https://doi.org/10.31449/inf.v49i18.7301 Informatica **49** (2025) 39-50 **39**

Optimizing Supply Chain Logistics with IOT And Machine Learning: From Data Collection to Decision Making Based on Refined Battle Royale Optimizer Weighted Random Forest

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Keywords: decision making, internet of things (IoT), refined battle royale optimizer weighted random forest (RBRO-WRF), supply chain logistics

Received: October 10, 2024

In today's interconnected and competitive global market, the efficiency of supply chain (SC) logistics plays a critical role in the success of businesses. As SCs become more complex and dynamic, traditional methods of managing logistics and inventory have struggled with the demand for real-time decision-making. The study's goal is to establish SC logistics using the Internet of Things (IoT) and machine learning (ML) to make decisions. This study proposed a novel Refined Battle Royale optimizer Weighted Random Forest (RBR-WRF) model is to improve SC performance through demand volume prediction. Real-time data collected through IoT sensors, the framework optimizes key logistics processes such as demand forecasting, inventory management, and transportation planning. The data was gathered from the Kaggle source. Data preparation includes data cleaning, outliers' detection to handling missing values and transforming raw data to improve analysis with min-max normalization with z-score. This framework is a predictive model based on the WRF, optimized through RBRO. The model accurately predicts demand volume by optimizing hyperparameters. Tuning the WRF model and adjusting the weight values of learning components. The suggested approach is implemented with Python software. The performance of the suggested method is evaluated in terms of MSE (0.00324), MAE (0.04315), RMSE (0.05412), and MAPE (3.41%) and the t-value statistical test is 3.37. The findings revealed that the suggested predictive model achieves an average inaccuracy in demand volume forecast, displaying a minimal reduction compared to traditional approaches. Also, this model's enhancement of SC logistics performance reduces delays and better efficiency in the company. This combination of IoT and ML in SC logistics provides businesses with a reliable solution for data-driven decision-making, allowing them to respond to changing market conditions while increasing operational efficiency.

Povzetek: Raziskana je optimizacija logistike dobavne verige z internetom stvari in strojnim učenjem, kjer nov prediktivni model RBRO-WRF izboljša napovedovanje povpraševanja ter učinkovitejše odločanje podjetij.

1 Introduction

The application of the IoT in SC logistics means that the fabrication, distribution, as well as control of items undergo a new transition. Through the use of IoT, business processes can be refined, productivity increased and the quality of decisions made concerning activities along withSC can be improved through real-time tracking, data analysis, and services. It is important and necessary for the SC to become more visible, accurate, and responsive than ever before as the global economy becomes more integrated and complex [1]. IoT gadgets are used in SC operations to monitor and control every process, from identifying sources for raw materials to delivering finished products to customers. Sensors can refer to temperature, humidity, position, and others transferring real-time data about the flow and state of commodities [2].

Asset tracking is one of the largest types of IoT applications in the context of SC logistics. Some other possibilities are IoT gadgets like RFID tags, GPS, and additional sensors can help the companies monitor the movement of products and minimize the risks of theft and losses and they deliver goods on time. Moreover, IoT provides a system to manage the stock of goods, so that their amount is optimal, and there is no need for interventions [3].

SC visibility helps in the search for issues, concerns, and risks with the SC. Data from smart devices in real-time enhances the flow of material through the SC at every stage. IoT allows companies to make decisions based on data and quickly adapt to any challenges, since it provides the choice of location, the storage location, and the expected delivery date of the product [4].

Human observation can be replaced by sensors that can be fixed around the warehouses to monitor storage factors such as humidity and temperature that affect most perishable goods. Logistics management can respond to the variations in the parameters swiftly, which allows them to protect the items before they are ruined. The actual SCtransparency creates a higher standard for quality control as well as the general durability of the SC [5].

Many developments of IoT technology can improve the logistics environment indirectly, such as automating other work, receiving support for equipment maintenance, and better transportation handling. For instance, IoT-powered fleet management can predict when a given car requires maintenance, which decreases the probability of developing problems and the minimum time out of service. This results in an enhanced transport network that is more reliable; hence reducing delivery time and satisfying the customers [6].

Innovative technologies allow companies to consider huge amounts of information, consumer behavior, tendencies in a given industry or market, and external conditions such as climate, to offer forecasts that are more dynamic and accurate. It can be said that the accuracy of demand volume is the key factor that determines the overall efficiency of the logistics SC. Optimization of routes and loads means the least affects the environment and fewer shipment delays, effectiveness on transport strategy [7].

This research presented a unique Refined Battle Royale optimizer Weighted Random Forest (RBR-WRF) strategy to increase SC performance by forecasting demand volume.

