International Journal of Applied Mathematics

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

AI-DRIVEN DECISION SUPPORT SYSTEM FOR OPTIMIZED MUNICIPAL SOLID WASTE MANAGEMENT: A MACHINE LEARNING AND ROUTE OPTIMIZATION FRAMEWORK FOR SMART CITIES

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Abstract

The task to manage the municipal solid waste (MSW) in the urban localities specifically in the cities which are growing faster is very challenging as the city administration need to cope up with the pace at which today's cities are growing which is almost impossible without incorporating the latest technologies like Artificial Intelligence (AI). The static waste collection system which is being used conventionally currently facing issues like inadequate allocation of the resources required which in turn raises the overall costs of the operations and ultimately harm the environment, too. To overcome this, the present study introduces an innovative approach of combining Decision Support System (DSS) with machine learning driven waste generation forecasts. This study attempts to optimize the vehicle routing to improve the MSW collection efficacy in the city of Surat, India. The framework proposed here combines Long Short-Term Memory (LSTM) neural networks for MSW prediction with Capacitated Vehicle Routing Problem (CVRP) algorithms for the optimization of routes. We have developed our LSTM model using the dataset of past 16 years (2009-2024) obtained from Surat Municipal Corporation which achieved considerable forecasting accuracy with RMSE of 0.1095 and R^2 value of 0.93. The integrated DSS demonstrated considerable benefits in operations, cutting the overall collecting distance by 50.31% and the use of vehicles by 24% compared to traditional static routing methods. The technology uses predictive analytics to dynamically allocate the required resources helping the waste management authorities make decisions in real time. This study enhances sustainable urban development by offering a data-driven methodology that corresponds with the objectives of the Smart Cities Mission and Sustainable Development Goals (SDGs) 11, 12, and 13. The suggested architecture provides scalable methods for implementing a circular economy and making municipal waste management systems more environmentally friendly.

Keywords: Artificial Intelligence, Machine Learning, LSTM, Municipal Solid Waste, Decision Support System, Vehicle Routing Problem, Smart Cities, Circular Economy

Received: August 04 2025

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

1. Introduction

1.1 Background and Problem Statement

The growth of cities and the economy have caused an unprecedented rise in the amount of solid waste produced by cities around the world. According to the World Bank, the amount of waste produced around the world will rise by 70% to 3.4 billion tonnes per year by 2050 (Kaza et al., 2018). Due to rapid urbanization in India, the amount of municipal solid waste (MSW) produced each year has grown to more than 62 million tonnes, but only 43% of it is treated properly (CPCB, 2019). This problem especially needs quick attention in tier-II cities like Surat, which produces about 1800 to 2100 tonnes of waste every day and is growing quickly in terms of industry and population.

Traditional waste management systems use fixed schedules and static collection routes, which cause a number of operational problems: (1) suboptimal resource allocation that leads to either overfilled bins or unnecessary collection trips, (2) more fuel use and greenhouse gas emissions from inefficient routing, (3) limited ability to predict changes in demand, and (4) inadequate data-driven decision support for municipal authorities (Ghahramani et al., 2022; Lin et al., 2021).

1.2 Research Objectives

The primary aim of the study is to address above discussed challenges by developing an integrated Decision Support System (DSS) with keeping in mind the following objectives:

1. Develop a robust predictive framework for waste generation forecasting using LSTM neural networks to facilitate data-driven planning.

2. Apply CVRP route optimization algorithms to minimize collection costs and environmental impact while ensuring service quality.

3. Create an integrated DSS platform combining forecasting and real-time optimization for municipal authorities.

4. Validate system performance and quantify operational improvements in cost, efficiency, and environmental metrics through Surat case study implementation.

1.3 Research Significance

This research addresses critical gaps in municipal waste management through:

1. Smart Cities Mission support via AI-enabled, technology-driven service delivery and real-time resource allocation

2. Environmental sustainability through operational efficiency and greenhouse gas emission reduction (46.8 tonnes CO_2/year)

3. Data-driven governance providing evidence-based support for policy

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

formulation and strategic planning

2. Literature Review

2.1 Machine Learning Applications in Municipal Solid Waste Forecasting

Recent studies observed that the use of machine learning algorithms for the prediction of municipal solid waste generation has gained momentum. Studies also highlights the noticeable improvements in the results compared to the conventional forecasting methods. It can be summarised based on comprehensive reviews that artificial intelligence (AI) approaches like machine learning (ML) and Deep Learning (D)L models exhibits superior accuracy in capturing the complex pattern of waste generation influenced by parameters like socio-economical, temporal, policy factors, etc. (Gudeta et al., 2025; A. Hussain et al., 202 0; Maturi et al., 2025; Thakur et al., 2024).

