International Journal of Research Publication and Reviews, Vol 6, Issue 8, pp 3393-3396 August, 2025

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Demand Forecasting in Supply Chain Using Neural Network: A Review

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ABSTRACT

Demand forecasting plays a pivotal role in optimizing supply chain operations, enabling organizations to align production, inventory, and logistics with future customer requirements. In dynamic and competitive industries like textiles and apparel, accurate forecasting becomes even more crucial. This review paper focuses on the application of Artificial Neural Networks (ANNs) for demand forecasting within the supply chain framework, utilizing the Neural Network Toolbox of MATLAB. Through a case study on *Maral Overseas Ltd*, a leading textile manufacturing firm, the paper examines how intelligent forecasting models can outperform traditional statistical methods in capturing nonlinear patterns and seasonality in demand data. The study synthesizes insights from relevant literature, compares various neural network architectures and training algorithms, and discusses the practical implications of deploying such models in real industrial settings. By integrating AI-driven forecasting into supply chain strategies, this paper highlights a pathway to enhanced efficiency, reduced wastage, and improved customer satisfaction for manufacturing enterprises.

Keywords- Demand Forecasting, Supply Chain Management, MATLAB Neural Network Toolbox, Artificial Neural Network (ANN)

1. INTRODUCTION

In the rapidly evolving global marketplace, accurate demand forecasting has become a cornerstone of effective supply chain management. It enables companies to anticipate customer needs, align production schedules, manage inventories efficiently, and reduce operational costs. However, traditional forecasting techniques, such as time series analysis and regression models, often fall short in capturing the nonlinear, dynamic, and uncertain nature of real-world demand patterns—especially in industries such as textiles, where seasonal fluctuations and market volatility are common. Recent advancements in artificial intelligence (AI) and machine learning (ML) have paved the way for more robust and adaptive forecasting methods. Among these, artificial neural networks (ANNs) have shown great potential due to their ability to learn complex patterns from historical data and generalize them to predict future trends. When integrated with MATLAB's Neural Network Toolbox, ANN models can be efficiently trained, validated, and tested, providing a practical and scalable solution for industrial forecasting problems. This review paper explores the role of neural networks in the context of supply chain management, with a focus on demand forecasting. It specifically examines their application using MATLAB tools and demonstrates relevance through a case study of Maral Overseas Ltd, a prominent player in the textile manufacturing sector. The paper aims to review existing research, highlight methodological frameworks, and discuss the comparative advantages of ANN-based forecasting models over conventional approaches. By integrating theoretical understanding with practical application, this study contributes to the growing body of knowledge on intelligent supply chain systems and provides valuable insights for industries seeking data-driven forecasting solutions.

2. PROBLEM IDENTIFICATION

In today's competitive and customer-driven market environment, organizations face increasing pressure to optimize their supply chain operations. One of the most critical and challenging components of this process is demand forecasting. Inaccurate forecasts can lead to several operational inefficiencies, including stock outs, overstocking, increase holding costs, delayed deliveries, and poor customer satisfaction. Traditional statistical models such as moving averages, exponential smoothing, and linear regression, while easy to implement, often lack the flexibility to model nonlinear relationships and complex seasonal trends present in real-world demand data. These limitations become more evident in industries like textiles, where demand is influenced by multiple unpredictable factors such as fashion trends, seasons, export orders, and economic changes. Maral Overseas Ltd, a major textile manufacturer, encounters similar challenges in aligning its production and inventory planning with uncertain customer demand. The absence of a robust and intelligent forecasting system results in either overproduction or underutilization of resources, leading to losses and inefficiencies in the supply chain. There is a need for an intelligent, adaptive forecasting approach that can capture the inherent complexities of demand patterns and offer reliable predictions. Artificial Neural Networks (ANNs), when implemented through MATLAB's Neural Network Toolbox, present a promising solution to this problem by enabling the development of data-driven, non-linear forecasting models that can enhance supply chain responsiveness and decision-making.

