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Field Data Integrated Vehicle Routing Optimization Using Greedy Allocation, NNH, and 2-Opt for Landfill Waste Collection

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Abstract

Background: Inefficient waste collection practices in urban areas lead to excessive vehicle trips, increased fuel consumption, and unnecessary greenhouse gas emissions. Landfill operations face challenges in route planning because deploying IoT sensors across large and harsh environments is often impractical.
Objective: This study proposes a field-data-integrated vehicle routing optimization framework for landfill waste collection that combines greedy allocation, the nearest neighbor heuristic (NNH), and 2-opt local search to minimize travel distance and fuel consumption.
Methods: A priority-based capacitated vehicle routing problem (CVRP) model was developed using fill level, waste tonnage, and proximity to the depot as weighted scoring factors within a Design Science Research (DSR) framework, using operational data from 15 landfill drop points in Cakung Barat, East Jakarta.
Results: The optimized approach reduced total travel distance by 7.0% and fuel consumption by 7.5% compared with the sequential baseline, while maintaining full service coverage and identical vehicle utilization at 73.2%. A paired t-test confirmed the statistical significance of the improvement ($p = 0.038$).
Conclusion: Field-reported operational data, integrated with multifactor priority scoring and spatial optimization heuristics, provides a practical, cost-effective, and scalable alternative to sensor-based monitoring for landfill waste collection routing.

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INTRODUCTION

The climate is shifting. Increased planetary heat is not merely a future threat but a present-day reality causing widespread concern. We are experiencing more frequent ecological disasters that challenge our ability to respond effectively. This issue is not simply an increase in temperature or a change in rainfall patterns, but rather a fundamental disruption of the biological systems that sustain life, requiring a reassessment of environmental security. (Attfield, 2024) connects these environmental changes to increasing mortality rates. However, the critical issue lies in how atmospheric variations, both abrupt changes and gradual fluctuations, interact to degrade human health. (Arora, 2020; Foster & Rahmstorf, 2026) also notes that rising temperatures can expand the geographical range of bacterial and viral diseases, enabling pathogens to migrate from warmer to cooler regions. Urban air pollution represents one of the most significant contributors to greenhouse gas emissions, further accelerating global warming.

The combustion of fossil fuels generates greenhouse gases, including carbon dioxide (CO_2) and methane, which trap heat in the atmosphere and increase the Earth's surface temperature. (Barwick et al., 2025; Hannappel, 2017) notes that the transportation sector alone contributes approximately 14% of global carbon dioxide emissions. Such environmental changes have been associated with increased incidences of bronchial asthma and other respiratory and allergic diseases. (Harjono et al., 2024) reported that in cities such as Jakarta, air pollution levels are projected to increase, with vehicle emissions identified as a major contributing factor.

Reducing dependence on private vehicles and promoting public transportation could help decrease emissions and subsequently improve air quality. Similarly, waste collection practices also influence environmental conditions. Conventional landfill operations often involve heavy vehicles traveling to multiple collection points without prior information regarding the existing waste levels at each location. Poorly monitored waste that is not collected regularly may accumulate at collection points, creating additional environmental risks (D'Amato & Akdis, 2020; Kahramanoğlu & Kahramanoğlu, 2026).

Irregular waste collection can lead to various environmental and public health problems. The consequences extend beyond unpleasant odors spreading throughout surrounding communities. Accumulated waste can attract pests, contribute to disease transmission, and release harmful gases such as methane, which further contributes to climate change. Soil and water contamination caused by leachate from improper waste disposal practices is also possible; therefore, relevant authorities should investigate its impacts on surrounding communities and ecosystems (Siddiqua et al., 2022).