This research is separated into the following categories: related works, methodology, results, and conclusion.

2 Related works

Hybrid demand prediction techniques, such as ARIMAX and neural network, based on ML, were generated in the investigation [8]. The presented technique incorporated both explanatory variables and temporal series. The results indicated that operational and financial indicators could be enhanced by applying the ML-based prediction methods. According to their findings, inventory efficiency had improved statistically significantly.

Employing past transaction records from a company, the research [9] improved the efficiency of the SC's demand prediction system by employing DL techniques, such as LSTM, and ARIMA. The findings allowed the most effective approach to be chosen, which might provide greater accuracy than the tested and established approaches.

A unique CTFF was proposed in the research [10] to produce predictions that were logical at every stage of a commercial SC. The LSTM network, a DL technique, served as the CTFF's fundamental prediction mechanism. The performance measures and test results showed that CTFF predictions outperformed direct predictions.

A novel framework based on LSTM and LightGBM was suggested in research [11] to anticipate SC sales. To confirm the precision and effectiveness of the approach, three relevant SC sales records were chosen for testing. The outcomes demonstrated that the combined approach had a high degree of comprehension, effectiveness, and accuracy when predicting SC sales.

Two data-driven strategies were presented in research [12] to assist SC management in creating improved choices. Specifically, they proposed a network-based approach based on LSTM for predicting multivariate time-series information and a network-based approach based on LSTM AE mixed with an OCSVM approach for identifying sales irregularities. The results found that the LSTM AE-based strategy outperformed the previous LSTM-based strategy in anomaly identification.

Through inventory mechanism process optimization, research [13] intended to save costs throughout the SC life cycle. Initially, the IM process was presented mathematically, with the goal of both minimizing the logistical cost and maximizing the profit. Employing DL's LSTM principle, a DIM approach was suggested to handle the system. The findings demonstrated that DIM could decrease total costs about 25 % and that its average forecasting accuracy was greater than 80%.

Using holistic methodologies, research [14] forecasted the unit sales of thousands of commodities sold at several chain stores. Forecasts were made using three DL techniques such as CNN, LSTM, and ANN.The outcomes demonstrated that, in terms of efficiency, the LSTM network typically performed better than the other two methods.

The effectiveness of ML and DL methods for predicting order volume was examined in research [15]. TheGBR, RFR, XGBoost, LightGBM Regressor, Cat Boost Regressor, LSTM, and BiLSTM were specifically utilized in their research. The statistical evaluations and outcomes indicated that the LSTM model performed better at prediction than any other approach.

Table 1: Related works on summary

Ref	Methods	Performance Metrics	Advantages	Limitations
[8]	ML-based hybrid demand forecast methods like ARIMAX and neural networks were developed.	Threshold level of 0.7	Improvements in inventory performance and statistically significant variations in supply chain performance improvement between ML-based and traditional demand forecasting methods were discovered in this study.	usage of a single dataset to assess forecasting techniques
[9]	Auto-Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM)	LSTM and ARIMA MSE values were computed to be 1.12 and 1.67, respectively. We presume that the LSTM model is appropriate for the dataset being used and may yield superior outcomes in terms of product demand prediction when taking into account the MSE and MAPE values.	Our goals are to compare the models' performance and train the models to choose the best one that can offer higher accuracy for the dataset being used.	Lack of statistical analysis of demand forecasting.
[10]	This study Proposes a cross-temporal supply chain forecasting framework.	The analysis of this study demonstrates how the temporal hierarchy might aid in producing forecasts with reduced variance and increased accuracy. . MAE 0.8085, MSE 0.6896, MAPE 0.8057.	This framework offers demand projections for a supply chain's strategic, tactical, and operational planning levels from the short term to the long term.	lack of hypotheses in more non-traditional fulfillment channels
[11]	This paper proposed a new model based on lightGBM and LSTM to forecast the supply chain sales.	Forecast supply chain revenues with a high degree of precision, effectiveness, and comprehensibility.	The suggested model has the benefits of the lightGBM model, including high efficiency, strong interpretability, and suitability for industrial production environments, in addition to inheriting the LSTM model's capacity to automatically my high-level temporal information.	Lack of statistical report
[12]	LSTM	When compared to current approaches, the highest accuracy was 0.98 and the lowest RMSE was 9.71.	Accurately identifying sales anomalies gives the business information into its operational and marketing plans.	One drawback is that the anomaly detection model only looks for anomalies in historical data and cannot access actual

