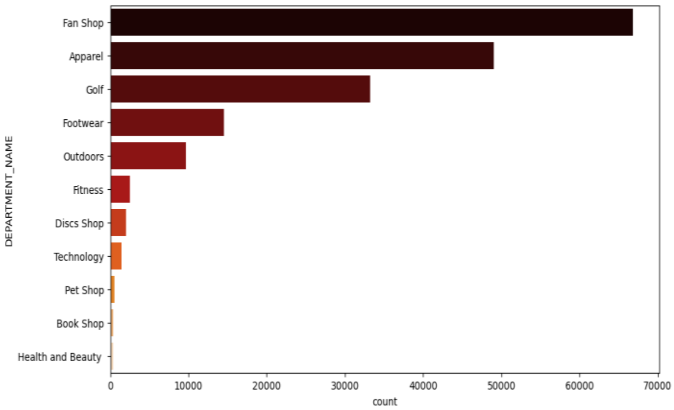

Fig 2.6: *Distribution of departments*

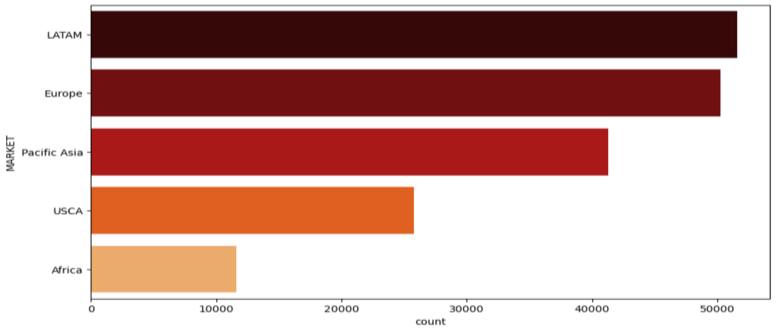

Fig 2.7: *Distribution of market where order is delivered*

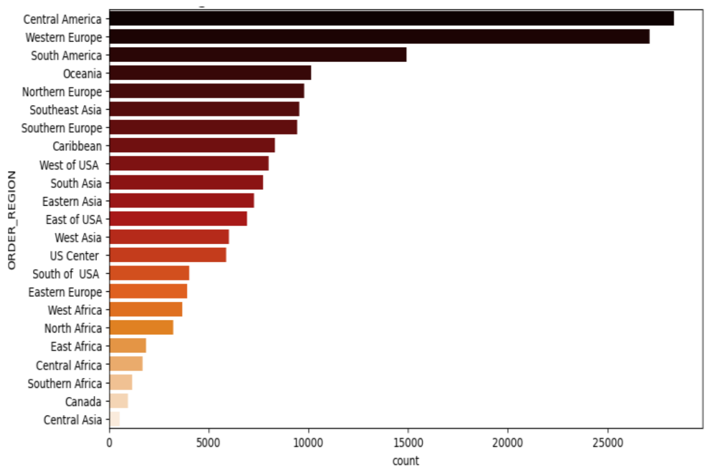

Fig 2.8: *Distribution of Region of the world where order is delivered*

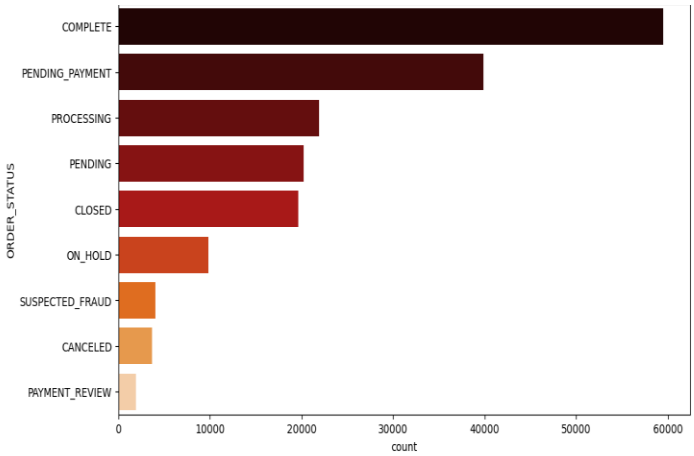

Fig 2.9: *Representation of order status*

a. Order Item Profit Ratio Distribution: Most orders exhibit positive profit ratios, with a peak around 0.5. However, there are orders with negative profit ratios, indicating losses. Some orders have profit ratios close to zero, suggesting they break even or have minimal profit

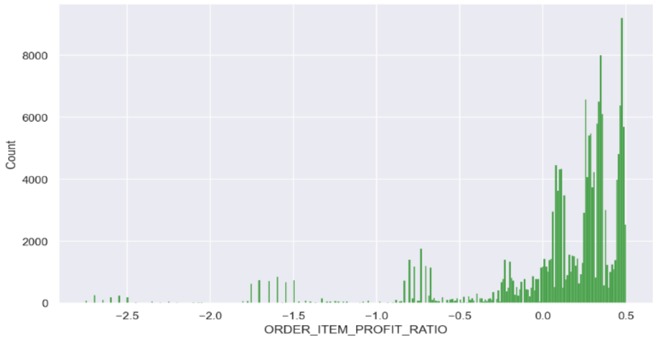

Fig 2.10: *Distribution of order item profit ratio*

b. Departmental Profitability: The Fitness department emerges as the most profitable, while the Book Shop department shows the lowest profitability. Most departments have profit ratios between 0.10 and 0.12, indicating relatively good profitability.

c. Product Profitability: The analysis identifies both top and bottom products based on profit ratios. For instance, the Polar FT4 Heart Rate Monitor exhibits the highest profit ratio, while the Nike Women's Legend V-Neck T-Shirt has the lowest among the top products.

