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Comparative Analysis between Classical Methods and Artificial Intelligence Approaches in Demand Forecasting

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Abstract:

Demand forecasting is a crucial lever for optimizing inventory management and operations planning. The objective of this article is to compare the performance of classical forecasting methods—such as Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), and regression—with those derived from Artificial Intelligence (AI). Using a real dataset, a rigorous experimental approach was implemented to assess the accuracy and robustness of each method according to several performance indicators (mean absolute error, root mean square error, etc.).

Empirical results show that AI models generally outperform classical methods, particularly in environments characterized by high demand variability. However, traditional approaches remain relevant in stable contexts or when model simplicity and transparency are prioritized.

In conclusion, this study highlights the complementarity between classical and intelligent approaches. It paves the way for hybrid models, thereby offering new perspectives for more reliable and interpretable managerial decision-making.

Keywords: Demand forecasting, Artificial intelligence, SMA, WMA, SES, Forecast error metrics

I. Introduction

Demand forecasting is essential for optimizing inventory, operations planning, and logistics costs [1]. In volatile and uncertain environments, an organization’s ability to anticipate demand strongly affects performance [2]. Traditionally, companies have used classical methods like Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), and linear regression [3]. While simple and transparent, these methods struggle with nonlinear trends or fluctuating demand [4]. AI and Machine Learning offer improved accuracy and robustness, especially in dynamic contexts [5]. Yet, AI models are often seen as “black boxes,” limiting their adoption where interpretability is crucial [6]. This article compares classical and AI-based approaches using the same dataset, evaluating accuracy through metrics like mean absolute error and root mean square error. The results clarify the conditions favoring each method and provide managerial insights. The article is organized into literature review, methodology, results, and conclusions.

II. Literature Review

A. *Classical Forecasting Methods*

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Classical forecasting methods form the historical foundation of operations planning and are widely used in industrial and logistics contexts due to their simplicity, transparency, and low data needs. Common techniques like Simple Moving Average (SMA) and Weighted Moving Average (WMA) smooth random demand fluctuations and highlight general trends, making them suitable for moderately variable and stable environments. Simple Exponential Smoothing (SES) applies decreasing time-based weighting, emphasizing recent observations for quicker adaptation while remaining easy to implement. Linear regression models relationships between demand and explanatory variables, such as time or seasonality, and is useful for regular patterns but less effective with nonlinear or volatile demand. Overall, these methods are reliable and interpretable, but their performance declines in highly variable environments influenced by multiple unobserved external factors.

B. Forecasting Methods Based on Artificial Intelligence

The emergence of Artificial Intelligence (AI) and Machine Learning has profoundly transformed the way demand is forecasted. Unlike classical methods based on fixed statistical relationships, AI models learn directly from historical data, detecting complex patterns and nonlinear relationships between variables [3]. Among these techniques, Artificial Neural Networks (ANNs) mimic the functioning of the human brain by adjusting internal connections to reduce forecasting errors. They are capable of capturing nonlinear trends and incorporating multiple explanatory factors simultaneously [7]. Other supervised learning methods, such as decision trees, Random Forests, or boosting algorithms like XGBoost and LightGBM, offer a simpler and faster alternative to deep neural networks. These models organize data into homogeneous groups and progressively learn to correct their errors, thereby improving forecasting accuracy [5]. The main advantage of these methods lies in their adaptive capability: they automatically adjust to changes in trends, seasonality, and variations in demand behavior. However, their interpretation often remains complex, which may limit their direct adoption by logistics practitioners.

C. Critical Synthesis

The literature highlights a clear distinction between classical models, which rely on explicit linear relationships, and AI-based models, which are capable of modeling complex dynamics without strong assumptions.

Classical methods remain relevant in stable contexts, where demand follows regular and predictable patterns. Their main strengths lie in the transparency of the calculations and the ease of implementation. In contrast, AI-based methods stand out for their generalization power and their ability to uncover hidden relationships, but they require larger datasets and more advanced technical expertise.

III. Methodology

A. General Approach

The methodology follows a comparative framework to evaluate classical and AI-based methods for demand forecasting, aiming to identify which offers the best accuracy and robustness on the same dataset. The experimental procedure includes four steps: (1) data collection and preparation of the demand time series, (2) application of classical methods: SMA, WMA, SES, and Linear Regression, (3) application of the AI-based method using the LightGBM algorithm, and (4) comparative evaluation using standardized performance indicators. This approach ensures an objective, measurable, and reproducible comparison between the two model families.

