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Multi-objective sustainable location-districting for the collection of municipal solid waste: Two case studies

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ABSTRACT

This paper presents a multi-objective location-districting optimization model for sustainable collection of municipal solid waste, motivated by strategic waste management decisions in Iran. The model aims to design an efficient system for providing municipal services by integrating the decisions regarding urban area districting and the location of waste collection centers. Three objectives are minimized, given as 1) the cost of establishing collection centers and collecting waste, 2) a measure of destructive environmental consequences, and 3) a measure of social dissatisfaction. Constraints are formulated to enforce an exclusive assignment of urban areas to districts and that the created districts are contiguous. In addition, constraints make sure that districts are compact and that they are balanced in terms of the amount of waste collected. A multi-objective local search heuristic using the farthest-candidate method is implemented to solve medium and large-scale numerical instances, while small instances can be solved directly by commercial software. A set of randomly generated test instances is used to test the effectiveness of the heuristic. The model and the heuristic are then applied to two case studies from Iran. The obtained results indicate that waste collection costs can be reduced by an estimated 20–30%, while significantly improving the performance with respect to environmental and social criteria. Thus, the provided approach can provide important decision support for making strategic choices in municipal solid waste management.

1. Introduction

Urban development, population growth, and lifestyle changes, including consumption patterns, have created a great deal of problems, and making efforts to tackle them are inevitable. Nowadays, with the increase of waste generation in urban communities, waste management systems can be considered as part of a comprehensive management system, which is currently one of the most important public issues. Developing efficient municipal solid waste (MSW) management systems is one of the most important efforts to protect resources, the environment, and public health. MSW management regulates the processes of production, warehousing or storage, collection, transfer and transportation, recycling, and disposal of solid waste, in which the best practices for health, economic and social considerations, as well as administrative, financial, and planning methods are applied (Fernández-Nava, Del Rio, Rodríguez-Iglesias, Castrillón, & Marañón, 2014).

Household waste, food waste, industrial waste, commercial waste, construction waste, and sanitary waste are known as solid waste (Edjabou et al., 2015). The focus in this paper is on MSW, which excludes hazardous waste and recyclable materials. MSW management is influenced by many environmental, social, financial, political, and technical factors considered directly in urban management (Agamuthu & Masaru, 2014). The important problems of MSW management include waste collection (Chi, Wang, & Reuter, 2014), waste treatment (Jouhara, Nannou, Anguilano, Ghazal, & Spencer, 2017), waste routing (Rabbani, Heidari, Farrokhi-Asl, & Rahimi, 2018), waste disposal (Şener, Sener, & Karagüzel, 2011), and waste location (Rabbani et al., 2018).

Operations research (OR) has many applications in solid waste management (Ghiani, Laganà, Manni, Musmanno, and Vigo, 2014). One of the most important applications is the collection network design in the form of a multi-echelon logistics structure including the location of collection centers and allocation of demand areas using mathematical models (Eiselt & Marianov, 2015), optimization algorithms (Rabbani

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et al., 2018), and multi criteria decision making (MCDM) methods (Soltani, Hewage, Reza, & Sadiq, 2015). The disposal collection and location problem has been studied both from a strategic perspective (Bing et al., 2016) and from a tactical perspective (Eiselt & Marianov, 2014).

This paper focuses on finding locations for collection centers and allocating urban areas to those centers. Three objective functions are proposed based on (Jaehn, 2016) in order to implement the sustainability concept. Sustainable development focuses on economic, environmental, and social dimensions which are conflicting in many cases (Silvestre & Ţîrcă, 2019). In particular, selecting more central locations may require higher costs to ensure similar environmental and social standards.

A main contribution is to integrate the decisions of locating collection centers and creating districts based on workload balance and contiguity constraints, which are fundamental constraints in districting problems (Kalcsics, 2015). There are three former studies that have considered a districting problem jointly with waste management, by Lin and Kao (2008), Ghiani, Manni, Manni, and Toraldo (2014), and Cortinhal, Mourão, and Nunes (2016). The contiguity of districts was not considered in the aforementioned papers; however, this fundamental constraint can reduce movements, decrease the number of required trucks to provide service, and facilitate management decisions to improve the level of service (Kalcsics, 2015).

In location problems, the main questions are where to establish facilities, how many to establish, and which type of facilities to establish. How to allocate customers to facilities is important, since the performance of facilities can only be evaluated after allocating customers to the established facilities. On the other hand, districting problems aim to create groups of areas that belong together. The criteria for deciding this involves making sure that the areas are geographically related, and that they are not spread out too much. This means that location problems and districting problems have different structures, as illustrated in Fig. 1. For location problems, any customer can be assigned to any facility, whereas in districting problems, only physically adjacent areas can be linked. Hence, location problems are typically defined on complete graphs, so that each vertex can be allocated to a specific facility, whereas districting problems are defined on planar graphs that better represent a geographically connected, urban structure. The typical location problem structure is not suitable for allocating urban areas to facilities, as it does not guarantee a contiguous allocation of urban areas to each facility.

Both location and districting problems are NP-hard (Kalcsics, 2015), and a multi-objective local search heuristic based on Chen, Zeng, Lin, and Zhang (2014) is presented for the combined problem. An initial population is generated and improved using local search, resulting in a better population. The new population for the next generation is generated based on the non-dominated ranking method on the set of solutions in the previous population and its improved solutions. The farthest-candidate method (FCM) (Tran, Taniar, & Safar, 2009) is used to improve the diversity of solutions, leading to an appropriate level of variation in the final set of solutions. In addition, the best-worst method (BWM) (Rezaei, 2015) is applied to select the most preferred solutions from the final population.

The remainder of the paper is structured as follows. In Section 2, the related research literature is reviewed, and research gaps are identified. The problem description and a mathematical model are given in Section 3. The proposed multi-objective local search heuristic is presented in Section 4. In Section 5, the computational results obtained from random generated instances and two case studies are reported, and sensitivity analysis is performed. The managerial implications are discussed in Section 6, after which Section 7 concludes the paper.

2. Literature review

Most applications of OR in MSW management involve a location problem to find strategic decisions (Ghiani, Laganà, et al., 2014). An appropriate allocation of urban areas to the established collection centers has rarely been considered and formulating the associated contiguity restrictions mathematically is challenging (Kalcsics, 2015). In the following we consider relevant studies over the last ten years in chronological order. The studies most central to the developments in this paper are listed and classified in Table 1. Additional references on multi-objective optimization in waste management, including older references, are given by Yu and Solvang (2017).

Lin and Kao (2008) partitioned urban areas using a mixed-integer programming (MIP) model with the aim of minimizing deviations of district sizes from the mean value; however, contiguity was not included in the model, and feasible districts were generated using a control parameter for district compactness. Faccio, Persona, and Zanin (2011) proposed a vehicle routing problem to optimize solid waste collection with a new traceability technology applied in an Italian city. Their approach led to the reduction of total costs and adverse environmental effects.

Site selection for waste landfill disposal was studied by Şener et al. (2011). The main criteria were weighted using an analytical hierarchy process and locations were mapped using a geographic information system (GIS). Suitable locations for a case study were determined by remote sensing. Samanlioglu (2013) developed a multi-objective mathematical model for location-routing of industrial hazardous waste. The model minimized total costs and different risk measures and was solved using the lexicographic weighted Tchebycheff method.

Mes, Schutten, and Rivera (2014) investigated a reverse inventory routing problem focusing on routing and container selection. The authors tuned the problem's parameters by combining optimal learning techniques with simulation. Ghiani, Manni, et al. (2014) extended a non-integrated location and districting approach to collect solid waste. They

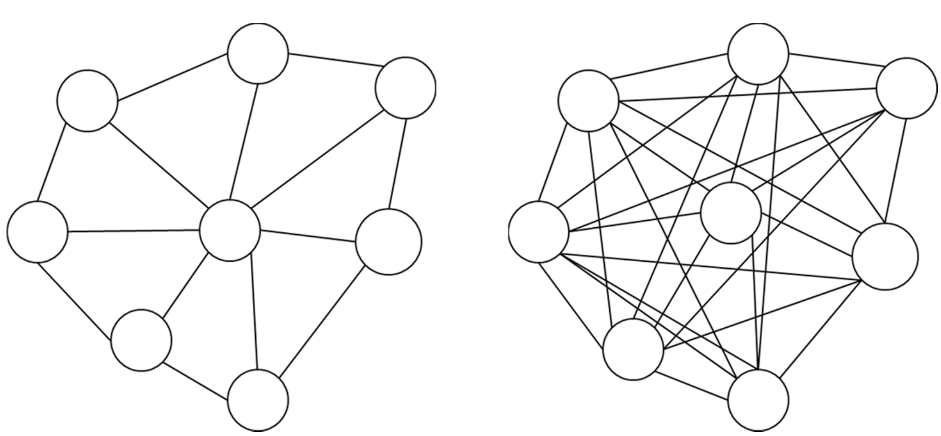

Fig. 1. Typical graph structure for districting problems (left) and location problems (right).