				firm data because of security concerns.
[13]	a deep inventory management (DIM) method is proposed to address this model by using the long short-term memory (LSTM)	DIM's average inventory demand prediction accuracy is over 80%, which can result in a 25% reduction in inventory costs.	The benefits mostly consist of maximising profits and minimising expenses.	Lack of large dataset
[14]	CNN, LSTM, and ANN	LSTM outperform in accuracy as compared with CNN, ANN	Predicting the unit sales of thousands of items offered at various chain stores in Ecuador is the goal in order to minimise understocking, prevent overstocking, cut down on waste and loss, and improve customer happiness.	Lack of elaborate statistical discussion with methods
[15]	TheGBR, RFR, XGBoost, LightGBM Regressor, Cat Boost Regressor, LSTM, and BiLSTM	RSMLE as 28.18, RMSE as 18.83, MAPE as 6.56, MAE as 14.18	Forecasting order numbers accurately informs authorities about inventory management, and LSTMs and Bi-LSTMs excel in handling time series data and predicting accurate results based on feature values. .	Lack of different dataset evaluation.
[16]	LSTM	Accuracy is 92.5%, It was successful in striking a balance between cost effectiveness and service quality, as seen by the 18% decrease in inventory holding costs and the 22% increase in order fulfilment rates.	The findings highlight the significant impact of machine learning on improving supply chain efficiency and show how it can result in significant cost savings and improve service quality.	Lack of analyse the data with different methods
[17]	IOT in SC	Highest performance and user satisfaction	The role in enhance efficiency, reduce cost ensure product quality and advancing sustainability.	lack of dataset

3 Methodology

The SC data was gathered from the Kaggle source. To improve analysis, the raw data is cleaned and transformed using data cleaning and min-max normalization. Then, an innovative Refined Battle Royale optimizer Weighted Random Forest (RBR-WRF) model is employed to anticipate demand volumes and enhance SC management.

3.1 Dataset

The supply chain data was gathered from the Kaggle sourcehttps://www.kaggle.com/datasets/shivaiyer129/supply-chain-data-set. The dataset comprises information about SC processes, such as orders, products, stock, suppliers, logistics, and demand. It uses analytical forecasting, inventory control, and logistics optimization to maximize SC effectiveness and enhance performance.

Experimental setup:
An HP brand system with an Intel Core i9-12900 processor, an Intel Core i7-13700 CPU type, 3.50 GHz clock speed, 64 GB RAM, Windows 11 Home operating system, Python version 3.10.0, and a 16 MB L3 cache size is described along with the hardware and software components of the computer.

3.2 Data cleaning

On the SC dataset, data cleaning must go through several processes to guarantee that the data is precise and reliable. Initially, it was decided to remove completely the affected rows or to apply some imputation techniques to complete the missing data. Then search and correct the inconsistencies with the order format, supplier details, or names. Remove duplicates to prevent unbalanced analysis. Date formats should be standardized, and numeric data types should be accurate for consistency. Finally, the integrity of the data is ensured through crosschecking with established benchmarks or company standards to ensure the overall quality of the dataset.
Eliminating duplicate or anomalous data points, checking unique entries using Euclidean distance Algorithms, and data correction improves data by avoiding redundancy, and guaranteeing the integrity of sensor data quality and stability. Duplicates are entries in sensor data that have the same attributes, such as from Multiple IoT sensors that simultaneously record the environmental variables.

- **Identifying duplicates**

The process involves comparing every entry to find a duplicate through an exact match is represents eq.1.

$$Duplicate(i,j) = \begin{cases} 1 & if\ xi = xj \\ 0 & otherwise \end{cases} \quad (1)$$

To achieve near matching, it is recommended to use a distance measure, such as Euclidean distance, for slightly different entries in eq.2.

$$d(xi, xj) = \sqrt{\sum_{k=1}^{n} n(xik - xjk)} \quad (2)$$

In this context, xi and xj represent the i^{th}- and j^{th} entries in the dataset, $Duplicate(i,j)$ indicates whether these entries are duplicates (1 for exact match, 0 otherwise), $d(xi, xj)$ measures the Euclidean distance between them, n is the total number of features, and xik and xjkdenote the values of the k^{th}feature for the respective entries.

- Removing duplicates

The process of removing duplicates (eq.3) involves keeping unique entries by only retaining the first occurrence of each duplicate.

$$Cleaned\ Dataset = \{xi \mid xi\ is\ unique\ in\ D\} \quad (3)$$

- Verifying the Cleaning Procedure

The original and cleaned sensor data sizes were compared to determine the number of duplicates removed using the Verification in eq.4.

$$Reduction\ Ratio = \frac{|D|-|C|}{|D|} \times 100 \quad (4)$$

Where$|\ C\ |$ represents the cleaned size and$|\ D\ |$denotes the original size.

