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Time-Series Demand Forecasting and Supply Chain Optimization Using ARIMA and SARIMA Statistical Models

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Abstract: Nowadays, companies are facing many problems because business conditions keep changing very fast. Customer needs can be varying from time to time which can result in change in competition, and market situations. Consequently, companies find it difficult to guess how much demand they will have in the future. If demand is not predicted correctly, it may result in extra stock or stock outs, which causes losses. So, demand forecasting has become an important part of supply chain planning.

In this project, past sales data is used to predict future demand. The data is studied based on time to understand how demand changes in a certain period of time. Simply this is known as time- series forecasting. Two models(ARIMA, SARIMA) are used in this work. ARIMA is used when the data does not show seasonal changes, and SARIMA is used when demand repeats in a seasonal manner.

The predictions obtained from these models help in planning inventory and purchasing activities. This allows companies to maintain enough stock without spending too much on storage. The method used in this project is easy to apply and is suitable for small and medium businesses. Overall, this project explains how previous sales data can be used in a practical way to support better planning and decision-making.

Index Terms: Time-Series Forecasting, Demand Forecasting, Supply Chain Optimization, ARIMA Model, SARIMA Model.

I. INTRODUCTION

In current days companies are facing a challenge i.e., rapid change in customer choice, which can lead to fluctuations in market trends.Major difficulty faced by the companies is predicting the demand for a product. If these expectations are not matched with reality, companies may produce more products than needed or less than the minimum to meet customer needs. This results in failure of proper utilization of money and affects customer trust. Because of this, demand forecasting has become an important part of business planning. Demand prediction plays a very crucial role in Supply chain management for every company. Companies use ana- lyzed results to determine the production quantity, inventory levels, and schedule for restocking. Although steps are known, companies are still facing challenges in forecasting. During festival days and any special occasional seasons, there can suddenly increase or decrease demand.

Time-series forecasting is a method where it uses the past data to predict the future demand. Instead of guessing randomly, this method gives an overview about how demand has changed earlier and uses that information to estimate future values. Models like ARIMA and SARIMA [1], [4] are commonly chosen because they are easy to understand and can give good results without needing high computing power or complex algorithms.

In this project, two time-series models are used for demand prediction. ARIMA is applied when the data does not show seasonal changes, while SARIMA is selected when seasonal patterns are present. The produced results are then used to support inventory and purchasing decisions. This approach is very useful for small and medium businesses because it does not require expensive software or complex systems, and also helps in improving supply chain planning using historical sales data.

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II. PROBLEM STATEMENT

In recent times, companies are facing struggles due to frequent change in customer interests which leads to variation in market competition and demand. This results in difficulty in predicting demand. Incorrect predictions can leads to great damage such as Overstocking, Stock-outs, and improper utilisation of resources. Many Small and medium sized business fails to handle costs and complexity. Previous models are expensive.

III. LITERATURE REVIEW

Demand forecasting helps in reducing inventory costs, eradicating shortages and meeting the ends of customer requirements. Already many researchers have worked on statistical time series models including ARIMA and SARIMA for sup- porting supply chain optimization.

This study includes the ARIMA framework in time series analysis by G. E. P. Box and G. M. Jenkins [1]. They stated how Time series data can be transformed to find out the trends and patterns. Their work doesn't completely contribute to the supply chain but has created a base for applying ARIMA model in real-world demand forecasting problems. Further studies made use of their methodology as foundation.

Makridakis et al [4]. assessed the standards of various statis- tical forecasting models with multiple datasets in 1988. Their findings proved that ARIMA models performed better than the other models with complex data. Their research concluded that simple statistical models can provide reliable forecasting resulting in supply chain optimization.

Several studies specifically applied ARIMA to supply chain demand forecasting. Kumar and Jain in 2010 used ARIMA models to forecast product demand in a manufacturing environment. Their research concluded that demand forecasts reduced inventory planning and holding costs. They identified that ARIMA failed to exhibit seasonal patterns that are common in any industry.

To overcome this, researchers started working on SARIMA models, an extension of ARIMA. Hyndman and Athanasopoulos [2] stated that SARIMA models are particularly effective for time-series data which involve seasonal trends.