Table 1
Selected recent studies in the field of MSW management.

Meta-heuristic	Exact	Multi-objective	Linear	Districting	Routing	Location	Case study	Reference
	✓	N	Y	✓			✓	(Lin & Kao, 2008)
✓		Y	Y		✓		✓	(Faccio et al., 2011)
	✓	Y	Y		✓	✓	✓	(Samanlioglu, 2013)
✓		N	Y		✓		✓	(Mes et al., 2014)
	✓	Y	Y			✓	✓	(Eiselt & Marianov, 2014)
✓		N	Y		✓		✓	(Das & Bhattacharyya, 2015)
	✓	Y	Y		✓		✓	(Son & Louati, 2016)
✓		N	Y	✓	✓		✓	(Cortinhal et al., 2016)
	✓	Y	Y			✓	✓	(Asefi & Lim, 2017)
	✓	Y	Y			✓	✓	(Hu et al., 2017)
	✓	Y	Y			✓	✓	(Habibi et al., 2017)
✓		Y	Y		✓	✓		(Rabbani et al., 2018)
✓		N	Y			✓	✓	(Sharif et al., 2018)
✓		N	Y			✓	✓	(Yadav et al., 2018)
	✓	Y	Y		✓	✓	✓	(H Asefi et al., 2019)
	✓	N	Y			✓	✓	(Gambella et al., 2019)
✓		**Y**	**Y**	✓		✓	✓	**The current paper**

first determined locations for collection centers using an exact algorithm, and then used a heuristic for districting. Contiguity was not considered as a constraint, and each urban area was allocated to districts based on a predetermined coverage radius.

Eiselt and Marianov (2014) proposed a bi-objective optimization model to determine the location and size of landfills and transfer stations, while considering the minimization of total cost and pollution levels. The model was applied to a case study in Chile. Das and Bhattacharyya (2015) presented a MIP model to determine the shortest waste collection and transportation strategy. They then proposed a heuristic to solve the problem. Eiselt and Marianov (2015) discussed some location decision-making models for MSW facilities and surveyed different models of landfill location. The authors then proposed a mathematical model to minimize cost.

Niziolek, Onel, Hasan, and Floudas (2015) considered production of liquid transportation fuel from MSW. Son and Louati (2016) modeled a generalized vehicle routing mathematically to optimize the total distance, emission, and cost in the MSW collection context. Cortinhal et al. (2016) divided a service territory of residential waste collection into sectors. The authors then considered routing decisions for vehicle trips to minimize the total travel time.

Asefi and Lim (2017) utilized a MCDM method in a GIS tool to develop a sustainability indicator for MSW management. They presented a multi-objective model to obtain locations for the system's facilities, type of treatment technology, load of waste, and routes between different components of the system. Hu, Liu, and Lu (2017) concentrated on the importance of waste to energy facilities in MSW management. A bi-objective two-stage robust model was proposed to find the best locations for these facilities under the minimization of government spending and environmental disutility.

Harijani, Mansour, Karimi, and Lee (2017) developed a mathematical optimization model to build a sustainable network for MSW, considering recycling and disposal decisions. The proposed model determined the optimal location of treatment facilities, allocation of waste to the facilities, and the amount of distributed waste in the network. The allocations were made based on considering parameters such as distance and sustainability. The model was applied to a case study in Tehran.

Habibi, Asadi, Sadjadi, and Barzinpour (2017) proposed a sustainable multi-objective optimization model to locate MSW processing and disposal facilities, optimize capacity allocation of different facilities, and determine the best technology and the number of transport vehicles. Gilardino, Rojas, Mattos, Larrea-Gallegos, and Vázquez-Rowe (2017) developed an optimization model to decide MSW collection sites. Then they determined collection routes by a vehicle routing heuristic. Rabbani et al. (2018) addressed a location-routing problem for industrial hazardous waste. Their multi-objective model minimizes total costs and the related risks.

Sharif, Pishvaee, Aliahmadi, and Jabbarzadeh (2018) developed a bi-level programming model to make decisions about network design (involving treatment center locations and outsourcing of different operations) and pricing problems in MSW management. The model was converted to a single-level model and applied to a case study. Hoang, Fujiwara, Phu, and Nguyen (2018) proposed a sustainable multi-objective model to manage MSW systems by allocating waste flow and determining the capacity of disposal facilities while minimizing costs, landfills, and emissions.

Yadav, Karmakar, Dikshit, and Bhurjee (2018) proposed an interval-valued facility location model to find the best locations for transfer stations. They investigated the uncertainty of MSW management systems by interval analyses. Asefi, Shahparvari, Chettri, and Lim (2019) presented a MIP model to determine the locations of different kinds of centers and vehicle routing decisions in MSW management system. They also proposed a heuristic to solve the problem.

Gambella, Maggioni, and Vigo (2019) developed a two-stage stochastic programming formulation to determine facility location, waste flow, and excess waste in a tactical MSW management system, and demonstrated the benefits of considering uncertainty when planning. Rathore and Sarmah (2019) found locations of transfer stations, minimized the overall cost of MSW management, and used GIS tools for the creation of datasets.

Yousefloo and Babazadeh (2019) presented a multi-objective model to design a MSW management network considering risk and cost objectives. The model suggests to managers how to establish transfer stations and waste collection centers, with decisions spanning allocation, transportation, and choice of technology. The model was solved by the ε-constraint method for a case study in Qazvin, Iran. Azadeh, Ahmadzadeh, and Eslami (2019) developed a multi-objective optimization model to find locations for pre-sorting and processing centers. They also determined the quantities of transported MSW between different sites. The objectives included considered health, safety, environment, and economic indicators. These were converted to a single objective by the weighted sum method. The model was solved for a case study with 360 population centers in Tehran.

Pouriani, Asadi-Gangraj, and Paydar (2019) studied MSW management by developing a bi-level MIP model. The lower level considered the location and establishment costs of solid waste collection stations, whereas the upper level considered the allocation of waste to centers. Several studies have focused on the determination of aspects related to transfer stations, especially regarding suitable locations. Asefi, Lim, Maghrebi, and Shahparvari (2019) addressed a multi-echelon fleet size and mix vehicle routing problem to optimize an integrated MSW management system. They minimized the transportation cost and the deviation from a fair load allocation to transfer stations.

In most of the previous studies, a direct connection between centers and all urban areas has been assumed, corresponding to the complete graph in Fig. 1. As argued, it is more realistic to consider a planar graph for the areas when reflecting an urban environment. This leads to the concept of districting, also known as zoning or territory design in the literature.

According to the literature review, only three studies (Cortinhal et al., 2016; Ghiani, Manni, et al., 2014; Lin & Kao, 2008) have investigated the districting problem for MSW management. However, they did not consider the contiguity of districts. Enforcing contiguous districts can help to reduce travel distances and the number of required vehicles, as well as to improve the service level. Surveying the specialized literature, there has been no research on integrated optimization of location and districting problems in MSW management. Moreover, criteria for sustainable development have not been addressed in previous studies. To cover these gaps, a sustainable multi-objective model integrating the minimization of establishment and waste collection cost, destructive environmental impacts, and social dissatisfaction is proposed in this paper.

3. Problem description

MSW management has always been a major concern in urban management (Hugos, 2018), because it directly deals with the basic needs of communities. In some countries like Iran, individual municipalities are responsible for waste collection management. They must identify some locations as collection centers and assign urban areas to districts surrounding each center. These decisions are subject to several types of constraints:

- Exclusive assignment: Each urban area should be allocated to one district (Butsch, Kalcsics, & Laporte, 2014)
- Contiguity: In a certain district, there exists a path from each two urban areas without leaving the district (Tavares-Pereira, Figueira, Mousseau, & Roy, 2007)
- Workload balance: Each collection center should process approximately the same amount of waste. In other words, the related service should be distributed over districts (Camacho-Collados, Liberatore, & Angulo, 2015)
- Compactness: Travel distances within each district should be modest, often implying that each district should have a relatively round shape (Ricca, Scozzari, & Simeone, 2011)

Each urban area can be served by only one center. Criteria such as establishment costs, waste collection costs, destructive environmental impacts, and social dissatisfaction come into play when selecting collection centers. In this paper, these criteria are divided into economic, environmental, and social objectives.

