Enhancing International Logistics and Supply Chain Management: Deep Learning Strategies for Enhanced Route Planning and Warehouse Optimization

[1]Shiyu Tian and [2]Jianghua Luo
[1,2]Business School, Marketing, Edutus Egyetem, Budapest, Hungary
[1]t18119732315@163.com

Correspondence should be addressed to Shiyu Tian : t18119732315@163.com

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Abstract – Logistics and Supply Chain Management (SCM) are both key areas in modern industry and commerce which need better route planning and warehouse optimization. Traditional methods that are in practice have often fall short in of addressing the dynamic complexities of modern logistics which results in inefficient travel times, fuel consumption, and space utilization. To counter these limitations this study introduces an integrated model that combines Long Short-Term Memory (LSTM) networks, Radial Basis Function Neural Networks (RBNN), and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for route planning and warehouse optimization. The proposed model employ LSTM to predict traffic patterns and RBNN to optimize space utilization in warehouse. The NSGA-II model is then utilized for multi-objective optimization of minimizing travel times and maximizing warehouse space utilization. In experiment analysis the proposed model achieved the highest accuracy and least variability in predictions, with mean MAE, RMSE, and MAPE values of 0.57, 1.12, and 5.9%, respectively.

Keywords – Supply Chain Management, LSTM, Radial Basis Function Neural Networks, Machine Learning, MAE, RMSE and MAPE.

I. INTRODUCTION

Logistics and Supply Chain Management (SCM) are always considered to be the critical components in global trade and commerce as these components ensure the efficient movement of goods from producers to consumers [1-3]. The complexities that are related to manage these operations have increased along with the tremendous growth in global trade volumes [4-5]. One of the key challenges in logistics is optimizing the transport network in terms of route planning for transportation and effective utilization of warehouse space [6-7]. Traditional methods that have been employed in managing the logistics have often based on methods like heuristic or rule-based approaches. Such approaches lack the ability to address the dynamic and complex nature of modern logistics systems [8-9]. The major problem in logistics management is that one is the need to minimize the travel time and fuel consumption across multiple routes and another is to maximize the warehouse space utilization [10]. In current practice the route planning is done using the static models that do not account for real-time changes in traffic conditions or weather [11-12]. Similarly, the warehouse management systems employ algorithms that fail to optimize space utilization dynamically based on changing inventory levels and item characteristics [13].

The solutions employed for logistics optimization typically involve linear programming, heuristic methods, and basic Machine Learning (ML) models. While these methods have brought some improvements, they exhibit significant limitations [14-15]. Linear programming approaches are rigid and may not handle the dynamic nature of logistics networks effectively [16]. Heuristic methods are though considered to be more flexible, often fail to find globally optimal solutions and are computationally intensive. Basic ML models like simple regression or decision trees provide predictive capabilities but fall in short of capturing the complex temporal and spatial relationships that are found inherent in logistics data [17-18].

To address these limitations this study proposes an integrated model that utilizes advanced Deep Learning (DL) and evolutionary optimization techniques. The model employs Long Short-Term Memory (LSTM) networks and Radial Basis Function Neural Networks (RBNN) to enhance the prediction and optimization processes. LSTMs that handle sequential data is used for predicting dynamic traffic patterns and travel times using both historical and real-time data. Whereas the RBNNs are used for optimizing warehouse space utilization based on current inventory layouts and item-specific requirements.

The proposed model integrates these DL techniques with the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for multi-objective optimization. NSGA-II is effective in managing conflicting objectives, such as minimizing travel times while maximizing warehouse space utilization. By combining LSTM and RBNN outputs with NSGA-II, the model dynamically optimize both route efficiency and warehouse management thereby addressing the logistical challenges. The model was evaluated using a dataset collected from a logistics company over a 3-year period. The dataset included route and traffic information, weather conditions, warehouse inventory levels, and operational parameters. The proposed model was compared for different metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). And the results have shown that the proposed model had shown better performance compared to other models.

The paper is organized as follows, Section 2 present the problem definition, Section 3 proposed the methodology, Section 4 analysis the findings and Section 5 concludes the work.