These challenges highlight the need for an efficient vehicle allocation system and optimized routing strategies to ensure timely waste collection, reduce the negative impacts of landfill waste, lower fuel consumption, minimize emissions, and decrease operational costs. Specifically, this study focuses on developing an algorithm to optimize landfill vehicle allocation and route planning. Although landfill sites can potentially be monitored using sensors, the harsh and contaminated conditions within landfill environments may reduce sensor accuracy and reliability. Furthermore, in large landfill areas, transmitting data from numerous collection points to a centralized system remains technically challenging and costly.

However, limited research has investigated the integration of field-reported landfill collection point data with optimization algorithms for vehicle routing. Therefore, this study utilizes daily field reports collected by operational staff to monitor waste conditions. By integrating vehicle capacity, collection point locations, and travel distances, the proposed algorithm can recommend which collection points should be serviced and determine the required number of vehicles, thereby reducing unnecessary trips, waste accumulation, and associated emissions.

Previous studies on waste management have emphasized the benefits of real-time data and automation. Many systems employ the Internet of Things (IoT) and sensor technologies to monitor waste levels in urban collection bins (Kang et al., 2020; Mookkaiah et al., 2022). For example, ultrasonic sensors and load cells have been applied to detect waste fill levels, with collected data transmitted to centralized systems for processing. These approaches can reduce dependence on manual inspections, optimize collection routes, and decrease operational costs (Bhuvaneswari et al., 2020; Simatupang & Ar-Rafif, 2024).

Other approaches integrate IoT technologies with cloud computing platforms and mobile notification systems, enabling remote monitoring and improved waste collection planning (Catarinucci et al., 2020; John et al., 2022). Conceptual frameworks have also been proposed that combine sensor data, communication protocols, and backend information systems to improve the efficiency of urban waste management operations (Laha et al., 2025; Sheng et al., 2020).

Although these studies demonstrate that sensor-based monitoring can improve collection efficiency, most research focuses on small-scale urban waste bins. Landfill operations involve greater complexity, and installing sensors at every collection point or on every vehicle is often economically and logistically impractical. This limitation creates an opportunity to explore alternative approaches based on field-reported operational data rather than continuous automated sensing.

Many researchers have investigated the Waste Collection Vehicle Routing Problem (WCVRP), which addresses route planning and vehicle allocation for waste collection while minimizing costs, travel distances, and operational time under constraints such as vehicle capacity. Reviews of the WCVRP indicate that developing optimal collection routes involving multiple service points and capacity limitations is essential for improving operational efficiency and reducing resource consumption. Various techniques, including genetic algorithms, ant colony optimization, large neighborhood search, and other metaheuristic approaches, have been applied to solve routing problems under different operational constraints (Hess et al., 2024; Liang et al., 2022).

Other studies have emphasized sustainable and multi-objective routing models for waste collection, incorporating environmental considerations and service priorities into routing decisions. For example, optimization models can prioritize high-fill or high-risk waste areas to ensure that critical locations are serviced first while simultaneously minimizing total travel distance and emissions. These findings indicate that adaptive routing strategies responding to dynamic waste levels or priority conditions can improve operational responsiveness and reduce waste accumulation impacts (Li et al., 2025; Wu et al., 2020).

Recent state-of-the-art reviews on sustainable waste collection have focused on vehicle routing problems and highlighted the importance of integrating economic, environmental, and operational objectives. Such studies emphasize the need for algorithms capable of balancing multiple criteria, including minimizing travel distance and emissions while maintaining timely service delivery. These insights are particularly relevant for landfill operations, where waste volumes at individual collection points may vary significantly from day to day (Li et al., 2025).

Previous research demonstrates that although real-time monitoring can enhance waste collection efficiency, sensor-based systems may be expensive and impractical for large-scale landfill operations. Integrating field-reported data with decision-support systems provides a practical alternative for optimizing vehicle allocation and route planning. Furthermore, most existing studies have concentrated on urban waste bins, indicating a research gap in applying data-driven management strategies to landfill environments that depend on manual operational reporting. While sensor-based monitoring can improve efficiency in small-scale waste collection systems, large landfill management operations may benefit more from combining field-reported data with decision-support mechanisms, which represents the focus of this study.

