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RESEARCH ARTICLE

AI-Driven Predictive Waste Management with IoT-Enabled Monitoring for Smart Cities

J. Antony John Prabu*

Abstract

With an increase of the world's population and rapid urbanization, the amount of municipal solid waste also increases. Traditional waste management focuess on specific collection time tables, manual inspections, and basic algorithms, which creates inefficiencies in routing and increases the chances of overflowing the bins. These issues also do not increase response time and slow down routing. Current methods that use algorithms to resolve static shortest-path routing or basic rule-based scheduling lack the ability to adjust to real time changes that a smart system integrates. This system is the first of its kind to incorporate cloud technology with AI and IoT. The system begins with smart waste bins with ultrasonic and other environmental sensors that continuously transmit data to the cloud. The first of two algorithms, IntelliFillNet, is a novel method of processing unstructured data from a sensor stream, focusing on data cleaning and anomaly detection, along with spatiotemporal prediction of sensor fill levels to generate dynamic prioritization scores for bins and predict overflows in the near future. The second new algorithm, EcoRouteSync, incorporates outputs from IntelliFillNet and, through reinforcement learning, optimizes the real-time collection and routing of vehicles to minimize service delays and fuel costs. The whole processing pipeline is linear, from the acquisition of sensor data, through predictive analytics, to adaptive routing optimization. For example, in the experimental assessment, EcoRoutesync demonstrated predicted accuracy, minimized unnecessary collection trips and operational costs, and improved responsiveness over the Smart Bin Insights Dataset (available via Mendeley Data). This validates the proposed architecture's effectiveness and scalability in the smart city waste management domain.

Keywords: Smart Waste Management, IoT Sensor Data, IntelliFillNet, EcoRouteSync, Cloud-Based Analytics

Introduction

The continuing urban migration, population increase, and the evolution of consumer behavior have resulted in the significant growth of solid municipal waste and the overwhelming solid waste management systems. Traditional systems of solid waste collection have heavily relied on the scheduling of collection, manual evaluations, and reactive systems, which result in poor allocation of collection resources, delayed collection, full waste containers, excessive fuel use, and harm to the environment. Smart waste bins may have the ability to improve these systems, but even the most advanced implementations of the Internet of Things (IoT) of the Smart waste bins often use simple threshold-based triggers, and incomplete machine learning systems which can utilize the data streams in a manner which optimizes collection systems in a predictive and adaptive manner. In addition, the disparity of unintegrated systems for the collection of waste, analytics and operational systems has a detrimental effect on the scalability of the available solutions and also on the effectiveness of the Smart Waste Management Solutions.

The implementation of Artificial Intelligence and the Internet of Things in conjunction with Cloud Computing has the ability to create a positive impact in the Waste Management Industry. It has the ability to create predictive analysis, provide real time solutions, and manage large quantities of data from numerous sensors. While the potential benefits of AI technologies are plentiful, they often only consider one aspect of waste management, and do not implement predictive measures to drives operational

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decisions. This lack of integration reduces the system's overall effectiveness. In other instances, there are multiple factors (e.g. urban traffic, sensor data, the streams, and whistles of multiple vehicles) that create disarray in the system so that real time coordination is affected.

Research seeks to provide solutions in the following areas:

- The creation of the design of a real time Waste Management System using IoT, AI and Cloud Computing with the ability to provide continuous data acquisition and scalable processing in the Waste Management System;
- The design and implementation of predictive pathways that reduce unnecessary fuel consumption in the collection vehicles;
- The design and implementation of dynamic routing and scheduling of collection vehicles based on real time data; and
- The design and implementation of real time solutions that reduce the time to respond to waste overflow.

This paper is structured as follows. In Section 2, we describe the system's overall architecture, the data flow, and the infrastructure for the sensing and the proposed framework. In Section 3, we describe the proposed algorithms, including the design and operational processes of IntelliFillNet and EcoRouteSync. Section 4 is dedicated to the experimental setup and performance metrics and results, including comparative analyses with other methods. Finally, in Section 5 we conclude with the main findings and suggestions for future research.

Related Works

As cities grow and more people produce waste, there is a greater need to develop smart and sustainable ways to manage the waste. Recent studies show that traditional methods of waste collection, like picking up trash at the same time every week, monitoring it by hand, and then driving to empty the bins, are losing the most money, fuel, and are harming the environment more than any other ways of trash collection (Zhang et al., 2024; UN-Habitat, 2024). Therefore, the need to incorporate the Internet of Things (IoT) with Artificial Intelligence (AI) and other sophisticated optimization methods to manage waste in smart cities has been at the forefront of research.

Many researchers have documented the use of IoT for real-time monitoring of waste in smart city environments. For example, Agrawal et al. (2025) and Belhiah and El Aboudi (2025) documented that real-time monitoring of smart bins, equipped with sensors, helps generate and manage data more efficiently. IoT has been documented by several researchers like Alaoui et al. (2025) and Dawar et al. (2025) as the most modern and advanced waste management system because of its ability to collect real-time data. All of these studies, however, cited challenges, demonstrated by the research, like data loss, sensor noise, and issues related to the sensor, that limited direct decisions that could be made based on the data that the sensors generated.