The studies suggest that Deep Learning (DL) modeling approaches, like Long Short-Term Memory (LSTM) networks, have shown very good performance in cases involved temporal changes in the waste generation time series dataset. (Gudeta et al., 2025) has done a comparative analysis of approaches like ARIMA, Random Forest (RF), and LSTM models for the prediction of MSW in Ethiopian cities in which LSTM model obtained the highest accuracy among all with Mean Squared Error (MSE) of 1.62×10^8 tonnes, Mean Absolute Error (MAE) of 9,500 tonnes, and coefficient of determination (R^2) of 0.93 (Gudeta et al., 2025). The LSTM approach of DL modeling is found suitable especially in the cases where dataset has some of the patterns like seasonal variation, evident trends in long term, etc. because of its inherent ability to model long-term dependencies and non-linear relationships in sequential data. (Ahmed et al., 2022; Gudeta et al., 2025).

If the dataset which is being used for the purpose of modeling is having bit complex nature Artificial Neural Network (ANN) proved to be giving substantially better output compared to the conventional linear regression approach of modeling. Shah and Shah (2024) demonstrated the effectiveness of ANN modeling in their study of the estimation of landfill volume and the same study also highlights the capability of ANN modeling approach to the number of input variables as well as a complex non-linear relationship characteristic of urban waste system. (CPCB, 2019). Further in input features different parameters like socio-economic indicators, population dynamics, policy variables, etc. can be integrated to witness the enhanced performance of the developed model. (Maturi et al., 2025; H. Wu et al., 2020).

To make our smart waste management systems more advanced integration of features like use of IoT sensors and real time data collection technique are inevitable in current times. A comprehensive framework developed by Maturi et al. (2025) for the smart bins with real time monitoring system exhibits outstanding performance and a substantial increase is monitored in the overall efficacy of the system by simply using continuous data streaming. (Allevi et al., 2021; Strand et al., 2020). This is how a paradigm shift is observed from the reactive to proactive system of urban waste management by following real time predictive systems. (Xia et al., 2022).

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

2.2 Vehicle Routing Optimization in Waste Collection Systems

Various Vehicle Routing Problem (VRP) applications in waste collection and management have exhibited a very substantial reduction in the cost of operations along with reducing the adverse impact on the environment. The Capacitated Vehicle Routing Problem (CVRP) and its variants are gaining importance in the framework designed for optimization through the algorithms. Different research in this area shows huge reduction in distance from the range of 23% to as good as 66%. (Agha, 2006; Kaza et al., 2018; Liu et al., 2025).

(H. Wu et al., 2020) deployed in their study a Priority Considered Green Vehicle Routing Problem (PCGVRP) model for waste collection systems which measured approximately 42.3% of reduction in the adverse effect caused to the environment compared to traditional route approaches (Kaza et al., 2018). The research further highlights the noticeable increase in overall efficiency in routine operations and it also showed the positive impact on environmental sustainability due to application of route optimization in the management system. CVRP and variants demonstrate substantial operational improvements, reducing travel distances 23-66% with 42.3% environmental impact reduction (Wu et al., 2020). GIS integration and meta-heuristic algorithms (genetic algorithms, PSO) effectively solve large-scale problems while maintaining solution quality-computational efficiency balance (Hannan et al., 2018). Indian municipal applications, including prior Surat studies, validate route optimization's potential for cost reduction and resource optimization.

2.3 Decision Support Systems for Sustainable Waste Management

DSS frameworks integrate multiple data sources, analytical tools, and diverse stakeholder requirements for effective waste management. Modular design supports flexibility through IoT sensors, real-time monitoring, and predictive analysis. Modern systems enable transition from static schedule-based collection to dynamic, demand-driven operations with real-time performance metrics and continuous optimization, supporting data-driven decision-making at organizational levels. Now, it has become possible to create smart waste management systems that allow flexibility in decision making because of use of individual or integration of latest technologies like IoT sensors, real time monitoring and using predictive analysis. Studies carried out in recent times, figure out how all these systems can be optimized by applying following measures: proper route planning, collection schedule optimization, sufficient resource allocation based on output received on real time bin filled levels and predictive demand forecasting (Strand et al., 2020) (Patel et al., 2023) . This technological evolution we are witnessing helps the transition from static schedule-based collection system to more dynamic and demand-driven operations.

2.4 Smart Cities and Circular Economy Integration

Idea of a smart city initiative now slowly turning from conceptualization to reality world-wide. With the increase in smart cities, the administration has identified the waste management as one of the most critical components of urban sustainability and citizen service delivery. Therefore, now integrating MSW management systems in smart city infrastructure enables

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

comprehensive optimization across multiple services, too. (Bhakkad, 2025; Maturi et al., 2025; Shah & Shah, 2024).

To make the idea of circular economy a success we need to make our planning sophisticated by optimizing the tools involved like resource efficiency, waste minimization and material recovery. Recent studies on the implementation of circular economy in smart cities also highlights the role of data-driven decision support systems to achieve the goal of sustainability (Dr. I. Hussain et al., 2024; Kumar et al., 2022). These systems enable municipalities to optimize not only collection efficiency but also material recovery, recycling logistics, and waste-to-energy operations.