The first objective involves the cost of establishing collection centers and the cost of waste collection. The cost of establishing a center varies based on the geographical location, proximity to commercial, recreational, and residential centers, and the proximity to the city. The second objective considers destructive environmental impacts. Since the infrastructure and environmental requirements in each potential location are different, the emissions resulting from constructing the collection center in each potential location differ. This is taken into account as the first part of the second objective. The transportation of municipal waste in urban environment also releases environmental pollutants in case of improper performing waste transportation operations (Expósito-Márquez, Expósito-Izquierdo, Brito-Santana, & Moreno-Pérez, 2019), and this constitutes the second part of the second objective.

The third objective focuses on the social dissatisfaction, such as traffic jams caused by waste vehicles transportation, inappropriate appearance in urban space, and the effect on the value of residential and commercial lands around the established sites. To collect data related to the social dimension, a researcher-made questionnaire was used, with criteria based on Fattahi (2020). The questionnaire was completed by a number of experts and the final score of each criterion determined using BWM. Finally, the rank of each potential location is obtained, yielding values forming the third objective.

Collection centers are established at district centers. Each district consists of a contiguous set of urban areas. Fig. 2 illustrates how a lack of contiguity can result in abnormal structures.

3.1. Mathematical formulation

The districting problem can be defined on an undirected graph $G = (V, E)$ with a vertex set $V = \{1, 2, \cdots, |V|\}$ and an edge set $E \subseteq V \times V$. Each vertex, i, is represented by two coordinates (x_i, y_i). In this paper V represents the set of urban areas, and E represents the set of links between urban areas, such that taking the urban areas as vertices and the links as edges forms a planar graph. The planarity is useful when considering districting (Dorn, Penninkx, Bodlaender, & Fomin, 2010). A main difficulty in districting problems is to design contiguous districts (Kalcsics, 2015). In this paper, a flow-based approach applied in (Shirabe, 2009) is used to tackle this difficulty. This guarantees that a district will be contiguous if there exists a positive flow from the district center to the urban areas allocated to it.

Sets	
V	Set of urban areas (vertices)
P	Set of districts ($\|P\|$ is equal to the number of established centers)
V^C	Set of potential locations for collection centers (vertices), $V^C \subseteq V$
E	Set of pairs of adjacent urban areas (edges)
Indices	
i,j	Urban areas $i,j \in V$
p,p'	Districts $p,p' \in P$
Parameters	
D_i	Demand of urban area i [tons]
W^{MAX}	Maximum acceptable difference [%] between the workloads of established centers
C^C	Waste collection cost per unit per kilometer
A^C	Pollutant emission amount of waste collection per ton of waste
L_{ij}	Distance between urban area i and urban area j
L^{MAX}	Maximum allowed distance between urban areas in each district
C_i^E	Establishment cost of a collection center in urban area $i \in V^C$
A_i^E	Pollutant emission amount in case of establishing center $i \in V^C$
S_i^E	Amount of social dissatisfaction in case of establishing center $i \in V^C$
Variables	
x_{ip}	Equals 1 if urban area i is assigned to district p, and 0 otherwise
w_{ip}	Equals 1 if location i is used for the collection center of district p, and 0 otherwise
y_{ijp}	Auxiliary flow variable used to enforce contiguous districts by creating an artificial flow from district centers to urban areas associated to the same district

$$Min : Z_1 = \sum_{i \in V^C} \sum_{p \in P} C_i^E w_{ip} + \sum_{i \in V^C} \sum_{p \in P} \sum_{j \in V} C^C L_{ij} D_j x_{jp} w_{ip} \tag{1.a}$$

$$Min : Z_2 = \sum_{i \in V^C} \sum_{p \in P} A_i^E w_{ip} + \sum_{i \in V^C} \sum_{p \in P} \sum_{j \in V} A^C D_j x_{jp} w_{ip} \tag{1.b}$$

$$Min : Z_3 = \sum_{i \in V^C} \sum_{p \in P} S_i^E w_{ip} \tag{1.c}$$

s.t

$$\sum_{i \in V} D_i x_{ip} - \sum_{i \in V} D_i x_{ip'} \le \sum_{i \in V} D_i W^{MAX}, p, p' \in P : p \neq p', \tag{2}$$

$$x_{ip} + x_{jp} \le 1, i, j \in V : L_{ij} \ge L^{MAX}, p \in P, \tag{3}$$

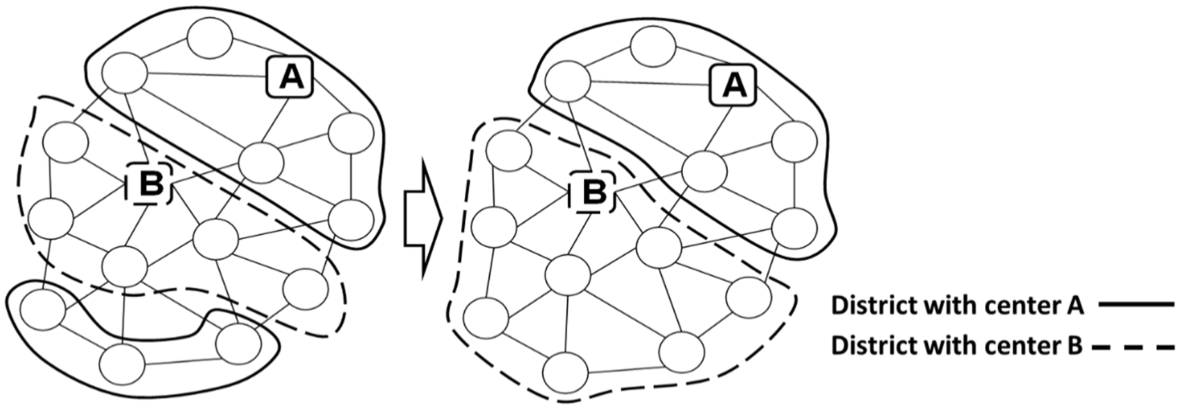

Fig. 2. Example of non-contiguous districts (left) and contiguous districts (right).

$$\sum_{p\in P}x_{ip} = 1, i \in V, \tag{4}$$

$$\sum_{i\in V^C}w_{ip} = 1, p \in P, \tag{5}$$

$$\sum_{j:(i,j)\in A} y_{ijp} - \sum_{j:(j,i)\in A} y_{jip} \geq x_{ip} - |V|w_{ip}, p \in P, i \in V, \tag{6}$$

$$\sum_{j:(j,i)\in A} y_{jip} \leq (|V| - 1)x_{ip}, p \in P, i \in V, \tag{7}$$

$$w_{ip} \in \{0,1\}, p \in P, i \in V^C, \tag{8}$$

$$y_{ijp} \geq 0, x_{ip} \in \{0,1\}, p \in P, (i,j) \in E, i \in V, \tag{9}$$

The first objective function (1.a) is to minimize the cost of establishing collection centers and collecting waste. The second objective function (1.b) is to minimize destructive environmental impacts caused by establishing collection centers and pollutant emission of waste collection. The third objective function (1.c) is to minimize the social dissatisfaction caused by establishing collection centers. This amount is calculated based on BWM using criteria of customer satisfaction defined in (Xiao & Boutaba, 2007) and some criteria in (Fattahi & Govindan, 2018), as shown in Fig. 3. In this method, complete dissatisfaction and complete satisfaction are equal to 9 and 1, respectively. This objective function will result in minimizing social dissatisfaction or, equivalently, maximizing social satisfaction.

Constraints (2) limit the maximum difference between the workloads of districts to a percentage of the total demand. This guarantees the workload balance in districts. Constraints (3) enforce compact districts by limiting the distance allowed between urban areas. Determining an appropriate value of L^{MAX} is important, since too large values will make the constraints redundant and too low values can make these constraints too strict, resulting in an infeasible instance. Constraints (4) ensure that each urban area is allocated to only one district. Based on constraints (5), only one urban area can be selected as the center of each district. Constraints (6) and (7) ensure contiguity of districts: Urban area i can be allocated to district p when a positive flow exists between the established center and urban area i. Constraints (7) guarantee that the maximum output flow from the established center to other urban areas in the district is not more than $|V| - 1$. In other words, each district p has a center i and at most $|V| - 1$ additional urban areas. Based on constraints (6), vertex i can be allocated to district p if the difference between output and input flows of vertex i is greater than 1 or when urban area i is the center of district p ($w_{ip} = 1$). Constraints (8) and (9) restrict the domains of the variables.

