

RESEARCH ARTICLE

OPEN ACCESS

QoS-AWARE INTERNET OF ENVIRONMENTAL THINGS ALGORITHM FOR IoT-FOG-ENABLED SMART WASTE MONITORING SYSTEM

Pooja Rani Agarwal¹, Komal Alwani², Amit Kumar Chaturvedi³

¹Department of Computer Science, Bhagwant University, Ajmer, India

²Department of Computer Science, Bhagwant University, Ajmer, India

³Department of Computer Application, Government Engineering College, Ajmer, India

¹<http://orcid.org/0009-0008-9240-7276> , ²<https://orcid.org/0009-0008-9308-0420> , ³<https://orcid.org/0000-0001-9515-7083> 

Email: * pooja.itindia33@gmail.com, komalrocks2@gmail.com, amit0581@gmail.com

ARTICLE INFO

Article History

Received: January 3, 2026

Reviewed: February 4, 2026

Accepted: March 10, 2026

Published: April 30, 2026

Keywords:

Internet of Things,
Fog,
Cloud,
Smart bins,
iFogSim.

ABSTRACT

Modern times have seen the rise of smart cities that rely on the Internet of Things. To process data, smart objects require multi-hop communication to transmit it to the sink. Internet of Things (IoT) enabled, data-driven smart cities enhance public utilities, infrastructure, and services for the benefit of residents. Smart towns that rely on the Internet of Things have a tough time collecting clean municipal garbage. Cities produce more waste as they expand. Two big problems with trash management are garbage collection and sorting. Public trash cans overflow before they are cleaned, leading to bacterial growth, unpleasant odours, and potential illness. Urbanization, inefficient technologies to aid solid waste management, and poor trash collection and disposal all contribute to these problems. Trash everywhere makes garbage collection more challenging. Solid waste management systems that aren't scientific, efficient, or good enough lead to a lot of issues. By combining the strengths of the IoT and fog computing, this paper proposed an integrated IoT-Fog-Cloud architecture for smart waste management systems and a QAIoET Algorithm for efficient resource allocation, which can improve service quality while reducing response time by 46.8% and costs by 2.6% compared to cloud solutions.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

The rapid population increase causes difficulties with waste dumping. They cause harm to humans by releasing fumes. To maintain a clean environment, intelligent waste classification and management are essential. Society and the environment are both negatively impacted by solid waste management, which is a big problem for smart cities [1], [2]. As the first step in the standard waste management procedure, city dwellers place trash cans at the collection point. Regular garbage hauls to recycling sites are made possible by municipal trucks. It is impossible to determine when to clean or refill exterior containers because municipalities and waste management organizations overlook them. The IoT paradigm enhances smart city applications through the real-time recording and management of municipal processes [3], [4]. By connecting to trash cans and recycling facilities, Internet of Things (IoT) devices can monitor local trash production and container conditions using sensors. An effective municipal waste management system relies on the data collected by the waste management center to plan the deployment and maintenance of adaptive equipment, the collection of rubbish, and the routes that vehicles will take. This paper proposed a holistic approach to smart waste management that leverages the Internet of Things (IoT), fog computing (for real-time, localized intelligence), and cloud computing (for long-term data storage, big data analytics, and global optimization). This integrated architecture's potential to transform garbage collection, resource distribution, and environmental sustainability may result in brighter, cleaner, and more livable smart cities.

II. RELATED WORKS

Cheema et al. [5] proposed a state-of-the-art method (SWMACM-CA) for real-time intelligent waste management and categorization. To sort trash at a landfill, the system employs the Internet of Things (IoT), deep learning, and sophisticated algorithms. Additionally, the author proposed a device for trash grid segmentation, which would separate the garbage yard pile into grids. The use of hybrid and decentralized computing models has improved resource consumption and decreased delays.

Wang et al. [6] developed a deep-learning and cloud-computing classifier for accurate trash categorization before garbage pickup. To simplify garbage disposal, the author grouped recyclables into plastic, glass, paper/cardboard, metal, fabric, and others. Garbage categorization used deep learning convolutional neural networks. The proposed system reduces costs for rubbish sorting, tracking, and collection.

Vishnu et al. [7] presented a solution that monitors public and residential garbage cans with PBLMUs and HBLMUs. They send the position and quantity of unemptied garbage cans to a central monitoring station. The garbage collection authority can use a sophisticated graphical user interface to examine each bin for emptiness.

Longo et al. [8] suggest a smart waste management system to improve campus recycling and rubbish management. A smart garbage bin prototype can locate and sort campus trash using a hybrid sensor/image classification system. The strategy focused on smart garbage bins and a better maintenance schedule.

Karthik et al. [9] created an affordable, integrated gadget for urban sanitation that records street positions and sends them to a web server. When the garbage can is complete, the bin collector receives an automatic signal when the level reaches a certain threshold. As soon as the trash collector gets online, they begin cleaning up the city.

