An AI-Driven Framework Combining K-Means Clustering and VRP Optimization for Sustainable Waste Collection

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ABSTRACT

Urban waste management in developing countries faces persistent challenges, including inefficient routing, high operational costs, and significant environmental impact. This study presents a hybrid framework that integrates K-means clustering with Capacitated Vehicle Routing Problem (CVRP) optimization to improve municipal waste collection efficiency within a reverse logistics perspective. Applied to the Technical Landfill Center (CET) of Guelma, Algeria, the model groups 23 urban sectors into operationally coherent clusters before optimizing collection routes. The results show a 63.6% reduction in fleet size, a 69.14% decrease in daily travel distance, and estimated annual CO_2 savings of 381 metric tons, while maintaining full-service coverage. Built entirely on open-source tools, the proposed framework offers a computationally efficient and interpretable optimization approach, providing a scalable decision-support tool for sustainable city logistics in resource-constrained settings.

Keywords-artificial intelligence; reverse logistics; vehicle routing problem; sustainable development; smart cities; waste management; k-means clustering

I. INTRODUCTION

Efficient waste management remains one of the most pressing challenges for urban sustainability, directly influencing public health, environmental protection, and economic performance [1]. Traditional linear logistics systems, designed primarily to transport goods from producers to consumers, have become inadequate to manage the growing complexity of waste collection and disposal in modern cities. In contrast, reverse logistics, which encompasses post-consumption processes such as collection, recycling, and final disposal, offers a circular and resource-efficient model aligned with Sustainable Development Goals (SDGs) [2]. The accelerating pace of global urbanization has further amplified the waste management crisis, particularly in developing countries that face technological and resource constraints [3]. According to the World Bank [4], global waste generation is projected to increase by nearly 70% by 2050, with the majority originating from developing countries. Conventional collection systems in these regions often rely on static schedules and manual planning, resulting in average operational efficiencies of below 40% and substantial environmental losses [5].

Despite numerous academic advances in vehicle routing and optimization, a persistent gap remains between theoretical models and their real-world implementation within municipal systems [6]. While commercial optimization platforms exist, they are often computationally intensive and unsuitable for municipalities with limited technical capacity. This disconnect represents a key barrier to sustainable urban development.

Artificial Intelligence (AI) and Machine Learning (ML) have increasingly been applied to urban logistics problems, demonstrating significant potential for automating complex routing decisions and enhancing operational efficiency [6]. The Vehicle Routing Problem (VRP) [7] remains one of the most studied combinatorial optimization challenges, with numerous extensions addressing capacity constraints, time windows, and environmental considerations. Although deep learning and reinforcement learning methods offer sophisticated modeling capabilities, their computational complexity often limits real-world implementation in municipal settings with scarce resources [8].

In contrast, clustering algorithms such as K-means have emerged as efficient preprocessing tools for large-scale routing problems, reducing problem dimensionality and computational time by up to 85% without major losses in optimality [9]. The combination of K-means clustering and VRP optimization has shown 40-60% improvements in route efficiency in commercial logistics [10]. Recent cluster-first approaches include metaheuristic-based VRP optimization [11] and enhanced VRPTW for perishable goods distribution [12], while IoT-driven systems have demonstrated potential for real-time waste monitoring [13]. However, these approaches have been validated primarily in commercial or simulated settings and without tests against real-world municipal waste contexts in developing countries.

Reverse logistics has evolved from a peripheral activity to a central pillar of sustainable supply chain management, integrating environmental and economic objectives within circular economy models [14]. In the context of waste management, it encompasses the collection, recycling, and disposal of post-consumer products, directly contributing to resource recovery and environmental preservation. Several studies emphasize that transitioning from linear to circular systems is essential for addressing the mounting environmental pressures in developing economies [5, 15].