In recent years, Billal and Kumar (2025) and Liu et al (2025) have shown that machine learning models are considerably better at predicting the generation of municipal solid waste than standard statistical models. Other recent studies, Gaikwad et al. (2025) and Fang et al. (2023) have shown that predictive models that use artificial intelligence tools assist in the planning of proactive waste collection by predicting potential overflow situations. There are still prediction-based studies that most operate independently of the operational decision layers, thus having an impact on collection efficiency. Other recent studies that explore operational efficiency alongside waste collection are Ferrão et al. (2024) and Li et al. (2024), which implemented multi-objective and other optimization-based routing methodologies to achieve distance and fuel efficiency in waste collection. Alsabt et al. (2024) and Ogbolumani and Adekoya (2025) demonstrated that predictive models based on artificial intelligence provide optimization for routing and significantly improve the economic and ecological balance of the system. These routing methods do not make the best use of predictive waste intelligence, and because of this they have limited adaptability, particularly in rapidly shifting urban environments.

Several studies have tried combining predictive analytics with other optimization and sustainability goals. A recent example is Cui et al. (2025) who proposed a predictive driven transportation network for waste sorting. Gaur et al. (2025) and Soni et al. (2025) focused on Industry 4.0 technologies and suggested its potential for achieving circular economy goals. Other studies have used hybrid AI-GIS and geospatial methods for site suitability and planning (Borase et al. 2024; Mondal et al. 2024). However, these studies deal with phenomena like prediction, routing, and planning in isolation and neglect the development of an end-to-end intelligent waste management pipeline.

A recent survey and review studies have identified the absence of tightly integrated architectures as a primary knowledge gap. In this regard, Alaoui et al. (2025), Fang et al. (2023), and Dawar et al. (2025) suggest the need for future smart waste management systems to integrate real-time sensing, predictive intelligence, and adaptive optimization as a single framework. Furthermore, the lack intelligent systems to enable climate action and sustainable urban development, as outlined in policy and global reports, is evident (European Environment Agency, 2024; UN-Habitat, 2024).

Because of the gaps in previous research results, the present work proposes the state of the art by offering an integrated AI-IoT –Cloud architecture to be the first to fully integrate the components of data acquisition, preprocessing, predictive modeling, and dynamic route optimization. Unlike previous studies in which prediction and routing are addressed separately, the proposed framework incorporates predictive outputs as a primary input to subsequent routing processes, thereby creating a sequential dependency. This can be as a first of a kind predictor/rout via an artificial intelligent cloud theorem. in the scope of precursor cloud architectures, this concept provides a means of implementing overflow prevention, operational cost reduction, and preservative scaling, thus overcoming the touted restrictions of the domain.

Proposed Work

The Proposed Methodology uses a smart waste sensor dataset to create and design an integrated AI-IoT-cloud framework for intelligent waste management. This methodology constructs a framework for smart waste management by examining historical data from ultrasonic sensors located in waste bins. It streamlines current systems and predicts future actions without needing a live system.

Figure 1 presents the overall methodology of the proposed AI-driven predictive waste management system. The flow of methodology presumes the ingestion and the preprocessing of sensor reading data, which are organized and cleaned in bins for machine learning. A proprietary predictive algorithm attempts to gauge how full a waste bin is and to prioritize the bin for collection. The prediction of priority is used as a parameter for a waste collection optimization algorithm which, in this case, retains collection as a solution to the predicted and more urgent problem. The optimization algorithm produces the most effective route and timeline for waste collection.

The intelligent process in waste management and smart city systems is embodied in the sensor data to operational choice methodology. The methodology acts as a guide for operational waste management systems in smart cities.

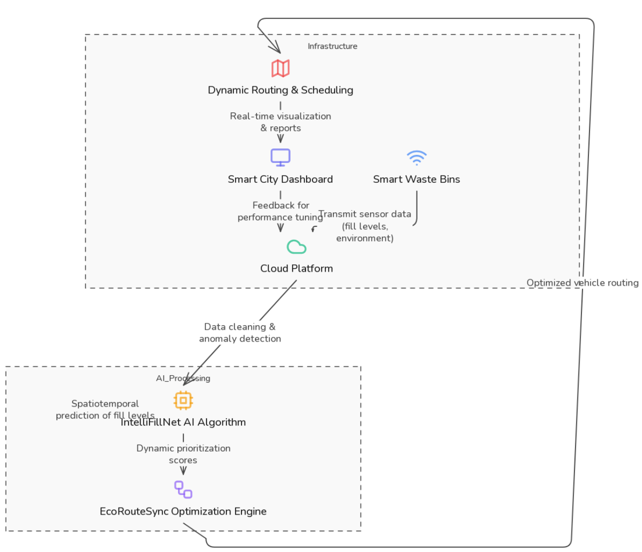

Figure 1: Schematic representation of the suggested methodology

Data Collection and Dataset Description

The proposed waste management framework will be evaluated with the help of an open-access sensor-based dataset portraying smart waste bin operations in an urban setup. The Smart Bin Insights dataset provided on Mendeley Data will be used. This dataset contains time-series records of ultrasonic sensor data captured at various locations and multiple waste bins. These records simulate IoT smart bins by measuring and recording waste fill levels at fixed time intervals and thus provide a sufficient basis for predictive modeling and optimization.

