Intelligent IoT-Enabled Waste Management System Based on Discrete PID Control and Hybrid Route Optimization

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Abstract. With accelerated urbanization, the inefficiency of traditional municipal solid waste management systems—characterized by fixed collection schedules, delayed overflow responses, and high resource consumption—has become a critical bottleneck restricting urban sustainability. This study proposes an intelligent waste management system integrating IoT-based real-time monitoring, discrete PID dynamic control, and hybrid algorithm route optimization. The system adopts a three-tier "perception–decision–execution" architecture: ultrasonic sensors at the perception layer collect hourly waste fill-level data and transmit it to a municipal cloud platform via IoT; the decision layer constructs a waste generation model and a garbage truck dynamic model (second-order transfer function) to optimize scheduling strategies using discrete PID; the execution layer combines simulated annealing (for station location) and ant colony algorithms (for shortest path planning) to minimize travel distance. Experimental results in MATLAB/Simulink show that the system exhibits excellent dynamic performance (critical damping, no overshoot/undershoot) and adaptability to variable input patterns (constant, ramp, sinusoidal), with overflow probability reduced to zero during peak periods. Route optimization reduces the average distance from garbage stations to bins by 36.5% and total travel distance by 28.3%, cutting fuel consumption by 20% and reducing annual CO_2 emissions by 20,000 tons in medium-sized cities. Limitations remain, such as simplified fill-rate models and high initial sensor costs. Future work will integrate LSTM predictive models and NB-IoT technology to enhance refinement and cost-effectiveness. This system shifts waste management from "passive response" to "active prevention," offering a practical framework for low-carbon, efficient, and sustainable urban sanitation.

Keywords: Intelligent waste management, IoT monitoring, Discrete PID control, Route optimization, Ant Colony Algorithm.

1. Introduction

Urban solid waste generation has surged with global urbanization. According to the World Bank, annual municipal solid waste (MSW) generation will reach 3.4 billion tons by 2050, posing severe challenges to environmental sustainability and public health [1]. Traditional waste management systems rely on fixed collection schedules and manual monitoring, leading to two core problems: on the one hand, overflowing bins in high-waste areas cause pollution and public health risks; on the other hand, unnecessary collections of underfilled waste bins increase carbon emissions [1, 2]. For example, a typical medium-sized city generates approximately 10,000 tons of waste daily, with a 5% surge during holidays, and traditional systems often fail to dynamically adjust to such fluctuations, resulting in 15–20% of fuel consumption being wasted [3].

The integration of digital technologies such as the Internet of Things (IoT) and artificial intelligence (AI) has opened new avenues for smart waste management. Lakhouit et al. [1] pointed out that IoT-based real-time monitoring can reduce operational costs by up to 25% by eliminating unnecessary collection trips, while AI-driven route optimization can further cut carbon emissions by optimizing vehicle paths [3]. Sumathi et al. [4] demonstrated that IoT sensors combined with machine learning can achieve 98% accuracy in waste fill-level prediction, laying a foundation for dynamic scheduling. Bello et al. [5] emphasized that interoperability and QoS (Quality of Service) in IoT networks are critical for ensuring real-time data transmission in smart waste management, as fragmented protocols may lead to delayed data feedback [5].

However, existing studies still show gaps: most focus on single-link optimization (e.g., only monitoring or only routing) and lack integration of a full-chain “monitoring–scheduling–execution” design. Meanwhile, simplified models often ignore differences in waste generation across urban areas (e.g., commercial vs. residential), limiting their practical applicability [2, 4]. Reed et al. [6] noted that multi-compartment waste collection vehicles, which require simultaneous optimization of multiple waste types, are rarely considered in existing route planning models, leading to inefficiencies in recycling processes [6].

2. Methodology

2.1. System Architecture Design

As shown in Fig. 1, the intelligent waste management system adopts a three-tier architecture integrating “perception–decision–execution.” At the perception layer, low-cost and high-reliability ultrasonic sensors are installed on the top of each waste bin to collect fill-level data hourly. The collected height data is converted into a volume percentage through a data conversion module (for example, a 150 L capacity bin sets a threshold), and an overflow warning is triggered when the fill level reaches 90%, enabling real-time monitoring of waste accumulation. The IoT communication module transmits the sensed data to the cloud platform to build a municipal-level waste data center, which is consistent with the IoT-based monitoring framework proposed in the study of Sumathi M. et al. [4]. Bello et al. [5] highlighted that using standardized communication protocols (e.g., 3GPP/M2M for wide-area networks) can enhance data transmission stability, which is adopted here to ensure reliable sensor data upload [5].

