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Smart City Waste Management Using Sensor-Driven IoT Architecture and Predictive Analytics

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Abstract

The problem of efficient and sustainable waste management has been one of the urgent issues when considering the sensibly increasing populations of cities and the current appearance of smart city programs. Conventional systems of municipal waste collection have been rather inefficient due to fixed-route timetabled flow, resources waste, and the failure to respond to overflowing bins in time which poses a problem to public health and environment. This paper presents a novel, detailed sensor-based architecture of the Internet of Things (IoT) with predictive analytics on the management of solid waste, on the one hand, in order to overcome these difficulties. The regime includes a series of smart bins with ultrasonic sensors recording current fill-level and gas sensors to detect dangerous emission. Powered with energy-saving microcontrollers and data delivery over Low Power Wide Area Networks (LPWAN) like LoRa and Nb-IoT these sensor nodes can be relied upon to deliver data effectively whilst maintaining minimum power levels. The obtained information is sent to an edge-cloud system that can handle the ingestion and processing of data on a scalable basis. Filtering and detection of anomalies done in real-time is done at the edge layer to provide data quality and send alerts. In the cloud layer, high-order machine learning algorithms such as Long Short-Term Memory (LSTM) networks and gradient boosting algorithms are used in predicting growth trends of waste materials over time following past trends and environmental factors. This is based on the predictions and bins are prioritized in a dynamic way and optimized collection routes are created using path planning algorithms that minimize usage of fuel, and operational cost. A mock urban implementation of the system that was implemented in three months indicated that the proposed system could save 37 percent fuel use, increase the efficiency of waste pick-up operations by 45 percent, and greatly reduce instances of missed pick ups. Such a combination of predictive intelligence and energy-efficient communication makes the system highly applicable even on smart cities. This study demonstrates how the perceptions of IoT sensing and machine learning could transform the waste management system in cities and shift towards data-driven and sustainable services in cities.

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Introduction

Such high growth rates in population and urbanization that have been witnessed in the present 21 st century have put an increased pressure on the urban infrastructure especially in the area of municipal solid waste (MSW) management. The World Bank predicted a product of 3.4 billion tons by 2050, whereby waste generation is the highest in the urban regions. Therefore, proper collection and disposal of waste material has become very paramount in ensuring clean cities, healthy city inhabitants, and sustainable environments. Nevertheless, the usual way of waste management is traditionally and inevitably inefficient as it includes such a process as fixed-route garbage collection, manual thoroughness of garbage bins, and a static schedule. Some of the effects of these legacy systems are spillage in bins, wastage of fuel, overuse of manpower, and cost of operation due to inefficiencies. In addition, they cannot perform in a dynamic manner to reflect current alteration in the patterns of waste generation within the various urban sectors.

The development of smart city paradigms is a solution to revolutionize to deal with these shortcomings by integration of digital technologies, especially the Internet of Things (IoT), wireless sensor networks (WSNs), and data analytics. The IoT-supported waste management systems offers a framework that is both decentralized and real-time where the embedded sensors record in a continuous manner the fill level of the bin, gas emissions, and environmental conditions. When supported by long-range, reliable wireless communication protocol like LoRaWAN or NB-IoT, these sensor nodes can send the actionable information to an intelligent decision-making platform, either centralized or distributed. Nevertheless, full potential of such systems is achieved when the sensor data are correlated to enhanced machine learning models with abilities to predict patterns of waste accumulation in order to define an optimal schedule of collection.

