Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 6, No.2, June : 2024

ADVANCING SUPPLY CHAIN DEMAND FORECASTING WITH AI TECHNOLOGIES: A REVIEW

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ABSTRACT
This review paper examines the integration of Artificial Intelligence (AI) into demand forecasting within supply chains, highlighting the limitations of traditional forecasting methods in managing complex and dynamic market data. By synthesizing recent advancements in AI, particularly machine learning and deep learning models like Long Short-Term Memory (LSTM) networks and Random Forests, the paper evaluates how these technologies surpass traditional methods in accuracy and efficiency. It discusses the potential of AI to transform supply chain operations by providing robust, scalable, and adaptive forecasting solutions. This paper aims to provide insights into how AI-driven tools can contribute to more informed decision-making and enhanced supply chain responsiveness.

Keywords:
Demand forecasting, Machine Learning, Deep Learning, Supply Chain Management, LSTM.

I. Introduction

In the rapidly evolving global marketplace, the efficiency of supply chains is paramount, and at the heart of this efficiency lies the accuracy of demand forecasting. Traditional demand forecasting methods, though well- established, are increasingly unable to cope with the complexities and fluctuations of current market dynamics. This paper investigates how Artificial Intelligence (AI) technologies, particularly through the utilization of machine learning (ML) and deep learning algorithms, are revolutionizing demand forecasting. These AI technologies not only offer improved accuracy but also excel at handling large, diverse datasets, which traditional models manage inefficiently. This review seeks to explore the advancements in AI that can significantly enhance demand forecasting in supply chains, thus addressing the shortcomings of existing systems while paving the way for more agile and informed decision-making processes.

II. Existing System

Traditional demand forecasting in supply chains has primarily depended on statistical techniques like Exponential Smoothing, simple linear regression, and unstructured analysis methods. Unstructured analysis methods involve qualitative techniques such as expert judgment and intuition, rather than quantitative models. These methods are particularly useful in scenarios where precise historical data is unavailable or rapidly changing market trends have not yet been captured quantitatively. However, while useful in certain contexts, these methods often falter in today's dynamic market, marked by rapid shifts and a high degree of unpredictability, due to their reliance on subjective assessments and their inability to systematically analyze large data sets.
Traditional systems often struggle with scalability issues, making it challenging to process the increasingly large datasets required for accurate forecasting in modern supply chains. They also lack the flexibility to quickly adapt to new information, resulting in a lag that can affect the entire supply chain's responsiveness to market changes. These limitations highlight the need for more sophisticated forecasting models that can dynamically adapt to new data and uncover complex patterns, a need that AI and machine learning models are well-positioned to fulfill.

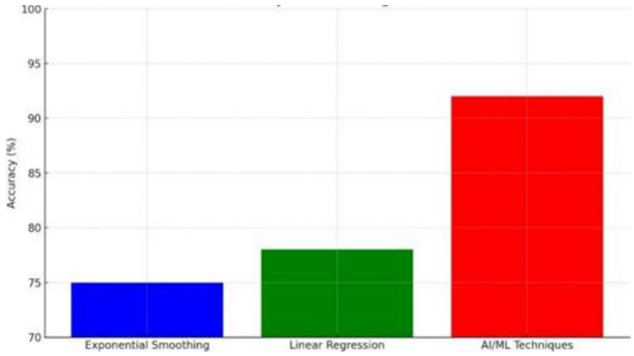

Figure 1: The accuracy of forecasting methods, comparing traditional techniques against AI/ML Techniques

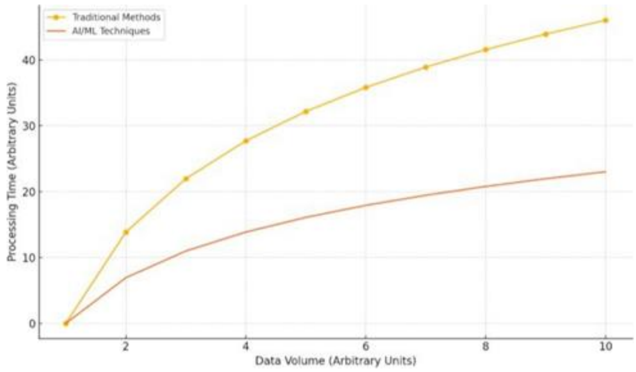

Figure 2 : Scalability issues, showing processing time as data volume increases.

Traditional methods require exponentially more time as data grows, whereas AI/ML techniques handle large datasets.

Figure 3: Adaptability to market changes, plotting forecast accuracy against the rate of market change.

The representation in Figure 1, Figure 2 and Figure 3 illustrates the general advantages of AI/ML techniques over traditional methods in terms of accuracy, scalability, and adaptability. The nuances of each model's performance can vary significantly based on the specifics of their implementation and the nature of the data they are used on.

Exploring advanced technologies in the subsequent literature review aims to demonstrate how integrating AI into demand forecasting can overcome these challenges, leading to more efficient and resilient supply chain operations.

