IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ※ Peer-reviewed & Refereed journal ※ Vol. 15, Issue 3, March 2026

DOI: 10.17148/IJARCCE.2026.15301

AI-Driven Model Predictive Control for Smart Waste Collection Routing in Urban Environments

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Abstract: Efficient municipal waste collection is still a big problem in cities that are growing quickly because more trash is being made, and routing plans are not working well. Traditional waste collection systems often use set schedules or simple threshold-based systems, which can cause vehicles to make unnecessary trips, raise operational costs, and cause bins to overflow. This paper puts forward a framework for smart waste collection routing called AI-Driven Model Predictive Control (AI-MPC). The suggested method combines model predictive control with artificial intelligence-based waste prediction to make routing decisions that are both flexible and proactive. The control system can predict when bins will reach critical fill levels by looking at smart bin data to see how waste is likely to build up in the short term. Then, the predictive information is used to make an MPC-based routing strategy that finds the best waste collection routes while keeping travel distance to a minimum and stopping overflow. The framework was tested in a Python-based simulation environment, where the performance of the suggested AI-MPC method was compared to that of traditional static and threshold-based routing methods. The simulation results show that the suggested method greatly improves routing efficiency, cuts down on overflow events, and makes overall waste collection performance better. The suggested AI-MPC framework is a smart and scalable way to manage waste in smart cities.

I. INTRODUCTION

Rapid urbanization and a growing population have caused a big increase in the amount of municipal solid waste that cities around the world produce. So, efficient waste collection and management have become very important parts of smart city infrastructure and sustainable urban development. Most traditional waste collection systems use set schedules and set routes, where trucks pick up trash from bins on a regular basis, no matter how full they are. This method often leads to operational problems like extra trips to bins that aren't full, bins that overflow before the scheduled collection, more fuel use, and higher operating costs.

Recent improvements in Internet of Things (IoT) technologies have made it possible to use sensors to monitor waste levels in real time in smart bins. These systems give waste management authorities useful information about how full the bins are and how much waste is being generated. A lot of the systems that are already in place, on the other hand, use simple threshold-based decision rules and can't predict how much waste will be produced in the future or change collection routes on the fly.

AI and machine learning can use past and present data, like the time of day, the day of the week, and patterns of activity in cities, to make very accurate predictions about how much trash will build up. AI models can help waste collection operations make decisions ahead of time by predicting how full the bins will be in the future. Model Predictive Control (MPC) is also a good way to optimize control actions over a future prediction horizon while still following system rules. Combining AI-based prediction with MPC optimization can make waste collection strategies more flexible and effective. This paper proposes an AI-Driven Model Predictive Control (AI-MPC) framework for smart waste collection routing in response to these challenges. The suggested framework combines AI-based predictions of how full bins will be with MPC-based route optimization to figure out when to pick up trash. An optimization model figures out the best routes for waste collection vehicles while keeping travel distance to a minimum and stopping bins from overflowing. It does this by using real-time bin data to guess how much waste will build up in the future.

The proposed approach is implemented and evaluated through Python-based simulation, where machine learning models are used to predict bin fill levels and an optimization algorithm determines collection routes under operational constraints. The main contributions of this paper are summarized as follows:

- Development of an AI-based predictive model for forecasting waste bin fill levels.
- Formulation of a Model Predictive Control optimization framework for dynamic waste collection routing.

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DOI: 10.17148/IJARCCE.2026.15301

- Integration of prediction and optimization into a unified AI-MPC architecture for smart waste management.
- Implementation and evaluation of the proposed system using Python simulation.

II. RELATED WORK

Municipal solid waste management has attracted significant research attention due to rapid urbanization and the increasing environmental impact of waste generation. Traditional waste collection systems rely on static schedules and predetermined routes, which often lead to inefficient resource utilization, excessive fuel consumption, and overflowing bins in high-generation areas. Consequently, researchers have explored intelligent waste management systems that leverage modern technologies such as the Internet of Things (IoT), artificial intelligence (AI), and optimization algorithms to improve waste collection efficiency.

A. IoT-Based Smart Waste Monitoring

Recent studies have emphasized the importance of IoT-enabled sensing infrastructure for real-time monitoring of waste bins. Smart bins equipped with sensors can measure parameters such as fill level, weight, gas emission, and temperature, and transmit this information to centralized control systems. These technologies enable waste management authorities to monitor waste accumulation and respond dynamically to service requirements. Several IoT-based systems have been proposed to automate waste monitoring and improve collection efficiency in urban environments [1]–[6].