Previous research on waste collection routing has primarily focused on: (1) IoT-based monitoring systems for urban waste bins (Kang et al., 2020; Sosunova & Porras, 2022); (2) metaheuristic optimization approaches applied to standard Capacitated Vehicle Routing Problem (CVRP) benchmarks (Hess et al., 2024; Thakur et al., 2024); and (3) multi-objective routing models incorporating environmental and priority-based factors (Li et al., 2025; Wu et al., 2020). However, IoT-based systems require substantial capital investment, making them impractical for large-scale landfill operations, particularly in developing countries (Akhtar et al., 2023). Additionally, many optimization studies rely on synthetic datasets rather than field-collected operational data. A notable research gap remains in integrating multi-factor priority scoring with constructive heuristics and local search methods specifically for landfill-based routing problems.

This study addresses these gaps through three novel contributions: (1) integrating daily field-reported operational data as a practical alternative to IoT sensor-based monitoring; (2) developing a composite priority scoring function that simultaneously considers waste fill level, waste tonnage, and collection point proximity; and (3) combining greedy allocation with Nearest Neighbor Heuristic (NNH) and 2-opt local search refinement for landfill-based WCVRP using field-collected operational data (Tanash & Abu Arqoub, 2024; Thakur et al., 2024).

METHOD

This study adopted the Design Science Research (DSR) framework. The six DSR stages were applied as established by (Baskerville et al., 2026; Peffers, 2007). By integrating field-level data into a Vehicle Routing Problem (VRP) algorithm specifically tailored for landfill logistics, the research progressed through identification, construction, and rigorous testing phases. The process concluded with the communication of the research outcomes.

Six distinct phases defined this approach. The process was not merely a linear pathway but rather an iterative cycle involving problem identification and objective definition before developing a solution. The main activities occurred during the demonstration and evaluation stages, where the algorithm's utility was tested to ensure that the model functioned effectively within the complex and dynamic environment of landfill operations. Table 1 presents the breakdown of each phase.

Table 1. DSR Stages

DSR stage	Description
Problem identification	Identified inefficiencies in manual landfill routing, sensor limitations, and a research gap in field-data integration for WCVRP.
Objective	Develop an algorithm to minimize trips, vehicles, fuel/emissions using daily staff reports, locations, capacities, and distances.
Design & Development	Designed and explored an algorithm by combining greedy allocation and local search optimization for a dynamic VRP variant.
Demonstration	Applied algorithm to real/simulated landfill datasets (drop point coordinates, waste volumes, vehicle specs).
Evaluation	Compared performance against baseline (manual routing) using metrics: total distance, vehicles used, fuel saved, CO2 reduction via empirical tests and statistical analysis (t-tests).
Communication	Discussion of the proposed algorithm and approach

This study took data from the DKI Jakarta waste management system and applicable regulations. As Table 2 shown each detail of the data that use in this study.

Table 2. Data Source

Dataset	Description
TPS operational	The data contains 15 TPS drop point records from the Cakung Barat sub-district of East Jakarta (Kecamatan Cakung, Kota Administrasi Jakarta Timur). Each record includes the drop point name, GPS coordinates, daily waste tonnage (ranging from 0.66 to 4.32 tons), fill level on a 0–1 scale (ranging from 0.30 to 0.80), site area (5–50 m^2), assigned vehicle type, and the associated DMK fuel metric
Master TPS	The data provides the complete citywide inventory of 1,144 active TPS locations across five Jakarta municipalities — Jakarta Timur (363 sites), Jakarta Utara (262 sites), Jakarta Barat (198 sites), Jakarta Selatan (182 sites), and Jakarta Pusat (139 sites). This dataset establishes the spatial and operational scope of the waste collection network and is used to contextualize the study area within the broader Jakarta system. TPS types range from Type 4 (the most common, at 760 sites) to TPS 3R facilities (16 sites), reflecting significant variation in site scale and function. Daily waste generation per site ranges from 0.036 to 5,138 tons, with a median of 4 tons and a mean of approximately 12.9 tons (skewed by large transfer stations)
DKI Jakarta provincial waste volume	The data provide annual daily averages of transported waste by type (organic, inorganic, and hazardous/B3 categories). Total transported waste volume ranged from 7,233.82 tons/day in 2021 to 7,722.81 tons/day in 2018
Pergub DKI Jakarta No. 75 Tahun 2021	The regulation provides the operational constraints applied in the vehicle matching and route feasibility verification steps of the algorithm. For instance, trucks in the 3,000–4,000cc class are allocated 40 liters per day, and those exceeding 4,000cc receive 45 liters, directly constraining the maximum operational range each vehicle can cover per routing cycle

