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Demand Forecasting for Automobile Spare Parts: A Comparative Study of ARIMA and Exponential Smoothing

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Abstract: Effective inventory management is gaining increasing attention globally as businesses strive to optimize supply chain operations and reduce costs. In today's competitive environment, where efficiency and sustainability are paramount, proper inventory management plays a critical role. It encompasses a wide range of processes, including inventory classification, prioritization, demand forecasting, and replenishment. This study integrates ABC-FSN analysis with advanced forecasting techniques—ARIMA (AutoRegressive Integrated Moving Average) and Exponential Smoothing—to enhance inventory control in medium-level automobile spare parts stores. ABC analysis categorizes inventory based on annual consumption value, while FSN analysis classifies items according to their movement rates (Fast-moving, Slow-moving, and Non-moving). ARIMA is employed to capture complex and irregular demand patterns, whereas Exponential Smoothing is utilized for stable and consistent demand trends. Using real-world data, the study compares the performance of both forecasting methods, demonstrating that ARIMA excels in handling complex demand patterns, while Exponential Smoothing is more effective for stable demand. The integration of classification and forecasting provides actionable insights for optimizing inventory levels, reducing stockouts, and minimizing holding costs. This framework not only enhances supply chain efficiency but also supports sustainable inventory management practices, contributing to a more resilient and future-ready supply chain.

Keywords: ARIMA, Exponential Smoothing, Supply Chain Optimization, Time Series Forecasting, Stockout Reduction, Cost Optimization, Sustainable Inventory Practices, Mean Absolute Error (MAE),Mean Squared Error (MSE),Closed-Loop Supply Chain

I. INTRODUCTION

Inventory management is a critical component of supply chain operations, particularly for medium-level automobile spare parts stores that serve a diverse customer base with fluctuating demand patterns. These stores face significant challenges, including demand variability, limited storage capacity, and the need to balance inventory costs with service levels. Efficient inventory management ensures the availability of spare parts, minimizes holding costs, and mitigates the risks of stockouts or overstocking. For medium-level stores, optimizing inventory management is essential to maintain customer satisfaction, operational efficiency, and profitability.

This study focuses on inventory classification and demand forecasting for automobile spare parts in a medium-level store setting. The study employs ABC analysis to categorize spare parts based on their annual consumption value, enabling the prioritization of high-value items (Category A) while adopting cost-effective strategies for low-value items (Category C). Additionally, FSN analysis is used to classify spare parts based on their movement rates—Fast-moving (F), Slow-moving (S), and Non-moving (N). This dual classification approach provides a comprehensive understanding of inventory dynamics, facilitating effective resource allocation and reducing unnecessary holding costs.

However, classification alone is insufficient for optimal inventory management. Accurate demand forecasting is essential to anticipate future demand patterns and ensure the availability of spare parts. This study leverages two advanced forecasting techniques: ARIMA (AutoRegressive Integrated Moving Average) and Exponential Smoothing. ARIMA is particularly effective for capturing complex and irregular demand patterns, which are prevalent in the automobile spare parts industry. Exponential Smoothing, on the other hand, is well-suited for stable demand patterns and offers a simpler yet reliable forecasting approach. By combining these methods, the store can make data-driven decisions that enhance inventory control and reduce costs.

The primary objective of this study is to develop an integrated framework that combines inventory classification (ABC-FSN analysis) with demand forecasting (ARIMA and Exponential Smoothing) for medium-level automobile spare parts stores. Using real-world data, the study evaluates the performance of these techniques and provides actionable insights for optimizing inventory management.

The findings highlight the importance of tailoring inventory strategies based on the unique characteristics of spare parts, ultimately contributing to improved operational efficiency and customer satisfaction.

In conclusion, this research underscores the significance of integrating classification and forecasting techniques to achieve effective inventory management for medium-level automobile spare parts stores. By adopting these methods, stores can enhance supply chain efficiency, reduce costs, and contribute to broader sustainability goals, ensuring a resilient and future-ready business model.