In Algeria, the issue is particularly critical. The National Waste Agency reports that only about 60% of urban waste is properly collected and processed through official channels [16]. The country's national environmental strategy recognizes the digital transformation of municipal operations as a strategic priority. Recent studies highlight that ML algorithms, especially unsupervised clustering combined with combinatorial optimization, can provide significant improvements in operational efficiency and environmental performance in developing-country contexts [17, 10].

The Technical Landfill Center (CET) of Guelma, which manages waste from 13 municipalities, representing more than 220 tons daily across 23 collection sectors, illustrates the operational and logistical challenges faced by many Algerian cities [16]. The current system depends heavily on manual route design and static timetables, leading to inefficient vehicle utilization, excessive fuel consumption, and increased carbon emissions [18].

Existing optimization solutions fail in such developing contexts due to: (i) high computational requirements incompatible with limited IT infrastructure, (ii) reliance on real-time data (IoT, GPS) that are unavailable in most Algerian municipalities, (iii) prohibitive commercial licensing costs for public-sector budgets, and (iv) algorithmic complexity hindering adoption by non-specialist municipal staff.

Recent literature highlights the rise of sustainable AI—an approach emphasizing environmental responsibility and computational frugality in algorithm design [18, 19]. Green AI initiatives aim to minimize energy use and model complexity while maintaining or improving solution quality. Such approaches are particularly relevant to public-sector applications, where efficiency, transparency, and sustainability are equally important [20].

This study aimed to bridge the gap between AI-driven optimization theory and municipal-level application by developing a framework that is computationally efficient, interpretable, and adaptable to data-scarce environments. The central research question addressed is: Can a computationally efficient, open-source AI pipeline based on clustering and constrained optimization achieve significant operational and environmental improvements in real-world municipal waste collection in a developing-country context?

The main contributions of this research are threefold:

1. The development of a hybrid AI optimization framework combining K-means clustering with Capacitated Vehicle Routing Problem (CVRP) modeling to intelligently segment and optimize municipal waste collection.
2. The demonstration of substantial environmental and economic benefits through a real-world case study at the Guelma CET, including significant reductions in fuel consumption, travel distance, and CO_2 emissions.
3. The implementation of responsible and sustainable AI principles, using a computationally efficient and interpretable algorithmic pipeline deployable within developing-country municipal systems [19, 21].

II. METHODOLOGY

This study presents a hybrid AI-driven optimization framework that combines ML clustering and Operations Research (OR) to improve the efficiency and sustainability of municipal waste collection. The model is intentionally designed to be computationally efficient and deployable, addressing the technological and resource constraints typical of developing-country cities.

A. Data Foundation and Framework Overview

The proposed framework integrates four interdependent components, problem diagnosis, data preparation, AI optimization, and validation, forming a unified pipeline from raw data to actionable routing plans.

Data were collected over a six-month operational period (January-June 2022) through three complementary channels: (i) institutional records from the CET and the Wilaya of Guelma, including daily tonnage logs, vehicle fleet specifications, and fuel consumption reports; (ii) field observations conducted at collection points to assess road accessibility and operational constraints; and (iii) semi-structured interviews with municipal managers and collection vehicle drivers to validate route configurations and identify recurring inefficiencies. Geographic coordinates were obtained via GPS survey and cross-referenced with municipal GIS data.

The dataset used in this study is classified as pseudo-real; it was compiled from official institutional reports published in French by the National Waste Agency (AND) and the Wilaya of Guelma, supplemented by field observations and interviews. Unlike purely synthetic benchmarks, these data reflect actual operational conditions; however, unlike real-time sensor data, they represent aggregated administrative records over a six-month period (January–June 2022), manually structured and cross-validated for optimization modeling. The resulting dataset covered geospatial information (coordinates and distances between the 23 urban sectors, depot, and CET), operational parameters (vehicle capacity of 16 tons, loading and maintenance data), historical performance indicators (fuel use, travel time, route length), and environmental coefficients related to emissions and waste composition [16]. Distances were computed using the road network (GIS-based), not Euclidean distances.

