



Operational Analytics Systems For Real-Time Data-Driven Optimization

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Abstract

Supply chain management faces challenges from dynamic demand, disruptions, and high-dimensional data. Traditional static batch methods lack responsiveness in changing environments. This research proposes a smart dynamic operational analytics system for optimized, data-driven supply chain decision-making. The architecture proposed integrates data streams using Smart Logistics Supply Chain Dataset with 1000 records. Principal Component Analysis (PCA) is used for feature extraction, dimensionality reduction, and consistency Min-Max normalization in data preparation. Processed features are given to the Wingsuit Flying Search driven Intelligent Backpropagation Neural Network (WFS-IntBPNN) for predicting the state of the system. Intelligent weights are optimized by WFS and learning and prediction of demands, anomalies, and system states are completed by IntBPNN. Experimental results are obtained by Python (version 3.10) and The data obtained indicate that the proposed WFS-IntBPNN model performs superior to the current models, which gives the minimum error value (MSE = 1.8420, MAE = 0.9820). In sum, the system is useful for optimizing resources and accelerating decision-making, for more accurate forecasting, faster response times and higher throughput in high-volume, high-variability situations.

Keywords: Operational Analytics, Dynamic Data Processing, Data-Driven Optimization, Dynamic Decision-Making, Streaming Analytics.

1 Introduction

In the current business world, businesses generate a huge amount of data from sensors, machines and digital platforms, which are produced dynamically in seconds-by-seconds [1]. The ability to make intelligent decisions on top of that, quickly and correctly, has become an imperative, especially in supply chain management, where a small delay can lead to significant financial gains or losses and the impact on customer service [2, 3]. However, most existing analytics systems, were not originally built to handle dynamic requirements [4]. The primary issues that they face include operating with outmoded batch processes, limited prediction models, and disjointed tools that can't catch up with rapidly changing demand, supply disruptions, or changes in resource requirements [5, 6]. This can lead to businesses making decisions on out-of-date information, which can decrease their efficiency [7].

Although a large amount of research has been conducted in the field, there is no comprehensive solution that combines high throughput streaming analytics, adaptive deep-learning, and heuristic optimization [8]. A wealth

of research exists on these subjects on their own, and these have limited usefulness in real-life applications [9]. This disconnection highlights the importance of having a dynamic, integrated and intelligent system to support operational decision making in complex environments [10].

In this research, to address these issues, a novel integrated Operational Analytics System for dynamic data streaming WFS-IntBPNN is proposed, along with adaptive heuristic optimization. The system has a strong emphasis on supply chain administration, including precise demand estimation, astute stock control, and adaptable logistics strategy.

The research organized as follows: in supply chain forecasting literature is discussed in Section 2. Section 3 provides an explanation of the suggested WFS-IntBPNN approach. The assessment of performance is reported in Section 4. Lastly, Section 5 outlines the constraints and potential areas for more study.

2 Literature Review

Prior studies use DL and ML methods to increase the precision of supply chain prediction. Research [11] uses ML techniques for supply chain and inventory optimization, improving forecasting accuracy, but lacks adaptability and real-time dynamic analytics for highly dynamic environments.

Furthermore, the research [12] aims to develop a predictive model for the optimization of the supply chain using AI. It uses statistical methods along with forecasting models based on deep learning. Efficient for PV reverse logistics only, not generalizable to other supply chain areas. Research [13] aimed to optimize inventory of e-commerce in agriculture using feedforward neural network and stacked auto encoders. It improves the prediction accuracy, but has domain restrictions and low adaptability to dynamic environments.

Examination [14] aims to enhance the prediction of demand and minimise the inventory in retail using ensemble deep learning techniques. Improved accuracy using historical ensemble models, but highly domain-specific and not easily transferable. In the research [15], the authors aim to improve the performance of condition-based maintenance forecasting by combining three algorithms: Extreme Gradient Boosting (XGBoost), Local Outlier Factor (LOF), and Bidirectional Long Short-Term Memory (Bi-LSTM). High accuracy and anomaly detection, but computationally expensive and domain-limited.

