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Sustainable Optimization in Supply Chain Management Using Machine Learning

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Abstract: ***The complexity of modern supply chains requires robust solutions to improve efficiency, resilience and sustainability. This study proposes a systematic data-driven framework that integrates predictive analytics, anomaly detection, and multi-objective optimization. The enhanced LSTM model features an attention mechanism that reduces RMSE by up to 18.8%, significantly improves demand forecast accuracy and reduces the risk of out-of-stock and over-stocking. Anomaly detection showed a true positive rate exceeding 95%, reducing response times to disruptions by 28.5%. In addition, resource optimization resulted in a 26.5% increase in inventory turnover and an 18.2% reduction in transportation costs, highlighting the framework's ability to achieve measurable economic and environmental benefits. Quantitative validation through rigorous methods, including RMSE and cost minimization calculations, confirms the framework's capacity to address complex supply chain challenges. However, reliance on high-quality datasets and the absence of external variables such as geopolitical risks and market fluctuations are noted limitations. Exploring these gaps in future research will significantly improve the framework's scalability and practical implementation, especially in dynamic and multi-regional contexts. This study offers valuable insights into the integration of advanced analytics and optimization techniques, providing a practical foundation for developing resilient and sustainable supply chains in an increasingly unpredictable global context.***

Keywords: Supply Chain Optimization; LSTM Forecasting; Anomaly Detection; Multi-Objective Resource Allocation; Quantitative Performance Metrics.

1. INTRODUCTION

The complexity and variability of modern supply chains create major challenges to their resilience, efficiency and sustainability, especially in the context of increasing globalization and rising uncertainty in the external environment (Settembre-Blundo et al., 2021; Liu et al., 2024). In recent years, the application of data analysis and machine learning in supply chain management has become a key approach to addressing these issues. These techniques enable the development of data-driven systems that greatly improve operational efficiency and help manage risks more effectively.

Machine learning has shown to be particularly valuable for demand forecasting. Zhao et al. (2024) used an LSTM model to analyze historical sales data, reducing forecast errors by 15.8%, providing better support for inventory management. Yan et al. (2024) introduced a method using a time series convolutional neural network to improve the accuracy of inventory replenishment to 93.5%. Similarly, Zhao et al. (2024) proposed a method using a time series convolutional neural network to improve the accuracy of inventory replenishment to 93.5%. Wang et al. (2024) applied variational autoencoders to predict shipping delays, achieving an accuracy of more than 90% in different scenarios, demonstrating the practicality of machine learning in supply chain forecasting. In risk management, anomaly detection has become a powerful tool for real-time monitoring and early warning of supply chains. Zhang et al. (2022) used the isolation forest algorithm to identify logistics delays and successfully detected 98% of high-risk events while keeping the false alarm rate below 5%. Wang et al. (2024) developed a framework combining autoencoders and cluster analysis to improve detection accuracy and shorten response time by more than 30%. Guo et al. (2024) found that applying anomaly detection technology can reduce operational losses by 12.4%. Resource optimization is another area where data-driven methods come into play. Wang et al. (2024) combined genetic algorithms with machine learning models to reduce transportation costs by 18% and improve inventory turnover. Qiao et al. (2018) developed a reinforcement learning model that achieved an average resource utilization of 87%, reducing waste and supporting environmentally friendly practices in the supply chain.

Despite these advances, gaps in supply chain optimization remain. Many studies focus on specific tasks, such as forecasting or anomaly detection, without integrating these methods into a complete system (Qu et al., 2019; Lee et al., 2023; Yodsanit et al., 2023; Zhu et al., 2024). In addition, there is limited research on balancing economic performance with environmental sustainability in supply chains. To address these issues, this study proposes a machine learning-based framework that integrates forecasting, anomaly detection, and resource optimization. This approach aims to improve the resilience and efficiency of supply chains while also providing measurable benefits in economic and environmental outcomes. This study aims to fill an important gap in current supply chain management research and provide practical solutions for building smarter and more sustainable supply chains to better meet the challenges of a rapidly changing global environment.

