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Simulation-Based Comparison of Urban Waste Collection in Resource-Constrained Settings: Traditional, Imported IoT, and Contextualized IoT

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Abstract

Urban waste collection in resource-constrained contexts faces significant challenges due to variability in waste generation and limited operational capacity. This study presents a simulation-based comparison of three collection strategies: traditional fixed-route collection, intelligent collection with imported IoT, and intelligent collection based on contextualized IoT. A discrete-event simulation model is developed to evaluate system performance across operational, environmental, and economic dimensions within a common experimental framework. The contextualized IoT approach integrates a Contextual Prioritization Index (CPI), which enables adaptive decision-making based on multiple criteria beyond simple fill-level thresholds. Results from 30 independent simulation runs show that traditional collection systems exhibit low operational activity but result in significant under-service, leading to high levels of uncollected waste and associated nuisance costs. The imported IoT approach improves collection efficiency but increases travel distance, emissions, and operational costs due to reactive routing behavior. In contrast, the contextualized IoT approach maintains a comparable level of service while reducing operational intensity, emissions, and total cost. Statistical analysis using the Friedman test and post-hoc Wilcoxon signed-rank tests confirms that the observed differences between scenarios are highly significant ($p < 0.001$). The integration of nuisance cost into the economic evaluation provides a more comprehensive assessment of system performance, particularly in environments where under-service generates substantial indirect impacts. These findings highlight the importance of context-aware decision mechanisms in designing sustainable waste collection systems under resource constraints, where efficiency depends more on adaptive prioritization than on technological sophistication alone.

Keywords

Urban Waste Management, Contextualized IoT, Resource-Constrained Settings

1. Introduction

Urban solid waste management remains a critical challenge for many cities, particularly in contexts characterized by resource constraints [1] [2]. Traditional collection systems, based on fixed routes and predefined schedules, quickly show their limitations in the face of spatial and temporal variability in waste generation, leading to logistical inefficiencies, recurrent overflows, and increased environmental impacts [3] [4].

In this context, smart waste collection solutions based on the Internet of Things (IoT) have emerged as a promising alternative. By relying on fill-level sensors and dynamic route optimization, these systems are theoretically able to reduce travel distances, fuel consumption, and associated emissions [5]-[7].

However, the adoption of imported IoT solutions in resource-constrained cities raises significant limitations. Acquisition, communication, and maintenance costs, as well as dependence on reliable technical infrastructures, often compromise their medium-term operational viability. Such solutions are generally poorly adapted to local constraints [8]-[10].

In response to these limitations, contextualized IoT approaches, combining a frugal IoT architecture with a Contextual Prioritization Index, aim to explicitly integrate the operational context into decision-making. Inspired by context-aware systems [11]-[13], these approaches favor pragmatic resource optimization rather than increased technological sophistication.

Within this framework, this paper proposes a simulation-based comparison of three urban waste collection scenarios: traditional collection, intelligent collection using imported IoT, and intelligent collection based on contextualized IoT. This comparative analysis is conducted within a controlled and reproducible simulation framework, ensuring that differences between scenarios can be attributed exclusively to their underlying decision rules rather than to variations in environmental or parametric conditions. The objective is to assess, using operational, environmental, and economic indicators, the relative relevance of each approach in a resource-constrained context. The decision mechanisms implemented in this study build on a previously developed Contextual Prioritization Index (CPI) and are evaluated using a simulation engine that has been independently validated for structural consistency and reproducibility.

2. Methods

2.1. General Framework and Simulation Engine

This simulation framework has been the subject of a dedicated methodological validation study [14], which established its structural consistency, reproducibility, and qualitative sensitivity under controlled conditions. In particular, reproducibility is ensured through explicit control of stochastic components using fixed random seeds and repeated simulation runs. The validation process confirmed that the engine constitutes a reliable experimental tool for analyzing decision-making mechanisms in resource-constrained urban systems.

Building on this validated framework, the present study mobilizes the simulation engine to compare alternative waste collection strategies, ensuring that observed differences in performance can be attributed to decision rules rather than to artifacts or inconsistencies in the modeling environment.