3.2. Linearization of the proposed model

The proposed model is a nonlinear MIP model due to the multiplication of x_{jp} by w_{ip} in the first and the second objective functions. An auxiliary variable is defined to linearize these terms as follows:

$$u_{ijp} = x_{jp}w_{ip},$$

By considering this variable, the following constraint should be added to the mathematical model.

$$x_{jp} + w_{ip} - 1 \leq u_{ijp} \leq \frac{x_{jp} + w_{ip}}{2}, p \in P, i \in V, j \in V, \tag{10}$$

$$u_{ijp} \in \{0,1\}.p \in P, i \in V, j \in V, \tag{11}$$

Therefore, the proposed linear mathematical programming model is

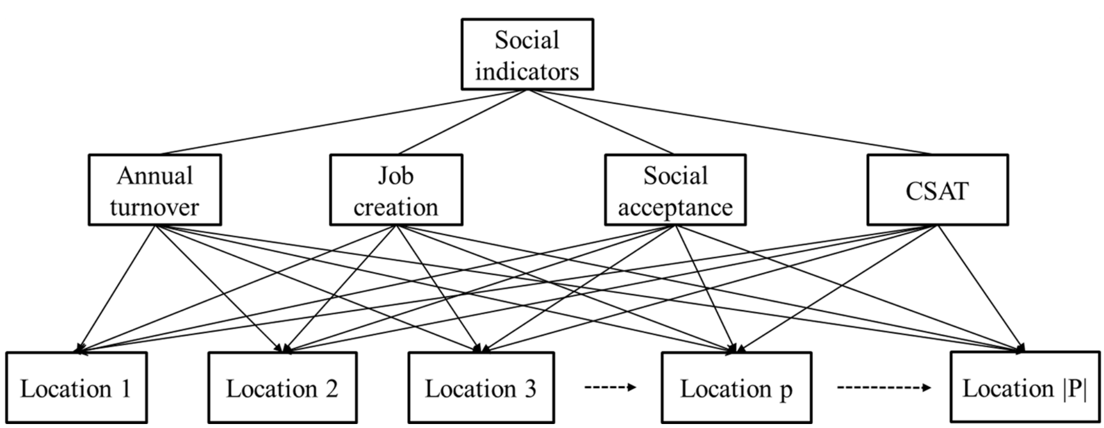

Fig. 3. Hierarchy of the decision-making problem.

as follows.

$$Min: Z_1 = \sum_{i\in V^C}\sum_{p\in P} C_i^E w_{ip} + \sum_{i\in V^C}\sum_{p\in P}\sum_{j\in V} C^C L_{ij} D_i u_{ijp} \quad (12.a)$$

$$Min: Z_2 = \sum_{i\in V^C}\sum_{p\in P} A_i^E w_{ip} + \sum_{i\in V^C}\sum_{p\in P}\sum_{j\in V} A^E D_i u_{ijp} \quad (12.b)$$

Objective function 3 (1.c)

s.t

Constraints (2) *to* (11).

4. Solution method

A multi-objective problem is generally defined as:

$$Minimize: F(X) = (F_1(X), \cdots, F_m(X))$$

$$Subject\ to: X \in S$$

Here, $F: S \rightarrow R^m$ defines m objective functions values, S is the set of feasible solutions, and R^m is the space of objective function values. Let X_1 and X_2 be two solutions. If $F_i(x_1) \leq F_i(x_2)$ holds for all $i \in \{1,2,\cdots,m\}$ and $F_i(x_1) < F_i(x_2)$ holds for at least one of $i \in \{1,2,\cdots,m\}$, X_1 is said to dominate X_2, represented by $X_2 \prec X_1$. The situation where X_1 does not dominate X_2 and X_2 does not dominate X_1 is denoted by $X_1 \prec\succ X_2$. Solution X is Pareto optimal if there is no $X^{`}$ such that $X \prec X^{`}$. The Pareto set P^S is defined to contain all non-dominated solutions. The Pareto front is defined as $P^F = \{F(X) \in R^m | X \in P^S\}$.

The augmented ε-constraint method can be applied to find optimal solutions for small instances (Mavrotas & Florios, 2013). Location (Sharif et al., 2018) and districting (Farughi, Tavana, Mostafayi, & Santos Arteaga, 2019) problems are both *NP-hard*, exact solution methods cannot reliably obtain good solutions for large instances in a reasonable running time. Therefore, a heuristic is proposed.

4.1. Solution representation and initial solutions

Solutions are represented using a structure proposed in (Steiner, Datta, Neto, Scarpin, & Figueira, 2015). This involves an encoding where each solution is stored as a vector of $|P| + |V|$ real-valued elements, each in the range $[0,1]$. The first $|P|$ of these elements are used to determine which locations are selected as collection centers, whereas the last $|V|$ elements are used to determine the assignment of areas to districts. The decoded solution is stored as two strings, with *S1* storing the indices of $|P|$ selected collection centers, and *S2* storing the districts to which each of $|V|$ areas are assigned.

Fig. 4 illustrates the solution encoding, in the vector X, for an instance with $|V^C| = 10$, $|P| = 5$, and $|V| = 20$. Initial solutions are generated randomly by drawing each element of X from a uniform distribution over $[0,1]$. To generate *S1* and *S2*, the real-valued elements of X must be converted to a discrete solution.

For *S1*, elements of X are divided into $|V^C|$ ranges and suitable locations are determined through a mapping from $[0,1]$ to $\{1,\cdots,|V^C|\}$. As *S1* cannot contain repeated values, in the case that an element of X is mapped to an already used location, the next higher unused location is chosen. *S2* is similarly generated by converting the corresponding real-values entries into values from *S1*.

From the instance illustrated in Fig. 4, the range $[0,1]$ is divided into $|V^C| = 10$ sections for $X_1,\cdots,X_5$. The generated number in X_1 is 0.51, which is in the sixth range and consequently is converted to 6. To generate *S2*, the values in $[0,1]$ are divided into $|P| = 5$ ranges. The number corresponding to urban area 1 is $X_6 = 0.44$, which is in the third range and consequently should be converted to the third entry of *S1*, which is 5.

The creation of contiguous districts is not guaranteed by these allocations; therefore, a BFS based method (Sbihi, 2007) is applied to ensure contiguity. The urban areas assigned to each center p are extracted from *S2* and stored in H_p. To guarantee contiguity, the BFS is used to assign $|H_p|$ urban areas to each collection center p. To prevent infeasible districts, a rejection strategy is used. For this purpose, equation (13) and (14) are designed for the calculation of infeasibility that may occur in constraints (2) and (3).

$$Q = \max_{\substack{p,p^{`}\in P\\ p\neq p^{`}}} \left(\sum_{i\in H_p} D_i - \sum_{i\in H_{p^{`}}} D_i \right), \quad (13)$$

$$H = \max_{p\in P} \left(\max_{\substack{i,j\in H_p\\ i\neq j}} (L_{ij}) \right), \quad (14)$$

For $Q > (W^{MAX} \times \sum_{i\in V} D_i)$, the amount of F1 $= Q - (W^{MAX} \times \sum_{i\in V} D_i)$, and for $H > L^{MAX}$, the amount of F2 =

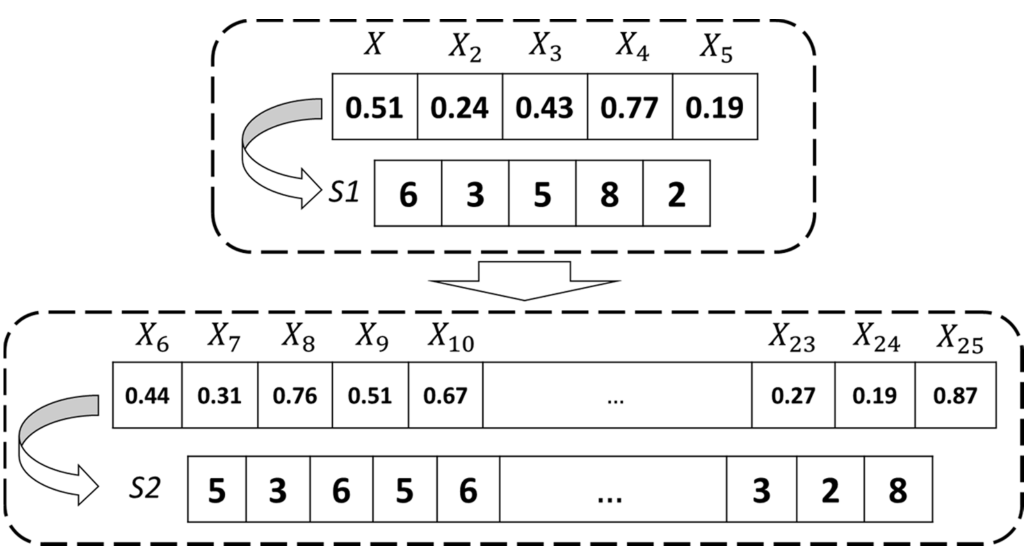

Fig. 4. Structure of initial solutions generation.