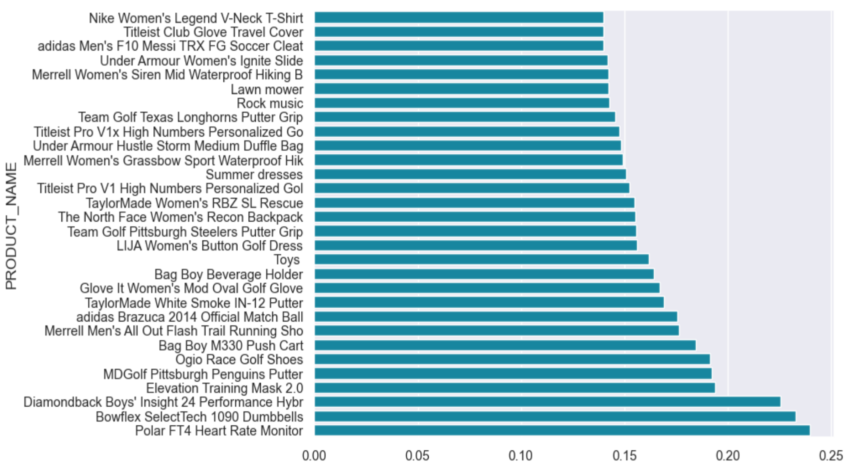

Fig 2.11: *Analysis of the profit ratio of top 25 product*

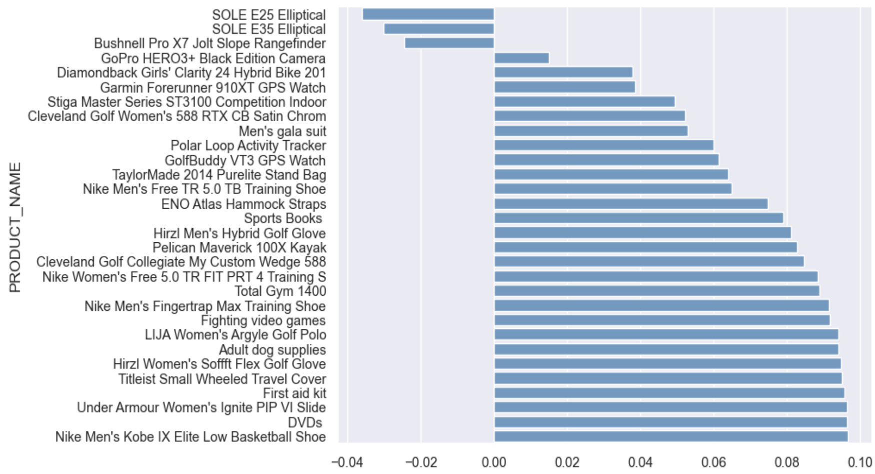

Fig 2.12: *Analysis of the profit ratio of worst 25 products*

d. Impact of Discounts on Profitability: Hypothesis testing suggests no strong evidence that discounts significantly affect order profitability, as the null hypothesis cannot be rejected.

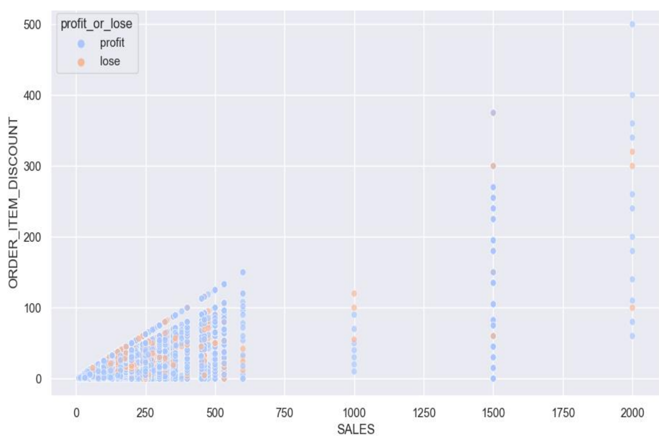

Fig 2.13: *Analysis of the relationship between the sales ,profit and discount*

e. Temporal Analysis: Distribution of orders across days of the week shows a uniform pattern, while orders on Fridays have a slightly higher risk of delay. Summer and spring months witness higher order frequencies.

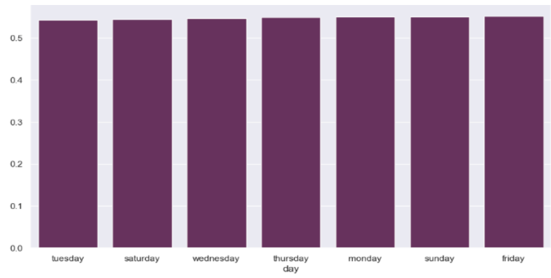

Fig 2.14: *Analysis of the late delivery risk proportion during week*

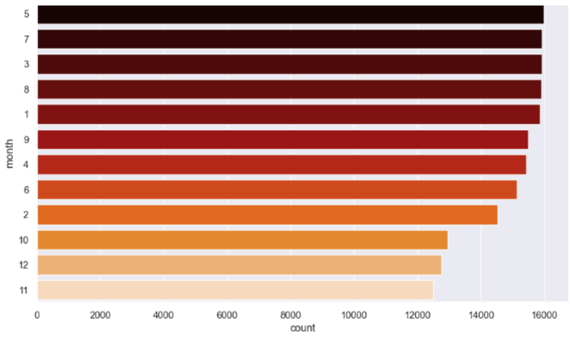

Fig 2.15: *Distribution of orders during months*

f. Sales and Profit Trends: Sales and profit analysis over the years reveals outliers in 2017, with overall negative progress in sales and profit during the available three years of data.

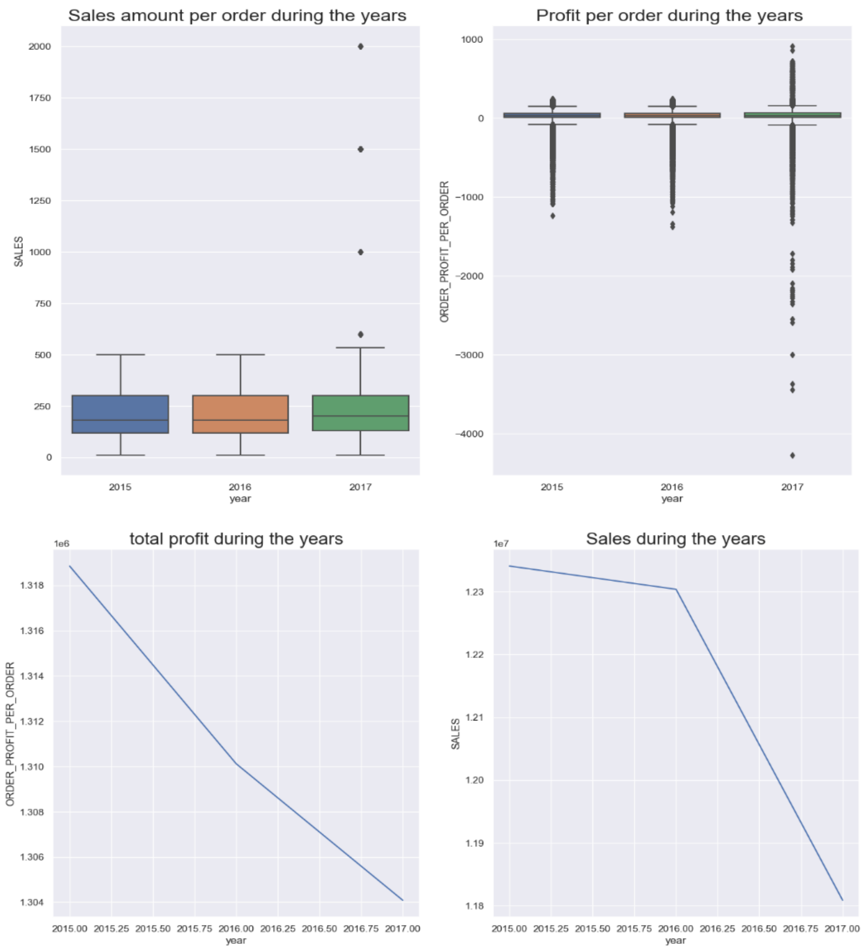

Fig 2.16: *Analysis of the sales , profit , discount during years*

g. Geographic Analysis: From the analysis, we tracked the flow of orders from the source to the market and calculated the average profit per order for profitable products and the average loss for unprofitable orders. This allows us to provide stakeholders with a better approach to optimizing the supply chain. For example, the average profit per order when shipping from the USA to the Caribbean market is 53 dollar, while shipping from Puerto Rico to the Caribbean market yields an average profit of 51 dollar per order. Conversely, the average loss for orders shipped from the USA to the Caribbean market is 109 dollar, compared to an average loss of 124 dollar for orders from Puerto Rico to the Caribbean market.