The engine relies on a discrete-event, multi-indicator simulation approach, enabling the modeling of interactions between waste bins, vehicle fleets, and scenario-specific decision rules. The simulated environment is based on an abstract virtual map, with no correspondence to a real territory, in order to ensure experimental reproducibility and to focus the analysis on decision-making mechanisms.

Structural parameters of the system are kept identical across all scenarios, so that observed differences in results can be attributed exclusively to the decision logics implemented.

2.2. Parameterization of the Simulated Environment

The simulation environment is defined by a set of parameters describing the operation of the urban waste collection system. These parameters are grouped into two categories: those related to the urban environment and those associated with the vehicle fleet, costs, and maintenance. Urban environment parameters characterize system structure and waste generation dynamics, including the number and capacity of bins, waste generation rates, and their spatial distribution within the virtual map.

The simulated environment is structured into distinct functional zones reflecting typical urban configurations in resource-constrained cities, including urban residential, peripheral residential, commercial, and industrial areas. These zones differ in terms of bin capacity, number of users per bin, and waste generation intensity, thereby introducing structured spatial heterogeneity into the simulation.

The waste generation rate was set at 0.5 kg per person per day, consistent with reported values for Sub-Saharan African cities, which typically range between 0.3 and 0.8 kg per capita per day [15]-[17]. Bin capacity varies depending on the zone type, reflecting differences in waste production and storage practices across urban functions. These values are intended to reflect realistic operational ranges observed in resource-constrained urban contexts rather than to represent a specific city.

Each bin is associated with a variable number of users depending on the zone type. The daily waste generation per bin is computed as the product of the number of users assigned to the bin and the per capita generation rate (0.5 kg/day).

To reflect real-world variability, spatial heterogeneity is introduced through zone-specific parameters, while temporal variability emerges from the continuous accumulation of waste over time within the simulation framework.

The characteristics of each zone, including bin capacity and user distribution, are summarized in Table 1.

Table 1. Functional zoning and waste generation parameters.

Zone type	Bin distribution (%)	Bin capacity (kg)	Users per bin (min-max)	Priority index (initial)
Urban residential	40	30	2 - 12	0.5
Peripheral residential	50	50	4 - 20	0.6
Commercial	7	350	20 - 150	0.8
Industrial	3	750	50 - 300	0.7

Presented in Table 2, these parameters are identical across all scenarios to ensure strict comparability.

Table 2. Urban environment parameters.

Parameter	Description	Value
Number of bins	Total number of bins in the simulated environment	10,000
Bin capacity	Maximum capacity of a collection bin	30 - 750 kg (depending on zone type)
Waste generation rate	Average waste generated per person per day	0.5 kg/day
Users per bin	Number of users assigned to each bin	Variable (2 - 300 depending on zone)
Spatial distribution of bins	Distribution of bins on the virtual map	Zone-based distribution
Overflow threshold	Fill level beyond which a bin is considered overflowing	100%
Time horizon	Total simulation duration	90 days

The second category of parameters concerns fleet characteristics, operational costs, and maintenance conditions. These parameters directly influence system performance in terms of operational efficiency, environmental impact, and economic cost, and are therefore essential for the comparative evaluation of the different collection strategies.

The fleet, cost, and maintenance parameters were defined based on literature-informed assumptions reflecting typical configurations of waste collection systems in resource-constrained urban contexts, including fleet size, vehicle capacity, fuel consumption, and labor organization [18]. These assumptions are complemented by empirical observations of operational practices and resource limitations, as identified through the analysis of waste management systems in Kinshasa [19], ensuring that the simulation captures realistic operational and economic conditions within a consistent comparative framework.

Table 3 summarizes the fleet, cost, and maintenance parameters used in the simulation.

Table 3. Fleet, cost, and maintenance parameters.

