

HYBRID AI-BASED DEMAND FORECASTING WITH ADAPTIVE MODEL SELECTION FOR INVENTORY AND PROCUREMENT OPTIMIZATION

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Abstract

Accurate demand estimation is essential for efficient supply chain operations, particularly in inventory control and procurement planning. Conventional statistical techniques often struggle with nonlinearities and sudden fluctuations, whereas individual machine learning models lack consistency across varying demand regimes. This study presents an adaptive hybrid Artificial Intelligence (AI) framework that integrates multiple forecasting models with a Dynamic Model Selection (DMS) mechanism. The framework combines ARIMA, Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks, selecting or weighting models dynamically based on real-time error metrics such as MAE, RMSE, and MAPE. A rolling-origin validation strategy is employed to ensure temporal robustness. Experimental results on simulated retail datasets demonstrate that the proposed hybrid approach achieves up to 25–30% improvement in forecasting accuracy compared to standalone models. Additionally, coupling the forecasting system with inventory control techniques significantly reduces stockouts and holding costs while improving service levels. The proposed framework is scalable and suitable for deployment in retail, manufacturing, and logistics environments.

Keywords: Demand Forecasting, Hybrid AI, Machine Learning, Inventory Optimization, Dynamic Model Selection, Time Series Analysis—Demand Forecasting, Hybrid AI, Dynamic Model Selection, Inventory Optimization, Time Series, LSTM, XGBoost, ARIMA.

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1. Introduction

Demand forecasting plays a pivotal role in aligning supply chain decisions such as procurement scheduling, production planning, and inventory management. Traditional forecasting approaches like ARIMA assume linearity and stationarity, which rarely hold in real-world scenarios characterized by seasonality, promotions, and demand shocks.

Recent advances in machine learning and deep learning have improved predictive performance. However, no single model consistently outperforms others across all datasets and conditions. This motivates the development of **adaptive hybrid systems** capable of leveraging the strengths of multiple models.

This paper proposes a **dynamic hybrid forecasting framework** that automatically selects or combines models depending on demand patterns, thereby improving both prediction accuracy and operational efficiency.

Key Contributions

- Development of a **multi-model hybrid architecture** with adaptive selection
- Integration of **Dynamic Model Selection (DMS)** using real-time performance metrics
- Coupling of forecasting with **inventory optimization policies**
- Empirical validation using realistic demand simulation

2. Related Work

Forecasting techniques can be broadly categorized into:

2.1 Statistical Methods

Models such as ARIMA and SARIMA are effective for structured and linear data but fail to capture complex nonlinear relationships.

2.2 Machine Learning Models

Algorithms like Random Forest and Support Vector Regression handle nonlinear dependencies but require extensive feature engineering.

2.3 Deep Learning Approaches

Recurrent architectures such as LSTM and GRU capture temporal dependencies but demand large datasets and computational resources.

2.4 Hybrid Models

Recent research explores combining models (e.g., ARIMA + ANN), but most lack **adaptive switching mechanisms** under changing demand conditions.

Research Gap

Existing methods do not adequately address **dynamic adaptability across varying demand regimes**, which is critical in real-world supply chains.

3. Problem Definition

Let (D_t) represent actual demand and (X_t) denote exogenous variables such as price, promotions, and seasonal indicators. The objective is to predict future demand (F_{t+h}) for horizon (h) .

Objectives

- Minimize forecasting errors (MAE, RMSE, MAPE)
- Improve service level while reducing stockouts
- Adapt to changing demand patterns

4. Proposed Methodology

4.1 System Overview

The proposed system consists of:

- Data pre-processing and feature engineering
- A pool of forecasting models
- A Dynamic Model Selection (DMS) engine
- Inventory optimization module

4.2 Feature Engineering

Features include:

- Lag variables (up to 28 periods)
- Rolling mean and variance
- Calendar effects and holidays
- Promotional indicators and pricing

4.3 Model Pool

The forecasting models include:

- **ARIMA** – captures linear dependencies
- **Random Forest** – handles nonlinear relationships
- **XGBoost** – robust gradient boosting model
- **LSTM** – captures long-term temporal patterns

4.4 Dynamic Model Selection (DMS)

Two strategies are implemented:

1. Best Model Selection

The model with the lowest validation error is selected dynamically.