II. PROBLEM DEFINITION

The logistics network is defined with sets of routes (R), inventory items (I), and warehouse locations (W), along with time series data (T) for periodic assessments. The first objective is to minimize travel times and fuel consumption across all routes, EQU (1).

$$\text{Minimize } F_1 = \sum_{r\in R} \int_0^T f\left(V_{r,t}, C_{r,t}\right)dt \quad (1)$$

where $f\left(V_{r,t}, C_{r,t}\right)$ is a function modeling the travel time affected by traffic volume $\left(V_{r,t}\right)$ and weather conditions $\left(C_{r,t}\right)$. The second objective focuses on maximizing warehouse space utilization EQU (2).

$$\text{Maximize } F_2 = \sum_{w\in W} \left(\frac{\sum_{i\in I} u_{i,w,t} \cdot x_{i,t}}{s_{w,t}}\right) \quad (2)$$

where $u_{i,w,t}$ indicates the unit space required for storing item i in warehouse w at time t.

To integrate these objectives into a cohesive framework, a weighted sum approach is employed, where weights λ_1 and λ_2 represent the relative importance of each objective, EQU (3).

$$\text{Minimize } \Lambda = \lambda_1 \cdot F_1 - \lambda_2 \cdot F_2 \quad (3)$$

The weights λ_1 and λ_2 are fixed based on strategic priorities, translating the maximization of F_2 into a minimization problem by taking its negative. The **Table 1** presents the notations used in this article.

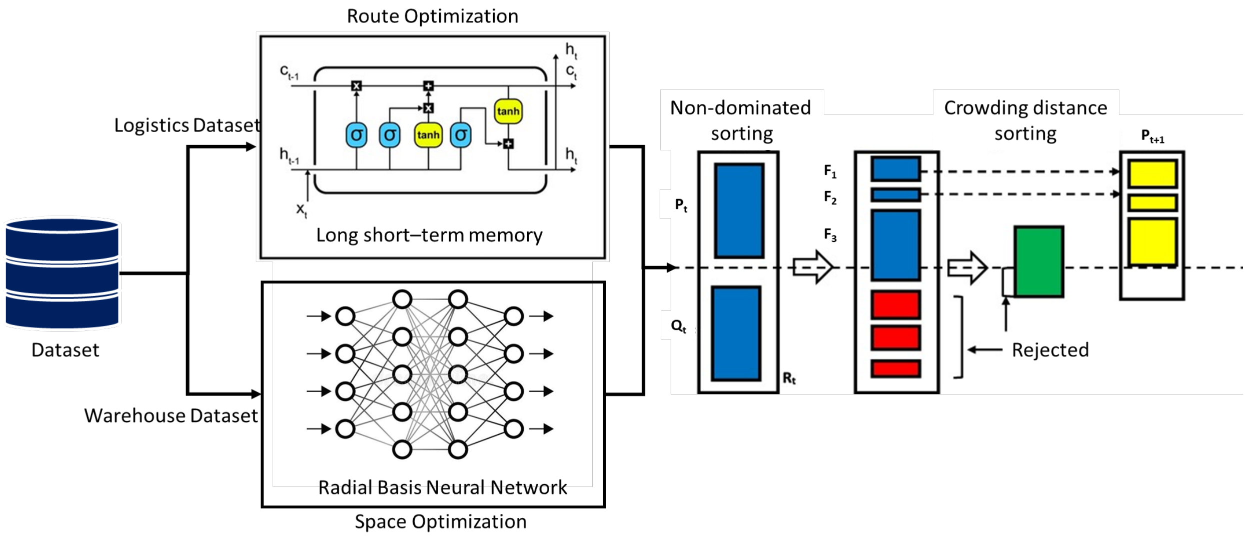

Fig 1. Model Architecture.