Parameter	Description	Value
Number of trucks	Total number of collection trucks	5
Truck capacity	Maximum waste capacity per truck	3000 kg
Agents per truck	Number of workers per collection team	4
Fuel consumption	Fuel consumption per kilometer	0.5 L/km
Fuel cost	Unit fuel cost	1.5 USD/L
Truck maintenance cost	Maintenance cost per vehicle	1500 USD
Maintenance interval	Distance between maintenance operations	2500 km
Labor cost	Daily cost per agent	4 USD/day
Service time window	Daily operational time range	02:00-23:00
Nuisance cost	Cost associated with uncollected waste	0.15 USD/kg

2.3. Definition of Simulated Scenarios

Three urban waste collection scenarios are defined to assess the impact of different decision strategies on system performance. The scenarios differ exclusively in their collection control logic, while all structural parameters of the simulated environment remain identical.

- S1: Traditional collection relies on fixed route planning, independent of actual bin fill levels. Collection is performed at predefined frequencies without sensors or adaptive mechanisms.
- S2: Intelligent collection with imported IoT introduces fill-level sensors, with collection decisions triggered when predefined thresholds are reached.
- S3: Intelligent collection with contextualized IoT combines a frugal IoT architecture with a Contextual Prioritization Index, integrating multiple contextual factors into decision-making. The formal definition and methodological development of the Contextual Prioritization Index (CPI) are detailed in [19]. The index aggregates key variables such as bin fill level and operational constraints into a composite prioritization score.

Formally, the CPI is expressed as a weighted aggregation of normalized criteria:

$$\mathrm{CPI}_j = \sum_{i=1}^{n} w_i \cdot x_{ij}$$

where w_i represents the empirical weight of criterion i and x_{ij} the normalized value of that criterion for bin j.

In the simulation, bins are dynamically ranked based on their CPI values, and collection decisions are triggered when the index exceeds a predefined threshold. This mechanism enables adaptive and context-aware routing, allowing the system to balance service efficiency and resource constraints more effectively than threshold-based approaches.

The main functional differences between the scenarios (regarding sensor types, collection triggering rules, and contextual awareness) are summarized in Table 4.

Table 4. Comparative description of scenarios S1, S2, and S3.

Characteristic	S1	S2	S3
Planning type	Fixed	Threshold-based dynamic	Context-aware dynamic
Sensors	None	Fill-level sensors	Frugal sensors
Collection triggering	Predefined frequency	Fill-level threshold	Contextual Prioritization Index
Context awareness	None	Limited	High
Adaptation to local constraints	Low	Moderate	High
Technological complexity	Low	High	Moderate

2.4. Evaluation Indicators

Scenario evaluation relies on a set of indicators covering three complementary dimensions: operational, environmental, and economic. These indicators allow comparison of overall performance across collection strategies in a resource-constrained context.

Operational indicators assess logistical efficiency through total travel distance, collected waste mass, and overflowed waste mass. Environmental indicators evaluate collection impacts via fuel consumption and CO_2 emissions. Economic indicators measure system operating costs, including fuel, maintenance, labor costs, and total collection cost. All indicators and their definitions are summarized in Table 5.

Table 5. Evaluation indicators.

Dimension	Indicator	Description	Unit
Operational	Travel distance	Total distance traveled by collection vehicles	km
Operational	Collected mass	Total mass of waste collected	kg
Operational	Overflowed mass	Waste mass not collected due to bin overflow	kg
Environmental	CO_2 emissions	Total emissions generated by collection operations	kg CO_2
Economic	Acquisition cost	Initial investment cost (bins, vehicles, IoT equipment)	USD
Economic	Operational cost	Cost related to fuel, labor, and maintenance	USD
Economic	Nuisance cost	Cost associated with uncollected and overflowed waste	USD
Economic	Total cost	Sum of acquisition, operational, and nuisance costs	USD

All indicators are computed consistently across scenarios using the same simulation framework, ensuring strict comparability of results.

Results are reported as mean values with associated standard deviations across simulation runs, allowing assessment of variability and robustness of observed differences between scenarios.

The total cost is defined as the sum of acquisition, operational, and nuisance costs, ensuring a comprehensive evaluation of economic performance.

3. Results

The results are presented for the three simulated scenarios (S1, S2, S3) based on 30 independent simulation runs under identical parameter settings. For each indicator, results are expressed as mean values with associated standard deviations to reflect variability across runs.