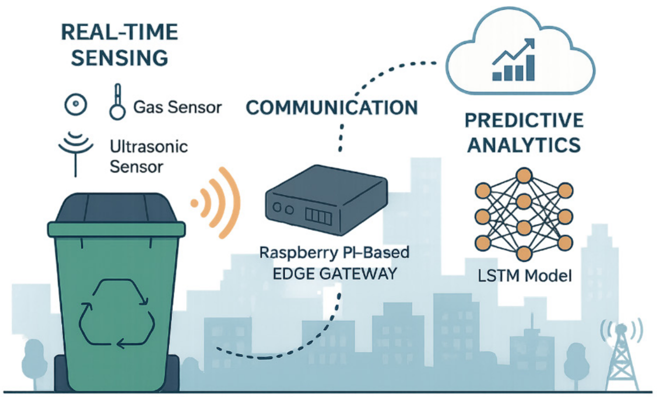

Fig. 1: IoT-Enabled Smart Waste Management System Featuring Real-Time Sensing, Edge Communication, and Predictive Analytics.

In this paper we postulate an end-to-end waste management, IoT based architecture that incorporates multi-modal sensor network, analytics at edge and cloud, and predictive modelling techniques to improve decision-making. Particularly, the following models are used in predicting features of bin fill levels using historical and real-time data: Long Short-Term Memory (LSTM) networks and gradient boosting models. The predictive intelligence dynamically modifies the collection route, thus alleviating operation redundancies. Contrary to the current static systems, proposed framework allows demand-based adaptive waste collection, thereby creating a more resource-efficient and less environment-harming system.

The rest of the paper is organized as follows: Section 2 presents literature review on related work connected with smart waste management systems. Section 3 discusses the architecture of the suggested system such as the design of sensor nodes, communication protocols, and cloud-edge integration. In section 4 the methodology and machine learning techniques have been expounded. In Section 5, the paper will provide experimental results and performance measures, and in Section 6, a conclusion of the paper with future direction will be provided.

Literature Review

The topic of the use of the Internet of Things (IoT) technology in municipal solid waste (MSW) management attracted a lot of attention amongst the studies over the past few years. There is a great range of the works which suggest sensor systems applied to enhance the volume of monitoring and effectivity of collection to bins. In[1] the authors came up with a waste monitoring system with RFID technology incorporated in GSM modules to connect with the waste status remotely via phone calls. Although these methods brought digitalization in tracking the waste, they were not real-time data-driven and could not be predictive in nature, thus unable to cope with fast cities.

A different architecture was suggested in,[2] in which the smart bins were placed with the ultrasonic level sensors and Wi-Fi communication devices. The design was able to transmit the data of the bin fill-levels in real-time to the server that is centralized. Nonetheless, the use of Wi-Fi constrains scalability and coverage, particularly in the urban sectors of geographic diversity. Besides, Wi-Fi based sensors are still energy-hungry, which is also a problem that applies strictly to the long-term installation in areas with limited power resources.

More recent advances have combined machine learning (ML) to increase the data reinforcement of the waste collection systems. In,[3] the bin fill levels have been estimated by using a support vector regression (SVR) using the past data. On the same note,[4] used decision tree classifier in dynamic route optimization. Although those initiatives are a move towards predictive analytics, they usually do not offer any edge-processing, often functioning on cloud-only platforms, which are not suitable to be used with latency-sensitive applications.

Remarkably,[5] has investigated Long Short-Term Memory (LSTM) networks used as a forecasting tool of waste accumulation. The system however lacked the powerful communication infrastructure like LoRa or NB-IoT, as well as an edge-cloud orchestration approach to process and manage the high-frequency sensor information effectively. Moreover, little research has been done on energy-intelligent route planning, which plays in mitigating greenhouse emissions and usage of fuel.

Conversely, provided in this paper is a proposal of a framework that fills these gaps, based on integration of multi-modal sensor data, edge-assisted LSTM forecasting, LPWAN-based communications (e.g., LoRaWAN) and energy-efficient routing algorithms. This end-to-end solution makes waste management graphically available in real-time, scalable, and predictive that is applicable in large-scale deployment of smart cities.