Kanade et al. [10] designed a system that incorporated a big battery, Wi-Fi module, ultrasonic sensor, and Arduino microcontroller. Arduino boards record information from ultrasonic sensors and burden cells. Measurements of trash depth and receptacle weight are taken from the heap cell using an ultrasonic sensor. An LCD panel shows the information. Data displayed earlier is transmitted online via the Wi-Fi module.

John et al. [11] developed an IoT-based smart garbage-disposal prediction and monitoring system that can measure the amount of trash in bins of any size using standard components. The proposed gadget monitors the bin's status at regular intervals using a GPS module, an Arduino microprocessor, and infrared (IR), ultraviolet (UV), and weight sensors. In the proposed setup, data is sent from the cluster network to the Wi-Fi-connected master module. A state-of-the-art neural network system known as Long Short-Term Memory (LSTM) learns from collected data and uses trends in garbage generation to forecast future waste.

Janani et al. [12] described the smart cities project & its development process, listed its uses, discussed its challenges, highlighted its real-time applications, and lastly, outlined its potential future applications. The author also covers related devices and Internet of Things technologies used to build smart cities.

Baldo et al. [13] illustrated the blueprint for a LoRaWAN network integrating several service types within SmartWaste Management, a crucial component of the Smart City ecosystem. All LoRaWAN classes are used in the proposed design, which combines nodes of progressively more complex function-based types and improves the technology's TRL 3 readiness.

Alam et al. [14] concluded that smart cities can benefit from cloud-hosted IoT applications that gather data from multiple sources, including citizens, devices, and homes. This information is examined to manage transportation, electricity, and resources. Public cloud services allow third parties to improve IoT ecosystems and integrate IoT data into electronic products.

Ali et al. [15] proposed an Internet-of-Things-based smart garbage can monitoring and MSW management system. In addition to collecting trash, the proposed system can also identify fires and foretell when more waste will be generated. Interconnected devices manage and monitor electric bins. Wirelessly, these devices communicate the level of the bin's fill to the central hub. One significant advantage of the system is that it ensures waste is collected on time, which helps to avoid bin overflow and contamination.

Pardini et al. [16] enhanced trash management through community engagement using software, communications, and hardware. IoT sensors in smart bins monitor disposal and compartment levels in real time. An Internet of Things middleware processes the data to improve trash collection routes and produce statistics for resource management and community service monitoring. Public garbage can information is available online and via mobile applications.

Abdullah et al. [17] proposed trash management by using IoT devices to communicate among smart bins, waste source sites, collection trucks, management centers, and trash-specific truck sizes. This system addresses population growth and urban expansion.

Sharmin et al. [18] developed a smart, flexible, and affordable waste management system. Using a microcontroller and GPRS, communicate trash weight and volume to a cloud server via inexpensive sensors. An Ant Colony Optimization (ACO) technique uses the locations of vehicles and trash bins to find each truck's shortest collection path. The system reacts to dynamic changes, such as blocked rubbish collection routes. A central monitoring system assures smart city inhabitants receive high-quality service.

Aazam et al. [19] proposed a cloud-based smart garbage management system that uses sensors installed in trash cans to report the current level of trash. Stakeholders have access to data stored in the cloud. City administration and waste management can save time and fuel by optimizing garbage collection routes based on the condition of a city's bins.

Table 1: Summary of Strengths & Limitations for Existing SWM Systems.

References	Strength	Limitations
[5]	Effectively reduce latency and optimize computational resource utilization.	The training dataset exhibits an unbalanced sample distribution.
[6]	Use of cloud computing allows for accurate and fast waste classification	Gas sensors are used for monitoring; their output can be affected by temperature and humidity
[7]	Offers a comprehensive overview of the current advancements in IoT-enabled SWM	Lack of a unified standard or architecture for IoT-based SWM systems
[8]	Integration of 5G technology, which provides high bandwidth and low latency	The system's effectiveness heavily depends on sustained user adoption.
[9]	Ability to provide real-time monitoring of garbage bin fill levels	Effectiveness could be compromised in areas with poor network coverage
[10]	Ability to automate waste level monitoring	Limited to monitoring fill levels and sending notifications
[11]	Integration of real-time IoT data sensing with robust processing in the cloud	Lacks precise technical details regarding the types of sensors utilized
[12]	Highlights the significant benefits of IoT integration, such as improved operational efficiency	Exclude pervasive challenges such as ensuring security and privacy.
[13]	Well-defined multi-layer architecture, providing a robust and scalable framework	Limitations of lower data rates compared to cellular technologies
[14]	Overview of cloud-based IoT applications across numerous sectors within smart cities	Limitations such as potential security and privacy issues
[15]	To tackle the critical issues of escalating waste generation	Heavily reliant on consistent and robust network connectivity
[16]	The solution is its citizen-centric approach	Heavily relies on consistent public participation and willingness
[17]	Direct engagement with the pressing issue of waste management	Lack provides specific technical details about the types of sensors
[18]	Dynamic approach to waste collection, based on real-time waste levels	Highly dependent on continuous and reliable wireless connectivity
[19]	Ability to provide real-time notifications about waste status	Lacks specifics regarding the types of sensors employed
[20]	The paper offers an examination of methods for scheduling jobs	The simulation results were missing to back the justification
[21]	The study was broken down by algorithm category and parameters	Exclude the study of load-balancing approaches in categories
[22]	Method that uses ECTS to distribute tasks to fog nodes efficiently	Lack considering effect on the mobility of end devices and fog nodes
[23]	Provided LCTS, or Laxyty-based solution to the scheduling problems	The trade-off between response time and energy usage persists

Source: Authors, (2026).