For instance, IoT-enabled smart waste management systems use ultrasonic or weight sensors embedded in bins to continuously transmit fill-level data to cloud-based platforms, allowing waste collection operators to identify bins that require immediate service and optimize collection routes accordingly [2], [6]. Such systems have demonstrated improved monitoring accuracy and reduced response time compared with traditional manual inspection methods. Furthermore, IoT-based waste monitoring frameworks can integrate wireless communication technologies such as GSM, LoRa, and Wi-Fi to provide real-time data transmission in smart city environments [3], [7]. These systems form the foundational data infrastructure required for intelligent waste collection optimization.

B. Waste Collection Routing Optimization

Beyond monitoring waste levels, efficient routing of waste collection vehicles remains a critical challenge in municipal waste management. The waste collection routing problem is commonly formulated as a variant of the Vehicle Routing Problem (VRP), where the objective is to determine the optimal routes for waste collection trucks while minimizing travel distance, operational cost, and service delay. Various optimization techniques have been proposed to solve this problem, including heuristic algorithms, genetic algorithms, and metaheuristic optimization approaches [8]–[12]. Studies have shown that route optimization algorithms can significantly reduce operational costs and travel distance in waste collection systems. For example, IoT-assisted routing optimization methods have demonstrated measurable improvements in vehicle utilization and route efficiency [8]. Similarly, metaheuristic approaches such as genetic algorithms and hybrid optimization models have been used to solve large-scale waste routing problems while considering constraints such as vehicle capacity, time windows, and environmental impact [9], [13]. Recent research also explores stochastic and probabilistic routing models that account for uncertainties in waste generation patterns and dynamic service requirements [14].

Although these approaches improve route planning efficiency, many existing solutions assume deterministic waste levels and do not incorporate predictive models for waste accumulation. As a result, routing decisions may not adequately anticipate future bin overflow or fluctuations in waste generation patterns.

C. Artificial Intelligence in Smart Waste Management

Artificial intelligence and machine learning techniques have increasingly been applied to smart waste management systems. AI models can analyze historical waste data to identify patterns and predict future waste generation, enabling proactive waste collection strategies. Several studies have demonstrated the effectiveness of machine learning algorithms such as neural networks, decision trees, and deep learning models for predicting waste accumulation and supporting intelligent waste management decisions [3], [15]–[18].

AI-enabled waste management frameworks often combine predictive analytics with sensor data collected from smart bins to estimate future bin fill levels and optimize collection scheduling. These systems can incorporate contextual variables such as time of day, population density, weather conditions, and urban activity patterns to improve prediction accuracy [15], [19]. AI techniques have been integrated with optimization algorithms to enhance route planning and resource allocation in waste collection operations [16], [17]. Despite these advances, most AI-based waste management studies

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focus primarily on prediction and do not integrate prediction models with dynamic control frameworks capable of continuously adapting routing decisions.

D. Model Predictive Control in Waste Collection Systems

Model Predictive Control (MPC) has emerged as a promising approach for solving complex optimization problems in transportation and logistics systems. MPC is a control strategy that predicts the future behavior of a system over a specified horizon and determines optimal control actions by solving an optimization problem subject to system constraints. This receding-horizon strategy allows MPC to adapt dynamically to disturbances and updated system information.

Previous research has applied MPC to waste collection scheduling and routing problems. Early studies demonstrated that MPC-based scheduling frameworks could optimize waste collection operations by considering dynamic waste levels and operational constraints [20]–[23]. By incorporating sensor data and predictive models, MPC can dynamically adjust waste collection schedules and routes to improve service efficiency and reduce operational costs.

Recent research has extended MPC approaches to smart city applications, including intelligent transportation systems and urban logistics optimization [24]–[27]. These studies highlight the ability of MPC to manage large-scale systems with multiple constraints, making it suitable for urban waste collection problems where vehicle capacity, routing constraints, and service priorities must be considered simultaneously.