$H - L^{MAX}$show the value of infeasibility for constraints (2) and (3), respectively. Each solution with $F1 > 0$ or $F2 > 0$ is excluded from the population, and replaced by another randomly selected solution with $F1$, $F2 \leq 0$. This process continues until a population of size *pop_size* has been reached.

4.2. Local search (evolutionary strategy)

In this paper, a population-based local search strategy is used based on (Chen et al., 2014) to improve solutions in an iterative process. Let X be a solution that should be improved. Each component j from X is considered in turn. For each component, two other solutions, U and V, from the current population is drawn randomly. A perturbation factor c is then drawn randomly from a normal distribution, $N(\mu, \sigma^2)$. Two new solutions, W^+ and W^-, are then created by setting:

$$W_j^+ = X_j + c(U_j - V_j) \tag{15}$$

$$W_j^- = X_j - c(U_j - V_j) \tag{16}$$

where for components $i \neq j$, no change is made: $W_i^+ = W_i^- = X_i$. As each component of the resulting solutions must be in the range $[0, 1]$, any values outside of this range is mapped back into the range.

The perturbation factor c affects the performance of the heuristic. Factors μ and σ should be set to reasonable values. Large absolute values of μ can lead to large perturbations, whereas too low absolute values can lead to slow convergence of the heuristic. Similar arguments can be made for σ. In the computational testing, both μ and σ have been constrained to the range $[0, 1]$.

Having generated W^+ and W^-, the solution X is potentially updated, before moving on to the next component. If we consider two solutions, X and a neighboring solution W, there are three situations that can occur: 1) Solution X is dominated by solution W, 2) Solution W is dominated by solution X, or 3) Neither solution is dominated by the other.

In the local search, the replacement strategy used considers three solutions at once, and decides whether or not to replace X with either W^+ or W^- according to the steps in Fig. 5. The heuristic converges to a final solution by replacing the current solution with a neighboring solution, as long as the current solution does not dominate both neighbors generated for a given component. To increase solution convergence, a neighbor solution replaces X also in the case of $W^+ \prec\succ$ X or $W^- \prec\succ$ X.

4.3. Population management

The population size used in each iteration is equal to *pop_size*. A population *pop_current* is generated in iteration t, and a better population *pop_improved* is generated based on the local search heuristic presented in Section 4.2. Finally, a new population for next generation is generated using the non-dominated sorting method and FCM on the set of solutions in *pop_current* ∪*pop_improved*.

An efficient multi-objective algorithm requires both that the non-dominated solutions are diverse, and that an appropriate convergence to good solutions is achieved (Deb, 2014). In this paper, the FCM is applied on solutions in *pop_current* ∪*pop_improved* to generate a new population based on (Tran et al., 2009). The FCM is inspired by the best-candidate sampling algorithm (Mitchell, 1991) in sampling theory. Suppose that we are going to iteratively select the K best points from F points. Whenever a new point is to be selected, the candidate points in the unselected points which is farthest from the selected points is accepted. The *pop_size* best solutions among a total of 2 × *pop_size* solutions should be selected such that each new member has the largest Euclidean distance to the previous members. Boundary solutions are selected first, and then the other solutions are selected for the new population iteratively.

Fig. 6 shows the FCM procedure for a population with *pop_size* members, where $K <$ *pop_size* solutions must be selected from a population. In this pseudo-code, P_{accept} stores the selected solutions, $D[X]$ stores the minimum Euclidean distance between X and the unselected points, and $dis(X, X^{'})$ is a function calculating the Euclidean distance between solution X and $X^{'}$.

4.4. Selection of the final solution from the heuristic solutions

The selection of a final solution from the Pareto set can be a management concern in real-world problems. BWM is a powerful technique to solve MCDM problems. In this paper, BWM is used to obtain more consistent results using a low number of pairwise comparisons (Gupta, 2018). Many researchers have recently employed BWM in different applications. For more details, see (Rezaei, 2016).

Following the BWM, the objective functions are considered as criteria and their ratings can be calculated based on experts' opinions. A unique rank is then assigned to each Pareto member through the multiplication of the objective functions rating matrix by the values of objective functions. Fig. 7 shows how the calculations are performed, enabling the identification of the Pareto member with the highest score.

5. Computational study

The proposed MIP model has been implemented in *IBM ILOG CPLEX Optimization Studio* and solved by CPLEX 12.6. The proposed heuristic has been coded in C# and run on a PC with 3.2 GHz processor and 16 GB of RAM.

$$If{:}(W^+ \succ X and W^- \succ X) then (X \leftarrow randomly(W^+ or W^-))$$
$$elseif{:}(W^+ \succ X or W^- \succ X) then (X \leftarrow dominated(W^+ or W^-))$$
$$elseif{:}(W^+ \prec\succ X and W^- \prec\succ X) then (X \leftarrow randomly(W^+ or W^-))$$
$$elseif{:}(W^+ \prec\succ X) then (X \leftarrow W^+)$$
$$elseif{:}(W^- \prec\succ X) then (X \leftarrow W^-)$$
$$else{:}Do\_nothing$$

Fig. 5. The replacement strategy steps.

Set $P_{accept} = \emptyset$
While $p < pop\_size$
  $D[X_p] = 0$
End while
For each objective function
  $P_{accept} = P_{accept} \cup \underset{X \in \text{population}}{\text{argmin}} \left(Z_i(X)\right) \cup \underset{X \in \text{population}}{\text{argmax}} \left(Z_i(X)\right)$
End For
For each $X \in \{\text{population} - P_{accept}\}$
  $D[X] \leftarrow \text{argmin}_{X' \in P_{accept}} dis(X, X')$
End For
While $i < K - |P_{accept}|$
  $X_1 = \text{argmax}_{X \in (\text{population} - P_{accept})} D[X]$
  $P_{accept} \leftarrow P_{accept} \cup X_1$
  For each $X_2 \in \{\text{population} - P_{accept}\}$
    $D[X_2] \leftarrow min(D[X_2], dis(X_1, X_2))$
  End For
End while

Fig. 6. Pseudo-code of the farthest-candidate method.

$$\begin{bmatrix} F_1(X_1) & F_2(X_1) & F_3(X_1) \\ \vdots & \vdots & \vdots \\ F_1(X_N) & F_2(X_N) & F_3(X_N) \end{bmatrix}_{N\times 3} \times \begin{bmatrix} Cost\_Score \\ Env\_Score \\ Soc\_Score \end{bmatrix}_{3\times 1} = \begin{bmatrix} 1_{st}\ pareto\ score \\ \vdots \\ N_{th}\ pareto\ score \end{bmatrix}_{N\times 1}$$

Fig. 7. The computational structure to select the best Pareto member.

5.1. Evaluation metrics

There are different ways to compare solution methods for multi-objective optimization problems. When tuning parameters and when evaluating the performance of the heuristic compared to the solutions obtained by commercial solvers, this paper uses the three measures known as mean ideal distance (MID), spread of non-dominance solutions (SNS), and maximum spread (MS). The MID was proposed by Karimi, Zandieh, and Karamooz (2010), and can be stated as follows:

$$MID = \sum_{i=1}^{|Q|}\left(\sqrt{\sum_{j=1}^{m}\left(\frac{F_j(X_i) - F_j(X_{best})}{F_j(X_{max}) - F_j(X_{min})}\right)^2}\right)/|Q| \quad (18)$$

where $F_j(X_i)$ is the value of the *j-th* objective function for solution *i*, and $F_j(X_{best})$ is the ideal solution of the *j-th* objective function, calculated as $F_j(X_{best}) = \{min(F_j(X_1)), min(F_j(X_2)), \cdots, min(F_j(X_{|Q|}))\}$. $F_j(X_{max})$ and $F_j(X_{min})$ are respectively the maximum and the minimum values among all Pareto optimal solutions of the *j-th* objective function, $|Q|$ is the number of non-dominated solutions, and m is the number of objective functions. The ideal solution is typically unobtainable, as illustrated in Fig. 8.