3.3 Min-Max normalization

Min-max normalization is a technique for normalizing that involves linearly transforming the initial data to create an equilibrium of value comparisons before and after the process. This approach could use the following Equation (5).

$$Y_{new} = \frac{Y - min\ (Y)}{max\ (Y) - min\ (Y)} \quad (5)$$

Where,
Y-Old value,
Y_{new}- The new value obtained from the normalized outcome,
$min\ (Y)$–Minimum value in the collection,
$max\ (Y)$–Maximum value in the collection.

3.4 Outlier detection and removal

Outliers can degrade the efficiency of machine learning models by distorting statistical relationships among features. To eliminate outliers, we employ Z-score evaluation, which determines how far each data point deviates from the mean in standard deviations. A Z-score greater than 3 or less than -3 denotes an outlier that should be eliminated. The Z-score is determined as equation 6:

$$Z = \frac{X-\mu}{\sigma} \quad (6)$$

where X is the data point, μ is the mean of the attribute, and σ is the standard deviation.

3.5 Data transformation using z-score normalization

Data transformation is a process that standardizes the sensor data to ensure the comparability across characteristics as well as reduce biases. Z-score normalization is a technique that centres every feature around a zero mean along with scales it by standard deviation, limiting the influence of outliers and ensuring all characteristics contribute equally to the study. This method improves the accuracy and reliability of study results by removing scale-related biases and enabling assessment across multiple subjects. As a result, it provides a more detailed and reliable examination of sensor data. This approach, which normalizes all input data to a single scale with 0 as the average and 1 as the standard deviation (SD), is amongst the most often used normalization procedures. For each satellite feature, the mean and SD are considered. The computed SD and mean have been standardized using it. Eq.7 provides the transformation of time series in sensor data quality.

$$Z = \frac{(y - mean(Y))}{std(Y)} \quad (7)$$

Here is the attribute's SD and the attribute Z's mean. The fact that this strategy reduces the impact of outliers on the sensor data is what makes it beneficial. $y$represents an individual observation of the attribute, $mean\ (Y)$ denotes the average of the data, $and\ std(Y)$ is the standard deviation of the IOT.

Z-score normalisation is a method that uses concepts like mean and standard deviation to provide normalised values or a range of data from the original unstructured data. Thus, the z-score parameter can be used to normalise the unstructured data using the following formulas 8:

$$v_j^1 = \frac{v_j - E}{std(E)} \quad (8)$$

Where,

v_j^1 is Z-score normalized one values.

v_j is value of the row E of ith column

$$Std(E) = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^{n} \left(v_j - E\right)^2} \quad (9)$$

The variables or columns that are "n" in each of the five rows—X, Y, Z, U, and V—are different. Therefore, the normalised ones can be calculated using the zscore technique in each of the rows above. All values for a row are set to zero if, for example, the standard deviation of that row is 0 and all of its values are identical. Similar to Min-Max normalisation, the z-score provides the 0–1 value range.

3.6 Refined battle royale optimizer weighted random forest (RBR-WRF)

An innovative approach known as RBR-WRF is employed to enhance the SC for logistics by accurately predicting the demand volume. This novel approach incorporates the power of the weighted random forest algorithm with the ability of the Battle Royale to optimize demand forecast. In SC management, the volume of demand becomes very important since it determines the inventory and overall expenses for services to be provided. The optimization method of the BRO is to achieve competition to increase the accuracy of the model’s parameters, while the RBRO-WRF predicts based on historical data and several parameters.

The random forest algorithm's weighted component used to build this model takes into the differing importance of characteristics, where major predictors will have more weights of impact on the predicting results. This combined approach helps in improving decision-making for logistics activities and, helps to improve the forecast demand for the particular items. By employing the RBR-WRF approach, companies could improve the results of the SC flexibility, adaptability and consequently increase the companies' productivity and client satisfaction. This approach is one of the potential options for companies that plan to improve their logistic processes by relying on sophisticated demand forecasting techniques.

- Weighted Random Forest prioritizes trees based on their performance makes better predictors contribute more to the final outcome of SC Logistics.
- Combining this with the competitive nature of a Refined battle royale structure improves overall predictive performance.
- WRF adjusts the contribution of each tree based on their performance, ensuring that week trees have minimal impacts. This weighted approach leads to better generalization on unseen data.
- The RBR-WRF process can filter out noise by over fitting trees. Trees that are overly sensitive to noise are less likely to survive or receive significant weighting.
- The suggested model is inherently scalable to large datasets and can be designed to operate in parallel, making it efficient for high-dimensional data or large dataset.