2.5 Environmental Impact and Sustainability Considerations

The waste collection optimization not only increase operational effectiveness, it also creates a positive impact on environment by reducing fuel consumption, greenhouse gas emissions and air pollution. According to a recent research, route optimization can reduce transportation related emissions by 20-50% along with maintaining and improving service quality. (Ross Fitzgerald, n.d.). Route optimization achieves 20-50% transportation emission reduction, aligning with India's NDCs and Paris Agreement commitments.(Dr. I. Hussain et al., 2024; Ross Fitzgerald, n.d.).

2.6 Integration Challenges and Research Gaps

Existing literature demonstrates these two parameters mostly separately ML forecasting and vehicle routing optimization. Very limited research addresses integration of these two into making a comprehensive decision support framework. Most studies focus on either prediction or optimization components independently, without considering the synergistic benefits of integrated approaches (A. Hussain et al., 2020; Kaza et al., 2018; Maturi et al., 2025).

The implementation of this type of integrated system is very demanding task particularly in the context of Indian cities because of number of parameters like quality issues of reliable dataset, constraints in the infrastructure, limitations of institute capacities, etc. It certainly required a further investigation and the current work attempts to addresses these gaps by developing as well as validating an integrated framework of forecasting and optimization using real world MSW generation data from Surat city.

If we see, current trends of research suggests that most of the studies of VRP carried out were based on static demand assumptions and without referring to the advanced forecasting approaches of modeling. To overcome all these, this study specifically demonstrates that a systematic integration of dynamic demand modeling and latest ML prediction approaches can improve the route optimization efficacy up to a great extent.

3. Methodology

A methodological approach has been imposed through development and validation of integrated framework of DSS and MSW management. A detailed four-module architecture has been developed to handle the complexities generated because of the interdependencies of these

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

two: (i) predictive forecasting analytics; and (ii) operational optimization. Due to institutional data access restrictions, a hybrid methodology was employed: real MSW generation data (2009-2024) from Surat Municipal Corporation combined with systematically validated synthetic infrastructure parameters per established research protocols and municipal standards.

3.1 Overall System Architecture

A Decision Support System (DSS) was developed to integrate the components of forecasting and optimization both. In which, standardized interfaces have been employed along with maintain the data exchange protocols. This approach applied here allowed the validation of individual modules while keeping the system in coherence overall. The framework proposed here has been made flexible enough to easily adapt to the changes occurred in operations due to various factors along with taking care of the constraints involved in technological aspects. (Bakhoum & Brown, 2015; M. Bani, 2009; Haastrup et al., 1998; Sharma et al., 2019).

Module 1: Data Processing and Feature Engineering

The process of data processing was carried out exhaustively ensuring quality of data including temporal consistencies. Further to make historical dataset available, fit for the modeling purpose different checks were performed like detection of statistical outlier, employment of interpolation techniques for missing values, application of temporal alignment with calendar dates, etc. In order to capture the multidimensional nature of waste generation patterns, various socio-economic and temporal features available in dataset were extracted. (Adeleye Yusuff Adewuyi et al., 2024; Adu et al., 2025; Ahmed et al., 2022; Ashutosh Deshpande et al., 2024; Henriksen, 2019; Velis et al., 2023).

Module 2: Predictive Analytics Engines

The predictive analytics engines used Long Short-Term Memory (LSTM) neural network which is tailor made to forecast municipal solid waste. Monthly waste generation patterns derived from dataset helps in making strategic planning more efficient. Whereas, the daily demand disaggregation uses patterns found from historical dataset to make decision making smoother in operations. The demand distribution algorithms applied for point-levels allows resource planning and deployment to be very precise. Which in turn, guarantee precise spatial allocation as per the capacity of different collection points. (Ahmed et al., 2022; Gudeta et al., 2025; Nezhaddehghan et al., 2023; Niu et al., 2021; Salawudeen et al., 2024).

Module 3: Route Optimization Engine

The route optimization engine formulates the waste collection problem as Capacitated Vehicle Routing Problem (CVRP) as the predictive analysis module employed here uses the dynamic demand inputs. Here, the adaptive planning was done based on potential of the real time route optimization. The multi-objective optimization process considers the time constraints, distance minimization, limitations of vehicle capacity, etc. all at the same time. The optimization engine takes care of environmental impacts by helping modeling greenhouse gas emission and the

Received: August 04 2025

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

estimating the consumption of fuel. (Akhtar et al., 2017; Hannan et al., 2018; Priyadarshi et al., 2023; F. Wu et al., 2020).

Module 4: Decision Support Interface

The administration of municipal corporation will get an extensive visualization and reports from the decision support interface using which key decisions can be made in real time. The decision-making process will be more effective with the help of the constant updates on the performance of different metrics, route visualization, etc. Thus, these insights received from the reporting framework will be useful for operational management ane strategic planning. (Bakhoum & Brown, 2015; M. S. Bani et al., 2009; Haastrup et al., 1998; Sharma et al., 2019).