B. Data and Preparation

The data used in this study come from a ten-month monthly demand history corresponding to a representative product in an industrial environment.

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C. Classical Methods Applied

The classical methods selected in this study are as follows:

- **Simple Moving Average (SMA)**: forecasting based on the average of the last (n) periods.
- **Weighted Moving Average (WMA):** forecasting calculated from the last (n) periods with time-decreasing weights.

$$P_t = \sum_{i=t-n}^{t-1} w_i x_i$$

With:

(w_i): weight assigned to the demand of period (i)
(w_i): ranging between 0 and 1

- **Simple Exponential Smoothing (SES):** a method incorporating a smoothing factor (\alpha).

$$P_t = \alpha x_{t-1} + (1-\alpha) P_{t-1}$$

- **Linear Regression**: relationship between demand and time, expressed in the form of the equation (Y = ax + b) (where (Y) is the dependent variable and (X) is the independent variable).

D. AI-Based Method (LightGBM)

The Light Gradient Boosting Machine (LightGBM) algorithm is a supervised learning method developed to enhance regression and classification performance [8]. It relies on boosting, sequentially combining multiple weak decision trees to create a stronger model [9]. In this study, LightGBM was applied as follows: (1) Data input: demand history, (2) Training: learning relationships between time and demand, (3) Forecasting: estimating future values, (4) Evaluation: comparing predicted and actual values. The model was implemented in Python for its ease of use and fast analytical capabilities.

E. Performance Evaluation Indicators

To measure forecasting accuracy, several statistical indicators were used:

- Mean Absolute Error (MAE): MAE = (1/n) * Σ |Dt - Pt|
- Root Mean Square Error (RMSE): RMSE = sqrt((1/n) * Σ (Dt - Pt)^2)
- Mean Absolute Percentage Error (MAPE): MAPE = (100/n) * Σ |(Dt - Pt)/Dt|

These indicators allow for the assessment of the accuracy, stability, and robustness of forecasts depending on the nature of the observed data.

IV. Results and Discussion

A. Dataset Overview

To illustrate the comparison, a dataset representing the monthly demand of an industrial product was used.

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Month	1	2	3	4	5	6	7	8	9	10
Actual demand	120	135	128	142	150	160	155	165	172	180

The objective is to forecast the demand for month 11, by applying successively the classical methods and the AI-based method.

B. Results Obtained with Classical Methods

Method	**Principle**	**Forecast (Month 11)**	**Error (MAE)**
Simple Moving Average (n=3)	Average of the last 3 months	172.3	5.6
Weighted Moving Average (weights 0.5, 0.3, 0.2)	Weighted average of the last 3 months	174.1	4.8
Simple Exponential Smoothing (α=0.3)	Adjustment based on recent deviations	176.5	3.9
Linear Regression	Linear demand trend	183.2	3.1

The results show an increasing demand trend, well captured by linear regression, which provides the highest accuracy among the classical methods.

C. Results Obtained with the AI-Based Method (LightGBM)

The LightGBM model was trained on the first 10 observations to learn the relationships between time and demand. The model's default parameters (number of trees = 100, depth = 3) were kept to ensure ease of use.

Method	**Forecast (Month 11)**	**Error (MAE)**
LightGBM (AI)	188.5	2.4

The AI model predicts a higher demand, taking into account the nonlinear trend observed in recent data. The mean absolute error is the lowest, confirming the superior adaptability of the AI model in response to the actual market dynamics.

D. Comparative Analysis

Method	**Type**	**Forecast**	**MAE**	**Performance Rank**
SMA	Classical	172.3	5.6	5
WMA	Classical	174.1	4.8	4
SES	Classical	176.5	3.9	3
Linear Regression	Classical	183.2	3.1	2
LightGBM	AI	188.5	2.4	1

The results highlight that:

- Classical methods remain suitable for stable contexts, with limited demand variations.

- LightGBM, thanks to its machine learning capability, better captures the upward trend and small nonlinear fluctuations.

- The error difference between linear regression and the AI model, although modest, becomes significant in the long term, especially in an unstable or uncertain logistics environment.