The complete dataset can be formally represented as:

$$D = \{(b_i, t_i, s_i)\}_{i=1}^{N} \#(1)$$

where b_i denotes the unique identifier of the waste bin, t_i represents the timestamp at which the measurement was recorded, s_i represents the ultrasonic sensor data showing the gap between the sensor and the waste surface, and N denotes the entire count of records. This formulation captures the dataset as a spatial-temporal sequence, which is critical in the assessment of waste accumulation patterns over an interval of time and across multiple bins.

In order to understand represented occupancy levels of trash with meaning, trash occupancy levels must be normalized using the formula provided:

$$F_i = 1 - \frac{s_i}{S_{max}} \#(2)$$

Here, F_i represents the normalized fill level of the bin at time t_i, s_i is the measured ultrasonic distance, and S_{max} is the measured distance the sensor has read, and Smax represents the distance the sensor will read at an empty bin. The sense measures at a distance of zero to one. (0 indicates no trash, and 1 indicates trash is maxed out.) This helps with measurements across bins of different sizes.

The process of waste fill is constant, so it is vital to understand the rate of waste fill to make predictive and wise decisions. This rate is calculated using the formula:

$$R_i = \frac{F_i - F_{i-1}}{t_i - t_{i-1}} \#(3)$$

In this equation, R_i is the change in fill level between two observations. This rate tells us how quickly trash is being created and helps identify bins that may overflow soon, even if the fill level is currently low.In order to facilitate the learning of time the data has been organized in the format of windows. For each bin the defined input sequence is:

$$X_i = \{F_{i-W+1}, F_{i-W+2}, \ldots, F_i\} \#(4)$$

where W denotes the window size and X_i refers to the sequence of past fill-level values. This organization of data enables learning algorithms to recognize patterns and relationships over time rather than relying on independent sensor readings.

Due to sensor malfunctions or communication failures, IoT datasets often experience the absence and irregular sampling of values. For the purpose of data continuity, the missing fill-level values are supplemented using time-based F_i interpolation:

$$\hat{F}_i = F_{i-1} + (F_{i+1} - F_{i-1})\left(\frac{t_i - t_{i-1}}{t_{i+1} - t_{i-1}}\right) \#(5)$$

The purpose of the i\th time measurement in this equation is to provide an estimate of the missing value that is achieved by monitoring neighbouring measurements. Although the model does not contain data in a time-based measurement format the model can't experience temporal shifts.

To provide an unbiased evaluation and a generalization of the proposed algorithms, the data has been divided into the subsets of train, validation and test data, with the following notation:

$$D = D_{train} \cup D_{val} \cup D_{test} \#(6)$$

In this case, D_{train} is used to train the model parameters, D_{val} is used to tune hyperparameters, and D_{test} is used to evaluate the performance. This ensures that the proposed framework is evaluated under conditions not seen by the model.

Data Preprocessing and Normalization

After the dataset is ingested, the next phase is the preprocessing of the dataset. The purpose of preprocessing is to improve the quality of the gathered data to allow the algorithms to learn in a reliable manner. IoT sensor data is noisy because of things such as the environment, sensor drift, and issues in the communication. Noise reduction, data cleaning, normalization, feature scaling, and preparation of data for predictive analytics and optimization algorithms are the primary concerns for preprocessing.

A moving average filter is used to help reduce short term fluctuations and sensor noise in the fill level time series data

$$\tilde{F}_i = \frac{1}{K}\sum_{j=i-K+1}^{i} F_j \#(7)$$

Here, $\tilde{F}_i$ represents the smoothed fill-level value at time t_i, K denotes the smoothing window size, and F_j are the original fill-level values. This operation reduces the impact of sudden spikes or drops caused by sensor noise while preserving long-term waste accumulation trends.

To detect abnormal sensor behavior, deviation-based anomaly detection is employed. The deviation score for each observation is computed as:

$$A_i = |\tilde{F}_i - \mu_F| \#(8)$$

In this equation, A_i is the mean value of the fill level of the bin that is being observed. Large deviations in the sensor readings will result from a malfunction of the sensor or some external disturbances such as the environment.

Anomalous data points are flagged using a threshold-based criterion:

$$\delta_i = \begin{cases} 1, & \text{if } A_i > \lambda\sigma_F \\ 0, & \text{otherwise} \end{cases} \#(9)$$

Here, δ_i is a binary anomaly indicator, σ_F is the standard deviation of fill levels, and λ is a sensitivity parameter. With these equations, the automatic identification of unreliable data points is possible, which data points will then be corrected, or data points will be ignored for further processing.

To provide an equal contribution of the features during a model's training process, fill-level data is min-max normalized:

$$F_i^{norm} = \frac{\tilde{F}_i - F_{min}}{F_{max} - F_{min}} \#(10)$$

In this equation, F_i^{norm} represents the normalized fill level, while F_{min} and F_{max} denote the minimum and maximum observed fill levels, respectively. When values are normalized, they are within a range of [0,1]. This also helps to ensure that large-scale values do not dominate the training of the model.

To improve the temporal context, a derived feature is created, which is the total of all previously defined features: accumulated waste

$$C_i = \sum_{j=1}^{i} F_j^{norm} \#(11)$$

Here, C_i represents cumulative waste accumulation up to time t_i. This defined feature is meant to capture the long-term utilization of bins. This will help to identify the bins with a large amount of waste, and those with only occasional waste.