3.2 Data Collection and Preprocessing

3.2.1 Municipal Solid Waste Data

Historical municipal solid waste data from January 2009 to December 2024 (192 monthly observations) were obtained from the authorities of Surat Municipal Corporation. The dataset has multi-dimensional characteristics like the value of total MSW in tonnes, residential, commercial, recyclable materials, street sweeping activities, and dead animal disposal. Further, the dataset was integrated with the population and the demographic indicators to get insights of the socio-economic parameters of the waste generation. Few more features like economic and policy related variables were also imbibed to provide understanding of influence of external factors in waste generation patterns. (Ashutosh Deshpande et al., 2024) (Velis et al., 2023) (Thakur et al., 2024) (Chowdhury, 2009) (Liu et al., 2025).

As the dataset thus prepared allows robust analysis of long-term trends, seasonal variations, policy driven changes in the waste generation patterns can also be obtained. As a part of measuring effects of major policy interventions, two major events were studied that influenced the waste generation behaviours: (i) Implementation of Swachh Bharat Abhiyan and (ii) Impacts due to COVID-19 pandemic. A temporal depth in dataset so obtained provides a rigorous dataset essential for the developing, training and validating a sophisticated ML model approach which can be generalize with no or little changes as per the other features. (Adeleye Yusuff Adewuyi et al., 2024) (Adu et al., 2025) (Liu et al., 2025).

3.2.2 Spatial and Fleet Infrastructure Data

The various waste management data maintained by any municipal corporations related to collection points, fleet deployment, etc. are difficult to made public due to various concerns like privacy, security, commercial sensitivity, etc. Here in this study, real historical MSW generation data (2009-2024) was obtained from Surat Municipal Corporation. Whereas, synthetic dataset was systematically developed for the collection infrastructure and vehicle fleet specifications following established standards and validation. Thus, a hybrid dataset was used of real for waste generation and synthetic for vehicle fleet and collection points. (Nurprihatin & Lestari, 2020) (M. S. Bani et al., 2009) (Akhtar et al., 2017)

Synthetic Data Generation Framework

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Because of the institutional security protocols and commercial sensitivity direct access to operational infrastructure data for the research is very limited. Therefore, the application of synthetic data in research involved in operations related to municipal corporations has gained the recognition as a legitimate methodology. The infrastructural operational data of the municipal corporations is mainly made restricted considering following three primary factors: (i) Security Concerns: The collection point locations being considered sensitive urban infrastructure, (ii) Commercial Sensitivity: The fleet deployment strategies constitute operational intelligence and (iii) Privacy Constraints: The detailed routing patterns may reveal residential and commercial activity patterns. (Kitchin, 2016) (Sanchez et al., 2025) (Annapolis et al., n.d.) (Shanley et al., 2024).

Synthetic Infrastructure Specifications

Following rigorous geographic and demographic validation protocols, synthetic infrastructure was developed per established municipal standards, as shown in Table 1:

Infrastructure	Specification	Validation_Basis
Collection Points	43 locations	Surat Municipal Corporation bounds
Geographic Bounds	21.15°N-21.24°N, 72.78°E-72.88°E	Surat Municipal Corporation bounds
Zone Distribution	40% residential, 25% commercial, 35% mixed-use	Census 2011, urban land-use patterns
Bin Capacity	1-5 tonnes	MoHUA Guidelines, IS:2240 standards
Service Distance	≤500m from main roads	Municipal service delivery standards
Fleet Size	25 vehicles	Municipal capacity requirements
Vehicle Mix	40% compactor, 35% tipper, 25% mini	CEEW 2025, industry practice
Vehicle Capacity	3-8 tonnes	CPCB standards 2021
Fleet Ratio	1 vehicle per 1000-1500 households	MoHUA guidelines

Table 1: Infrastructure Specifications

Validation and Quality Assurance Protocol

Synthetic data was validated against MoHUA guidelines, CPCB standards, and tier-II city benchmarks (Vadodara, Rajkot, Ahmedabad) for statistical consistency and operational feasibility.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3.2.3 Data Quality and Preprocessing

In the research usage of reliable analytical approaches were made in order to maintain the overall data quality in preprocessing part. In the dataset the temporal consistency and the data integrity was maintained nicely. A detailed comprehensive workflow which is essential in this kind of research was employed in multiple stages have been developed with taking utmost care in the preprocessing process. The application of systematic quality assurance protocols in preprocessing phase took good care of feature engineering requirements of MSW dataset like temporal misalignments, incomplete dataset, statistical anomalies like outliers, etc. (Crudu, 2025) (Adeleye Yusuff Adewuyi et al., 2024) (Gupta_omg, 2025) (Novogroder, 2024).

Temporal Alignment and Synchronization

Temporal alignment of 192-month records (Jan 2009-Dec 2024) to standardized calendar dates ensured chronological consistency and enabled precise identification of long-term trends, seasonal variations, and policy-driven shifts in waste generation patterns.

Missing Value Treatment and Imputation

Missing values were treated using linear and spline interpolation methods specific to municipal waste time series characteristics, validated against comparative city datasets to prevent artificial trends.

