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Cluster-Based Optimization for Sustainable Municipal Solid Waste Collection Sectorization*

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Abstract

Efficient and sustainable municipal waste collection is a critical challenge in urban management, requiring data-driven strategies that align operational performance with environmental objectives. Despite the increasing use of clustering and routing techniques in waste management, current approaches often fail to fully integrate spatial clustering with optimization models that account for real-world constraints such as vehicle capacities and workload balancing. This paper addresses that gap by proposing a novel framework that combines clustering algorithms with mixed-integer linear programming (MILP) to optimize the division of a city into sustainable municipal solid waste collection sectors. Using real-world data from Tarnów, Poland, we apply the *k*-means algorithm to generate spatially and quantitatively balanced clusters of over 10,000 collection points. These clusters serve as input to a MILP model that solves the Sustainable Sectorization of Municipal Solid Waste Collection Problem (SSMSWCP), aiming to minimize disparities in either route lengths or collected waste volumes across a heterogeneous vehicle fleet, including diesel and electric trucks. The proposed method supports strategic decision-making by enabling planners to evaluate alternative sector layouts, fleet configurations, and environmental trade-offs. Computational experiments demonstrate the feasibility and flexibility of the approach and highlight how operational constraints and balancing criteria affect service equity and environmental outcomes. The entire methodology is implemented in open-source software and is transferable to other municipalities facing similar planning challenges.

Keywords: Strategic Decision-Making, Mixed-Integer Linear Programming, Strategic Management, Municipal Solid Waste Collection

Introduction

The generation of municipal solid waste is an inherent consequence of human activity and poses a significant global challenge. Effective waste management is essential to mitigate environmental impacts and conserve natural resources. Excessive waste generation leads to adverse effects such as water and soil pollution, underscoring the need for a conscious and sustainable management approach. In recent decades, municipal solid waste volumes have increased substantially. According to Eurostat (2025b), for example, household-generated municipal waste in Poland grew by nearly 50% in the decade preceding 2020. This trend is driven in part by modern consumer behaviors, including the “fear of missing out” (FOMO) and “bandwagon consumption,” where purchasing decisions are influenced more by popularity than necessity (see Alfina et al., 2023; Kang and Ma, 2020). The rise of e-commerce has further exacerbated the problem, contributing to a surge in packaging waste (see Ciechomski, 2023). Eurostat (2025a) reports that, on average, each resident of the European Union generated 188.7 kg of packaging waste in 2021, an increase of 20% compared to 2011.

In response, the concept of a circular economy has gained prominence, reframing waste as a potential resource rather than merely something to be discarded (see Smol et al., 2020). This approach is structured around the “9R” framework, which prioritizes actions such as Refuse, Rethink, Reduce, Reuse, Repair, Refurbish, Remanufacture,

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Repurpose, Recycle, and Recover, as discussed in detail by Munoz et al. (2024) and Hunger et al. (2024). The overarching aim of sustainable development, defined by the United Nations as meeting present needs without compromising the ability of future generations to meet theirs, is embedded in international agreements and national policies, emphasizing the reduction of both solid waste and the carbon footprint of human activities (European Commission, 2020).

Modern municipal solid waste management increasingly leverages advances in computer science and artificial intelligence to support decision-making. These technologies offer powerful tools for data analysis, pattern recognition, and system optimization (Abdallah et al., 2020). According to Jain (2010), clustering algorithms such as the *k*-means algorithm are widely used to group waste collection points based on geographic proximity or other relevant features, enabling initial sector design and spatial visualization. These methods are typically implemented in Python using data science libraries like Pandas, NumPy, and scikit-learn, which facilitate efficient exploratory analysis and clustering (see Pedregosa, 2018). However, while effective for preliminary grouping, unsupervised learning algorithms like *k*-means do not inherently ensure that operational constraints, such as vehicle capacities or service time windows, are satisfied.

To address such constraints, Operations Research techniques, particularly mixed-integer linear programming (MILP), play a critical role in optimizing solid waste collection systems. MILP models allow for the explicit inclusion of complex factors such as vehicle load limits, collection time windows, heterogeneous waste types, and sustainability objectives. This enables the generation of efficient, feasible, and well-balanced collection routes, as demonstrated by Hess et al. (2023), Ghiani et al. (2014), and Vecchi et al. (2016). Integrating heuristic clustering methods with MILP-based routing optimization has emerged as a common framework for solving large-scale solid waste collection problems in a way that balances operational feasibility with environmental considerations.

As noted by Korcyl et al. (2020), optimizing the collection process itself is a key component of sustainable solid waste management. Accordingly, this paper addresses the strategic challenge of dividing an urban area into balanced collection sectors. The proposed framework generates sectors, clusters of similar collection points, based on criteria such as the travel distance for recycling collection vehicles (RCVs) or the quantity of waste to be collected. Equitable workload distribution among collection crews helps ensure efficient fleet utilization, reduces emissions, and prevents preferential treatment in cases where multiple contractors are involved in service delivery.