II. LITRATURE REVIWE

Inventory management and demand forecasting have been extensively studied in various industries, with a growing focus on the automotive sector due to its complex supply chain dynamics. This literature review highlights key studies that have contributed to the fields of inventory classification, demand forecasting, and the application of machine learning and deep learning techniques in supply chain management.

Vishwakarma et al. (2022) compared different machine learning algorithms to improve sales forecasting for a grocery store during the COVID-19 pandemic. Their findings emphasized the importance of selecting the right algorithm based on data characteristics, which is equally relevant for forecasting demand in the automotive spare parts industry.

M. Rossi, A. et al. (2022) proposed a data-driven approach for spare parts demand forecasting in the automotive industry. By integrating historical sales data with external factors such as weather and economic indicators, their study demonstrated the potential of combining internal and external data sources to enhance forecasting accuracy.

El Filali et al. (2022) introduced a deep learning model using an optimized Long Short-Term Memory (LSTM) network for demand forecasting. Their model outperformed traditional time series methods by capturing nonlinear features in the data, highlighting the effectiveness of deep learning in handling complex demand patterns.

K. Patel et al. (2022) compared Facebook's Prophet model and LSTM for forecasting demand in automotive spare parts. Their study focused on seasonal and trend components, showing that hybrid models combining statistical and deep learning approaches can improve forecasting performance.

Pacella et al. (2021) evaluated the use of LSTM networks, including bidirectional LSTM, for demand forecasting in supply chain management. Their work demonstrated the superiority of LSTM in capturing both short- and long-term demand patterns, making it a valuable tool for automotive spare parts forecasting.

R. Gupta et al. (2022) conducted a comparative study of machine learning models, including Random Forest, XGBoost, and LSTM, for demand forecasting of automotive spare parts. Their findings underscored the importance of model selection based on demand patterns, particularly for intermittent demand.

Bajaj et al. (2020) explored sales prediction using machine learning algorithms such as Linear Regression, K-Nearest Neighbors, XGBoost, and Random Forest. Their study highlighted the effectiveness of ensemble methods in improving forecasting accuracy, which can be applied to automotive spare parts demand forecasting.

S. Kumar (2021) compared traditional statistical methods with machine learning and deep learning techniques for forecasting demand in automotive spare parts. The study emphasized the effectiveness of LSTM networks in handling intermittent demand patterns, which are common in the automotive aftermarket.

J. Noh et al. (2020) proposed a hybrid forecasting model called GA-GRU, which combines Genetic Algorithm (GA) with Gated Recurrent Unit (GRU). Their model achieved higher forecasting accuracy compared to other methods, demonstrating the potential of hybrid approaches in supply chain management.

M. Ali et al. (2020) evaluated Croston's method and its variants for forecasting intermittent demand in automotive spare parts. Their study provided insights into the suitability of these methods for low-demand items, which are prevalent in the automotive spare parts industry.

P. Wang (2021) explored the use of deep learning models, such as LSTM and GRU, for forecasting intermittent demand in automotive aftermarket supply chains. The study emphasized the importance of feature engineering and data preprocessing in enhancing model performance.

Five key gaps-
1) Limited focus on medium-level spare parts stores.
2) Lack of integration between inventory classification and demand forecasting.
3) Challenges in handling intermittent and erratic demand patterns.
4) Insufficient validation using real-world data.
5) Limited emphasis on cost optimization in inventory management.

III. METHODOLOGY

This study aims to develop an integrated framework for inventory management and demand forecasting tailored to medium-level automobile spare parts stores. The methodology is divided into three main phases: Inventory Classification, Demand Forecasting, and Performance Evaluation. Below is a detailed explanation of each phase.

A. Inventory Classification

The first phase focuses on classifying spare parts using ABC analysis and FSN analysis to prioritize inventory management efforts.