This research study sheds light on a smart city solid waste management system that leverages the Internet of Things to circumvent such limitations. Several cities have trash cans overflowing with garbage. The trash cans cleaner is running behind schedule. As a result, the air, the environment, and the town become polluted. The foul stench of excrement poses a health risk to people. The expansion of the IoT and related technologies is causing a shift in the global industry. To take advantage of the Internet of Things (IoT), many company executives are investing more time and money in adapting their services. Thus, decision-makers in public waste management are competitive, making it difficult to provide an effective, real-time waste management system.

III. METHOD & EXPERIMENT

A. Proposed IoT-Fog-Cloud Layer Architecture

To improve efficiency, scalability, and real-time responsiveness, the proposed architecture, as shown in Figure 1, outlines a multi-layered strategy for smart waste management (SWM) system. This strategy distributes intelligence and processing capabilities among IoT devices, fog nodes, and the cloud. The proposed multi-layered architecture of the SWM system includes the following essential components.

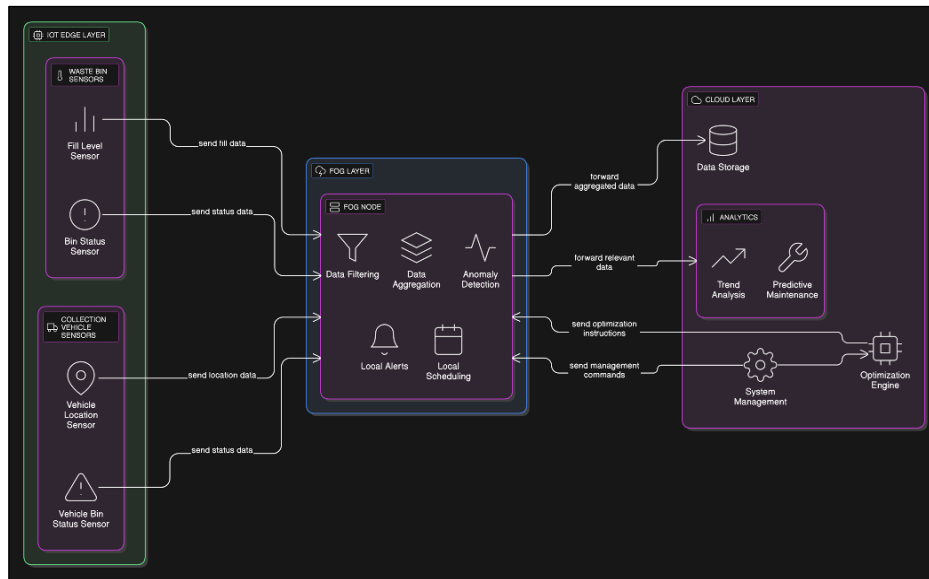


Figure 1: Proposed Multi-Layered Architecture of Smart Waste Management System.

Source: Authors, (2026).

The lowest layer is nearest to trash generation and collection. Smart gadgets and sensors interact with garbage containers and pickup vehicles. This layer includes components such as intelligent waste bins, weight sensors, gas sensors, GPS modules, RFID/NFC tags, microcontrollers, communication modules, GPS trackers, onboard sensors, RFID/NFC readers, and cameras for visual inspection or garbage classification upon collection. The fog layer connects the Internet of Things/Edge and Cloud levels. Moving networking, storage, and computation closer to the network edge reduces latency and bandwidth. This layer includes the components, such as fog nodes, strategically placed in neighbourhoods or collecting depots. Local data storage to hold raw and processed data temporarily. Local processing for instant data analysis, filtering, aggregation, and IoT device communication interfaces. The cloud layer is a centralized, high-performance computer and storage infrastructure. This layer's subcomponents include cloud servers/platforms for long-term storage of garbage data; complex algorithm-running analytics and machine learning platforms; and data visualization tools, such as municipal waste management and citizen dashboards. This tiered strategy makes trash management smart, efficient, scalable, and resilient for smart cities' dynamic demands. Figure 2 demonstrates how smart waste management units exchange data to work efficiently.

