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Industry 4.0 in waste management: An integrated IoT-based approach for facility location and green vehicle routing

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ABSTRACT

The increasing production of solid waste rate in urban areas plays a critical role in sustainable development. To mitigate the adverse effects of waste and enhance waste management efficiency, this paper introduces a holistic approach that notably reduces the overall cost while mitigating social and environmental impacts. Central to the system's efficacy is the critical process of waste sorting, which enhances the output value of the waste management system. While previous studies have not extensively addressed simultaneous waste collection and sorting, this paper provides an innovative integrated framework. This approach Integrates waste collection with various bins, followed by their transfer to separation centers. At these centers, waste is categorized into organic and non-organic varieties, which are then dispatched to a recovery center at the second level. In the context of optimizing the routes at both levels, this paper presents a green, multi-objective location-allocation model. This model is designed to optimize the number and location of separation center facilities. Since the routing problem is influenced by the facility location model, it is addressed as a multi-depot green vehicle routing problem, integrating real-time information from IoT-equipped bins. This paper also proposes the vehicle routing problem with a split pickup, aiming to minimize cost, CO_2 emissions, and visual pollution. The developed mathematical models formulate the proposed problem and it is solved by the GAMS optimization software, to apply an exact method, while Social Engineering Optimization and Keshtel algorithms are deployed to solve the routing problem for larger sizes. The proposed approach offers a comprehensive and sustainable solution to waste management, filling crucial gaps in current research and practice.

1. Introduction

Due to the rapid rise of world population, urbanization, and growth of industrial production, the amount of waste generated worldwide is projected to surge to 2.2 billion tons over the next thirty years [1]. This substantial increase leads to an approximate cost of $600 billion for managing Municipal Solid Waste (MSW) [2]. The MSW concept refers to the unwanted remnants originating from households, institutions, industrial establishments, and construction and demolition sites. These wastes can be broadly categorized into six main groups: bio-waste, plastics, paper, glass, metals, and other miscellaneous waste types [61][3]. On the other hand, with the continuous reduction in available space for municipal waste in landfills, the spotlight in waste management is progressively shifting toward thermal waste recovery. As illustrated in Fig. 1a, the significant presence of bio-waste (31 % contribution) within solid waste streams presents an optimistic potential for energy recovery via Waste-to-Energy (WTE) technology. This optimistic potential of WTE technology in harnessing energy from bio-waste further emphasizes the importance of exploring and implementing sustainable waste management strategies.

Biowaste, which encompasses all biodegradable organic waste along with fossil fuels like oil, coal, and natural gas, is emerging as a dominant source of renewable energy today [4]. As seen in Fig. 1b, there has been a notable increasing trend in biopower generation. In 2019, electricity generated globally from biomass reached a total value of 655 terawatt-hours, underscoring its potential as a significant contributor to meeting worldwide electricity demand. Additionally, the waste-to-energy market, encompassing digestion and thermal power generation techniques, mitigates the risks associated with pollutants emitted from landfills. These pollutants include parasites, volatile or-

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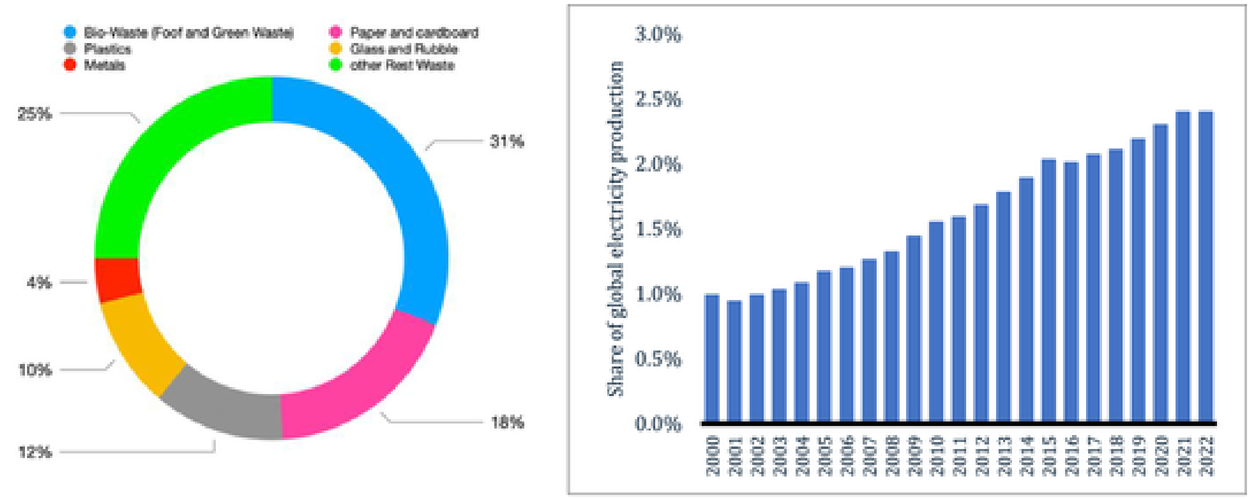

a. Contribution of different MSW categories in European countries

b. Biomass electricity generation worldwide from 2000 to 2022.

Fig. 1. Biomass contribution and worldwide electricity generation by Biomass (a. Source: http://www.seperate-wastesystems.eu/, b. www.statista.com,World Bioenergy Association; IEA; ID: 481743).

ganic compounds, carbon dioxide, and methane gas. Therefore, transforming waste into energy not only provides a sustainable energy solution but also plays a crucial role in reducing environmental hazards.

MSW management encompasses a range of activities, including waste generation, monitoring of storage sites, waste collection, transportation, processing, and disposal [5]. In order to effectively address waste-related challenges, municipalities require an efficient mechanism to control waste, monitor the status of waste bins, optimize capacity, and plan collection routes in a sustainable manner. To address these needs, an Internet of Things (IoT)-based smart waste management solution can provide cities with the necessary tools to manage the increasing volume of MSW [65]. The proposed technique relies on data collected from smart bins installed throughout the city to determine the waste level [6,7].

In this study, the filling status of smart IoT-based bins is simulated based on real-time information obtained from the smart bins and through interviews conducted with municipal authorities. The simulation considers two distinct time periods: nighttime collection and daytime collection, with the latter prioritizing areas with higher levels of garbage production, such as those near markets or other high-traffic areas. By incorporating smart waste management practices, the study aims to address the inefficiencies observed in traditional waste management approaches, such as unnecessary collection of waste, leading to increased costs and delays in waste collection. These inefficiencies can result in a significant increase of approximately 70 % in annual collection costs. Additionally, inefficient route planning leads to congestion, requiring more fuel and trucks to complete the collection process. Therefore, the carbon footprint associated with waste collection is amplified by approximately 50 % .

The proposed smart waste management system aims to mitigate these issues by leveraging real-time data and optimizing waste collection routes. By accurately monitoring the fill levels of bins and implementing efficient collection schedules, unnecessary pick-ups can be minimized, resulting in cost savings and reduced environmental impact. Through the implementation of IoT solutions, garbage vehicles can be equipped with more efficient routes and receive notifications from drivers when emptying is required. By utilizing smart IoT-based bins in both time periods, we gain access to real-time information about the amount of trash in each bin. This allows us to create a list of bins that require emptying, enabling us to optimize routing specifically for this category of bins. This approach eliminates the need to visit all bins, reducing transportation costs and the associated pollution caused by unnecessary travel [8,9].

One of the methodological contributions of this proposed study is the development of a three-step framework that considers the following models: facility location for separation centers, vehicle routing optimization from separation centers to bins, and from the recovery center back to the separation centers. The first model focuses on long-term and strategic objectives, while the second model addresses operational objectives in routing optimization, resulting in the minimization of transportation costs and the use of the fewest possible number of vehicles for waste collection. In the proposed waste collection framework, the location of separation centers is of particular importance as it impacts transportation costs and pollutant emissions. Moreover, the location of separation centers influences the determination of their number. Also, the location and number of separation centers play a vital role in determining the routes taken by vehicles for waste collection from bins, delivery to separation centers, and subsequent transfer to recovery centers. Finally, the three-step framework is extended to include the optimization of separation center locations, waste collection from bins to separation centers, and the transfer of waste to recovery centers. This comprehensive approach aims to address real-world waste collection challenges and achieve sustainable waste management practices.

2. Literature review

The management of Municipal Solid Waste (MSW) comprises five critical elements, including source waste handling, collecting and transferring, dumping, processing, and treating [10,11]. A significant portion of the resources and cost is dedicated to the collection and transportation of waste, accounting for approximately 80 % of the overall MSW expense. This operation is influenced by different factors, such as the city's road network, congestion, weather conditions, and citizen interactions [12,13]. Concurrently, waste management's hierarchy underlines the importance of source reduction, recycling, and waste transformation in the overall waste management system. Source reduction primarily aims to minimize waste generation, while recycling and waste transformation are significant for reusing materials and have been the focus of considerable research [14]. Moreover, it is essential to consider non-decomposable waste since the processing and potential transportation of non-decomposable waste to recycling centers can lead to additional costs. In this regard, the optimization of separation center

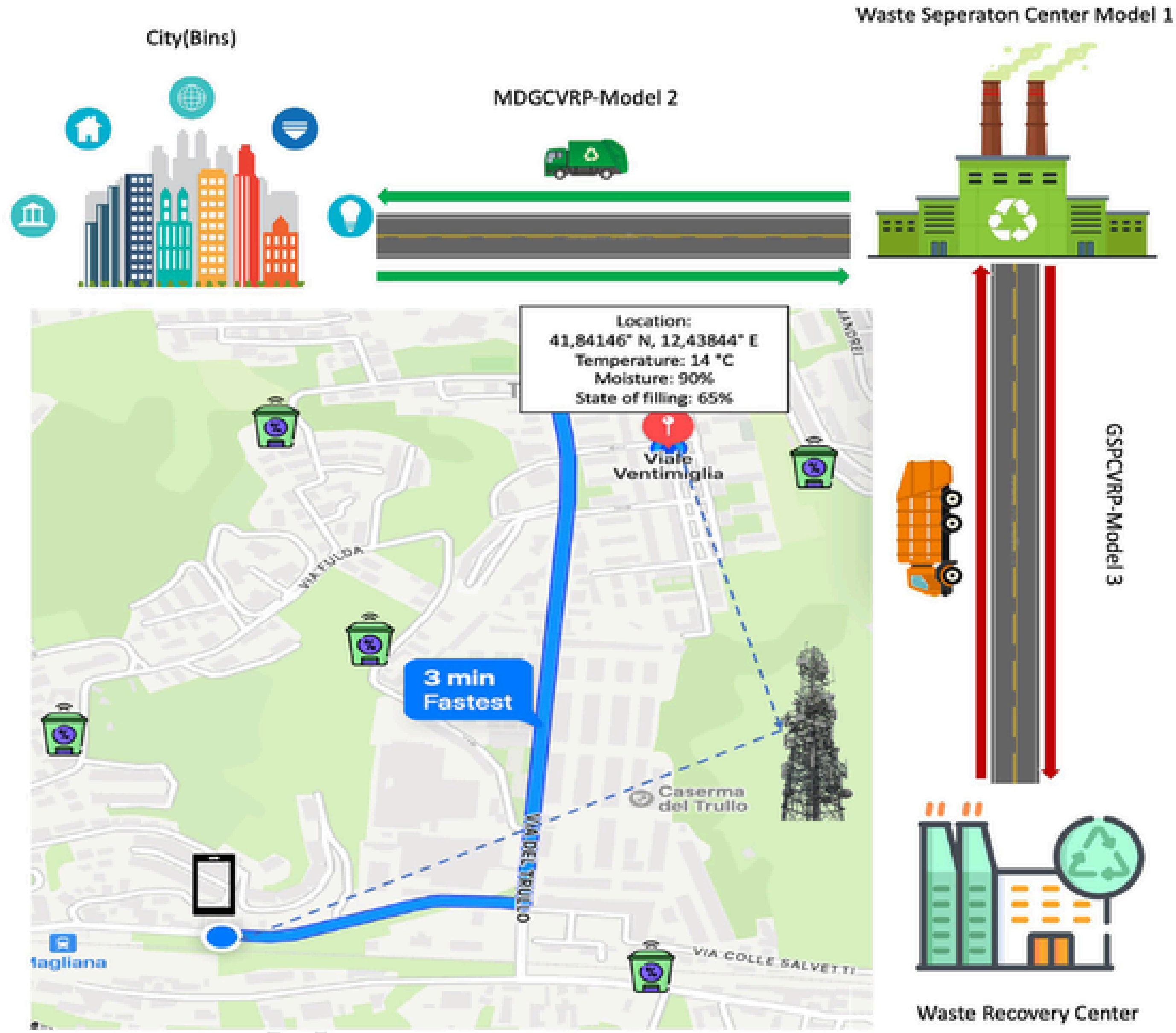

Fig. 2. A snapshot of the proposed network.

Table 1
Set of proposed models.

Sets	Description
I	Set of bins,
J, W	Set of candidate locations for separation centers,
RE	Set for recovery centers,
i	Index of demand points,
j, w	Index of candidate locations for separation centers,
Re	Index of recovery centers.

locations plays a key role in enhancing the overall efficiency and effectiveness of waste management systems, minimizing costs, and maximizing resource utilization.

Hence, it is worth noticing that MSW is a labor-intensive management system that necessitates strategic efficacy due to the significant distances (2 to 50 km for European and Central Asian cities) of bins from separating waste production sites and final destinations such as disposal or recovery facilities [15]. Given the transportation expenses for waste, which lie between \$20 to \$50, formulating an efficient and sustainable model to reduce costs while minimizing environmental, social, and economic impacts is necessary [16]. The sustainable development goals outlined by the United Nations offer a framework to balance the mentioned dimensions. Many of these goals can be achieved directly or indirectly through operational improvements and reductions in fleet emissions. Numerous techniques have been explored to optimize collection and transportation costs while minimizing environmental impacts. For instance, the Backtracking Search Algorithm has been developed to address the capacitated vehicle routing problem by optimizing vehicle routes minimizing distance, fuel consumption, CO_2 emissions, and collected waste. It introduces the concept of threshold waste level (TWL) to reduce the number of bins that need to be visited, with an optimal TWL range of 70 % to 75 % of total bin capacity . [17] Proposed two multi-objective evolutionary algorithms to solve the urban waste collection problem considering priorities and the conflicting goals of minimizing the total distance while maximizing the quality of service. The results of their tests showed that the evolutionary algorithms outperformed greedy strategies and the current routing method-

Table 2
Parameters.