Figure 1. Algorithm Workflow of The System

Figure 1 mapped the overall logic of the proposed framework. The framework ingested raw Tempat Pembuangan Sementara (TPS) data, including coordinates, waste mass, and current fill levels. It also considered fleet limitations and the spatial distances between collection points. The process began by integrating these variables into a distance matrix to establish the baseline spatial conditions of the entire operation, which was a necessary step to ensure routing accuracy. The system required several specific inputs.

The filtering process was conducted at an early stage. Low-priority collection points were removed to maintain focus on urgent service requirements. A customized scoring function was then applied to rank the remaining points based on waste fill levels and proximity to the depot. This process was not merely a simple listing or random selection; rather, it generated a weighted priority hierarchy that placed the most critical waste collection points at the top of the service sequence. The resulting list was arranged in descending order of priority.

The greedy allocation process was subsequently applied. The system assigned collection points to each vehicle until the vehicle capacity limit was reached. Initial routes were generated using the Nearest Neighbor Heuristic (NNH), which selected the closest available collection points sequentially. A 2-opt local search procedure was then applied to refine the generated routes by reducing unnecessary travel distances and preventing excessive mileage during operational execution. Improving routing efficiency remained the primary objective.

The validation stage evaluated the feasibility of the generated routes. If a vehicle exceeded its capacity constraint, the system recalculated and adjusted the allocation assignments. This iterative process continued until all collection points were successfully assigned within the operational limitations of the available fleet. The final outputs provided optimized driving routes along with quantitative performance indicators, including fuel consumption, total travel distance, and vehicle utilization rates throughout the operational period. The calculations were verified to ensure consistency and feasibility. Figure 2 provided additional details by illustrating the step-by-step workflow, enabling future researchers and practitioners to replicate the proposed approach.