The main research question is formulated as:

MRQ*: How can an urban area be divided into service sectors to minimize waste collection costs while ensuring a balanced workload for collection crews?*
The detailed research questions derived from the MRQ are as follows:
DRQ01*: How can a city be effectively divided into solid waste collection sectors to minimize the total cost of service provision?*
DRQ02: How do environmental impacts, such as emissions or kilometers traveled, change based on the criterion used for balancing crew workload?
DRQ03: How does the limited number of available crews influence overall costs?

This paper proposes using a *k*-means clustering algorithm and mixed-integer linear programming to solve the Sustainable Sectorization of Municipal Solid Waste Collection Problem. We aimed to create operationally balanced clusters of adjacent sectors while balancing the load on collection crews, providing a practical tool for organizing municipal waste management.

Paper Positioning

Sustainable solid waste collection in urban environments presents a complex optimization challenge that requires integrating environmental objectives with real-world operational constraints. Recent research has focused on developing frameworks based on a two-phase, “cluster-first, route-second” paradigm, in which demand nodes, such as individual households or solid waste drop-off points, are first grouped into clusters, followed by the application of exact vehicle routing algorithms to determine optimal collection routes. The primary motivations behind this approach include scalability to large urban instances, the minimization of sustainability metrics such as emissions or energy consumption, and the ability to accommodate constraints like vehicle capacities, time windows, and heterogeneous solid waste streams.

A targeted literature review reveals a range of approaches addressing these goals, with varying degrees of alignment to the core elements of the framework. Several studies explicitly adopt capacity-aware clustering followed by exact routing methods. For instance, Bihun and Lytvyn (2022) apply an improved *k*-means clustering algorithm constrained by RCV tonnage to ensure feasible cluster sizes, followed by solving a traveling salesman problem within each cluster to optimize routes. Similarly, Ruiz-Meza et al. (2021) divide an urban solid waste collection network into five clusters and solve a bi-objective MIP model within each cluster, optimizing for both economic cost and carbon dioxide emissions. Lesieur et al. (2025) investigate biowaste collection strategies by comparing periodic and signal-based (dynamic) collection approaches, using clustering and capacitated vehicle routing problem optimization under both economic and environmental scenarios.

Other studies integrate operational constraints and sustainability metrics within broader routing frameworks. Rabbani et al. (2019), for example, address heterogeneous RCV fleets and multi-compartment vehicles by formulating a multi-objective model that minimizes cost, emissions, and time window violations. Erdem (2022) explores urban recycling routing using heterogeneous electric vehicles, although details on clustering and routing procedures remain limited. Assignment- or decomposition-based approaches have also been proposed; for instance, Pop et al. (2018) introduce a two-level clustered vehicle routing optimization, while Katragjini et al. (2012) first assign containers to service days before applying exact routing. Additionally, DehghanChenary et al. (2025) present a hybrid optimization framework combining conventional and pneumatic waste collection systems within a two-stage decision model.

Despite these developments, no existing study fully integrates capacity- and constraint-aware clustering with exact routing focused on a single sustainability objective, comprehensive real-world constraints, and robustness validation via simulation. Most clustering methods still rely on heuristics based on cluster size or spatial proximity, without strictly enforcing vehicle capacities, time windows, or multi-stream constraints before routing, as seen in studies such as Ruiz-Meza et al. (2021), Lesieur et al. (2025), and Bihun and Lytvyn (2022). This raises important questions about how to design clustering algorithms that ensure feasibility under complex constraints, and how such “constraint-aware” clustering methods compare to heuristic ones in terms of solution quality and operational performance.

Moreover, while many sustainability-focused models optimize cost, distance, or combine multiple objectives, such as in Ruiz-Meza et al. (2021), Lesieur et al. (2025), and Rabbani et al. (2019), few adopt pure single-objective formulations that explicitly minimize emissions or energy consumption using realistic emission factors. Open questions remain regarding how routing outcomes differ when emissions or energy are optimized as standalone objectives, and how to incorporate detailed emission models (e.g., speed/load-dependent or stop/start dynamics) into both clustering and routing stages. In the case of Ruiz-Meza et al. (2021), exact methods such as branch-and-cut are applied only to small clusters (typically with no more than 10 nodes), often after extensive decomposition, with limited reporting on optimality guarantees or computational scalability. This highlights the need to further investigate the scalability of exact methods for larger problem instances, the trade-offs between cluster size, solution quality, and computational effort, as well as the potential role of hybrid or approximate algorithms. Detailed reporting of optimality gaps and exploration of scalable hybrid metaheuristics remain critical areas for future research.