Research [16] compares three methods regression, Artificial Neural Network (ANN), and decision tree to predict bus spare parts demand, evaluating which model provides more accurate forecasting performance. Investigation [17] attempts to enhance demand forecasting in supply chain by employing attention-based advanced learning technique with Convolutional Neural Network (CNN) and channel attention. The results indicate lower forecasting error; however, the model suffers from a decrease in robustness when data is missing or incomplete. The study [18] aims to reduce the Mean Absolute Error (MAE) by 37% for the demand forecasting using VMD and attention mechanism, but it has some disadvantages in terms of computational complexity and robustness in highly heterogeneous demand data. In the research [19], was to improve the demand forecasting using a Multi-Channel Deep Fusion Network (MCDFN), which is a hybridization of CNN, LSTM, and Gated Recurrent Unit (GRU). It achieves MSE 23.57. However, it is constrained by the model's complexity and a decrease in the interpretability of the predictions.

2.1 Research Gap

In recent years, Machine learning and deep learning approaches have improved the supply chain's precision in forecasting, however, it is still far from comprehensive and lacks a unified framework of optimization. Existing methods are insufficient to deal with the non-linear, dynamic nature of the data [11] and several models have been shown to be not as robust as they could be, and to perform poorly in unseen data sets, causing their predictive ability to be unstable [17]. Also, using static training methods without smart optimization results in sub-optimal convergence and in higher sensitivity to errors.

To address these limitations, the authors propose a novel solution called WFS-IntBPNN that combines the two novel optimization methods, Intelligent Backpropagation Learning and Wingsuit Flying Search, with the PCA-based feature reduction technique to boost the accuracy of prediction, stability of convergence, and generalizability of models by forecast applications in the supply chain.

3 Proposed Methodology

The methodology proposed for dynamic optimization of the supply chain process starts with the acquisition of supply chain data. The operational attributes are normalized by Min-Max normalization, and the significant

features are extracted, and redundant variables are eliminated by PCA. An optimized IntBPNN model with WFS is used to enhance the demand forecasting, anomaly detection, and operational prediction functions for supporting dynamic supply chain decision making and operational performance evaluation. The overall flow of the proposed framework is shown in Figure 1.

Figure 1: Proposed Operational Workflow for Dynamic Supply Chain Decision Support



3.1 Dataset

This research uses the Smart Logistics Supply Chain Dataset (<https://www.kaggle.com/datasets/ziya07/smart-logistics-supply-chain-dataset>), which was acquired from Kaggle, with an 80:20 training and testing split. Table 1 summarizes the key characteristics of the dataset.

Table 1: Characteristics of the Smart Logistics Supply Chain Dataset

Attribute	Details
Total Records	1,000
Total Features	16
Target Variable	Logistics Delay (Binary: 0 = No Delay, 1 = Delay)
Class Distribution	Delay: 56.6% (566), No Delay: 43.4% (434)
Missing Values	Minimal (263 in delay reason field only)
IoT Sensor Features	Temperature, Humidity, Asset Utilization
Geospatial Features	Latitude, Longitude, Asset_ID
Operational Features	Shipment Status, Traffic Status, Inventory Level, Waiting Time
Transactional Features	User Purchase Frequency and Transaction Amount,
Forecasting Feature	Demand Forecast (100-300 range)

3.2 Min-Max Normalization for Feature Scaling and Data Standardization

Min-Max normalization scales heterogeneous supply chain data to [0,1], ensuring stable learning, faster convergence, and robust decision-making in dynamic operational environments; defined in Equation (1):

$$y' = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \quad (1)$$

Here, y is a raw dynamic supply chain data, y_{\min} and y_{\max} are observed minimum and maximum values for data stability over the range, and y' is a normalized feature for efficient learning and dynamic operational decision.