Parameters	Explanation
f_j	Land price of separation center *j*,
q_i	The amount of generated waste in bin *i* (kg),
d_{ij}	The distance between *jth* separation center and *ith* bin,
dm_{jw}	The distance between two separation centers,
e_{tij}	Cost of carbon emission associated with transportation between separation centers and bins,
e_{trRej}	Cost of carbon emission associated with transportation between separation centers and recovery centers,
N_j	The construction cost of separation centers,
v_j	Capacity of *jth* separation center,
v_{min}	Minimum required capacity if a facility location is opened,
e_{gj}	Cost of carbon emission associated with gas consumption at separation center,
e_{ej}	Cost of carbon emission associated with electricity consumption at separation center,
md	Minimum allowed distance between two opened separation centers,
γ	The minimum level of using an opened facility,
δ	The maximum level of using an opened facility,
K	The minimum number of required facilities,
C	Unitary transportation cost per kilometer.

Table 3
Decision variables.

Variables	Description
x_{ij}	A binary variable and it equals to one if bin number *i* is assigned to separation center *j*,
y_j	Equals to 1 if jth potential location is opened, otherwise it is 0,
u_{RRej}	Equal to 1 if separation center *j* is allocated to recovery center *Re* and 0, otherwise.

Table 4
Set of proposed models.

Sets	Description
I, J	Set of all nodes including separation centers, Dummy waste separation centers, and garbage bins $\in \{1, \ldots, N+M\}$,
M	Set for separation centers,
N	Set for bins,
K	Set of low capacitated vehicles,
j, i	Index of nodes,
k	Index of nodes.

ology applied in Montevideo. Furthermore, the best results are obtained for a dynamic version of the problem using real-time information.

Indeed, the implementation of tracing systems to provide real-time information plays a vital role in sustainable waste management by reducing unnecessary bin visits. As such, the application of IoT technology becomes crucial in the design of sustainable MSW management systems [18,19]. A smart integrated system consisting of four parts based on the application of IoT was presented by [20]. The proposed system measures the garbage level using sensors and displays it on a liquid crystal display, allowing for efficient waste management by reducing manpower, waste spillage, time, and overall costs. The IoT-based waste collection system was evaluated by applying modified Entropy measures and a multi-criteria decision-making method and considering uncertain parameters [21,22].

Also, the use of IoT for real-time information makes it possible to have dynamic routing that is currently underutilized in such systems [23–25]. [26] Designed a greedy adaptive search procedure to determine the routes for visiting the selected bins that minimize the number of visited bins. Only bins with the highest fullness level can be selected to collect because of the maximum shift duration constraints. Jorge et al., [12] designed a framework to consider dynamic routes for the smart waste collection system using real-time information and developed a hybrid metaheuristic algorithm to determine, firstly, the day of collection and then the bins that must be visited. Moreover, collection of waste in a two-echelon waste collection, leveraging Industry 4.0 concepts and IoT devices is addressed to minimize operational costs and environmental impact. The system focuses on optimizing waste collection from bins to separation centers and the transfer to recycling centers by implementing meta-heuristic algorithms and novel heuristics [27].

Table 5
Parameters.

Parameters	Description
FC_k	Fixed cost of low capacitated vehicle *k*,
GA_k	Carbon dioxide emission penalty for each vehicle per kilometer,
SI_k	Social impact cost associated with each vehicle *k*,
c_j	The amount of waste in the *jth* bin (kg),
Cap_k	Vehicle capacity k (kg),
d_{ij}	Distance between two nodes *i* and *j*,
td_{ij}	travel time between two nodes *i* and *j*,
tl_i	Time to load waste from the *ith* bins,
$LimTime_k$	Maximum time available to collect waste and transport it to waste separation centers,
CT_k	Maximum time available for garbage collection,
Lim_{GA}	Maximum allowed emission amount,
Lim_{SI}	Maximum social impact allowed,
n	scalar for the sub-tour deletion constraint,
M	A big number,
Tc	Transportation cost per unit kilometer,
p_j	Priority of bin j which higher value indicates a higher priority,
ths	Threshold to determine the high priority bins if the waste exceeds a predefined value,
Lim_{tran}	maximum allowed transportation cost,
Pen	Penalty for violation of collection hours limit.

Table 6
Decision variables.

Variables	Description
x_{ijk}	It is equal to 1 if the vehicle *k* moves between two nodes *i* and *j*, otherwise is equal 0,
y_{ik}	It is equal to 1 if the *ith* bin is assigned to the *k*, otherwise is equal 0,
q_{ijk}	The amount of waste collected between two nodes *i* and *j* by the vehicle *k*,
A_{jk}	The time of the *kth* truck arriving at the node *j*,
α_j	It is equal to 1 if the arrival time of the *kth* vehicle to the *jth* garbage bin is greater than the maximum time available for garbage collection otherwise 0,
z_{ijk}	It is equal to 1 if the *ith* bin with priority j is assigned to the *kth* vehicle, otherwise is equal 0.
u_i	Variable for sub-tour elimination constraint,
AOW_k	Total waste collected by vehicles with low-capacity *k*.

Recently, [28] proposed WMS in smart cities by incorporating real-time waste bin fill level data obtained through IoT-based devices. Two different sub-models were proposed based on the vehicle routing problem: the first determines the optimal routes to collect waste from bin to separation centers while the second one maximizes the recovery value and minimizes visual pollution by efficiently transporting waste from separation centers to recovery centers. Different threshold waste levels were investigated and a waste level between 70 % and 75 % was found as the best one to optimize transport efficiency, traveled distance, and collected waste amount. While dynamic routing is crucial, which optimizes the collection of waste from bins to separation centers and further to recovery centers, it's equally important to consider the strategic, tactical, and operational decisions in WMS. These decisions have significant impacts on the environmental, social, and economic aspects of waste management, highlighting their vital role in sustainable development [29].

While most of the previous research considered a separate waste management center for each zone of the smart city, the current paper highlights that the location and the number of these centers are crucial elements of the logistic network that directly influence the routing

Table 7
Set of proposed models.

Sets	Description
I, J	Set of all nodes including separation centers and recovery centers,
K	Set of high capacitated vehicles,
P	Set for recovery center,
N	Set of separation centers,
j, i	Index of nodes,
k	Index of nodes,

Table 8
Parameters.

Parameters	Description
FC_k	Fixed cost of high capacitated vehicle *k,*
GA_k	Carbon dioxide emission penalty for each vehicle per kilometer,
Vp_k	Maximum allowable visual pollution,
AOW_i :	Amount of waste in the *ith* separation canter (kg),
Cap_k	Vehicle capacity *k (kg),*
d_{ij}	Distance between two nodes *i* and *j,*
td_{ij}	Travel time between two nodes *i* and *j,*
tl_i	Time to load waste from the *ith* separation centers,
$LimTime_k$	Maximum time available for waste collection,
CT_k	Maximum time available for waste collection,
Lim_{GA}	Maximum amount of allowed emission,
Lim_{VP}	Maximum social impact allowed,
Lim_{tran}	Maximum allowable transportation cost,
n	Scalar for the sub-tour deletion constraint,
Tc	Transportation cost per unit kilometer.

Table 9
Decision variables.

Variables	Description
x_{ijk}	It is equal to 1 if the vehicle *k* moves between two nodes *i* and *j*, otherwise is equal 0,
y_{ik}	It is equal to 1 if the *ith* bin is assigned to the *k*, otherwise is equal 0,
q_{ijk}	The amount of waste collected between two nodes *i* and *j* by the vehicle *k,*
u_i	variable for sub-tour elimination constraint,
Tw_k	The total amount of waste collected by the *kth* high-capacitated vehicle,
Avg	Average load of vehicles which can be calculated by division of Tw_k to number of vehicles,
Twc_i	Total amount of waste collected by all high capacitated vehicles at the recovery center.

problem solution. However, facility location decisions are long-term and unchangeable, unlike flexible routing decisions which bins location problem, for example, has been investigated in several previous works [30–33]. As routing problems can be solved using real-time data from sensor-equipped bins, the routes can be updated frequently but the related problem cannot be integrated with static facility location. This paper extends the previous work by [28]. Instead of assuming different zones and one separation center for each one, the proposed model develops a green facility location model that determines the number and location of separation centers and to assign bins to each opened facility. Moreover, the formulated location problem avoids establishing separation centers that are near other opened facilities. Regarding the routing problem, a multi-depot routing problem is suggested, enabling depot resource sharing to cover all bins. Additionally, constraints are implemented to maximize utilized truck capacity, minimize travel distance, ensure maximum load, and reducing energy consumption and pollution.

Moreover, it is important to mention that the sustainability of MSW management practices calls for a shift from incineration towards more environmentally friendly options such as composting, which presents a viable solution for waste transformation [34]. This context forms the basis of our proposed two-stage mathematical model to address the routing problem. This system facilitates waste movement from bins to separation centers and subsequently to recovery centers separately. Separating them into two distinct models is justified by several motivations. Firstly, the processing time and storage requirements at separation centers, where sorting and pre-processing take place, can extend beyond a day. So, it is more practical to model them separately from collection and transportation processes. Secondly, since separation centers can store collected waste for extended periods, the transportation of waste from these centers to the recovery centers does not need to happen on the same day as the collection. Also, the storage capacity at separation centers provides a buffer that decouples the first and second levels of routing. This buffer allows for differences in the capacity of the vehicles used in the two routing levels. Lastly, dynamic factors such as processing rates, demand, and vehicle availability can vary independently, and separate models provide flexibility to adapt to these changes. These motivations highlight the practicality, flexibility, and efficiency of treating the two routing levels as separate models.

3. Problem statement and mathematical formulation

Problem statement and mathematical formulation are discussed in this section. The models introduced here address the following issues: location of waste separation facilities, vehicle routing for urban waste collection, and transfer of waste from separation to recovery centers. Each of them is presented in the subsequent subsections. The initial issue involves identifying the optimal vehicle routing within the city center, whereas the subsequent issue involves mapping the routes between the separation center and the recovery center, both of which are situated on the city's outskirts. Since the routing problem is affected by the location of the separation center, a location facility problem is proposed to find the optimal position of separation centers, which is a long-term decision plan (See Fig. 2).

It is crucial to note that the primary challenge is mainly within the city center, because of some factors such as changes in travel time and other uncertain factors that can affect routing problems. Using IoT devices to collect real-time information is a convenient strategy as it promotes efficient decision-making and manages such uncertainties. By leveraging IoT-based smart waste management systems, municipalities can enhance their waste management practices, improve operational efficiency, and contribute to the overall sustainability of their cities. A key use of IoT devices in waste management systems is the measurement fill-up levels by smart waste bins. In the proposed approach, the system defines three fill-up levels to monitor the status of waste in the bins. This information enables cities to efficiently allocate resources and optimize waste management processes. These three levels are identified as follows:

- Empty Level: This is the initial stage of the waste bin, indicating that it has recently been emptied. The empty level serves as a reference point for the system to monitor the bins' status and predict the time it takes to fill up again.
- Half Level: The half level is used to check the new status of bins. It allows the system to anticipate the fill-up time of these bins based on historical data and patterns. By predicting the fill-up time, waste collection drivers can incorporate the collection of bins at the half level during their regular visits, further optimizing their routes and reducing operational costs.
- Full Level: Upon detecting a full level, the system promptly notifies both the municipal authority and waste collection drivers of the need for a high-priority collection service. This ensures that full bins are promptly addressed and prevents any potential overflow or inconvenience to residents.

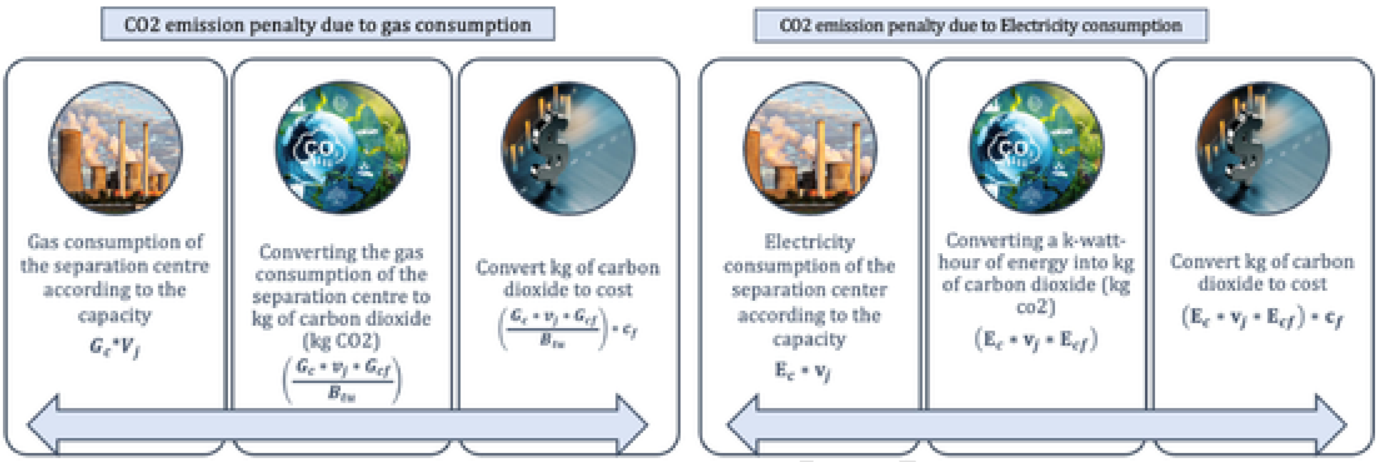

Fig. 3. The CO_2 emission penalty is attributable to electricity and gas consumption.

Table 10
Data related to the location-allocation model.