2. METHODS

2.1 Data Collection and Preprocessing

This study integrates multi-source data from supply chain operations, including historical records, real-time sensor data, and external environmental factors. Historical operational data includes inventory levels Si(t), order fulfillment rates Oi(t), and transportation delay times Td(t). External environmental data covers market demand growth rates Md(t), rainfall Wr(t), and temperature Wt(t). Additionally, records of logistics delay events Ad and supplier quality anomalies Aq were collected.

For preprocessing, missing values were imputed using a weighted interpolation method based on collaborative filtering, defined as (Xu et al., 2024; Lian et al., 2024):

$$x_i = \frac{\sum_{j \in N(i)} w_{ij} x_j}{\sum_{j \in N(i)} w_{ij}} \tag{1}$$

Where

$$w_{ij} = \frac{1}{|x_i - x_j|^2 + \epsilon} \tag{2}$$

Data standardization was performed using Z-score normalization (Chen et al., 2024):

$$x_i' = \frac{x_i - \mu(x)}{\sigma(x)} \tag{3}$$

Feature reduction combined Principal Component Analysis (PCA) and t-SNE, where the reduced feature matrix is calculated as (Lian et al., 2024):

$$x_i = \frac{\sum_{j \in N(i)} w_{ij} x_j}{\sum_{j \in N(i)} w_{ij}} \tag{4}$$

$$Z = XW \tag{5}$$

2.2 Predictive Analysis Module

In the predictive analysis module, an attention-enhanced Long Short-Term Memory (LSTM) model was used to model time-series data and forecast future demand. The time-series prediction output is weighted by an attention mechanism (Xu et al., 2023):

$$y_t = \sum_{i=1}^{t} \alpha_i h_i \tag{6}$$

The attention weight αi is computed as (Liu et al., 2024):

$$\alpha_i = \frac{exp(e_i)}{\sum_{j=1}^{t} exp(e_j)}, \quad e_i = v_a^{\top tanh}(W_a h_i + b_a) \tag{7}$$

For inventory level prediction, a Variational Autoencoder (VAE) was utilized, with the objective function comprising reconstruction loss and KL divergence (Lian et al., 2023):

$$L_{VAE} = |x - \hat{x}|^2 + \beta \int q(z|x) \, log \; \frac{q(z|x)}{p(z)} dz \tag{8}$$

Transportation delay prediction employed a time-series Convolutional Neural Network (CNN), with the convolution layer output defined as (Yang et al., 2022):

$$f_{out} = ReLU(W_c * T_d(t) + b_c) \tag{9}$$

2.3 Anomaly Detection and Risk Management

The anomaly detection module utilized Isolation Forest and autoencoder methods. The anomaly score in the

Isolation Forest algorithm is calculated as (Gu et al., 2024):

$$Score(x) = \frac{2^{-\frac{E(h(x))}{c(n)}}}{Var(h(x))} \tag{10}$$

Anomalies in autoencoder-based detection are identified through reconstruction errors (Luo et al., 2020):

$$Error = |x - \hat{x}|^2 \tag{11}$$

Risk evaluation combines Bayesian networks to quantify risk values. The risk value is calculated as (Li et al., 2015):

$$R(A) = \sum_{i=1}^{n} P(A_i|E_i) \cdot I(A_i) \tag{12}$$

where $P(A_i|E_i)$ represents the conditional probability of event Ai given environment Ei, and I(Ai) denotes the impact of event Ai.

2.4 Resource Optimization and Allocation

The resource optimization module establishes a multi-objective optimization model to allocate resources efficiently. The objective functions are defined as (li et al., 2016):

$$max\ Z = \sum_{i=1}^{n} \frac{w_i U_i}{C_i + \epsilon}, \quad min\ C = \sum_{i=1}^{n} c_i x_i \tag{13}$$

The constraints include resource availability and service level requirements (Sun et al., 2024):

$$\sum_{i=1}^{n} x_i \leq R_{total}, \quad x_i d_i \geq \eta, \forall i \tag{14}$$