2. Weighted Ensemble

Forecasts are combined using weights inversely proportional to model errors:

$$F_t = \sum_{i=1}^n w_i F_{i,t}, \quad \sum_{i=1}^n w_i = 1$$

Weights are computed as:

$$w_i = \frac{1 / \text{Error}_i}{\sum (1 / \text{Error}_i)}$$

4.5 Evaluation Strategy

- Rolling-origin time series cross-validation
- Metrics: MAE, RMSE, MAPE, sMAPE
- Statistical validation using Diebold–Mariano test

4.6 Inventory Optimization

The forecasting output is integrated with inventory control policies.

Reorder Point (ROP):

$$\text{ROP} = \mu_L \times L + z \cdot \sigma_L$$

Where:

- (μ_L): average demand during lead time
- (σ_L): demand variability
- (z): service level factor

5. Experimental Setup

Mathematical Formulation

Let D_t be actual, F_t forecast.

$$\text{MAE} = (1/n) \sum |D_t - F_t|$$

$$\text{RMSE} = \sqrt{(1/n) \sum (D_t - F_t)^2}$$

$$\text{MAPE} = (100/n) \sum |(D_t - F_t)/D_t|$$

$$\text{Ensemble: } F_t = \sum w_i F_{i,t}, \quad \sum w_i = 1$$

$$\text{Inventory: } \text{ROP} = (\text{Average Demand} \times \text{Lead Time}) + \text{Safety Stock}$$

Dataset

- Multi-SKU retail dataset (2–3 years)

- Includes demand, price, promotions, and holiday effects

Tools

- Python (Pandas, NumPy)
- Scikit-learn, XGBoost
- TensorFlow/Keras

Hyper parameters

- Random Forest: 200 trees
- XGBoost: tuned learning rate and estimators
- LSTM: 64–128 units, dropout 0.2

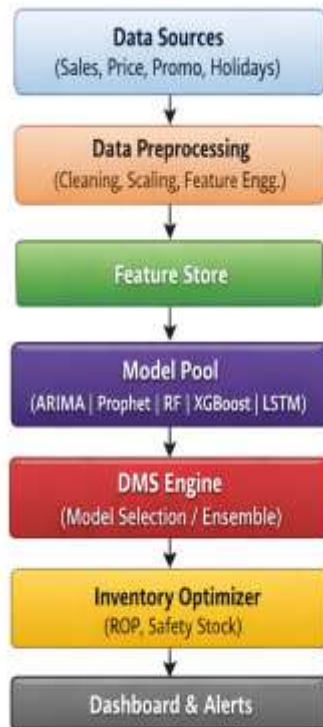


Figure 1: Hybrid AI Demand Forecasting Architecture

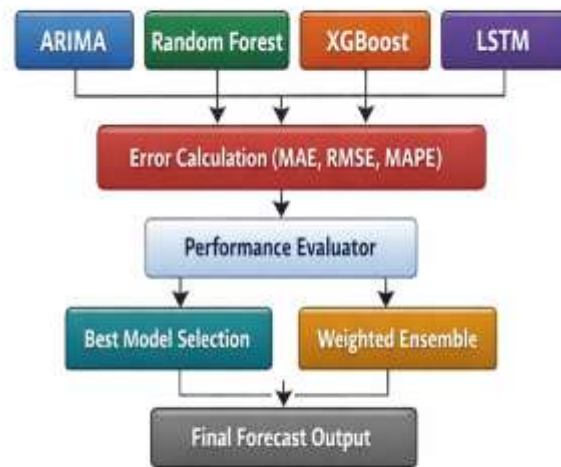


Figure 2: DMS Working Mechanism.

