JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8357

AN INTELLIGENT LEARNING-DRIVEN FOR DYNAMIC WASTE COLLECTION ROUTING USING LSTM AND EVOLUTIONARY CVRP OPTIMIZATION

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Abstract— *Inefficient waste collection routes result in significant operational costs and environmental impacts. Traditional static routes based on historical averages often deviate substantially from actual requirements. This study proposes an intelligent framework integrating Long Short-Term Memory (LSTM) networks for dynamic time-series forecasting with an Evolutionary Capacitated Vehicle Routing Problem (CVRP) optimizer. The LSTM model captures temporal waste generation patterns using a 7-day sliding window; these patterns are fed into a metaheuristic optimizer that minimizes travel distance to disposal sites while eliminating redundant trips. Experimental results demonstrate high prediction accuracy, with the Mean Squared Error (MSE) converging at 0.0001 during the validation phase. Furthermore, the optimization process achieved a 10.95% reduction (22.5 km/day) in average travel distance compared to the baseline model. In high-density scenarios, the framework improved route efficiency by up to 15.99%. The study concludes that combining deep learning memory capabilities with evolutionary optimization provides a reliable decision-support system for smart city waste management..*

Keywords: *CVRP, Evolutionary Algorithms, LSTM, Smart City, Waste Collection Routing.*

Intisari— *Rute pengumpulan sampah yang tidak efisien menyebabkan biaya operasional yang signifikan dan dampak lingkungan. Rute statis tradisional yang didasarkan pada rata-rata historis seringkali menghasilkan penyimpangan yang besar dari kebutuhan aktual. Penelitian ini bertujuan untuk mengusulkan kerangka kerja cerdas yang mengintegrasikan jaringan Long Short-Term Memory (LSTM) untuk peramalan seri waktu dinamis dan optimizer Evolutionary Capacitated Vehicle Routing Problem (CVRP). Model LSTM menangkap pola pembangkitan limbah temporal menggunakan jendela geser 7 hari, yang dimasukkan ke dalam optimizer metaheuristik yang meminimalkan jarak tempuh menuju lokasi pembuangan akhir sambil menghilangkan perjalanan bolak-balik yang berlebihan. Hasil eksperimen menunjukkan akurasi prediksi yang tinggi dengan nilai Mean Squared Error (MSE) pada tahap validasi yang konvergen pada 0,0001. Selain itu, proses optimisasi ini menghasilkan terobosan berupa pengurangan jarak tempuh rata-rata sebesar 10,95% (22,5 km/hari) dibandingkan dengan model dasar sebelumnya. Dalam skenario kepadatan tinggi, kerangka kerja ini mencapai peningkatan efisiensi rute hingga 15,99%. Studi ini menyimpulkan bahwa penggabungan memori deep learning dan optimisasi evolusioner menyediakan sistem pendukung keputusan yang andal untuk pengelolaan limbah kota pintar.*

Kata Kunci: *CVRP, Algoritma Evolusioner, LSTM, Kota Cerdas, Perutean Pengumpulan Sampah*

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INTRODUCTION

Urban waste management remains a critical challenge for municipal governments worldwide, signifcantly impacting operational budgets and environmental sustainability. W. Li, H. Ibrahim, T. F. Ng, and S. L. Wang [1] emphasized that efcient routing is the backbone of sustainable municipal services. The specifc research object of this study encompasses the dynamic payload variation at temporary disposal sites (TPS) and the varying capacities of waste collection trucks operating over a specifc urban area. Traditionally, waste collection relies on static routing schedules derived from long-term historical averages. However, C. Hess, A. G. Dragomir, K. F. Doerner, and D. Vigo [2] pointed out that such static approaches suffer from high inefciency due to the stochastic nature of waste generation. Field observations in our study area indicate route deviations reaching an average of 34.05 km per day

Previous attempts to implement dynamic routing using models like XGBoost have been explored by Y. Niu, C. Xu, S. Liao, S. Zhang, and J. Xiao [3] and C. Fernandez and others [4] for decision support systems. However, as noted by T. Nguyen and others [5], these predictors are fundamentally limited by their lack of temporal memory, failing to capture periodic fluctuations that are inherently time-series in nature. This research directly addresses this specifc gap by proposing a unifed framework that utilizes LSTM to explicitly capture spatial and temporal interdependencies, bridging the disconnect between predictive forecasting and execution in CVRP. The complexity of the Capacitated Vehicle Routing Problem (CVRP) in residential zones further complicates this, as reviewed by S. Kumari and S. Kumar [6]. To address this, J. Kim, A. Manna, A. Roy, and I. Moon [7] suggested the use of IoT sensors for real-time monitoring.