Based on this data, we can advise stakeholders to consider increasing shipments from the USA to the Caribbean and reducing shipments from Puerto Rico to optimize profitability.

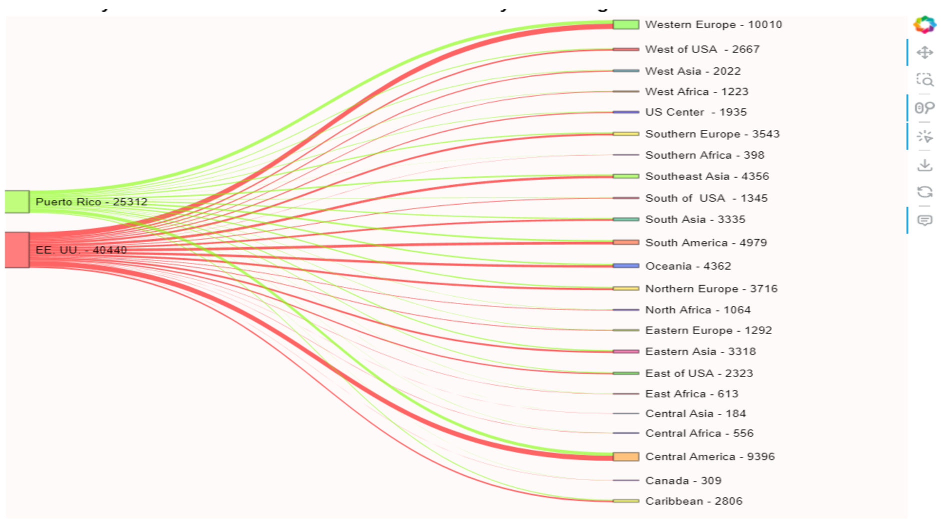

Fig 2.17: *Sankey flow of the orders from customer's country to region of the world*

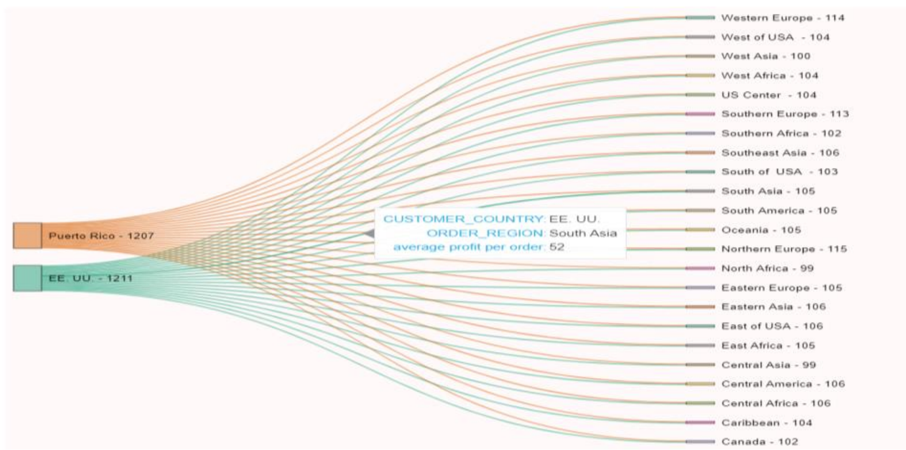

Fig 2.18: *Sankey flow of the average profit per orders from customer's country to region of the world*

2.2.3 Demand Forecasting:

- Time series analysis is conducted using ARIMA, SARIMA, Holt-Winters, and Prophet models to forecast future demand accurately.
- Model performance is evaluated using metrics like MAPE , with Prophet demonstrating the lowest MAPE [7] for both training and testing datasets.
- Components of the forecast, including trend and seasonality, are visualized for better understanding.

2.2.4 Inventory Management:

- Safety stock and reorder points are calculated based on demand forecasts.
- Standard deviation of weekly forecasts is utilized to calculate weekly safety stock and reorder point. Visualized safety stock and reorder point along with actual and predicted demand, for inventory replenishment.

2.2.5 Business Insights and Applications:

- To get idea of profitability markers for specific products and how rebates affect order profitability is used to identify ideal Product mix along with the price ranges.
- Sankey diagrams and flow analysis give information to make the supply chain efficient, increase profit and minimum loss makers throughout the globe separated by classes of products. It is incorporated into a system for inventory control that enables businesses to determine when inventory replenishment is necessary and where to distribute it.

2.2.6 Implementation and Optimization:

- A basic approach to demand forecast for inventory management is given together with focusing on certain aspects.
- It is advisable to carry out additional fine-tuning of the inventory management system and conduct further analytical work in order to determine the specifics of the installation in the context of the company's given goals and objectives.

By following this structured approach, businesses can correspondingly use the identified data analysis and demand forecasting information about their supply chains to determine the right amounts of stock that must be held, how to improve operations, and how to increase profits.

2.2.7 Time Series Models

Understanding the underlying causes of long-term trends or systemic patterns is made easier by time-series models. By using data visualizations, business users can identify seasonal trends and gain more insight into the causes of these trends . For this study, I employed the time series models Holt Winter, SARIMA, and ARIMA. These models are used on non-stationary data, or items that are constantly changing or affected by time. Given the frequent fluctuations in sales and currency values, time series analysis finds extensive application in the banking, retail, and economics industries. Stock market analysis is an excellent example of time series analysis, especially when paired with automated trading systems [8].

2.2.7.1 ARIMA

Time series data analysis and forecasting are made possible by the robust statistical tool known as (ARIMA) model. It combines moving average ,differencing and auto-regression to create a powerful tool for capturing different dependencies in data .
Components of ARIMA :

i. Autoregressive (AR) Component:

Part of the AR process involves current value of the series to forecast by regressing it on its past values. It depicts how an observation is dependent on several observations of that same variable occurring in the past.
Following is mathematical equation of model:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \ldots + \emptyset_P Y_{t-P} + \in_t \tag{2.1}$$

Where , p is the order of the auto-regressive process ,Y_t is the value of the time series at time t ,Y_{t-1}, Y_{t-P} are the lagged values of the time series, $\emptyset_1, \emptyset_2, \emptyset_P$ are the parameters (coefficients) of the AR model, the error term (white noise) at time t is $\in_t$.

ii. Integrated (I) Component:

To make series stationary differencing is applied, which means removing trends and seasonality. This component specifies the count of differencing transformations required to achieve stationarity.

Following equation shows differenced series :

$$\text{differenced series(Yt)} = \Delta\text{dXt} \qquad (2.2)$$

Where , Xt is an original series and d is differencing factor.

iii. Moving Average (MA) Component:

This part shows the relationship between an observation and a residual-error from a MA model applied on lagged observations. Dependency between observation and residual-error is captured by using this.