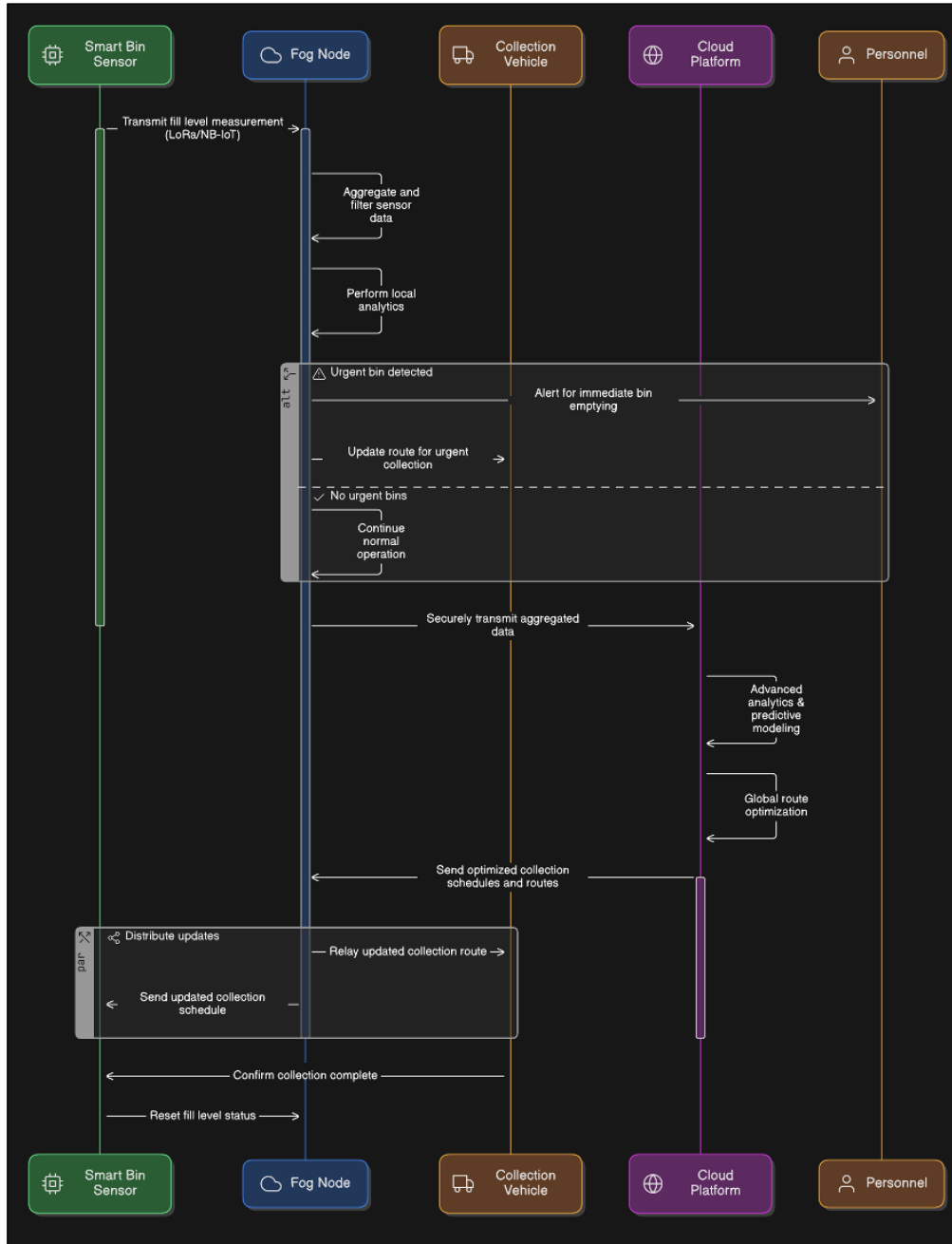


Figure 2: Sequence Diagram of Smart Waste Management System. Source: Authors, (2026).

According to the proposed figure 2, Smart bin sensors send data to fog nodes. Fog nodes aggregate, filter, and analyze data locally, decreasing cloud data traffic and enabling fast local responses. Fog node data is safely sent to the cloud for analysis and storage. Cloud computing conducts sophisticated analytics, predictive modeling, and global route optimization. Fog nodes communicate collections, car or smart bin orders, or updated schedules from cloud decisions and optimal plans. Citizens use mobile applications to communicate with the cloud (for general information) or smart bins (via Bluetooth/NFC for local interactions).

B. Proposed Resource Allocation Approach

The QoS-Aware Internet of Environmental Things (QAIoET) Algorithm optimizes key performance parameters in an IoT-enabled environmental monitoring and waste management ecosystem, with a focus on smart trash bins. The primary orchestrator, this algorithm, minimizes response time and operating expenses to ensure the efficiency and sustainability of large-scale IoT deployments. The system intelligently launches the Task Categorization Algorithm and the Dynamic Resource Provisioning Algorithm for each work. Modularity allows context-aware processing. For instance, the categorization algorithm may evaluate resource demands, activity type, and urgency. Identifying computational demands helps the dynamic resource provisioning algorithm allocate resources to cloud and fog nodes. The future smart environmental infrastructure needs intelligent orchestration to develop a robust, efficient system from basic tasks to dynamic resource allocation while minimizing operational costs and preserving service quality.

Algorithm 1: QoS Aware Internet of Environmental Things (QAIoET) Algorithm.