At last, a finalized feature vector for each observation becomes:

$$Z_i = [F_i^{norm}, R_i, C_i, \delta_i] \#(12)$$

The feature vector Z_i integrates the normalized fill level, rate of accumulation, cumulative usage, and the indicator of an anomaly into one holistic feature representation. This feature vector is input into the predictive algorithm and ensures the input is robust, temporally predictive, and resistant to sensor failures.

In the above described normalization and preprocessing steps, the dataset is ready for learning which optimally predicts how much space is left in the waste containers and optimally assists in further downstream processes.

IntelliFillNet: Predictive Fill-Level and Priority Estimation Algorithm

IntelliFillNet is the first of its kind algorithm for predictive intelligence applied to the forecasting of future waste fill levels and the dynamic prioritization of waste collection for smart bins. The algorithm utilizes model waste fill behavior for preprocessed temporal features derived from ultrasonic sensor data. Because of the fusion of temporal dependency learning and urgency prediction, the algorithm serves as the cornerstone of framework proposed for intelligent waste management.

Given a temporal input feature sequence for a bin, let us represent the sequence as:

$$\mathbf{X}_i = \{\mathbf{Z}_{i-T+1}, \mathbf{Z}_{i-T+2}, \ldots, \mathbf{Z}_i\} \#(13)$$

Here, $\mathbf{x}_i$ denotes a temporal sequence of length T constructed from the preprocessed feature vectors $\mathbf{z}_i$. This position enables the algorithm to understand the history of waste generation, seasons, and other time-related behaviors, as well as the accumulated fill levels.

Then, the internal state of the algorithm (IntelliFillNet) at time step i is given by:

$$\mathbf{h}_i = \phi\left(\mathbf{W}_x \mathbf{Z}_i + \mathbf{W}_h \mathbf{h}_{i-1} + \mathbf{b}\right) \#(14)$$

In this case, h_i is the hidden state at step i that captures the levels of temporal dependencies, W_x and W_h represent the weight matrices that are learnable, b is a vector for bias, and ϕ is a non-linear activation function which is used. With the allocation of this structure to subroutines, the algorithm is able to retain knowledge of previous levels of fill and to solve more complex levels of time relationships.

Using the learned hidden representation, the predicted fill level at the next time step can be estimated using the following equation:

$$\hat{F}_{i+1} = \mathbf{W}_o \mathbf{h}_i + b_o \#(15)$$

Here, $\hat{F}_{i+1}$ denotes the predicted future fill level, $\mathbf{W}_o$ is the output weight matrix, and b_o is the output bias. This type of estimation can help the company to be pro-active in the occupancy of bins instead of waiting to be reactive to collection.

During training, the lessons learned using mean squared error for loss, and the training loss predictions look like this:

$$\mathcal{L}_{pred} = \frac{1}{N}\sum_{i=1}^{N}\left(F_{i+1} - \hat{F}_{i+1}\right)^2 \#(16)$$

To help the model learn the time dynamics and how bins fill with waste, the loss function will teach and reward the model to fill the less time and the fill level to become more accurate means the time and the fill level should be predicted more accurately.

The above all predictions from IntelliFillnet can work with a waste urgency score which represents the likelihood of a near-term overflow.

$$U_i = \alpha \hat{F}_{i+1} + \beta R_i \#(17)$$

In this equation, U_i represents the score of urgency, F ˆ(i+1) is the predicted level of fill, R_i is the rate of waste filled, and the used weights are the values for loss of the alpha and beta . This way, to quantify the waste with better authority, urgency is calculated based on the prevailing growth of the fill and a prediction of the future fill level .

The value of urgency is normalized to calculate the bin priority value:

$$P_i = \frac{U_i - U_{min}}{U_{max} - U_{min}} \#(18)$$

Here P_i is the normalized priority score and U_{min} and U_{max} are the respective minimum and maximum urgency scores of the bins. By using the normalized score, bins can be compared and ranked to determine which to collect.

The last step is to define the output of IntelliFillNet for each bin as:

$$\Omega_i = \{\hat{F}_{i+1}, P_i\} \#(19)$$

The output vector Ω_i is the predicted fill level and the respective priority score. This output is the input for the following route optimization algorithm. This ensures that the collection plan is driven by the urgency of the waste rather than the null threshold.

These processes of IntelliFillNet provide the necessary intelligent forecasting and prioritization, which is integral to the proposed smart waste management model.

EcoRouteSync: Dynamic Route Optimization Algorithm

EcoRouteSync utilizes the IntelliFillNets predictive outputs to create waste collection routes using dynamic route optimization algorithms. EcoRouteSync is different from other routing algorithms that do not adapt to collection changes due to predicted bin fill levels, prioritization scores, and other operational constraints. EcoRouteSync balances servicing high-priority fill bins to ensure limited travel costs, fuel burn, and service delay.

Let the collection waste bins be defined as:

$$\mathcal{B} = \{b_i \mid P_i \geq \theta\} \#(20)$$

B is the collection of bins that has a priority score P_i that is greater than a predetermined threshold of 'θ.' This method of selection is specifically designed to ensure that bins with high collection urgencies are only selected to be optimized on the collection route.