TABLE I. INPUT DATA SUMMARY

Variable	Unit	Source	Preprocessing
Coordinates	Lat/Lon	GPS + GIS	Z-score normalized
Waste volume	t/day	CET logs (6-mo)	$T'_i = T_i/16$
Distance	km	Road network	Symmetric matrix
Vehicle cap.	t	Fleet data	Q = 16
Fuel rate	L/km	Historical data	1.174 L/km
CO_2 factor	kg/L	ADEME standard	2.68 kg/L

The optimization follows a sequential pipeline: Data Input → K-means clustering → CVRP optimization (per cluster) → Route generation → KPI evaluation.

B. Clustering Stage

K-means clustering groups collection sectors into k spatially and operationally coherent clusters. The optimal number of clusters is determined by $k = \lceil \sum T_i/T_{max} \rceil$, where T_i denotes the waste tonnage of sector i and T_{max} is the vehicle capacity (16t). This capacity-based formula computes the minimum number of vehicles needed under strict capacity constraints, and is standard in cluster-first, route-second VRP approaches [20]. Unlike general-purpose methods (Elbow, Silhouette), this formulation directly ties cluster count to the physical constraint of the problem, ensuring operational feasibility by design rather than through post-hoc correction.

The clustering stage relies on multiple input features capturing spatial and operational characteristics of collection points. Geographic coordinates are normalized using Z-score standardization to ensure comparability across spatial dimensions. Daily waste volumes are normalized with respect to vehicle capacity ($T_i' = T_i/16$) to prevent dominance of high-demand locations. Accessibility constraints are represented as ordinal indicators ({0, 1, 2} mapped to [0, 1]). Equal weighting of normalized variables is adopted to preserve interpretability and limit model complexity. Capacity feasibility is ensured through iterative cluster balancing: after initial K-means assignment, any cluster exceeding vehicle capacity is rebalanced by reassigning boundary sectors to adjacent clusters, guaranteeing that each cluster can be feasibly served by a single vehicle.

Through iterative assignment and centroid recalculation, sectors are balanced across clusters, thereby reducing problem dimensionality and ensuring operational feasibility.

C. Routing Optimization Stage

Each cluster is then optimized independently using a CVRP formulation that minimizes total distance and associated CO_2 emissions while respecting vehicle capacity and route-continuity constraints. The integrated K-means and VRP approach effectively merges the exploratory strength of AI with the precision of OR modeling, achieving high-quality routing solutions in a fraction of the computation time required by metaheuristic alternatives [20]. This synergy not only enhances technical performance but also supports equity in service distribution and transparency in decision making, which are key aspects of responsible public-sector AI [18, 19].

D. Implementation and Experimental Setup

The framework was implemented in Python 3.9 using scikit-learn 1.2 (K-means) and Google OR-Tools 9.5 (VRP solver) on standard hardware (Intel Core i7, 16 GB RAM). K-means parameters were: initialization via k-means++ [22], Euclidean distance, convergence tolerance 1e-4, 300 maximum iterations, and fixed random seed (random_state = 42) for full reproducibility. The OR-Tools routing solver was configured with PATH_CHEAPEST_ARC as the first solution strategy and GUIDED_LOCAL_SEARCH for improvement, with a 30-second time limit per cluster. Constraints were: vehicle capacity (Q = 16 t), single depot, mandatory visit of all nodes. Total runtime was under 5 minutes end-to-end (K-means < 2 s, CVRP < 4 min), with peak memory below 500 MB.

E. Validation and Limitations

The optimized routes were validated through both quantitative and qualitative assessments to ensure their practical applicability. Feasibility checks verified compliance with capacity and accessibility constraints, while comparisons with baseline routes confirmed significant efficiency gains. Operational staff participated in reviewing and approving the proposed routes, reinforcing the interpretability and acceptance of the AI-based recommendations. Informal feedback from collection vehicle drivers confirmed the practical feasibility of the proposed routes.