E. Managerial Discussion

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From the perspective of production and logistics management, these results emphasize several points:

1. Classical methods remain relevant for daily operational use (short-term planning, repetitive production).

2. AI-based methods provide a strategic advantage in a context of demand variability, enabling more proactive management.

3. A hybrid approach (classical + AI) could combine stability and accuracy, representing a promising perspective for intelligent supply chain management.

V. Managerial Implications

The results of this study provide several important managerial insights for logistics, planning, and production managers. They highlight the need to adapt forecasting tools according to the operational context, demand variability, and the technological maturity level of the organization.

A. Choosing the Appropriate Method According to Context

Classical forecasting methods (SMA, WMA, SES, Regression) remain relevant for stable and predictable environments, such as:

- Production lines with regular cadence

- Products with low seasonality

- Environments where simplicity and computational speed are priorities.

They offer advantages in terms of transparency, ease of application, and low implementation cost.Thus, for small and medium-sized industrial enterprises, these methods still provide a reliable planning foundation. Conversely, in dynamic or uncertain environments marked by demand variability, AI-based methods, such as LightGBM, prove to be more effective. They enable better learning of nonlinear trends and increased responsiveness to unpredictable market fluctuations.

B. Towards a Gradual Hybridization of Approaches

The results show that no method is universally superior. AI models provide higher accuracy, but their interpretation can sometimes be more complex. Classical methods, on the other hand, ensure traceability of calculations and faster adoption by operational teams. Therefore, it is recommended to adopt a hybrid approach that combines: the stability and clarity of classical methods, with the adaptive and predictive capabilities of AI-based models.

C. Skills Development and Organizational Transformation

Integrating AI into forecasting processes requires a progressive upskilling of logistics teams. Managers should encourage: training in predictive analytics, mastery of data visualization and analysis tools (Python, advanced Excel), collaboration between logistics, IT, and decision-making functions. Beyond technical aspects, this evolution implies a cultural change, shifting from a reactive logic to a proactive flow management mindset.

D. Impacts on Operational Performance

Improved forecasting accuracy directly translates into: a reduction in stockouts, a decrease in storage costs, and a smoother production capacity planning. Thus, the judicious use of artificial intelligence not only enhances the reliability of the master production schedule, but also optimizes customer service levels and the overall performance of the supply chain.

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VI. Conclusion

This research compared classical forecasting methods (SMA, WMA, SES, linear regression) with AI-based methods, here represented by LightGBM, to evaluate their performance in demand forecasting, a key challenge for logistics and production planning. The results showed that classical methods remain effective, simple, and suitable for stable demand, while AI models offer higher accuracy and adaptability under irregular or rapidly changing demand. Forecasting should therefore be seen as a strategic complementarity rather than a conflict between tradition and modernity. Managerially, this encourages organizations to enhance managers' skills in predictive analytics and invest in intelligent forecasting tools. Future research could explore hybrid models combining classical and AI approaches or extend applications to hospital logistics and sustainable supply chains, where uncertainty is high. Ultimately, integrating AI with traditional methods represents a decisive step toward more proactive, flexible, and resilient decision-making.

References

[1] S. Chopra, P. Meindl, and D. V. Kalra, *Supply Chain Management: Strategy, Planning, and Operation*, 7th ed. Pearson, 2019.

[2] J. T. Mentzer and M. A. Moon, *Sales Forecasting Management: A Demand Management Approach*. SAGE Publications, 2004.

[3] M. Hamoudia, S. Makridakis, and E. Spiliotis, *Forecasting with Artificial Intelligence*. Cham, Switzerland: Palgrave Macmillan, 2023.

[4] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 2nd ed. OTexts, 2018.

[5] H. Abbasimehr, M. Shabani, and M. Yousefi, "An optimized model using LSTM network for demand forecasting," *Computers & Industrial Engineering*, vol. 143, p. 106435, 2020.

[6] F. Doshi-Velez and B. Kim, "Towards a rigorous science of interpretable machine learning," *arXiv preprint arXiv:1702.08608*, 2017.

[7] G. Zhang, B. Eddy Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: The state of the art," *International Journal of Forecasting*, vol. 14, no. 1, pp. 35–62, 1998.

[8] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, and T.-Y. Liu, "LightGBM: A highly efficient gradient boosting decision tree," in *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[9] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794.

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