<p>Input: Tasks with smart waste bins status attribute Number of tasks (T), Number of Fog Nodes (F), Cloud (C) Output: Optimize response time and cost incurred Begin</p> <ol style="list-style-type: none"> 1. Input tasks (T) 2. For each task $t_i \in T$ 3. Call Task Categorization Algorithm 4. Call Dynamic Resource Provisioning Algorithm <p>End</p>
--

Source: Authors, (2026).

The QoS-Aware Internet of Environmental Things (QAIoET) Framework employs the Task Categorization Algorithm for smart garbage prioritization tasks. Fog servers effectively order jobs into priority queues. The system evaluates the garbage bin attributes and the task (t_i) before determining the job priority and urgency. Lines 3–4 are the most crucial steps for checking "Abnormal" work over $delay_thrl$. This significant delay circumstance upgraded the job to Queue-significant, requiring immediate attention. Long-standing issues or processing delays can make a non-critical event critical. To illustrate its environmental expertise, it classifies operations by garbage can status in real time (Lines 6–14). Marking "Overflow" bin jobs as "Critical" and adding them to Queue-Critical emphasizes ecology and logistics. Trash jobs designated "Jam-packed" are marked "Abnormal" and forwarded to Queue-Abnormal, signifying a non-urgent but high-priority issue that must be resolved quickly. Documentation and progress reports for "Partly-filled" containers are "Normal" and low priority. Hierarchical categorization, clear delay limits, and understandable waste-bin fill levels dynamically prioritize QAIoET resources, enabling efficient and quick environmental crisis resolution while managing less essential processes.

Algorithm 2: Task Categorization Algorithm.

<p>Input: Tasks with waste bins attribute at the fog server Output: Set priority queue for task execution Begin</p> <ol style="list-style-type: none"> 1. Input tasks T 2. For each task $t_i \in T$ do 3. If($t_i \in \text{Queue-Abnormal} \ \&\& \ t_i.delay_time > delay_thrl$) 4. Add Queue-Critical[k] $\leftarrow t_i$ 5. Else 6. If(waste bins fill status = Overflow) Then 7. Category = Critical 8. Add Queue-Critical[k] $\leftarrow t_i$ 9. Else If(waste bins fill status = Jam-packed) Then 10. Category = Abnormal 11. Add Queue-Abnormal[k] $\leftarrow t_i$ 12. Else If(waste bins fill status = Partly-filled) Then 13. Category = Normal 14. Add Queue-Normal[k] $\leftarrow t_i$ 15. End <p>End</p>

Source: Authors, (2026).

In the QoS-Aware Internet of Environmental Things (QAIoET) Framework, the Dynamic Resource Provisioning Algorithm distributes computations to nearby fog nodes or to distant clouds to reduce response time and costs. The app efficiently manages scattered IoT. The algorithms in the prioritized task queue make complex judgments for each item (t_i). Line 2 rapidly discovers all fog node clusters. Determine each fog node's resources and network distance from the task's origin (Line 3). Fog nodes near resources (QF) are used first (Line 4). The central cloud (RT_{icloud} and CT_{icloud}) receives estimates of response time (RT) and cost (CT) from each fog node (F_{ij}) that processes work (Lines 5-6). The foresight helps make informed decisions. Repeating Lines 7–13 determines which sorted fog node has a lower response time and cost than the cloud. Edge computing rapidly distributes work to the best fog node (Lines 8–10). Due to limited fog resources, the software judiciously offloads the operation to the cloud (Line 15) when no local fog node satisfies both optimization conditions (i.e., when the loop terminates without an optimal fog node, as implicitly evaluated in Line 14). Hierarchical, cost-conscious provisioning techniques that improve service quality by reducing cost and delay provide a flexible resource management paradigm for the Internet of Environmental Things.

Algorithm 3: Dynamic Resource Provisioning Algorithm.

Input: Task Queue $[t_i, T]$, Number of Fog Nodes (F), Cloud
Output: Task allocation to the optimal fog node or cloud
Begin
1. For each task $t_i \in$ Queue $[t_i, T]$ do
2. Find the available fog node clusters in the system
3. Calculate resource & distance for all available fog nodes
4. Sort all available fog nodes by the nearest available resource (Q_F)
5. Calculate RT (F_{ij}) & CT (F_{ij}) // RT-Response Time, CT-Cost
6. Calculate RT_{icloud} & CT_{icloud} // RT-Response Time, CT-Cost
7. For each $f_j \in Q_F$ do
8. If $(RT(F_{ij}) < RT_{icloud} \ \&\& \ CT(F_{ij}) < CT_{icloud})$
9. Assign the t_i to F_{ij}
10. Break
11. Else
12. Continue
13. End
14. If $(t_i \in$ Queue $[t_i, T])$ // Not found optimal fog node
15. Assign the t_i to the cloud
16. End
End

Source: Authors, (2026).