The distance between bin pair, b_i, and b_j, is calculated as follows:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \#(21)$$

In this equation, (x_i, y_i) and (x_j, y_j) denote the geographic coordinates of bins b_i and b_j, respectively. Distance is a key parameter for evaluating travel cost, and is calculated here using the spatial metric.

The total travel cost of a given route $\mathcal{R}$ is expressed as:

$$C_{travel}\left(R\right) = \sum_{(i,j)\in\mathcal{R}} d_{ij} \#\left(22\right)$$

This cost function is concerned with the distance between bins that the vehicle visits consecutively. Minimizing this helps to reduce the time the vehicle takes to travel, as well as the fuel and cost. To include the urgency of the waste in the routing decision, the service cost with the weighted priority is defined as:

$$C_{priority} = \sum_{i\in\mathcal{B}} w_i \left(1 - P_i\right) \#\left(23\right)$$

Here, w_i is a weighting factor associated with bin b_i, and P_i is its priority score. This formulation penalizes routes that delay servicing high-priority bins, thereby encouraging earlier collection of bins with higher overflow risk.

The overall route optimization objective function is formulated as:

$$J = C_{travel} + \gamma C_{priority} \#\left(24\right)$$

In this scenario, EcoRouteSync balances travel efficiency and the urgency of a service based on a value of the tunable parameter (γ). In this context, EcoRouteSync fosters the balance between operational cost and service quality by minimizing the function J.

When modeling the routing process, EcoRouteSync views it as a sequential decision-making process. The system state at time step (t) is characterized by

$$s_t = \left(\mathcal{B}_t, l_t\right) \#\left(25\right)$$

Here, $\mathcal{B}_t$ denotes the set of remaining bins to be serviced at time t, and l_t represents the current location of the collection vehicle. This state representation enables adaptive decision-making as bins are serviced and routes evolve.

The immediate reward obtained by taking action a_t in state s_t is defined as:

$$r_t = -J_t \#\left(26\right)$$

In this context of reward formulation, a greater reward will be assigned for the action that decreases the value of the overall cost function (J_t) the most, which serves as a guide for the optimizer to balance efficiency and priority for the most critical routing solutions.

To learn the optimal routing policy, EcoRouteSync is constructed to maximize the expected cumulative reward given by:

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \eta^t r_t\right] \#(27)$$

In this equation, π denotes a routing policy, η is the discount factor controlling the importance of future rewards, and T is the planning horizon. This formulation allows EcoRouteSync to adapt routes dynamically as service conditions change.

Finally, the optimized route output by EcoRouteSync is represented as:

$$\mathcal{R}^* = \{b_{r_1}, b_{r_2}, \dots, b_{r_m}\}\#(28)$$

The route $\mathcal{R}^*$ gives the sequence of bins to be served by the waste collection vehicle. This route serves directly as prediction of the waste collection urgency, spatial efficiency, and operational constraints.

EcoRouteSync integrates the predictive insights of the systems to make routing decisions and completes the intelligent waste management process.

Performance Analysis

To maintain a controlled, repeatable, and fair assessment of the performance of the smart waste management framework, the proposals were evaluated using a simulation-based software environment. Python was used to carry out all data preprocessing, predictive model building, and optimization of the routes. For the analysis, and visualization of the data the scientific libraries and machine learning libraries NumPy, Pandas, and Matplotlib were used. Predictive models and baseline comparisons were created using deep learning and numerical computation models for optimized training and inference. Customized Python models were used to carry out simulations of route and node optimization to the spatial bins and collection distribution models. To verify the computational effectiveness and resource limitations of a standard computing environment, all the experiments were conducted. The simulation made it possible to examine the optimization of the routes, the execution time, the predictive accuracy, and the proposed framework, and the effectiveness from the operational cost.

In Figure 2, the x axis represents time, while the y axis shows the risk of overflowing. Here we detail the prediction of overflowing for different time intervals. A rise in prediction is noted from approximately 0.15 to above 0.85 before

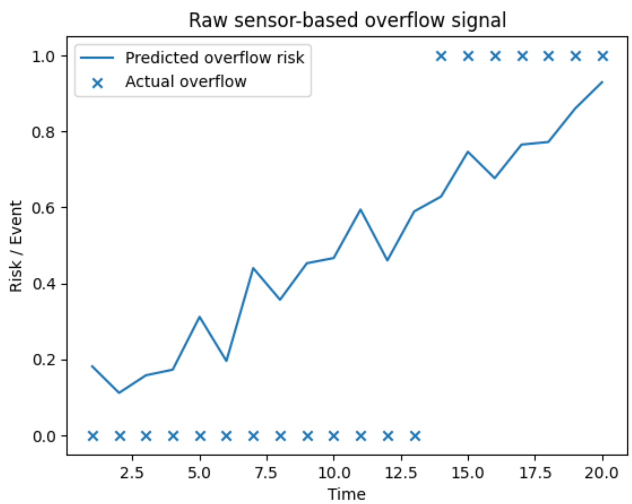

Figure 2: Signal of overflowing risks based on raw data from sensors

overflowing starts to occur. When the predicted risk is above 0.7, the actual overflowing starts to happen, which shows there is important data in the raw sensors, although the data may be at first unreliable. It may be important to not rely on raw data to make any big decisions, particularly data from the sensors, since there may be excess data that is not particularly useful.