Parameter	Values	Unit
i	1000	–
j, w	6	–
Re	1	–
F_j	[1.764e +11, 2.06e +11, 2.1e +11, 3.68e + 11, 1.842e +11, 1.276e +11, 1.83e +11]	IRR
q_i	Uniform ~ [362, 394, 418, 449, 480]	Kilogram (Kg)
d_{ij}	Uniform ~ [1.1672, 23,1432]	km
dm_{jw}	Uniform ~ [0.0012, 26.57]	km
d_Re_j	[12.2162, 24.8776, 29.6532, 31.7656, 23.8765, 10.9845, 9.1021]	km
TE	6000	CO_2 emission per Km
CF	400	Kg CO_2 to cost
V_j	Uniform ~ [300,000, 365,159, 456,280, 834, 470, 417,690, 289,340, 414,970]	Kilogram (Kg)
N_j	Uniform ~ [7e +11, 8.1746e +11, 8.33332e + 11, 1.46032e +12, 7.20458e +11, 6.6235e + 11, 7.26198e +11]	IRR
Gcf	64	Gas conversion factor
Ecf	0.64	KWh to kg CO_2
G_c	1000	The British thermal unit (Btu) per kg
E_c	0.15	KWh per kg
C	1200	Transportation cost per Km
md	4	Kilogram (Kg)
B_{tu}	1000,000	Btu factor

3.1. Separation center location problem

The number of optimal facilities is determined based on initial fixed costs, transportation costs, emission costs associated with transportation services, pollution costs for opened facilities, and capacity utilization. Some constraints are introduced to ensure that candidate locations are not opened near other existing facilities and that the total capacity must be able to comply with the total generated demand. The single allocation hub location problem is also considered in this paper, which implies that each demand point must be allocated and served by only one of the opened facilities [35]. The costs associated with opening a potential location include the cost of land and the construction of separation centers. Also, the opening costs depend on the different capacities of each candidate location. In addition to opening costs, the objective function also considers transportation costs, carbon emission costs associated with transportation at the first level, and pollution costs related to gas and electricity consumption at separation centers.

However, the carbon emission cost of vehicles from separation centers to recovery centers and the deviation from the minimum required capacity for each opened separation center have been considered separately. These costs are included in a second objective function, which considers the opening of facilities with the required capacity and incentives for larger capacity to minimize operational costs. The model is encouraged to open facilities with a capacity closer to the required value by penalizing the deviation from the minimum required capacity. The trade-off between minimizing carbon emissions and maximizing capacity utilization is made by defining a weighting factor that gives more importance to maximizing capacity utilization. The value of this factor can be adjusted using information integration methods by leveraging real-time or historical data. This process involves identifying the relevant data sources for the decision-making and setting criteria to adjust the weighting factor considering various factors such as fluctuations in energy prices and changes in waste generation rates [36].

The location problem is solved when the emission costs of transporting waste are minimized at both levels, from bins to separate centers and from separate centers to recovery centers. The two goals are conflicting because minimizing the emission costs of the first level forces the model to open candidate locations near bins while minimizing the emission costs of the second level aims to close separation centers to recovery centers. The model also considers a minimum distance between every two locations before opening a new location, which can result in a wider coverage area. The main assumptions are reported in the following.

- The amount of waste generated in each bin is deterministic.
- Only one recovery center is assumed.
- Different construction costs are assumed to open candidate locations.
- The land price is fixed and equal for all locations.
- The candidate locations are assumed to have different capacities.

The sets of variables, the model parameters, and the decision variables of the model are reported in Tables 1–3. Eqs. (1)–(10) provide the formulation of the optimization problem.

$$\text{minimize } Z_{cost} = \sum_{j\in J} f_j * y_j + \sum_{j\in J} N_j * \ y_j \ + C^* \sum_{i\in I}\sum_{j\in J} d_{ij} * x_{ij} + \sum_{i\in I}\sum_{j\in J} e_{tij} * x_{ij} + \sum_{j\in J}\left(e_{gj} + e_{ej}\right) * v_j * \ y_j \quad (1$$

$$\text{minimize } z_{CO2emission} = \sum_{Re\in RE}\sum_{j\in J} e_{trRej} * u_{RRej} + B * \ \left(v_j - v_{min}\right) * \ y_j \quad (2)$$

subject to:

Fig. 4. The optimal location for separation centers.
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Table 11
Optimization results of the separation center location problem.

Dimension	Number of bins	1000
	Candidate Location	6
	Recycling center number	1
Objective elements	Optimal Location for separation center	1 and 3
	Optimal number of assigned bins to separation center number 1	400
	Optimal number of assigned bins to separation center number 6	600
	Land cost	2,404,000,000,000 IRR
	Capacity cost	2,110,000,000,000 IRR
	Transportation cost	34,600,000,000 IRR
	Pollution penalty from bin and separation center cost	44,300,000,000 IRR
	Separation center pollution penalty cost	27,400,000,000 IRR
	Pollution cost penalty from separation center and recycling center	84,600,000 IRR
	Value of the first objective function	1,730,000,000,000 IRR
	Value of the second objective function	83,600,000 IRR
	Value of the total objective function	1,730,083,600,000 IRR

Table 12
The data related to routing problem to collect waste from bins to separation centers.

Parameter	Values	Unit
i,j	1000	–
k	120	–
FC_k	293,499,996	The cost of utilizing vehicles
S	[1,2]	Time interval
GA_k	1100	CO2 penalty per unit distance and vehicle
SI_k	Uniform ~ [10, 10 × 10^6]	Social penalty per unit distance and vehicle (dollars)
c_j	Uniform ~ [350, 500]	Kg
$\mathbf{Cap}_k$	[2500,6000]	Kg
d_{ij}	Uniform ~ [0.0096, 8.0603]	km
td_{ij}	With respect to distance	Time in minutes
tl_i	2	Time in minutes
$LimTime_k$	320	Time in minutes
CT_k	250	Maximum time available
Lim_{GA}	400,000,000	Maximum pollution (IRR)
Lim_{SI}	400,000,000	Maximum social impact (IRR)
n	2	–
Tc	1500	Cost per Km
Lim_{tran}	400,000,000	Maximum cost (IRR)
Pen	900,000	Penalty for violation of available time

$$\sum_{i \in I} q_i * x_{ij} \le v_j * y_j \ \forall j \in J \tag{3}$$

$$\sum_{j \in J} x_{ij} = 1 \ \forall i \in I \tag{4}$$

$$y_j \le 1 \ \forall j \in J \tag{5}$$

$$\sum_{Re \in RE} u_{RRej} = y_j \ \forall j \in J \tag{6}$$

$$dm_{jw} < md \ \rightarrow \ y_j + y_w \le 1 \ \forall j \in J, \ w \in J, \ j \ne w \tag{7}$$

$$\sum_{i \in I} q_i * x_{ij} \le \ \gamma * v_j * y_j \ \forall j \in J \tag{8}$$

$$\sum_{i \in I} q_i * x_{ij} \le \delta * v_j * y_j \ \forall j \in J \tag{9}$$

$$\sum_{j \in J} y_j \le K \tag{10}$$

Eq. (1) represents the first objective, which is composed of land and construction costs, transportation costs of the first level, carbon emission costs associated with transportation between separation centers and bins, and pollution costs related to gas and electricity consumption at separation centers. Eq. (2) considers the carbon emission costs of vehicles from separation centers to recovery centers. Hence, the locations must be selected by trading off these two conflicting objectives, with the aim of minimizing environmental impact of transportation at both levels and opening facilities with a capacity closer to the required value. The conflicting objectives force the model to balance the need for meeting demand with the goal of minimizing operational costs

Table 13
Optimization results of the routing model from bins to separation center (First period).

Dimension	Number of bins	600
	number of separation center	2
	Total travel time	4678.2689 min
	Total distance	1732 km
Objective elements	maximum traveled distance	45.6732 km
	Waste quantity in separation center number 1	274,266 kg
	Waste quantity in separation center number 3	0 kg
	Number of vehicles	56
	Number of assigned bins to separation center number 1	667
	Number of assigned bins to separation center number 6	0
	Sustainability goal	16,143, 426.6 IRR
	Vehicle fixed cost	12,450,400 IRR
	Transportation cost	10,865,000 IRR
	Cost of capacity	457,210 IRR
	Penalty of time window	0 IRR
	Total cost	37,637, 036.7 IRR

Table 14
Optimization results of the routing model from bins to the separation centers (second period).

Dimension	Number of bins	400
	Number of separation center	2
	Total travel time	4448.9614 min
	Total distance	1568 km
Objective elements	Maximum traveled distance	41 km
	Waste quantity in separation center number 1	114,230 kg
	Waste quantity in separation center number 6	109,103 kg
	Number of vehicles	53
	Number of assigned bins to separation center number 1	271
	Number of assigned bins to separation center number 6	256
	Sustainability goal	15,445, 985 IRR
	Vehicle fixed cost	38,429, 000 IRR
	Transportation cost	10,976, 000 IRR
	Cost of capacity	402,280 IRR
	Penalty of time window	0.00 IRR
	Total cost	65,253, 447 IRR

through the utilization of larger capacity separation centers. Eq. (3) ensures the capacity constraints of the opened separation centers. Eq. (4) guarantees the assignment of each bin to only one separation center. Eq. (5) indicates that one potential location can be opened or not, and all locations should not be necessarily opened. Eq. (6) assigns all established separation centers to the recovery centers to calculate the last part of the first objective function. Eq. (7) represents that a candidate location can be opened if it is not near other opened facilities. Eq. (8) ensures that the total waste assigned to each separation center is at least a certain percentage of its capacity and encourages so a minimum level of capacity utilization to optimize operational costs. The maximum capacity utilization is satisfied by Eq. (9) and prevents excessive capacity utilization that may lead to operational inefficiencies or reduced service quality. The number of opened facilities is controlled by Eq. (10) to balance operational costs and overall system efficiency.

3.2. Mathematical formulation of the routing model from bins to separation centers

The second model implemented is the Multi-Depot Green Capacitated Vehicle Routing Problem (MDGCVRP), predominantly employed within urban settings due to environmental considerations. This model

Table. 15
The pattern of routes in the routing model from bins to separation center (First period).

Vehicle	Operational time (hours)	Amount of collected waste	Vehicle capacity	Goods quantity/ capacity	Number of visited bin to empty	Routes
1	102.256495	5761.5	6000	0.835	12	D1 – 100 - 195 - 112 - 20 - 277 - 278 - 10 - 15 - 181 - 161 - 620 - 750 – D1
2	67.059168	3466.1	6000	0.502	7	D1 – 550 - 280 - 451 - 550 - 650 - 452 - 707 – D1
3	98.722327	6518.2	6000	0.944	13	D1 – 625 - 212 - 222 - 635 - 202 - 222 - 427 - 224 - 325 - 250 - 352 - 228 - 268 – D1
4	101.142327	6591.8	6000	0.955	14	D1- 589 - 220 - 520 - 35 - 85 - 77 - 12 - 20 - 42 - 32 - 45 - 44 - 49 - 245 – D1
5	102.848185	6575.7	6000	0.953	13	D1 –125 – 325 - 258 - 652 - 265 - 125 - 265 - 254 - 452 - 185 - 249 - 513 - 582 – D1

employs the use of Low-Capacity Vehicles (LCVs). In this routing model, the sequence of bin collection is determined along with the optimal number of vehicles required, leading to the minimization of the fixed vehicle cost. Moreover, bins are equipped with IoT devices and should be emptied during two distinct periods, maintaining a 70 % threshold level [37,27]. In the current model, bins are classified based on two visitation periods (day and night). The main assumptions are reported in the following.

- The amount of waste generated in each bin is deterministic;
- There is no direct trip between the separation centers;
- The travel time between the nodes is pre-defined;
- The amount of waste in the bins is certain;
- The transportation cost per kilometer is the same for all vehicles;
- The carbon dioxide emission penalty is not the same for all vehicles;
- The social impact cost is not the same for all vehicles and it is the summation of the weighted impact costs of all the contributed factors which is represented in monetary terms (e.g., dollars or euros) for ease of comparison and aggregation with other objective function elements.

The elements of the model are described in Tables 4–6, while the mathematical formulation is provided by Eqs. (11)–(30).

Table 16
The pattern of routes in the routing model from bins to separation center (Second period).