Outlier Detection and Statistical Correction

Outliers were identified using Z-score and IQR analysis. COVID-19 period (2020-2021) was flagged as legitimate exceptional event; other anomalies were corrected or flagged for specialized analysis.

Advanced Feature Engineering Framework

In advanced feature engineering framework proposed in this study, a careful implementation of the latest temporal encoding techniques was carried out. This technique employed here was robust enough to capture various patterns like cyclical patterns, historical dependencies, contextual relationships, etc. which is usually found out in these types of historical datasets of municipal corporations. Specifically in this study, cyclical month encoding utilized trigonometric transformations through sine and cosine functions ($\sin(2\pi \times \text{month}/12)$, $\cos(2\pi \times \text{month}/12)$) which preserves temporal continuity and cyclical relationships between consecutive months. This approach addressed the fundamental limitation of linear temporal encoding where December and January appear maximally distant despite being consecutive months. (Crudu, 2025) (David Andrés, 2025) (The Scikit-learn Developers, n.d.) (The Feature-engine developers, n.d.) (The skforecast team, n.d.).

Lag feature construction incorporated historical waste generation values at strategically selected intervals (1, 2, 3, 6, and 12 months) to capture short-term dependencies and annual cyclical patterns essential for accurate forecasting. Rolling statistical calculations including moving averages and standard deviations across 3, 6, and 12-month windows provided trend smoothing and variability assessment capabilities, enhancing model sensitivity to gradual

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

changes in waste generation patterns. (Novogroder, 2024) (Crudu, 2025) (Adeleye Yusuff Adewuyi et al., 2024).

3.3 LSTM-Based Waste Generation Forecasting

3.3.1 Model Architecture

The deep LSTM network architecture comprised three sequential LSTM layers with 50 units each, incorporating dropout regularization layers (rate: 0.2) between consecutive LSTM layers to prevent overfitting. The first two LSTM layers-maintained sequence return capabilities to enable hierarchical temporal feature extraction, while the final LSTM layer fed into dense layers with 25 units before the single-unit output layer for waste generation prediction. (Hannan et al., 2018) (Venes et al., 2023) (Adu et al., 2025).

3.3.2 Feature Engineering

Comprehensive feature engineering constituted a critical component of the LSTM model development, systematically designed to capture multidimensional temporal and contextual patterns inherent in municipal solid waste generation data. The feature engineering framework incorporated sophisticated encoding techniques to transform raw temporal data into analytically meaningful representations capable of enhancing model predictive performance across multiple temporal scales. (Shi et al., 2024) (Olawumi et al., 2024) (Cubillos, 2020).

Temporal Feature Construction

Temporal feature construction employed advanced cyclical encoding techniques to preserve the inherent periodicity and continuity of monthly waste generation patterns. Cyclical month encoding utilized trigonometric transformations through sine and cosine functions ($\sin(2\pi \times \text{month}/12)$, $\cos(2\pi \times \text{month}/12)$) to address the fundamental limitation of linear temporal encoding where consecutive months (December and January) appear maximally distant despite temporal adjacency. Year and quarter indicators provided hierarchical temporal context, enabling the model to distinguish between annual growth trends and seasonal variations. Time-since-project-start variables (measured in months) captured long-term developmental trajectories and policy implementation effects across the 16-year observation period. (Shi et al., 2024) (Cui & Wei, 2024) (Nagpure et al., 2015) (The Scikit-learn Developers, n.d.)

Feature Engineering Framework

A comprehensive feature engineering framework was implemented to capture multidimensional temporal and contextual patterns (as shown in Table 2). The framework incorporates sophisticated encoding techniques across four major categories: temporal features using cyclical encoding and year/quarter indicators, historical patterns through lag features and rolling statistics, policy/external factors including Swachh Bharat and COVID-19 impacts, and waste stream characteristics capturing composition dynamics.

Feature_Category	Feature_Type	Implementation	Temporal_Scope	Purpose

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Temporal	Cyclical Encoding	sin(2π×month/12), cos(2π×month/12)	12-month cycle	Monthly periodicity
Temporal	Year/Quarter Indicators	Numerical indices	Full dataset	Annual trends vs seasonal
Temporal	Time-since-start	Monthly increments	16 years	Long-term trajectories
Historical Patterns	Lag Features	Previous values	1,2,3,6,12 months	Short-term & annual cycles
Historical Patterns	Rolling Averages	3,6,12-month windows	Sequential	Trend smoothing
Historical Patterns	Rolling Std Dev	3,6,12-month windows	Sequential	Volatility assessment
Policy/External	Swachh Bharat	Binary indicator	Post-2014	Sanitation initiative impact
Policy/External	COVID-19 Impact	Indicator + seasonal factors	2020-2021	Pandemic anomalies
Waste Stream	Composition Growth	M-o-M, Y-o-Y rates	Sequential	Dynamic waste trends
Waste Stream	Stream Components	Residential, recyclable, sweeping %	Full dataset	Waste stream characteristics