C. Experimental Setup

Fog design has a component-specific network setup simulated using the ifogsim toolkit [24], [25]. Cloud servers had 40,000 MB of RAM, 44,800 MIPS of CPU, 100 ms latency, and a cost of 0.01/MIPS. The upload and download speeds are 10,000 Mbps. These are the proxy server specs: 8000 MB RAM, 12800 MIPS CPU, 10000 Mbps UP-BW/DW-BW, 10 ms latency, 0.04 Cost/MIPS. Fog Gateway (Fog Server) specs: 8000 MB RAM, 12800 MIPS CPU, 10,000 Mbps UP-BW/DW-BW, 5 ms latency, 0.08 Cost/MIPS. The IoT end device has a 2800 MIPS CPU, 4000 MB of RAM, 10 ms latency, 10,000 Mbps upload and download bandwidth, and a cost of 0.16 MIPS.

Table 2: Simulation Configuration.

Parameter	CPU (MIPS)	RAM (MB)	UP-BW (Mbps)	DW-BW (Mbps)	Latency (ms)
IoT Device	2800	4000	10000	10000	10
Fog Node	12800	8000	10000	10000	5
Proxy	12800	8000	10000	10000	10
Cloud	44800	40000	10000	10000	100

Source: Authors, (2026).

The experiment tested system included an end device, a proxy server, a fog server, a fog node, and a cloud server. Each test setup contained 1, 4, and 4 Cloud, Proxy, Fog Server, and Node/Server instances. The progressive rise in end devices to imitate rising user loads was the primary variable across all five settings. To clarify, Configurations 1–5 employed 50 End Devices, 100 in 2, 200 in 3, 400 in 4, and 500 in 5. This ongoing change in end-device count enabled a comprehensive investigation of system behavior and scalability across varied operational scenarios using ifogsim.

Table 3: Simulation Topology.

Config	Cloud	Proxy	Fog Server	Fog Node	End Device
Setup-1	1	1	4	4	50
Setup-2	1	1	4	4	100
Setup-3	1	1	4	4	200
Setup-4	1	1	4	4	400
Setup-5	1	1	4	4	500

Source: Authors, (2026).

IV. RESULTS AND DISCUSSIONS

The simulation results for the proposed technique are shown in Table 4. Complexity increases response time and cost (Setup-1–Setup-5). From setup-1 to setup-5, response time (milliseconds) and total cost (dollars) increase continuously, indicating workload or size growth. Setup-1's response time is 974.10 ms and cost is \$174926.67; Setup-5's is 6815.57 ms and \$761432.49. The proposed technique can manage growing demand; however, this pattern illustrates that the simulated environment's complexity increases response time and cost.

Table 4: Proposed (QAloET) Simulation Result.

Config.	Response Time	Cost
	(millisecond)	(Dollar)
Setup-1	974.10	174926.67
Setup-2	1810.67	415883.87
Setup-3	2591.45	621628.49
Setup-4	5495.42	756691.46
Setup-5	6815.57	761432.49

Source: Authors, (2026).

Table 5 compares fog node response time (milliseconds) for CF-1 to CF-5 setups with different end devices. It then compares the proposed method to cloud-only performance. Every arrangement has four fog nodes; however, CF-1 to CF-5 have 50 to 500 end devices. With both approaches, the response time increases with the number of end devices. The proposed method outperforms the cloud-only method in all settings, with quicker response times. In CF-1 with 10 end devices, the proposed solution responded in 974.10 ms, whereas the cloud-only method took 1548.90. The proposed strategy recorded 6815.57 ms in CF-5 with 500 end devices, half of the cloud-only approach's 12750.51 ms. More end devices aggravate this performance disparity. The proposed technique reduces response time and manages growing workloads more effectively than a cloud-only solution.

Table 5: Comparison of Response Time (ms).

Setup	Fog Node	End Device	Proposed approach	Cloud-only
CF-1	4	50	974.10	1548.90
CF-2	4	100	1810.67	4445.90
CF-3	4	200	2591.45	4882.20
CF-4	4	400	5495.42	9806.50
CF-5	4	500	6815.57	12750.51

Source: Authors, (2026).

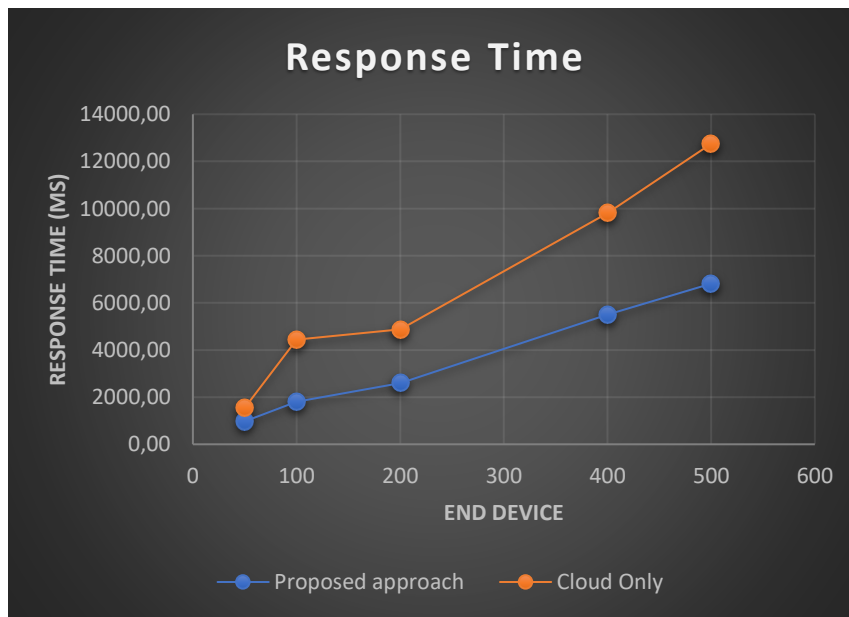


Figure 3: Comparison Chart for Response Time.