IV. OBJECTIVES

- To analyze historical sales data in order to understand demand patterns, trends, and variations over time for effective forecasting.
- To apply time-series forecasting techniques such as ARIMA and SARIMA models to predict future demand based on past sales behavior.
- To handle non-stationarity and seasonality in demand data by applying statistical tests and transformation techniques to improve model accuracy.
- To compare the performance of ARIMA and SARIMA models using appropriate evaluation metrics to identify the most suitable model for different demand patterns.
- To support inventory planning and supply chain decision- making by generating accurate short-term and long-term demand forecasts.
- To develop a cost-effective and simple forecasting system that can be easily implemented by small and medium-sized enterprises with limited computational resources.
- To improve overall business planning and resource utilization by minimizing overstocking, stock-outs, and in-efficiencies in supply chain operations.

V. PROPOSED SYSTEM

A. System Overview

The proposed system focuses on predicting future scope based on the existing and previous data. This uses Stat models ”ARIMA” and ”SARIMA”.This is best suited for making wise decisions in supply chain Management. This involves a framework that can provide strong forecasts that helps in maintaining an adequate amount of stock.

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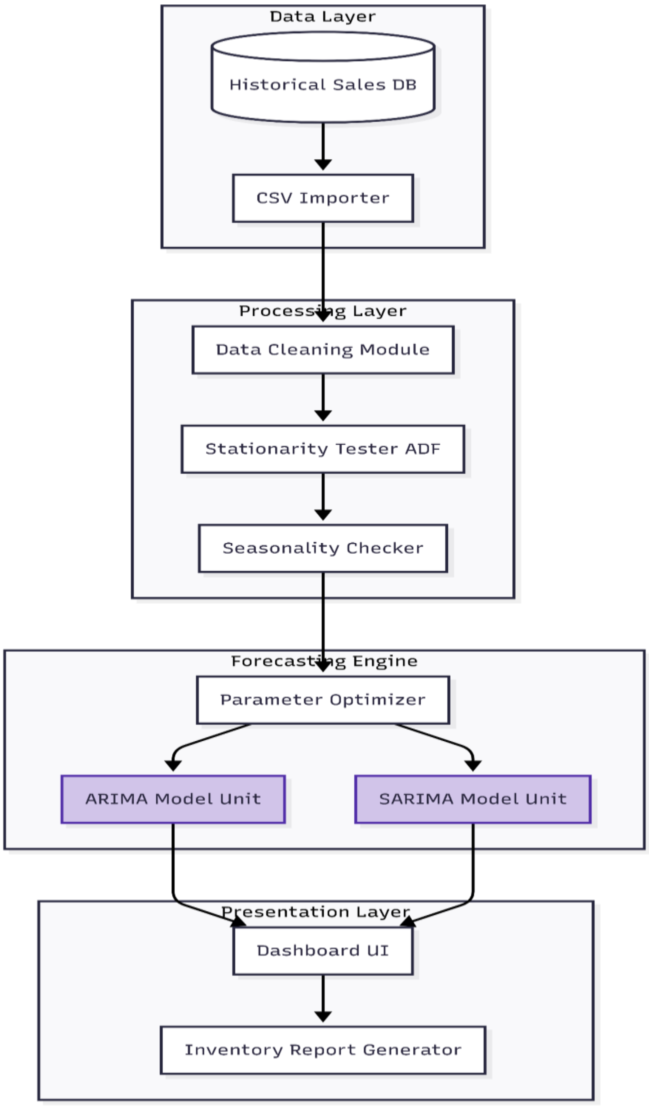

Fig. 1. System architecture for time-series demand forecasting using ARIMA and SARIMA models

VI. METHODOLOGY

A. Data Collection and Preprocessing

For the System,the main important requirement is data. So , the data need to be collected from retailers , suppliers. The data is organised into a csv file. Later many processing steps are performed on the data. These steps involve(Handling missing data,Removing Null values and duplicates). Aggregate columns are created such that continuous data is converted into regular intervals such as (Daily, Weekly, Monthly).

B. Exploratory Data Analysis

This step is performed to identify hidden patterns and demand trends such as increasing or decreasing. ADF test is performed. Most of the models including ARIMA and SARIMA work properly when statistical values such as mean and variance remain unchanged. To verify this Augmented Dickey- Fuller test is applied. If the result is non-stationary. Then differencing is applied to stabilize. Differencing is very important to find 'd' parameters in ARIMA and SARIMA.