Vehicle	Operational time (hours)	Amount of collected waste	Vehicle capacity	Goods quantity/ capacity	Number of visited bin to empty	Routes
1	100.437792	3378.7	6000	0.563	7	D1 - 359 - 339 - 337 - 248 - 466 - 348 - 362 - 328 - 226 - 405 - 202 - 102 – D1
2	89.269264	4671.3	6000	0.778	10	D1 – 48 - 10 - 11 - 62 - 127 - 26 - 129 - 164 - 132 - 180 – D1
3	112.725312	6551.55	6000	1.091	14	D1 - 89 - 90 - 49 - 402 - 12 - 54 – 41 - 40 - 68 - 482 - 70 - 39 - 141 - 347 – D1
4	88.631984	4774.8	6000	0.795	10	D1 – 12 - 13 - 11 - 52 - 227 - 27 - 135 - 251 - 235 - 280 – D1
5	86.92824	5868.45	6000	0.978	12	D1 - 359 - 354 - 337 - 348 - 166 - 148 - 162 - 202 - 205 - 257 - 215 - 405 - D1

$$\text{minimize } z = \sum_{i=1}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K}\left(GA_k + SI_k\right) * d_{ij} * x_{ijk} + \sum_{i=1}^{M}\sum_{j=M+1}^{n}\sum_{k=1}^{K} FC_k * x_{ijk} \quad \Omega + p_j \sum_{i=1}^{M}\sum_{j=M+1}^{n}\sum_{k=1}^{K} FC_k * z_{ijk} + Tc \sum_{i=1}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} d_{ij} * x_{ijk} + \sum_{i=1}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} d_{ij} * q_{ijk} + \sum_{j=M+1}^{n} \alpha_j * Pen - \sum_{k=1}^{K} AOW_k / Cap_k \tag{11}$$

subject to:

$$\sum_{\substack{i=M+1 \\ i\neq j}}^{n} \sum_{k=1}^{K} x_{ijk} + \sum_{i=1}^{M}\sum_{k=1}^{K} x_{ijk} = 1 \ \forall j = M+1, \ldots, n \tag{12}$$

$$\sum_{\substack{j=M+1 \\ i\neq j}}^{n} \sum_{k=1}^{K} x_{ijk} + \sum_{j=n+1}^{n+M}\sum_{k=1}^{K} x_{ijk} = 1 \ \forall i = M+1, \ldots, n \tag{13}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{M} x_{ijk} \leq 1 \ \forall j = M+1, \ldots, n \tag{14}$$

$$\sum_{\substack{j=M+1 \\ j\neq i}}^{n} x_{ijk} + \sum_{j=n+1}^{n+M} x_{ijk} + \sum_{\substack{j=M+1 \\ j\neq i}}^{n} x_{jik} + \sum_{j=1}^{M} x_{jik} = 2 * y_{ik} \ \forall i = M+1, \ldots, n; k = 1, \ldots, K \tag{15}$$

$$\sum_{i=1}^{M}\sum_{j=M+1}^{n} x_{ijk} \leq 1 \ \forall k = 1, \ldots, K \tag{16}$$

$$\sum_{i=M+1}^{n}\sum_{j=n+1}^{n+M} x_{ijk} \leq 1 \ \forall k = 1, \ldots, K \tag{17}$$

$$u_i - u_j + n * x_{ijk} \leq n - 1 \ \forall i,j = M+1, \ldots, n; i\neq j; k = 1, \ldots, K \tag{18}$$

$$\sum_{j=M+1}^{n} q_{ijk} = 0 \ \forall k = 1, \ldots, K; i = 1, \ldots, M \tag{19}$$

$$c_i * x_{ijk} = q_{ijk} \ \forall i,j = 1, \ldots, n+M; k = 1, \ldots, K \tag{20}$$

$$\sum_{i=1}^{n+M}\sum_{j=1}^{n+M} q_{ijk} = AOW_k \ \forall k = 1, \ldots, K \tag{18}$$

$$\left(\sum_{\substack{i=M+1 \\ i\neq j}}^{n}\sum_{j=M+1}^{n} c_i * x_{ijk} + \sum_{i=M+1}^{n}\sum_{j=n+1}^{n+M} c_i * x_{ijk} \right) \leq \text{Cap}_k \ \forall k = 1, \ldots, K \tag{21}$$

$$A_{jk} \geq A_{ik} + \left(tl_i + td_{ij}\right) - M\left(1 - x_{ijk}\right) \ \forall i,j = 1, \ldots, n + \text{M}; i\neq j; k = 1, \ldots, k \tag{22}$$

$$\text{A}_{jk} \leq A_{ik} + \left(tl_i + td_{ij}\right) + M\left(1 - x_{ijk}\right) \ \forall i,j = 1, \ldots, n + \text{M}; i\neq j; k = 1, \ldots, k \tag{23}$$

$$A_{jk} > CT_k \rightarrow \alpha_j = 1 \ \forall j = M+1, \ldots, \text{n}; k = 1, \ldots, K \tag{24}$$

$$\sum_{\substack{i=1 \\ i\neq j}}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} GA_k * d_{ij} * x_{ijk} \leq Lim_{GA} \tag{25}$$

$$\sum_{\substack{i=1 \\ i\neq j}}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} SI_k * d_{ij} * x_{ijk} \leq Lim_{SI} \tag{26}$$

$$\sum_{\substack{i=1 \\ i\neq j}}^{n+M}\sum_{j=1}^{n+M} td_{ij} * x_{ijk} + \sum_{i=M+1}^{n} tl_i * y_{ik} \leq LimTime_k \ \forall k = 1, \ldots, K \tag{28}$$