Source: Authors, (2026).

Figure 3 shows the millisecond response times of the proposed and cloud-only approaches. No matter the final device count, the proposed technique is faster than cloud-only. Both methods take longer to react with more end devices, but the cloud-only strategy has a response time above 12,500 ms, demonstrating that the proposed solution is more consistent and better. Table 6 shows the hypothetical dollar expenses of the proposed method relative to a cloud-only approach across various configurations. The setup column presumably indicates an increase from CF-1 to CF-5 end devices, but fog nodes stay at 4. In all cases, the proposed method is cheaper than a cloud-only approach. The cloud-only approach would cost \$177,825, whereas the proposed method would cost \$174,926.67 for CF-1 with 50 end devices. 2. At CF-5 (500 end devices), the suggested method is cheaper than cloud-only (\$761,432.49 vs. \$789,092). This tendency continues as more end devices are added. This method saves money, especially as end devices get bigger.

Table 6: Comparison of Cost (Dollar).

Setup	Fog Node	End Device	Proposed approach	Cloud-only
CF-1	4	50	174926.67	177825.2
CF-2	4	100	415883.87	432528.16
CF-3	4	200	621628.49	636952.08
CF-4	4	400	756691.46	775443.9
CF-5	4	500	761432.49	789092

Source: Authors, (2026).



Figure 4: Comparison Chart for Cost.

Source: Authors, (2026).

Figure 4 illustrates dollar simulations comparing the proposed method with a cloud-only strategy as the number of end devices increases. The proposed way appears cheaper, yet both methods have comparable prices with 50-100 fewer end devices. Expanding devices increases costs for both processes. Still, the proposed technique is cheaper than cloud-only for all end devices. As the number of end devices increases, the cost disparity widens, indicating that the suggested strategy improves cost efficiency as the system scales.

V. CONCLUSIONS

The study shows that an IoT-Fog-Cloud architecture for smart waste management may resolve many environmental challenges. Our proposed technique (QAIoET) minimizes the inefficiencies of traditional garbage collection by merging fog computing for localized intelligent processing with IoT-enabled smart trash bins. Our comparison study showed that this synergistic paradigm has several benefits. Regardless of end device count, the proposed solution (QAIoET) always beats cloud-based alternatives and reduces response time by 46.8%. Optimizing routes and collecting trash fast requires this responsiveness, which boosts operating efficiency. The proposed system's long-term operating savings and environmental benefits make it a cost-effective and environmentally responsible option, even though the initial cost reduction of 2.6% may be similar. This study shows that fog computing and the Internet of Things have several benefits. It makes urban waste management systems more efficient, sustainable, and responsive, proving it works. Results may be used to improve resource allocation and environmental management, creating intelligent and adaptive urban settings. The next step would be to integrate GenAI solutions into the proposed system to enable future predictions & proactive actions.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Methodology: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Investigation: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Discussion of results: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Writing – Original Draft: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Writing – Review and Editing: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Resources: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Supervision: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

Approval of the final text: Pooja Rani Agarwal, Komal Alwani, Amit Kumar Chaturvedi.

VII. ACKNOWLEDGMENTS

I express my gratitude to MIET, Meerut, for their intellectual support during the research assignment.