Table 1. Parameter Description

Notation	Description
R	Set of all routes in the logistics network
I	Set of all inventory items across warehouses
W	Set of all warehouse locations
T	Time series data for periodic assessments
F_1	Objective function to minimize travel time and fuel consumption
F_2	Objective function to maximize warehouse space utilization
$V_{r,t}$	Traffic volume on route r at time t
$C_{r,t}$	Weather conditions affecting route r at time t
$f(V_{r,t}, C_{r,t})$	Function modeling the travel time influenced by traffic and weather
$x_{i,t}$	Stock level of item i at time t
$u_{i,w,t}$	Unit space required for storing item i in warehouse w at time t
$S_{w,t}$	Available space in warehouse w at time t
λ_1, λ_2	Weights applied to the objectives in the weighted sum approach
Λ	Combined weighted objective function
W_f, b_f	Weights and biases for the forget gate of the LSTM
W_i, b_i	Weights and biases for the input gate of the LSTM
W_C, b_C	Weights and biases for creating candidate memory in the LSTM
W_o, b_o	Weights and biases for the output gate of the LSTM
f_t	Output of the forget gate at time t
i_t	Output of the input gate at time t
$\bar{C}_t$	Candidate memory state at time t
o_t	Output of the output gate at time t
h_t	Hidden state of the LSTM at time t used for predictions
C_t	Cell state of the LSTM at time t, represents long-term memory
y_{t+1}	Predicted output of the LSTM for the next time step

III. METHODOLOGY

The proposed optimization model for route planning and warehouse space utilization is presented in **Fig 1**. The LSTM networks and RBNN are implemented as two pipelines. In which the LSTMs process the sequential data for predicting and optimizing traffic patterns and travel times based on historical and real-time data. Concurrently, RBNNs are used to analyze and maximize warehouse space by handling the spatial distribution of inventory according to current layouts and inventory data. These tasks are integrated and simultaneously optimized using the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for multi-objective optimization by employing a weighted sum method that applies weights λ1 and λ2 to the objectives of minimizing route times and maximizing space utilization, respectively.

LSTM for Travel Optimization

The LSTM model receives structured input data streams, consisting of traffic volume $(V_{r,t})$, weather conditions ($C_{r,t}$), time of day, historical delays, and any planned events impacting traffic. The input data is normalized to scale the input features and one-hot encoding is employed for categorical data such as weather conditions. This step transforms raw data into a machine readable format, optimizing it for effective learning by the LSTM model. Within the LSTM architecture, the forget gate controls information flow by removing irrelevant past data to maintain model focus on current influential factors by using the EQU (4):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

Using the above equation it decide which information to discard. Concurrently, the input gate updates the cell state by incorporating new, relevant information through the EQU (5) and EQU (6):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \text{ and} \tag{5}$$

$$\tilde{C}_t = \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C), \tag{6}$$

Whuch directly influencing the model's next output. The output gate then determines the actual output of the LSTM using, EQU (7) and EQU (8),

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \text{ and } \tag{7}$$

$$h_t = o_t * \tanh(C_t), \tag{8}$$

which provides predictions on upcoming traffic conditions and potential delays. The final output of the LSTM, EQU (9).

$$y_{t+1} = \sigma(W \cdot [h_t, x_t] + b), \tag{9}$$

provides the estimated travel times for the next time step.

RBNN for Warehouse Space Optimization

RBNNs process defined inputs that include current inventory levels ($x_{i,t}$) for each item i at time t, the unit space required for each item $(u_{i,w,t})$, and the available space in each warehouse $(S_{w,t})$. The objective is to maximize the utilization of this space, ensuring efficient storage and accessibility for order fulfillment.

The RBNN receives the input vector comprising inventory levels, space requirements for each item, and additional warehouse operational data. It then employs the hidden Layer with Radial Basis Functions that uses radial basis functions, typically Gaussian, to transform the input space. The activation of a neuron j in the hidden layer is determined by, EQU (10)

$$\phi_j(x) = \exp\left(-\beta_j \|x - c_j\|^2\right) \tag{10}$$

Here, c_j denotes the center of the j-th neuron, β_j controls the width of the radial basis function, and x is the input vector. Next the output Layer compiles activations from the hidden layer to compute a scalar output estimating space utilization, EQU (11).

$$y = \sum_j w_j \phi_j(x) + b \tag{11}$$

w_j are weights linking the hidden layer to the output, $\phi_j(x)$ is the activation of the j-th hidden neuron, and b is a bias term. Training the RBNN involves adjusting the neuron centers c_j, spread parameters β_j, and weights w_j to align the predicted space utilization closely with actual utilization metrics.

NSGA-II for Multi-Objective Optimization in Logistics

NSGA-II begins with the generation of a random initial population P_0 where each individual represents a potential solution encoding logistics configurations, such as route choices and warehouse layouts.