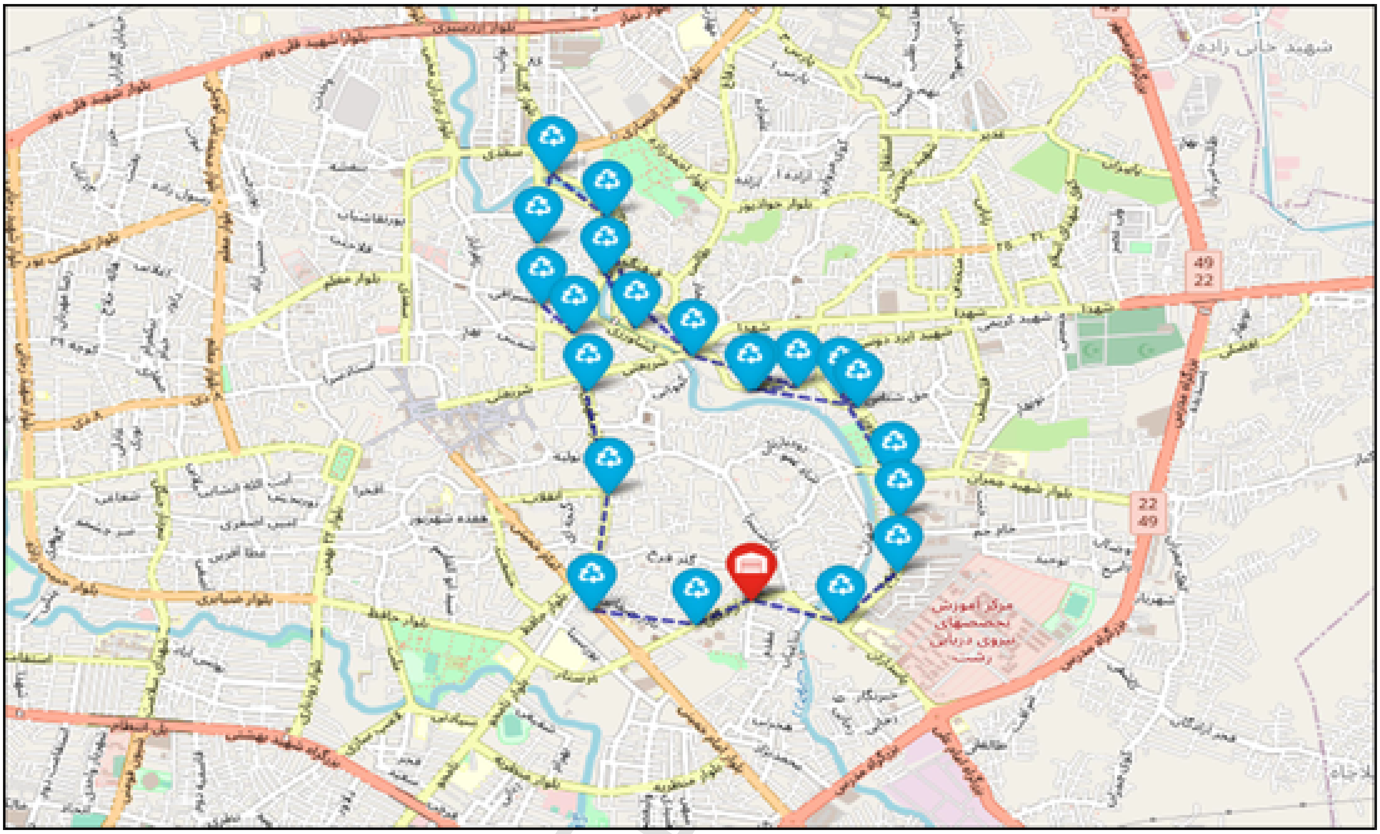

Fig. 5. An example of route in the routing model from bins to the separation centers.
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```
Solution representation Pseudocode
Create empty matrix with size (3*number of bin)
Filling first row by random permutation of number of bins
Filling each element of the second row with a random number between (1 to the number of
opened separation centers)
To assign bins to vehicles in each separation center:
Determine the number of separation centers
Determine the unique number of vehicles at each separation center
   for i=1: number of columns of the proposed matrix
       S <<= Finding the corresponding separation center at the location of i^th in the second row
       V <<= Generate a random number between (1 to the number of vehicles belonging to S)
  end
```

Fig. 6. Pseudocode of explained solution representation.

$$Tc * \sum_{\substack{i=1 \\ i \neq j}}^{n+M} \sum_{j=1}^{n+M} \sum_{k=1}^{K} d_{ij} * x_{ijk} \leq Lim_{tran} \tag{29}$$

$$\sum_{j=M+1}^{n} p_j * z_{ijk} \leq ths \; \forall \; i = 1, \ldots, n+M; k = 1, \ldots, k \tag{30}$$

In Eq. (11), minimization of the total cost composed of carbon dioxide emission, social impact, cost of utilizing vehicles, transportation cost, cost of exceeding the maximum available time to collect, and finally, total transported load by vehicles is minimized by the last element of the objective function. Vehicles are forced to collect waste from the farthest bins because of this part of the objective function. In this way, vehicles can travel longer distances with a lower load, thereby minimizing the amount of fuel consumed based on the load of vehicles. Moreover, the last element of the objective function rewards higher vehicle utilizations. Thus, the optimization model is incentivized to use vehicles at their maximum capacity. Eqs. (12) and (13) ensure that each bin must be visited one time. Eq. (14) guarantees that each bin must be assigned to one separation center. Eq. (15) provides the continuity of flow. Eqs. (16) and (17) force vehicles to start and finish their trips at separation centers. The elimination of sub-tour is guaranteed by Eq. (18). Eq. (19) determines that the loads of vehicles are zero when they are departing from separation centers. Eqs. (20) and (21) add the quantity of the waste in a visited bin to the vehicle's load and update the total weight of collected waste by each vehicle. The capacity constraint of the vehicles is satisfied by Eq. (22). Eqs. (23) and (24) specify that the arrival time of the vehicle to a bin is the summation of visiting time at the previous bin and the travel time between them. The violation of the

Bin	1	3	2	4	7	5	8	6	10	9
Separation center	1	1	2	1	2	2	1	1	1	2
Vehicle	1	1	3	2	3	3	1	1	2	3

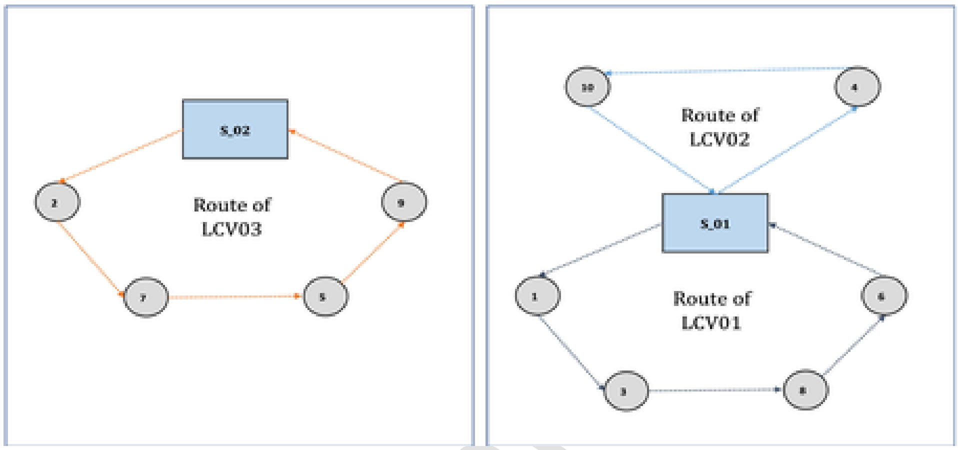

Fig. 7. An illustrative example of the solution representation.

Table 17
The proposed levels for the parameters of the meta-heuristic algorithms.

Algorithm	Factor	Levels L1	L2	L3	L^*
KA	A: Population size (n-pop)	750	950	1250	**950**
	B: Percentage of the population of Lucky Keshtel (P_{N1})	0.5	0.6	0.7	**0.7**
	C: percentage of N_2 Keshtel (P_{N2})	0.25	0.3	0.35	**0.3**
SEO	A: Collecting data rate(α)	0.15	0.2	0.25	**0.25**
	B: Connecting attacker rate(β)	0.03	0.05	0.07	**0.05**
	C: Number of connections (N)	40	60	80	**80**

Table 18
Detail objective function, RPD, HT results for each algorithm.

		SEO			KA		
		OF	RPD	HT	OF	RPD	HT
Small-Size	1	970.587294	0.26	14.60	786.025810	0.00	35.45
	2	623.369167	0.10	18.15	607.491547	0.07	46.44
	3	1571.770609	0.48	21.08	1095.075226	0.00	73.47
	4	1443.326234	0.12	34.71	1628.976513	0.28	94.31
	5	2512.425661	0.38	41.17	2172.225297	0.18	100.09
Medium-Size	6	1313.652181	0.00	71.44	1590.557534	0.23	167.17
	7	2233.581490	0.07	65.45	2104.471854	0.00	244.63
	8	2406.191218	0.15	111.80	2635.945074	0.27	287.82
	9	3598.036100	0.35	158.50	3164.251401	0.18	374.98
	10	4516.893992	0.29	198.55	4230.561568	0.20	494.12
Large-Size	11	5255.841734	0.31	981.02	5091.592361	0.27	2062.62
	12	5473.837033	0.18	1237.40	4827.620163	0.03	2998.55
	13	5773.298732	0.20	1681.40	5352.035797	0.10	3518.63
	14	5931.818440	0.07	1952.02	6193.835699	0.12	4752.89
	15	7741.404196	0.14	3152.20	8562.998426	0.27	7029.60

Note: HT: The first-time algorithm that can find the best solution (HT).

maximum available time for each vehicle is monitored by Eq. (25). Eq. (26) and Eq. (27) ensure the maximum allowable carbon dioxide emission and social impact, respectively. Accordingly, the maximum available time of each vehicle and total costs of utilizing vehicles are met by Eqs. (27) and (28). Eq. (29) ensures that each vehicle is assigned to bins with a total priority exceeding a predefined threshold. The highest priority bins are selected first by this constraint.

3.3. Mathematical formulation of the routing model from the separation center to recovery center

A mix-integer linear model of the Green Split Pick-up Capacitated Vehicle Routing Problem (GSPCVRP) is applied in this layer, in which the demand of a node can be divided among multiple vehicles assuming a homogeneous fixed fleet. High-capacity Vehicles (HCVs) are considered in this model. To pursue sustainable goals with respect to social and environmental impacts, the objective is to minimize fleet costs and total distance traveled. Split pickup services can be beneficial in reducing the number of vehicles used by improving capacity utilization. In addition, the model minimizes the variance of loads between vehicles to create load balancing among vehicles. Following the main assumptions are described in the following while the corresponding elements of the model are defined in Tables 7–9.

- The amount of waste from separation centers is deterministic.
- There is no direct trip between the separation centers.
- The travel time between the nodes is pre-defined and deterministic.
- The recovery center is considered in this model.
- The transportation cost per kilometer is the same for all vehicles.

The mathematical formulation of the model is provided by equations from (30) to (45).

$$\text{minimize } z = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K}(GA_k + Vp_k)*d_{ij} * x_{ijk} + Tc*\sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} d_{ij} * x_{ijk} + \sum_{i=0}^{p}\sum_{j=P+1}^{n}\sum_{k=1}^{K} Fc_k * x_{ijk} + \sum_{k=1}^{K} Tw_k - Avg \quad (31)$$

subject to:

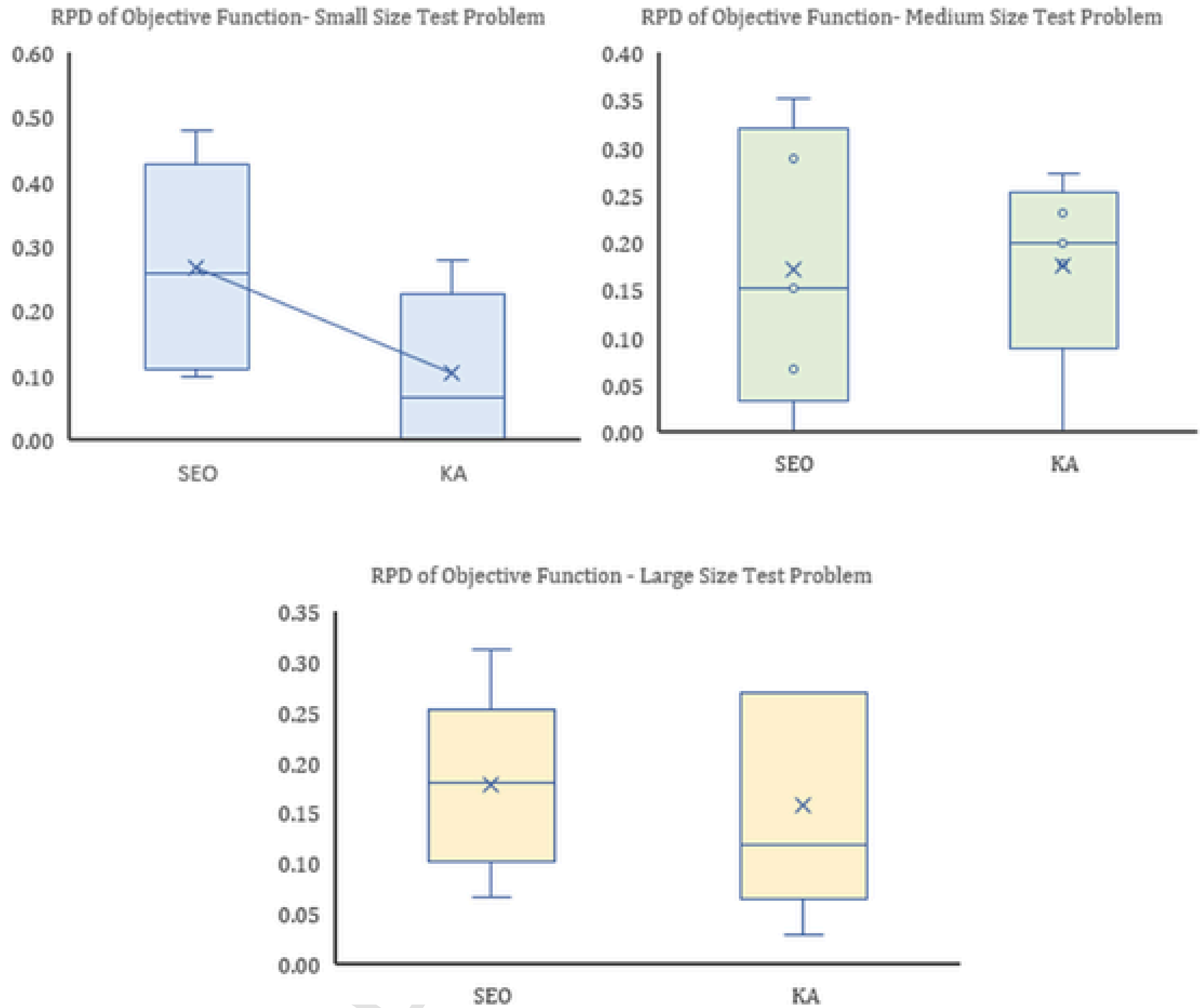

Fig. 8. The comparison of algorithms behavior concerning RPD in small, medium, and large size.

$$\sum_{\substack{i=P+1\\ i\neq j}}^{n}\sum_{k=1}^{K}x_{ijk} + \sum_{i=0}^{P}\sum_{k=1}^{K}x_{ijk} \geq 1 \;\forall\, j = P+1,\ \ldots,\ n \tag{32}$$

$$\sum_{\substack{j=P+1\\ j\neq i}}^{n}\sum_{k=1}^{K}x_{ijk} + \sum_{j=0}^{P}\sum_{k=1}^{K}x_{ijk} \geq 1 \;\forall\, i = P+1,\ \ldots,\ n \tag{33}$$

$$\sum_{\substack{j=P+1\\ j\neq i}}^{n} x_{ijk} + \sum_{j=0}^{P}x_{ijk} + \sum_{\substack{j=P+1\\ j\neq i}}^{n} x_{jik} + \sum_{j=0}^{P}x_{jik} = 2*y_{ik} \;\forall\, i = P+1,\ldots,n;\ k = 1,\ldots,K \tag{34}$$

$$\sum_{\substack{i=0\\ i\neq j}}^{n} x_{ijk} - \sum_{\substack{i=0\\ i\neq j}}^{n} x_{jik} = 0 \;\forall\, k = 1,\ldots,K;\ j = 0,\ldots,n \tag{35}$$

$$u_i - u_j + n * x_{ijk} \leq n-1 \;\forall\, i,j = P+1,\ \ldots,\ n;\ i\neq j;\ k = 1,\ldots,K \tag{36}$$

$$\sum_{j=P+1}^{n} q_{ijk} = 0 \;\forall\, k = 1,\ldots,K;\ i = 0,\ldots,P \tag{37}$$

$$q_{ijk} \leq AOW_i * x_{ijk} \;\forall\, i,j = 0,\ldots,n;\ k = 1,\ \ldots,\ K \tag{38}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n} q_{ijk} = Tw_k \;\forall\, k = 1,\ \ldots,\ K \tag{39}$$

$$\sum_{k=1}^{K} TW_k = TWC_i \;\forall\, i = 0,\ \ldots,\ P \tag{40}$$

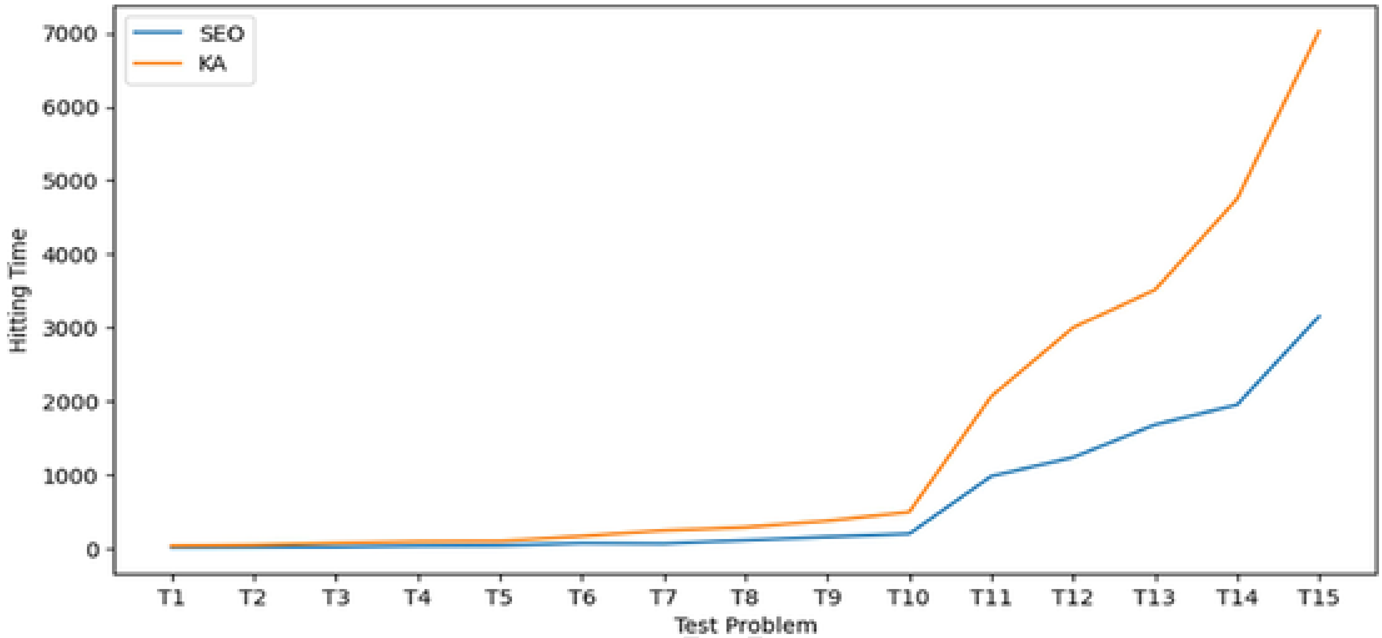

Fig. 9. Hitting time values for all test beds.

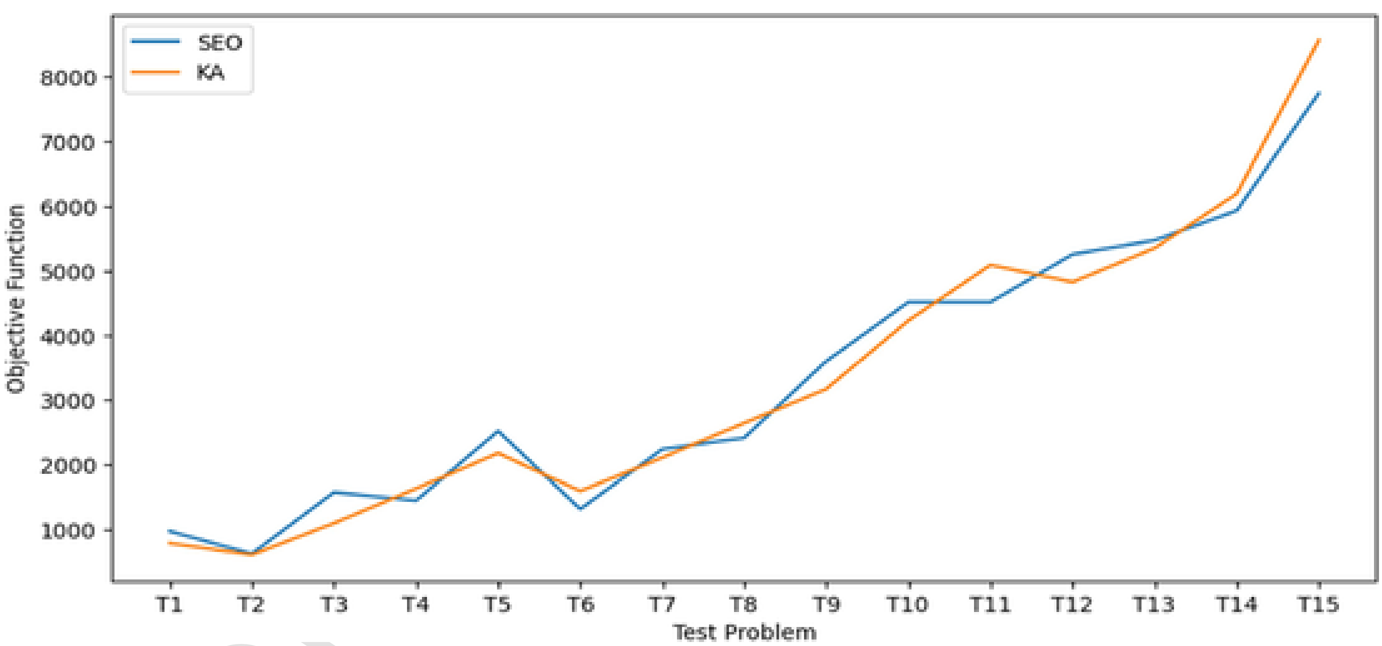

Fig. 10. Objective values for all test beds.

$$\left(\sum_{\substack{i=0 \\ i\neq j}}^{n}\sum_{j=0}^{n} q_{ijk}\right) \leq \mathrm{Cap}_k \ \forall\ k = 1, \ldots, K \tag{41}$$

$$\sum_{j=0}^{n}\sum_{k=1}^{K} q_{ijk} = AOW_i \ \forall\ i = P+1, \ldots, n \tag{42}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} GA_k * d_{ij} * x_{ijk} \leq Lim_{GA} \tag{43}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} Vp_k * d_{ij} * x_{ijk} \leq Lim_{VP} \tag{44}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n}\sum_{j=0}^{n} td_{ij} * x_{ijk} + \sum_{i=P+1}^{n} tl_i * y_{ik} \leq LimTime_k \ \forall\ k = 1, \ldots, K \tag{45}$$

Table 19
The parameters of the routing model from separation centers to recovery center.

Parameter	Values	Unit
i,j	0, 1, 6	–
FC_k	296,599,992	–
k	[1,32]	–
GA_k	1500	CO2 penalty per unit distance and vehicle
Vp_k	1200	Visual pollution per HCV k
AOW_i	[0, 171,253, 71,988.5]	Kg
$\mathbf{Cap}_k$	10,000	Kg
d_{ij}	Uniform ~ [7.4226, 13.2284]	km
td_{ij}	Uniform ~ [8.9072, 15.8741]	Time in minutes
tl_i	[0, 10, 10]	Time in minutes
$LimTime_k$	480	Time in minutes
Tc	1500	Cost per Km
Lim_{GA}	800,000,000	Gas conversion factor
Lim_{VP}	800,000,000	KWh to kg CO_2
n	2	–

Table 20
Optimization results of second-level routing problem - routing model from separation centers to waste bins.

Dimension	Number of separation center	2
	Number of recycling center	2
	Total travel time	803.445
Objective elements	maximum traveled distance	41
	Waste quantity in separation center	508,699.00
	Waste quantity in recycling center	254,349.50
	Number of vehicles	26
	Number of assigned vehicles to separation center number 1	26
	Number of assigned vehicles to separation center number 6	6
	Sustainability goal	6695,372.02
	Vehicle fixed cost	21,127, 670.00
	Transportation cost	4686,760.42
	Total cost	32,509, 802.44

Table 21
List of routes in the routing model from the recovery center to the separation centers.

Vehicle	Operational time (hours)	Traveled distance	Amount of collected waste	Vehicle capacity	Goods quantity/ capacity	Routes
1	31.74	26.44	9798	10,000	0.9798	$Re-1-Re$
2	31.74	26.44	9848	10,000	0.9848	$Re-1-Re$
3	31.74	26.44	9998	10,000	0.9998	$Re-1-Re$

$$Tc * \sum_{\substack{i=0 \\ i \neq j}}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} d_{ij} * x_{ijk} \leq Lim_{tran} \tag{46}$$