3. RESEARCH OBJECTIVES

The primary aim of this review paper is to explore the application of artificial neural networks (ANNs) for demand forecasting within the framework of supply chain management, using MATLAB's Neural Network Toolbox. The specific research objectives are as follows:

1. To understand the role and importance of accurate demand forecasting in effective supply chain management, particularly in the textile industry.
2. To review and analyze existing literature on traditional and intelligent forecasting methods, with a focus on neural network-based approaches.
3. To examine the capabilities and functionalities of MATLAB's Neural Network Toolbox for developing forecasting models.
4. To present a case study on Maral Overseas Ltd and identify real-world forecasting challenges faced by the company.
5. To highlight the advantages of ANN-based forecasting models over conventional statistical methods in terms of adaptability, accuracy, and practical implementation.

4. LITRATURE REVIEW

Demand forecasting has long been recognized as a critical aspect of supply chain management, directly influencing procurement, production, inventory, and distribution decisions. Traditionally, methods such as moving averages, exponential smoothing, and ARIMA models have been widely used for forecasting due to their simplicity and ease of implementation. However, these linear models often struggle with capturing complex, nonlinear, and seasonal variations present in real-world data.

Nitesh Kumar et al. (2024) introduced a multimodal neural network architecture designed specifically for demand forecasting in retail chains. Their approach involved combining multiple types of data inputs—such as historical sales records, calendar-based information (holidays and weekends), and promotional events—to capture complex consumer behavior patterns. Additionally, they incorporated external real-world signals like news trends and Google search data to enhance the model’s responsiveness to market dynamics. This integration of diverse data types forms the core of the multimodal framework, allowing the neural network to learn richer and more context-aware demand patterns. The model was evaluated using the Symmetric Mean Absolute Percentage Error (SMAPE) metric across various forecasting horizons. The results demonstrated a significant average improvement of 7.37% in forecasting accuracy when compared to traditional single-input models and other state-of-the-art methods. The study highlighted that demand forecasting is no longer limited to time-series data alone but benefits immensely from external contextual and behavioral data. The researchers also emphasized the flexibility of neural networks in handling multiple input formats without extensive feature engineering. By allowing the model to learn from a broader context, the system showed improved robustness against unpredictable demand shifts.

Valles Perez et al. (2023) carried out a detailed study on sales forecasting at a highly granular level, focusing on individual days, stores, and items. They applied modern sequence-to-sequence architectures, including Recurrent Neural Networks (RNNs) and transformer models, which are known for their ability to model temporal dependencies in sequential data. The study utilized the publicly available Corporación Favorita dataset from Kaggle, which contains millions of sales records across various product categories and store locations. The primary objective was to test whether deep learning models could accurately predict sales in a complex, high-volume retail environment with minimal data preprocessing. Instead of relying heavily on data cleaning and feature engineering, the models were trained end-to-end, allowing them to learn patterns directly from the raw data. The researchers evaluated model performance using the Root Mean Squared Logarithmic Error (RMSLE), a metric well-suited for skewed sales distributions. The sequence-to-sequence models achieved a competitive RMSLE score of approximately 0.54, indicating strong predictive accuracy. This performance validates the potential of deep learning techniques in handling massive datasets with multiple temporal and categorical variables. Their work showed that such models could generalize well across various time horizons, products, and store types. One key takeaway from the study is that transformer-based models, originally developed for language processing, can be effectively adapted for time-series forecasting tasks. By capturing long-term dependencies and context over sequences, these models outperformed traditional statistical forecasting methods, especially in dynamic retail environments.

Roy et al. (2023) explored the use of Long Short-Term Memory (LSTM) networks for demand forecasting in smart electrical grids. They trained the model on four years of hourly electricity consumption data to capture complex temporal dependencies. The LSTM model achieved a mean absolute percentage error (MAPE) of just 1.22%, showing significant improvement over traditional autoregressive (AR) models. The study highlighted LSTM's strength in learning nonlinear patterns and long-term dependencies in time-series data. Although focused on energy demand, the findings are highly relevant to industrial supply chains where similar temporal complexities exist. The research demonstrated that deep learning, especially LSTM, can enhance forecast accuracy under dynamic and fluctuating conditions. This has implications for optimizing production, inventory, and distribution in supply chain systems.