3.3 PCA Feature Extraction for Dimensionality Reduction

PCA reduces supply chain data dimensionality by extracting principal components capturing key operational features for forecasting and optimization; covariance matrix is computed using Equation (2):

$$\sum_{M-1} \frac{1}{M-1} \sum_{j=1}^M (y_j - \bar{y})^2 (y_j - \bar{y}) \tag{2}$$

The covariance matrix of the supply chain data is represented by Σ , and M indicates the overall number of entries, y_j is the j^{th} operational instance with features like demand, inventory, delivery time, and cost, and \bar{y} is the mean feature vector. The reduced feature set is obtained using equation (3):

$$X = Y \times W \tag{3}$$

Where W contains all the information from the standardized data set, Y, which is subsequently used by the transformed feature set, X, for predictive analytics in supply chain management operations.

3.4 Wingsuit Flying Search-driven Intelligent Backpropagation Neural Network (WFS-IntBPNN) for Optimized Supply Chain Prediction

The pipeline of the WFS-IntBPNN is initiated by supplying the features of the supply chain normalized by PCA into IntBPNN to gain the nonlinear relationship between inventory, demand, logistics, and operational variables. IntBPNN first produces predictions, and WFS then adapts the weights, biases, and learning parameters in the network by exploring neighbouring areas and selecting the best performing individuals. In every iteration, the prediction error is calculated, and the parameters of the network are adjusted to enhance convergence and prediction accuracy. Finally, the optimized IntBPNN model generates dynamic predictions for demand forecasting, inventory optimization, logistics planning, and operational decision-making in supply chain management.

3.4.1 IntBPNN for Nonlinear Learning and Forecasting

The IntBPNN is an improved version of an existing BPNN model to achieve better prediction accuracy in dynamic supply chain environments. For the dynamic supply chain prediction, the nonlinear relations among inventory status, customer demand, logistics activities, transportation delays, and operational cost variables are modeled by IntBPNN in this research. IntBPNN combines adaptive learning with intelligent weight optimization, enhancing convergence speed, minimizing prediction errors, and enhancing management of supply chains decision-making resources including predicting demand and recognizing anomalies, and operational state prediction, compared to traditional BPNN.

- **Input Encoding:** The PCA-normalized supply chain features are used as inputs to IntBPNN, where the total trainable parameters (weights and biases) are represented in equation (4):

$$k = (m + 1)o + (o + 1)n \tag{4}$$

where k denotes the total trainable parameters (weights and biases) in IntBPNN; m denotes supply chain input features; o is the hidden neurons for extracting nonlinear operational patterns; n is the output nodes for predictive analytics; $(m + 1)o$ and $(o + 1)n$ represent input and hidden-output layer connections, respectively.

- **Initialization:** Set initial population, WFS parameters and count of iterations, $l=0$. The upper bound, u_{\max} , and lower bound, u_{\min} , are used to randomly initialize and to limit the optimization algorithm's search space.

- **Forward Learning and Fitness Evaluation:** The operational characteristics of the normal situation are propagated in IntBPNN for forecasting demand fluctuation, logistics delay and operational situation. The fitness function shown in equation (5): is used to measure the predictive performance.

$$e = 1/(1 + F) \tag{5}$$

where e is the IntBPNN fitness score and lower error increase e, which improves demand forecasting and operational prediction accuracy; F is the supply chain prediction error.

- **Error Estimation:** Prediction performance is evaluated by mean square error between the operational outcomes and the prediction of IntBPNN was expressed in equation (6).

$$O_j = e_j / \sum_{j=1}^t e_j \tag{6}$$

The normalized contribution of prediction for the j^{th} supply chain observation is denoted as O_j , while the prediction error is denoted as e_j , and $\sum_{j=1}^t e_j$ is total aggregated prediction error over t observations in the operational sample.

- **Crossover Operation:** To improve predictive accuracy, optimized candidate solutions are generated through crossover and mutation operations in equations (7) and (8):

$$W'_1 = fW_1 + (1 - f)W_2 \tag{7}$$

$$W'_2 = (1 - f)W_1 + fW_2 \tag{8}$$

In the WFS optimization, (W_1, W_2) are candidate vectors for IntBPNN parameters. After crossover, the offspring solutions are (W'_1, W'_2) , where f is a random between 0 and 1 scaling factor that induces exploration, and $(1 - f)$

is a scaling factor to maintain diversity and avoid premature convergence. Elite solutions are carried forward from generation to generation.