Municipal Solid Waste Collection Sectorization

This research addresses the optimization of municipal solid waste collection sectorization, with the primary objective of minimizing operational costs while ensuring an equitable workload distribution among waste collection crews. The term “optimal” refers to a sector division that achieves balanced clusters based on an operational criterion, explicitly focusing on equalizing solid waste collection volumes or total travel distances within each sector. Such a balance enhances operational efficiency and mitigates the environmental impact (e.g., emissions, fuel consumption) associated with solid waste collection, ensuring an environmentally sustainable service across the city. Achieving balanced sectorization is particularly crucial when multiple contractors are involved in solid waste collection, as it ensures fairness by preventing any service provider from being disproportionately burdened – see Zaucha (2024).

To investigate research questions, the Sustainable Sectorization of Municipal Solid Waste Collection Problem (SSMSWCP) was developed and solved using a dedicated MILP model run on a data instance (i.e., clusters) prepared using a *k*-means algorithm. The SSMSWCP focuses on the strategic planning level, where the objective is to ensure that available solid waste collection crews are evenly distributed across the city over a week. The approach employs *k*-means clustering algorithm to partitioning the city’s solid waste collection network and exact optimization based on the Allocation Problem and the Assembly Line Balancing Problem to assign sectors to servicing crews in the most sustainable way. The problem formulation's generic nature ensures the developed approach's applicability to various urban contexts.

Sectorization by Clustering

The dataset included 10,096 collection addresses, the number and types of waste collection vehicles, discharge locations, and staffing levels – detailed description of the data set and data acquisition method are described in Zaucha (2024). To enable spatial analysis, address coordinates were generated using the Geoapify geocoding API, which allowed batch processing of up to 500 points. Geocoded data enabled both spatial visualization and assignment of each address to one of Tarnow's administrative neighborhoods. Assuming uniform population density (9 people per pickup point), the number of clusters was determined based on the maximum capacity of collection vehicles, ensuring each cluster would correspond to a full load. This approach enabled the application of the *k*-means algorithm to define preliminary collection sectors presented in Figure 1. Due to its speed, scalability, and flexibility regarding cluster shapes, *k*-means algorithm is particularly well-suited to Tarnow's non-uniform distribution of pickup points. Unlike algorithms that force circular cluster boundaries, *k*-means algorithm adapts to the actual spatial layout, improving practicality in real-world settings.

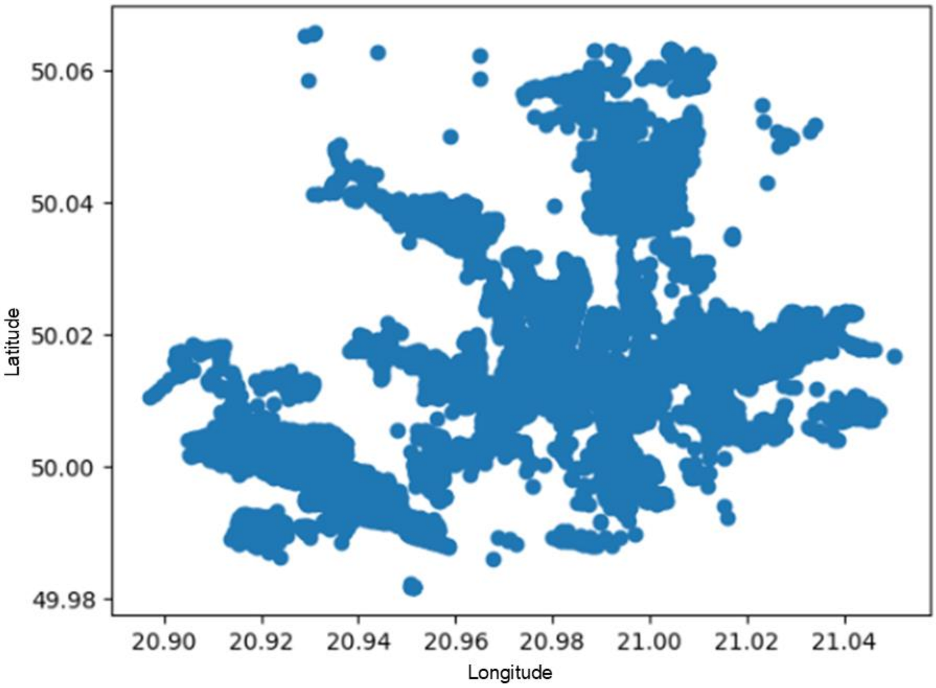

Fig 1. Map-based visualization of geocoded municipal solid waste collection points in Tarnow, Poland, showing their spatial distribution across the city

Computational experiments were conducted on a Lenovo Legion 5-15ARH05H laptop (AMD Ryzen 7 4800H, 2.90 GHz, 32 GB RAM), with implementation in Python using the following libraries: Pandas for data structuring, NumPy for numerical operations, matplotlib.pyplot for visualizations, and sklearn.cluster for the *k*-means algorithm. The algorithm's output for electric vehicle scenarios (137 clusters) is illustrated in Figure 2, including the calculated cluster centroids, which serve as helpful reference points for routing. A similar process was conducted for diesel vehicles with 126 clusters, each containing 81 pickup points; the result is shown in Figure 3. In both cases, the *k*-means algorithm executed in under 6 seconds.