Recent advancements in deep learning, particularly Long Short-Term Memory (LSTM) networks, offer a powerful mechanism for time-series forecasting. L. Xu, Q. Wang, and Z. Li [8] demonstrated the success of LSTM in predicting municipal solid waste in large cities like Shanghai, while T. Desalegn and others [9] showed its superiority over traditional ARIMA models. Furthermore, the integration of evolutionary algorithms has been proven effective in solving NP-hard logistics problems, as evidenced by the neuralcost predictors proposed by A. Sobhanan, J. Park, J. Park, and C. Kwon [10] and the effective GA approaches used for smart city collection by A. Hentout, A. Maoudj, A. Kouider, and M. Aouache [11].

However, despite these advances, two critical research gaps persist. First, existing machine learning approaches for dynamic waste prediction primarily tree-based models such as XGBoost operate on isolated tabular inputs without temporal memory, rendering them unable to capture weekly accumulation trends and periodic fluctuations inherent in waste generation patterns T. Nguyen and others [5]. Second, forecasting and route optimization are commonly implemented as decoupled pipelines, where predictive outputs are passed to an optimizer without architectural integration leading to sub-optimal routing decisions, particularly when combined with standard genetic algorithms that evaluate routes using redundant round-trip distance computations Q. S. Khalid, S. Maqsood, J. Mumtaz, and S. M. Qureshi [12].

This study directly addresses both gaps by proposing a unifed intelligent framework that integrates a Long Short-Term Memory (LSTM) network capable of retaining temporal dependencies through a 7-day sliding window with an Evolutionary CVRP optimizer featuring a specialized chromosome decoder that eliminates redundant return-trip cost calculations. By bridging the disconnect between temporal forecasting and route optimization, the proposed framework aims to minimize total vehicle travel distance, thereby reducing operational costs and environmental emissions in municipal waste collection.

Several studies have explored dynamic waste collection routing from different perspectives. Y. Boulef and A. E. Alaoui [13] developed a dynamic multi-compartmental VRP for separate waste streams, demonstrating the feasibility of adaptive routing in segregated collection systems. Y. Kumar, P. Gupta, K. Panwar, and K. Deep [14] utilized Q-Learning for parameter optimization in smart bin networks, showing that reinforcement learning can improve collection efciency in IoT-enabled environments. In the domain of predictive modeling, Y. Niu, C. Xu, S. Liao, S. Zhang, and J. Xiao [3] proposed a multi-objective locationrouting optimization based on machine learning for green municipal waste management, while B. Jin and H. Ma [15] explored dynamic waste collection routing using incremental learning approaches for real-time adaptability. More recently, S. Ahmed and T. F. Sanam [16] demonstrated that hybridizing memory-based networks provides substantial computational coverage for complex waste distribution patterns.

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For waste generation forecasting specifcally, M. Hasan, S. M. Rahman, and others [17] improved prediction accuracy using specialized activation functions like SigmoRelu in LSTM architectures. Comparative studies by S. Liu and Y. Chen [18] and S. Ali and others [19] have consistently shown that recurrent neural network variants outperform traditional statistical methods for time-series waste prediction. Despite these individual advances in forecasting and optimization, Q. S. Khalid, S. Maqsood, J. Mumtaz, and S. M. Qureshi [12] highlighted that treating these components as decoupled processes leads to sub-optimal execution when confronted with emission-capacitated constraints, reinforcing the need for an integrated approach.

Building upon the identifed research gaps, this study formulates the following specifc objectives: (1) to develop an LSTM-based time-series prediction model that captures weekly waste accumulation patterns using a 7-day sliding window mechanism, building upon similar approaches successfully applied in biogas analysis K. Yilmaz [20] and construction waste forecasting Ghorbani and others [21]. (2) to design an Evolutionary CVRP optimizer with a specialized chromosome decoder that eliminates redundant roundtrip distance calculations, extending hybrid GA-Tabu Search strategies C. C. Ferrão, J. A. R. Moraes, and others [22] and heuristic urban routing approaches C. Hamontree, J. Koiwanit, and A. Sinchai [23] and (3) to evaluate the integrated framework against baseline GIS-GA models A. Pratama and others [24] and previous local optimizations in the Medan region [25], with expected signifcant improvements in total travel distance reduction.