- **Learning Update:** The Wingsuit Flying Search (WFS) mechanism adaptively updates network parameters to avoid local minima and improve convergence. The objective variation is estimated in equation (9):

$$h'(l) = h(l) + \beta \tag{9}$$

$$\Delta D = D(h'(l)) - D(h(l)) \tag{10}$$

where $h(l)$ is the current solution, $h'(l)$ is the updated solution, and $\beta \in (-1,1)$ introduces a stochastic perturbation for exploration. In equation (10), ΔD indicates prediction cost change for optimization, and $D(\cdot)$ is a function which assesses the quality of the solutions. The acceptance probability is computed using equations (11-12), to decide if this new solution should be adopted or not.

$$O_r = \min \left[1, \exp \left(-\frac{\Delta D}{s_l} \right) \right] \tag{12}$$

Where \exp ensures the probabilistic acceptance behavior, s_l is the temperature at iteration l , ΔD is the cost difference, and O_r is the acceptance probability. The process of parameter updating is iterated and iteratively improved using equation (13):

$$s_{l+1} = \lambda s_l \tag{13}$$

Where the search-control parameters, s_l and s_{l+1} , are the search and updated search parameters, respectively; and λ is a progressive parameter within $(0,1)$ that is used to improve the operational prediction accuracy of IntBPNN.

- **Convergence & Deployment:** WFS iterates until convergence or max iterations; best solution updates network weights and biases, and the trained WFS-IntBPNN is deployed for supply chain prediction and optimization.

3.4.2 Wingsuit Flying Search for Adaptive Weight Optimization and Parameter Tuning

WFS algorithm is a nature-inspired metaheuristic optimization algorithm, adapted from the adaptive flight of a wingsuit flier. This research was conducted using WFS for its efficient exploration and exploitation, the ability to converge quickly, and avoid getting stuck in local optima. In the suggested Dynamic Operational Analytics, WFS optimizes network weights, biases, and learning parameters to minimize the prediction error and thereby increase the forecasting accuracy of demand, inventory, and logistics operations.

- **Candidate Initialization (Dynamic Analytics):** Candidate IntBPNN parameter solutions are first generated using the Halton sequence to ensure the diversity of the search distribution. Optimization inputs are supplied by the chain operational data, such as inventory, logistics, and customer transactions.

- **Adaptive Optimization (Operational Analytics):** At iteration $(n \geq 2)$, the candidate solution is ranked by prediction fitness, with the lowest prediction error being the best solution. The neighborhood size of each candidate solution is calculated using equation (14):

$$O^{(n)(j)} = \left\lceil O_{\max}^{(n)} \left(1 - \frac{(j-1)}{M^{(n)}-1} \right) \right\rceil \tag{14}$$

Where, $O^{(n)(j)}$ denotes the neighborhood size of the j^{th} candidate solution at iteration n , $O_{\max}^{(n)}$ represents the maximum neighborhood size, $M^{(n)}$ indicates the total number of candidate solutions, and the scaling factor adaptively balances exploration and exploitation for optimizing IntBPNN parameters in dynamic supply chain analytics. The number of candidate solutions generated during each iteration is determined using Equation (15).

$$M^{(n)} = \frac{2M^{(n-1)}}{O_{\max}^{(n)}} \tag{15}$$

Where $M^{(n)}$ denotes the candidate neural network solutions generated during the n^{th} iteration for optimizing supply chain predictions, M represents the initial solution population, $O_{\max}^{(n)}$ indicates the maximum neighborhood exploration size, and n refers to the current optimization iteration in the WFS-IntBPNN model. The maximum neighborhood size is computed using equation (16).