This Population Undergoes Evaluation Against the Logistics Objectives, Which Are

Minimize Travel Time (F_1)

Aims to reduce the total travel time across all routes within the logistics network.

Maximize Warehouse Utilization (F_2)

Focuses on optimizing the use of available space in warehouses to ensure efficient storage.

Each solution is assessed based on how well it achieves these conflicting objectives, using a fitness function. NSGA-II employs tournament selection based on dominance (non-domination sorting) and diversity (crowded distance calculation). Next Simulated Binary Crossover (SBX) is employed for the Crossover operation, which depends on a probability p_c and a distribution index η_c. This operator helps explore new solution spaces by combining parts of two parent solutions. Mutation is induced using a polynomial mutation, defined by a probability p_m and a distribution index η_m, enhancing the genetic diversity within the population. Each new solutions are evaluated against the logistics objectives F_1 and F_2. Each individual is then ranked based on non-domination, Front 1, Front 2, ... are determined by non-dominated sorting, where individuals in Front 1 are those that no other individual dominates. Solutions that are not dominated by any other are placed on the first front, considered the best solutions under current genetic diversity. Within each front, the crowding distance is calculated to estimate the density of solutions surrounding a particular individual, EQU (12).

$$d_i = d_{i+1} - d_{i-1} \tag{12}$$

where d_i is the crowding distance for the i-th individual. This measure helps in preserving solution diversity by maintaining a spread of solutions across the objective space. The next generation is populated starting with individuals from the lowest-ranked nondominated front (Front 1) and moving to higher fronts. If a front cannot fully fit into the next generation, individuals from that front are selected based on their crowding distances, ensuring that only the most diverse solutions are carried forward. This process repeats over multiple generations. In each cycle, NSGA-II refines the solutions, continuously pushing towards an optimal Pareto front where no single objective can be improved without degrading another. The algorithm stops when it reaches a specified number of generations or when the improvements between generations fall below a minimal threshold.

Algorithm: Integrated Optimization for Logistics Using LSTM, RBNN, and NSGA-II

Input:
- Historical and real-time traffic data
- Inventory levels and warehouse layout data
- Initial logistics configurations

Output:
- Optimized route plans
- Optimized warehouse space utilization
- Pareto-optimal solutions balancing travel time and space utilization

Procedure:

1 **Initialize Models:**
- **LSTM:** Load and initialize LSTM with pre-trained weights for predicting travel times based on traffic and weather data.
- **RBNN:** Initialize RBNN for optimizing warehouse space utilization using current inventory and warehouse layout data.
- **NSGA-II:** Initialize NSGA-II with a population size N of potential logistics configurations.

2 **Data Preprocessing:**
- Normalize and preprocess traffic and weather data for LSTM input.
- Scale and encode warehouse data for RBNN input.

3 **Run Predictive Models:**
- **LSTM Processing:**
  - **For Each** route r and time t, compute travel times using LSTM: TravelTime $r, t =$ LSTM(TrafficData $_{r,t}$, WeatherData $_{r,t}$).
- **RBNN Processing:**
  - **For Each** warehouse w and time t, compute space utilization using RBNN: SpaceUtilization $_{w,t} =$ RBNN(InventoryData $_{w,t}$, LayoutData $_{w,t}$)

4 **Set Objectives for NSGA-II:**
- Define the fitness functions based on outputs from LSTM and RBNN:
  - $F_1(r, t) =$ Minimize TravelTime $_{r,t}$
  - $F_2(w, t) =$ Maximize SpaceUtilization $_{w,t}$

5 **Optimize with NSGA-II:**
- Perform non-dominated sorting of the initial population based on F_1 and F_2.
- Calculate crowding distance for diversity preservation.
- **Selection:** Use tournament selection based on dominance and crowding distance.
- **Crossover and Mutation:** Apply genetic operators to generate new offspring.
- Update population based on elitism and generate the next generation.

6 **Iteration:**
- Repeat the optimization steps in NSGA-II until a termination criterion is met (*e.g.,* maximum number of generations or stability of the Pareto front).