Table 2: LSTM Feature Engineering Summary

3.3.3 Model Training and Validation

The LSTM model training and testing used a temporal partitioning method to ensure a reliable performance and to prevent the data leakage between training and testing phase. 80% of data was splitted as training (2009-2020) and remaining 20% as testing (2020-2024) to maintain the chronological integrity in dataset which is must in the application of timeseries forecasting methods.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The application of Mean Squared Error (MSE) as the main loss function in model training phase was done because of its inherent capability to maintain adequate sensitivity while making the prediction of errors. In order to obtain convergence characteristics suitable for temporal sequences the Adam Optimization Algorithm was applied here with its default learning parameters. To overcome the overfitting issues and obtain the best generalization performance, training was done for a max of 100 epochs with application of early stopping mechanism. The performance of model was monitored constantly during the training phase with the help of the 20% split of data for the purpose of validation. A batch size configuration of 16 samples was kept to maintain the balanced computational efficiency with suitable gradient estimation accuracy.

3.4 Daily Demand Disaggregation

Monthly LSTM predictions were disaggregated into daily waste estimates using weighted distribution techniques based on historical temporal patterns. Daily totals were distributed to specific collection points considering bin capacity and local service area characteristics, enabling tactical-level route optimization integration.

3.5 Capacitated Vehicle Routing Problem (CVRP) Formulation

3.5.1 Mathematical Formulation

With the use of multi-objective optimization criteria and dynamic demand inputs received from the predictive analytics module, the waste collection routing optimization problem was methodically formulated as a Capacitated Vehicle Routing Problem (CVRP). The mathematical formulation addressed the basic problem of minimizing total travel distance while meeting comprehensive collection requirements and operational constraints inherent in municipal waste collection systems.

The objective function gave priority to the total travel distance minimization along with ensuring the complete coverage of waste collection across all the designated points within limitations of the capacity of the vehicle. Constraint formulation included demand satisfaction requirements that ensured full waste collection from all active collection points. The vehicle capacity restrictions prevented overloading and single-visit requirements ensured each collection point received exactly one service visit. Also, there is the route continuity constraints that required departure from and return to the central depot facilities.

3.5.2 Distance Matrix Calculation

Distance matrix computation applied the Haversine formula to calculate great-circle distances between all location pairs providing accurate geographic distance measurements required for the route optimization. The mathematical formulation is as follows:

$$d(i,j) = 2R \times arcsin\left(\sqrt{\left(sin^2\left((\Delta\phi)/2\right) + cos(\phi_1)cos(\phi_2)sin^2\left((\Delta\lambda)/2\right)\right)}\right)$$

Received: August 04 2025

Volume 38 No. 12s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

which utilized Earth's radius (R = 6,371 km), latitude coordinates (φ_1, φ_2), latitude differences ($\Delta\varphi$), and longitude differences ($\Delta\lambda$) to ensure precise distance calculations across the urban geographic area. (Salawudeen et al., 2024) (Priyadarshi et al., 2023).

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3.5.3 Optimization Algorithm

To solve CVRP problems the Google OR-Tools Optimization library was used here because of the strong algorithmic capability in solving such kind of problems. As the first solution strategy in the algorithmic configuration PATH_CHEAPEST_ARC was used because of its effectiveness in initial solution generation which was followed by further refinement in the optimization process. The system adopted both the branch and bound approach and heuristic improvements on the systematic exploration of the solutions. The default search parameters were a good trade-off between solution quality on one hand and the speed of the computation on the other. (H. Wu et al., 2020) (Salawudeen et al., 2024) (Priyadarshi et al., 2023).

3.6 Performance Evaluation Framework

3.6.1 Forecasting Performance Metrics

Forecasting performance assessment applied here used a comprehensive metric frameworks specifically designed to assess the predictive accuracy across different dimensions of model performance. Root Mean Square Error (RMSE) calculation through the following equation;

$$RMSE = \sqrt{\left(\left(\sum \quad \left(y_p red - y_a ctual\right)^2\right)/n\right)}$$

which provided sensitivity to large prediction errors and overall model accuracy assessment. (Cubillos, 2020)(Tamilmani et al., 2024). Mean Absolute Error (MAE) computation via following equation;

$$MAE \ = \ (\sum|y\_pred \ - \ y\_actual|)/n$$

which offered interpretable error magnitude quantification resistant to outlier influence. (Shi et al., 2024). Coefficient of Determination (R^2) calculation using the following equation;

$$R^2 = 1 - (SS_r es)/(SS_t ot)$$

which quantified explained variance proportion and model explanatory power. (Olawumi et al., 2024) (Cubillos, 2020).

3.6.2 Routing Performance Metrics

Routing performance metrics evaluated optimization effectiveness via: total travel distance (km), vehicle fleet utilization (count), route efficiency (% improvement vs. baseline static routing), fuel consumption (liters/day), and CO_2 emissions (tonnes/year). These metrics

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

quantified transportation efficiency, resource utilization, and environmental impact improvements.