C. Model Selection

Seasonality plays a crucial role in choosing a model. ARIMA(AutoRegressive Integrated Moving Average) is opted when data represents no seasonal changes. SARIMA(Seasonal AutoRegressive Integrated Moving Average) is preferred when data exhibits seasonal patterns. SARIMA prolongs ARIMA by incorporating seasonal constraints.

ARIMA contains parameters (p,d,q). P denotes Autoregres- sive order , it represents "Number of lagged observations" by PACF . D stands for Differencing order where it considers the number of times the data is differenced to obtain

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stationary can be known by ”ADF”test . Number of lagged forecast errors involved can be considered by parameter ”Moving Average order”(q).

Parameters needed for SARIMA are (p,d,q)(P,D,Q,s) where (p,d,q) are common for both. (P,D,Q,) are parameters as above that considers seasonal conditions. The duration of the seasonal cycle is considered using the parameter ”Seasonal period”(s).

D. Model Implementation

In this phase , the selected model is trained by using historical data . The data is divided into two sets (Training and Testing). Training data is used to find coefficients. ARIMA and SARIMA are present in statmodels Python library. The parameters are adjusted continuously such that Prediction errors are reduced to produce sound models.

E. Model Validation

Evaluation of assumptions made by model are done by using various Performance Evaluation Metrics. For the evaluation of the model, the metric used is RMSE ”Root Mean Square Error”. This metric can inflict a penalty on large errors. Low RMSE values indicate better performance of the model and vice-versa. RMSE is calculated for both ARIMA and SARIMA.

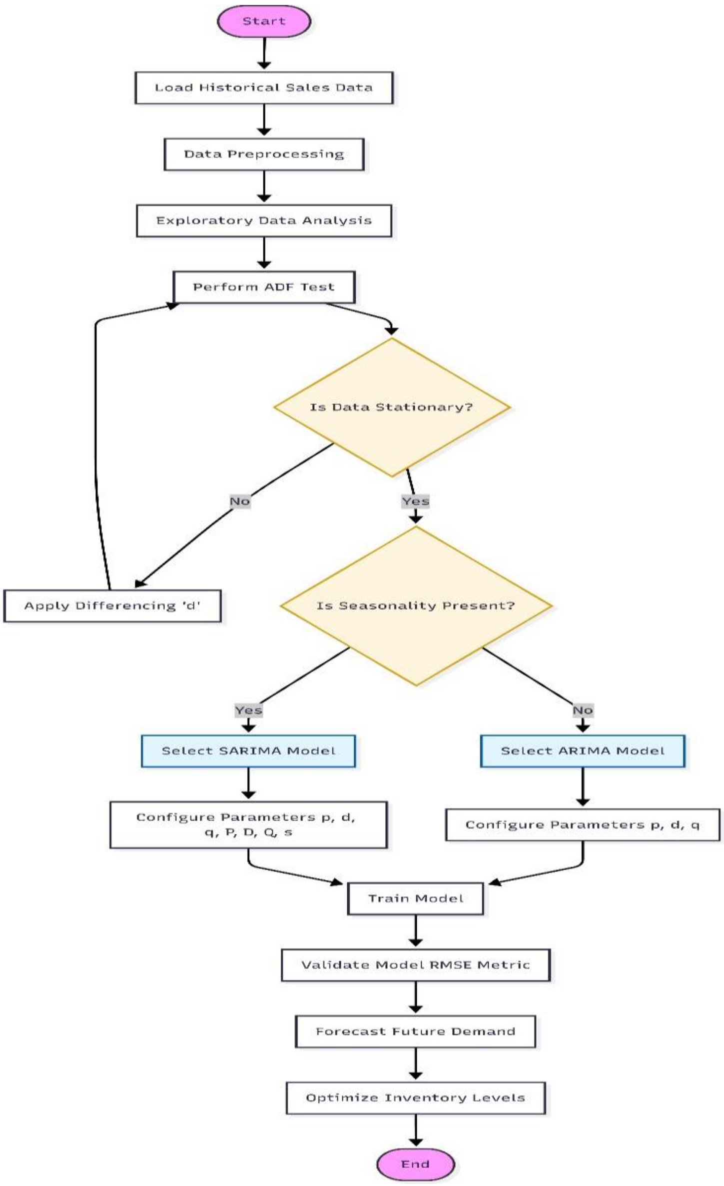

Fig. 2. Comparison of ARIMA and SARIMA model parameters and their selection criteria