7 **Output Results:**
- Extract and present Pareto-optimal solutions for route planning and warehouse space utilization.
- Implement the best solutions in real-world logistics operations based on decision-maker preferences and operational constraints.

IV. EXPERIMENT

Data Sources

This study utilizes a dataset sourced from a single logistics company over a period from January 2020 to December 2022. This dataset includes: Route and Traffic Data, which captures GPS tracking information detailing routes, speeds, and stop durations, with traffic conditions recorded at 15-minute intervals; Weather Data, linked to specific routes, including parameters such as temperature, precipitation, and wind conditions; Warehouse Data, from the company's inventory management system, providing details on inventory levels, item dimensions, storage duration, and warehouse space configurations; Operational Data, which includes fuel consumption rates, vehicle maintenance records, and driver schedules. The data variable of all data are presented in **Table 2** to **5**.

Table 2. Route and Traffic Data Variables

Variable Name	Data Type	Description
Date	Date	The specific day on which the route and traffic data was recorded.
Time	Time	The time of day when the data point was recorded.
Vehicle ID	String	Identifier for the vehicle from which the data was collected.
Route ID	String	Identifier for the specific route the vehicle was following.
Latitude	Float	Geographic latitude coordinate where the data was recorded.
Longitude	Float	Geographic longitude coordinate where the data was recorded.
Speed (km/h)	Float	The speed of the vehicle at the time of data recording.
Stop Duration (min)	Integer	Duration the vehicle was stopped, measured in minutes.
Traffic Level	String	Qualitative assessment of traffic conditions (e.g., Low, Moderate, High), affecting the route.

Table 3. Weather Data Variables

Variable Name	Data Type	Description
Date	Date	The specific day on which the weather data was recorded.
Time	Time	The time of day when the weather data was recorded.
Route ID	String	Identifier for the specific route affected by the weather.
Temperature (°C)	Float	The ambient temperature recorded at the time of logging.
Precipitation (mm)	Float	The amount of rainfall or precipitation recorded.
Wind Speed (km/h)	Float	The speed of the wind affecting the route conditions.
Weather Condition	String	A qualitative description of the weather (e.g., Clear, Partly Cloudy, Rainy).

Table 4. Warehouse Data Variables

Variable Name	Data Type	Description
Date	Date	The specific day on which the warehouse data was recorded.
Time	Time	The time of day when the data point was recorded.
Warehouse ID	String	Identifier for the specific warehouse where the data was collected.
Inventory Item ID	String	Identifier for the specific inventory item.
Quantity	Integer	Quantity of the inventory item in stock at the time of recording.
Item Dimensions (cm)	String	Dimensions of the item, typically in length x width x height format.
Storage Duration (days)	Integer	Duration for which the item has been stored in the warehouse.
Warehouse Space (m^2)	Float	Total available space in the warehouse at the time of recording.
Utilization (%)	Float	Percentage of warehouse space utilized at the time of recording.

Table 5. Operational Data Variables

Variable Name	Data Type	Description
Date	Date	The specific day on which the operational data was recorded.
Time	Time	The time of day when the data point was recorded.
Vehicle ID	String	Identifier for the vehicle relevant to the operational data.
Fuel Consumption (L)	Float	Amount of fuel consumed by the vehicle during operations, measured in liters.
Maintenance Status	String	Describes the maintenance condition of the vehicle (e.g., Good, Needs Repair).
Driver ID	String	Identifier for the driver operating the vehicle.
Shift Duration (hrs)	Integer	Duration of the driver's shift on the day of recording, measured in hours.
Route Efficiency (%)	Float	Percentage representing the efficiency of the route taken by the vehicle.

Training the Proposed LSTM, RBNN, and NSGA-II Models
The data is split into training and testing sets following an 80:20 ratio. Using the training set the LSTM model, the RBNN model and the NSGA-II models are trained using the hyperparameters listed in **Table 6**.