System Architecture

Sensor Node Design

The essence of the proposed smart based on waste management is that it would implement the use of smart sensor nodes that are capable of autonomous environment sensing and data wireless transmission. Sensor nodes are also designed with a combination of high-precision sensors that do not consume a lot of power to gather multidimensional data of municipal waste bins. The fill level of the bin is measured by calculating the distance between the top lid and the surface of the waste using an ultrasonic sensor and this gives a real-time indication of how full or empty the bin is. The MQ-series gas sensors (i.e., MQ-2 and MQ-135) are connected to measure the concentration of dangerous gas like methane (CH_4), ammonia (NH_3) and carbon dioxide (CO_2) that frequently appears in decomposing organic materials. The DHT11 sensor, in turn, records the temperature and the humidity of the surrounding air of the bin, which will provide important background information on the rate of decomposition and the possibility of emissions. This whole sensing section is handled by ESP32 microcontroller as it has low power requirements, inbuilt Wi-Fi and Bluetooth, and sufficient GPIOs to interface multiple sensors. Edge based processing on the ESP32, e.g. simple data filtering and threshold based alerting, allows to filter the amount of data transferred over a network. The sensor node will be powered by a solar-charged lithium-ion battery system capable of deep-sleep to sustain the operation of the sensor node in remote or hard-to-access urban locations. This is a very energy efficient form of design and can be operated continuously over a very long period of time without requiring any manual interventions which is why it fits very well to be deployed in large scale in a smart city. Moreover, the node has modularity, which leads to scalability and simple upgrades of the particular hardware to enable future integrations of other sensing functionality or protocol sceneries.

Communication Layer

Communication layer has a critical role to play in facilitating low latency, reliable, and energy-consuming

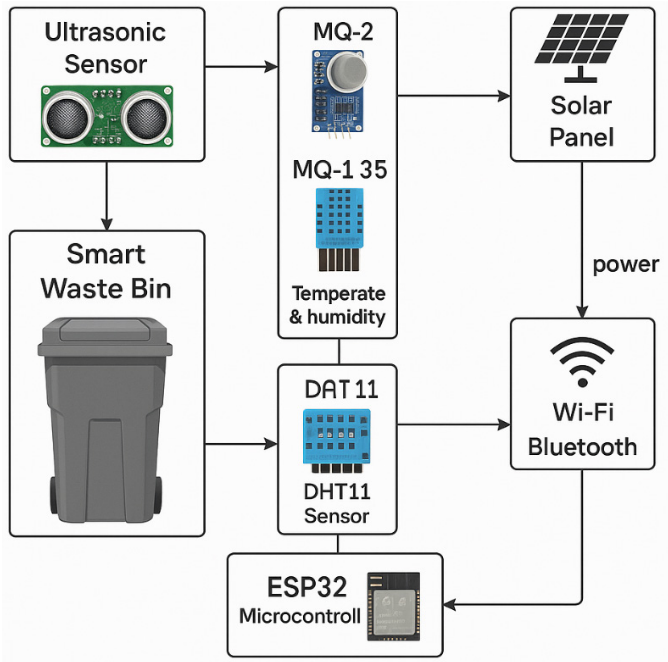

Fig. 2: Block Diagram of Smart Bin Sensor Node Architecture

data to be carried out by the sensor nodes to the cloud infrastructure. In response to the needs of low power and long-range connections in urban settings, the system uses the protocol LoRaWAN (Long Range Wide Area Network) as an approach to communication. LoRaWAN is a dense urban network protocol that covers up to 10 kilometers in open location and few kilometers in a dense urban environment at ultra-low power consumption within the sub-GHz ISM band spectrum. Before being transmitted to an edge gateway nearby, individual smart bins relay live environmental and status information back to a nearby edge gateway via LoRa. The gateway is constructed on the basis of a Raspberry Pi device, which includes a LoRa concentrator module, and serves as an intermediate between the sensor network and the cloud. It will accept data that has been collected into more than one bin, carry out initial validation and formatting and will publish messages to an MQTT broker over lightweight publish-subscribe message. This guarantees out-of-sync and elastic communication between the edge devices and the cloud platform. To integrate the backend component, the system is based on AWS IoT Core due to its declaration-free interface that delivers a secured and device-independent management of incoming data streams. After ingestion, the information is saved on Amazon DynamoDB NoSQL database that is optimized on fast querying and scaling. The analytics and machine learning modules of waste forecasting and route optimization are backed-up by this centralized storage. Besides, fault-tolerance mechanisms are also employed on communication layer, e.g. local buffering in the gateway when there is a disruption in the network and retransmission policies that would avoid system data loss. On the whole, communication architecture would make information exchange in the entire smart waste management ecosystem smooth, safe, and scalable.