Mathematically, it is expressed as :

$$X_t = \mu + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \qquad (2.3)$$

Where , the value of the time series at time t is represented by Xt , μ is mean of series, The white noise error term at time t is represented by ϵ_t , θi are the parameters of the

MA model , $\in_{t-i}$ are the lagged error terms , The order of the MA model order is shown by q.

iv. ARIMA Equation

The general form of the ARIMA model combines these components and is shown as ARIMA(p, d, q)
Where, the order of the autoregressive part is p, order of differencing is d, order of the moving average part is q.
Mathematically the model can be written as:

$$(1-\sum_{i=1}^{p}\emptyset_i\, L^i)(1-\mathrm{L})^d X_t = (1+\sum_{i=1}^{q}\theta_j\, L^j)\in_t \tag{2.4}$$

Where , The value of the time series at time t is Xt , ϕi is the parameter of the (AR) part of the model, θj are the parameter of the (MA) part, L is the lag operator, εt Is the white-noise error term at time t, p is the order of AR part , d is the degree of differencing , q is the order of MA part.

In the study the model performed by giving the MAPE scores as: training MAPE of 4.6% and a testing MAPE of 8.7% . The ARIMA model showed better accuracy, particularly during the training phase, but during testing phase its performance got decreased, indicating potential overfitting.

2.2.7.2 SARIMA

It is an extension of the ARIMA , that specifically supports univariate time series data having a seasonal component. The SARIMA model is defined by a set of parameters and is used for analysing and forecasting time-series data that exhibits seasonality.

i. Components of SARIMA model:

P is the no. of seasonal AR terms
D is the no. of seasonal differences.
Q is the no. of seasonal moving average terms.
m is the no. of time steps for a single seasonal period (e.g., 52 for weekly data with yearly seasonality).

ii. SARIMA Equation

SARIMA model extends the ARIMA model to cover seasonal components. The seasonal part of the SARIMA model can be represented by:

$$(1 - \emptyset_1 B)(1 - \varphi_1 B_{s)}(1 - B)(1 - B_S)_{Y_t} = (1 + \theta_1 B)(1 + \vartheta_1 B_s) \in_t \quad (2.5)$$

Where , the observed time series at time t is Y_t , the backward shift operator representing the lag operator is B , is the non- seasonal AR coefficient is $\emptyset_1$, φ_1 is the

SAR coefficient , $\theta 1$ is the non-SMA coefficient , s is the S component , $\in_t$ is the white-noise error term at time t.

The SARIMA model helped us better capture seasonal trends in the data. However, its performance was slightly less accurate compared to ARIMA, with a training MAPE of 6.6% and a testing MAPE of 9.23%. As compared to ARIMA ,the SARIMA model had higher error rates compared to in both training and testing phases, this suggests that it was less effective in capturing seasonal components.

2.2.7.3 Holt-Winters

This model, also familiar as the TES [8] model, is a time series forecasting method that extends SES to capture trends as well seasonality in data. It is widely used for univariate time series data with a clear seasonal pattern the model has two variations as Additive holt-winters and multiplicative holt winter. When seasonal variations and fluctuations are consistent in magnitude irrespective of the level of series , also trend in the data is more linear and interpretation of component is more distinct additive approach is used ,we are using additive approach in this thesis.

i. Components of the Model:

The model has three main components:
Level (ℓ) is the average value of the series.
Trend (b) is is the increasing or decreasing value in the series.
Seasonality (s) is the repeating short-term cycle in the series.

ii. Holt-Winters Equations for additive approach:

Equation for level:

$$\ell_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(\ell_t - 1 + b_{t-1}) \tag{2.6}$$

Equation for trend**:**

$$\text{bt} = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{2.7}$$

Equation for seasonality component:

$$S_{t-m} = \gamma(Y_t - \ell_t) + (1-\gamma)S_{t-m} \tag{2.8}$$

Equation for forecast:

$$\hat{Y}_{t+h} = \ell_t + hb_t + S_{t-m+h} \tag{2.9}$$

Where , the level component at t is ℓ_t , smoothing parameter for the level (0 < α <1) is α, the observed value at t is Y_t, smoothing parameter for the trend ($0 < \beta < 1$) is β , is a smoothing parameter for the seasonal-component($0 < \gamma < 1$) is γ , is a seasonal component is S_t, trend component at time t is b_t , the length of seasonal cycle is m, the forecast horizon is h , the forecasted value for t is $\hat{Y}_{t+h}$. We are considering t as time .

The Holt-Winters model achieving a training MAPE of 3.9% but a higher testing MAPE of 11.4%, indicating some overfitting The Holt-Winters model performed better during training but shows significant drop in accuracy during testing, this indicates that it may have struggled with variability of the data.

2.2.7.4 Prophet

Prophet is an open source forecasting tool used by Facebook to provide cumulative forecasting data. It has been designed to be a tool for time series forecasting easy to use by people with no codification experiences and it has a simple yet powerful built-in functions for the time series forecasting. Prophet can be extremely beneficial for dynamic datasets that contain both multiple seasonality and anomalous trends that adjust seasonally.

a) Components of Prophet Model

Prophet decomposes time series data into the following components:

1. **Trend**: The trend of the time series which is extendable into the long-run.
2. **Seasonality**: These are transients which vary in a cyclic nature in the course of daily, weekly, or even annually.
3. **Holidays**: Variables or events that can affect the time series results in special days or holidays.
4. **Error**: These include fluctuations, distortions, or variation from the expected source of variation or simply scattered values in a data set

b) Prophet Model Equation

Prophet models time series data using the following equation:

$$y(t) = g(t) + s(t) + h(t) + \epsilon t \qquad (2.10)$$

where , $y(t)$ is a value at time t, $g(t)$is a component of trend , $s(t)$ is a seasonality component , $h(t)$ is a holiday's effect, ϵt is the error term.

Prophet demonstrated strong performance with a training MAPE of 3.28% and a testing MAPE of 7.13%, making it one of the best-performing models in our analysis by showing minimum MAPE score in both training and testing phase, This highlights its robustness in handling patterns and trends. Following figure shows the predicted training and testing values of data by using prophet model

2.2.8 Deep Learning Models

We are using a basic neural network architecture with an input layer and a hidden layer utilizing the ReLU function. Due to limited resources, we have not implemented more advanced deep learning models. With adequate resources, we could have used LSTM, Bi-LSTM, and other powerful deep learning models, which might have outperformed the other models we applied for forecasting .The neural network architecture had an input layer to take raw data consisting of several constituents such as product descriptor, date-time features, client info, and many more relevant aspects. There were many layers, which is the so-called hidden layer, and in each such a layer, many neurons are used to determine some data patterns. The first transaction layer was configured with 512 nodes and used the ReLU which is the Rectified Linear Unit to handle non-linearity. To bring more complexity, four additional hidden layers with 256 neurons and the ReLU activation function helped fine-tune the learned features in the inputs. The output layer yielded an only scalar value of expected ‘Order Item Quantity’ by using a linear activation function that was fit for regression problems. The Adam optimizer is suitable for use because of its capacity of adjusting the training rate. The loss function employed was Mean Absolute Error and this evaluated the difference between intended and realized results, thus aiding the model in reducing this error as the training progressed. The input data was further preprocessed for proper feature scaling; min-max scaling was applied to map the matrix values between 0 and 1 to ensure equal contribution by all the features without the large numbers overwhelming the training phase. Predictions were created through forward propagation, where input data traversed the network layer by layer. In backpropagation, the network adjusted its weights based on the error computed by the loss function, continuing until the model converged to an optimal set of weights where error was minimized. Notably, the feedforward neural network model's identical MAPE values for both training and testing datasets indicated potential overfitting, where the model performed well on training data but failed to generalize to unseen data. In contrast, Prophet's lower MAPE values for both training and testing datasets suggested better generalization and accuracy in forecasting future demand.