Table 6. Key Training Parameters and Their Respective Values

Parameter	LSTM	RBNN	NSGA-II
Learning Rate	0.01	0.02	N/A
Epochs	50	50	200 generations
Batch Size	32	16	N/A
Optimizer	Adam	Adam	N/A
Loss Function	MSE	MSE	Custom
Validation Split	20%	20%	N/A
Activation Function	ReLU (output: sigmoid)	Gaussian	N/A
Population Size (NSGA-II)	N/A	N/A	100
Mutation Rate (NSGA-II)	N/A	N/A	0.1
Crossover Rate (NSGA-II)	N/A	N/A	0.9

Evaluation Metrics
The Models are Evaluated Using The Following Metrics
Mean Absolute Error (MAE)
The MAE measures the average magnitude of errors in the predictions, EQU (13)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{13}$$

where, n is the number of observations, y_i is the actual value, $\hat{y}_i$ is the predicted value

Root Mean Square Error (RMSE)
The RMSE evaluates the standard deviation of prediction errors, EQU (14)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{14}$$

where, n is the number of observations, y_i is the actual value, $\hat{y}_i$ is the predicted value

Mean Absolute Percentage Error (MAPE)
The MAPE expresses the prediction accuracy as a percentage, EQU (15)

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{15}$$

where, n is the number of observations, y_i is the actual value, $\hat{y}_i$ is the predicted value

Route Efficiency (RE) (%)
RE measures the percentage of routes optimized for travel time and fuel consumption, EQU (16)

$$\text{Route Efficiency (\%)} = \left(1 - \frac{\text{Actual Travel Time}}{\text{Optimal Travel Time}}\right) \times 100\% \tag{16}$$

Space Utilization Efficiency (SUE) (%)
SUE measures the percentage of available warehouse space that is effectively utilized, EQU (17).

$$\text{Space Utilization Efficiency (\%)} = \left(\frac{\text{Total Used Space}}{\text{Total Available Space}}\right) \times 100\% \tag{17}$$

To evaluate the effectiveness of the integrated LSTM+RBNN+NSGA-II model, we compare its performance with the models such as LSTM, RBNN, LSTN+RBNN

Table 7. MAE Results Comparison

Model	Min MAE	Max MAE	Mean MAE	Std MAE
LSTM	0.42	1.28	0.75	0.22
RBNN	0.53	1.47	0.89	0.27
LSTM + RBNN	0.38	1.12	0.68	0.19
LSTM + RBNN + NSGA-II	0.31	0.98	0.57	0.16

Table 8. RMSE Results Comparison

Model	Min RMSE	Max RMSE	Mean RMSE	Std RMSE
LSTM	0.83	2.77	1.49	0.45
RBNN	1.12	3.05	1.82	0.52
LSTM + RBNN	0.79	2.53	1.34	0.40
LSTM + RBNN + NSGA-II	0.67	2.22	1.12	0.37

Table 9. MAPE Results Comparison

Model	Min MAPE (%)	Max MAPE (%)	Mean MAPE (%)	Std MAPE (%)
LSTM	4.3	12.5	7.6	2.3
RBNN	5.1	14.3	8.8	2.7
LSTM + RBNN	3.8	10.6	6.5	2.0
LSTM + RBNN + NSGA-II	3.1	9.7	5.9	1.8

The performance of the models was evaluated using MAE, RMSE, and MAPE. The results as shown in **Fig 2**.

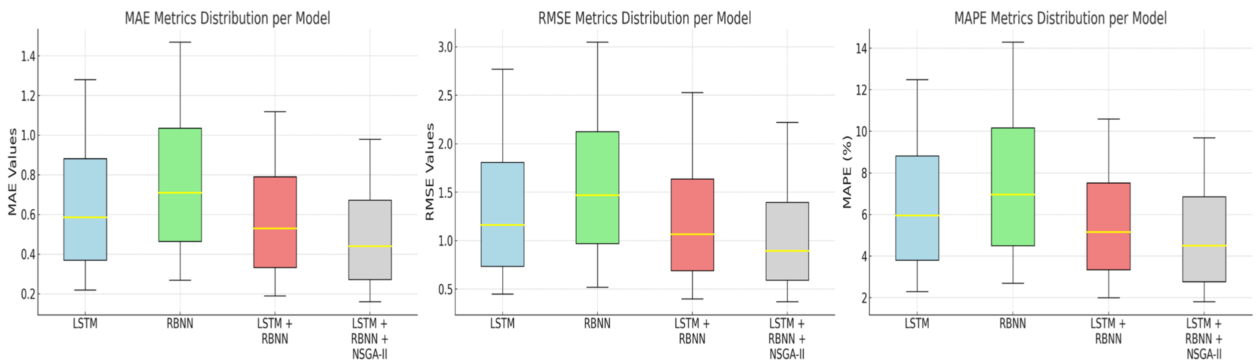

Fig 2. MAE, RMSE and MAPE Result Comparison.