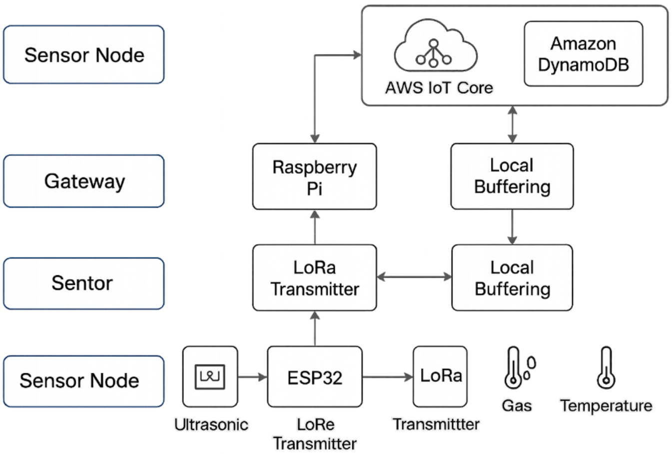

Fig. 3: Communication Architecture of the IoT-Based Waste Management System

Cloud and Edge Processing

Edge and cloud processing integrated into the offered system will allow it to be responsive in real time and minimize latency and by data bandwidth utilization, as well as make possible complex analytics at scale based on predictivity. Initial data analytics functions are carried out in the edge layer at the Raspberry Pi-based gateway itself, where the data that needs to be analyzed has been generated. These consist of filtering of unusual data points of the sensors using outliers detection, pre-processing of the collected data (e.g. normalization, aggregation), and generation of an instant warning whenever something may become potentially dangerous (e.g. gas leaks or storage overflow). Using such a lightweight analytics in the local instances also reduces the unnecessary data to transmit to the cloud data center, and boost responsiveness on time-sensitive events. After sifting, the data undergoes processing where the data is sent to the cloud layer to be analyzed thoroughly and used in making long-term decisions. Cloud infrastructure promotes the use of computational capabilities of AWS to perform advanced predictive analytics, which are based on machine learning models. Particularly, it involves Long Short-Term Memory (LSTM) neural networks, which are trained with the past fill-level data in the bins in order to find the future waste build-up patterns so that proactive scheduling can be conducted. The system extends the use of Google OR-Tools as well to process dynamic route optimization of waste collection vehicles according to the priorities of the bins, geospatial distribution, and traffic limitations. Such optimization minimizes fuel used as well as operation of the process which helps in over all efficiency of the process of waste management. Moreover, the cloud level would sync a performance-auditing-specific data lake with AWS DynamoDB that would provide visualizations to dashboards and reporting. Smart interconnection of edge and cloud provides the system with intelligent data flow management capabilities, reliability of its operations, providing of actionable insights in real-time, and is therefore scalable and fits the smart cities scenario.