Statistical significance of differences between scenarios was assessed using the Friedman test, followed by post-hoc Wilcoxon signed-rank tests with Bonferroni correction.

3.1. Overall Simulation Results

The overall results are summarized in **Table 6**. The three scenarios exhibit markedly different performance profiles across all evaluated dimensions.

Table 6. Overall comparative results of the simulation (mean ± standard deviation, n = 30).

Indicator	S1	S2	S3
Travel distance (km)	31,976 ± 3314	1,197,582 ± 7234	853,228 ± 8132
Collected mass (kg)	904,666 ± 158,769	8,776,765 ± 66,500	8,711,728 ± 66,650
Overflowed mass (kg)	7,497,394 ± 140,013	28,407 ± 1820	38,362 ± 2381
CO_2 emissions (kg)	41,569 ± 4309	1,556,856 ± 9404	1,109,196 ± 10,572
Acquisition cost (USD)	1,192,000	2,995,000	1,542,500
Operational cost (USD)	50,288 ± 4475	1,784,128 ± 9765	1,356,236 ± 10,978
Nuisance cost (USD)	$6.64 \times 10^{10} \pm 1.37 \times 10^{9}$	$6.62 \times 10^{6} \pm 4.64 \times 10^{5}$	$4.61 \times 10^{6} \pm 4.80 \times 10^{5}$
Total cost (USD)	$6.64 \times 10^{10} \pm 1.37 \times 10^{9}$	$8.40 \times 10^{6} \pm 4.68 \times 10^{5}$	$5.96 \times 10^{6} \pm 4.81 \times 10^{5}$

The traditional system (S1) is characterized by low operational intensity but results in substantial under-service, as reflected by high levels of uncollected and overflowed waste. The resulting nuisance cost dominates the total cost, highlighting the limitations of fixed-route collection strategies in variable environments.

The imported IoT system (S2) achieves high collection efficiency with minimal overflow. However, this performance relies on a substantial increase in operational effort, leading to higher travel distances, emissions, and operational costs.

The contextualized IoT system (S3) achieves a more balanced performance. It maintains a level of service comparable to S2 while reducing operational intensity and associated impacts. This configuration leads to a significant reduction in both environmental and economic costs, particularly through lower nuisance and operational components.

Statistical analysis confirms that the observed differences between scenarios are highly significant for all indicators (Friedman test, $p = 9.36 \times 10^{-14}$), with all pairwise comparisons also significant (Wilcoxon signed-rank test with Bonferroni correction, $p = 1.86 \times 10^{-9}$).

3.2. Analysis of Operational Performance

Operational performance differences between the three scenarios are primarily driven by their underlying collection strategies and decision mechanisms.

The comparative operational performance of the three scenarios is illustrated in Figure 1(a) and Figure 1(b).