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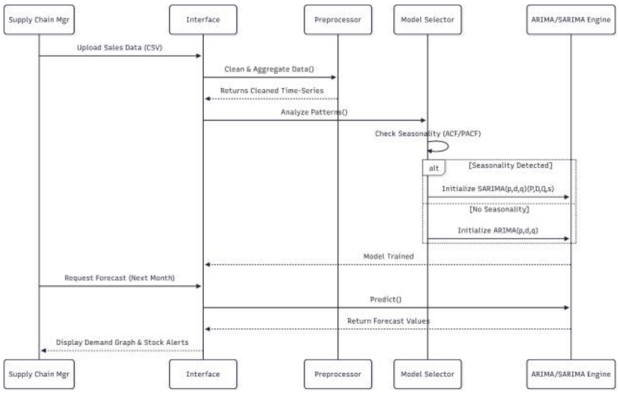

Fig. 3. Model training and validation workflow for ARIMA and SARIMA implementation

F. Demand Forecasting

With the trained model, future demand predictions are made. The forecasting period may vary based on requirement. For the decisions related to inventory replenishment, order scheduling Short-Term Demand Forecasting is made.These forecasts are suitable for day-to-day supply chain operations. For the operations that involve capacity planning, budget al- location and procurement, Long-Term Demand Forecasting is used. These forecasts are useful for estimating growth, decline and minimising uncertainity.

G. Decision Support and Reporting

This module converts predictions into decisions related

.These decisions include ”Inventory planning” . It provides scope for optimising stock such as avoiding overstock and stockout. It minimises losses that occur due to inappropriate stocks. The only limitation of this study is its accuracy can be low with non-linear patterns.

VII. DISCUSSION

The outcome of this study demonstrates the effectiveness of the models in Demand forecasting and supply chain man- agement. Both the models are effective for identifying hidden patterns from the data, but differentiates in performance with the presence of seasonality.

ARIMA model performed well with the datasets that doesn’t contain seasonal constraints showing stable patterns. As the requirements for the model are less , make it fit for short-term scenarios which have negligible demand fluctuations due to seasonal changes. Although it performs well,it has limitations when dealing with data that has seasonal trends.
In addition, SARIMA model improved accuracy for the datasets with seasonal behaviour. The evaluation metrics indicate that SARIMA exceeded ARIMA in data that incorporates seasonal patterns [2].

Even though advanced machine learning concepts such as LSTM were used earlier and became popular, they require large datasets , effective computational resources. Compared to earlier, this project is less expensive and efficient for small and medium sized companies where the data available is less.

VIII. RESULTS

While developing ,both the models were trained on past data and evaluated the accuracy. Evaluation metrics RMSE, MAPE, and MAE were used .SARIMA reduced the errors in the prediction than ARIMA . On providing the forecast values, there was an improvement in the inventory management.The various evaluation values achieved by the both models are as follows

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TABLE I
PERFORMANCE METRICS COMPARISON BETWEEN ARIMA AND SARIMA MODELS

ARIMA	
Model	ARIMA(1,1,1)
MAE	1.31502
MSE	3.87563
RMSE	1.96866
MAPE	12.4552
SMAPE	12.7168
R2	0.890246
Adjusted R2	0.889702
MASE	0.988884
Correlation	0.945835
ME	-0.38958
MPE	-1.86403
NRMSE	18.4083
AIC	855.524
BIC	865.463
Log-Likelihood	-424.762

TABLE II
SARIMA MODEL FORECAST RESULTS WITH CONFIDENCE INTERVALS

ID	mean	mean se	mean ci lower	mean ci upper
204	23.7906	0.926411	21.9749	25.6063
205	24.5962	0.928588	22.7762	26.4162
206	23.8554	0.973746	21.9468	25.7639
207	25.4401	1.00101	23.4782	27.4021
208	27.3458	1.03134	25.3244	29.3671
209	27.7477	1.0598	25.6706	29.8249
210	31.6610	1.08777	29.5290	33.7930
211	22.2968	1.11497	20.1115	24.4821
212	22.0393	1.14155	19.8019	24.2767
213	23.2511	1.16751	20.9628	25.5393
214	25.0680	1.19291	22.7300	27.4061
215	23.1276	1.21778	20.7408	25.5144