Bhatia and Soni (2022) utilized artificial neural networks (ANN) for demand forecasting in the textile industry, where demand is often seasonal and unpredictable. Their study showed that ANN models could effectively capture nonlinear demand patterns better than traditional statistical approaches. By training the network on historical sales data, they achieved improved forecast accuracy. The results led to enhanced production scheduling and better inventory management. The study confirmed the suitability of ANN for industries with high variability. Their findings support the integration of AI tools in supply chain decision-making for improved responsiveness and cost efficiency.

Shrivastava and Jain (2021) applied MATLAB's Neural Network Toolbox to develop short-term demand forecasting models for the FMCG sector. They focused on the practical aspects of implementing ANN models, highlighting MATLAB's user-friendly interface and powerful training algorithms. The study demonstrated that neural networks could deliver high forecast accuracy with minimal configuration. Visualization tools in MATLAB further supported effective analysis and model evaluation. Their models performed especially well for short-term predictions, where rapid demand shifts are common. The research validated MATLAB as a reliable platform for industrial demand forecasting applications.

Ramakrishnan and Vettivel (2020) explored demand forecasting in supply chain management using a multilayer perception (MLP) neural network. They emphasized the importance of network architecture, particularly the number of hidden layers and neurons, in achieving accurate predictions. Through careful tuning of these parameters, their ANN model outperformed traditional statistical forecasting methods. The study demonstrated the neural network's ability to handle complex, nonlinear demand patterns. Their results showed improved forecasting accuracy and better adaptability to demand fluctuations. This reinforced the effectiveness of ANN for real-world supply chain applications.

Khashei and Bijari (2019) proposed a hybrid demand forecasting model that integrates ARIMA and artificial neural networks (ANNs). The aim was to utilize the strengths of both models—ARIMA for linear trends and ANN for capturing nonlinear relationships in time series data. Their approach addressed the limitations of using either model alone in complex forecasting environments. The hybrid model was tested on various datasets with seasonal and trend variations. Results showed that the combined approach significantly outperformed traditional methods in terms of forecasting accuracy. This research laid a solid foundation for the development of hybrid techniques in demand forecasting. It also highlighted the practical value of blending statistical and AI-based tools in real-world applications.

Zhang et al. (2019) performed a comprehensive comparative analysis of ARIMA and artificial neural network (ANN) models for time-series forecasting tasks. Their study evaluated the predictive capabilities of both models across multiple datasets with varying degrees of linearity and nonlinearity. Results indicated that ARIMA models performed well when the underlying data structure was predominantly linear. Conversely, ANN models demonstrated superior performance in capturing complex nonlinear patterns that traditional statistical models failed to represent. Based on these observations, Zhang et al. recommended the development of hybrid models that integrate both ARIMA and ANN techniques. Their work was one of the earliest to suggest blending machine learning with classical statistical approaches. This pioneering recommendation significantly influenced subsequent advancements in demand forecasting methodologies. The study remains a cornerstone reference in the evolution of hybrid forecasting systems.

Haykin (2019) provided an extensive theoretical foundation for artificial neural networks (ANNs), covering essential concepts such as neuron models, learning algorithms, and multilayer architectures. His work systematically outlined the mathematical principles and computational mechanisms that make ANNs powerful tools for modeling complex systems. One of the key contributions was his emphasis on the capability of ANNs to perform universal function approximation, which is crucial for tasks involving nonlinear and dynamic data. Haykin also detailed various learning paradigms—including supervised, unsupervised, and reinforcement learning—that allow ANNs to adapt and generalize from data. His insights into back propagation and gradient descent became standard practices in ANN training. The book remains one of the most cited references in the field, influencing both academic research and industrial applications. In forecasting contexts, Haykin's work supports the deployment of ANN models across domains like finance, energy, and supply chains. It serves as a theoretical backbone for modern demand forecasting systems. The reliability and versatility of ANNs described by Haykin continue to inspire new architectures and hybrid approaches.