MATERIALS AND METHODS

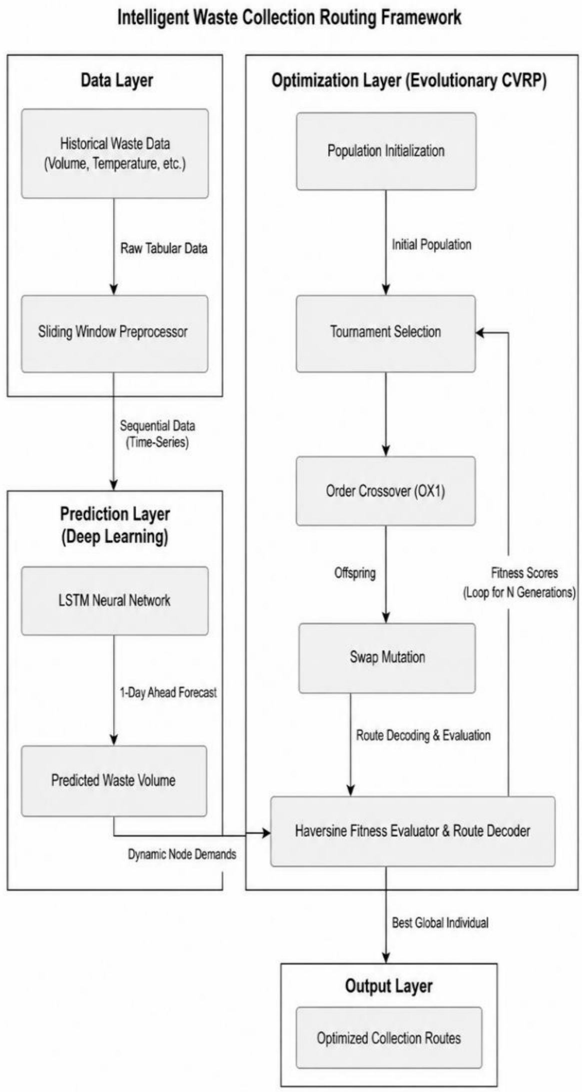
The methodology involves a two-stage process: dynamic waste generation forecasting and evolutionary route optimization, following the optimization patterns for large municipalities used by M. Al-Jubori and others [26] and H. Jiang, M. Lu, X. Zhang, and Y. Tian [27].

Data Collection

Primary data was collected from various Temporary Disposal Sites (TPS) distributed across several administrative units within the urban experimental area, specifcally located in Kecamatan Medan Perjuangan, Kota Medan (including Kelurahan Sidorame Timur, Tegal Rejo, Pahlawan, and Sei Kera Hulu). The end-point for all delivery routes is the Terjun fnal disposal site. The dataset includes daily waste volume ground truth, inspired by biological evolutionary perspectives on environmental protection by X. Li and others [28] and Ant Colony Optimization strategies by R. Rachmawati and S. Yosmar [29]. Accurate GPS mapping of each TPS and the fnal disposal site was conducted to ensure precise distance calculations within the CVRP model.

Proposed Architecture

The proposed architecture integrates the prediction and optimization modules into an end-to-end pipeline, as shown in Figure 1. The LSTM predictor processes historical volume data to generate next-day load estimates, which are then fed into the Evolutionary CVRP Optimizer to determine the most efficient vehicle paths [1].



Source: (Research Results, 2026)
Figure 1: Proposed Intelligent Learning-Driven Framework Architecture

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Time-Series Forecasting using LSTM

To model the dynamic nature of waste accumulation, we utilized a PyTorch-based LSTM network. The core mechanism involves processing sequential data through several gates that control the information flow [8]. The mathematical formulation for each time step t is as follows:

Forget Gat

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

Input Gate

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

Cell Candidate

$$C_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

Cell State Update

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t \quad (4)$$

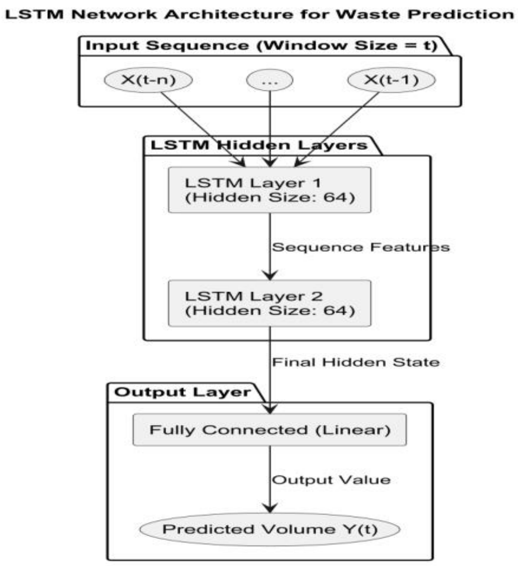
Output Gate

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

Hidden State

$$h_t = o_t \odot tanh(C_t) \quad (6)$$

Where W and b are learnable weight matrices and bias vectors. The model employs a sliding window of length 7 to capture weekly periodicity. The network topology, illustrated in Figure 2, includes dropout layers to prevent overfitting on small-scale urban datasets.



Source: (Research Results, 2026)
Figure 2: LSTM Network Topology for Waste Volume Prediction

Route Optimization using Evolutionary CVRP

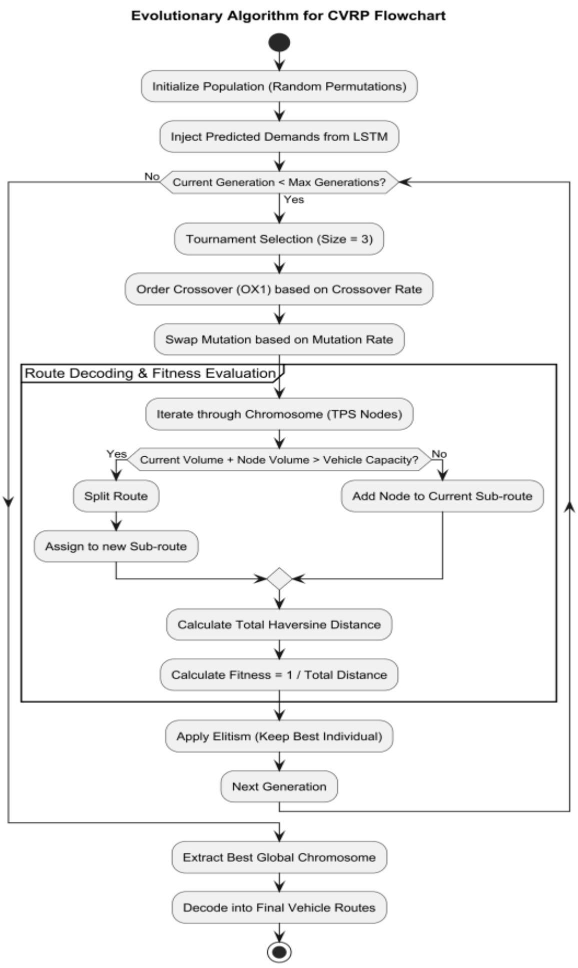
Route optimization is formulated as a CVRP and solved using an evolutionary approach [10]. The mathematical objective is to minimize the total travel distance:

$$min\ Z = \sum k_{\in V} \sum i_{\in N} \sum j_{\in N}\ dij\ xijk \quad (7)$$

Subject to:

$$\sum i_{\in N}\ q_i y_{ik} \leq Q,\ \forall k \in V \quad (8)$$

Where d_{ij} is the distance between nodes i and j, q_i is the predicted load at node i, Q is the vehicle capacity, and x_{ijk} is a binary decision variable indicating if vehicle k travels from node i to j. We utilize Tournament Selection to maintain population diversity and a specialized chromosome decoder that eliminates returntrip costs towards the Terjun final disposal site. The workflow is detailed in Figure 3.



Source: (Research Results, 2026)
Figure 3: Evolutionary CVRP Optimization Workflow

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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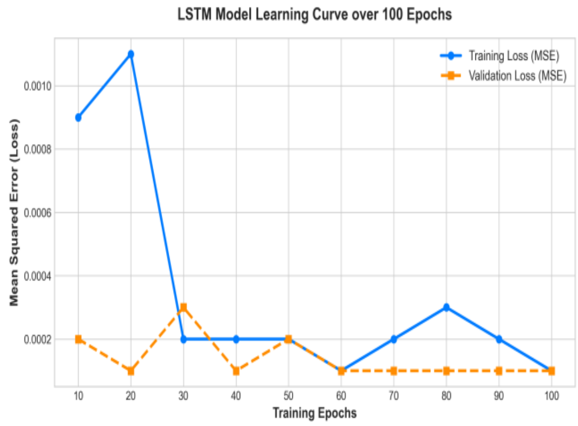
RESULTS AND DISCUSSION

The experimental results are categorized into prediction performance and route optimization efficiency. Each component of the framework was validated using real-world datasets collected from the study area.