In the context of Nigeria, Ozor, Aniugo, and Agu proposed an MPC-based framework for optimizing waste collection routing in Enugu State, demonstrating that predictive control can significantly improve waste collection efficiency compared with static routing approaches [28]. Their study highlighted the limitations of existing waste collection practices and emphasized the need for intelligent routing strategies capable of adapting to real-time operational conditions.

E. Research Gap

Despite the significant progress in smart waste management research, several limitations remain. Many IoT-based systems focus primarily on real-time monitoring without integrating predictive analytics into operational decision-making. Similarly, traditional routing optimization approaches often assume deterministic waste levels and fail to capture the stochastic nature of waste generation. Although MPC has been applied to waste collection optimization, relatively few studies have integrated AI-based prediction models with MPC optimization frameworks to create a fully adaptive and predictive waste collection system.

Furthermore, most existing studies rely on static datasets or simplified routing assumptions and do not explore integrated predictive-control frameworks implemented within modern computational environments. Therefore, there is a need for an integrated approach that combines AI-based waste prediction with MPC-based routing optimization to support proactive and adaptive waste collection strategies.

To address these challenges, this paper proposes an AI-Driven Model Predictive Control (AI-MPC) framework for smart waste collection routing, implemented and evaluated through Python-based simulation.

III. SYSTEM ARCHITECTURE OF THE PROPOSED AI-MPC SMART WASTE COLLECTION SYSTEM

The proposed AI-driven Model Predictive Control (AI-MPC) framework integrates Internet of Things (IoT) sensing infrastructure, artificial intelligence prediction models, and model predictive control optimization to enable intelligent waste collection routing in urban environments. The architecture is designed to support real-time monitoring, predictive analytics, and dynamic route optimization for waste collection vehicles.

Fig. 1 illustrates the overall architecture of the proposed AI-MPC smart waste collection system. The framework consists of five major components: (1) smart waste sensing infrastructure, (2) communication networks, (3) data processing and storage layer, (4) AI-based prediction module, and (5) MPC-based routing optimizers. These components operate within a closed-loop control structure to ensure adaptive and efficient waste collection operations.

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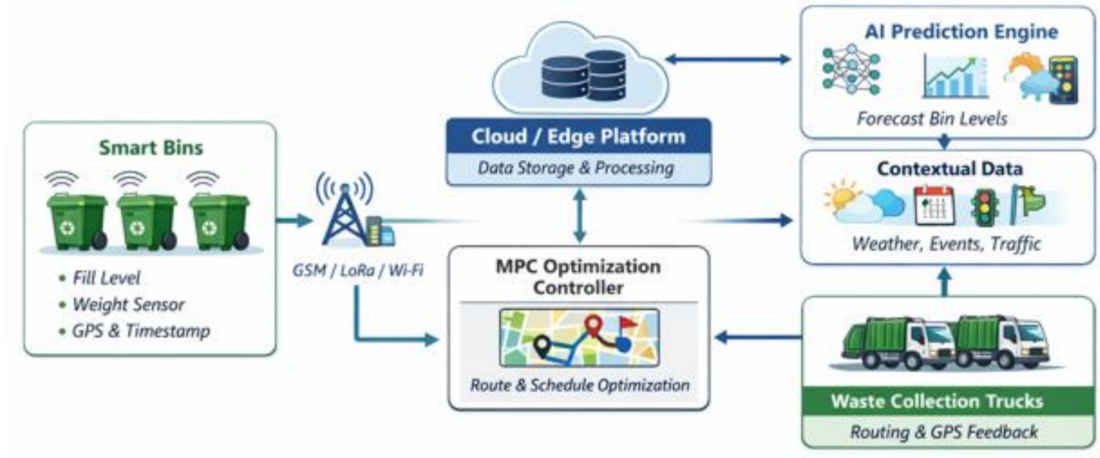

Fig. 1. Architecture of the proposed AI-MPC smart waste collection system.

A. Smart Waste Sensing Infrastructure

The first layer of the system consists of smart waste bins equipped with sensors capable of monitoring bin fill levels and transmitting operational data. Sensors such as ultrasonic or weight sensors continuously measure the waste level inside each bin. Let the fill level of bin i at time step k be represented as

$$b_i(k) \tag{1}$$

Where
$b_i(k)$ represents the amount of waste contained in bin i at time k .
The state vector representing the fill levels of all bins in the system can be expressed as

$$x(k) = [b_1(k) \quad b_2(k) \,.... \; b_N(k)^T \tag{2}$$

where N denotes the total number of monitored bins. These sensor measurements provide real-time information about waste accumulation across the city and serve as the primary input for predictive analysis and routing optimization.