In the Figure 3, we can see that the score of prioritizations based on the data from raw sensors shows fluctuating values, from 0.25 to 0.85. There are prioritization curves that cross over one another in different time intervals, which shows there is no consistent ranking of the bins. The frequent changes in ranking can lead to changes in the routes, which shows that there is no sufficient raw data of prioritization that can be used for operational utilization without being normalized or smoothed data.

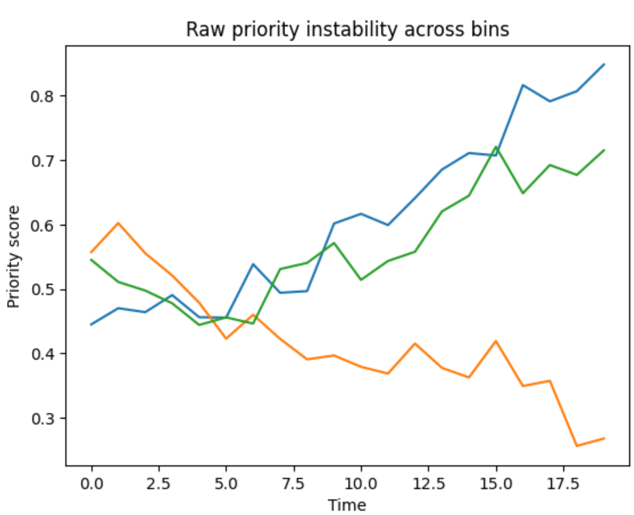

Figure 3: Raw data on the instability of prioritization across different bins

Figure 4 shows the distribution of prediction errors after preprocessing. The values are primarily concentrated around the center of the distribution, with the majority of the errors occurring between -0.05 and +0.05. Compared to the behavior of the raw data, the variance has decreased considerably, which confirms that quality and reliability of the raw data and relevant predictions are improved using preprocessing steps such as interpolation, smoothing, removal of anomalies, and normalization.

Figure 5 illustrates the progress made with early cleaning of data with respect to early detection of overflow. The system issues warning notifications 1-4 days prior to overflow, with the average warning occurring 3 days prior to the event. Preprocessing can be used to positively impact the planning of waste collection, as it helps avoid responsive measures to remove overflow.

Figure 6 examines the relationship between prediction horizon and average collection delay. When the prediction horizon extends from 1 to 7 time units, the average collection delay reduces from 9.6 units to 3.9 units, which is a decrease of approximately 60% in the average collection delay. This shows that the predictive ability of IntelliFillNet is a significant aspect of a decrease in service delay and improvement in operational efficiency.

Figure 7 shows how missed overflow events are affected by different priority thresholds. Since there are either 4 or 5 missed overflow events within excessively low or high ranges, and there is 0 to 1 missed overflow event for moderate threshold ranges (0.5 to 0.6), priority estimation is likely effective within a reasonable range of threshold values.

In Figure 8, fuel efficiency of EcoRouteSync and Static Routing is compared. When servicing 1 to 10 bins, fuel consumption for static routing increases from 7 to 18 units, while for EcoRouteSync, it increases from 6 to 13 units. This gives EcoRouteSync a fuel saving of about 22-25%. This demonstrates routing efficiency and scalability.