The proposed framework assumes static waste generation and simplified emission modeling, and does not explicitly account for real-time traffic, seasonal road accessibility variations, or variable service times. This design choice ensures computational tractability and methodological transparency. Nevertheless, the framework is inherently extensible and could incorporate future developments such as scenario-based analysis, IoT-enabled data collection, or dynamic and stochastic routing strategies.

III. RESULTS AND DISCUSSION

The results are organized to highlight three complementary dimensions: quantitative performance improvements across operational metrics, algorithmic behavior in adapting to heterogeneous urban conditions, and the environmental and managerial implications of the optimized solution.

A. Quantitative Performance Analysis

The implementation of the proposed K-means+VRP hybrid framework produced substantial operational and environmental improvements across all performance indicators compared with manual planning and standard OR-Tools optimization. For fair comparison, the OR-Tools baseline solves the same CVRP under identical data, constraints, and vehicle capacity, but without prior clustering—treating all 23 sectors as a single routing instance. This ensures that observed performance gains stem from problem decomposition rather than differing assumptions.

As summarized in Table II, the AI-optimized model reduced the fleet from 22 to 8 vehicles (−63.6%), daily travel distance from 562.5 to 173.6 km (−69.14%), and CO_2 emissions by 69.1%, with over 95% computational time savings. While the standalone OR-Tools baseline achieved moderate gains (~36% vehicle reduction), the integration of K-means clustering significantly amplified routing efficiency, confirming the value of problem decomposition before optimization. This confirms that decomposing large municipal networks into spatially coherent clusters before solving the VRP significantly improves scalability and solution quality/findings consistent with [11, 12], which reported similar cluster-first efficiency gains in transport logistics.

TABLE II. PERFORMANCE COMPARISON

Metric	Manual	OR-Tools	AI-Optimized	Δ%
Daily vehicles	22	14	8	−63.6%
Daily distance (Km)	562.50	289.30	173.6	−69.14%
Daily fuel (L)	660	385	203.6	−69.15%
Daily CO_2	1768.8	1031.2	545.6	−69.16%
Computational time	Hours	15-30 min	<5 min	>95 % Faster
Scalability	Poor	Moderate	Excellent	Superior

The distance reduction (−69.14%) compares favorably with the improvements of 40–60% typically reported in cluster-first VRP studies applied to commercial logistics [12, 18]. This performance gap is attributable to the high inefficiency of the baseline manual system in developing-country contexts. The absolute performance (173.55 km/day for 23 sectors) confirms operationally competitive routes. Annual CO_2 savings are estimated at 381 t, corresponding to ~166,500 L fuel saving.

B. Algorithmic Behavior and Cluster Insights

Beyond numerical performance, the hybrid model demonstrated strong adaptability to heterogeneous urban conditions. The optimized solution successfully served all 23 collection sectors (127.7 t/day) while maintaining 100% service coverage. Figure 1 shows the resulting route network consisting of eight distinct circuits with varying density and efficiency characteristics. Routes serving high-density urban cores achieve efficiency ratios up to 0.74 m^3/km (Route 2), routes covering geographically dispersed peripheral sectors operate at 0.40 m^3/km (Route 8), while smaller routes handle low-density or geographically dispersed sectors with appropriate vehicle allocation. The K-means clustering stage proved instrumental in balancing operational load and minimizing travel redundancy.