3.6.1 Weighted random forest

The decision tree node division technique uses an adaptive parameter selection approach to increase the system's categorization accuracy.

Although the properties change, choosing alternative node-splitting strategies for the same data set also produce distinct decision trees. The result is that random forest categorization has a different accuracy. To create a new splitting rule that is used for choosing and splitting of node characteristics, it is suggested that a decision tree be chosen, with the best feature chosen to split the nodes. The node splitting method is divided into a linear combination. The Gini index and the information gain that is achieved when the sample set C is divided using features are displayed, employing the node splitting formula 10 and 11.

$$Gain(C, b) = Ent(C) - \sum_{u=1}^{U} \frac{|C^u|}{|C|} Ent(C^u) \quad (10)$$

$$Gini(C, b) = \sum_{u=1}^{U} \frac{|C^u|}{|C|} Gini(C^u) \quad (11)$$

Where C^u denotes that every sample in the C with a value of b^u on a feature b is found in the u branch node.

$$Ent(C) = -\sum_{l=1}^{|z|} o_l log_2 o_l \quad (12)$$

$$Gini(C) = \sum_{l=1}^{|z|} \sum_{l' \neq l}^{|Z|} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \quad (13)$$

The adaptive parameter selection procedure and combination node splitting formula are as follows. The idea behind node splitting is to attempt an increased purity of the data set after splitting in equation 14.

$$G = \min_{\alpha,\beta \in Q} E\{C,b\} = \alpha Gini(C,b) - \beta Gain(C,a)$$
$$s.t.\begin{cases} \alpha+\beta = 1 \\ 0 \le \alpha,\beta, \le 1 \end{cases} \quad (14)$$

Where, α, β stands for the characteristic's splitting weight coefficient. In the meantime, G has a very low value. The procedure of adaptive parameter choice is utilized to obtain the ideal combination of parameters.

The accuracy rate and categorization error rate are utilized in the study to evaluate efficiency. Equation (15) defines the sample C categorization error rate.

$$F(e;C) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{II}\left(e(w_j) \neq z_j\right) \quad (15)$$

Equation (16) defines the accuracy percentage.

$$acc(e;C)\frac{1}{n}\sum_{j=1}^{n} II\left(e(w_j) = z_j\right) = 1 - 1F(e;C) \quad (16)$$

3.4.2 Refined battle royale (RBR)

Refined Battle Royale optimization (BRO) method incorporates a powerful bootstrap process to enhance population variety. Elite players $(W_f)$and ordinary players (W_p) are the two groupings into the system separates the player population. Elite players include top 20% of players in the population with high fitness scores; the remaining players are ordinary players.

A novel distance calculation approach, represented by the Euclidean distance value (K) between the individual location and the solution space center location, is presented alongside an update of the selection process for adjacent players, displayed in Equation (17). The BRO approach resolves the issues of significant computational complexity and extended execution duration.

$$K^s = \sqrt{\sum_{C=1}^{m}\left(W_{j,C}^s - D_C^s\right)^2} \quad (17)$$

Where,

j - Individuals, and

$W_{j,C}^s$ - Position of the individual,

C – Dimensions, and

D_C^s - Center of the solution space, as indicated by Equation (18).

$$D_C^s = \frac{(ub_C - lb_C)}{2} \quad (18)$$

Adjacent player $\left(W_j^s,\ W_i^s\right)$ is selected from the two individuals who have the closest K ratings. Players are classified as winners or losers based on their fitness values; those with low fitness values are considered losers. Equal opportunities for updating, will be provided for both winners and losers. For modifications on player location, a well-balanced learning technique is created. Equations (19 and 20) display the position modification of the winners and losers. The low convergence accuracy and single-way player update issues with the BRO method are resolved by this technique. The winners who are considered elite players are updated to get global optimal location data $\left(W_{H_{best}}\right)$. The remaining winners utilize the data of these elite players to shift in the radius (T_K).The winner can investigate the details around the individual location in addition to swiftly moving to the $\left(W_{H_{best}}\right)$. Fast multidirectional optimization is achieved. Using $\left(W_{H_{best}}\right)$as a shifting target and individual previous optimal location data $\left(W_{O_{best}}\right)$, the losers of the elite players are modified when the damage degree. The rest of the losers must stay away from their winners to look for other excellent locations.