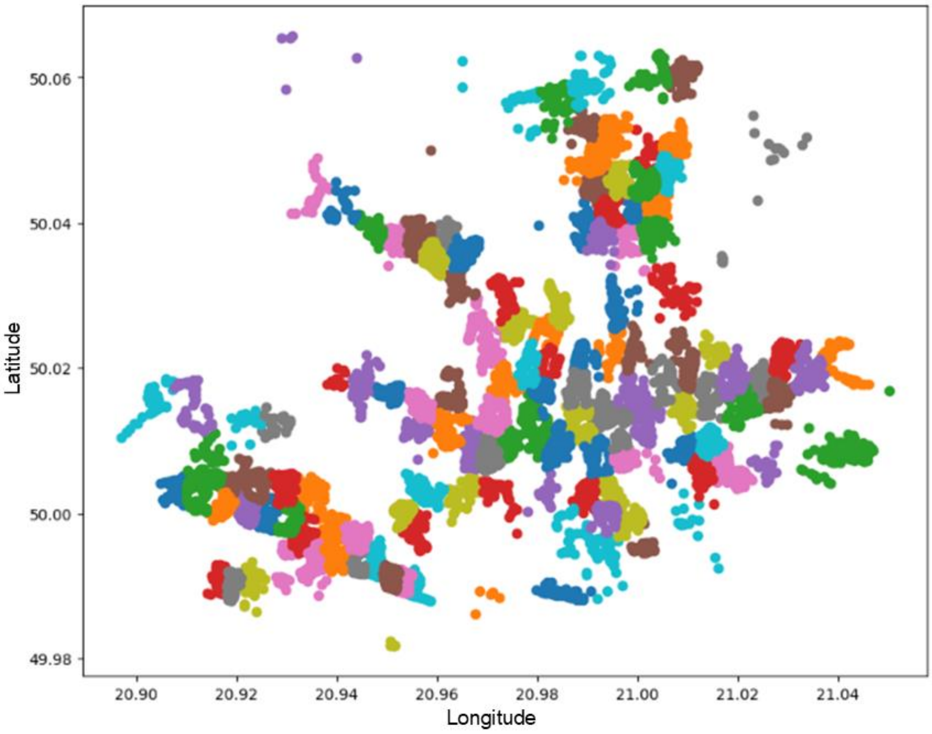

Fig 2. Spatial representation of solid waste collection clusters to-be-assigned electric garbage trucks, generated using the *k*-means algorithm

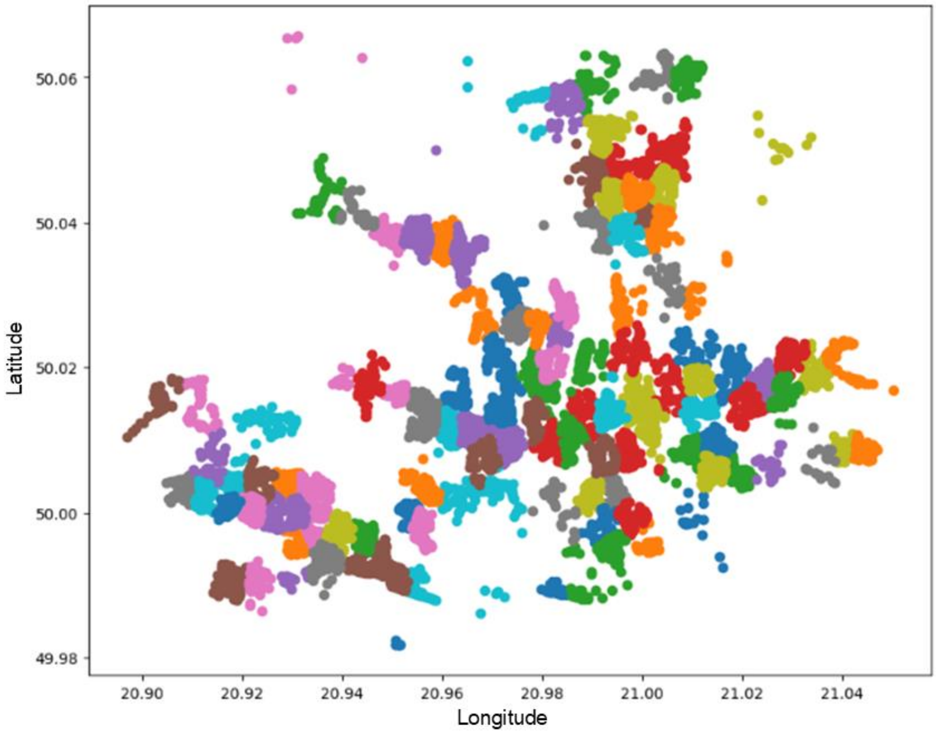

Fig 3. Spatial representation of solid waste collection clusters to-be-assigned to diesel garbage trucks, generated using the *k*-means algorithm