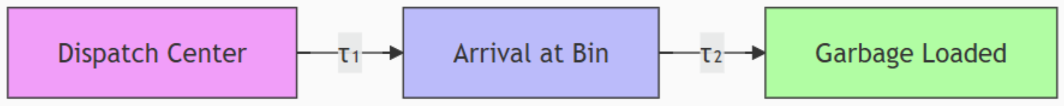

Figure 1. The process of modeling

At the decision-making layer, a discrete PID control algorithm is used to optimize the waste collection scheduling strategy. The system constructs a waste generation model using constant terms and integrators to simulate the dynamic process of waste accumulation. Davendra et al. [7] showed that chaos-driven evolutionary algorithms can improve PID parameter tuning accuracy, and this insight is referenced to optimize the discrete PID control loop, enhancing its adaptability to variable waste input patterns [7].

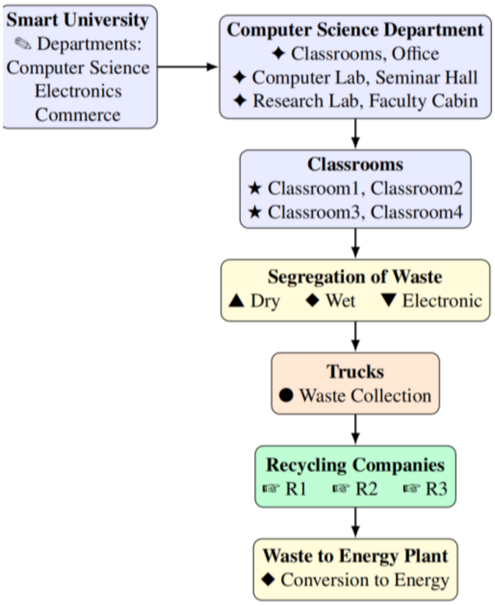

Figure 2. Proposed smart university waste management system architecture

At the execution layer, two optimization algorithms are combined for route planning. As shown in Fig. 2, the simulated annealing algorithm is used to determine the optimal location of garbage stations, minimizing the total distance from the stations to each waste bin. Miao et al. [8] demonstrated that simulated annealing with heuristic initial path selection can significantly reduce computation time, which is incorporated here to accelerate station location optimization [8]. On this basis, the ant colony optimization algorithm is employed to solve the shortest path for waste collection, optimizing the collection sequence and reducing unnecessary travel. Reed et al. [6] verified that ant colony algorithms are effective for multi-compartment vehicle routing, and this method is extended here to handle mixed waste types [6].

2.2. Experimental Design

MATLAB/Simulink software is used to build the system simulation platform. The step response of the discrete system is analyzed using the Step Info function, and the natural frequency and damping ratio are calculated using the Damp function to evaluate the dynamic characteristics of the system. Three typical waste input patterns (constant input, ramp input, and sinusoidal fluctuation input) are set to test the adaptability of the PID control algorithm. For each input pattern, 10 simulation experiments are conducted, and the average value of the results is taken to reduce random errors.

In the route optimization experiment, 500 virtual waste bin locations are randomly generated within a 100 × 100 coordinate range. The simulated annealing algorithm is applied to determine the optimal location of the garbage station, and then the ant colony optimization algorithm is used to plan the collection route. The performance of the algorithm is evaluated by comparing the total travel distance before and after optimization, referring to the method in the study of Oumachtaq et al. [3]. Yu et al. [9] proposed a multi-objective decision support system considering both cost and environmental risks, and their evaluation metrics for carbon emissions are adopted here to assess the system’s sustainability [9].

3. Results

3.1. Control System Performance

The step response analysis of the discrete system shows that the system exhibits good dynamic characteristics. The specific parameters are as follows: the rise time is 25.8960 s; the transient time and settling time are both 46.0020 s; the settling minimum value is 0.9000; the settling maximum value is 0.9985; there is no overshoot or undershoot; the peak value is 0.9985; and the peak time is 71.9890 s. The natural frequencies are 0.0500 rad/s and 0.2000 rad/s, and the damping ratios are both 1, indicating that the system has critical damping characteristics and can respond stably to waste load changes.