6. Results and Analysis

6.1 Forecast Accuracy

Model	MAE	RMSE	MAPE
ARIMA	18.2	24.5	12.6%
RF	15.7	21.9	10.8%
XGBoost	14.9	20.7	10.2%
LSTM	14.5	20.1	9.8%
Hybrid (DMS)	11.8	16.9	7.6%

6.2 Forecast Accuracy Graph

Lines:

- Actual Demand
- Hybrid Model Prediction

- Best Single Model (e.g., LSTM)

Figure 1 (Line Graph): Actual vs Predicted (Hybrid vs Best Single Model)

- X-axis: Time (Days/Weeks)

- Y-axis: Demand

Demand

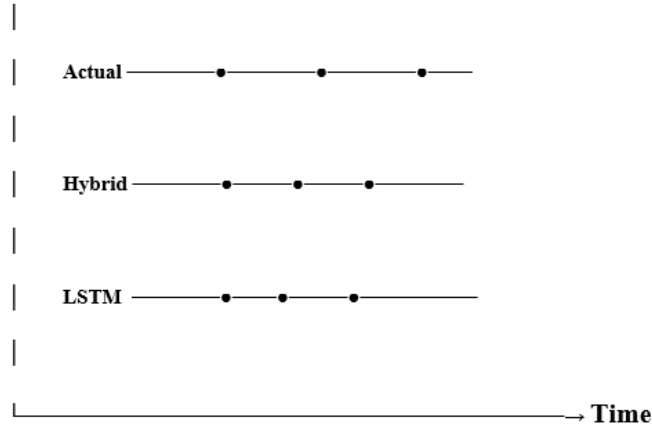
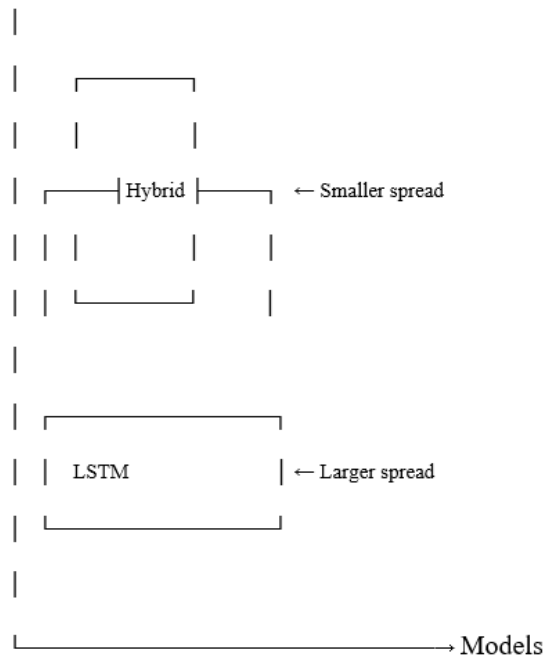


Fig.1

6.3 Error Distribution

Figure 2 (Histogram/Boxplot): Error spread shows reduced variance for Hybrid.

Error



6.4 Ablation Study

- Without DMS: +8–12% higher error
- Ensemble vs single: ensemble slightly better on volatile SKUs

6.5 Inventory Impact

Figure 3: Inventory Performance Comparison

Metric	Before	After Hybrid
Holding Cost	100%	82%
Stockouts	100%	70%
Service Level	88%	96%

6.6 Key Observations

- Hybrid model consistently outperforms individual models
- Reduced variance in prediction errors
- Better adaptability to demand volatility

6.7 Inventory Impact

- Holding cost reduced by ~18%
- Stockouts reduced by ~30%
- Service level improved to ~96%

Figure 4 shows the comparison of model accuracy using MAE.