By determining the coordinates of the cluster centroids, it is possible to estimate routes starting from the depot, passing through the center of each cluster, and returning to the depot, assuming a closed-loop route. The Google Routes API may be used to calculate these distances. The *k*-means algorithm is a valuable tool for visualizing the spatial distribution of waste collection points across the city. When additional information is available, such as the number of declared residents per pickup point or the average filling rate of dumpsters over time, *k*-means algorithm clustering results can be compared to alternative approaches, such as those based on integer programming. However, while *k*-means algorithm is effective for visualization and exploratory clustering, it is unsuitable for finding exact solutions for strategic-level optimization problems. The algorithm cannot incorporate operational constraints and decision variables essential for comprehensive system-level planning.

Sustainable Sectorization of Municipal Solid Waste Collection by Optimization

To achieve equitable workload distribution among collection crews, the problem was formulated as an optimization problem titled the Sustainable Sectorization of Municipal Solid Waste Collection Problem (SSMSWCP), based on the classical Allocation Problem and Assembly Line Balancing Problem, enabling the city's division into balanced service sectors. Notation used for the SSMSWCP is presented in Table 1. The SSMSWCP was formulated in two variants: SSMSWCP(A) which aims to balance the number of kilometers driven by each crew, and SSMSWCP(B) aiming to balance the amount of solid waste collected by each crew.

Table 1: Notation used for the Sustainable Sectorization of Municipal Solid Waste Collection Problem

Indices	
$\mathcal{V}$	set of crews
$\mathcal{S}$	set of sectors
Parameters	
p_r	maximum amount of solid waste that can be collected by crew *r*
s_i	amount of solid waste in sector *i*
a_{ij}	incidence between sectors
d_i	number of garbage collection points in sector *i*
M	big constant
α	weighting coefficient for the adjacency-based clustering objective in multiple-criteria objective function
β	weighting coefficient for the workload balancing objective in multiple-criteria objective function
Decision variables	
x_{ir}	1, if sector *i* is assigned to crew *r*; 0, otherwise
y_{ijr}	1, if sectors *i* and *j* are both assigned to crew r; 0, otherwise
D_{max}	maximum number of kilometers traveled by crew *r*
S_{max}	maximum amount of solid waste collected by crew *r*
b	auxiliary variable

For SSMSWCP(A), a MILP model (1)–(11) was formulated.

$$\min\ f = \alpha \left(-\sum_{\substack{r\in V,\\ i\in S,\\ j\in S,\\ i<j}} a_{ij}\, y_{ijr} \right) + \beta \cdot D_{max} \tag{1}$$

$$\sum_{r\in V} x_{ir} = 1, \qquad i \in S \tag{2}$$

$$\sum_{i\in S} s_i\, x_{ir} \le p_r, \qquad r \in V \tag{3}$$

$$2 - \left(x_{ir} + x_{jr}\right) \le M\left(1 - y_{ijr}\right), \qquad r \in V, i \in S, j \in S, i < j \tag{4}$$

$$\sum_{i\in S} x_{ir} \ge 1, \qquad r \in V \tag{5}$$

$$\sum_{i\in S} x_{ir}\, d_i \le D_{max}, \qquad r \in V \tag{6}$$

$$b = \sum_{\substack{r \in V,\\ i \in S,\\ j \in S,\\ i<j}} a_{ij} y_{ijr} \tag{7}$$

$$x_{ir} \in \{0,1\}, \qquad i \in S, r \in V \tag{8}$$

$$y_{ijr} \in \{0,1\}, \qquad i \in S, j \in S, r \in V \tag{9}$$

$$D_{max} \geq 0, \text{integer} \tag{10}$$

$$b \geq 0, \text{integer} \tag{11}$$

The MILP model for SSMSWCP(B) comprises the objective function (12), and constraints (2)–(5), (13), (7)–(9), (14), and (11).

$$\min \ \mathrm{f} = \alpha \left(- \sum_{\substack{r \in V,\\ i \in S,\\ j \in S,\\ i<j}} a_{ij}\, y_{ijr} \right) + \beta \cdot \mathrm{S}_{max} \tag{12}$$

$$\sum_{i \in S} x_{ir}\, s_i \leq S_{max}, \qquad r \in V \tag{13}$$

$$S_{max} \geq 0, \text{integer} \tag{14}$$

Objective functions (1) and (12) minimize two aspects: the formation of large clusters of adjacent sectors and the even distribution of, respectively, distance driven or the waste collection load among crews; these components are balanced using the coefficients α and β, respectively. Constraint (2) ensures that each sector is assigned to exactly one crew. Constraint (3) guarantees that the total amount of waste collected by each crew must not exceed the SCV's capacity. Constraint (4) forces that the binary variable y_{ijr} equals 1 if both sectors i and j are assigned to the same crew r. Constraint (5) ensures that each crew is assigned to at least one sector. Constraints (6) and (13) guarantee that the distance driven or amount of solid waste collected by each crew is balanced to ensure equitable distance or load distribution. Constraint (7) computes the values of the auxiliary variables used to evaluate the part of the objective function responsible for forming the largest clusters of adjacent sectors. Constraints (8) and (9) ensure that variables x_{ir} and y_{ijr} are binary.