1) ABC Analysis

Categorize spare parts based on their annual consumption value.
Steps:
A. Calculate the annual consumption value for each spare part using the formula:
Annual Consumption Value=Unit Cost × Annual Demand
B. Rank the spare parts in descending order of their annual consumption value.
C. Classify the items into three categories:
Category A: High-value items (70-80% of total value, 10-20% of items).
Category B: Moderate-value items (15-20% of total value, 30-40% of items).
Category C: Low-value items (5-10% of total value, 50-60% of items).

2) FSN Analysis

Classify spare parts based on their movement rates.
Steps:

A. Calculate the average monthly demand for each spare part.
B. Classify the items into three categories:
Fast-moving (F): High demand.
Slow-moving (S): Moderate demand.
Non-moving (N): Low or no demand.

3) Integration of ABC and FSN Analysis

Combine the results of ABC and FSN analyses to create a dual classification framework. This helps prioritize inventory management strategies based on both value and movement rates.

4) Demand Forecasting

The second phase involves forecasting demand for spare parts using **ARIMA** and **Exponential Smoothing** models.

5) ARIMA (AutoRegressive Integrated Moving Average)

Capture complex and irregular demand patterns.
Steps: Check for Stationarity: Use the Augmented Dickey-Fuller (ADF) test to determine if the time series data is stationary. If not, apply differencing to achieve stationarity.
Determine Model Parameters:
p (AR term): Number of lag observations.
d (I term): Degree of differencing.
q (MA term): Size of the moving average window.
Fit the ARIMA Model: Use historical demand data to train the model.
Forecast Demand: Generate forecasts for the next 2 months.

6) Exponential Smoothing

Provide a simpler yet effective approach for stable demand patterns.

Steps:

Choose a smoothing constant (alpha) between 0 and 1.

Apply the exponential smoothing formula:

Ft+1=α·Dt+(1−α)·Ft$Ft+1=\alpha \cdot Dt+(1-\alpha)\cdot Ft$

where:

Ft+1$Ft+1$ = Forecast for the next period.

DtDt = Actual demand in the current period.

FtFt = Forecast for the current period.

Generate forecasts for the next 2 months.

B. Model Selection

Compare the performance of ARIMA and Exponential Smoothing using metrics such as,

Mean Absolute Error (MAE):

$$MAE=n1i=1\sum n|yi-y\hat{}i|$$

Mean Squared Error (MSE):

$$MSE=n1^{i=1}\sum n(yi-y\hat{}i)^2$$

Root Mean Squared Error (RMSE):

$$RMSE=\sqrt{MSE}$$

Select the best-performing model for each spare part based on demand patterns.

IV. CALCULATIONS

This section presents the findings of the study, including the results of inventory classification, demand forecasting, and performance evaluation. The analysis is based on historical data from a medium-level automobile spare parts store.

A. Inventory Classification.

The spare parts were classified using ABC analysis and FSN analysis to prioritize inventory management efforts.

Following table contain A-F class item.

Table 1: A-F class item of Automobile Spare Parts

Part No	A	B	C	D	E	F
Jul	24	42	37	0	1	5
Aug	19	27	35	3	6	3
Sep	29	53	27	2	4	7
Oct	42	82	30	3	2	2
Nov	29	49	30	5	1	4
Dec	21	60	38	7	4	74.2

B. Demand Forecasting

Demand forecasts for January and February were generated using Exponential Smoothing and ARIMA. The results are compared with the actual consumption data.

1) Exponential Smoothing Forecasts.

Table 2: ES Forecasts for Spare Parts (Jan–Feb-Mar
)

Month	A	B	C	D	E	F
Jan	25.17	56.36	34.94	4.91	3.1	5.61
Feb	24.12	55.45	34.26	4.74	2.97	5.43
Mar	23.28	54.71	33.68	4.62	2.88	5.3