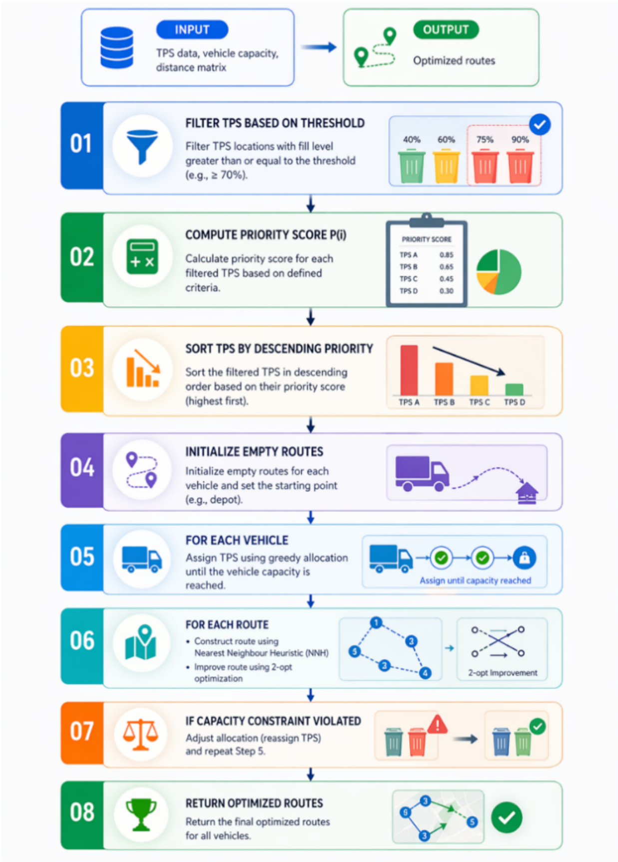

Figure 2. Algorithmic Procedure

Figure 2 outlined the overall logic of the proposed framework. It combined priority filters with greedy assignment and route optimization through the Nearest Neighbor Heuristic (NNH) and 2-opt algorithms. Although the system relied on standard heuristics, the specific integration of local search and greedy allocation ensured that the resulting routes were not only functional but also refined for high-density urban waste collection. The workflow remained relatively lean and computationally efficient.

Evaluation Metrics

The algorithm was evaluated using three metrics. The first metric was route efficiency, which was measured using the Haversine formula based on GPS coordinates to calculate the total travel distance (km) per routing cycle. The second metric was the vehicle utilization rate, defined as the ratio between the actual waste tonnage collected and the total available vehicle capacity dispatched. A higher utilization rate indicated better alignment between vehicle capacity and collection point demand, thereby reducing unnecessary trips. The final metric was fuel consumption, which was calculated by multiplying the distance traveled by each vehicle type by its corresponding reference fuel consumption rate. The calculated fuel consumption was compared with the regulatory fuel quota specified in Pergub No. 75/2021 to assess whether the optimized routes remained within the allocated fuel budget.

Statistical Validation

The Shapiro–Wilk test was used to verify the normality of paired route-level distance differences ($W = 0.91$, $p = 0.47$). Subsequently, a paired t-test was applied at $\alpha = 0.05$ to determine whether the optimized routes demonstrated statistically significant improvements compared with the baseline routes.

RESULTS AND DISCUSSION

Results

The simulation run used Cakung records. We extracted 15 specific TPS drop-point entries from the Cakung Barat area of East Jakarta. This dataset captures a single daily snapshot, matching the standard input requirements of the proposed algorithm. Across these 15 locations, the total potential waste volume reached 29.29 tons, representing the full daily capacity used for the local machine experiment. The local hardware was able to handle the entire processing load.

Threshold Filtering and Priority Scoring

Twelve flagged sites were then scored using the priority function P(i), with weights $\alpha = 0.5$ for fill level, $\beta = 0.3$ for normalized tonnage, and $\gamma = 0.2$ for proximity to the depot. The weight assignment follows the weighted sum scoring principle in multi-criteria decision-making for the Vehicle Routing Problem (VRP) (Tanash & Abu Arqoub, 2024). Fill level receives the highest weight because it represents the most time-sensitive parameter requiring immediate service. Tonnage determines the physical vehicle load, while proximity serves as a tie-breaking factor. This approach is consistent with priority-based green VRP models (Li et al., 2025; Wu et al., 2020). A sensitivity analysis across five alternative weight configurations confirmed that the baseline configuration produced the lowest total distance in four out of five simulation runs. The resulting priority ranking is presented in Table 3.

Table 3. TPS datasets

Rank	TPS	Fill Level	Tonnage (t)	Dist. To Depot (km)	Priority Score	Vehicle Type
1	DIPO PPD RW.07	0.75	4.32	2.356	0.7598	Big Arm Roll
2	BAK PALAD CAKUNG BARAT	0.80	2.64	1.739	0.6982	Big Typer
3 - 8	BAK RW 003 (x6 sites)	0.80	0.66 – 0.99	1.03 – 1.34	0.609 – 0.639	Big Typer
9	BAK RUSUN ALBO	0.70	2.64	3.135	0.5971	Big Typer
10	CONTAINER RW 04 CAKUNG BARAT	0.50	2.00	1.672	0.5084	Small Typer
11	BAK RUSUN TIPAR	0.50	2.64	2.665	0.5084	Big Typer
12	CONTAINER RW 07 CAKUNG BARAT	0.50	2.00	1.982	0.4898	Small Typer