$$O_{\max}^{(n)} = \lceil \alpha^{(n)} M \rceil \tag{16}$$

Where $O_{\max}^{(n)}$ denotes the maximum neighborhood size, $\alpha^{(n)}$ represents the adaptive scaling factor controlling exploration and exploitation, M indicates the total candidate solution population, and n refers to the current optimization iteration for improving prediction accuracy and operational efficiency. To support fine-grained parameter tuning, the discretization step is progressively reduced in equation (17):

$$\Delta W^{(n)} = (1 - \alpha^{(n)}) \Delta W^{(1)}, n \geq 2 \tag{17}$$

Where $\Delta W^{(n)}$ denotes the discretization step size at iteration n , $\alpha^{(n)}$ represents the adaptive convergence factor controlling exploration and exploitation, $\Delta W^{(1)}$ indicates the initial search step size, and n defines the iteration number, where the adjustment process starts from ($n \geq 2$). Finally, neighborhood search regions are generated using directional vectors to refine IntBPNN parameter exploration using equation (18):

$$\begin{aligned} T_{1,1}(w_j^{(n)}) &= \{w_{l,j}^{(n)} - \Delta w_{l,j}^{(n)}, w_{l,j}^{(n)}\}, \text{if } u_{l,j}^{(n)} < 0; \\ T_{1,2}(w_j^{(n)}) &= \{w_{l,j}^{(n)}, w_{l,j}^{(n)} + \Delta w_{l,j}^{(n)}\}, \text{if } u_{l,j}^{(n)} > 0; \\ T_{1,3}(w_j^{(n)}) &= T_{1,1}(w_j^{(n)}) \cup T_{1,2}(w_j^{(n)}), \text{if } u_{l,j}^{(n)} = 0; \end{aligned} \tag{18}$$

Where $T_{1,1}(w_j^{(n)})$, $T_{1,2}(w_j^{(n)})$, and $T_{1,3}(w_j^{(n)})$ represent lower, upper, and combined neighborhood search spaces for optimizing IntBPNN parameters. $w_j^{(n)}$ and $w_{l,j}^{(n)}$ denote candidate solutions and parameter values, while $\Delta w_{l,j}^{(n)}$ represents discretization step size. $T_{1,1}$, $T_{1,2}$, and $T_{1,3}$ define neighborhood search regions guided by direction vector $u_{l,j}^{(n)}$. Here, l , j , and n represent parameter index, candidate solution index, and iteration number, respectively, while ($u_{l,j}^{(n)} < 0, > 0$, and $= 0$) indicate local, global, and balanced exploration.

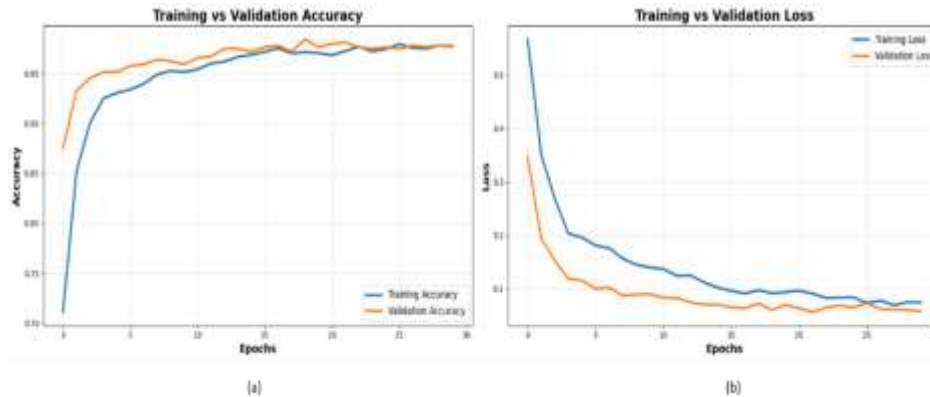
- **Optimal Selection (Decision Analytics):** Newly generated candidate solutions are added to $M^{(n)}$ evaluates prediction accuracy, and selects optimal IntBPNN by optimizing weights, biases, learning parameters to minimize error and improve convergence in supply chain forecasting.