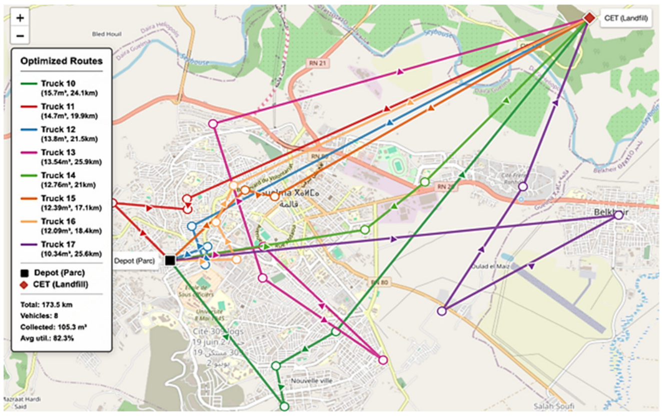

Fig. 1. AI-optimized route network configuration.

As shown in Figure 2, the algorithm partitioned the 23 sectors into eight operationally balanced clusters, each respecting vehicle capacity constraints (Q = 16 t) that are both geographically compact and tonnage-balanced. Cluster 1 consolidates nine high-density sectors representing nearly 40 % of total tonnage, whereas smaller clusters (3–6) manage peripheral or specialized areas. This spatially intelligent decomposition reduced VRP dimensionality and produced routes that are not only optimal but also interpretable for municipal planners—an essential criterion for transparent public decision systems.

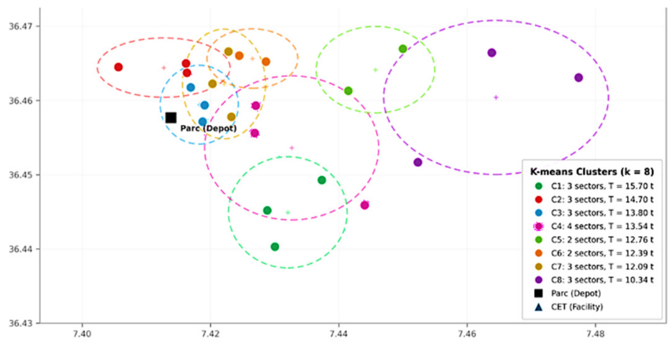

Fig. 2. Spatial distribution of waste collection sectors organized using the K-means algorithm.

C. Robustness, Sensitivity, and Scalability

To assess solution stability, K-means clustering was executed 50 times with different random seeds. Cluster assignments were identical in 94% of runs, and the variation in total optimized distance remained below 2.3%, confirming the robustness of the deterministic optimization.

TABLE III. SENSITIVITY TO DEMAND VARIATIONS

Scenario	Δ waste	k	Dist. (km)	Δ Dist.
Low demand	−20%	7	155.2	−10.6%
Baseline	**0%**	**8**	**173.6**	**—**
High demand	+20%	9	187.7	+8.2%
Peak demand	+40%	11	224.3	+29.2%

The framework responds proportionally to demand variations: a ±20% change in waste volume leads to approximately 1-2 additional vehicles and a proportional distance increase, without algorithmic failure. The capacity-based cluster formula adapts naturally to demand fluctuations.

TABLE IV. SCALABILITY TESTS ON SYNTHETIC INSTANCES

Sectors	Clusters	K-means	CVRP	Total
23 (Guelma)	8	< 1 s	3.5 min	< 4 min
50 (synthetic)	13	< 1 s	8 min	< 9 min
100 (synthetic)	26	< 2 s	18 min	< 20 min

Runtime scales approximately linearly with the number of clusters, confirming practical scalability up to 100 sectors on standard hardware. Beyond this threshold, parallel cluster solving or heuristic solvers may be needed.

D. Practical Implications and Deployment Challenges

The environmental and economic implications of the proposed AI optimization are considerable. Annual CO_2 emissions are estimated to decrease by 381 t, corresponding to a ~166,500 L fuel saving and an operational cost reduction of approximately 4.13 million DA per year. These results directly contribute to SDGs 11 (Sustainable Cities) and 13 (Climate Action) by reducing the carbon footprint of municipal operations. Moreover, the entire optimization cycle runs in under five minutes on standard computing hardware, demonstrating the framework's suitability for municipalities with limited digital infrastructure. The model's simplicity and scalability, characterized by an algorithmic complexity of $O(n \times k \times iterations)$, enable its extension to larger urban systems without exponential increases in computation time.