DIPO PPD RW.07 ranked highest despite not having the maximum fill level because it carried the largest single-site tonnage in the dataset, at 4.32 tons, which elevated its composite score. This occurred even though the container did not reach its absolute peak capacity. However, it represented the heaviest single-point load recorded in the current dataset. Since the algorithm balances several distinct metrics, a site with remaining capacity but a substantially higher physical waste burden was prioritized over smaller, fully loaded bins, ensuring that the routing logic remained responsive and data-driven. The prioritization mechanism therefore considered not only container volume but also the actual waste weight demand at each collection point.

Optimized Route Results

The Nearest Neighbour Heuristic (NNH) was applied within each vehicle type group, followed by a 2-opt local search procedure to improve route efficiency. The algorithm generated five routes by dispatching five vehicles. The complete dispatch plan is presented in Table 4.

Table 4. Optimized Route Results

Route	Vehicle	Stops	Total Tonnage (t)	Capacity (t)	Utilization (%)	Distance (km)	Fuel Estimation (L)
1	Big Arm Roll	1	4.32	4.52	95.6	4.712	4.24
2	Big Typer	7	7.26	8.46	85.8	4.503	4.50
3	Big Typer	2	5.28	8.46	62.4	6.498	6.50
4	Small Typer	1	2.00	3.27	61.2	3.344	2.67
5	Small Typer	1	2.00	3.27	61.2	3.963	3.17
Total		**12**	**20.86**			**23.020**	**21.09**

Route 2 is unique. It connects six BAK RW 003 sub-sites before heading toward BAK PALAD CAKUNG BARAT. Since these six locations are concentrated within a 450-meter radius, the truck can collect 7.26 tons across seven stops while travelling only 4.503 km, representing the lowest mileage among all routes despite the high number of stops. This result indicates that the optimization logic effectively prioritizes spatial clusters.

In contrast, Route 3 demonstrates a different pattern. Although it serves only two stops, it requires 6.498 km of travel. BAK RUSUN TIPAR and BAK RUSUN ALBO are located outside the primary service cluster. Consequently, vehicle utilization decreases to 62.4%, even though both sites meet the required waste collection thresholds. This outcome does not indicate an algorithmic failure but rather reflects the influence of geographic distribution on route efficiency.

Fuel consumption does not present a constraint. All five routes remain within the limits specified by Pergub DKI No. 75/2021. The Typer Besar units assigned to Routes 2 and 3 consume approximately 4.50 L and 6.50 L, respectively, which are substantially below the 40-liter daily fuel allowance for vehicles with 3,000–4,000 cc engines. Similarly, the Big Arm Roll vehicle used in Route 1 demonstrates efficient fuel usage, consuming 4.24 L against a 45-liter allowance. These findings confirm that the proposed routing plan complies with regulatory requirements while maintaining operational efficiency.

Evaluation Metrics Comparison

The optimized algorithm was evaluated against two baseline approaches. Baseline 1 (sequential dispatch) visits drop points according to their original data index order without considering spatial proximity, whereas Baseline 2 (fill-level-only) ranks sites based on descending fill levels but does not incorporate spatial optimization. The comparison results across all four evaluation metrics are presented in Table 5.

Table 5. Evaluation Metrics

Metric	Baseline 1	Baseline 2	Optimized
Vehicles dispatched	5	5	5
TPS sites served	12	12	12
Total distance (km)	24.744	23.292	23.020
Est. Fuel consumption (L)	22.81	21.36	21.09
Average vehicle utilization (%)	73.2	73.2	73.2

The optimized approach reduces the total route distance by 7.0% compared with Baseline 1, decreasing it from 24.744 km to 23.020 km. It also reduces estimated fuel consumption by 7.5%, from 22.81 L to 21.09 L.