For both variants of the SSMSWCP, computation experiments were conducted for two cases: (1) with a fixed number of clusters and (2) allowing for a maximum number of clusters to be defined. The experimental setup was designed based on realistic assumptions derived from municipal data, specifically reflecting the waste collection conditions in Tarnow. The following parameters were used in the computational model:

- the total number of waste collection points was set to 10,096, corresponding to the actual number in Tarnow;
- the city was divided into 25 sectors arranged in a 5×5 grid;
- clusters calculated by the model represent weekly service areas for each SCV;
- solid waste collection was provided by 5 crews;
- each crew was assigned a maximum collection capacity of 4,973 points, corresponding to approximately 184,000 kg of solid waste;
- each collection point was assumed to generate a fixed amount of waste equal to 37 kg;
- the weight-to-volume conversion assumes that 1 cubic meter of waste weighs 400 kg, accounting for compaction inside the RCV;
- the average distance between two collection points within a sector was set to 200 meters.

These assumptions provided a practical foundation for evaluating the mathematical model's performance under real-world constraints. They allowed the simulation of sector clustering and workload balancing in a manner aligned with municipal operations.

A 5×5 grid was overlaid on the geocoded map of waste collection points to operationalize the problem, partitioning the city into 25 sectors (see Fig. 4). These sectors served as the basis for the assignment constraints of the model.

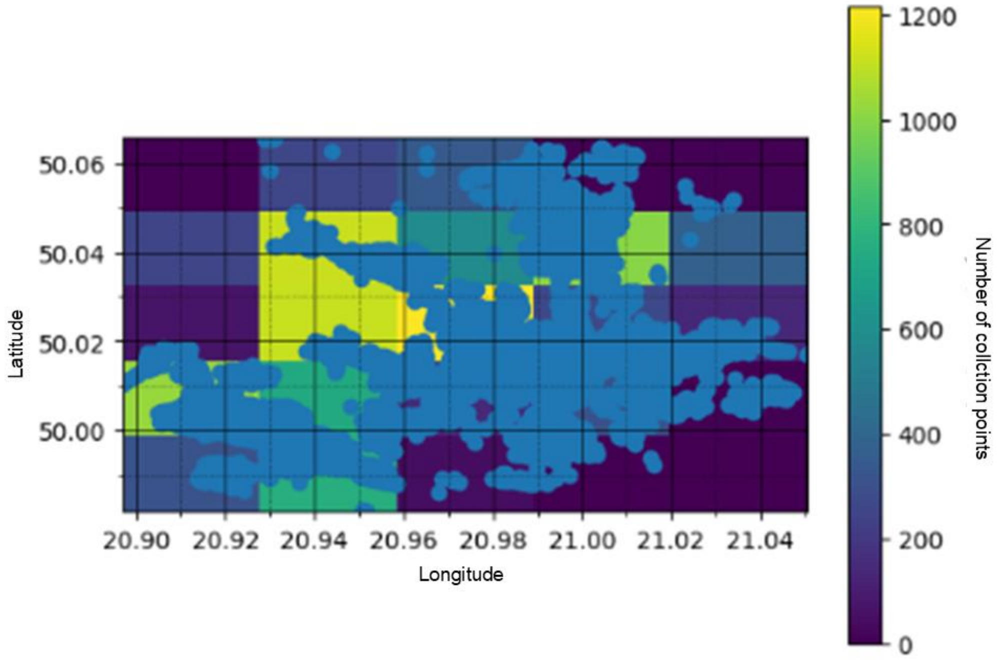

Fig 4. Heat map of solid waste collection point density across the city, divided into a 5×5 sector grid

The clustering process, implemented through pairing adjacent sectors, defined service areas for each crew and provided a practical basis for strategic planning. This modeling framework supports scalable scenario analysis, including evaluating heterogeneous SCV fleets and alternative collection technologies like electric versus diesel-powered trucks.