$$W_x^{s+1} = \begin{cases} W_x^s + \alpha_1\left(W_{H_{best}} - W_x^s\right), W_x^s \in W_f \\ W_x^s + \alpha_2\left(W_{j,f}^s - W_x^s - T_K\right), W_x^s \in W_p \end{cases} \quad (19)$$

$$W_v^{s+1} = \begin{cases} W_v^s + \alpha_3\left(W_{H_{best}} - W_v^s\right) + \alpha_4 \\ \left(W_{O_{best}} - W_v^s\right), W_v^s \in W_f \\ W_v^s + \alpha_5\left(W_{j,f}^s - W_v^s\right) + \\ \delta.\alpha_6(W_n^s - W_v^s), W_v^s \in W_p \end{cases} \quad (20)$$

The random numbers in $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, and\ \alpha_6$ range from 0 to 1. The elite player's location is indicated by $W_{j,f}^s$. W_n^s represent a random individual's location data. With the v^{th} loser, $W_{v,x}^s$ represents the winner's data. Equation (21) indicates that (T_K) is the radius that ordinary players in the winner examined. According to Equation (22), δ represents the modified step size for losers in the ordinary players. Random exploration in the initial stages and elite placement in the later stages enable the quick convergence procedure.

$$T_K = \frac{ub_C - lb_C}{M} \quad (21)$$

$$\delta = 1 + \cos\left(\frac{\pi s}{S}\right) \quad (22)$$

The Big O notation (O) is used to characterize the time complexity of the RBR and BRO methods to calculate time consumption.Calculating the Euclidean distance between the two outcomes $O(M^2 \times S \times C)$, updating individual positions $(O(2M \times S \times C))$, and population initialization $(O(2M \times C))$ all contribute to the time complexity of the BRO method.The population initialization $O(2M \times C)$, center distance computation $O(M \times S \times C)$, and individual position update $O(2M \times S \times C)$ are included in the time complexity of the RBR method, as indicated by Equations (23&24).

$P(BRO) = O(2M \times C) + O(M^2 \times S \times C) + P(2M \times S \times C)$(23)

$P(RBR) = O(2M \times C) + O(M \times S \times C) + P(2M \times S \times C)$ (24)

A lower time complexity for the RBR approach than the BRO approach is indicated by $M > 1$, which means that $O(M \times S \times C)$ is substantially smaller than $O(M^2 \times S \times C)$.

The RBR algorithm finds a positive integer to represent the candidate's ideal results and grows an FF to achieve a higher classifier effectiveness. In this case, FF improves scalability and convergence and correlates to a lower classifier error rate as shown in equation 25.

$fitness(xi) = ClassifierErrorRate(xi)$ (25)

$= No. of\ misclassified\ instances\ /$

$Total\ no. of\ instances \times 100.$

To improve replicability, Suggested method provide a step-by-step procedural walkthrough. Particularly, the adaptive parameter selection strategy, node splitting technique, and Euclidean distance-based player selection could

benefit from Algorithm 1.

Algorithm 1. Pseudocode of RBR-WRF algorithm.

1. Start
2. Initializing a Random population (xm), and every parameter;
3. $Shrink = ceil(Iog10(Pmax))$;
4. $\Delta = round\ (Pmax\ /Shrink)$;
5. For $j = I$: Pmax Find the closest player $(xi\ p)$ by analyse the Euclidean distance;
6. $c = j; u = i$
7. $If\ f(yj\ p) < f(yi\ p)$
8. $c = i; u = j;$
9. End if
10. If $Xd, dam\ p < thre$
11. Upgrade the damage level and the location of the loser;
12. Else
13. The loser respawns in the present safer region;
14. $yd, damp = 0$
15. End if
16. Re-evaluate the fitness value of $yj\ p$;
17. yu,$damp$ = 0;
18. If p ≥ Δ Upgrade ub_e and Ib_b;
19. Upgrade the threshold (Δ) ;
20. End if
21. If Ib_e/ub_e exceeds the Lower or upper limits of the solution space, then set to the original ub_e and Ib_e;
22. Record the better individual and the fitness value.
23. End

4 Result

The suggested approach was executed with Python 3.11 on a Windows 11 laptop with an Intel i5 core processor and 12GB of RAM.The proposed RBR-WRF approach is compared to other approaches, such as Back Propagation Neural Network (BPNN) [18], and Genetic Algorithm - Back Propagation Neural Net (GA-BPNN) [18].

The actual number of customer demand values and the corresponding anticipated values using the RBR-WRF model are given in Figure 1 for the actual values over five weeks and the projected values to be measured against the anticipated volumes. Every record also demonstrates disparities in terms of accuracy by revealing the actual demand and the expected demand. For instance, in Week 4, the accuracy estimate is 700 units against the actual 680 units and the forecast of 500 units during Week 1 differs slightly from the actual demand of 520 units.