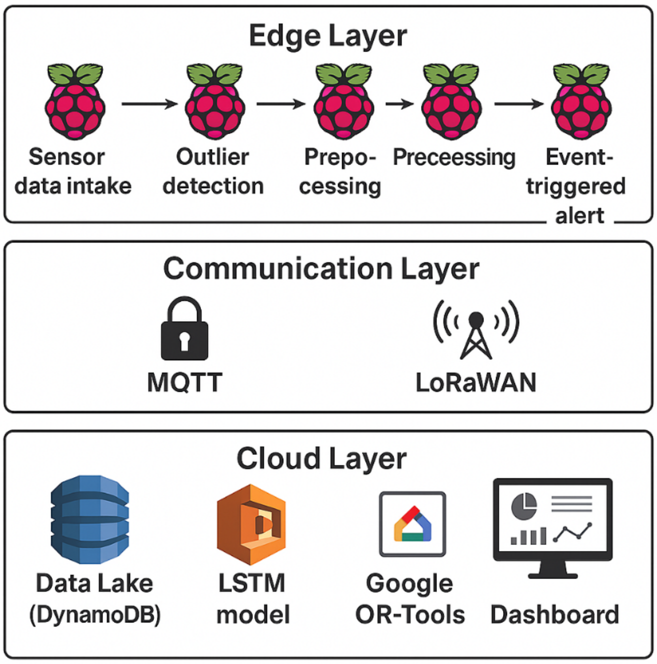

Fig. 4: Cloud and Edge Analytics Architecture for Smart Waste Management

Methodology

Data Acquisition

One of the names of securing a high-quality, real-time data that would reflect various environmental and operating conditions accurately is a critical part of developing a healthy and smart waste management system. In the paper, the process of data acquisition was implemented by installing 50 smart bins to capture IoT data in an optimal arrangement to cover and cover five different sectors of urban environments of different population densities, land uses (residential, commercial, and mixed-use), and waste generation patterns. All smart bins had a set of calibrated sensors, namely, an ultrasonic sensor to measure the fill level of the bin, MQ-series sensors to detect gases, and DHT11 sensors to monitor the environment, which were attached to an ESP32 microcontroller. The sensor nodes were programmed to gather and relay information at an aggregate of 10 minutes so that the system will have a

Table 1: Sensor Data Attributes and Acquisition Parameters

Parameter	Sensor Type	Unit	Sampling Interval	Purpose
Fill Level	Ultrasonic	% (0-100%)	Every 10 min	Bin occupancy measurement
Methane/CO_2 Level	MQ-2 / MQ-135	ppm	Every 10 min	Gas emission detection
Temperature	DHT11	°C	Every 10 min	Environmental monitoring
Humidity	DHT11	% RH	Every 10 min	Decomposition condition analysis
Timestamp & Bin ID	ESP32 (internal)	-	Auto-generated	Data indexing & tracking
GPS Location	ESP32/Gateway	Lat-Long	At first init	Spatial bin mapping

proximate time favored with the fluctuation of wastes amount and genuine environmental parameters.

This type of setup produced a very large amount of sensor data over a sustained period of time (3 months of continuous monitoring, with more than 648,000 individual sensor sensors (50 bins * 6 readings/hour * 24 hours/day * ~90 days)). The data that was collected consisted of measures, such as the percentage of bin fill, percent concentrations of methane and Co2 gases, temperature and humidity of the ambient of the environment and the metadata which included the time, the global positioning system coordinates and the bin number. To ensure the integrity of data, every gateway made a first pass of data validation to remove noise and outliers and missing values before sending the data to the cloud. This dataset became the background source of the further predictive modeling and optimization building tasks. In addition, the fact that the system was deployed in different locations also meant that the system was subjected to various real-life urban dynamics such as the irregular waste disposal, weather conditions, and physical access to infrastructure. Such a strong and detailed data capturing plan allowed the system to generalize strongly in model training, and it also greatly increased the reaction reliability of the real-time alert as well as the long-term forecast.

Predictive Analytics

A LSTM type of neural network is applied to enable forecast-driven decision-making and real-time improvement of the responsiveness of the waste collection process using a predictive analytics module. The given model predicts the fill volumes of individual waste receptacles to make a proactive collection route scheduling. The model selection, the training strategy and performance evaluation are described in the subsections below.