4 Result and Discussion

This section presents the empirical findings of the Python-developed WFS-IntBPNN model, demonstrating the model's strong performance in dynamic supply chain prediction and optimization applications, such as convergence analysis, performance evaluation, comparative benchmarking, and cross-validation.

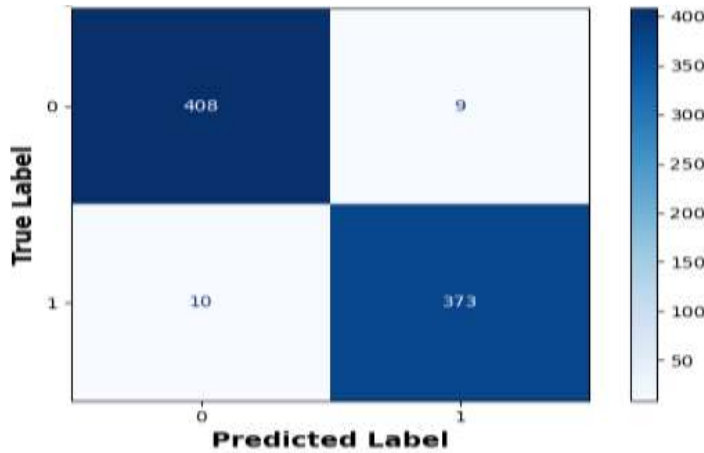
As shown in Figure 2(a), the accuracy of the trained and tested models both approach a steady value, ~ 0.71 and ~ 0.88 , respectively, and converge after 20 epochs, indicating good generalization and no overfitting. Figure 2(b) shows that the loss values of both the training process and the validation process approach zero at a rapid rate, reaching near-zero values of $\sim 0.07-0.08$ in epoch 30, which indicates accurate optimization of the model and high learning ability in the supply chain prediction task.

Figure 2: Classification (a) Accuracy and (b) Loss Optimization Curves of the Proposed Model



The figure 3 confusion matrix demonstrates the suggested model's higher binary classification performance. Of the 800 samples, 408 were true negatives, and 373 were true positives, meaning that only 9 were misclassified as true positives and 10 as true negatives. This yields an overall accuracy of about 97.6%, which indicates the model's accuracy in anomaly detection and supply chain demand classification, allowing very few misclassifications in both classes.

Figure 3: Binary Classification Confusion Matrix of the Proposed WFS-IntBPNN Model