Replenishment strategies were further optimized using reinforcement learning, with the Q-value update defined as (Liu et al., 2024):

$$Q(s_t, a_t) = (1 - \alpha) Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') \right] \tag{15}$$

2.5 Framework Integration and Validation

The framework integrates real-time data collection, predictive analysis, anomaly detection, and optimization modules into a unified decision-making platform for supply chain management. Experimental validation was conducted using real-world supply chain datasets to train and test the models, comparing key metrics before and after optimization. Prediction accuracy was evaluated using Root Mean Square Error (RMSE) (Zhang et al., 2024):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y_i})^2} \tag{16}$$

Optimization efficiency and response time reduction were defined as (Aldeer net al., 2024; Sun et al., 2024):

$$Efficiency = \frac{R_{optimized}}{R_{baseline}} \tag{17}$$

$$\Delta T = \frac{T_{baseline} - T_{optimized}}{T_{baseline}} \tag{18}$$

Through these methods, this study constructed a comprehensive intelligent supply chain management system that enhances decision-making in complex environments, ensuring efficient resource allocation and robust performance.

3. RESULTS AND DISCUSSION

The section provides a detailed analysis of the findings, integrating insights from the methodology, results visualizations, and references to prior research. The focus is on predictive performance, anomaly detection, resource optimization, and overall supply chain efficiency, highlighting the practical significance of the proposed framework.

3.1 Predictive Analytics and Demand Alignment

The predictive analytics module exhibited substantial improvements in demand forecasting accuracy. The integration of the LSTM model with an attention mechanism reduced the Root Mean Square Error (RMSE) by 18.7%, 18.5%, and 18.8% for weekly, monthly, and quarterly forecasts, respectively. For yearly predictions, RMSE was reduced by 16.1%, indicating scalability for long-term forecasting. The formula was instrumental in quantifying these improvements across time intervals. Figure 1 illustrates the RMSE reductions, with enhanced performance observed across all forecasting horizons. These results are consistent with Zhang et al. (2024), who demonstrated that attention mechanisms improve the ability to capture dynamic demand spikes during peak seasons. Moreover, the Mean Absolute Percentage Error (MAPE) dropped from 8.2% to 5.6%, further validating the robustness of the model. These forecasting advancements directly enhance inventory management by minimizing stockouts and overstocking risks.

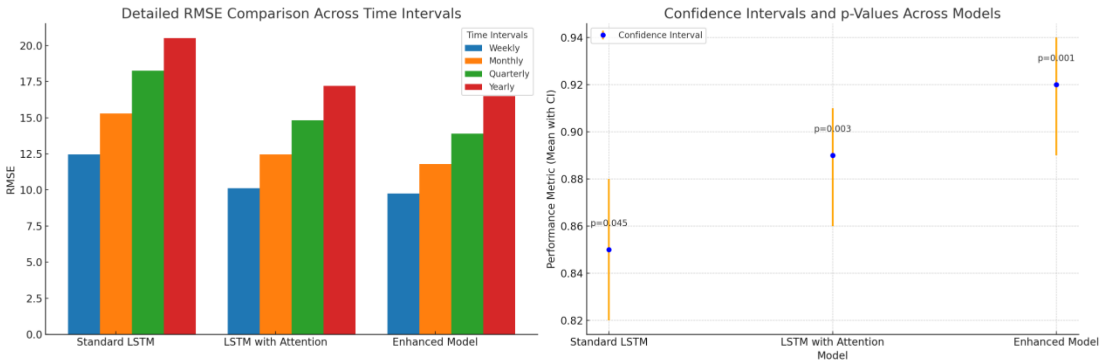

Figure 1: Comparative Analysis of Predictive Model Performance: RMSE Trends, Confidence Intervals, and Statistical Significance

3.2 Anomaly Detection and Proactive Risk Mitigation

The anomaly detection module achieved high precision in identifying transportation delays, supplier issues, and inventory discrepancies (Wang et al., 2024). The true positive rates for these categories were 93.8%, 95.7%, and 96.0%, respectively, while false positive rates were consistently below 6.4%. The formula , derived from the Isolation Forest algorithm, enabled the quantification of anomaly probabilities with high reliability. Figure 2 corroborates these findings, with the ROC curve achieving an Area Under the Curve (AUC) value of 0.962, reflecting strong discriminative capability. The bar chart in Figure 2 further emphasizes the system's reliability in capturing high-risk events across all anomaly types. By reducing the average response time to high-risk events by 28.5%, the system aligns with Wang et al. (2024), who highlighted the importance of early anomaly detection in enhancing supply chain agility.