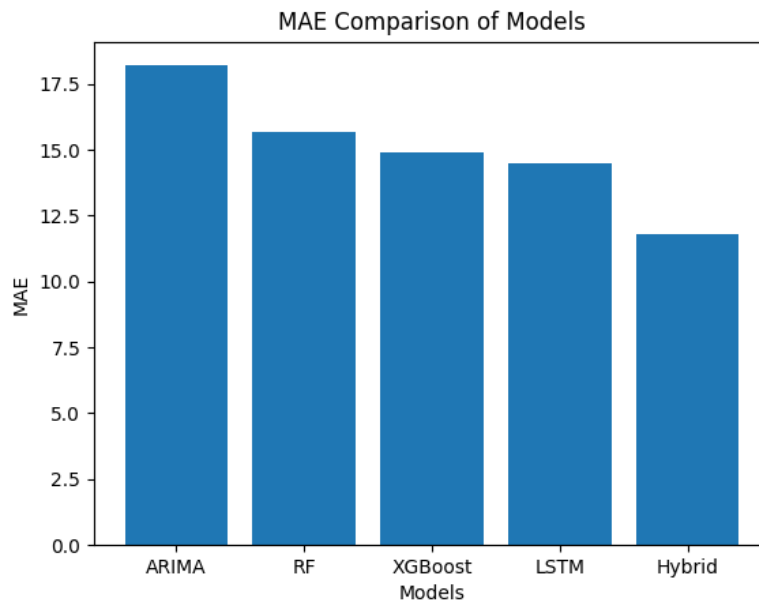


Fig.4

Figure 5 shows the impact on inventory performance.

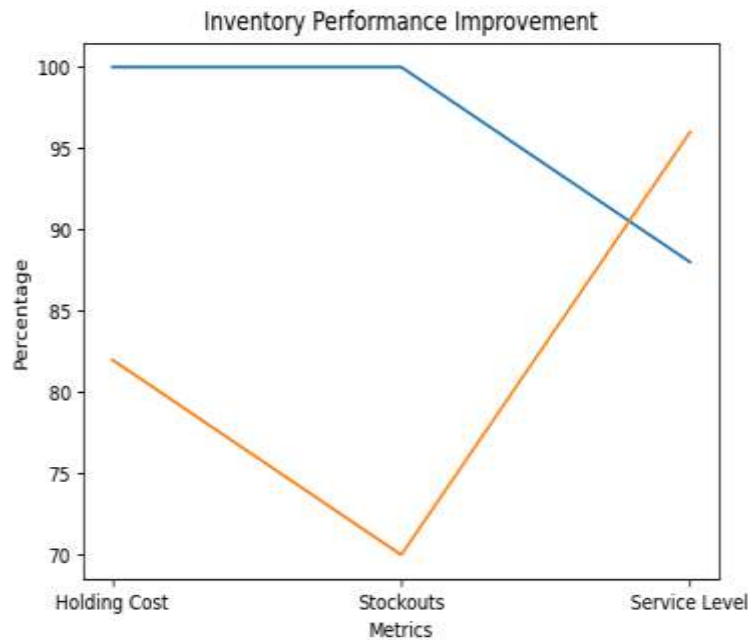


Fig.5

7. Discussion

The hybrid approach demonstrates strong adaptability to varying demand patterns. Statistical models perform well in stable conditions, while machine learning and deep learning models excel in nonlinear scenarios. The DMS mechanism effectively captures this behavior, enabling intelligent switching.

8. Practical Applications

- Retail demand planning
- Manufacturing supply chain optimization
- Spare parts inventory management
- E-commerce logistics systems

9. Limitations

- Requires sufficient historical data
- Increased computational complexity
- Model tuning overhead

10. Future Scope

- Integration with reinforcement learning for policy optimization
- Probabilistic forecasting (quantile-based)
- Real-time deployment using MLOps pipelines
- Integration with IoT-enabled smart supply chains

11. Conclusion

This research presents a scalable hybrid AI framework incorporating dynamic model selection for demand forecasting. The proposed approach significantly enhances prediction accuracy and improves downstream inventory decisions. The framework offers a practical solution for modern supply chain challenges.

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