For MAE as shown in **Table 7** the LSTM model showed moderate prediction accuracy with a mean MAE of 0.75 and a standard deviation of 0.22, indicating some variability. The RBNN model exhibited higher errors and variability, with a mean MAE of 0.89 and a standard deviation of 0.27. Combining LSTM and RBNN reduced the errors, resulting in a mean MAE of 0.68 and a standard deviation of 0.19, suggesting improved performance and consistency. The proposed LSTM+RBNN+NSGA-II model achieved the best results with a mean MAE of 0.57 and a standard deviation of 0.16. For RMSE as shown in **Table 8**, the LSTM model had a mean RMSE of 1.49 and a standard deviation of 0.45, reflecting moderate prediction errors. The RBNN model showed higher errors with a mean RMSE of 1.82 and a standard deviation of 0.52. The combined LSTM+RBNN model improved the mean RMSE to 1.34 and reduced the standard deviation to 0.40. The LSTM+RBNN+NSGA-II model performed the best, with a mean RMSE of 1.12 and a standard deviation of 0.37. For MAPE as shown in **Table 9**, the LSTM model had a mean MAPE of 7.6% with a standard deviation of 2.3%, while the RBNN model showed higher errors with a mean MAPE of 8.8% and a standard deviation of 2.7%. The combined LSTM+RBNN model improved accuracy, achieving a mean MAPE of 6.5% and a standard deviation of 2.0%. The proposed model outperformed all others with a mean MAPE of 5.9% and a standard deviation of 1.8%.

Table 10. Route Efficiency Over Epochs

Epochs	LSTM Efficiency (%)	RBNN Efficiency (%)	LSTM + RBNN Efficiency (%)	LSTM + RBNN + NSGA-II Efficiency (%)
10	70	65	75	78
20	75	68	80	83
30	80	72	85	87
40	82	74	86	89
50	85	78	88	92

Table 11. Space Utilization Efficiency Over Epochs

Epochs	LSTM (%)	RBNN (%)	LSTM + RBNN (%)	LSTM + RBNN + NSGA-II (%)
10	70	72	75	78
20	75	76	79	83
30	77	79	83	86
40	80	82	85	89
50	81	83	87	92

The performance of the models was evaluated for both route efficiency and space utilization efficiency over different epochs, and the results are shown in **Fig 3** and **4**.

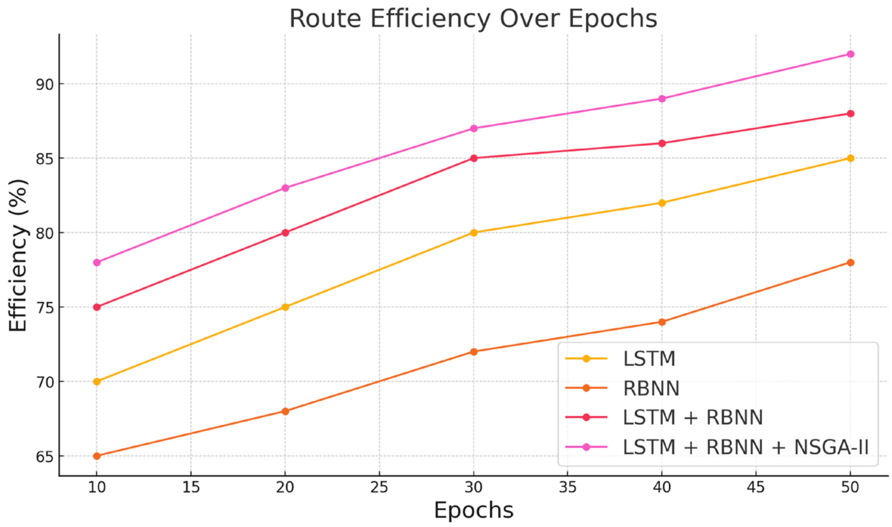

Fig 3. Route Efficiency.