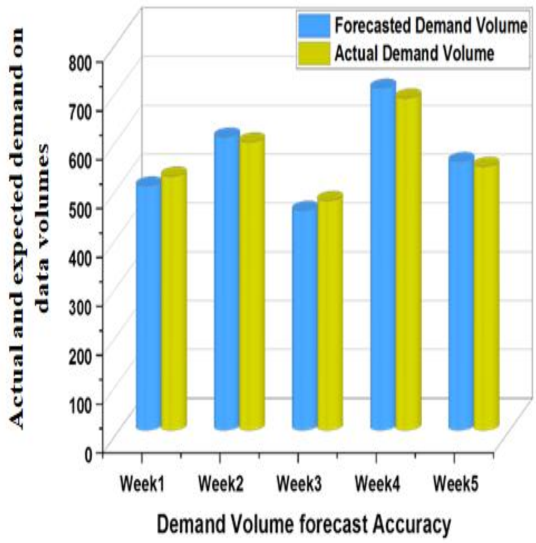

Figure 1: Output of demand volume forecast accuracy

Evaluation metrics:

The MSE averages all of the predictions in this way. It draws attention to bigger mistakes, which may be important in situations where big mistakes are more harmful, like financial predictions. When there are outliers in the data, MSR and RMSE can be avoided. Larger mistakes brought on by outliers are penalised. MAPE provides a scale-independent view of the error, in contrast to MAE or MSE/RMSE, which are scale-dependent and impacted by the size of the data. Because of this, it is particularly useful for evaluating how well models function across datasets with various sizes or units.

4.1 MSE

The MSE is a significant predictive measure used to gauge the reliability of the demand volume forecasts within the logistic SC management. It estimates the expected AS difference between the demand as anticipated and the actual demand, a useful approach to managing stock and costs. The suggested RBR-WRF approach has an MSE value of 0.00324 when compared to the traditionalBPNN, and GA-BPNN approaches, which have MSE values of 0.00407, and 0.00461, respectively as shown in Figure 2.

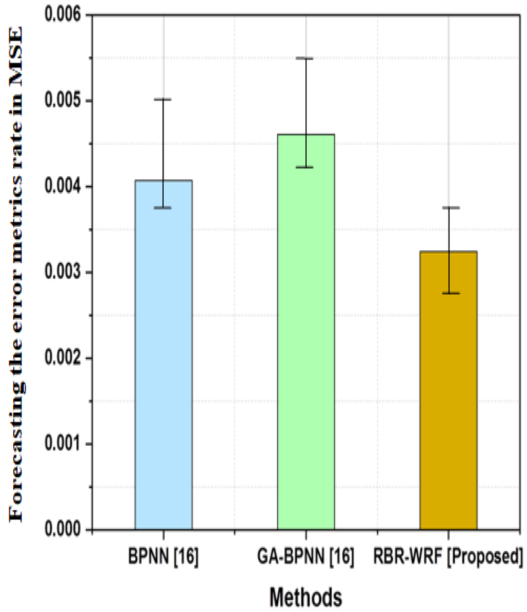

Figure 2: Result of MSE

4.2 MAE

The MAE quantifies the average size of errors in the anticipated demand volume for products within structural logistic SCs. It determines the difference between forecasted and actual results, providing insights into the accuracy of forecasts and supporting better SC decisions and actions. Compared to the conventional BPNN and GA-BPNN techniques, which have MAE values of 0.05616 and 0.05291, thesuggested RBR-WRF strategy has an MAE value of 0.04315, which is displayed in Figure 3.

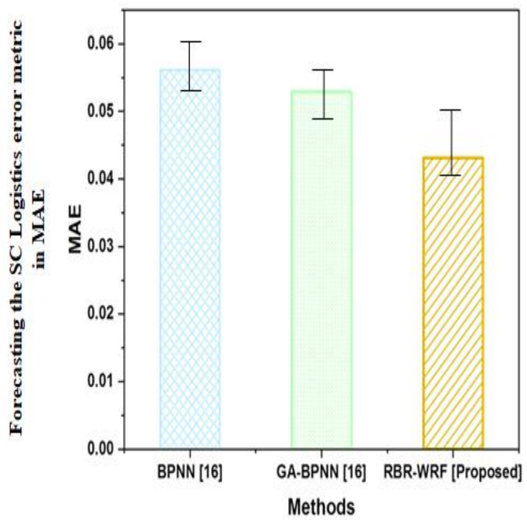

Figure 3: Output of MAE

4.3 RMSE

RMSE computes the square root of the AS variations between anticipated and observed values, and its results provide a perspective about the average size of the forecasting errors. When compared with traditional BPNN and GA-BPNN approaches, the suggested RBR-WRF approach has an RMSE value of 0.05412, whereas the traditional BPNN and GA-BPNN methods have high RMSE values of 0.06378 and 0.06792. This shows the RBR-WRF method is more significant, which is displayed in Figure 4.