Given this, it's reasonable to conclude that Prophet [9] is performing better overall compared to other models in this scenario. Its ability to provide accurate forecasts while minimizing errors on unseen data makes it a reliable choice for demand forecasting in inventory management applications. Therefore, businesses may benefit from leveraging Prophet for optimizing inventory levels, improving production planning, and enhancing overall supply chain efficiency. From above it is clear that prophet [9] is performing better than other models as its error in training is 3.28 % and in testing is 7.13% , which is minimum of all.

2.2.9 Safety Stock

Safety stock [10] is the excess inventory hold, that is expected to be consumed during stockout time .The two main categories of stock inventory are safety stock and time frame. Safety stock serves as a buffer to take into consideration unforeseen circumstances like:

- Excessive demand
- Delays from suppliers
- Wrong demand
- Not placing timely reorders
- Monetary limitations

Safety stock enables your industry of supply and demand to continue operating normally even when available stocks runs out , by reducing the risks of stockouts. The weekly safety supply is determined using the following formula, which is based on anticipated demand:

$$Safety\ Stock = Z \times \sigma_f \times \sqrt{L} \tag{2.11}$$

Where , Z is score corresponding to the required confidence interval or service level , which is 1.65 z score is for 95 % service level , σ_f is the standard deviation of the forecasted demand over a week , L is the time taken to deliver the inventory in weeks, during implementation it is taken as 1 week .

Urgent reorders are frequently necessary in stockout [10] circumstances, but most suppliers dislike being rushed because it might interfere with their business and affect their clients. Having safety stock on hand gives providers a consistent workload and lessens the need for urgent orders. Similarly, businesses that partner with retailers can preserve positive relationships by ensuring that the products they provide are always available [10].

2.2.10 Reorder Point

The "reorder point" is the inventory level at which a business needs to make a new order or take on the risk that stock could drop to zero, leaving customers unhappy and orders unfilled. Typically, ROP [11] refers to buying inventory to replenish supplies. The concept is not only limited to businesses that buy products to resale (e.g., buying at wholesale and selling at retail). In addition it is applicable to major firm storefront sites where the "supplier" is a warehouse owned by the same company, reorder point logic and math can also be used when purchasing materials from suppliers to manufacture things that your business then sells.
The weekly reorder point is determined using the following formula, which is based on anticipated demand:

$$Reorder\ point = (d \times L) + Safety\ Stock \tag{2.12}$$

Where , d is the average weekly demand from the forecasted data, L is the lead time in weeks.

Reorder points are a useful technique for ensuring that you keep enough inventory on hand to meet client demand without going overboard and becoming unmanageably expensive. Simple computations can produce useful suggestions, and more customisation can make an otherwise difficult aspect of inventory management nearly automatic with no need for concern or interaction. Establishing intelligent reorder points now can pay off in years to come in terms of increased efficiency.

CHAPTER 3

FINDINGS AND RESULT

3.1 Findings

For effective inventory management estimated demand forecasting is important. From the graphical analysis we obtained correlation analysis, distribution analysis, geographic analysis , customer region analysis .This provided the valuable information for inventory optimization , production planning and enhancing distribution efficiency. After applying different time series models, deep learning model and prophet model, the prophet [9] model performed best by handling complex timeseries data and forecasting demand with estimated highest accuracy.

3.1.1 Correlation Analysis

- We observed that scheduling shipping days correlates negatively (-0.37) with late delivery risk . This suggests that extending scheduled shipping dates can reduce the likelihood of late deliveries.

- Sales and discounts exhibited a clear positive correlation (0.62), indicating that higher discounts tend to result in increased sales.
- There was a negative correlation (-0.48) between the price of products and the quantity ordered, implying that more expensive products are ordered in lower quantities.

3.1.2 Distribution Analysis

- Among the types of transactions, debit transactions had the highest count (around 68k), while cash transactions had the lowest count (around 20k).
- Late delivery was the most common delivery status, with a count of 90k, while shipping canceled had the lowest count (8k).
- In terms of customer locations, EE.UU. had the highest count of purchases (1.5 lakh), followed by Puerto Rico with 65k purchases. Consumer customers outnumbered Corporate and Home Office customers, with around 95k transactions compared to 30k for Home Office.
- Among departments, the Fan Shop category had the highest count (around 68k), while Health and Beauty had the lowest count (1k).

3.1.3 Geographic Analysis

- Central America and Western Europe emerged as the top regions with the highest order counts, each having over 25,000 orders. South America followed closely with nearly 15,000 orders, while Oceania and Northern Europe also showed significant order volumes, each with over 10,000 orders. Southeast Asia and Southern Europe rounded out the top regions, indicating a strong demand across diverse geographic locations.

3.1.4 Order Status Analysis

- The most frequent order status was "COMPLETE," with nearly 60,000 orders, indicating successful transaction completions. "PENDING_PAYMENT" followed with over 30,000 orders, while "PROCESSING" and "PENDING" statuses each had around 20,000 orders. Lesser statuses such as "CLOSED," "ON_HOLD," "SUSPECTED_FRAUD," "CANCELED," and "PAYMENT_REVIEW" had fewer orders, each under 10,000, highlighting areas needing attention due to potential issues or cancellations.

3.2 Results

The thesis aimed inventory optimization through estimated demand forecasting by applying different Time series models on DataCo [6] Global supply chain dataset. The models which are used here are ARIMA, SARIMA, Holt-Winters [12], and Prophet ,evaluated using MAPE as the accuracy measure.

3.2.1 Accuracy measures and performance of models

A. MAPE

One of the most common metrics used to measure the forecasting accuracy of a model is MAPE, Lower MAPE values indicate better model accuracy. The results for each model are as follows:

The formula to calculate MAPE [7] is as follows:

$$MAPE = \left(\frac{1}{n}\right) \sum X\ (|\ actual\ -\ forecast\ |\ /\ |actual|)\ X\ 100 \qquad (3.1)$$

Where , Σ is a symbol that means "sum" , n is the sample size ,actual is the actual data value, forecast is the forecasted data value.

B. Performance of each model on Time series dataset

i. ARIMA Model:

The ARIMA model showed better accuracy, particularly during the training phase as 4.6 % , but during testing phase its performance got decreased to 8.7 %, indicating potential overfitting.