The SNS (Maghsoudlou, Kahag, Niaki, & Pourvaziri, 2016) and MS (Samadi, Mehranfar, Fathollahi Fard, & Hajiaghaei-Keshteli, 2018) are defined in Equations (19) and (20). SNS evaluates the standard deviation of the distance of an ideal point from a non-dominated set, and MS calculates the spread of non-dominated solutions. Therefore, higher values of SNS and MS indicates better solution quality, as opposed to MID, where lower values are better.

$$SNS = \sqrt{\frac{\sum_{i=1}^{|Q|}\left(MID - \sum_{j=1}^{m} F_j(X_i)\right)^2}{|Q| - 1}} \quad (19)$$

$$MS = \sqrt{\sum_{j=1}^{m}\left(F_j(X_{max}) - F_j(X_{min})\right)^2} \quad (20)$$

To calculate the MID, the ideal solution is first obtained for each objective j, providing the values for $F_j(X_{best})$. This is done either by solving the corresponding model using CPLEX, or by applying the heuristic in single objective mode if the instance is too large to be solved by CPLEX. The method to be evaluated is then used to solve the multi-objective version of the problem, obtaining a set of Pareto solutions and their corresponding objective function values. This step is performed either using the epsilon-constraint method with CPLEX and the mathematical model, or with the heuristic in multi-objective mode. For each j, one can then obtain $F_j(X_{max}) = F_j\left(\max_i(X_i)\right)$ and $F_j(X_{min}) = F_j\left(\min_i(X_i)\right)$, and MID, SNS, and MD can be calculated.

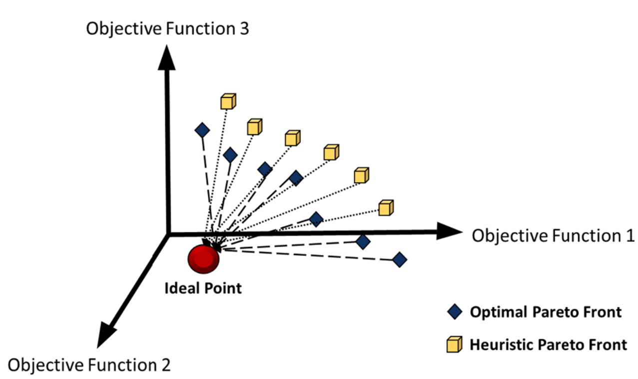

Fig. 8. An example for MID calculation.

When evaluating heuristics for multi-objective problems, the Euclidean distance between the members of the algorithm's Pareto front and the ideal point is among the most useful criteria (Li & Yao, 2019). Another important criterion is the spread of the solutions. MS calculates the Euclidean distance between the upper and lower bounds of the Pareto front (Zitzler, Deb, & Thiele, 2000). The drawback of MS is that it may present a Pareto front with a great distance from the global optimal Pareto front as an efficient one only due to the large spread between the upper and lower bounds of the front. Therefore SNS is proposed, calculating the standard deviation of the Pareto front members of the algorithm and the ideal point (Farughi, Mostafayi, & Arkat, 2019).

5.2. Evaluation of heuristic solution method

The performance of the proposed heuristic is sensitive to the user-defined parameters, including *pop_size*, *max_iteration*, σ, and μ. Since the performance of heuristics may differ when solving problems with different sizes, the parameters for small, medium, and large size problems are set separately (Chalmardi & Camacho-Vallejo, 2019). Table 2 shows the range of possible parameter values considered.

To set these parameters for solving test problems with different sizes, response surface methodology (RSM) experimental design (Bezerra, Santelli, Oliveira, Villar, & Escaleira, 2008) is applied. The response variable is calculated as in Equation (17).

$$Reponse\ \ Variable = S(MID) + S(SNS) + S(MS \quad (17)$$

where $S(MID)$, $S(SNS)$, and $S(MS)$ are standardized values of MID, SNS, and MS given in Equations (18) to (20). The RSM requires much fewer experiments than a full factorial design (Bezerra et al., 2008). For more information, see (Hadavandi, Mostafayi, & Soltani, 2018). Table 3 presents the final parameters for small, medium, and large instances.

To evaluate the heuristic, it is compared to the performance of CPLEX when directly solving the mathematical model using the augmented ε-constraint method (Mavrotas & Florios, 2013). The latter is achieved using the software GAMS and involves solving 492 instances with different weights on the objective functions. Since the proposed model cannot be used to solve large-scale instances, ten small and two

Table 2
The interval values of parameters.

Standardized factors			
1	0	−1	
$3\times\lvert V\rvert$	$1.5\times\lvert V\rvert$	$\lvert V\rvert$	*pop_size*
2000	1050	100	*max_iteration*
1	0.5	0	σ
1	0.5	0	μ

Table 3
Final parameters of the heuristic.

	pop_size	*max_iteration*	σ	μ
Small size	$1.1 \times \lvert V\rvert$	200	0.12	0.27
Medium size	$1.8 \times \lvert V\rvert$	800	0.16	0.54
Large size	$2.6 \times \lvert V\rvert$	1400	0.37	0.68

medium size, randomly generated, instances are studied.

In the randomly generated instances, a number of urban areas $|V|$ and districts $|P|$ are given, resulting in a planar graph. The coordinates of the urban areas are generated from a uniform distribution on the interval $[10, 1000]$. The demand of each urban area is generated from a uniform distribution on the interval $[50 \times 10^3, 300 \times 10^3]$ t/year. Finally, the number of potential locations is randomly selected from $[2|P|, 3|P|]$.

To compare the quality of the heuristic Pareto front with the optimal Pareto front, the distance between the heuristic solutions and ideal solutions and the distance between optimal solutions and ideal solutions are calculated separately. Table 4 shows the gap between MID for the optimal Pareto front and MID for the heuristic solutions.

The largest instance that can be solved by using the mathematical model has 100 urban areas, 10 potential locations, and 5 districts. It takes much more time to solve larger problems, and it can be observed that the CPU time of the model increases exponentially. On the other hand, the heuristic can solve the largest instance in less than 5 min for 200 iterations.

As the size of instances increases, the MID Gap% value increases for all values of W^{MAX}. In the largest instance, the selected centers and the created districts are approximately the same for different values of the parameter W^{MAX}.

To further examine the performance of the heuristic, a sensitivity analysis is performed over different values of W^{MAX}. Ten small, ten medium, and ten large-scale instances are generated and evaluated using *SNS* and *MS*. The *SNS* and *MS* metrics are usually used to compare a set of algorithms (Deb, 2014). However, in this paper, they are applied also in the sensitivity analysis. Tables 5 and 6 show the obtained results for different values of the parameter W^{MAX} related to small and large size instances. Results for medium size instances are not reported, but show the same behavior as the results for small and large instances.

When the parameter W^{MAX} is decreased, the feasible region becomes smaller, and more CPU time is required, as shown in "Seconds" column of Tables 5 and 6. According to Table 5, MS has the minimum value for $W^{MAX} = 0.3$ and the maximum for $W^{MAX} = 0.45$. The trends of variation in MS and SNS are similar for small, medium, and large instances. Increasing W^{MAX} leads to more diversity in the solutions found. With increasing problem dimensions, the CPU time increases as a polynomial function. For the larger instances in Table 6 the CPU time varies from 1000 to 3000 s. These instances are similar in size to the largest expected real-world instances.

5.3. Case study 1

A MSW collection problem in Birjand, in the East of Iran, is considered as the first case study. The related input parameters are presented in Tables 7 and 8 and Fig. 9. All input parameters are gathered from Birjand municipality, which is the responsible organization for MSW management in Birjand. As the resulting instance is relatively small, it is solved with CPLEX using the augmented ε-constraint method. If instead using the heuristic, the obtained MID Gap% is 12.7, based on 37 solutions in the heuristic Pareto front.