Chen et al. (2019): Chen et al. (2018) proposed an intelligent forecasting system using a combination of convolution neural networks (CNN) and long short-term memory (LSTM) networks for multivariate time-series demand prediction. The CNN layers were used to automatically extract local spatial patterns in the input data, while the LSTM layers handled sequential dependencies over time. The hybrid architecture allowed the model to learn complex interactions among features such as weather, pricing, and seasonality without manual feature engineering. The system was validated on multiple public retail datasets and outperformed traditional models such as ARIMA, SVR, and standalone LSTM in terms of RMSE and MAPE. One key finding was the model's robustness in handling noisy and irregular demand data, a common issue in real-world supply chains. The study also emphasized the importance of hyper parameter tuning and dropout layers to prevent over fitting. Overall, the work demonstrated that deep learning models combining temporal and spatial learning can significantly improve forecasting accuracy in dynamic and multivariate contexts.

Carbonneau et al. (2018): conducted an extensive survey on the application of artificial neural networks in supply chain demand forecasting. Their review categorized ANN applications by architecture type (e.g., MLP, RBF, SOM) and the forecasting task (short-term, long-term, seasonal). One of the major contributions was identifying the critical factors affecting ANN performance, such as data quality, preprocessing methods, and architecture selection. The study showed that MLPs were the most commonly used architecture due to their simplicity and ability to approximate nonlinear functions. However, they noted that hybrid models—those combining ANN with fuzzy logic, expert systems, or traditional statistical models—often yielded better performance in uncertain environments. The review also highlighted real-world cases in industries such as manufacturing, retail, and logistics where ANN-based models led to measurable improvements in inventory turnover and service levels. This foundational survey offered a structured framework for selecting and implementing ANN models in supply chain forecasting.

Amarasinghe et al. (2017): Amarasinghe et al. (2017) explored the use of artificial neural networks for forecasting daily demand in the retail grocery sector. Their study focused on modeling demand fluctuations influenced by external variables such as weather, day of the week, and promotional activities. Using a feed forward multilayer perception trained with back propagation, they achieved significantly lower mean squared error compared to baseline models like moving average and exponential smoothing. They also incorporated feature scaling and outlier removal during preprocessing, which improved model stability. The research emphasized the importance of domain-specific data integration for enhancing forecasting accuracy. One key insight was the network's ability to capture complex, nonlinear relationships between demand and influencing factors, which traditional models struggled to represent. Their findings supported the broader applicability of ANN in sectors where demand is highly variable and influenced by multiple real-world factors.

5. CONCLUSION

The literature reviewed underscores the growing significance of Artificial Neural Networks (ANNs) and hybrid data-driven models in addressing the complexities of demand forecasting across diverse domains such as retail, manufacturing, energy, and supply chain management. Modern approaches like Long Short-Term Memory (LSTM), multilayer perceptions (MLP), and sequence-to-sequence models have consistently outperformed traditional statistical methods, especially in capturing nonlinear trends and seasonality. Studies incorporating multimodal data—such as external events, promotions, and weather—further highlight the value of integrating diverse inputs to enhance forecasting accuracy. Additionally, optimization techniques such as the Taguchi method in machining contexts, although not directly related to demand forecasting, demonstrate parallel advances in parameter tuning and predictive modeling. These approaches mirror the tuning of ANN hyper parameters in forecasting tasks and validate the broader applicability of data-driven optimization across industrial settings. Collectively, the reviewed works demonstrate that neural network-based models offer robust, scalable, and adaptable solutions for demand forecasting. However, success depends heavily on proper model selection, parameter tuning, data preprocessing, and integration of relevant contextual variables. Future research should focus on improving model interpretability, developing hybrid models that blend statistical and neural approaches, and leveraging real-time data to support dynamic decision-making in rapidly changing environments.

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