B. Communication Network and Data Acquisition

Sensor data collected from smart bins is transmitted through a communication infrastructure such as GSM, Wi-Fi, LoRaWAN, or NB-IoT networks to a centralized data processing platform. The communication layer ensures reliable data transmission between distributed waste bins and the control system. The measured system state at time step k can therefore be represented as

$$x(k) = x_m(k) + v(k) \tag{3}$$

where
$x_m(k)$ represents the measured bin state vector and
$v(k)$ represents measurement noise or communication uncertainties.
The collected data are stored in a cloud or edge computing environment where they are processed for predictive analysis and optimization.

C. AI-Based Waste Prediction Module

The prediction module uses artificial intelligence techniques to estimate future waste generation patterns. Machine learning models such as Random Forest, Gradient Boosting, or neural networks are trained using historical waste data and contextual features such as time of day and day of the week.

Let the predicted waste generation for bin i at time k be denoted by

$$\hat{w}(k) \tag{4}$$

The vector of predicted waste inputs for all bins can be expressed as

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$$\widehat{w}(k) = [\widehat{w_1}(k) + \widehat{w_2}(k) \dots \widehat{w_N}(k)]^T \tag{5}$$

Using this predicted waste input, the future bin fill level is estimated as

$$\hat{x}(k+1) = x(k) + \widehat{w}(k) \tag{6}$$

where $x(k+1)$ represents the predicted bin state at the next time step.
These predictions enable proactive waste collection planning by estimating which bins are likely to reach critical levels.

D. Model Predictive Control Routing Optimizer

The predicted bin states are used as inputs to the Model Predictive Control (MPC) optimization module. MPC determines the optimal waste collection actions by minimizing a cost function while satisfying operational constraints such as vehicle capacity and travel distance.
Let

$$u_i(k) \tag{7}$$

represent the control decision for bin i at time k, where

$$u_i(k) = \begin{cases} 1, & if\ bin\ i\ is\ scheduled\ \ for\ collection \\ 0, & otherwise \end{cases} \tag{8}$$

The system state evolution, considering waste collection, can then be expressed as

$$x(k+1) = x(k) + w(k) - Cu(k) \tag{9}$$

where
C represents the waste removal capacity during collection ,and $u(k)$ represents the vector of control decisions. The MPC optimizer determines the optimal control input $u(k)$ over a prediction horizon to minimize operational costs such as travel distance and overflow risk.

E. Waste Collection Fleet Execution and Feedback

The optimal routing and collection decisions generated by the MPC controller are transmitted to waste collection vehicles. Each vehicle follows the assigned route to service the selected bins.
Let the travel distance between bins i and j be represented by $d_{i,j}$ The total routing cost for the fleet can be approximated As

$$D = \sum_{i=1}^{N} \sum_{j=1}^{N} d_{i,j}\, r_{i,j} \tag{10}$$

where $r_{i,j}$ represents the routing decision variable indicating whether the vehicle travels from location i to location j. After executing the route, updated bin measurements are transmitted back to the system, thereby closing the control loop. The updated state information is then used in the next prediction and optimization cycle.

F. Closed-Loop AI-MPC Framework

The overall AI-MPC system operates in a closed-loop predictive control framework where sensor data, AI prediction, and routing optimization are continuously updated. At each sampling interval, the system performs the following steps:

- Acquire real-time bin fill level data.
- Predict future waste accumulation using AI models.
- Determine optimal waste collection actions using MPC optimization.
- Dispatch optimized routes to waste collection vehicles.
- Receive updated system measurements and repeat the process.

This closed-loop architecture enables the system to dynamically adapt to changing waste generation patterns and operational conditions.

The simulation parameters used in the Python-based evaluation of the proposed AI-MPC waste collection framework are summarized in Table I. In order to maintain scalability across different bin sizes, waste levels are expressed as a percentage of bin capacity, where 100% represents a completely filled bin.