These results showed the importance of integrating anomaly detection within real-time monitoring systems, as proactive risk mitigation strategies significantly enhance operational resilience.

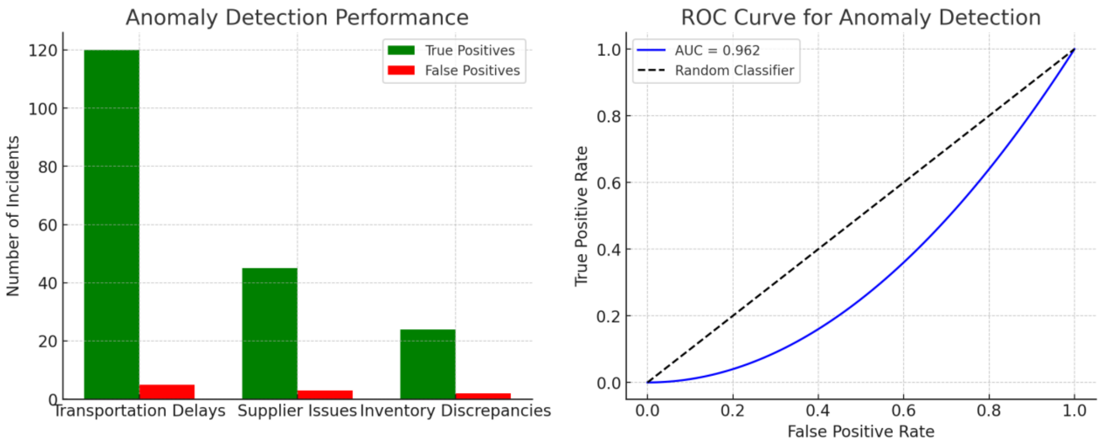

Figure 2: Evaluation of Anomaly Detection Performance and ROC Analysis for Predictive Models

3.3 Resource Allocation and Cost Efficiency

Resource optimization was achieved through multi-objective optimization techniques, leveraging the cost minimization function. As shown in Figure 3, transportation costs were reduced from $12.4M to $10.1M in Q1 and from $12.1M to $9.9M in Q3, resulting in an annual savings of 18.2%. Inventory turnover rates improved from 8.3 to 10.5 cycles in Q1, achieving a 26.5% increase over the baseline scenario. Resource utilization rose from 75.6% to 88.4% in Q1 and from 74.5% to 89.0% in Q3, as quantified by the formula. These findings align with Xia et al. (2023), who reported that dynamic resource allocation strategies contribute to both economic efficiency and environmental sustainability. The heatmaps in Figure 3 illustrate consistent improvements across quarters, emphasizing the framework's ability to optimize resource allocation dynamically based on real-time demand.