3.6.3 Data Quality and Validation Metrics

Data quality and validation assessment implemented comprehensive synthetic data validation protocols to ensure parameter authenticity and operational realism. Parameter realism assessment evaluated synthetic infrastructure specifications against established municipal standards and published benchmarks. Statistical property verification examined distribution consistency and spatial uniformity to ensure realistic geographic and demographic representation. Operational feasibility validation evaluated capacity-demand alignment and system coherence in real-world operational scenarios. Benchmarking protocols checked the validity of the methods by comparing synthetic parameters to published studies of municipal fleets and government guidelines. (Lan et al., 2025) (Shanley et al., 2024) (Khrulkov et al., 2022) (Alam et al., 2023) (Breck et al., n.d.).

3.7 Research Ethics and Data Transparency

For the process involved developing LSTM model for the purpose for forecasting a real dataset obtained from authorised sources have been employed. But in lieu of real-world data of operations and maintenance of city of Surat due to institutional policies and security concerns synthetic dataset for vehicle fleet and bin locations were created based on the most suitable approach permissible in research. This is how the hybrid data methodology was used to generate forecast and to create optimization modeling based on it. (Olawade et al., 2024) (Singagerda et al., 2024).

4. Results and Analysis

4.1 LSTM Model Performance

The forecasting performance of LSTM model was much above conventional benchmarks in all the metrics of evaluation patterns. In training phase, the LSTM model obtained a Root Mean Square Error (RMSE) value of 0.0754 clearly demonstrating its superior capabilities in recognising various temporal pattern available in dataset. The testing phase, encompassing 34 validation samples (2020-2024), yielded an RMSE of 0.1095 and coefficient of determination (R^2) of 0.93, comparable to leading studies in municipal waste forecasting applications. The model successfully captured long-term growth trends in Surat's waste generation, showing 150.1% growth from 2009 to 2024, with average monthly MSW of 59,255 tonnes. Feature importance analysis revealed that historical lag variables and rolling averages were most significant for prediction accuracy. (Ahmed et al., 2022) (Kannan et al., 2024) (aiforgoodstg2, 2024).

4.2 Route Optimization Results

4.2.1 Single-Day Optimization Performance

Comprehensive evaluation of the route optimization framework was conducted using the test date of December 1, 2024, representing typical operational conditions within the municipal

Received: August 04 2025

International Journal of Applied Mathematics

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

waste collection system. The optimization process demonstrated substantial performance improvements across all evaluated metrics, establishing the system's practical viability for real-world implementation. (Bharadhwaj et al., 2025) (*The Ultimate Guide to Waste Collection Route Optimization in 2025 - NextBillion.Ai*, 2025)

Demand Distribution Analysis

The spatial demand analysis revealed significant heterogeneity in waste generation patterns across the collection network. Total daily waste volume reached 993.4 tonnes distributed across 40 active collection points, with individual point demands ranging from 15.5 to 54.3 tonnes per collection site. This substantial variation in point-level demand (coefficient of variation = 0.42) underscores the importance of dynamic optimization approaches over static routing methodologies. Three collection points registered zero demand, comprising depot facilities and inactive locations, which were appropriately excluded from active routing calculations. (Kocsis et al., 2024) (*What KPIs and Analytics Are Used on Waste Collection Software Dashboards?*, n.d.)

Optimization Performance Metrics

The CVRP optimization algorithm achieved remarkable efficiency improvements through systematic route planning and vehicle allocation strategies. Optimized total travel distance was reduced to 194.78 km from the theoretical baseline, utilizing 19 vehicles from the available fleet of 25 units. This represents a 24% reduction in vehicle utilization while maintaining complete collection coverage, demonstrating the algorithm's capacity for resource optimization without service degradation.

4.2.2 Comparative Analysis with Static Routing Systems

Quantitative comparison between the optimized system and traditional static routing approaches revealed substantial operational improvements across all performance indicators. Static routing methodology, characterized by individual depot-to-point round trips, served as the baseline for performance evaluation, representing current operational practices in many municipal waste collection systems.

Performance Improvement Analysis

If we compare static routing techniques with the optimized system, the later system showed remarkable efficiency gains. Total travel distance observed to be decreased from 392.04 km to 194.78 km giving a 50.31% reduction in transportation requirements. By increasing vehicle utilization from 25 to 19, fleet deployment was reduced by 24% without sacrificing quality of service. If we make comparison of the baseline operations, we may see that overall route efficiency increased by 197%, suggesting significant potential for lowering operating costs and mitigating environmental effects.

4.3 Multi-Day Performance Analysis

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The consistency and dependability of the framework has been evaluated over several forecast dates. Further to confirm resilience and usefulness of the system the multi-day analysis included diversification in waste generation patterns, seasonal variations, demand fluctuations, etc.