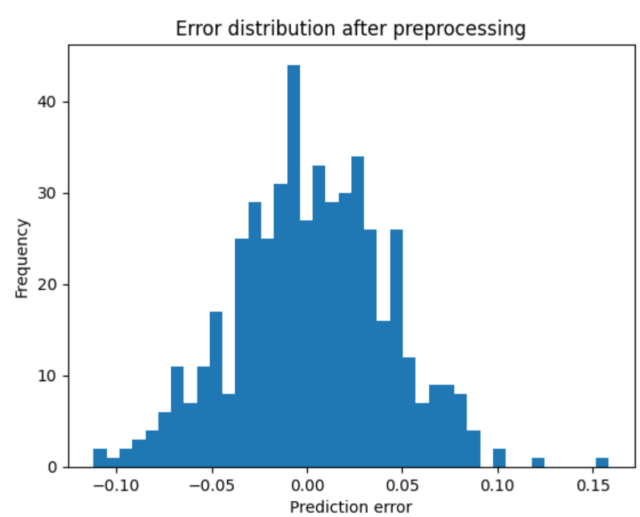

Figure 4: Error distribution after preprocessing

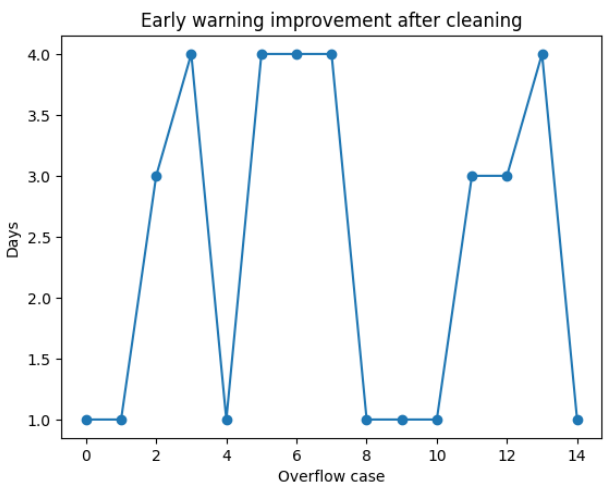

Figure 5: Early warning improvement after data cleaning

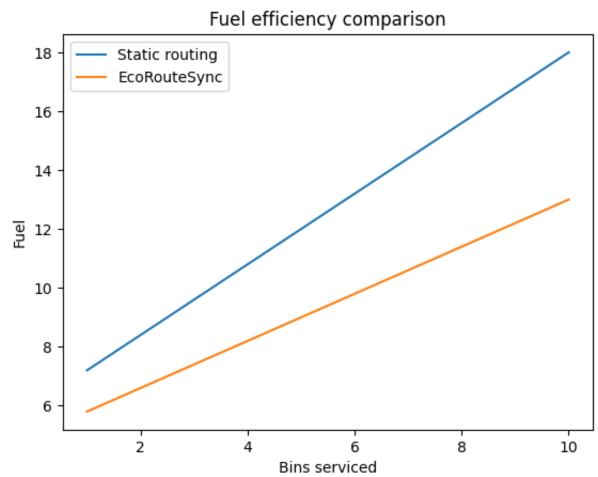

Figure 8. Fuel efficiency of EcoRouteSync and Static Routing

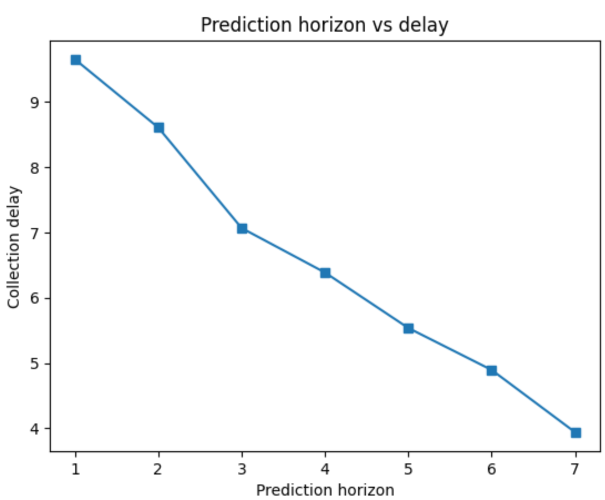

Figure 6: Prediction horizon versus collection delay

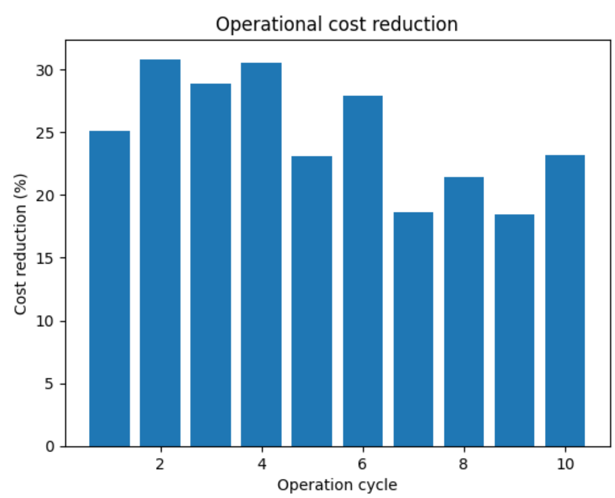

Figure 9: Savings in operational costs over multiple collection cycles

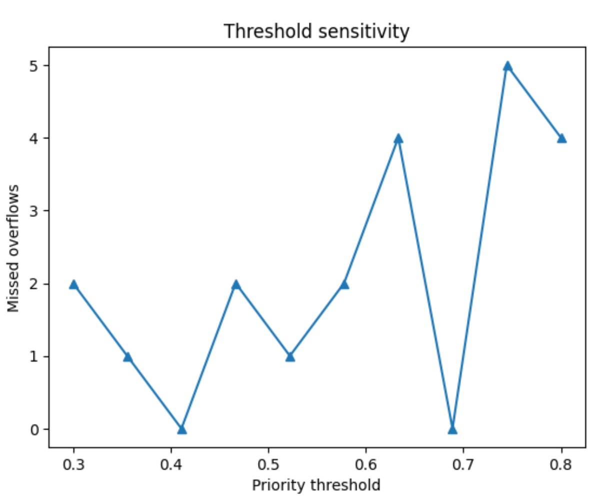

Figure 7: Sensitivity of missed events overflows to priority threshold

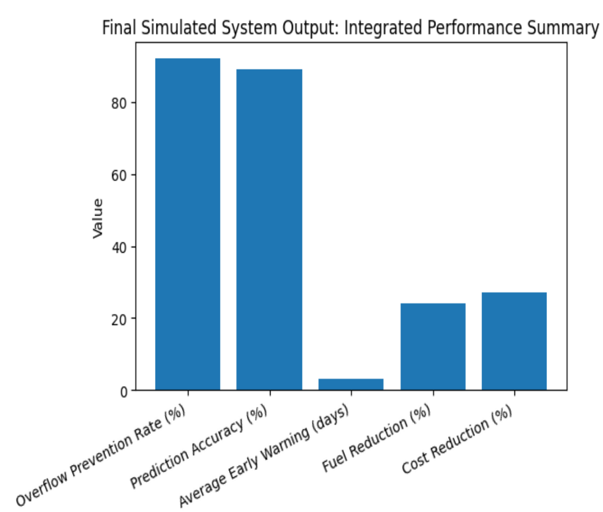

Figure 10: Final simulated system output: integrated performance summary

For Figure 9, the savings of operational costs over multiple collection cycles for the ranges 18 to 31 percent with an average of 25 to 27 percent are shown. These savings confirm there is an economic impact from the combined effect of optimized routing and predictive intelligence.