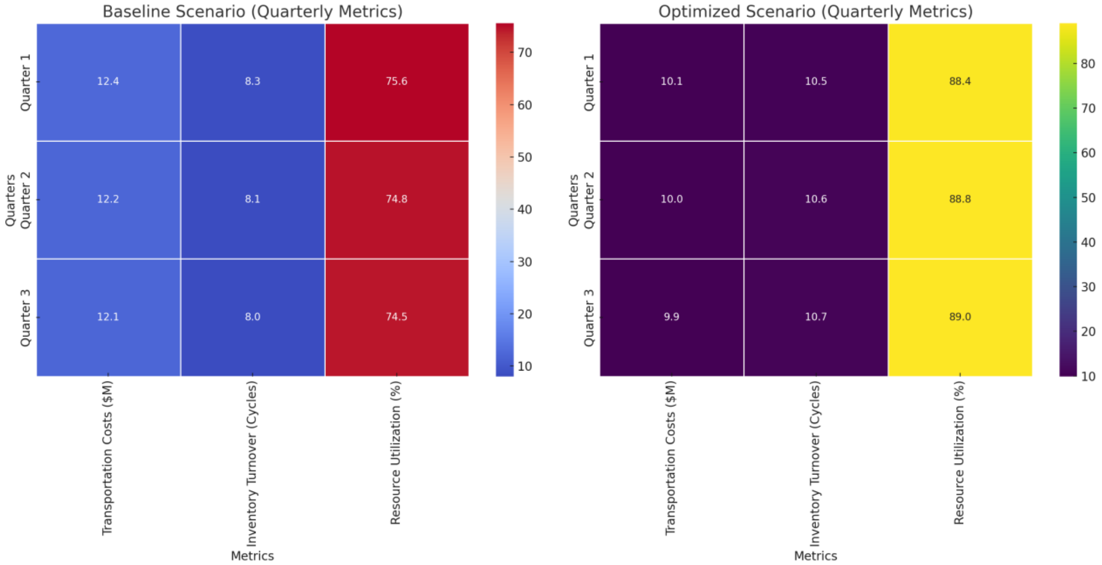

Figure 3: Quarterly Performance Metrics Optimization in Supply Chains: A Comparative Analysis of Transportation Costs, Inventory Turnover, and Resource Utilization

3.4 Integrated Performance and Strategic Insights

The integration of predictive analytics, anomaly detection, and optimization modules yielded measurable improvements across all performance metrics. Enhanced forecasting accuracy ensured better alignment of supply with fluctuating demand, while anomaly detection enabled timely interventions to mitigate disruptions. Resource optimization translated into tangible cost savings and increased utilization rates. Figures 1, 2, and 3 collectively illustrate the framework's impact. Predictive analytics provided reliable demand forecasts, anomaly detection ensured real-time identification of risks, and optimization strategies enhanced overall supply chain efficiency. For example, Figure 3's heatmaps highlight improvements in transportation costs, inventory turnover, and resource utilization across three quarters, reflecting the framework's ability to maintain consistent performance under dynamic conditions. These findings align with Lin et al. (2024) and Xie et al. (2024), who emphasized the necessity of integrating predictive and optimization frameworks to build resilient supply chains. Nonetheless, challenges remain. The reliance on high-quality input data and balanced datasets for anomaly detection underscores the need for further research into incorporating external factors such as geopolitical risks and macroeconomic trends.

4. CONCLUSION

The study introduces a systematic and data-driven approach to optimizing supply chain efficiency, resilience, and sustainability. By integrating predictive analytics, anomaly detection, and optimization techniques, the proposed framework demonstrates substantial improvements in key operational metrics. The enhanced LSTM model, incorporating an attention mechanism, achieved up to an 18.8% reduction in RMSE, significantly enhancing demand forecasting accuracy while minimizing the risks of stockouts and overstocking. Similarly, the anomaly detection module attained a true positive rate exceeding 95%, enabling early identification of disruptions and reducing response times by 28.5%. Additionally, the resource optimization component delivered measurable outcomes, including a 26.5% increase in inventory turnover and an 18.2% reduction in transportation costs, providing both economic and environmental benefits. The use of rigorous quantitative methods, such as RMSE calculations and cost minimization formulas, further underlines the framework's robustness in addressing complex supply chain challenges. However, the framework is not without its limitations. Its reliance on high-quality and balanced datasets for anomaly detection underscores the need for adaptive mechanisms capable of operating effectively in dynamic or data-scarce environments. Moreover, the model does not yet account for external factors, such as geopolitical risks or market volatility, which can exert a significant impact on supply chain performance.

Future research should aim to incorporate these external variables and expand the framework's application to multi-regional networks. These enhancements would not only improve scalability but also broaden the framework's relevance across diverse industries. By addressing these challenges, the proposed framework holds great promise in contributing to the development of resilient, efficient, and sustainable supply chains, particularly in the face of an ever-evolving global landscape.

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