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Table I: Simulation Parameters Used in the Python-Based Evaluation

Parameter	Symbol	Value	Unit
Number of smart bins	N	20	bins
Simulation duration	T	24	hours
Maximum bin capacity	B_max	100	% of bin capacity
Collection threshold	B_th	80	% of bin capacity
Collection amount per service	C_amt	75	% of bin capacity
Vehicle capacity	Q	500	% of bin capacity equivalent
Prediction horizon	H_p	5	time steps
Sampling interval	T_s	1	hour

IV. Mathematical Formulation of the AI-MPC Controller

This section presents the mathematical formulation of the proposed AI-Driven Predictive Model Predictive Control (AI-MPC) framework used to optimize waste collection routing. The formulation builds directly on the system architecture presented in Section III. In particular, the bin state representation defined in equations (1)–(2), the predicted waste input defined in equations (4)–(5), and the routing cost model defined in equation (10) form the foundation of the optimization model. The objective of the AI-MPC controller is to determine optimal waste collection decisions and routing strategies that minimize travel distance and overflow risk while satisfying operational constraints such as bin capacity and vehicle capacity.

A. Predictive State Model

Based on the bin state representation introduced in equation (2) and the predicted waste generation defined in equation (5), the future bin state can be predicted using the system dynamics model introduced in Section III. The predicted state evolution is therefore expressed as

$$\hat{x}(k+1) = x(k) + \widehat{w}(k) - Cu(k) \tag{11}$$

where
$x(k)$ is the current bin state vector, $\widehat{w}(k)$ represents the predicted waste generation vector obtained from the AI model, and $u(k)$ represents the waste collection decision vector defined in equations (8)– (9). Equation (11) enables the controller to estimate future bin fill levels over the prediction horizon.

B. Overflow Risk Modeling

To prevent waste bins from exceeding their maximum capacity, an overflow penalty term is introduced in the optimization model. Let b_{max} denote the maximum bin capacity defined in Section III. The overflow risk associated with bin i is defined as

$$O_i(k) = \max\left(0, \left(b_i(k) - b_{max}\right)\right) \tag{12}$$

This formulation ensures that bins approaching or exceeding the capacity threshold are prioritized for collection.

C. MPC Optimization Objective

The AI-MPC controller determines the optimal routing and collection decisions by minimizing a multi-objective cost function over a prediction horizon H_p. The cost function incorporates three key components: overflow risk, bin fill levels, and routing distance.

The optimization objective is defined as

$$J = \sum_{l=0}^{H_p-1} \left(\alpha \sum_{i=1}^{N} o_i(k+l)^2 + \beta \sum_{i=1}^{N} b_i(k+l)^2 + \gamma D(k+l)\right) \tag{13}$$

where
$D(k+l)$ is the routing distance defined in equation (10). α , β *and* γ are weighting parameters used to balance overflow prevention, bin utilization, and travel cost.

D. Optimization Problem

Using the predictive model in equation (11) and the cost function in equation (13), the AI-MPC routing problem can be formulated as the following constrained optimization problem:

$$\min_{u,r} J \tag{14}$$

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subject to the operational constraints defined in Section III, including bin capacity limits, vehicle capacity constraints, and routing feasibility.

E. Receding Horizon Control Strategy

The proposed AI-MPC controller operates using a **receding horizon strategy**. At each control step, the system performs the following sequence of operations:

- Acquire the current bin state (x(k)) from sensor measurements.
- Predict future waste generation using the AI model.
- Estimate future bin states using the predictive model in equation (11).
- Solve the optimization problem defined in equation (13).
- Apply the first optimal control action and update system states.

This closed-loop control strategy allows the system to continuously adapt to changing waste generation patterns and operational conditions.

V. AI-MPC ROUTING ALGORITHM AND PYTHON IMPLEMENTATION

This section presents the routing algorithm used to implement the proposed AI-Driven Model Predictive Control (AI-MPC) framework described in Sections III and IV. The algorithm integrates real-time waste monitoring, artificial intelligence–based prediction, and predictive control optimization to determine adaptive waste collection routes. The overall workflow of the proposed method is illustrated in Fig. 2.