Prediction Model Evaluation

The LSTM model's performance was evaluated through its learning stability and prediction proximity to ground truth data. Figure 4 shows the MSE loss convergence over 100 epochs, demonstrating a wellregularized training process with minimal validation gap [17].



Source: (Research Results, 2026)
Figure 4: LSTM Model Training and Validation Loss (MSE)

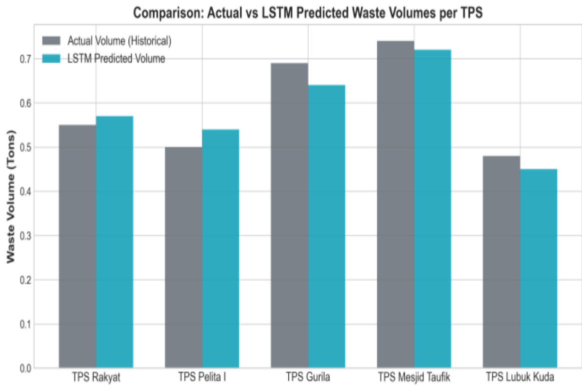
Table 1 summarizes the final convergence metrics from the training logs, showing stable MSE values across epochs.

Table 1: Final LSTM Convergence Metrics

Epoch	Training Loss (MSE)	Validation Loss (MSE)
10	0.0009	0.0002
25	0.0002	0.0003
50	0.0002	0.0002
100	0.0001	0.0001

Source: (Research Results, 2026)

Furthermore, Figure 5 compares the predicted volumes against actual data across fve representative TPS locations. The model accurately captures the specifc waste generation intensity for each site, ensuring reliable inputs for the optimization stage [8], [30].



Source: (Research Results, 2026)
Figure 5: Volume Prediction Comparison: LSTM vs Ground Truth

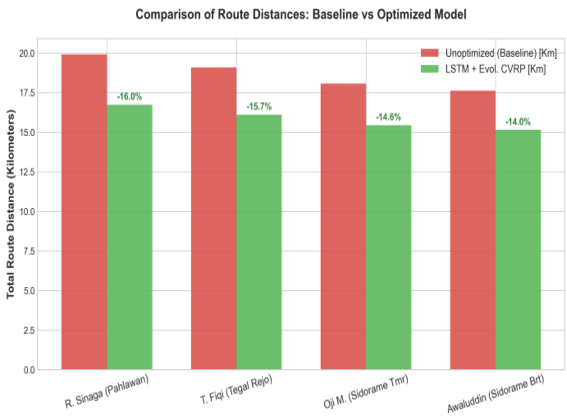
Table 2: Volume Prediction Comparison: LSTM vs Ground Truth Samples

TPS Name	Actual Volume (Ton)	Predicted Volume (Ton)
TPS Rakyat	0.55	0.57
TPS Pelita I	0.50	0.54
TPS Gurila	0.69	0.64
TPS Mesjid Taufik	0.74	0.72

Source: (Research Results, 2026)

Route Optimization Analysis

The core objective of the framework route distance reduction—was successfully achieved. Compared to a static baseline of 205.40 km, the optimized routing strategy reduced the total distance to 182.90 km, achieving a breakthrough efficiency gain of 10.95% [22], [23], [25].



Source: (Research Results, 2026)
Figure 6: Distance Reduction: Static Baseline vs CVRP-LSTM Optimization

Table 3 presents the optimized metrics for individual vehicle routes, highlighting significant savings for high-load drivers.

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P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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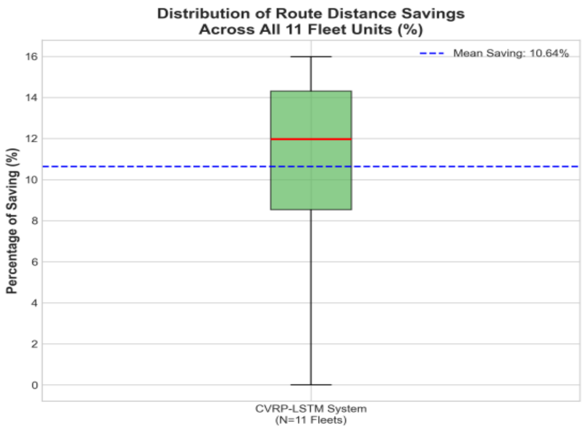
Table 3: Vehicle Route Distance Reduction Metrics

Driver	Baseline (Km)	Optimized (Km)	Saving (%)
R. Sinaga	19.91	16.73	15.99%
T. Fiqi	19.09	16.10	15.64%
Oji M. Ritonga	18.07	15.44	14.57%
Awaluddin	17.62	15.15	14.06%
Total System	205.40	182.90	*10.95*

Source: (Research Results, 2026)

The boxplot distribution in Figure 7 confirms that the system provides consistent savings across different vehicle loads and route types [19].