VIII. REFERENCES

- [1] Goel, G., & Chaturvedi, A. K. (2023, January). A systematic review of task offloading & load balancing methods in a fog computing environment: Major highlights & research areas. In 2023 3rd International Conference on Intelligent Communication and Computational Techniques (ICCT) (pp. 1-5). IEEE.
- [2] Goel, G., & Chaturvedi, A. K. (2023, April). A comprehensive review of QoS aware load balancing techniques in generic & specific fog deployment scenarios. In 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES) (pp. 983-987). IEEE.
- [3] Goel, G., & Chaturvedi, A. K. (2024). Multi-Objective load-balancing strategy for fog-driven patient-centric smart healthcare system in a Smart City. *Engineering, Technology & Applied Science Research*, 14(4), 16011-16019.
- [4] Goel, G., & Chaturvedi, A. K. (2024). Fog-Based Smart Infection Detection System (SIDS) Architecture Using Energy-Efficient Geese Optimization Load Balancing Approach (GOLBA). *Journal of Advances in Information Technology*, 15(11).
- [5] Cheema, S. M., Hannan, A., & Pires, I. M. (2022). Smart waste management and classification systems using cutting edge approach. *Sustainability*, 14(16), 10226.
- [6] Wang, C., Qin, J., Qu, C., Ran, X., Liu, C., & Chen, B. (2021). A smart municipal waste management system based on deep-learning and Internet of Things. *Waste Management*, 135, 20-29.
- [7] Vishnu, S., Ramson, S. J., Senith, S., Anagnostopoulos, T., Abu-Mahfouz, A. M., Fan, X., ... & Kirubaraj, A. A. (2021). IoT-enabled solid waste management in smart cities. *Smart Cities*, 4(3), 1004-1017.
- [8] Longo, E., Sahin, F. A., Redondi, A. E., Bolzan, P., Bianchini, M., & Maffei, S. (2021). A 5g-enabled smart waste management system for university campus. *Sensors*, 21(24), 8278.
- [9] Karthik, M., Sreevidya, L., Devi, R. N., Thangaraj, M., Hemalatha, G., & Yamini, R. (2023). An efficient waste management technique with IoT based smart garbage system. *Materials Today: Proceedings*, 80, 3140-3143.
- [10] Kanade, P., Alva, P., Prasad, J. P., & Kanade, S. (2021, April). Smart garbage monitoring system using Internet of Things (IoT). In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 330-335). IEEE.
- [11] John, J., Varkey, M. S., Podder, R. S., Sensarma, N., Selvi, M., Santhosh Kumar, S. V. N., & Kannan, A. (2022). Smart prediction and monitoring of waste disposal system using IoT and cloud for IoT based smart cities. *Wireless personal communications*, 122(1), 243-275.
- [12] Janani, R. P., Renuka, K., Aruna, A., & Lakshmi Narayanan, K. (2021). IoT in smart cities: A contemporary survey. *Global Transitions Proceedings*, 2(2), 187-193.
- [13] Baldo, D., Mecocci, A., Parrino, S., Peruzzi, G., & Pozzebon, A. (2021). A multi-layer lorawan infrastructure for smart waste management. *Sensors*, 21(8), 2600.
- [14] Alam, T. (2021). Cloud-based IoT applications and their roles in smart cities. *Smart Cities*, 4(3), 1196-1219.
- [15] Ali, T., Irfan, M., Alwadi, A. S., & Glowacz, A. (2020). IoT-based smart waste bin monitoring and municipal solid waste management system for smart cities. *Arabian Journal for Science and Engineering*, 45, 10185-10198.
- [16] Pardini, K., Rodrigues, J. J., Diallo, O., Das, A. K., de Albuquerque, V. H. C., & Kozlov, S. A. (2020). A smart waste management solution geared towards citizens. *Sensors*, 20(8), 2380.
- [17] Abdullah, N., Alwesabi, O. A., & Abdullah, R. (2019). IoT-based smart waste management system in a smart city. In *Recent trends in data science and soft computing: Proceedings of the 3rd international conference of reliable information and communication technology (irict 2018)* (pp. 364-371). Springer International Publishing.
- [18] Sharmin, S., & Al-Amin, S. T. (2016, November). A cloud-based dynamic waste management system for smart cities. In *Proceedings of the 7th Annual Symposium on Computing for Development* (pp. 1-4).
- [19] Aazam, M., St-Hilaire, M., Lung, C. H., & Lambadaris, I. (2016, October). Cloud-based smart waste management for smart cities. In 2016 IEEE 21st international workshop on computer aided modelling and design of communication links and networks (CAMAD) (pp. 188-193). IEEE.
- [20] Mishra, P.K. and Chaturvedi, A.K., 2023, January. State-of-the-art and research challenges in task scheduling and resource allocation methods for cloud-fog environment. In 2023 3rd International Conference on Intelligent Communication and Computational Techniques (ICCT) (pp. 1-5). IEEE.
- [21] Mishra, P.K. and Chaturvedi, A.K., 2023, April. Research challenges in job scheduling and resource distribution methodology for cloud fog atmosphere: An organized analysis. In 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) (pp. 292-299). IEEE.
- [22] Mishra, P.K. and Chaturvedi, A.K., 2024. Vehicular Traffic Congestion Detection System and Improved Energy-Aware Cost-Effective Task Scheduling Approach for Multi-Objective Optimization on Cloud Fog Network. *International Journal of Advanced Computer Science & Applications*, 15(9) eISSN: 2156-5570.
- [23] Mishra, P.K. and Chaturvedi, A.K., 2024. Improved Laxity Based Cost Efficient Task Scheduling Approach for Cloud-Fog Environment. *Engineering, Technology & Applied Science Research*, Vol. 15, No. 1, 2025, 19037-19044 eISSN: 1792-8036.
- [24] Gupta, H., Vahid Dastjerdi, A., Ghosh, S. K., & Buyya, R. "iFogSim: A toolkit for modeling and simulation of resource management techniques in the Internet of Things, Edge and Fog computing environments. *Software: Practice and Experience*", 47(9), 1275–1296, 2017.
- [25] Mahmud, R., Pallewatta, S., Goudarzi, M., & Buyya, R. (2022). Ifogsim2: An extended ifogsim simulator for mobility, clustering, and microservice management in edge and fog computing environments. *Journal of Systems and Software*, 190, 111351.