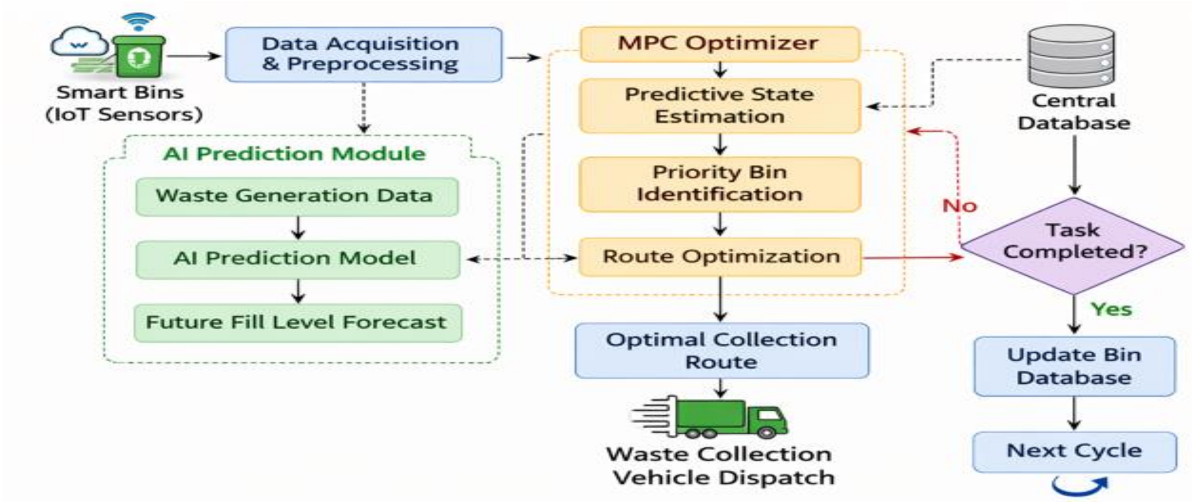

Fig 2: Flowchart of the AI-MPC Waste Collection Routing Algorithm

The proposed approach operates within a closed-loop architecture in which smart bin data are continuously collected via the sensing and communication infrastructure described in Section III. The AI prediction module processes this data to estimate future waste accumulation patterns. The predicted information is then supplied to the Model Predictive Control (MPC) optimizer developed in Section IV, which determines the optimal bins to be serviced and the most efficient routing strategy for the waste collection vehicle.

Unlike conventional waste collection strategies that rely on static schedules or simple threshold rules, the proposed AI-MPC algorithm anticipates future waste levels and proactively schedules collection operations. At each control interval, the system analyzes current bin states, predicts future waste generation, and determines which bins are most likely to approach critical capacity levels. The controller then computes an optimized collection route that minimizes travel distance while preventing potential overflow events.

The routing procedure follows an iterative decision-making process. First, the system acquires real-time fill-level information from all smart bins in the network. The AI module then predicts short-term waste generation trends using historical and contextual data. Based on these predictions, bins that are expected to reach high fill levels within the prediction horizon are identified as priority collection points. The MPC optimizer then determines the optimal set of bins to be serviced and generates the corresponding collection route while considering operational constraints such as vehicle capacity and service coverage.

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After the optimal route is determined, the collection vehicle follows the recommended path to service the selected bins. Updated bin measurements are subsequently transmitted back to the system, allowing the controller to update its predictions and routing decisions during the next control cycle. This iterative feedback process forms a predictive and adaptive waste collection strategy capable of responding dynamically to changes in waste generation patterns.

To evaluate the effectiveness of the proposed framework, the AI-MPC routing algorithm was implemented in a Python-based simulation environment. Python was selected due to its extensive support for data processing, machine learning, and optimization. The implementation integrates several widely used scientific computing libraries, including NumPy for numerical computation, Pandas for data processing, Scikit-learn for machine learning prediction models, and Matplotlib for visualization of simulation results.

The simulation framework consists of three primary modules. The first module generates and manages smart bin data representing waste accumulation across the simulated urban environment. The second module implements the AI prediction model that forecasts future bin fill levels using historical data patterns. The third module executes the AI-MPC routing algorithm, which determines optimized waste collection routes based on predicted system states.

The integration of AI prediction with predictive control represents the key novelty of the proposed method. By combining short-term waste forecasting with dynamic route optimization, the AI-MPC framework enables proactive waste collection decisions that improve operational efficiency and reduce the likelihood of bin overflow. The performance of the proposed algorithm is evaluated in the next section through Python-based simulation experiments.