III. Literature review

The existing systems in demand forecasting largely depend on traditional statistical methods, which often fall short in handling the complexities of modern supply chains. These methods typically struggle with large, volatile datasets and fail to incorporate non-linear relationships, leading to inaccuracies and inefficiencies in forecasting. This review addresses these deficiencies by examining a variety of AI-driven approaches detailed in recent scholarly papers. The focus is on advanced machine learning models, particularly those utilizing deep learning and hybrid techniques, and their ability to overcome the limitations of traditional models. The exploration focuses on the effectiveness of AI models in improving forecast accuracy, managing large and complex datasets, and adapting to rapidly changing market conditions. The insights from these studies provide a foundation for understanding how AI can be integrated into supply chain systems to enhance the overall effectiveness of demand planning processes. This section will correlate specific AI advancements with the previously identified gaps in traditional forecasting systems, highlighting the practical implications of adopting these technologies in real- world scenarios.

A notable development in AI-driven forecasting is the introduction of a multi-layer LSTM network tailored for predicting erratic demand patterns. By utilizing a grid search approach to optimize LSTM hyperparameters, this model effectively captures nonlinear relationships in time series data. [1] The results, as shown in Figure 4, demonstrate that the LSTM model significantly outperforms traditional forecasting methods like ARIMA and ANN, especially in scenarios with non-stationary data.

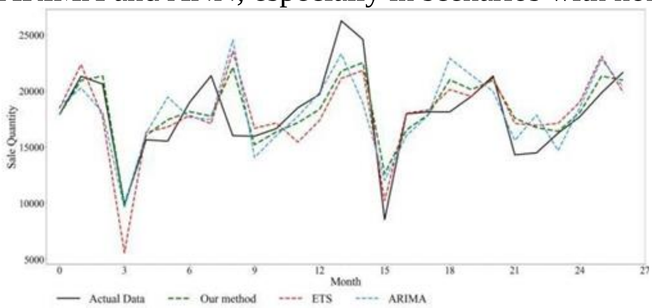

Figure 4: Actual data vs prediction using “our method” [1] (a method based on a multi-layer LSTM network by using the grid search approach) and the statistical methods (ETS and ARIMA)

Another innovative approach combines LSTM networks with Random Forests to create a novel forecasting model. This hybrid method leverages the LSTM's proficiency with temporal data alongside the robust regression capabilities of Random Forests. [2] Tested on a multivariate dataset from a multi-channel retailer, the hybrid model not only enhances accuracy but also ranks explanatory variables by importance, offering valuable insights for demand planning.

The evaluation of various forecasting performance metrics has also seen advancements. It is found that sRMSE is more reliable for detecting changes in a model's variance, whereas sPIS is highly sensitive to bias. [3] These insights are crucial for selecting appropriate metrics to assess different forecasting models accurately.

In the realm of wind power generation, a new metric called the error dispersion factor (EDF) has been introduced to compare the nRMSE and nMAE. [4] Understanding error characteristics and their implications on model performance across different forecasting scenarios is emphasized, highlighting the importance of robust error analysis.

Sector-specific applications showcase the adaptability of AI models to industry-specific forecasting needs. For example, in oil production forecasting, a combination of ARIMA, LSTM, and Prophet models has been used. [5] The LSTM model stands out for its ability to handle non-seasonal data, outperforming the Prophet model and demonstrating its versatility.

In environmental monitoring, the Prophet forecasting model has proven effective in predicting air pollution levels. The model's capability to handle missing data, trends, and seasonality makes it suitable for this purpose, showing robust performance in forecasting both short-term and long- term pollutant levels. [6]

The application of Support Vector Regression (SVR) in predicting bending angles in laser tube bending processes demonstrates high accuracy and reliability, emphasizing the potential of applying machine learning in manufacturing settings. [7]

In retail sales forecasting, a comparative study of LSTM and LGBM models has shown that LGBM consistently outperforms LSTM, particularly in capturing and predicting complex sales patterns. [8] These findings are crucial for retailers looking to optimize inventory and sales strategies.

Another study on solar radiation forecasting highlights the use of ARIMA models in different geographic locations. [9] This work underscores the importance of location-specific models to account for variability in solar radiation, showcasing the model's potential in renewable energy forecasting.
Lastly, an evaluation of LSTM and Prophet models in forecasting air temperature in Bandung reveals that while Prophet excels in predicting minimum temperatures, LSTM shows better performance for maximum temperatures. [10] This illustrates the strengths of each model in different aspects of meteorological forecasting.
This comprehensive review of AI applications across various sectors not only demonstrates the robustness of AI models in diverse scenarios but also highlights their superior performance over traditional forecasting methods. These advancements pave the way for more specialized and efficient AI applications in demand planning and supply chain management.

IV.Conclusion

This review highlights the transformative role of Artificial Intelligence (AI) in enhancing demand forecasting within supply chains. AI-driven models like Long Short-Term Memory (LSTM) networks and Random Forests surpass traditional methods, offering superior handling of complex, dynamic market data. These advancements not only improve forecasting accuracy but also contribute to operational efficiency by facilitating real-time, data-driven decision- making. As the integration of AI continues to redefine supply chain management, further research is vital to fully leverage its potential, ensuring supply chains are both efficient and adaptable in facing global market challenges. This paper underscores the necessity for a shift towards more AI-centric approaches in supply chain strategies.
Further research could explore the integration of these AI models into existing supply chain infrastructures, examining their impact on operational agility and cost-effectiveness.

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