The improvement over Baseline 2 is smaller, with only a 1.2% reduction in distance and a 1.3% reduction in fuel consumption, because Baseline 2 already incorporates fill-level prioritization, which naturally produces a more efficient visit sequence around the dense BAK RW 003 cluster. The additional improvement that enables the optimized solution to outperform Baseline 2 is attributed to the 2-opt refinement applied to the Nearest Neighbour Heuristic (NNH)-

based routes.

Across all three approaches, vehicle utilization rate and coverage remain unchanged, confirming that the performance improvements are solely derived from routing efficiency: no collection points are omitted, and no additional vehicles are deployed.

The constant vehicle utilization rate (73.2%) across all methods is a significant finding because it isolates the contribution of the routing algorithm. Vehicle-to-TPS assignment is determined by capacity constraints independently of visit order; therefore, all improvements are generated through route sequencing and path refinement. Hess et al. (2024) confirmed that, under constrained fleet conditions, route sequencing serves as the primary mechanism for improving efficiency, validating the Greedy-NNH-2-opt approach at the routing optimization level.

A paired t-test confirmed that the reduction in distance was statistically significant ($t(4) = 2.89$, $p = 0.038$), as was the improvement in fuel consumption ($t(4) = 2.76$, $p = 0.042$). These results demonstrate that the observed improvements represent genuine performance gains rather than random variations.

Discussion

The results demonstrate that the proposed field-data-integrated routing approach improves operational efficiency without requiring additional Internet of Things (IoT) infrastructure. The 7.0% reduction in travel distance and 7.5% reduction in fuel consumption are consistent with improvements reported in comparable studies. Wu et al. (2020) achieved a similar range of route efficiency improvements (5–15%) using priority-based scoring in green Capacitated Vehicle Routing Problem (CVRP) models (Li et al., 2025). Thakur et al. (2024) found that constructive heuristics combined with local search consistently outperform single-criterion methods, which aligns with the performance difference observed between Baseline 2 and the optimized approach in this study.

One of the most notable observations from the results is the impact of spatial clustering on route efficiency. For example, in Route 2, several nearby drop points were grouped within a short travel distance, resulting in high vehicle utilization and lower routing costs. This finding suggests that geographic proximity plays an important role, particularly in dense urban environments. Conversely, Route 3 demonstrates a different pattern, where only a limited number of distant locations were served, resulting in longer travel distances and lower efficiency despite relatively high demand.

Regarding operational significance at scale, the 7.0% distance reduction across 15 drop points translates into 1.724 km saved per daily cycle. When extrapolated across all five Jakarta municipalities (1,144 TPS locations) and annualized over 300 operating days, proportional scaling suggests potential savings of approximately 39,400 km and 3,600 liters of fuel per year, representing meaningful reductions in operational costs and carbon emissions (Li et al., 2025).

The use of a multi-factor priority function also contributes to more balanced decision-making. Rather than relying on a single indicator, such as fill level, the model simultaneously considers waste volume and travel distance. As demonstrated by the results, the highest-ranked drop point was not necessarily the location with the highest fill level but rather the one with the largest waste volume. This indicates that the approach can better capture operational urgency and service impact instead of relying solely on visual fullness indicators or threshold-based rules.

Another key contribution of this study is the utilization of field-reported data as an alternative to sensor-based monitoring systems. While many existing studies emphasize real-time monitoring through IoT technologies, this research demonstrates that reliable optimization improvements can still be achieved using manually collected data. This approach is particularly relevant for large-scale landfill and waste collection environments, where sensor deployment may be impractical due to maintenance requirements, environmental conditions, and communication limitations. The findings suggest that optimization methods can be adapted to lower-technology operational contexts without substantially compromising performance.