Four experiments were conducted to analyze the usefulness of the SSMSWCP models under different conditions:

- Case A: Balanced the creation of the largest possible clusters from adjacent sectors with the crews' workload regarding distances traveled, under the condition that all crews must serve at least one sector (SSMSWCP(A)).
- Case B: Balanced the creation of the largest possible clusters from adjacent sectors with the crews' workload regarding distances traveled, without the condition that all crews must serve a sector (SSMSWCP(A)).
- Case C: Balanced the creation of the largest possible clusters from adjacent sectors with the crews' workload regarding the amount of waste collected, under the condition that all crews must serve at least one sector (SSMSWCP(B)).
- Case D: Balanced the creation of the largest possible clusters from adjacent sectors with the crews' workload regarding the amount of waste collected, without the condition that all crews must serve a sector (SSMSWCP(B)).

The cases mentioned above allowed for a comparison of the model's behavior depending on whether the workload is measured by distance or solid waste volume and whether the requirement for all crews to be active is enforced. Models were implemented in AMPL and solved using the GLPK solver. Computational experiments were conducted on a Lenovo Legion 5-15ARH05H laptop with an AMD Ryzen 7 4800H processor (2.90 GHz) and 32 GB RAM. Due to the significant instance size, 1537 constraints and 1627 variables, computational experiments were limited to 20 minutes, and the obtained results are feasible solutions.

The weight coefficients were arbitrarily set to $\alpha = 0.4$ and $\beta = 0.6$ in the experiments. For Case A, which included the constraint that each crew must serve at least one sector, the resulting GAP value was 5.30%. In Case B, where this constraint was removed, the GAP was slightly higher at 5.8%. After determining which sectors were assigned to which crews, the results were visualized in a 5×5 matrix, where each sector was assigned to a crew responsible for servicing it (see Tables 2 and 3). Workload per crew is presented in Table 4.

Table 2: Case A – Division of sectors among five crews

index	x1	x2	x3	x4	x5
y1	Crew **3** (313)	Crew **3** (764)	Crew **5** (43)	Crew **5** (0)	Crew **5** (0)
y2	Crew **3** (1030)	Crew **1** (737)	Crew **5** (144)	Crew **5** (305)	Crew **5** (6)
y3	Crew **1** (69)	Crew **4** (1113)	Crew **5** (1216)	Crew **5** (269)	Crew **5** (142)
y4	Crew **1** (256)	Crew **2** (1117)	Crew **2** (588)	Crew **4** (1001)	Crew **2** (371)
y5	Crew **1** (0)	Crew **1** (257)	Crew **2** (343)	Crew **2** (3)	Crew **4** (9)

Table 3: Case B – Division of sectors among five crews

index	x1	x2	x3	x4	x5
y1	Crew **2** (313)	Crew **2** (764)	Crew **1** (43)	Crew **1** (0)	Crew **1** (0)
y2	Crew **3** (1030)	Crew **2** (737)	Crew **2** (144)	Crew **1** (305)	Crew **1** (6)
y3	Crew **2** (69)	Crew **3** (1113)	Crew **5** (1216)	Crew **1** (269)	Crew **1** (142)
y4	Crew **4** (256)	Crew **4** (1117)	Crew **5** (588)	Crew **1** (1001)	Crew **1** (371)
y5	Crew **5** (0)	Crew **4** (257)	Crew **2** (343)	Crew **1** (3)	Crew **1** (9)

Table 4: Workload assigned to crews in Cases A and B

	Solid waste collected (Case A)	Solid waste collected (Case B)	Distance driven (Case A)	Distance driven (Case B)	Share of total (%) (Case A)	Share of total (%) (Case B)
Crew 1	1319.0	2149.0	263.8	429.8	13.0	21.0
Crew 2	2422.0	2370.0	484.4	474.0	24.0	23.0
Crew 3	2107.0	2143.0	421.4	428.6	21.0	21.0
Crew 4	2123.0	1630.0	424.6	362.0	21.0	16.0
Crew 5	2125.0	1804.0	425.0	360.8	21.0	18.0

In Cases A and B, at least one cluster was created in which a sector was not adjacent to the other assigned sectors. Interestingly, even though the model was not required to assign every crew to a sector in Case B, all crews were still utilized in the final solution. Conversely, in Case A, the solution included one pair of neighboring sectors in a shared cluster, possibly influenced by the constraint requiring all teams to be used. However, this cannot be confirmed definitively. The results also indicate that the uniformity of the clusters remains an area for improvement, particularly in fine-tuning the weighting factor that governs this criterion in the objective function. Furthermore, each team has a maximum collection capacity, directly influencing how the city is divided into clusters and contributing to their uneven size and shape.

In Cases C and D, coefficient values were tuned to $\alpha = 0.999$ and $\beta = 0.001$, ensuring that the influence of both objectives was preserved without numerical dominance of one term. Given that the absolute values associated with waste quantities at individual collection points are significantly larger than those representing clustering objectives, preliminary tests revealed a tendency for the objective function to be dominated by the waste-related criterion. Compared to Cases A and B, the resulting optimality gaps (GAP) were noticeably higher, due to large differences in scale between the objectives. For Case C, which includes the constraint that each crew must serve at least one sector, the GAP reached 55.3%, while in Case D, where this constraint is relaxed, the GAP was 22.8%. Following optimization, the assignment of crews to sectors was presented in Tables 5 and 6. Workload per crew is presented in Table 7.