The environmental and social dimensions of sustainable goals are minimized in Eq. (30), as well as total transportation costs and fixed costs of utilizing vehicles. Moreover, the last element of the objective function provides a load balancing among vehicles by minimizing the deviation of loads between vehicles. In this context, the variance is considered as the sum of the difference between each vehicle's load and the average load. Eqs. (31) and (32) ensure that each separation center must be visited at least once to provide split collection. It is possible to visit a separation center following a visit to another separation center or a recovery center due to the constraints. The constraint in Eq. (33) is defined to assure the conservation of flow, and each separation center can be visited once by each specific vehicle but can be visited more than once by different vehicles. The constraint in Eq. (34) guarantees that all tours must be ended at the recovery center. The elimination of the subtour is provided by Eq. (35). The constraint in Eq. (36) is defined to ensure each vehicle is empty at the departure time from the recovery center. Eq. (37) coordinates the route construction, transported load, and split collection decision variables. Constraints in Eqs. (38) and (39) calculate the total weight of collected waste by each vehicle and then determine the total collected waste at the recovery center. The constraint in Eq. (40) ensures that the total collected waste by each vehicle does not exceed its capacity. Eq. (41) is designed to ensure the collection of all the waste in each separation center by different vehicles. Having a split collection without defining this constraint may result in a portion of the waste being left in the separation center. Constraints in Eqs. (42)–(45) are defined to set the maximum limit for carbon dioxide emission, visual pollution, available time, and maximum possible transportation costs. A user may use this set of constraints as an option, for instance, if financial resources are limited.

Table 22
The impact of the significant parameters of the model for the separation center location on the total cost.

Parameters	Parameter change (%)	Total cost	Change in total cost (%)
Land purchase cost	50 %	1781,754,628, 000	9.30 %
	25 %	1,705,754,628, 000	4.60 %
	0 %	1629,754,628, 000	0.00 %
	-25 %	1553,754,628, 000	-4.60 %
	-50 %	1477,754,628, 000	-9.30 %
Cost of creating capacity	50 %	2232,924,628, 000	37.00 %
	25 %	1931,344,628, 000	18.50 %
	0 %	1629,754,628, 000	0.00 %
	-25 %	1328,174,628, 000	-18.50 %
	-50 %	1026,584,628, 000	-37.00 %
Transportation cost	50 %	1648,044,628, 000	1.12 %
	25 %	1638,904,628, 000	0.56 %
	0 %	1629,754,628, 000	0.00 %
	-25 %	1620,614,628, 000	-0.56 %
	-50 %	1611,464,628, 000	-1.12 %
CO_2 emission cost	50 %	1500,837,933, 800	1.12 %
	25 %	1593,068,933, 800	0.56 %
	0 %	1585,291,433, 800	0.00 %
	-25 %	1577,522,433, 800	-0.56 %
	-50 %	1569,744,933, 800	-1.12 %

4. Solution approach

The complexities of urban waste management necessitate creative and systematic approaches. This section elaborates on the solution

Table 23
The impact of the significant parameters of the first routing model on the total cost.

Parameters	Parameter change (%)	Total cost	Change in total cost (%)
CO_2 emission cost	50 %	78,622,392	10.80 %
	25 %	74,611,103	5.20 %
	0 %	70,905,850	0.00 %
	-25 %	66,750,236	-5.80 %
	-50 %	62,403,445	-11.90 %
Fixed cost of vehicle	50 %	93,510,204	31.80 %
	25 %	82,300,076	16.06 %
	0 %	70,905,850	0.00 %
	-25 %	60,107,942	-15.20 %
	-50 %	49,773,095	-29.80 %
Transportation cost	50 %	75,468,867	6.40 %
	25 %	74,285,974	4.70 %
	0 %	70,905,850	0.00 %
	-25 %	66,641,174	-6.10 %
	-50 %	64,256,676	-9.30 %

Table 24
The impact of the significant parameters of the second routing model on the total cost.

Parameters	Parameter change (%)	Total cost	Change in total cost (%)
CO_2 emission cost	50 %	35,857,490	10.30 %
	25 %	34,183,650	5.10 %
	0 %	32,509,800	0.00 %
	-25 %	30,835,960	-5.10 %
	-50 %	29,162,120	-10.30 %
Fixed cost of vehicle	50 %	43,073,640	32.50 %
	25 %	37,791,720	16.20 %
	0 %	32,509,800	0.00 %
	-25 %	27,227,890	-16.20 %
	-50 %	21,945,970	-32.50 %
Transportation cost	50 %	34,853,180	7.20 %
	25 %	33,681,490	3.60 %
	0 %	32,509,800	0.00 %
	-25 %	31,338,110	-3.60 %
	-50 %	30,166,420	-7.20 %

methodology behind our proposed three-step waste management system designed to balance economic efficiency, environmental sustainability, and societal considerations. The proposed methodology is grounded in three main components: the Facility Location Problem (FLP), the first-level routing problem, and the second-level routing problem. The FLP is vital in determining the optimal locations for waste separation centers, a task complicated by various factors like cost, service quality, and meeting customer demands. To tackle this issue, our study employs a combination of mathematical models and numerical methods, providing solutions for both small-scale and large-scale instances of FLP. The Simplex Method and Newton-Raphson iterations form the backbone of our approach to smaller instances, whereas heuristic or approximation algorithms come into play for larger-scale problems. Next, the First-Level Routing Problem addresses the crucial task of waste collection [38]. It involves the strategic planning of vehicle routing to ensure efficient waste collection from various points within specific timeframes. Due to its dynamic nature and inherent complexities, this routing problem requires the use of powerful meta-heuristic algorithms, like the Social Engineering Optimization (SEO) and Keshtel Algorithm (KA). These algorithms have proven to be effective in tackling the dynamic VRP that characterizes waste collection. The Second-Level Routing Problem focuses on the routing model from the recovery center to the separation centers. Here, we use the linear programming Simplex method, combined with the GAMS optimization software, to deliver an efficient and optimal solution. This combination allows for the accurate determination of optimal routes, hence enhancing the transportation and logistical aspects of the waste management system. Incorporating these three components, the proposed methodology offers a resilient and adaptable solution to waste management. To demonstrate the practicality and applicability of this methodology, we apply it to a case study of a small city in Iran.

4.1. Facility location problem – separation center location problem solution methodology

Facility Location Problem (FLP) is a crucial optimization challenge within the field of supply chain management and logistics. Its objective is to determine the optimal location of facilities, such as warehouses or factories, considering factors like cost, service quality, and meeting customer demands. FLP is formulated as a Multi-Objective Optimization (MOO) that searches for the optimal facility locations that balance between minimizing transportation costs and reducing environmental impact. MOO seeks to find a set of solutions that account for conflicting objectives, rather than a single optimal solution. To tackle this challenge, the epsilon-constraint method is a widely adopted approach that is formulated in Eq. (46). It transforms conflicting objectives into constraints, designating one objective as the primary optimization goal while treating the others as constraints with an upper limit (epsilon). By varying the value of epsilon, a range of solutions along the Pareto frontier, representing optimal trade-offs between objectives, can be generated.

In the presented problem, the epsilon-constraint method can be employed to navigate the trade-off between transportation costs and environmental impact. By setting an upper limit (epsilon) for the carbon emission costs and treating it as a constraint, a diverse set of solutions that offer various compromises between transportation costs and environmental sustainability can be obtained. Utilizing the epsilon-constraint method empowers decision-makers to thoroughly analyze and select solutions from the Pareto frontier that align with their specific preferences and priorities. It offers a comprehensive perspective on optimal trade-offs, facilitating an informed decision-making process within the context of FLP with multiple conflicting objectives.

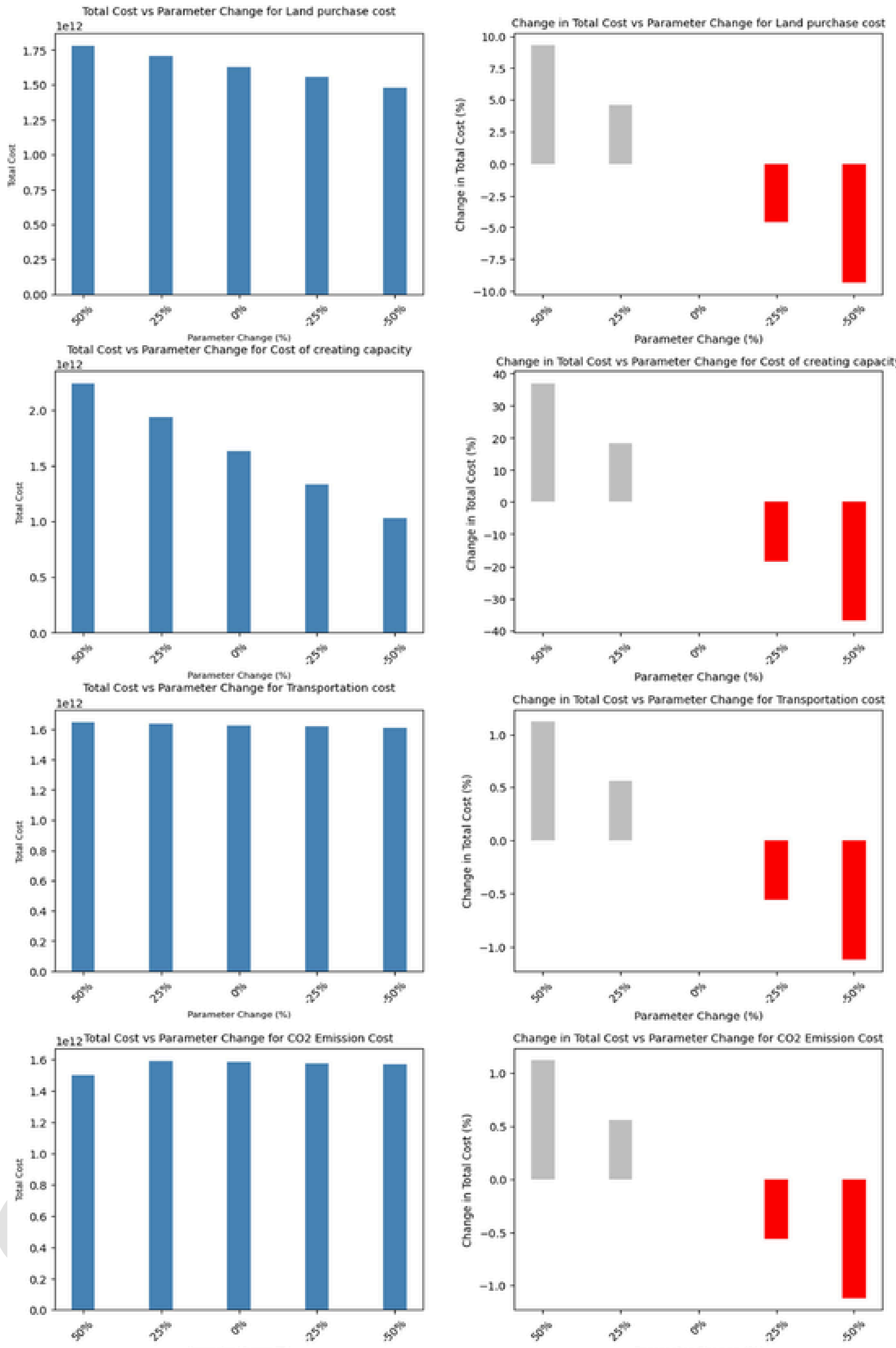

Fig. 11. The impact of the significant parameters of the model for the separation center location on the total cost.

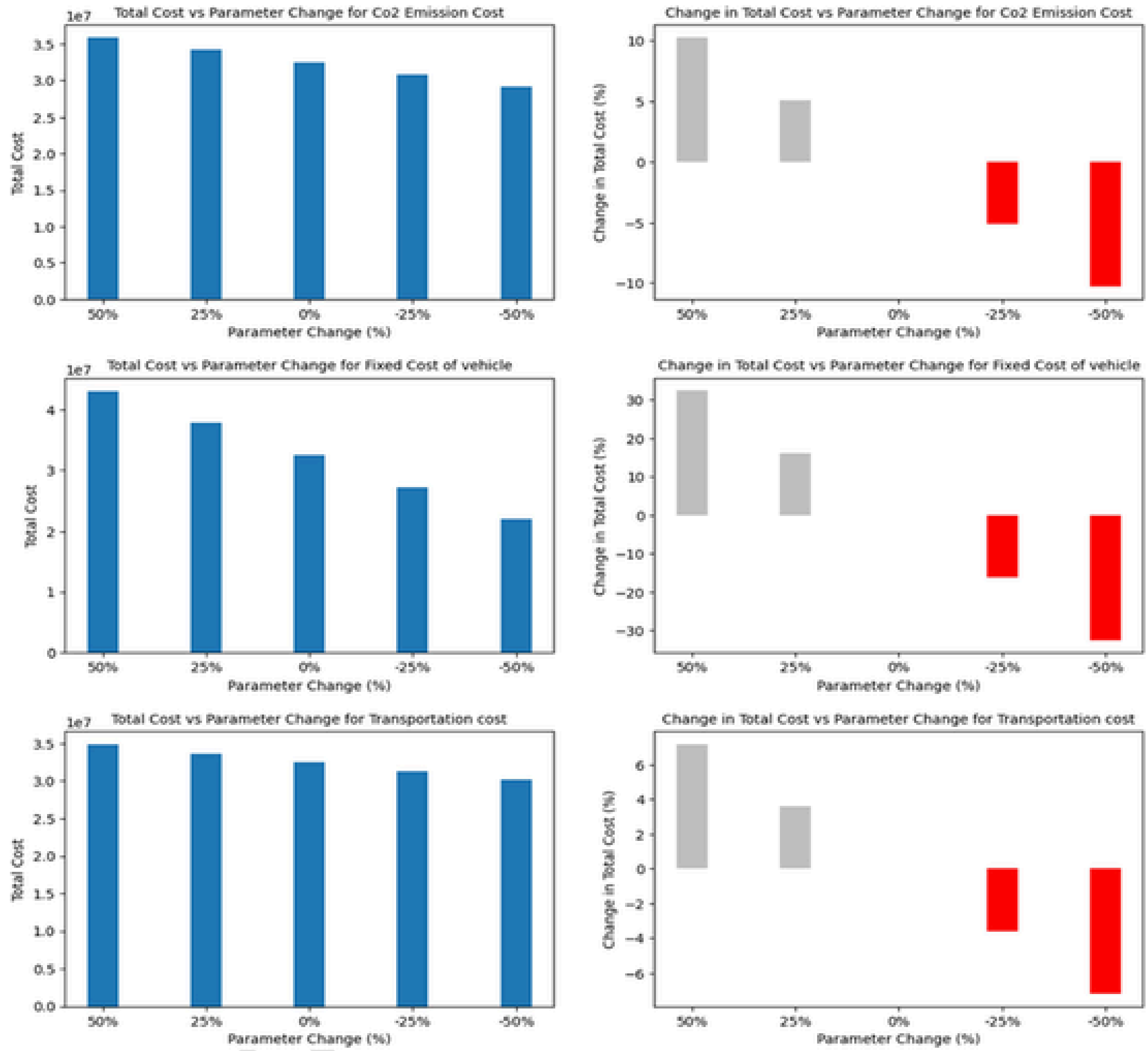

Fig. 12. The impact of the significant parameters of the first routing model on the total cost.

$$\begin{aligned} &\text{minimize} f_l(x) \\ \textit{subject to } & f_j(x) \le \ \varepsilon_j \text{ for all } j = 1,\dots,k,\ j \ne l \\ & x\ \in S \end{aligned} \tag{47}$$

Where $l \in \{1,\dots,k\}$ *and* $^{\varepsilon}j$ are upper bounds for the objective, *(j≠ l)*.

4.2. Solution approach of routing model from bins to separation centers solution approach

The first-level routing problem addresses the waste collection of waste from bins to separation centers. It involves the strategic planning of vehicle routing to ensure efficient waste collection from various points within specific timeframes. Due to the inherent complexity of VRP –recognized as NP-Hard combinational optimization problems– these exact methods prove insufficient for real-sized scenarios, as they fail to provide solutions in a reasonable timeframe. Consequently, heuristic and meta-heuristic approaches have become increasingly preferred [21,39]. So, to address the proposed problem, two suitable meta-heuristic algorithms, Social Engineering Optimization (SEO) and Keshtel Algorithm (KA), are applied from both categories[62–64].

The SEO algorithm, a single-based solution metaheuristic, has recently emerged as a successful approach to solving various combinatorial optimization problems, including VRP, supply chain network design, and scheduling problems. The algorithm starts with the generation of two randomly generated solutions, known as the attacker and defender, based on their fitness function values. Inspired by the training and retraining activities observed in the human behavior, the algorithm designs random experiments for each characteristic of the defender. The attacker then assesses the defender based on these extracted characteristics and traits. During this process, some features of the attacker are converted to match those of the defender in the search space, while simultaneously computing the retraining rate of the attacker based on the defender. In the subsequent phase, a Social Engineering (SE) attack procedure is detected as an effective method to alter the defender's po-

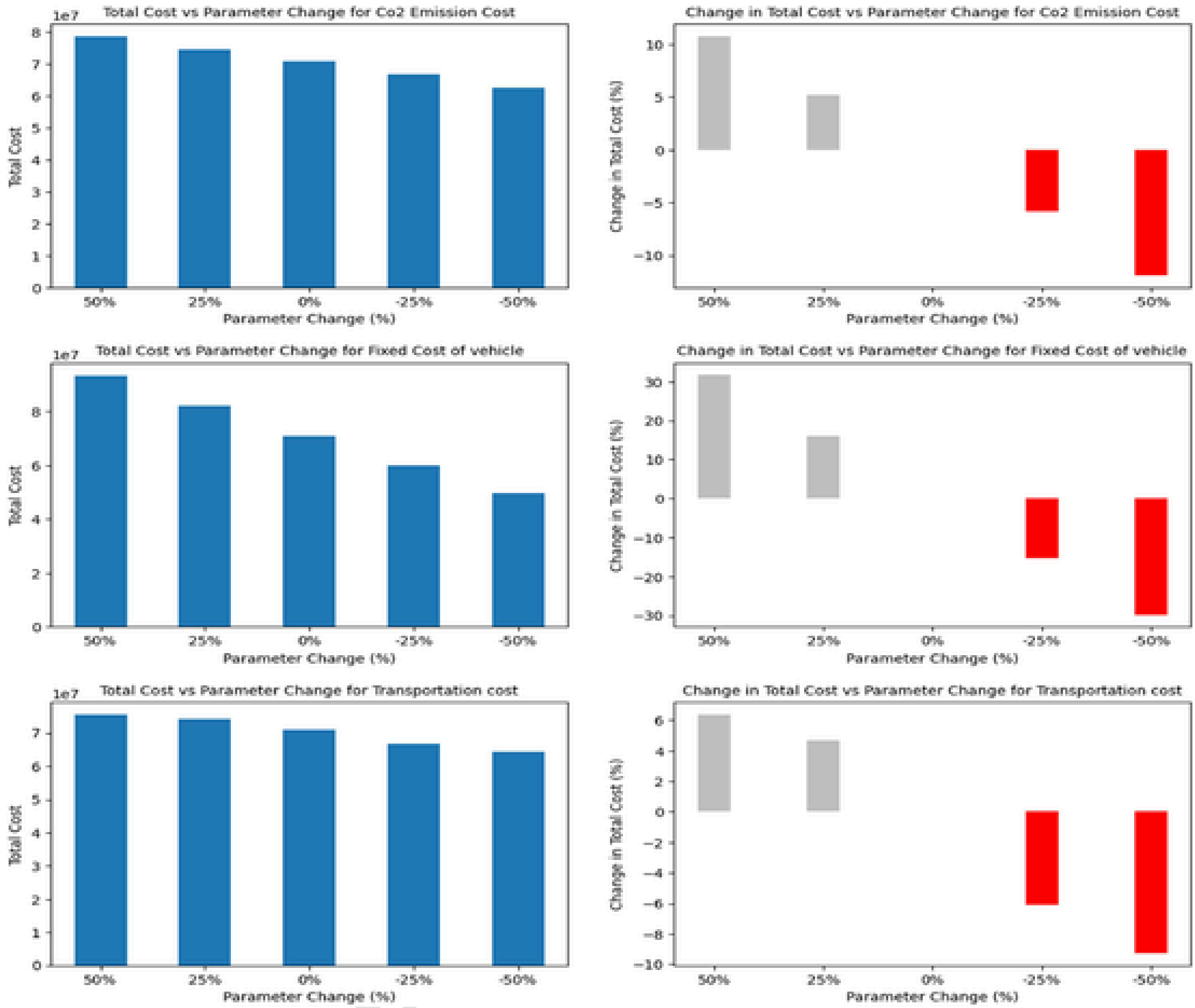

Fig. 13. The impact of the significant parameters of the second routing model on the total cost.

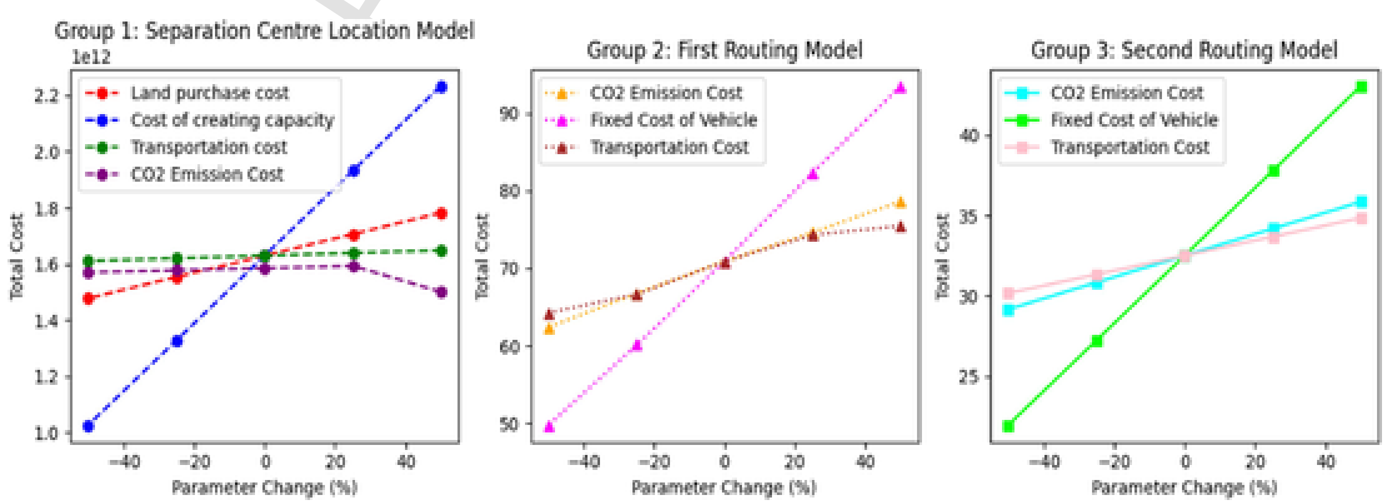

Fig. 14. The impact of the significant parameters of all models on the total cost.

sition within the feasible space. To respond to a SE attack, the fitness value of the new defender's position is calculated, and a comparison is made between the old and new position. The best position is then selected based on these comparisons. If the fitness value of the defender surpasses that of the attacker, a change in position occurs between the attacker and defender. Finally, to maintain the effectiveness of the attacker, the defender is replaced by a new random solution within the search space [40].