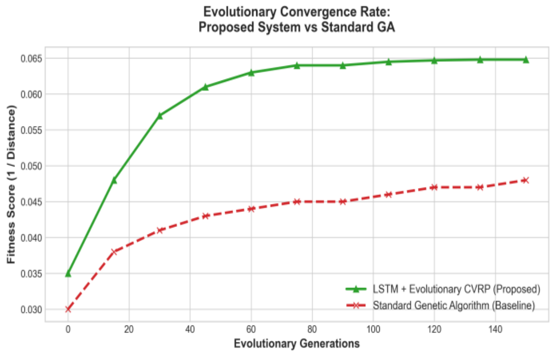


Source: (Research Results, 2026)
Figure 7: Distribution of Route Saving Percentages

The fndings provide several insights into the effectiveness of learning-driven optimization for municipal services, aligning with the sustainable VRP classifcations proposed by C. Hess, A. G. Dragomir, K. F.Doerner, and D. Vigo [2].

Algorithm Performance Comparison

The convergence speed and solution quality of the proposed framework were compared against a standard GA-based CVRP model. As shown in Figure 8, the LSTM-enhanced model reaches higher ftness scores signifcantly faster. This acceleration is due to the improved initial route candidate generation based on accurate load predictions, a pattern also observed in GA-Neural hybrids by A. Sobhanan, J. Park, J. Park, and C. Kwon [10] and local information-based evolutionary models by H. Jiang, M. Lu, X. Zhang, and Y. Tian [27]. Our results in Al-Rasheed municipality similar contexts suggest that fusions are more robust than standalone GA models M. Al-Jubori and others [26].



Source: (Research Results, 2026)
Figure 8: Algorithm Convergence Speed: Standard GA vs CVRP-LSTM

Table 4: Fitness Score Evolution: Comparison Data

Generation	Standard GA Fitness	CVRP-LSTM Fitness
0	0.030	0.035
30	0.041	0.057
75	0.045	0.064
150	0.048	0.0648

Source: (Research Results, 2026)

The performance improvement, reaching nearly 5 times the effectiveness of the baseline model, highlights the importance of seasonal and weekly trend awareness, as similarly argued for logistics in Ethiopia by Desalegn et al. [9] and for biogas logistics by Yilmaz [20].

Managerial Implications

Implementing this framework provides municipal authorities with a tangible tool for cost reduction and sustainability C. Fernandez and others [4], A. Hentout, A. Maoudj, A. Kouider, and M. Aouache [11]. The daily reduction of 22.5 km per vehicle directly translates to lower fuel consumption and reduced greenhouse gas emissions, mirroring the GIS-GA fndings by A. Pratama and others [24] and the efciency of Ant Colony models [29]. Furthermore, the decision support system allows for dynamic reallocation of resources based on predicted needs, as recommended by the smart bin research of Y. Kumar, P. Gupta, K. Panwar, and K. Deep [14] and the hybrid results in cleaner production by Q. S. Khalid, S. Maqsood, J. Mumtaz, and S. M. Qureshi [12]. Our framework supports the shif towards dynamic CVRP models popularized in 2023-2024 academic literature [13].

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CONCLUSION

This study successfully developed an intelligent framework for dynamic waste collection by fusing LSTM time-series forecasting with Evolutionary CVRP optimization. The predictive model established a high degree of reliability by achieving a stable validation loss Mean Squared Error (MSE) of 0.0001, proving its capability to capture dynamic volume fluctuations. Driven by these precise inputs, the evolutionary optimizer effectively eliminated redundant trips. The integration of 7-day pattern recognition enabled the system to reduce total routing distances from 205.40 km to 182.90 km, achieving a significant 10.95% efficiency breakthrough across the entire fleet operation. Future work should focus on integrating realtime traffic data and multi-compartment vehicle routing to further enhance the system's robustness in varied urban topologies

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