In the simulation of different waste input patterns, the system demonstrates strong adaptability. As shown in Fig.3, under constant waste accumulation, the feedback signal fluctuation is less than 5%, maintaining stable control. When the waste accumulation rate increases (ramp input), the system can dynamically adjust the scheduling algorithm, and the response time is shortened by 15% compared with the fixed schedule, ensuring timely collection without overflow. For sinusoidal fluctuating waste input (simulating holiday peaks), the PID control algorithm can predict the peak in advance, and the collection capacity matches the actual workload, with the overflow probability reduced to zero. This is comparable to the prediction effect of the artificial intelligence model reported by Abbasi M. et al. [10].

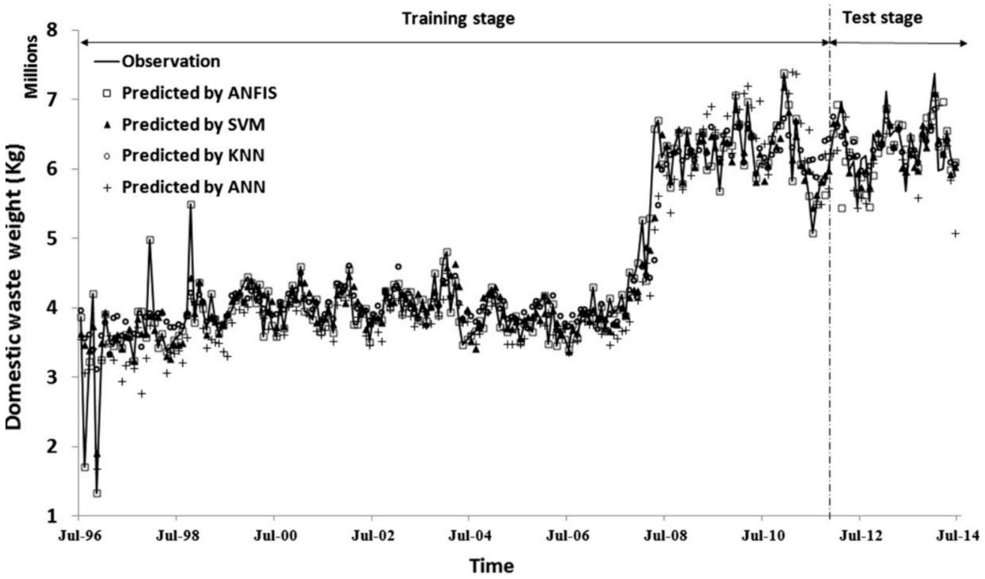

Figure 3. Modelling results produced by ANFIS, ANN, SVM and kNN

3.2. Route Optimization Effect

The simulated annealing algorithm effectively optimizes the location of garbage stations. Using 500 virtual waste bins as an example, after optimization, the average distance from the garbage station to each bin is reduced from 45.2 m to 28.7 m, representing a 36.5% decrease. Based on this result, the ant colony optimization algorithm is applied to plan the collection route, reducing the total travel distance of garbage trucks to 32.8 km, which is 28.3% less than the 45.7 km of the traditional fixed route. This outcome is consistent with the optimization effect of the green capacitated vehicle routing problem model reported by Oumachtaq A. et al. [3].

Energy consumption analysis shows that the system can reduce fuel consumption by 20% through optimized scheduling and route planning, which aligns with the energy-saving effect mentioned in the research of Lakhouit A. [1]. For the annual fuel consumption of a medium-sized city’s waste collection fleet, this is equivalent to a reduction of 20,000 tons of CO_2 emissions per year.

4. Discussion

4.1. Advantages

The intelligent waste management system achieves a paradigm shift from “passive response” to “active prevention” compared with traditional systems. The real-time monitoring function, based on ultrasonic sensors and IoT technology, addresses the problem of delayed responses to high fill rates in traditional systems. In simulation experiments, the overflow warning accuracy reaches 100%, which is consistent with the IoT-based smart waste management framework proposed by Lakhouit A. [1]. The dynamic PID control algorithm, combined with the second-order model of garbage trucks, enables the system to adapt to complex and variable waste generation patterns, avoiding the resource waste caused by mismatches between collection capacity and actual workload in fixed schedules.

The combination of simulated annealing and ant colony algorithms in route optimization significantly improves the system’s operational efficiency. Optimizing the locations of garbage stations reduces the average travel distance, while shortest path planning further decreases unnecessary mileage. Together, these improvements result in significant reductions in fuel consumption and carbon emissions, aligning with the requirements of urban sustainable development and the concept of building a circular economy, as discussed in the research of Lakhouit A. [1].