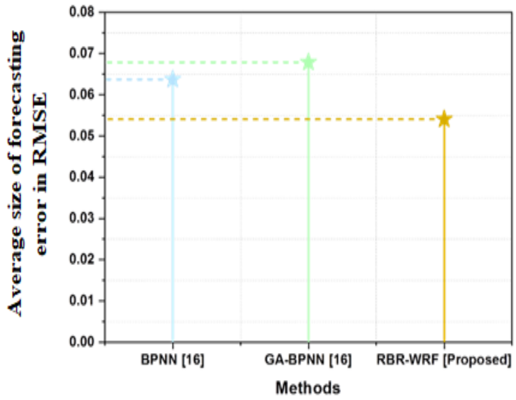

Figure 4: Result of RMSE

4.4 MAPE

The MAPE calculates an average of the absolute percentages of the errors among the actual and anticipated demand values, and it is used by enterprises to improve the management of inventories to improve the standards of service delivery.In contrast to the conventional BPNN and GA-BPNN techniques, the proposed RBR-WRF strategy has a MAPE value of 3.41%, while the MAPE values of the conventional BPNN and GA-BPNN approaches are 5.53% and 4.08%, which is shown in Figure 5.

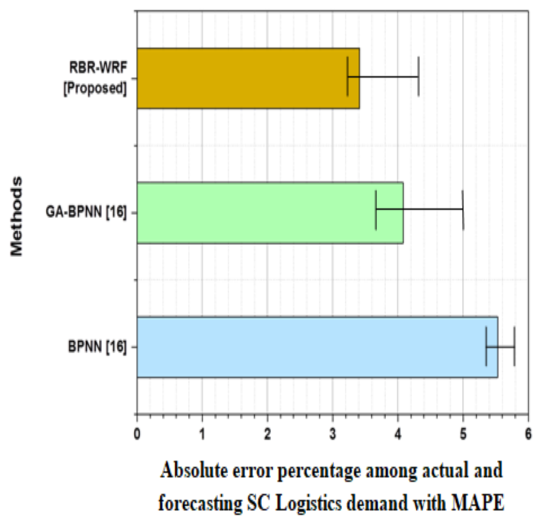

Figure 5: Output of MAPE

The formula to determine the t-statistic is: $t = x - \mu / s / \sqrt{n}$ Here, s is the sample standard deviation. The better understanding of the suggested model t-test. Actual demand and expected demand for stated that the average Unit for per month is 12,000. When the mean was 13,105 and the standard deviation was 1638.4**.**

The hypothesis for this case will be:
Ho: μ = There is no significant difference in the performance before and after implementation IOT/ML
H1: μ ≠ There is a significant improvement in the performance after implementation IOT/ML

$t = (x - \mu) / (s/\sqrt{n})$

$= (13105 - 12000) / (1638.4/\sqrt{25}) = 1105/327.68 = 3.37$

4.5 Discussion

Table 2: Comparison of LSTM, GA-BPNN and Suggested method RBR-WRF

Features	**LSTM**	**GA-BPNN**	**RBR-WRF**
Data Dependency	Sequential/Time series	Static	Static (can also handle some imbalance data)
Learning paradigm	Deep learning	Deep learning	Ensemble Learning
Computational complexity	High	Moderate	Moderate
Performance	Best for temporal data	general task	Classification on robust on imbalanced data
Scalability	High (small data)	Moderate	High
Interpretability	Low	low	High

5 Conclusion

The effectiveness of SC logistics is crucial to a company's accomplishment in the modern highly competitive and associated the global marketplace. In this study, a novel RBR-WRF technique is introduced for improving SC efficiency by anticipating demand volume. The data was obtained from the Kaggle platform. The suggested approach's performance is measured in terms of MSE (0.00324), MAPE (3.41%), RMSE (0.05412), and MAE (0.04315). It may affect logistics performance because there is always overfitting due to the complex relations and sparsity in the SC data, high processing resource demands, and problems with generalizing the forecasts across different demand patterns and SC characteristics.Future studies could focus on developing more effective algorithms, integrating framework styles, enhancing the utilizing of computational resources, and improving the methods of generalization to enhance the precision of predictions in an environment of SC logistics. For additional research, provide a general framework that can be adjusted to various supply chain scenarios and train models that generalise across scenarios using meta-learning.

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