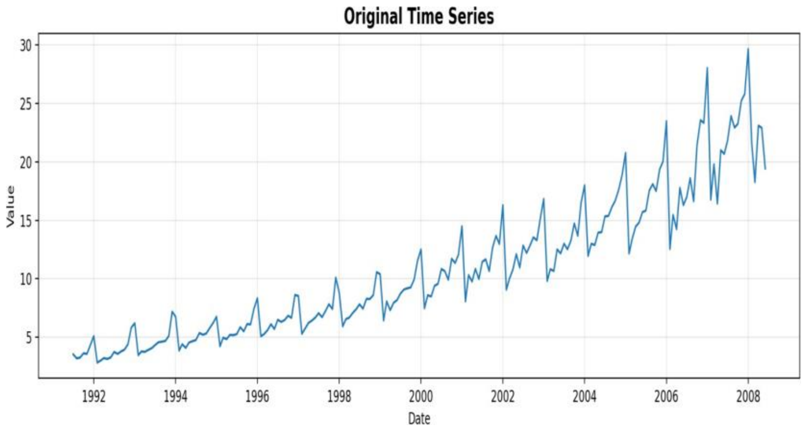

Fig. 4. ARIMA model performance visualization showing actual vs predicted values

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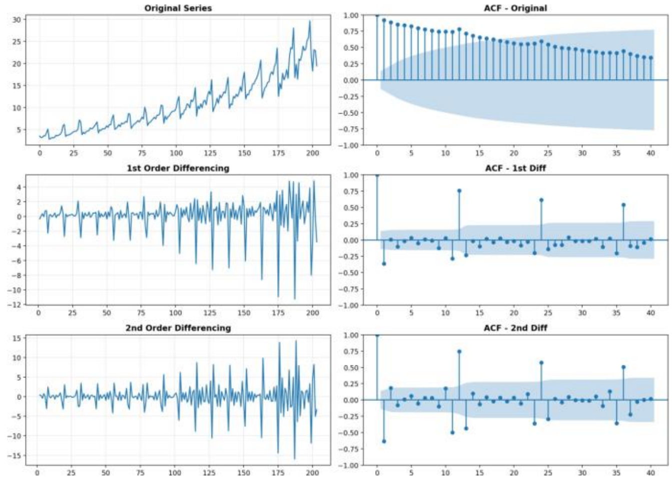

Fig. 5. SARIMA model performance visualization showing actual vs pre- dicted values with confidence intervals