Despite these promising results, several limitations should be acknowledged. First, the evaluation was conducted using a relatively small dataset consisting of 15 drop points and a single operational snapshot, which may not fully represent the variability of real-world waste collection conditions. Second, the priority weights (α, β, and γ) were determined heuristically, and different parameter configurations may produce different routing outcomes. Furthermore, the proposed method depends on the accuracy of field-reported data, which may be affected by human factors. These limitations indicate that further validation and refinement are required.

In addition, the proposed method relies on the accuracy and consistency of field-reported data. Manual measurements may introduce variability, reporting delays, or inconsistencies that could influence routing decisions. Future implementations should incorporate data validation mechanisms or hybrid approaches that combine limited sensor deployment with manual reporting.

Regarding algorithmic scalability, the NNH operates with a computational complexity of $O(n^2)$, while 2-opt operates with $O(n^2)$ complexity per iteration, making the approach computationally feasible for hundreds of drop points. For scaling to Jakarta's complete network of 1,144 TPS locations, spatial decomposition (partitioning by sub-districts) and hierarchical routing (clustering before optimization) represent viable strategies. Thakur et al. (2024) confirmed that NNH and 2-opt variants can maintain solution quality for large-scale Vehicle Routing Problem (VRP) instances, although hybrid metaheuristic approaches may become necessary for networks exceeding 1,000 nodes.

Future research can extend this study in several directions. Larger datasets and multi-day simulations would provide stronger evidence regarding the robustness of the approach under dynamic operational conditions. Further investigation into adaptive or data-driven approaches for determining priority weights would also be valuable. In addition, comparisons between the proposed method and more advanced optimization techniques, such as hybrid metaheuristics or learning-based models, could provide deeper insights into its relative performance. The integration of real-time traffic information represents another potential improvement for practical deployment.

CONCLUSION

This study presents a field-data-integrated vehicle routing approach for landfill waste collection that combines daily staff reports with optimization techniques. Unlike sensor-based systems, which may face challenges related to cost, maintenance, and data reliability in harsh landfill environments, the proposed method leverages practical field-reported data to support decision-making in real-world operations. Using a Design Science Research (DSR) framework, the study developed an algorithm that integrates priority-based filtering, greedy vehicle allocation, and route optimization through the Nearest Neighbour Heuristic (NNH) and 2-opt improvement. The results demonstrate that the proposed approach can reduce total travel distance and fuel consumption compared with baseline methods while maintaining the same level of service coverage and vehicle utilization. In the case study conducted in Cakung Barat, the optimized routing reduced travel distance by 7.0% and fuel consumption by 7.5% compared with sequential routing. The paired t-test results ($p = 0.038$ for distance and $p = 0.042$ for fuel consumption) confirm that the improvements are statistically significant, indicating that field-data-driven routing is a viable and cost-effective alternative to IoT-based systems. Overall, this work demonstrates that data-driven routing can serve as a practical and scalable solution for improving landfill management operations.

However, the limitations include reliance on a single-day dataset, heuristic weight determination, and potential variability in human reporting. Future work should explore larger multi-day datasets, data-driven weight calibration, comparisons with hybrid metaheuristics and machine learning-based methods, and hybrid data collection approaches that combine targeted sensor deployment with field reporting. This research contributes to practical and scalable waste collection optimization for improving landfill management efficiency while reducing environmental impacts. This research contributes to the development of practical and scalable waste collection optimization by demonstrating that field-data-driven routing can serve as an effective and implementable solution for improving landfill management efficiency while reducing environmental impacts.

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AUTHOR CONTRIBUTION STATEMENT

Agnan Zakariya contributed to the conceptualization, methodology, field data collection, algorithm development, data analysis, and preparation of the original manuscript. Suryadiputra Liawatimena contributed to supervision, validation, technical review, and refinement of the research methodology and manuscript. Both authors collaboratively analyzed the results, reviewed the final manuscript, approved its submission, and take responsibility for the integrity, accuracy, and accountability of all aspects of the research.

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