VI. RESULTS AND DISCUSSION

This section presents the results obtained from the Python-based simulation used to evaluate the proposed AI-MPC waste collection routing framework. The analysis focuses on prediction accuracy, route optimization behavior, and comparative performance against conventional waste collection strategies.

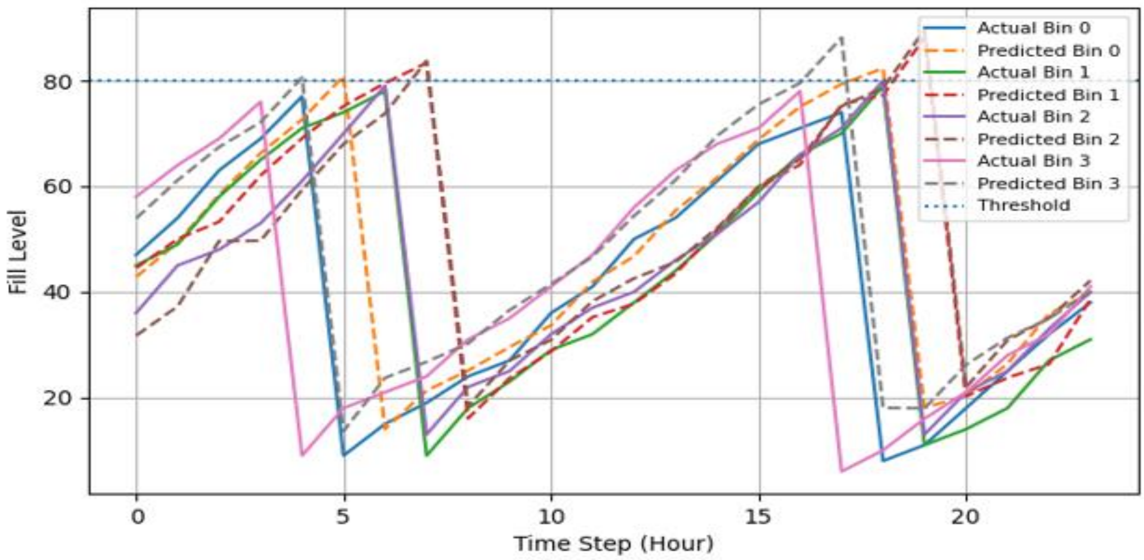

Fig. 3 Actual versus predicted bin fill levels for selected smart bins.

The prediction capability of the AI module is illustrated in **Fig. 3**, which compares the actual and predicted fill levels for selected smart bins over the simulation period. The results indicate that the prediction model closely follows the actual waste accumulation trends, enabling the controller to anticipate bins approaching critical capacity levels. This predictive capability provides the foundation for proactive waste collection decisions.

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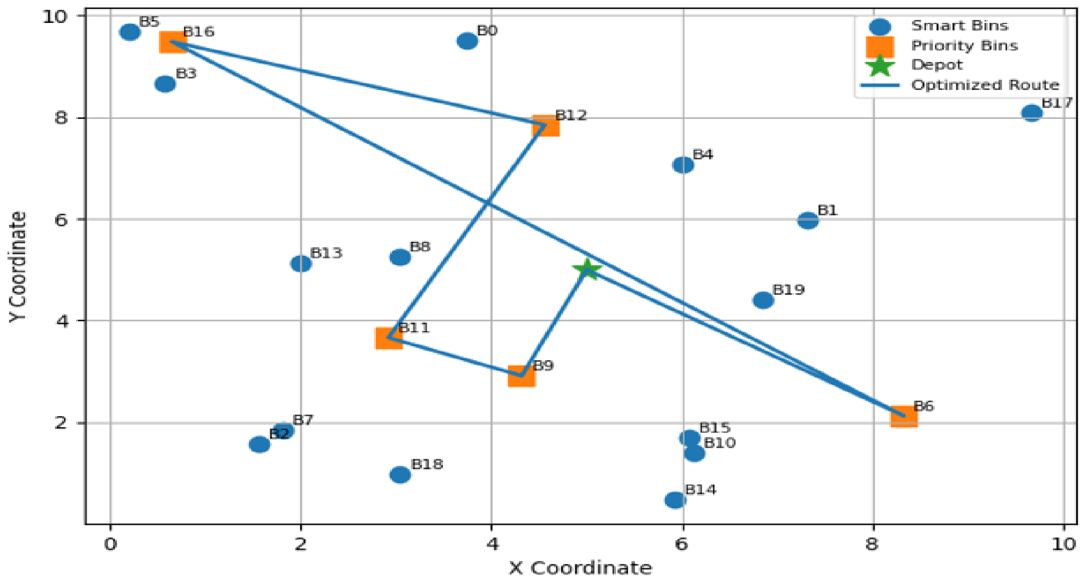

Fig. 4 Spatial distribution of smart bins and optimized waste collection route.