Four potential locations are considered for construction of waste collection centers to cover the demands of 30 urban areas. To provide services, two centers must be established, resulting in two districts. The workload balance percentage in districts is $W^{MAX} = 0.3$ and it is also considered that $L^{MAX} = \max_{i,j \in V}(L_{ij})/2$. The value of C^C is 0.1 M Rial and A^C is 36 cubic feet CO_2 per ton of waste.

Fig. 9 shows the urban structure of Birjand (left) and the connections between urban areas (right). The available information in the municipality database of Birjand from 2014 to 2018 is presented in Table 7. The demand of all urban areas is between 35 and 65 thousand tons per month. The values for the establishment cost, the pollutant emission amount, and the social dissatisfaction are presented in Table 8. The establishment cost is provided by the department of construction and development of Birjand municipality, and related data about the pollutant emission and social dissatisfaction are provided by the department of statistics and information of the environmental organization of Birjand. The distances between the urban areas are calculated using their UTM coordinates and GIS maps.

Fig. 10 shows the 50 Pareto optimal solutions generated. The value of the first objective function is between $2.15 \times 10^8$and 2.35×10^8, and that of the second objective function is between $3.6 \times 10^5$and 4.4×10^5. The third objective function varies between 10 and 13. How to select one of the Pareto members to implement in real-world applications is important (Mavrotas, Figueira, & Siskos, 2015). In this paper, BWM is applied to select the preferred solution from the Pareto front. To this end, questionnaires were completed by eight waste management experts in Birjand. The ratings for each criterion are presented in Tables 9 and 10.

To determine the weights of the criteria, the linear model in BWM was implemented in GAMS and solved by CONOPT. The mean weights for each criterion are shown in Table 11. The value of the consistency indicator ξ^{L^*} is close to zero; therefore, the obtained weights are reliable

Table 4
Comparison of the obtained results.

$W^{MAX} = 0.35$			*$W^{MAX} = 0.3$*			*$W^{MAX} = 0.2$*			*Instance*	*Instances Size*
MID Gap%	*Run time (s)*		*MID Gap%*	*Run time (s)*		*MID Gap%*	*Run time (s)*			
	Heuristic	*CPLEX*		*Heuristic*	*CPLEX*		*Heuristic*	*CPLEX*		
8.07	24	35	6.92	26	37	6.84	21	32	*N10P3D2*	*Small*
11.09	29	56	10.46	27	60	7.94	23	47	*N12P3D2*	
14.35	29	93	10.78	27	96	10.55	23	74	*N15P3D2*	
16.54	31	115	13.26	32	102	10.91	25	91	*N18P4D2*	
17.70	39	145	15.54	39	145	13.05	31	122	*N20P5D3*	
18.07	53	284	16.40	54	264	14.32	44	219	*N25P5D3*	
19.37	58	515	17.95	56	510	15.37	45	412	*N30P6D3*	
19.39	55	802	19.01	54	802	15.98	47	617	*N35P6D3*	
19.42	70	1328	19.03	71	1328	16.10	55	1046	*N45P6D3*	
20.06	75	1463	19.87	73	1631	16.66	67	1295	*N50P6D3*	
21.65	194	3563	20.69	194	3535	17.52	174	2784	*N100P10D5*	*Medium*
–	267	>3000	–	294	>3000	–	243	>3000	*N110P12D5*	

N = nodes P = Potential Location D = districts.

Table 5
Evaluation of heuristic results related to small size instances.

$W^{MAX}=0.35$			$W^{MAX}=0.3$			Instance
MS	**SNS**	**Seconds**	**MS**	**SNS**	**Seconds**	
2311.6	2043.1	21	1708.35	2535.2	24	N10P3D2
4016.5	5568.6	25	3244.75	5905.9	28	N12P3D2
5736.1	8238.2	27	4561.73	9243.9	28	N15P3D2
5757.5	11,606.7	28	5686.10	11,417.0	26	N18P4D2
6736.4	16,628.4	32	7037.30	17,580.9	32	N20P5D3
10,392.6	23,576.1	53	7728.97	22,835.3	51	N25P5D3
8327.2	24,266.8	55	8415.40	24,627.4	56	N30P6D3
8792.2	30,820.0	50	8634.20	31,497.9	48	N35P6D3
10,603.0	43,974.2	66	11,558.77	49,986.3	69	N45P6D3
13,661.9	49,151.3	71	12,219.21	52,579.9	85	N50P6D3
$W^{MAX}=0.45$			$W^{MAX}=0.4$			**Instance**
MS	**SNS**	**Seconds**	**MS**	**SNS**	**Seconds**	
2816.3	2503.7	22	2393.26	2018.8	21	N10P3D2
5197.6	5745.3	23	4496.16	6749.9	25	N12P3D2
5403.7	7915.5	29	5045.03	8064.4	23	N15P3D2
6411.1	10,483.3	27	5681.68	10,551.8	32	N18P4D2
8357.9	17,337.2	31	7402.32	18,508.6	36	N20P5D3
11,643.0	23,443.2	53	8702.00	22,872.2	55	N25P5D3
9358.6	25,504.5	53	8566.71	24,784.8	51	N30P6D3
9434.8	32,625.2	47	8544.10	32,144.6	48	N35P6D3
13,844.7	42,918.1	60	13,029.76	45,837.0	70	N45P6D3
15,613.4	52,075.3	71	14,117.13	45,328.4	79	N50P6D3

Table 6
Comparison of heuristic results related to large-scale instances.

$W^{MAX}=0.35$			$W^{MAX}=0.3$			*Instance*
MS	*SNS*	*Seconds*	*MS*	*SNS*	*Seconds*	
3575.2	3184.6	691	2834.8	3628.7	989	N700P50D5
6463.4	7801.3	1323	5613.0	7153.8	1107	N750P80D10
6962.0	11,029.9	1364	6983.1	11,223.0	1251	N800P100D12
8021.4	15,409.4	1975	7261.0	17,854.4	1397	N850P120D12
10,586.0	24,331.3	1977	10,068.5	26,408.9	1663	N900P140D15
13,636.1	26,792.1	2173	12,299.6	28,989.1	1931	N950P140D15
11,540.2	35,101.4	2376	11,401.9	38,280.2	1984	N1000P150D18
10,760.4	41,352.7	2507	11,587.0	41,382.8	2481	N1100P160D18
16,978.2	64,755.0	2826	16,773.4	59,862.3	2621	N1500P180D20
19,516.8	66,038.5	2903	17,614.6	74,033.6	2956	N2000P200D20
$W^{MAX}=0.45$			$W^{MAX}=0.4$			*Instance*
MS	*SNS*	*Seconds*	*MS*	*SNS*	*Seconds*	
7720.7	8763.7	583	7559.0	7532.0	542	N700P50D5
7744.8	10,702.0	670	7542.7	10,622.8	853	N750P80D10
8682.9	14,047.1	1076	11,382.6	16,728.5	1693	N800P100D12
16,948.8	24,489.4	1386	6433.7	23,414.8	1710	N850P120D12
16,462.7	27,436.4	1387	10,728.1	26,405.2	2185	N900P140D15
13,172.8	35,572.4	1530	12,391.3	32,843.4	2285	N950P140D15
11,806.3	43,046.2	1699	10,003.5	37,762.3	2776	N1000P150D18
18,610.1	66,025.2	1868	18,823.1	54,510.8	2779	N1100P160D18
22,913.4	66,999.6	2813	18,730.5	73,668.7	2852	N1500P180D20
23,412.1	67,125.8	2908	19,142.1	73,919.1	3107	N2000P200D20

and can be used to rank the Pareto members. The selected centers and the created districts are illustrated in Fig. 11.

The total cost, the emission amount, and the social dissatisfaction amount are equal to 221,495,485 rial, 418,432 cubic feet, and 12, respectively. The social dissatisfaction has no unit and is calculated based on experts' opinion. The obtained value is the sum of the scores of locations selected in the final solution. It can be normalized by dividing by $\sum_{i\in V^c} S_i^E$. In this case study, the social dissatisfaction is 50%.

5.4. Case study 2

In this section, the proposed heuristic is applied to a MSW management problem in Tehran as the second case study. With CPLEX and the augmented ε-constraint method, the solver runs out of memory after 2 h of computing time. Based on the strategic planning of the municipality of Tehran, it is necessary to establish a number of waste collection centers in different regions of the city so that they can provide required services to urban areas (Damghani, Savarypour, Zand, & Deihimfard, 2008).