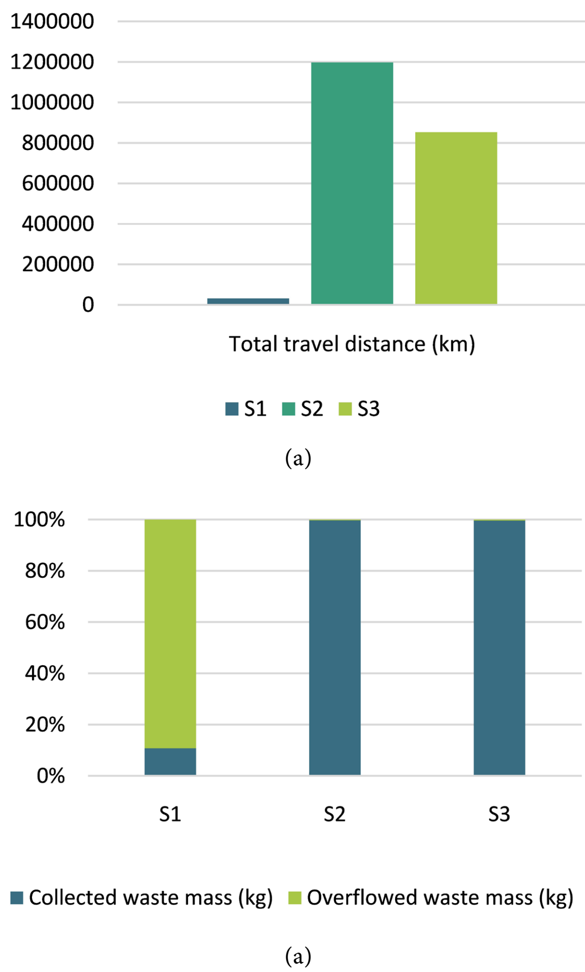

Figure 1. (a) Comparison of total travel distances across waste collection scenarios; (b) Comparison of collected and overflowed waste masses across waste collection scenarios.

The traditional system (S1) operates independently of actual waste accumulation, resulting in inefficient service allocation. Bins are collected according to fixed schedules rather than need, which leads to significant overflow in high-demand areas while other bins may be serviced unnecessarily. This mismatch explains the combination of low travel distance and poor collection performance.

In contrast, the imported IoT system (S2) dynamically responds to bin fill levels, ensuring that collection is triggered when needed. This demand-driven mechanism significantly improves collection efficiency and minimizes overflow. However, this reactivity comes at the cost of increased routing activity, as vehicles are frequently dispatched to respond to localized fill-level thresholds, leading to a substantial increase in travel distance.

The contextualized IoT system (S3) modifies this behavior by introducing a prioritization mechanism based on contextual criteria. Instead of reacting solely to fill levels, collection decisions are guided by a ranking of bins that integrates operational and environmental constraints. This allows the system to avoid unnecessary trips while still targeting the most critical bins. As a result, S3 maintains a level of collection performance comparable to S2 while reducing travel distance and limiting overflow.

These results highlight that operational efficiency is not solely determined by responsiveness, but by the ability to structure decision-making in a way that balances urgency and resource constraints.

Statistical analysis confirms that the differences observed between scenarios for all operational indicators are highly significant (Friedman test, $p = 9.36 \times 10^{-14}$). Pairwise comparisons further indicate significant differences between all scenarios (Wilcoxon signed-rank test, $p = 1.86 \times 10^{-9}$).

3.3. Analysis of Environmental Impacts

Environmental performance across the three scenarios is primarily reflected in CO_2 emissions, which are directly linked to operational activity levels.

The traditional system (S1) exhibits the lowest emissions due to its limited operational intensity. However, this apparent environmental advantage is a consequence of reduced service delivery rather than improved efficiency. The high levels of uncollected and overflowed waste indicate that emissions are minimized at the expense of service quality.

The imported IoT system (S2) generates the highest emissions, reflecting its increased operational activity and extensive routing required to maintain high collection performance. The continuous response to fill-level thresholds leads to frequent vehicle dispatching and longer travel distances.

The contextualized IoT system (S3) achieves a reduction in emissions compared to S2 by optimizing routing decisions through contextual prioritization. By avoiding unnecessary trips while still targeting critical bins, S3 reduces operational effort without significantly compromising collection performance.

These results demonstrate that environmental impact must be interpreted in relation to service level. Lower emissions do not necessarily indicate better performance if they result from insufficient waste collection.

Statistical analysis confirms significant differences in CO_2 emissions between scenarios (Friedman test, $p = 9.36 \times 10^{-14}$). Pairwise comparisons indicate that all differences are statistically significant (Wilcoxon signed-rank test, $p = 1.86 \times 10^{-9}$).

Figure 2 illustrates this distinction among the evaluated strategies.