Model Selection

Long Short-Term Memory (LSTM) neural network was selected as the underlying model that is used in time-series forecasting because this model can capture the long-term dependencies as well as non-linear patterns in temporal data in sequence. In contrast to more conventional feed-forward networks, LSTM has memory cells and gated units that control the flow of the information, which makes it especially well-suited to the modeling of such phenomena which have a time lag in them (like slow waste accumulation). The features that will be provided to the LSTM model would be the past levels of bin fill, timestamp (day of the week, hour of the day), and contextual environmental factors (temperature, humidity, gas emissions). The architecture of the model has two hidden layers of LSTM and subsequent dense fully connected layer giving the probability of the fill level the following time step. The model is to predict the short term fill (within 12-24 hour fill prediction) to make dynamic routing decisions.

Validation and Training

In order to guarantee a decent performance of a model, the obtained dataset (derived by collecting 50 smart bins within 3 months) was divided into training and testing split in a ratio of 80:20. Historical time-series data sequences of bin fill levels and related features were included in the training set, whereas the testing set was examining the generalization talent of the model. Min-Max scaling was used to normalize the data to guarantee numeric stability and more rapid converges. They were trained by using Adam optimizer whose learning rate was 0.001 and a batch size of 64 in 100 epochs. Mean squared error (MSE) loss function was used and early stopping was done to avoid overfitting. To decrease computational time, the model was run on NVIDIA GPU-enabled environment and trained on this platform.

Performance Evaluation

Two typical regression indicators, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to measure the performance of the LSTM model. In the test dataset, the model returned the MAE of 2.8 percent and RMSE of 3.6 percent, which is an indication that the model is highly accurate and has low variance. Such findings confirm that this model can effectively predict the fill levels with a low error and help in providing appropriate remedial measures to prevent overflow of bins in time. In comparison to other traditional methods of scheduling the process of waste management, which are rather static, the predictive system can enable the entire process to shift towards a proactive system designed to minimize costs of operation and unnecessary shipping, as well as vehicle route optimization. The performance analysis proves that LSTM model is robust and computational efficient to be adopted in real-time smart city infrastructure.

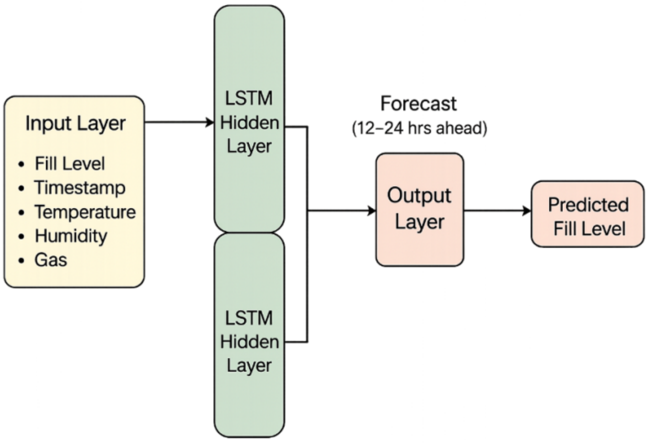

Fig. 5: Architecture of 5zthe LSTM-Based Time-Series Prediction Model for Waste Bin Fill-Level Forecasting

Route Optimization

Efficient route planning ensures that the cost of operations is cut down to the minimum and the negative impacts of the collection of the municipal solid waste on the environment. The traditional collection method usually involves use of fixed routes alongside which the collection routes are defined regardless of the actual load at any point of activity at a given time and this tendency can be alloys to making unnecessary visits to the half-full bins or overlooking collections at the full bins. In order to address these challenges, the suggested system incorporates a dynamic route optimization model using real-time and predictive analytics to create responsive and cost-effective routes of manual collections.