In recent years, a population-based metaheuristic algorithm inspired by the feeding behavior of Keshtel birds has been developed by Hajiaghaei-Keshteli [41]. The algorithm draws its core concept from the natural process in which Keshtel birds search for valuable food sources in lakes and engage in a swirl and circling procedure until the food is depleted[66]. At the start of the algorithm, a population of initial solutions, represented as Keshtel birds, is randomly generated to address an optimization problem. The population is then divided into three distinct groups: *N1, N2*, and *N3*. *N1* comprises the "lucky" Keshtels that have successfully located a good food source, while N3 consists of the poorest solutions in the population. The algorithm calculates the nearest neighbors around these lucky Keshtels, which is an essential step in the process. The swirling procedure continues around the current food source until a better source is found, and the population belonging to *N2* moves between the other two groups. In this way, *N1* is responsible for the intensification phase of the algorithm, focusing on exploiting the promising solutions; however, *N2* and *N3* contribute to the diversification phase, ensuring the exploration of the search space. To enhance the computational efficiency of the algorithm, researchers have focused on developing solution representations that reduce the running cost. The specific procedure used to represent the solutions of the proposed problem is described in detail in the subsequent section.

4.3. Solution approach of routing model from separation centers to waste bins

To address the routing model from the recovery center to the separation centers a simplex method is applied. This method systematically explores the feasible solution space, iteratively improving the objective function to determine the optimal solution. Given the presence of linear constraints and objectives in the routing model, the simplex method is well-suited for efficiently obtaining an exact solution. To accomplish this, we employed the GAMS optimization software, which seamlessly integrates the simplex method into its framework. By leveraging GAMS alongside the simplex method, we were able to effectively solve the routing model, optimizing the routes from the recovery center to the separation centers. This approach successfully addresses the transportation and logistical intricacies associated with waste management. These findings emphasize the suitability and effectiveness of utilizing the simplex method within GAMS to solve routing models in waste management scenarios. The accurate determination of optimal routes contributes to the efficient operation of the system, enhancing sustainability and resource allocation within the waste management process.

5. Computational results

The applicability of a proposed solution is assessed through its outcomes. This section, therefore, explores the computational results derived from implementing the three-step waste management system and applies a sensitivity analysis to them. These analyses offer insight into the system's performance and aim at highlighting its adaptability and efficiency. The computational results are analyzed in two ways: the primary results are the immediate outcomes from deploying the proposed methodology; the sensitivity analysis investigates the models' responses to variations in key parameters. This comprehensive exploration provides a thorough understanding of the model's capabilities and potential improvement areas.

5.1. Model I – solution methodology of the separation center location problem

A significant aspect of waste management involves the strategic placement of separation centers. Determining the location of these centers involves considering multiple factors, including population density, waste generation rates, proximity to waste sources, existing transportation infrastructure, and potential environmental impacts particularly carbon dioxide (CO_2) emission. The objective is not just to minimize transportation costs but also to reduce environmental impacts, specifically CO_2 emissions. This emphasis on CO_2 emissions is of critical importance, because transportation is a relevant contributor to greenhouse gas emissions and thereby climate change. To integrate this important environmental consideration, our model incorporates a penalty factor for CO_2 emissions. This emission penalty is applied to waste transportation between separation centers and waste bins as well as between recovery centers and separation centers. The penalty is calculated based on the distance of transportation and the CO_2 emission penalty per kilometer (TE), as described in Eqs. (43) and (44) respectively.

Additionally, the proposed model considers CO_2 emissions from gas and electricity consumption at each separation center. It is well-known that energy consumption for operations at these centers contributes significantly to the total emissions footprint. The CO_2 emission penalty due to gas consumption at each separation center is determined using Eq. (45), which follows from the method described by Harris et al., [42]. Similarly, the CO_2 emission penalty attributable to electricity consumption at each separation center is calculated using Eq 47. The corresponding steps are outlined in Fig. 3. By integrating these emission penalties, our model offers a holistic approach to urban waste management that accounts for both economic and environmental aspects, encouraging more sustainable practices. This comprehensive strategy ensures that the various sources of emissions in the waste management process, from transportation to operational energy consumption, are addressed effectively.

$$\mathrm{e\_t}_{ij} = d_{ij} \ * \ TE \tag{49}$$

$$\mathrm{e\_tr}_{Rej} = \mathrm{d\_}Re_{Rej} * TE \tag{50}$$

$$e\_g_j = \left(\frac{G_c * v_j * G_{cf}}{B_{tu}} \right) * c_f \tag{51}$$

$$\mathrm{e\_e}_j = \left(\mathrm{E}_c * \mathrm{v}_j * \mathrm{E}_{cf} \right) * \mathrm{c}_f \tag{52}$$

Moreover, this model is designed to find the best location of the separation centers. In designing this model, two main points were considered: the ability of proposed locations to effectively handle the task of waste separation, and their potential to reduce overall costs. A mathematical model was developed to optimize the selection process in small size problems. The model is solved for a test problem obtained from a real case in Iran whose corresponding data are reported in Table 10. The result of the model strongly suggested that separation centers number one y(1) and number six y(6) are the best options for setting up these facilities (See Fig. 4 and Table 11). The proposed model ensures the capacity of potential locations that effectively handle waste separation, considering also the costs associated with these locations. For instance, in a specific solution given by the model, separation center number 1 is given 932 waste bins and separation center number 6 is assigned 352 waste bins. This unequal distribution is designed to favor the first separation center. The reasons for this are several, but include its strategic location and increased capacity, which leads to lower transportation costs. The main goal of this model is to figure out the best way to distribute separation centers. It accomplishes this task by finding the best spots for these centers in areas that have enough room for waste separation, while also trying to keep the overall costs as low as possible. Deciding how many waste bins to assign to each center is a complex task that involves balancing many factors. These include the costs to transport waste to each center and the amount of waste each center can handle. Thus, the model provides a strong plan to manage different separation centers improving efficiency and reducing costs.

5.2. Routing model from separation centers to waste bins

This section gives detailed computational results of the routing problem associated with waste collection from bins to separation centers. The data related to the problem are outlined in Table 14. The structured design of the waste management network required an initial solution to the location-allocation model. This crucial first step determines the count of operational separation centers, setting the stage for the subsequent processes in the waste management system. In addition to the transportation and environmental costs, the social impact cost is considered in this step. Measurement of social impact cost can indeed be a difficult task due to the multifaceted nature of the factors involved. However, relevant social and environmental impact is achievable based on several studies, and they are generally represented in monetary terms for ease of comparison and aggregation with other objective function elements. After identifying these factors and their relevance to the specific situation, data related to these factors need to be collected; for instance, measurements of noise levels or air pollution caused by waste collection vehicles, or data regarding additional travel time caused by these vehicles when inducing traffic congestion. The following stage, as the most challenging one, involves quantifying these impacts, which requires determining their social cost. Once the impact of each factor is quantified, it may need to be weighted based on its perceived significance or severity. Then, the total social impact costs can be determined by the summation of the weighted impact costs of all the factors [10,43,44]. Optimization results of the routing model from bins to separation center for the first and second periods are reported in Tables 12–16 and the patterns of the resulting routes are illustrated in Fig. 5.

5.2.1. Solution representation

Solution representation is integral to the functionality of the metaheuristic algorithm employed: a matrix consisting of three rows, corresponding to bins, separation centers, and vehicles are utilized for the proposed problem [45–47]. Let us consider the first row of the matrix which is related to the bins of the proposed problem. This matrix length depends on the number of bins. The first row gives the sequence of visiting bins based on a random permutation of the number of bins, while the second row indicates which bin is assigned to each separation center. The last row in the matrix represents the assignment of the vehicles in each separation center to visit the assigned bins. Fig. 6 is the pseudocode of explained solution representation.

Fig. 7 gives an illustrative example of the solution representation that contains a randomly generated matrix as a possible solution and the corresponding routes. In this example, the numbers of objects that define the problem are generated randomly to take a generic possible solution. This example contains 10 bins, 2 separation centers, and 3 vehicles. The first row of the matrix [1, 3, 2, 4, 7, 5, 8, 6, 10, 9] indicates the sequence of bin visits; the second row [1, 1, 2, 1, 2, 2, 1, 1, 1, 2] assigns each bin to a separation center; and the third row [1, 1, 1, 2, 1, 1, 1, 1, 2, 1] designates the vehicle for each bin. In this case, bins 4 and 10 are assigned to the truck LCV02 of the separation center number 1 (S_01). Bins 1, 3, 8, and 6 are assigned to the truck LCV01 of the first separation center, while bins 2, 7, 5, 9 are assigned to a single vehicle LCV03 that visits the second separation center (S_02).

5.2.2. Parameter level of the proposed metaheuristic algorithm