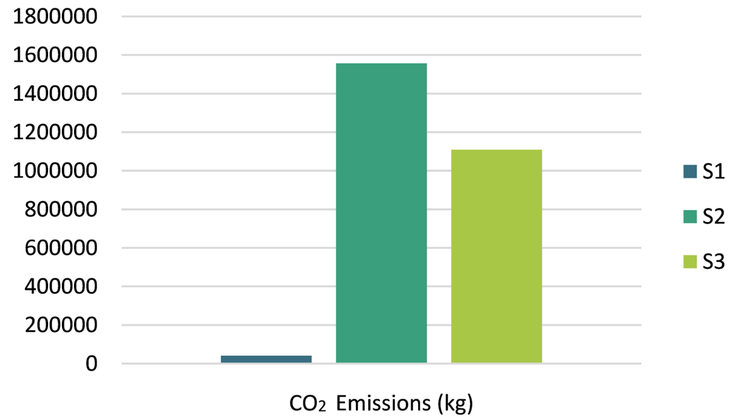

Figure 2. CO_2 emissions by scenario.

3.4. Economic Analysis

The economic performance of the three scenarios is determined by the combined effect of acquisition, operational, and nuisance costs.

The traditional system (S1) is characterized by very low operational costs due to limited collection activity. However, this apparent economic advantage is offset by an extremely high nuisance cost resulting from large quantities of uncollected and overflowed waste. As a result, the total cost is dominated by this component, making the system economically inefficient despite its low operational requirements.

The imported IoT system (S2) incurs high acquisition and operational costs due to the use of sensor-based technologies and increased routing activity. Nevertheless, the improved collection efficiency significantly reduces nuisance costs, resulting in a substantially lower total cost compared to S1.

The contextualized IoT system (S3) achieves a more balanced economic profile. While its acquisition and operational costs remain lower than those of S2, it also maintains low levels of overflow, leading to a reduced nuisance cost. This combination results in the lowest total cost among the three scenarios.

These results highlight the importance of integrating service-related externalities into economic evaluation. Focusing solely on operational costs can lead to misleading conclusions, particularly in contexts where under-service generates significant indirect costs.

Statistical analysis confirms that differences in total cost between scenarios are highly significant (Friedman test, $p = 9.36 \times 10^{-14}$). Pairwise comparisons indicate significant differences between all scenarios (Wilcoxon signed-rank test, $p = 1.86 \times 10^{-9}$).

A detailed breakdown of costs is provided in Figure 3.

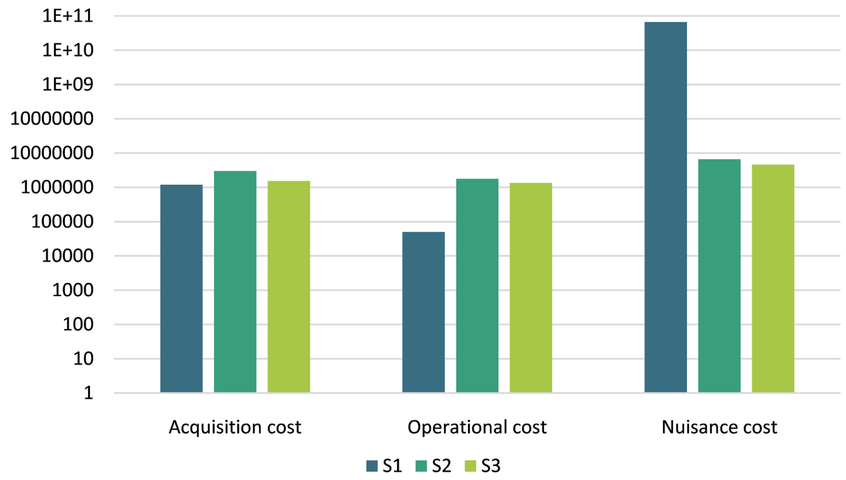

Figure 3. Cost structure decomposition across scenarios (logarithmic scale, base 10).

4. Discussion

4.1. Comparative Interpretation of Scenarios

The comparative analysis highlights the structural limitations of traditional collection systems, whose low apparent costs and environmental impacts are offset by a pronounced inability to cope with variability in waste generation [3] [4] [20]. This operational inefficiency significantly limits their relevance in highly constrained urban contexts. The results show that this apparent efficiency is largely driven by reduced operational activity rather than effective service delivery, leading to substantial levels of uncollected and overflowed waste. Intelligent collection based on imported IoT substantially improves service quality by reducing overflows and increasing collected waste [5] [7] [21] [22]. However, these gains rely on operational intensification, resulting in significant economic and environmental surcharges, particularly related to maintenance and fleet overuse [23] [24]. This confirms that responsiveness based solely on fill-level thresholds can lead to excessive routing activity and increased system costs.