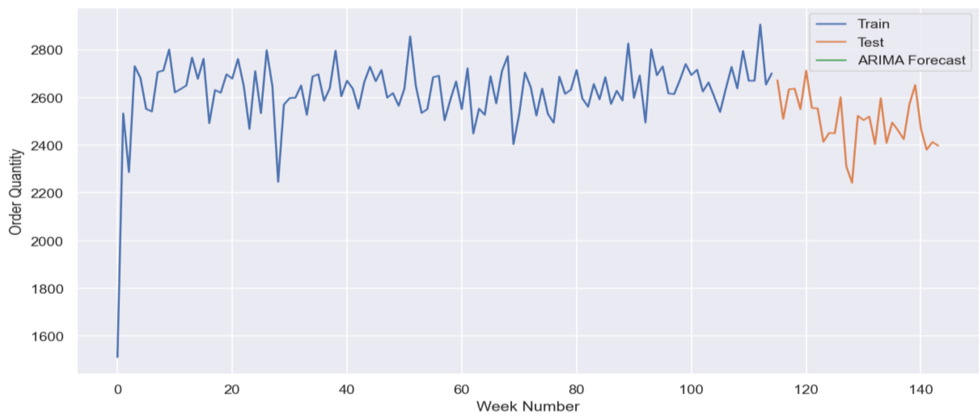

Fig 3.1: *ARIMA model performance for train ,test and forecast*

ii. SARIMA Model:

As compared to ARIMA ,the SARIMA model had higher error rates compared to both training and testing phases, as its training MAPE was 6.6 % and testing MAPE was 9.23 % this suggests that it was less effective in capturing seasonal components.

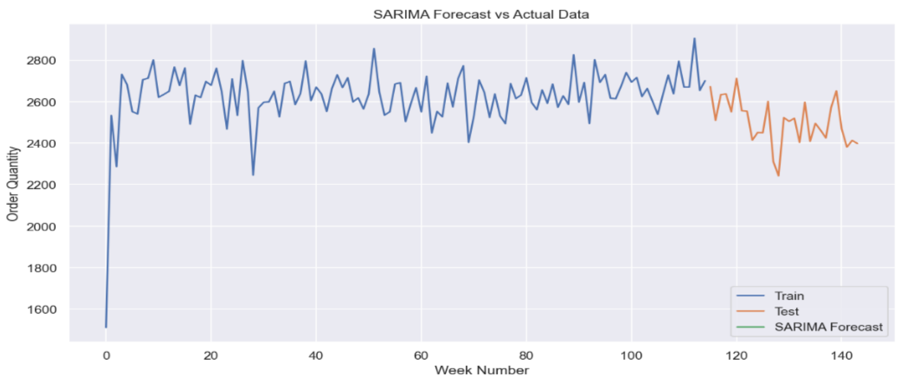

Fig 3.2: *SARIMA model performance for train ,test and forecast*

iii. Holt-Winters Model :

The Holt-Winters model performed better during training showing MAPE of 3.9 % but shows significant drop in accuracy during testing as 11.4 %, this indicates that it may have struggled with variability of the data.

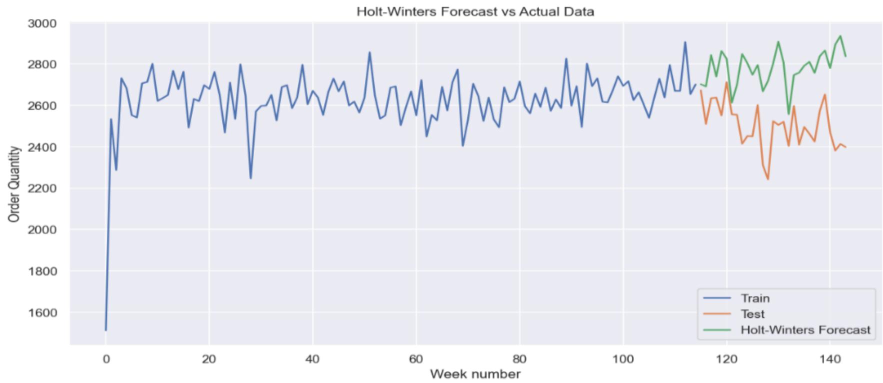

Fig 3.3: *Holt-Winter model performance for train ,test and forecast*

iv. Feed forward neural network:

The feed forward neural network performed better during training showing MAPE as 1.8 % and testing phase showing MAPE as 1.7 % but MAPE error in both phase is exact same , this shows overfitting of the model , so we will not consider it as better performance than other.

v. Prophet Model:

The Prophet model shows better performance than all the other models showing minimum MAPE score in both training as 3.28 % and testing phase as 7.13 % , This highlights its robustness in handling patterns and trends. Following figure shows the predicted training and testing values of data by using prophet [9] model.

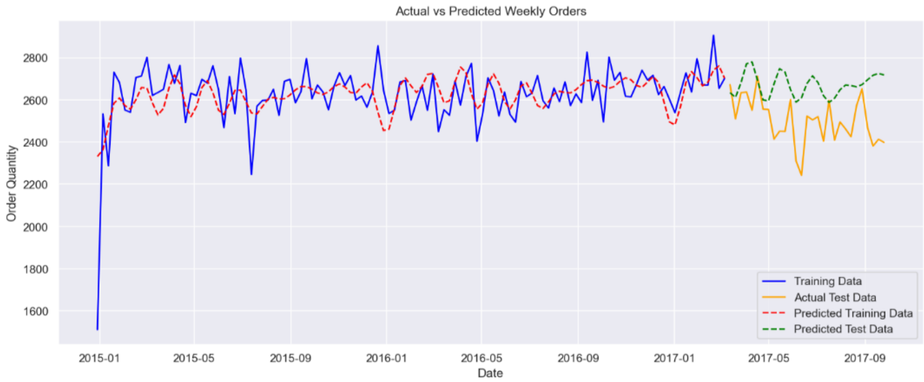

Fig 3.4: *Prophet model performance for train ,test and forecast*

3.2.2 Inventory Management:

Estimated demand forecasts are crucial for effective inventory management. By using the forecasted demand, This thesis calculates Safety tock and Reorder point for better inventory management. Predicted vs actual demand is shown in Fig. 3.5 along with Safety stock and Reorder Point.

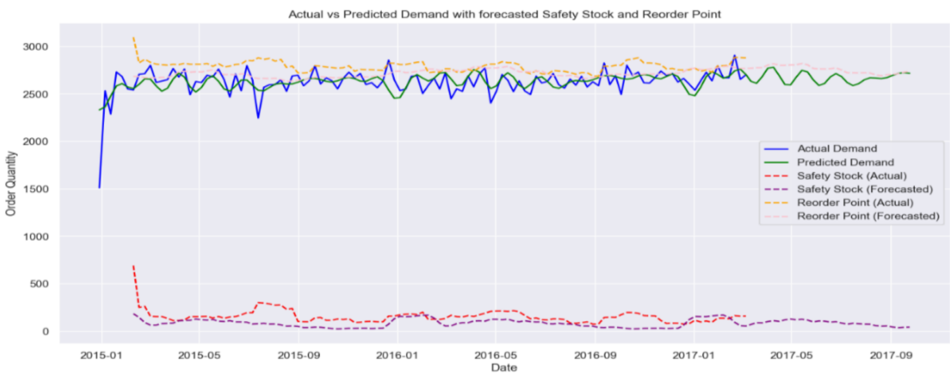

Fig 3.5: *Using Prophet model for Actual vs predicted demand with forecasted Safety stock and Reorder Point*

Table 3.1: *MAPE performance of all the models*

Model	**Training MAPE**	**Testing MAPE**
ARIMA	4.603744	8.713654
SARIMA	6.597750	9.225938
Holt-Winters	3.898565	11.389827
Prophet	3.283817	7.133634
Feedforward Neural Network	0.175451	0.172337