Since the parameters of a metaheuristic algorithm directly affect its performance, a fine tuning is necessary to get the desired performance. In this paper, the Taguchi method is applied to fix the values of each parameter of the metaheuristic algorithms [48–50][60]. Generally, the Taguchi method is a robust problem-solving method to improve the process performance and productivity of algorithms. This method ensures the quality of a process by a reasonable test number [51–53]. The variation of each parameter and its optimal level is determined according to the signal-to-noise (S/N) ratio. Two equations for standard ratios are defined in Eqs. (53) and (54). The parameters Y_i and n represent the response value and the number of observations, respectively. If the response is maximum, the "Larger is better" state is considered by Eq. (53) to optimize the process. Otherwise, the "Smaller is a better" state is considered when the response is a minimum and is calculated by Eq. (54) [54–56]. Accordingly, the proposed levels of parameters for each algorithm are listed in Table 17 and one of them, determined as L^*, is selected as the best one. Testing all combinations of parameters for each algorithm is time-demanding because of the Taguchi orthogonal array. A proportion of these tests should be investigated instead to find the minimum S/N to select the best levels of parameters [57,58].

$$S/N\ ratio = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^{\,2}\right) \tag{53}$$

$$S/N\ ratio = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^{\,2}}\right) \tag{54}$$

To ensure comparability of the objective function across different trials, the relative percentage deviation (RPD) method is employed. This method normalizes the objective function values, allowing for a consistent scale of comparison. To calculate the RPD the objective function values in the algorithm (Alg_{sol}) and the best solution for the trial (Min_{sol}) are utilized. The RPD is then computed, and the average RPD is determined for each trial. The Taguchi approach develops orthogonal arrays according to the mean signal-to-noise ratio estimated by RPD in Eq. (55).

$$RPD = \frac{|Alg_{sol} - Min_{sol}|}{Min_{sol}} \tag{55}$$

5.2.3. Computational results of the proposed algorithms

This section presents a computational study to test the performances of the proposed metaheuristic algorithms to solve generated random instances, which are classified into three groups: small, medium, and large size problems. These test problems are solved by each algorithm thirty times to consider the approximate nature of the metaheuristic algorithms. For each run, three indicators are calculated to evaluate algorithms and finally the average value of each indicator is computed for each algorithm. Detailed results of the minimum values of the objective function for each algorithm and other indicators are reported in Table. 18 for each instance.

As depicted in Fig. 8, in small-sized test problems, SEO exhibits a greater variation in RPD values compared to KA, indicating that SEO's response time might fluctuate more widely for this set of instances. This could potentially affect the efficiency of SEO in small-sized problem sets. For medium-sized test problems, the deviation in RPD values for SEO increases compared to the small-sized problems, suggesting less consistency in response times. On the other hand, KA exhibits a tighter range of RPD values, and is a more consistent performer in terms of response time for medium-sized test problems. However, the scenario changes for large-sized problems. Here, the KA algorithm shows a higher variation in RPD values than SEO, implying that the former's efficiency may drop with the increase of the problem size. SEO performs more consistently in these instances, highlighting its robustness to problem size in terms of response time. Figs. 9 and 10 illustrate the behavior of hitting time and objective function, respectively. Across all problem sizes, SEO consistently outperforms KA in terms of hitting time. This suggests that SEO, irrespective of the problem size, is more likely to arrive at a solution faster than KA. This robust performance of SEO across different problem sizes underscores its superior efficiency.

The comparison in terms of the objective function highlights that in larger test problems both algorithms show considerable deviations in their solutions. However, SEO exhibits a more tightly clustered set of outputs, implying better precision and reliability than KA in larger problem contexts. To summarize, while both algorithms show strengths in different areas: SEO demonstrates more robust and consistent performances across different problem sizes, especially in terms of response time and hitting time. However, it is important to consider the specific context and requirements when choosing an algorithm, as KA also shows potential advantages, particularly in the response time when handling medium-sized test problems.

5.3. Routing model from separation centers to waste bins

The second level of the routing problem involves the collection of sorted waste from various separation centers and its transfer to recovery centers. The volume of waste at each separation center can potentially exceed the capacity of each vehicle, thereby necessitating the concept of split pickups. Despite the potential requirement for multiple vehicles to gather all waste from a single separation center, the relatively small number of such centers, as determined by the facility location model, allows the efficient use of exact methods to solve the problem within a reasonable timeframe. This problem has been encoded and resolved using GAMS/CPLEX. The data pertaining to the second-level routing problem are also influenced by the output of the facility location model. These data are reported in Table 19. It is important to mention that the distance between every two nodes is calculated based on the Haversine formula. The optimization results of the second-level routing problem from separation centers to waste bins is summarized in Tables 20 and 21.

5.4. Sensitivity analysis

Sensitivity analysis is a method that measures how the impact of uncertainties of one or more input variables can lead to uncertainties in the output variables and investigates how small changes in inputs affect the outcomes. This analysis is useful because it allows to improve the predictions produced by the model and to reduce it by studying qualitatively and/or quantitatively the model response to changes in input variables. In this section, the capacity of the separation centers $v(j)$ and the minimum distance *md* between two separation centers are analyzed through the sensitivity analysis. The corresponding results are reported in Tables 22–24. Moreover, the impact of significant parameters on the total cost for each model is illustrated in Figs. 11–14.

6. Conclusions

Waste collection is a critical step in waste management with significant economic, societal, and environmental impacts. This study focuses on enhancing the efficiency of this crucial component, focusing on the challenge of insufficient land in urban areas for separation center facilities. Since the usual assumption of one separation center per zone presents a barrier to progress, incorporating both the facility location and routing problems within our management system is the goal of this study. Hence, a location-allocation model is proposed followed by the formulation of two sustainable routing problems to enable an efficient collection of waste from bins to separation centers and then to recovery centers. This novel approach brings a new perspective to the logistics of waste management and has the potential to significantly improve system efficiency.

The facility location model proposes an innovative method to locate and distribute waste separation centers. Through optimization, optimal locations such as are proposed based on strategic location, increased capacity, and overall cost-efficiency. By considering the capacity and costs associated with potential locations, we offered a strategy to manage waste more effectively and economically. Determining the number and location of facilities is a long-term decision that is made at the strategic level. So, instead of assuming a predefined number of separation centers, a multi-objective location-allocation model is presented to determine the opened facility with sustainable goals in this paper and solved by the epsilon constraints method in GAMS. Then, the first-level routing problem was addressed using low capacitated vehicles for the day and night intervals integrating real-time data from sensor-equipped bins. The Social Engineering Optimizer and the Keshtel Algorithm were tested and compared to select the most suitable method to solve the problem. The former showed the smallest variation in objective function for small test instances in comparison to the latter, while the opposite conclusion was achieved for larger instances. For the second-level routing problem, a split pickup approach was utilized because of the larger amounts of waste to handle in each separation center. The optimization of the route was performed in GAMS/CPLEX with considerations for sustainable goals such as CO_2 emissions, social impact, and economic factors. The results highlight the potential benefits of leveraging real-time data, mathematical modeling, and strategic allocation to improve waste management systems. Further work could be conducted to refine the model and test its performance in larger-scale applications.

Future research should consider incorporating transshipment points into the waste management network, where vehicles can exchange loads without requiring additional storage capacity. This is particularly applicable to crowded urban areas, where the use of even low-capacity vehicles can exacerbate traffic and environmental issues. Therefore, a practical solution would involve a three-tier routing system, where waste is collected at these transshipment points before being transported to separation centers. This approach would require an integrated solution, where the first and second routing levels are solved simultaneously, allowing efficient waste collection. Future work should not only investigate optimal locations for separation centers but also analyze the optimal number and locations for these transshipment points within the facility location model. Moreover, future studies should consider more specific characteristics of real-world scenarios, such as the handling of hazardous waste, the weight of waste, and the use of historical data on each bin's filling rate. This would allow for different thresholds for different bins in various zones, leading to more accurate waste collection schedules. Furthermore, the incorporation of socioeconomic factors of the zones in dynamic routing could significantly improve the quality of routes provided by the optimization approach, making the waste management system even more efficient and effective.

Credit authorship contribution statement

Mostafa Mohammadi and Golman Rahmanifar did the conceptualization, formal analysis, investigation, methodology, and writing - original draft. **Mostafa Hajiaghaei-Keshteli, Gaetano Fusco,** and **Chiara Colombaroni** supervised the project, validation, visualization, writing - review & editing.

Uncited references

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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