Contextualized IoT emerges as a more balanced compromise. By explicitly integrating decision context into collection rules, it maintains service levels comparable to imported IoT while reducing travel distances, environmental impacts, and overall costs. In particular, the integration of contextual prioritization allows the system to better allocate limited resources by targeting critical bins while avoiding unnecessary collection operations. This positioning underscores the value of approaches tailored to local constraints rather than generic technological solutions [25] [26]. The results therefore support the idea that context-aware decision mechanisms can improve both efficiency and robustness in resource-constrained environments.

4.2. Trade-Offs in Resource-Constrained Contexts

The results confirm the inherently multi-objective nature of urban waste collection, where improving one performance criterion often degrades another. In resource-constrained settings, these trade-offs are particularly critical due to limited economic and operational margins [27]-[29]. In particular, the findings show that maximizing collection efficiency without considering operational constraints leads to increased costs and environmental impacts, as observed in the imported IoT scenario.

Rigid rule-based approaches, such as fixed thresholds, are especially vulnerable to operational uncertainty and technical failures, potentially leading to system instability. This limitation is reflected in the tendency of threshold-based systems to trigger frequent and localized collection actions, which can result in inefficient routing patterns and increased system stress. In contrast, contextualized decision logic enhances decision robustness by reducing reliance on punctual information and improving tolerance to unanticipated variations [7]. By integrating multiple criteria into the decision process, contextual prioritization allows for more stable and adaptive system behavior under fluctuating conditions.

For urban authorities, these findings suggest that system sustainability depends less on technological sophistication than on contextual appropriation, which is essential for effective and durable waste management under resource constraints [2]. This implies that the design of decision mechanisms should prioritize adaptability and resource efficiency rather than purely technological performance.

4.3. Study Limitations

This study relies on a simulation model that necessarily involves simplifications of real-world systems. The urban environment is represented abstractly, and some complex operational dimensions are not explicitly modeled. In particular, factors such as traffic conditions, road network constraints, and user behavioral variability are not directly integrated into the simulation framework.

In addition, the absence of field-based calibration limits the predictive scope of the results, as the primary objective is comparative rather than absolute assessment. The results should therefore be interpreted as relative performance comparisons between scenarios rather than exact predictions of real-world outcomes.

Finally, fixing certain key parameters may influence observed differences between scenarios, calling for further sensitivity analyses. Future work could extend the model by incorporating real urban data, testing additional decision rules, and evaluating system performance under varying parameter configurations to assess robustness.

5. Conclusions

This paper presented a simulation-based comparison of three urban waste collection scenarios in a resource-constrained context: traditional collection, intelligent collection with imported IoT, and intelligent collection based on contextualized IoT. The multi-indicator evaluation highlights significant differences among these approaches in terms of operational performance, environmental impacts, and economic costs.

The results show that traditional collection, while apparently inexpensive, remains structurally inefficient when faced with variability in waste generation, leading to substantial levels of uncollected waste and associated indirect costs. Imported IoT substantially improves service quality but at the expense of increased operational intensity, resulting in higher economic and environmental impacts. In contrast, contextualized IoT emerges as a more sustainable compromise, maintaining high service levels while reducing travel distances, CO_2 emissions, and overall costs.

A key contribution of this study lies in the integration of contextual decision-making through the Contextual Prioritization Index, as well as the explicit consideration of nuisance cost in the economic evaluation. These elements allow for a more comprehensive assessment of system performance, particularly in environments where resource constraints amplify the consequences of under-service.

These findings emphasize the relevance of smart collection approaches adapted to local constraints, where value creation lies more in contextual decision integration than in technological sophistication. Future work will focus on integrating field data for model calibration, conducting sensitivity analyses, and extending the simulation framework to diverse urban contexts in order to strengthen its operational relevance as a decision-support tool.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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