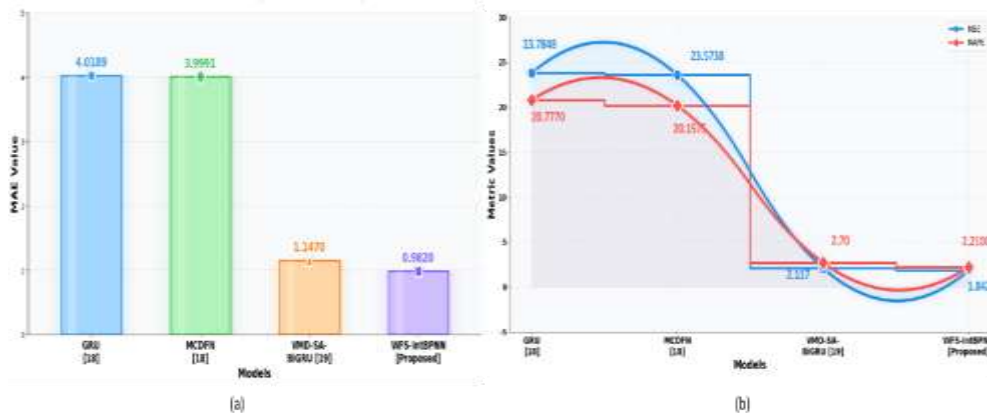
4.1 Performance Evaluations

To evaluate the effectiveness of the proposed framework, the performance of the proposed framework is compared with the existing deep learning-based forecasting methods like Gated Recurrent Unit (GRU) [18], Multi-Channel Deep Fusion Network (MCDFN) [18], and the hybrid Variational Mode Decomposition with Self-Attention based Bidirectional Gated Recurrent Unit (VMD-SA-BiGRU) [19] model. These are the error measures: Mean Squared Error (MSE) evaluates squared prediction error; Mean Absolute Error (MAE) measures absolute prediction error; Mean Absolute Percentage Error (MAPE) determines percentage prediction error; and Root Mean Squared Error (RMSE) estimates overall error magnitude; and while evaluating recommendations in a dynamic supply chain, assess predictions' accuracy and reliability collectively. Table 2 shows the performance evaluation of proposed and existing methods.

Table 2: Comparative Performance Analysis of Forecasting Approach

Model	Dataset	MSE	MAE	MAPE	RMSE
GRU [18]	Historical Sales Dataset	23.7848	4.0189	20.7770	4.8770
MCDFN [18]	Historical Sales Dataset	23.5738	3.9991	20.1575	3.9991
VMD-SA-BiGRU [19]	Custom Data	2.117	1.147	2.70	-
WFS-IntBPNN [Proposed]	Smart Logistics Supply Chain	1.8420	0.9820	2.2100	1.3570

Figure 4: Error Metric Comparison of (a) MAE and (b) MSE and MAPE in Supply Chain Demand Forecasting



The decomposition and attention mechanism errors for VMD-SA-BiGRU [19] are lower as compared to GRU [18] and MCDFN [18], as seen in Table 2 and Figure 4, indicating that it is more capable of capturing complex temporal dependencies in the supply chain data. The proposed WFS-IntBPNN has the forecasting accuracy and stability

of MSE = 1.8420, MAE = 0.9820, MAPE = 2.2100%, and RMSE = 1.3570. The improved performance is claimed to result from feature refinement by PCA, intelligent nonlinear learning and optimization of parameter updates within WFS to reduce convergence limits. On the Smart Logistics Supply Chain dataset, WFS-IntBPNN outperforms baseline models (GRU, MCDFN, VMD-SA-BiGRU) in Table 3, achieving the lowest errors and demonstrating superior accuracy, robustness, and dynamic forecasting capability.

Table 3: Training Performance Evaluation of Forecasting Models on Smart Logistics Supply Chain Dataset

Model	MSE	MAE	MAPE	RMSE
GRU	23.7848	4.0189	20.7770	4.8770
MCDFN	23.5738	3.9991	20.1575	3.9991
VMD-SA-BiGRU	2.1170	1.1470	2.7000	1.4550
WFS-IntBPNN [Proposed]	1.8420	0.9820	2.2100	1.3570

4.4 Discussion

The proposed WFS-IntBPNN combines feature reduction, neural learning, and metaheuristic optimization to model complex, dynamic supply chain patterns effectively. Traditional models such as GRU and MCDFN [18] struggle with nonlinear relationships and noise sensitivity, while VMD-SA-BiGRU [19] improves accuracy but increases computational complexity in dynamic environments. The proposed approach addresses these limitations by enhancing convergence stability and learning efficiency using PCA-based feature refinement and WFS optimization. IntBPNN reduces local minima issues, improving generalization. Robustness is ensured through cross-validation and ablation studies, enabling balanced, reliable forecasting under uncertainty in supply chain decision-making.

5 Conclusion

The proposed WFS-IntBPNN model integrates PCA-based feature reduction, Min-Max normalization, adaptive neural learning, and WFS optimization for efficient supply chain forecasting. Extracted features are processed through IntBPNN, while WFS optimizes network weights to enhance learning and reduce prediction error. The model achieves strong performance with MSE (1.8420), MAE (0.9820), MAPE (2.21%), and RMSE (1.3570), indicating high predictive accuracy for complex, non-linear supply chain dynamics. However, it has limitations in computational cost and scalability for real-time large-scale applications. Future work will focus on lightweight, parallel, and distributed optimization for improved efficiency and deployment.

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