The routing behavior of the proposed framework is shown in **Fig. 4**, where the spatial distribution of smart bins and the optimized waste collection route are presented. The figure demonstrates how the AI-MPC controller dynamically selects priority bins and generates an efficient collection path that minimizes travel distance while servicing bins likely to reach high fill levels.

Table II: Comparative Performance of Waste Collection Strategies

Method	Travel Distance (km)	Overflow Events	Efficiency (%)	Distance Reduction (%)
Static Routing	120	14	65	—
Threshold-Based Routing	98	8	78	18.3
Proposed AI-MPC	**74**	**3**	**92**	**38.3**

The overall performance of the proposed system is summarized in **Table II**, which compares the AI-MPC framework with static routing and threshold-based routing strategies. The results show that the proposed approach significantly reduces travel distance and overflow events while achieving the highest operational efficiency.

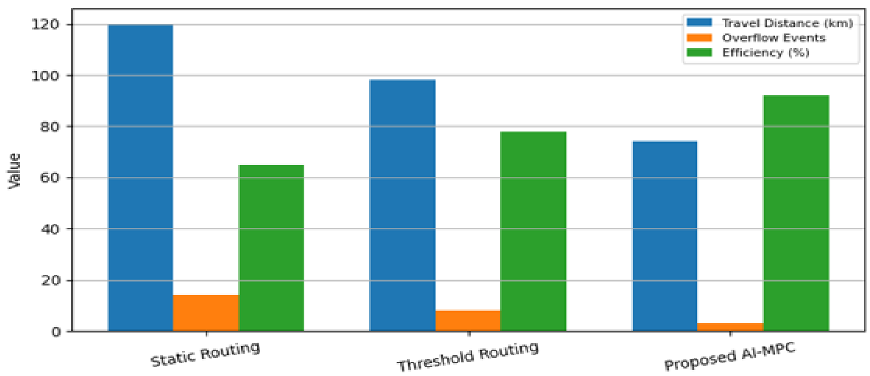

Fig. 5 Performance comparison of static routing, threshold-based routing, and the proposed AI-MPC strategy.

These improvements are further illustrated in Fig. 5**,** where the performance comparison highlights the advantages of the AI-MPC strategy. The results confirm that integrating AI-based prediction with predictive control enables more efficient and adaptive waste collection compared with conventional routing methods.

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VII. CONCLUSION

This paper presented an AI-Driven Predictive Model Predictive Control (AI-MPC) framework for smart waste collection routing. The proposed approach integrates artificial intelligence–based prediction with model predictive control to enable adaptive and proactive waste collection in smart city environments. The framework utilizes real-time smart bin data to predict future waste accumulation patterns and determine optimized waste collection routes that minimize travel distance while preventing bin overflow.

A Python-based simulation environment was developed to evaluate the performance of the proposed AI-MPC routing strategy. The results demonstrate that integrating predictive analytics with control-based routing significantly improves operational efficiency compared with conventional waste collection methods such as static routing and threshold-based strategies. The proposed framework reduces unnecessary vehicle trips, improves route efficiency, and minimizes the occurrence of bin overflow events.

The novelty of this work lies in the integration of AI-based waste prediction with model predictive control for dynamic waste collection routing, providing a predictive and adaptive decision-making mechanism that improves waste management performance in urban environments.

Future work will focus on enhancing the proposed framework through multi-vehicle and traffic-aware routing, incorporation of uncertainty-aware and reinforcement learning models for improved prediction and control, and validation using real-world smart bin and municipal waste dataset

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ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁝⁝ Peer-reviewed & Refereed journal ⁝⁝ Vol. 15, Issue 3, March 2026
DOI: 10.17148/IJARCCE.2026.15301

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