Compared to previous clustering-enhanced VRP studies, the proposed pipeline achieved equivalent or superior optimization levels while remaining computationally efficient and fully reproducible. This aligns with the principles of Green and Responsible AI [19], emphasizing energy efficiency and transparency in algorithmic design. Real-world deployment observations revealed several challenges:

- Data quality: Municipal records contained inconsistencies (missing tonnage entries, approximate GPS coordinates) requiring manual cleaning and cross-validation with field observations.
- Staff adoption: While managers expressed interest, driver resistance to changing established routines necessitates gradual implementation with training sessions.
- IT infrastructure: The absence of centralized IT systems requires route communication via printed maps; integration with mobile applications would enhance usability.
- Maintenance: the static model requires periodic re-optimization (e.g., quarterly) to reflect changes in urban expansion, waste generation patterns, or fleet composition.

From a managerial perspective, these findings highlight three main implications:

- Scalability: The framework can be transferred to other mid-sized cities by adjusting clustering granularity and vehicle parameters.
- Sustainability: Its measurable CO_2 reduction strengthens municipal sustainability reporting and compliance with environmental policies.
- Integrability: The system can later incorporate IoT data for dynamic routing and predictive waste-volume estimation, building on existing work on smart-waste architectures [13].

Although these results rely on static daily scheduling, future enhancements will focus on real-time adaptation to traffic or weather variations and on integrating predictive analytics for demand forecasting. Nevertheless, the success achieved in Guelma provides a proof-of-concept for responsible AI deployment in public logistics, combining economic rationality, operational feasibility, and environmental stewardship within a single methodological framework.

IV. CONCLUSION

This study demonstrated the significant potential of a hybrid AI framework that integrates K-means clustering and VRP optimization to enhance the efficiency and sustainability of municipal waste collection. Applied to the CET of Guelma, the proposed model replaced traditional manual and static scheduling with an intelligent, data-driven decision process. The results are compelling: a 63.6% reduction in fleet size, a 69.2% decrease in daily travel distance, and an annual CO_2 reduction of nearly 381 t, all achieved while maintaining complete service coverage and computational feasibility on standard hardware.

The contributions of this research are threefold. First, it introduces a robust yet computationally efficient optimization pipeline, easily deployable in resource-constrained environments such as mid-sized developing cities. Second, it provides quantitative validation of how interpretable, low-complexity AI algorithms can generate substantial economic savings and environmental gains, directly supporting SDGs 11 (Sustainable Cities) and 13 (Climate Action). Third, it demonstrates that transparent and interpretable optimization methods can effectively support public-sector logistics decision-making, thus bridging the gap between theoretical models and practical implementation.

Although the framework achieved substantial efficiency and environmental gains, several extensions are still possible. Future work should integrate real-time IoT sensing for adaptive routing, dynamic traffic, and weather data for responsive operations, and predictive analytics to anticipate waste-generation patterns. Such improvements would further strengthen proactive decision-making and operational resilience. Beyond waste management, the same methodological foundation can be applied to other urban logistics domains, including emergency response, public-transport scheduling, and infrastructure maintenance, laying the groundwork for fully integrated, intelligent, and sustainable smart-city ecosystems.

Ultimately, this work demonstrates that computationally efficient and transparent optimization approaches offer a viable pathway toward sustainable urban logistics, directly supporting municipal efforts to meet environmental and operational targets.

DATA AVAILABILITY STATEMENT

The pseudo-real dataset used in this study was compiled from published institutional reports and unpublished, but non-restricted, operational data provided by the CET and Wilaya of Guelma. The aggregate data and model parameters sufficient for replication are provided in Tables II–V. Additional data and optimization code are available upon reasonable request from the corresponding author.

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