Consistent Performance Metrics

During the evaluation period it is observed that the distance reduction performance remained consistent with an average improvement in total travel distance of 45–55% over baseline operations. Vehicle utilization demonstrated parallel improvements, achieving consistent 20-30% reduction in required fleet deployment across varying demand conditions. Operational efficiency metrics indicated improved service coverage with reduced resource requirements, confirming the system's ability to adapt to dynamic operational environments while maintaining performance standards.

4.4 Environmental Impact Assessment

Route optimization achieved substantial emissions reductions through fuel savings. Daily fuel reduction of 49.3 liters (at 4 km/liter efficiency) corresponds to 128.2 kg daily CO_2 reduction using standard conversion factors (2.6 kg CO_2/liter), scaling to 46.8 tonnes annually. Beyond direct emissions, secondary benefits include reduced noise pollution, improved air quality, and extended infrastructure longevity through minimized road wear.

4.5 Economic Impact Analysis

Operational efficiency translates to substantial economic benefits. Daily fuel savings of 49.3 liters at ₹90/liter yield ₹4,437 daily savings (₹1,619,505 annually). Fleet optimization reducing vehicle requirements by 6 units diminishes maintenance costs ~20% and extends vehicle lifespan. Enhanced crew productivity through minimized travel time reduces labor inefficiencies and overtime expenses. Cumulative benefits like fuel savings, reduced maintenance, improved labor efficiency position the system as economically viable for municipal waste management implementation.

5. Discussion

5.1 Technical Innovations and Contributions

The research introduces an integrated LSTM-CVRP framework advancing waste management through combined predictive analytics and dynamic route optimization. LSTM neural networks forecast monthly waste generation, enabling real-time resource allocation through demand-driven CVRP routing with continuous performance feedback loops. The multi-scale approach spans strategic planning (monthly forecasts), operational scheduling (daily disaggregation), and tactical execution (real-time routing optimization), providing coherent decision support across temporal horizons and ensuring efficient resource utilization at all operational scales.

5.2 Practical Implementation Considerations

The modular architecture supports scalability across cities, requiring robust historical data (3-5 years), API integration with municipal systems, and standardized validation protocols.

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5.3 Smart Cities, Sustainability, and Circular Economy Integration

The DSS supports India's Smart Cities Mission through technology-driven governance. The system addresses UN SDGs 11, 12, and 13 via: operational efficiency (46.8 tonnes CO_2/year reduction), resource efficiency through predictive planning, and enhanced material recovery supporting circular economy principles. The framework demonstrates practical climate action implementation aligned with national and international sustainability commitments.

5.4 Limitations and Future Research Directions

5.4.1 Limitations

Synthetic infrastructure data, while validated against municipal standards and tier-II city benchmarks, may not fully capture site-specific operational constraints. Actual deployment may encounter complexities beyond synthetic scenario validation.

5.4.2 Future Research Directions

Future enhancements include: (i) IoT sensor integration for real-time bin monitoring, (ii) reinforcement learning for algorithm refinement, (iii) multi-city comparative studies for model generalizability, (iv) life-cycle impact assessments, (v) policy impact studies on waste generation patterns, and (vi) social impact and worker productivity evaluations.

6. Conclusion

This research has delivered a robust AI-driven Decision Support System that marries LSTM-based waste generation forecasting with dynamic CVRP route optimization to transform municipal solid waste collection. By leveraging sixteen years of historical data from Surat, the LSTM model achieved an RMSE of 0.1095 and an R^2 of 0.93, underscoring its superior predictive accuracy. When integrated with real-time routing, the system halved collection distances and reduced fleet requirements by nearly a quarter, yielding 46.8 tonnes of annual CO_2 savings and over ₹1.6 million in fuel cost reductions.

Theoretically, this work advances waste management scholarship by introducing a novel integration methodology that unifies time-series forecasting and multi-objective routing, and by demonstrating a multi-scale modeling framework that seamlessly spans strategic, operational, and tactical horizons. Practically, the DSS provides municipalities with a replicable, modular platform for data-driven planning, rapid deployment across tier-II cities, and evidence-based policy support. Aligned with India's Smart Cities Mission, the Swachh Bharat Abhiyan, and UN Sustainable Development Goals 11, 12, and 13, the proposed DSS enhances urban service delivery, circular economy practices, and climate action efforts. To realize its full potential, municipal authorities should invest in robust data infrastructures, cultivate technical expertise, engage stakeholders across public and private sectors, and institute continuous monitoring and evaluation processes.

Looking ahead, embedding real-time IoT sensor data, expanding to multi-city comparative studies, and exploring reinforcement-learning-driven optimization will further elevate system performance. As urbanization intensifies global waste challenges, integrating advanced

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

analytics, optimization algorithms, and stakeholder collaboration promises more sustainable, cost-effective, and resilient waste management systems worldwide.

Acknowledgments

The authors thank Surat Municipal Corporation for providing access to historical waste generation data and spatial information essential for this research. Special appreciation is extended to the waste management teams who provided insights into operational challenges and system requirements. We also acknowledge the open-source community for providing the tools and libraries that made this research possible.

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