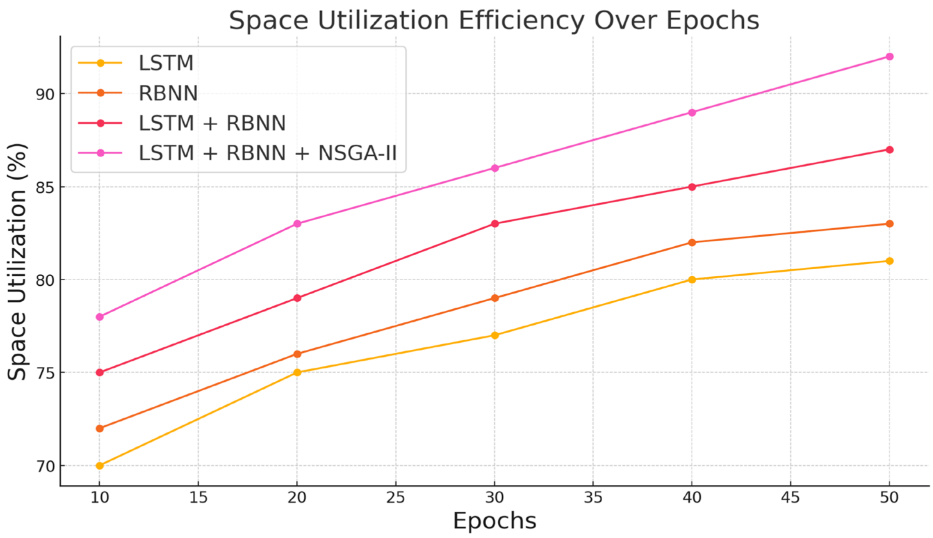

Fig 4. Space Utilization Efficiency.

For route efficiency as shown in **Table 10**, at epoch 10, the LSTM model achieved 70% route efficiency, while the RBNN model lagged slightly behind at 65%. The combined LSTM + RBNN model showed improved performance with a route efficiency of 75%, and the integrated LSTM+RBNN+NSGA-II model led with 78%. As training progressed to epoch 20, all models improved, with the LSTM+RBNN+NSGA-II model reaching 83% efficiency. By epoch 30, the route efficiencies were 80%, 72%, 85%, and 87% for LSTM, RBNN, LSTM+RBNN, and LSTM+RBNN+NSGA-II, respectively. The trend continued with the LSTM+RBNN+NSGA-II model consistently outperforming the others, reaching a peak efficiency of 92% at epoch 50. For space utilization depicted in **Table 11**, the LSTM model started at 70% efficiency at epoch 10, with the RBNN model slightly ahead at 72%. The combined LSTM + RBNN model achieved 75%, and the LSTM + RBNN + NSGA-II model achieved 78%. By epoch 20, the efficiencies improved to 75%, 76%, 79%, and 83%, respectively. At epoch 30, the models demonstrated further gains, with efficiencies of 77%, 79%, 83%, and 86%. By epoch 40, the LSTM+RBNN+NSGA-II model maintained its lead with 89% efficiency. Finally, at epoch 50, the space utilization efficiencies were 81%, 83%, 87%, and 92% for LSTM, RBNN, LSTM+RBNN, and LSTM+RBNN+NSGA-II, respectively.

V. CONCLUSION AND FUTURE WORK

The study in this paper had addressed two of most essential challenges in logistics and Supply Chain Management (SCM) such as the route planning and warehouse space utilization. The work had proposed an integrated model that combined LSTM for route planning, RBNN for space optimization and NSGA-II for combined multi objective optimization. This combined approach was built with a focus to overcome the limitations of traditional models such as linear programming and heuristic approaches, often fall short in handling the modern logistics networks. The proposed model leverages the strengths of Deep Learning (DL) and evolutionary optimization to overcome these limitations and provide a better solution. Through series of experiments the efficiency of the proposed model was compared with other models and the results have shown that the proposed model has better accuracy and consistency in predictions, models.

Future work will be focused to explore further enhancements to the model, such as incorporating additional data sources, refining the optimization algorithms, and testing the approach in different logistics environments.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests

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