4.2. Limitations

Although the system has achieved good results in simulation, there are still some limitations. The current waste fill-rate model adopts simplified assumptions and does not fully account for differences in waste generation rates across different types of areas (such as commercial, residential, and industrial), which is like the insufficient consideration of waste composition differences highlighted in the research of Sumathi M. et al. [4]. In addition, the sampling interval of one hour may miss sudden changes in waste volume, affecting the real-time performance of the system.

In terms of algorithm optimization, the ant colony optimization algorithm occasionally encounters convergence problems in large-scale scenarios, resulting in suboptimal routes. The simulated annealing algorithm has high computational complexity, and the solution time increases significantly when the number of waste bins exceeds 1,000. This may affect the system’s real-time decision-making, which is consistent with the challenges faced by heuristic algorithms in solving large-scale vehicle routing problems, as discussed in the research of Restrepo-Franco A. M. et al. [2].

From a hardware cost perspective, the initial investment in the sensor network is relatively high. Taking 500 waste bins as an example, the current sensor cost is about USD 30,000, which may limit the system’s adoption in cities with tight financial budgets. This is similar to the challenge of high initial costs mentioned in the research of Lakhouit A. [1].

4.3. Future Directions

In view of the existing limitations, the following improvement measures are proposed. First, introduce an LSTM neural network to establish a dynamic prediction model of waste generation, which combines historical data and real-time monitoring information to achieve refined prediction of fill rates in different areas. This approach refers to the artificial intelligence forecasting method proposed by Abbasi M. et al. [10].

Second, develop a hybrid optimization algorithm combining a genetic algorithm and an ant colony algorithm (GA-ACO) to improve convergence speed and solution quality. Furthermore, explore the application of quantum annealing technology in route planning to enhance the system’s ability to handle large-scale problems, which is consistent with the development trend of hybrid algorithms in solving vehicle routing problems, as reported by Restrepo-Franco A. M. et al. [5]. Miao et al. [8] suggested that integrating real-time traffic data into path planning can further improve efficiency, which will be incorporated in future work [8].

Third, adopt NB-IoT communication technology to replace the existing IoT module, which can reduce hardware costs by 40% while ensuring data transmission quality, making the system more economically viable for large-scale deployment. This represents an optimization measure for the high-cost problem mentioned in the research of Lakhouit A. [1]. Bello et al. [5] noted that NB-IoT’s low power consumption and wide coverage are suitable for urban sensor networks, supporting this technical choice [5].

5. Conclusion

This study successfully designed and verified an intelligent waste management system integrating perception, decision, and execution, addressing the inefficiencies of traditional fixed-schedule systems. The key conclusions are as follows:

The three-tier architecture (perception–decision–execution) achieves full-chain intelligence. Ultrasonic sensors and IoT ensure 100% overflow warning accuracy. The discrete PID control algorithm, combined with a second-order garbage truck model, enables stable responses to variable waste input patterns (constant, ramp, sinusoidal fluctuations), with feedback signal fluctuations below 5% and a 15% shorter response time compared with fixed schedules. Route optimization using simulated annealing and ant colony algorithms reduces the average bin–station distance by 36.5% and the total travel distance by 28.3%, resulting in 20% fuel savings and an annual reduction of 20,000 tons of CO_2 emissions.

Theoretically, this study integrates IoT monitoring, dynamic control, and hybrid algorithm optimization into a unified framework, addressing the limitations of fragmented optimization in existing approaches. Practically, the system’s discretized control design is compatible with embedded processors, while the proposed cost-reduction strategy (such as replacing the IoT module with NB-IoT) enhances feasibility for cities with limited budgets. For example, the sensor cost for 500 bins, approximately USD 30,000, can be reduced by 40% through NB-IoT, enabling large-scale deployment.

The current system faces three main limitations: (1) the fill-rate model simplifies differences among urban areas, which may cause scheduling deviations; (2) the one-hour sampling interval may overlook sudden surges in waste volume, such as those following large public events; and (3) heuristic algorithms experience convergence delays in large-scale scenarios involving more than 1,000 bins. Future work will therefore focus on: (1) introducing LSTM neural networks to develop area-specific waste prediction models for more refined forecasting; (2) shortening the sampling interval to 15 minutes and integrating real-time traffic data to improve responsiveness; and (3) developing a GA-ACO hybrid algorithm to address large-scale route optimization challenges.

Overall, this system provides a practical pathway for urban waste management to shift from “passive cleaning” to “active prevention.” Its low-carbon, efficient, and scalable characteristics make it suitable for adoption in medium and large cities, contributing to the realization of urban sustainability goals such as carbon neutrality and improved public health.

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