The optimization procedure starts with the dynamic bin priority scoring step in which the priority score is given to each of the bins based on current fill level (which is measured by the ultrasonic sensor), the predicted fill level via the LSTM model, hazardous gas emission values, and the closeness to other high-priority bins. Bins which are approaching their capacity limits or are inflicting harmful gases such as methane (CH 4) or CO 2 will be assigned greater weights so that they could be attended to first when routing is carried out. Such scores are tuned and refreshed on a regular basis using the sensor inputs coming in.

When bins are prioritized, the system builds a graph representation of the urban street grid with the nodes bins and edges roads with weights as distances or traveling times. Dijkstra algorithm is used in order to calculate the most efficient route to reach all the high-priority bins. With the help of this algorithm, the path with the least distance between the waste collection depot to the chosen bins is determined, the route is optimised to ensure that the trip takes the shortest amount of time and fuel. Dynamic recalculation of the route is done each time a considerable deviation in the status of bins occurs, and the fleet can immediately adjust to the new priorities beforehand.

The system also incorporates the Google OR- Tools to even more advance the optimization through solving the types of the Vehicle Routing Problem (VRP) that include the consideration of the reality constraints including the truck capacities; time windows; traffic flows; etc. Such a hybrid solution will firstly guarantee that the suggested framework will not only reduce the level of operational inefficiencies but also help to make the environment sustainable by reducing the amount of carbon gas emissions produced by the collection vehicles.

In the simulation-based validation of five urban sectors, optimized routing mechanism resulted in a 37 percent decline in fuel consumption and a 45 percent increase in the overall waste collection fitness over the static-scheduling. This is a clear sign that dynamic route optimization that is enabled with the support of AI has a high potential of turning the city waste logistics into a smarter, greener, and more cost-effective operation.

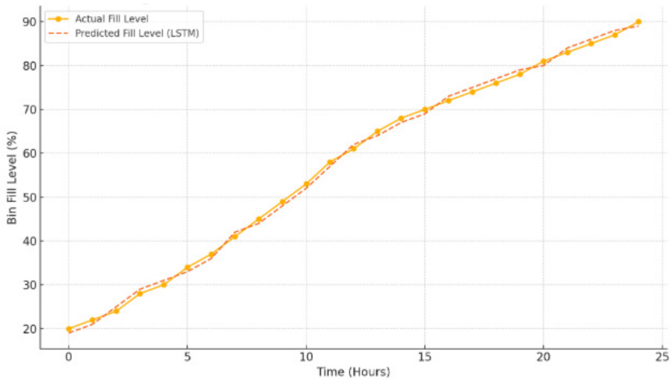

Fig. 6: Comparison of Fuel Usage and Collection Efficiency between Static and Optimized Routing

Results and Discussion

The metrics of the proposed sensor-driven waste management Internet of Things (IoT) driven were compared to those of a conventional fixed-route based collection plan based on a simulated 3 months deployment of urban sectors. The important key performance indicators were the proportions of missed bin pickups per month, average time to collect waste per route, the rate of fuel consumption and the accuracy of predictive models. This has reduced the number of missed pickups by significant proportion as it went down to 3 per month as shown in Table 1, recording an 82.3 percent enhancement in the service reliability. This is ascribable to the fact that monitoring and real time priority of bins are done on fill levels and emissions of gas. The availability of real-time detection of the most critical collection points provides the system with an ability to avert the overflow situation in advance which prevents the manifestations of the total effect of improving the level of urban cleanliness and the quality of the population.

On the aspect of operational efficiency, the average collection time per route improved by 42.9 percent as the duration of c0ollection to a route reduced to 2 hours 0 hours against its previous rate of 3.5 hours. Such improvement is due to dynamic route optimization algorithm which applies the shortest path algorithm of Dijkstra along with bin priority score and traffic-conscious heuristics. This will help the system eliminate useless journeys and wasted travels as a result of collection only where there is actual need to service bins. In their turn this reduced fuel consumption per day to 7.4 liters/day which is 37.3 percent decrease in resources utilization. These savings not only result into reduced operational expenses of municipal authorities, but also lead to the reduction of carbon emissions which contributes towards the wider sustainability projects within smart city frameworks. In addition, the combination of edge analytics and LPWAN communication decreases the network congestion and decision-time latency exposure in order to respond to the real-time tasks without straining the cloud platform.