Table 5: Case C – Division of sectors among five crews

index	x1	x2	x3	x4	x5
y1	Crew **4** (313)	Crew 3 (764)	Crew 4 (43)	Crew 4 (0)	Crew 4 (0)
y2	Crew 5 (1030)	Crew 4 (737)	Crew 4 (144)	Crew 4 (305)	Crew 4 (6)
y3	Crew 5 (69)	Crew 4 (1113)	Crew 4 (1216)	Crew 4 (269)	Crew 4 (142)
y4	Crew 2 (256)	Crew 2 (1117)	Crew 4 (588)	Crew 1 (1001)	Crew 1 (371)
y5	Crew 2 (0)	Crew 2 (257)	Crew 1 (343)	Crew 1 (3)	Crew 1 (9)

Table 5: Case D – Division of sectors among five crews

index	**x1**	**x2**	**x3**	**x4**	**x5**
y1	Crew **5** (313)	Crew **5** (764)	Crew **3** (43)	Crew **3** (0)	Crew **3** (0)
y2	Crew **5** (1030)	Crew **3** (737)	Crew **3** (144)	Crew **3** (305)	Crew **3** (6)
y3	Crew **4** (69)	Crew **4** (1113)	Crew **3** (1216)	Crew **3** (269)	Crew **3** (142)
y4	Crew **4** (256)	Crew **4** (1117)	Crew **3** (588)	Crew **3** (1001)	Crew **3** (371)
y5	Crew **4** (0)	Crew **4** (257)	Crew **3** (343)	Crew **3** (3)	Crew **3** (9)

Table 7: Workload assigned to crews in Cases C and D

	Solid waste collected (Case C)	Solid waste collected (Case D)	Distance driven (Case C)	Distance driven (Case D)	Share of total (%) (Case C)	Share of total (%) (Case D)
Crew 1	1727.0	-	345.4	-	17.0	-
Crew 2	1630.0	-	326.0	-	16.0	-
Crew 3	764.0	4440.0	152.8	888.0	8.0	44.0
Crew 4	4876.0	2812.0	975.2	562.4	48.0	28.0
Crew 5	1099.0	2844.0	219.8	568.8	11.0	28.0

The results indicate that Case D performs better in crew workload balance and cluster configuration. Specifically, the solution suggests that the same coverage can be achieved with only three crew, rather than five, assuming an acceptable deviation of approximately 20% from the optimal.

Conclusions

This study investigated the spatial partitioning of urban solid waste collection services using *k*-means algorithm and mixed-integer linear programming. The computational experiments demonstrated a robust and flexible approach to sustainable sectorization for a city for municipal waste collection, offering optimized solutions that are computationally tractable on standard hardware. The models for the SSMSWCP were designed to balance operational efficiency, resource allocation, and environmental considerations. Conclusions are drawn in response to the main research question and the derived detailed questions.

The study confirmed that MILP models supported with *k*-means clustering algorithms can effectively segment the city into collection sectors that minimize service provision costs. This is achieved by enforcing clusters homogeneity based on selected balancing criteria, such as distances traveled or the volume of solid waste collected. The SSMSWCP supports strategic planning by enabling planners to allocate collection crews equitably across the urban area over a defined time horizon. The results underscore the flexibility of the models in accommodating different structural and operational constraints, which can significantly affect the configuration and efficiency of the resulting sectorization (MRQ and DRQ01).

The results showed optimizing sector boundaries concerning distance traveled can significantly reduce emissions. When the optimization objective focused on minimizing travel distances, the resulting solutions led to shorter vehicle routes and thus lower fuel consumption and greenhouse gas emissions—an especially important consideration for internal combustion fleet segments. The results also revealed that balancing criteria, such as solid waste volume or distance, lead to differing operational configurations and environmental implications, highlighting the trade-offs between service efficiency and ecological sustainability (DRQ02).

The findings indicate that the assumed number of available crews has a measurable impact on workload distribution and overall service costs. Specifically, requiring all crews to serve at least one sector significantly limited the SSMSWCP models' ability to optimize assignments, often resulting in less efficient distributions, and, in contrast, relaxing such a constraint allowed for more flexible and cost-effective solutions. In Case D, the model indicated that the same level of service could be achieved with three teams instead of five. This suggests that the optimization framework can uncover opportunities to reduce the number of crews and improve cost efficiency under more flexible operating conditions.

In conclusion, the MILP models for the SSMSWCP developed in this study offer a data-driven, strategic approach to waste collection planning in urban environments. They support cost minimization, equitable workload distribution, and environmental performance through efficient routing and resource deployment. Furthermore, the models offer insight into how varying operational constraints affect outcomes, informing sustainable and effective municipal solid waste management strategies.

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