Table 3.2: *MAE performance of all the models*

Model	**Training MAE**	**Testing MAE**
ARIMA	110.48	212.73
SARIMA	162.96	225.93
Holt-Winters	96.97	279.96
Prophet	80.74	173.90
Feedforward Neural Network	0.0055	0.00556

Table 3.3: *MSE performance of all the models*

Model	Training MSE	Testing MSE
ARIMA	45509.54	57056.28
SARIMA	76658.88	64749.18
Holt-Winters	16973.85	95313.05
Prophet	14969.87	41927.91
Feedforward Neural Network	0.0003	0.0003

Table 3.4: *RMSE performance of all the models*

Model	Training RMSE	Testing RMSE
ARIMA	213.32	232.86
SARIMA	276.87	254.45
Holt-Winters	130.28	308.72
Prophet	122.35	204.76
Feedforward Neural Network	0.0175	0.0179

3.3 Discussion

The analysis of this work focuses on the most important findings concerning the application of the modern approaches to data analysis and forecasting for inventory management and supply chain processes. The time series analysis conducted for this study, involving comparative analyses of ARIMA, SARIMA, Holt-Winters, feedforward neural networks, and Prophet models indicated the importance of model selection in the determination of data variance and seasonality. However, when comparing the four models; Prophet model presented the highest accuracy with the smallest MAPE values in both the training phase of 3. 28% and the testing phase of 7. 13% which proves it to be the most appropriate in modeling patterns as well as trends. That is the reason it is equipped with seasonality modes and changepoint detection; play a crucial role in defining simple parameters of this model successfully.

Similar to the MAE, the model had relatively lower MAPE during the training phase and only 4 percent during the testing phase. The SARIMA model had a high error margin both in the training phase with MAPE of 6. 6% and in the testing phase with MAPE of 9. 23% indicating that the model lacked the capacity to understand the true essence of seasonality. During training, the Holt-Winters model yielded a MAPE of 3%, which was indicative of its accuracy in the model. But it is only 9% on average during training and its accuracy sharply declined during testing with MAPE of 11. 4% which should indicate its weakness in handling variability in the data. The feedforward neural network reproduced the exact input in the training set and only the feedforward neural network represented the correct input of MAPE 1.8 percent during training and 1 percent during competition. During training as well as testing, the percentage of impairment is 8% and 1% respectively. During testing the accuracy was 7% lower than in training, but equal errors for the training and testing sets suggested overfitting of the method, which is not very effective.

The Holt-Winter uses two parameters for trend and seasonality; however, the Holt-Winters model considers parameters for working day adjustment. In all models examined here, the replenishment lead time of all inventory was assumed to be one week. Therefore, the thesis used forecasted demand data to determine safety stock and reorder points with the aim of increasing efficiency of inventory control. These accurate figures are crucial for holding the right inventory quantities in place, avoiding excessive investment in unnecessary stocks and their consequent write-offs, and improving consumer satisfaction.

The study offloads a central concentration on the regional sale and methods of payments helping in the determination of inventory management. For example, strategy areas like Western Europe, and Central America reported bigger volumes of sales but at the same time steep revenue drops due to fraudulent orders and delayed shipments. The overall study clearly proves that nested techniques such as advanced forecasting and inventory optimization are undeniably valuable for businesses. In particular, by applying these insights, more effective inventory management techniques, less operational risks, improved competitive advantage, and overall organizational sustainability especially in the current fluid market context can be attained. This thesis also emphasized how the predicted change helped to enhance the efficiency of inventory operation and customer satisfaction with a data-driven solution.

3.4 Implementation

The application of this thesis entailed applying the higher-level forecasting models in a bid to enhance controls of inventories and the supply chain. The common model that was used in the case of the timeseries was called the ARIMA model where it had an acronym that stands for autoregressive-integrated moving average and was represented as ARIMA(p, d, q). In this model, it was possible to develop a linear equation that would address the time series data set, using the best of the number of AR terms (p), the differencing order (d) and the MA terms (q) to address errors of prediction. The results presented in table 3.1 shows that ARIMA had a good performance with overall training MAPE 4. It achieved a training MAPE below 2% at 1. 93% and a testing MAPE of 8%. 7%. SARIMA is the expanded version of ARIMA for seasonal data, and includes new parameters for seasonal component: order of autoregression (P), order of differencing (D), order of moving average (Q), and the frequency of seasonal factor (m). Although, ability of seasonality detection was enhanced, the accuracy of the SARIMA model was slightly inferior to the basic ARIMA model with the training and testing MAPE of 6. 6% and 9. 23%, respectively.

Another technique that can be used for modeling data, which exhibits both seasonality and trend, is the Holt-Winters method which uses parameters to forecast , which are the alpha – the level smoothing factor, the beta – the trend ratio, and gamma – the seasonal estimate. In the training phase, it was observed that this model is accurate with a MAPE of 3 percent. When it was the turn of testing the model, the MAPE was at 9% whereas when the model was being tested, MAPE inflated to 11%. 4%, indicating overfitting. Hence, the Prophet model created by Facebook was able to handle seasonality and holidays by moving the handles like – the Seasonality Mode, Changepoint Prior Scale and Seasonality Prior Scale. It had high performance concerning train and observed test MAPE of 3. 28% and 7. Besides the conventional methods, another experimental method for the prediction of order item quantity was performed through a feed forward artificial neural network with deep learning capabilities. The used neural network structure consisted of an input layer with several features, and then several hidden layers with the ReLU activation function, and finally the binary output layer with an appropriate continuous value prediction. However, some of the findings of this study include the use of identical training and testing MAPEs of 1 hence pointing to increased energy efficiency through the use of smart technologies in buildings. 8% and 1. Overall, it can be seen that while the total accuracy of the model has increased by 6% from the previous run at 92%, the test accuracy has actually decreased from 77.

In addition to setting inventory control procedures, it is a standard practice to establish safety stock and reorder point based on forecasted demand. Additional units known as safety stocks meant to cater for some unpredicted circumstances was determined using parameters such as the z-score with a value of 1. It means, that if the service level is 95%, the reorder point can be calculated using average weekly demand for the week that is equal to lead time and standard deviation of forecasted demand, All these calculations are made to determine the reorder point, which depends on the service level, average weekly demand and standard deviation of the forecasted demand for the week that equals lead time. It reduces inventory holding costs associated with high inventory levels and stockouts because this approach expected and ordered only what would be used in the coming days.

CHAPTER 4

CONCLUSION AND FUTURE SCOPE

4.1 Conclusion

In conclusion, this thesis has given detailed analysis of the findings from literature, how the concept of inventory management affects the overall performance of the supply chain and the results achieved by analyzing the DataCo Global dataset. Therefore, the sales pattern of regions revealed that even though there were higher volumes of sales in the Western Europe and Central America, the company suffered high levels of fake transactions and late deliveries affecting its revenues. It is therefore pertinent to observe that inventory optimization not only has to take into account absolute inventory levels, but also relative risks that may be present per location as well as the robustness of the transactional processes in place.

The study also explained the trends relating to sales dynamics; the figures showed constant increase up to Q3 2017 and a major drop in Q1 2018. This finding further emphasizes the need for specific attention to sales trends and taking necessary actions to control or react to any concluded demand volatility. Conversely, knowledge of months that customer orders are high for example, the 10th and 11th months of that year, can be useful planning advertising campaigns and anticipating when inventory may need to be replenished.