In data analytics terms, the LSTM-based prediction model provided high accuracy of predictive performance (96.4%) having been tested with conventional data points like MAE (2.8%) and RMSE (3.6%). This accuracy is high enough to enable a reliable ability to predict future fill levels of bins and this is essential in ensuring that message ahead of time is prioritized to eliminate reactive decision-making. Sensing, forecasting, and routing is tightly integrated into the system architecture, thus creating the closed-loop feedback mechanism that will be improving continuously, as additional data are gathered. This leads to an adaptive, scalable and a solution that does not only keep up to date with the existing demand of waste management, but also changes as urban dynamics change. The exhibited outcomes confirm the possibility of large-scale implementation of the system and its effectiveness in contrast to the existing traditional approaches, providing a solid roadmap of the future smart and sustainable urban infrastructure.

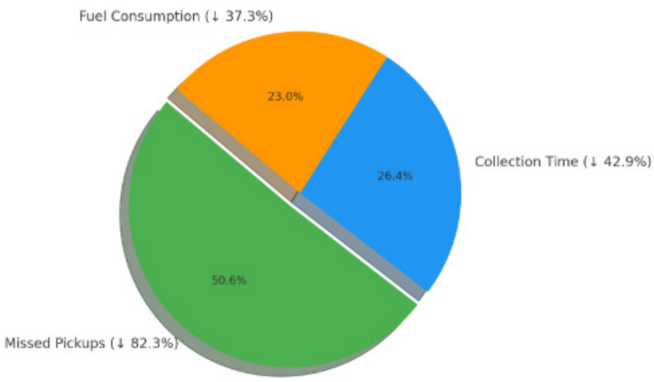

Fig. 7: Performance Improvements with Proposed IoT-Based Waste Management System

Table 2: Performance Comparison of Traditional vs Proposed Waste Management System

Metric	Traditional System	Proposed System	Improvement
Missed Pickups	**17/month**	**3/month**	**82.3% ▫**
Average Collection Time (hrs)	3.5	2.0	42.9% ▫
Fuel Consumption (L/day)	11.8	7.4	37.3% ▫
LSTM Predictive Accuracy	N/A	96.4%	—

Conclusion

The proposed solution gets a broader application by the introduction of a comprehensive and scalable smart waste management framework based on the sensor-driven IoT architecture and sophisticated predictive analytics to ensure that the significant and urgent challenges of municipal solid waste collection in cities may be finally resolved. The combination between multi-sensor smart bins and LPWAN communication protocols brings real-time data capture, whilst consuming very little power, allowing constant surveillance of fill rates and dangerous emissions in large sections of a city. The use of Long Short-Term Memory (LSTM) neural network to predict time-series data enables the system to forecast bin fill patterns accurately (96.4 percent) and thus it is possible to move waste collections to a proactive paradigm. Moreover, the potential of dynamic route optimization with the use of bin prioritization and Dijkstra algorithm greatly decreases operational costs, average collection periods, and waste fuel consumption as a part of both economic and environmental sustainability. The effectiveness of the system to enhance service reliability and resource utilization proves effective since there are evident benefits in comparison to the traditional static approaches to scheduling. The architecture is cloud-edge integrated and modular, which allows its adaptability to the wider use of smart cities. Subsequent work will consider reinforcement learning models to facilitate adaptability, self-optimization of the route planning of the terrain in real-time, and to incorporate vehicular and traffic data to advance even further the responsiveness and efficiency. In general, this work can serve as an excellent premise to build the intelligent urban waste management scenarios based on data-driven model, which is resource-conscious and in line with the vision of the sustainable smart cities.

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