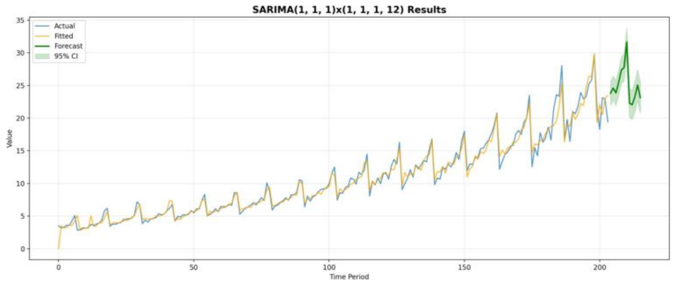

Fig. 6. Comparison of ARIMA and SARIMA forecast accuracy metrics

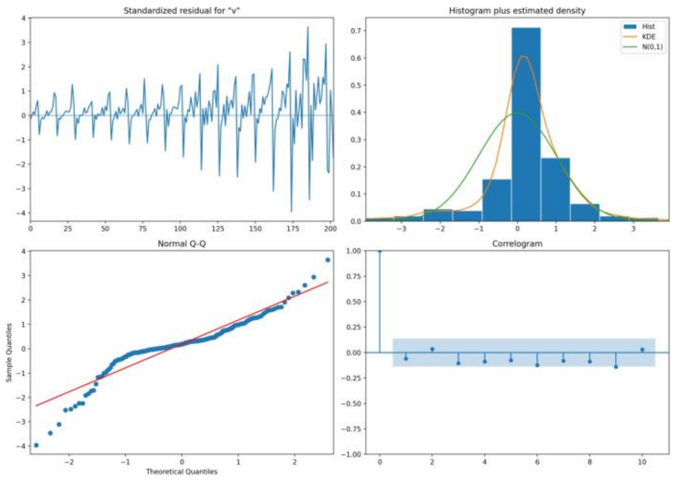

Fig. 7. Short-term demand forecasting results using ARIMA model

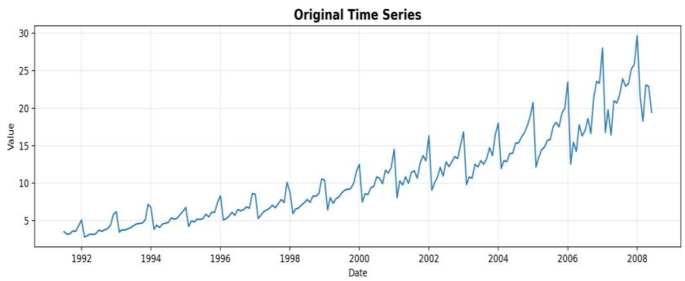

Fig. 8. Short-term demand forecasting results using SARIMA model

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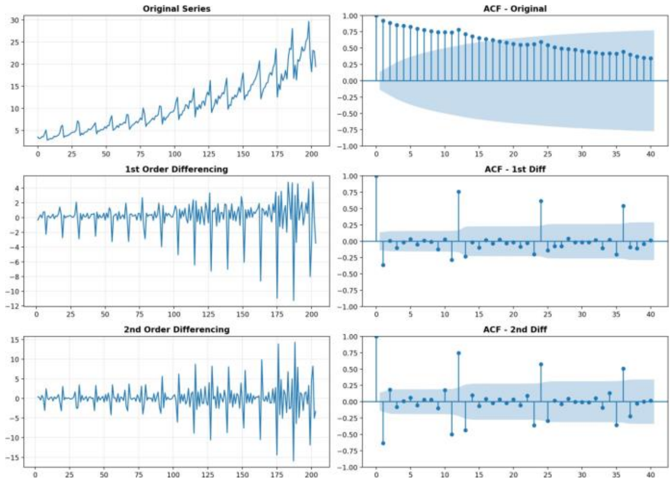

Fig. 9. Long-term demand forecasting results using ARIMA model

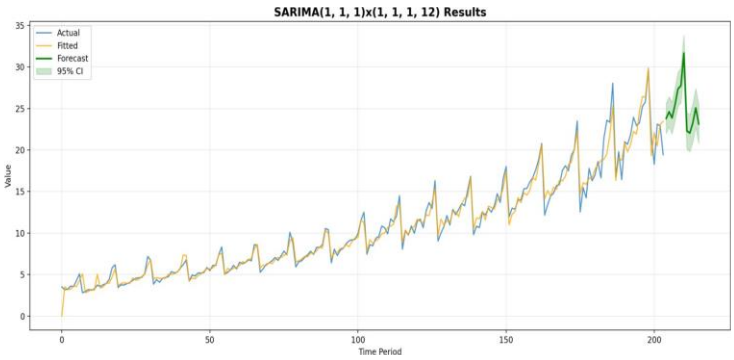

Fig. 10. Long-term demand forecasting results using SARIMA model

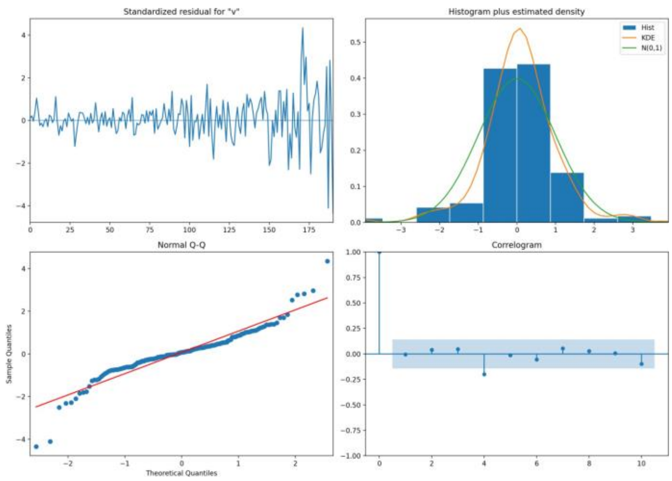

Fig. 11. Supply chain optimization results based on demand forecasts

IX. CONCLUSION

This project mainly focuses on time series demand fore- casting and supply chain optimization using ARIMA and SARIMA models which are used to analyze the historical data patterns. The fundamental objective is to estimate the effectiveness of these two traditional forecasting techniques which are best suited for demand prediction. Both models perform well but they differ in nature of the data. ARIMA works on non seasonal demand patterns whereas SARIMA works on seasonal demand patterns. However the limitations present in the ARIMA extended in the SARIMA.

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