Analyzing the potential threats to the kinds of payments that customers make, including debit card and wire transfer payments, and realizing that wire transfers are very susceptible to fraud indicate why payment protection is important and why it is important for organizations to come up with payment protection solutions and technologies. To achieve this, organizations ought to have several measures in place to control wire transfers with an attempt of performing analytical data check for fraudulent acts. Compared different demand forecasting models, and concluded that the prophet model was the best performing among the other models that were used, making it the best criterion to use when looking for a model that will efficiently predict the demand of the products. Through the utilization of enhanced modeling methodologies and identifying relationships between various models that are risk analysis along with safety stock and reordering point formula, replenishment cycle of inventory can be made efficient and organizations can reduce or avoid stockouts or high holding cost inventories.

The findings from the evaluation of demand forecasting models are as follows:

- The performance of the MAPE of the model appeared to be slightly better during the training phase being around 4 percent. 6% while touching 8% performance level over the time. It has also been seen that it is as low as 7% in the testing phase which may mean overlearning or overfitting.

- The SARIMA model seemed to produce higher errors within the training phase (MAPE = 6. 6%) and within the testing phase (MAPE = 9. 23%) and therefore appeared to have less ability at capturing the seasonal factors to the same extent as the other models.

- The Holt-Winters was properly trained for the sets with a MAPE of around 3. 9% but only achieved 11. 4% only in testing proposing system has some weaknesses with data variability.

- However, the feedforward obtained almost the same MAPE errors during training (1. 8 %) and testing (MAPE = 1. 7 %), which are indicative of overfitting even though the performance was optimized.

- Among all the models, the most optimal was the Prophet model that had the lowest MAPE coefficient both in the training phase 3. 28% and the testing phase 7. 13% while emphasizing its stability in terms of patterns and trends.

Based on the estimated values of demand the thesis determines safety stock and reorder points to optimize inventory. These demand forecasts are crucial in Inventory Management since they help organizations ensure they carry the right amount of stock, in order to both minimize costs and to provide customers with the best satisfaction level.

Therefore , the overall analysis of the DataCo [6] Global dataset with the help of accurate forecasting and inventory optimization helps businesses to provide effective understandings regarding its supply chain effectiveness and customer satisfaction. When applied together, these strategies help companies reduce their operational risks as well as improve their standings in the market to ultimately manage to succeed in an environment that is full of uncertainty.

4.2 Future Scope

It is necessary to find and analyse the further potential opportunities for the enhancement of the work on this thesis in the context of mastering the rules and principals of improving the processes of the inventory optimization and supply chain management.

a. Integration of Advanced Forecasting Techniques: It is possible to also use other better forecasting techniques that have not been applied in the undertaking at the moment; this is embracing models and ensemble approaches. A majority of the hybrid models adapt features from different forecasting methods, for instance, the time series models coupled with machine learning approaches; whereas, ensemble models engage several models to boom the forecasts’ reliability. Exploring these complex techniques might further increase the level of forecasting accuracy of demand and enhance decision making on inventory management.

b. Integration of External Factors: The thesis can expand further by analysing the impact of influential variables which are not under one's control such as the economic pull factors, weather, and the general trends of the market. Forecasting originally developed for simple demand models can be more complex by including external data sources to increase the models' robustness and capture other factors affecting demand variability. This may help in making the procedures of inventory management far superior and responsive to new trends in the market.

c. Real-time Forecasting and Dynamic Inventory Optimization: One could also imagine an even more accurate and promising development direction for the future moving the forecasts toward real-time and dynamic stock management. Companies can real-time adjust inventory amounts based on updated demand signals through continuous forecasting methods and data stream feeds [13]. It is a useful business approach for managing the inventory and helps in avoiding stock-out situations, minimizing the holding cost of excess inventory and improving the flexibility of operations to match up with the changing consumption patterns of the customers.

d. Improved Visualization and Decision Support Tools: By improving tools for the visualization of related issues or challenges and tools for decision-making, stakeholders can be provided with relevant data regarding inventory optimization. Decision makers can act in real time, understand the impact of different choices, and compare different inventory management approaches by using real-time decision support that is added to rich dashboards containing information and interactive tools based on more analytic scenarios. Decision support tools should be designed in a way that enhances ease of use and accessibility so as to foster Integration systems across these departments.
e. Supply Chain Collaboration and Integration: The case can be taken further by including supply chain coordination alongside inventory management enhancing its optimization efforts by working with other organizations. Consistent and accurate communication of demand planning, inventory information, and manufacturing plans with the supply chain partners like suppliers, manufacturers

and distributors can helps the businesses to improve co-ordination and synchronisation throughout the management of the flow of products and related information. Through such integration, it is possible to discover better control of inventory, faster inventory cycles and an overall, a more enhanced supply chain.

f. Utilizing Artificial Intelligence and Machine Learning: The future prospects of further studies in the methods described above when using artificial intelligence and machine learning are significant. Reinforcement learning , predictive analytics algorithms and deep learning technologies are capable of mining the information that exist in distinct large databases, identifying the patterns that exist and produce intuitive and accurate predictions. The implementation of AI solutions will be helpful in augmenting more measures of accurate and intelligent operation in the inventory of the new thesis and will increase the efficacy and flexibility of the supply chain management system.

Finally, the ideas for the further development of this thesis include the enhancement of the forecasting methods, the specifics of external factors, real-time and dynamic forms of inventory management, advancement of decision-making instruments, supply chain integration and the application of AI and machine learning. There are various areas where businesses can build up their competitiveness to tap into the opportunities being offered in the constantly evolving supply chain management terrain; such are mentioned below, thus helping such realizing better flexible inventory management strategies.

4.3 Social Impact

This concern affects several aspects of the society, and coupled with the need to meet inventory and supply chain requirements, this intervention is of wide social benefit. A direct effect as to be observed is the level of satisfaction of the customer since handling of control inventory is well addressed. Under this premise, the general goal of having efficient shipping schedules, the possibility of stockout and ensuring the availability of stock if employed by the businesses will assist them in fulfilling the need of the customers to the level of ensuring that they establish customer loyalty.

In a way that is more indirect, the formalized effort contributes toward the economy's stability by providing information on operating costs while at the same time improving the profitability of organizations. Holding cost reduction is also within per cent according to efficient management of inventory as wasting reduces the enhanced financial performance. In a social context, it results in economic development and enhances the prospect of creating employment chances in the context of the SMSE supply chain.

It is clearly seen that the paradigm of the thesis is the identification and prevention of fraud in contracting and other financial transactions which has a clearly evident high societal significance. Companies protect consumers money through various ways in a bid to ensure that there are cushions against any loses or frauds that may occur in the business. It is crucial in enhancing a secure business environment by summoning and ensuring truthful and reliable business relations and procedures.

The increase of the quality of the delivery timeliness, and the optimality of the shipping schedules that every organization can adopt in the delivery of goods and services has some environmental effects in the reduction of carbon emissions. The benefits of saving oil that accrue from effective logistic operation in SW include; Climate change and thereof sustainable development goals seek to reduce negative impact of climate on the earth hence an efficient logistic ensures that minimal amount of petroleum is used to finance such program.

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