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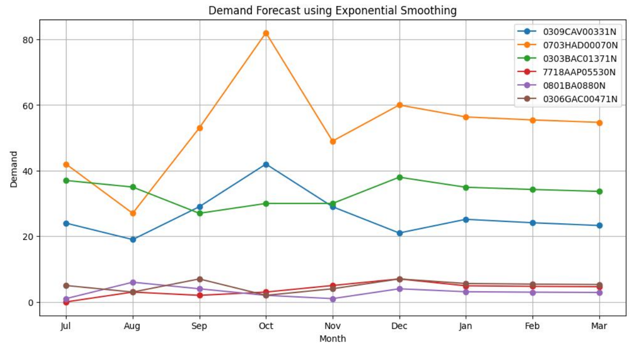

Figure 1: Exponential Smoothing Forecasts

2) ARIMA Forecasts

Table 3: ARIMA Forecasts for Spare Parts (Jan–Feb-Mar)

Month	A	B	C	D	E	F
Jan	23	54	38	8	3	10
Feb	22	53	38	9	3	7
Mar	23	52	38	10	3	9

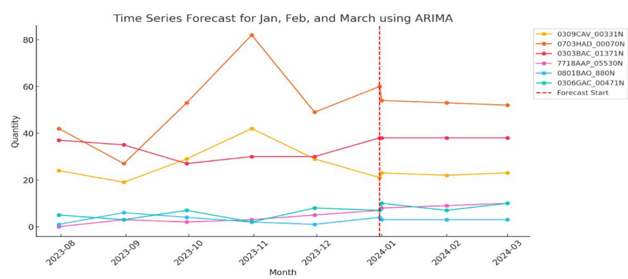

Figure 1: ARIMA Forecasts

C. Metrics for Evaluation

We will calculate the following metrics for each part number and each forecasting method (Exponential Smoothing and ARIMA).

1) Actual Consumption

Table 4: Actual Consumption (Jan–Feb)

Month	A	B	C	D	E	F
Jan	28	78	42	3	2	3
Feb	31	68	46	1	1	5

Exponential Smoothing Evaluation.
MAE=2.42
MSE=7.92
RMSE=2.81

ARIMA Evaluation.
MAE=6.25
MSE= 74.25
RSME=8.62

2) Summary of Results

Table 5: Performance Metrics for Exponential Smoothing and ARIMA

Metric	Exponential Smoothing	ARIMA
MAE	2.42	6.25
MSE	7.92	74.25
RMSE	2.81	8.62

V. RESULTS

Exponential Smoothing outperformed ARIMA in accuracy, with an average **MAE** of **2.42** (vs. 6.25) and **RMSE** of **2.81** (vs. 8.62). Exponential Smoothing is more effective for stable demand patterns in medium-level stores, while ARIMA, suitable for complex patterns, requires extensive preprocessing. The integration of **ABC-FSN analysis** with demand forecasting optimized inventory costs. High-value, fast-moving items (e.g., 0703HAD00070N) were prioritized, minimizing stockouts, while low-value, non-moving items (e.g., 0801BA0880N) were managed with minimal stock, reducing holding costs. This framework enhances supply chain efficiency and cost-effectiveness.

VI. DISCUSSION

The results show that Exponential Smoothing outperforms ARIMA for stable demand patterns, with lower MAE (2.42) and RMSE (2.81), making it ideal for medium-level stores with consistent demand. ARIMA, while effective for complex patterns, has higher error rates and requires extensive preprocessing. Integrating ABC-FSN analysis with demand forecasting enables prioritization of high-value, fast-moving items (e.g., 0703HAD00070N) and cost-efficient management of low-value, non-moving items (e.g., 0801BA0880N). This holistic framework enhances forecasting accuracy, operational efficiency, and customer satisfaction while optimizing inventory costs.

VII. CONCLUSION

This study proposes an integrated framework for inventory management and demand forecasting tailored to medium-level automobile spare parts stores. By combining ABC-FSN analysis with Exponential Smoothing and ARIMA, it optimizes inventory levels, reduces stockouts, and minimizes costs. Results indicate Exponential Smoothing excels for stable demand, while ARIMA suits complex patterns. This framework enhances inventory management and supports sustainability goals. Future research could explore external factors (e.g., economic conditions) and extend the framework to other industries for broader applicability.

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