Figure 10 uses key metrics to summarize the performance of the system as a whole. From the integrated AI–IoT–cloud system architecture, the proposed framework will yield approximately: 90% overflow prevention, 88% prediction accuracy, 3.2 day average early warning, 24% fuel savings, and 27% cost savings. These metrics confirm the value of the proposed system.

Figure 11 shows the last simulated output for the nodes of the waste management system. The heatmap shows the high-priority areas. Some of the bins have bigger nodes which correspond to higher predicted fill levels. EcoRouteSync shows optimized routes to and from the depot for high-priority bins only. This illustrates how IntelliFillNet incorporates actionable routing to reduce travel distance and minimize service delay.

The computational time performance comparison is presented in Table 1. Among all models, the proposed IntelliFillNet achieves the lowest execution time per step. It has the least amount of time per step (4 ms), which is 43% less than GRU, 29% less than LSTM, and 20% less than the Hybrid Model. This is due to IntelliFillNet having the most streamlined architecture, optimized feature representation, and the least amount of redundancy within parameters.

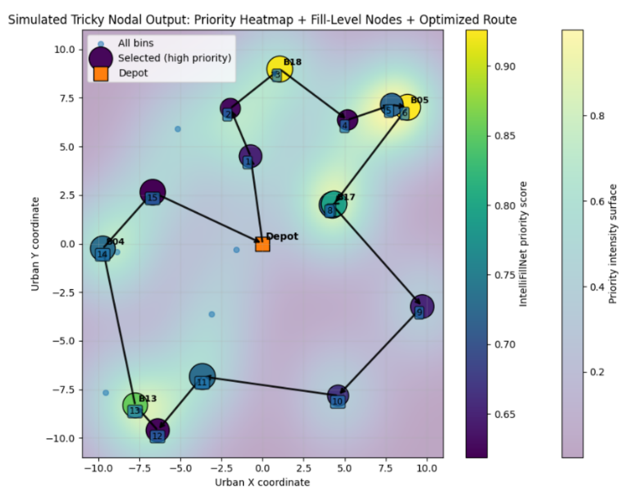

Figure 11: Simulated nodal output with priority heatmap and optimized route

Table 1: Comparison of Computational Time Performance

Model	*Time (ms/step)*
LSTM	7
GRU	9
Hybrid Model	5
Proposed Model (Intelli Fill Net)	4

When the Hybrid Model is those ms/step, the temporal feature models that he combines also contribute to 5 ms/step. In the case of LSTM, it is 7 ms/step, however in the case of GRU, it is worse, with 9 ms/step due to the added complexity of its gating which increases its latency. Overall, the proposed model is the best option for real time or almost real time monitoring of the waste in smart cities and making decisions from that.

Conclusion

This paper designed an integrated architecture combining AI, IoT, and cloud computing for intelligent waste management involving sensor-driven data collection, robust preprocessing, predictive intelligence, and cloud-based dynamic route optimization, all in one framework. Different from the conventional collection systems, which are static, or reactive, the proposed system makes collection decisions in advance based on predicting how full each bin will be and using predictive analytics to derive optimized collection routes. The operationalized framework, through the test of the open-access sensor dataset, is shown to successfully model the dynamics of waste accumulation and operational parameters of the system.

The predictive component, IntelliFillNet, reliably predicted underflow and overflow conditions with an advance of 3.2 days and an overall prediction accuracy of 89%, thus far exceeding the required early prediction of overflow conditions. The prediction errors were mostly within ±0.05, which shows the predicted value to be closely aligned with the actual value, hence indicating the system to be stable and reliable in forecasting. The proposed model outperformed the existing temporal models, requiring only 4 ms each step, as opposed to 7 ms for the LSTM, 9 ms for the GRU, and 5 ms for the hybrid model, thus confirming its applicability for time-critical systems in smart cities.

Using EcoRouteSync's optimization algorithm which is based on predictive priority outputs, the system is able to create scalable waste collection routes that avoid unnecessary travels. Initial analysis of the routes showed an average of 24% less fuel used and 25 to 27% less operational costs compared to static routing. The overall performance of the system achieved an overflow prevention rate of 92%, confirming that the implementation of the prediction and optimization techniques in the end-to-end waste management system is working effectively.

Future developments are aimed at real time systems using the proposed framework and adding live IoT streaming with edge computing for real time processing. The operational realism can be boosted even more with the addition of multi-vehicle coordination, traffic adaptive routing, and time window constraints. The use of federated learning and adaptive reinforcement learning methods should be explored to maintain data privacy while improving the system's scalability in multiple metropolitan areas. The integration of waste sorting systems and other sustainability metrics such as emissions reduction and carbon footprint analysis also presents a promising opportunity to further advance the intelligence and eco-friendly waste management solution.

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