Tehran is currently divided into 22 regions. According to the available datasets of Tehran municipality, 65% of the total waste in Tehran is solid waste. The waste generation varies between regions by a factor of up to seven. The lack of adequate infrastructure to separate collected waste in collection centers is a serious problem; only about 17% of the waste is currently separated. This increases pollution, social dissatisfaction, and destruction cost of non-separated waste. Therefore, managers plan to determine suitable locations for waste collection centers and to separate the collected waste. Fig. 12 shows a map of Tehran and potential locations determined by experts.

According to the available information, it is necessary to select 11 centers among the 30 potential locations. Thus, $|V^C| = 30$, $|P| = 11$, while $|V| = 3{,}147$. Furthermore, $W^{MAX} = 0.1$, $C^C = 0.22$, $A^C = 44$, and

Table 7
Geographic coordinates and demand of urban areas.

$D_i \times 10^3$ (t/month)	Coordinates (UTM)		node	$D_i \times 10^3$ (t/month)	Coordinates (UTM)		node
	y-dimension	x-dimension			y-dimension	x-dimension	
60.83	715,913	3,639,489	16	35.91	717,410	3,636,540	1
58.75	716,469	3,639,036	17	37.25	716,683	3,637,358	2
41.33	716,529	3,639,016	18	65.50	716,173	3,637,763	3
40.75	717,306	3,639,081	19	54.08	715,707	3,638,006	4
56.16	717,317	3,637,451	20	62.00	714,496	3,638,268	5
61.34	717,143	3,641,265	21	53.91	714,482	3,639,063	6
54.16	717,925	3,640,672	22	58.41	713,880	3,639,691	7
62.00	717,811	3,640,242	23	62.58	713,776	3,639,854	8
37.41	718,220	3,639,427	24	63.00	713,026	3,640,477	9
37.34	717,759	3,639,709	25	41.25	713,404	3,641,811	10
52.16	718,766	3,641,289	26	46.16	713,864	3,640,546	11
50.84	719,355	3,641,150	27	41.41	714,089	3,640,142	12
36.00	719,194	3,640,628	28	41.83	714,132	3,640,134	13
50.81	719,949	3,641,091	29	40.58	715,083	3,639,490	14
64.08	719,531	3,639,320	30	62.00	715,894	3,639,436	15

Table 8
Related information of potential locations.

S_i^E (score)	A_i^E (cubic foot)	C_i^E (M rial)	Corresponding nodes	Potential centers
7	442,474	4310	7	Potential Center 1
6	657,742	6120	1	Potential Center 2
5	485,547	5880	24	Potential Center 3
6	524,688	4750	21	Potential Center 4

$L^{MAX} = 4,079$. The connections and distances between urban areas are obtained from the Transportation and Traffic Organization of Tehran municipality. Additional information necessary to calculate the objective functions is presented in Table 12.

Fig. 13 shows the 97 members of the heuristic Pareto front generated. The value of the first objective function is between 7.1×10^9 and 7.7×10^9, and that of the second objective function is between 7×10^3 and 9×10^3. The third objective function varies between 50 and 80. The first and the second objective functions of Pareto members are mostly in the intervals $[7.4, 7.7] \times 10^9$ and $[7, 8] \times 10^3$, respectively, as can be observed in Fig. 13a. To select one final solution, 12 experts from the waste management department of Tehran municipality were chosen to assess cost, environmental, and social criteria through a questionnaire according to BWM. After doing the required calculations as for case study 1, the obtained weights of cost, pollutant emission, and social dissatisfaction are 0.623, 0.271, and 0.106, respectively.

After running BWM, one of the 97 solutions in the Pareto front is selected as the final solution. Fig. 14 displays the final structure of selected locations and the created districts, and Fig. 15 shows the amount of waste collected in each district.

The highest and the lowest amounts of waste are in districts 9 and 10, respectively. The maximum difference in workload is 14,520 t, corresponding to 5.06% of the total demand. The workload balance will be different when changing the value of L^{MAX}. Therefore, a sensitivity analysis over parameters L^{MAX} and W^{MAX} is carried out and reported in Tables 13–16. All the calculations in the tables are done by running the proposed heuristic for different parameter values, reporting the highest-ranked solution.

All three objective functions worsen by decreasing parameter L^{MAX} because constraints (2) become stricter. Table 13 indicates a high sensitivity of solutions to different W^{MAX} values. Therefore, this parameter should be specified carefully. The heuristic cannot obtain feasible solutions for $W^{MAX} < 0.2, L^{MAX} = 2000$ and also $W^{MAX} = 0.05$, $L^{MAX} = 2500$.

Based on Table, when W^{MAX} decreases and L^{MAX} increases, the workload balance is improved. The sensitivity to changes of L^{MAX} varies for different values of W^{MAX}. In fact, the more the parameter W^{MAX} increases, the more the solutions change when L^{MAX} decreases. According to the analysis, the proposed heuristic has a logical behavior in generating final solutions and can be used as a new development tool for MSW

Fig. 9. Map of Birjand city in the East of Iran.

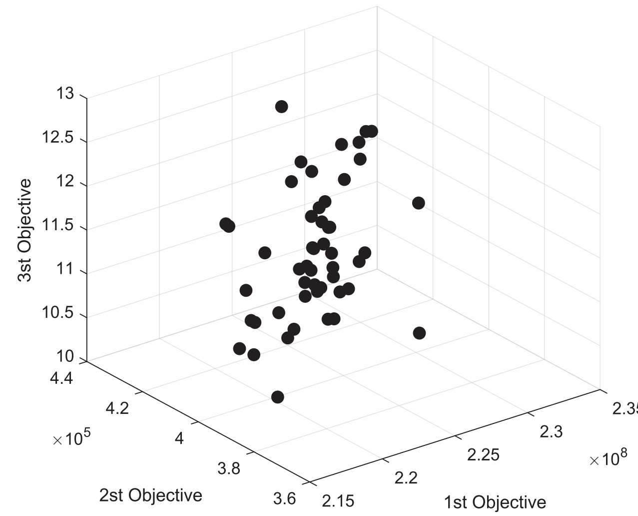

Fig. 10. The obtained Pareto front of the numerical example.

Table 9
Best to others vectors.

Soc	Env	Cost	The best criterion	Experts
9	3	1	*Cost*	**Expert 1**
3	4	1	*Cost*	**Expert 2**
4	6	1	*Cost*	**Expert 3**
8	3	1	*Cost*	**Expert 4**
9	2	1	*Cost*	**Expert 5**
4	3	1	*Cost*	**Expert 6**
6	5	1	*Cost*	**Expert 7**
3	6	1	*Cost*	**Expert 8**

management problems.

6. Discussion

Determining suitable locations of waste collection facilities and an appropriate allocation of urban areas to them are strategic decisions. To provide proper waste collection services, two main criteria are contiguity and workload balance. Municipalities and private sector companies are responsible for providing MSW collection services. Their goals naturally involve economic criteria, including the minimization of establishment and waste collection cost. However, environmental and social objective functions follow as additional criteria in accordance with the laws of environmental protection and laws related to the rights of citizens. These criteria together can lead to more sustainable managerial decisions to minimize environmental and social rights vulnerability.

The first case study dealing with MSW management in Birjand is solved by the augmented ε-constraint method. The results show that considering environmental and social objective functions together with the economic objective leads to a variety of solutions that can provide managers with alternative options. Information about the current waste collection system in Birjand was gathered directly from conversations with local representatives by the first author. Taking into account that there is currently only one waste collection center in Birjand, adequate services are not provided to some urban areas. This is due to the extreme workload of the main center and the lack of proper manpower allocation to provide complete service to all parts of the city. According to interviews with the waste management experts in South Khorasan, the collection center is currently in an inappropriate location in terms of environmental and social aspects.

Available geographical maps in the municipality show that the current waste collection center is located near agricultural fields where large amounts of microorganisms enter the area by wind, consequently polluting water supplies and potentially causing diseases. The current location of the center, near one of the main routes of the city, has led to a huge reduction in price of agricultural fields and houses in the surrounding area. Due to the lack of proper management, there are currently only 24 people working in the center. This number is insufficient to handle the great amount of generated waste. However, there is no possibility for more human resources because of a lack of proper infrastructure in the center. Comparisons between the obtained solution and the existing situation shows the potential for more than 32% saving in waste collection cost. The corresponding establishment cost, however, is higher than in the existing situation, as two facilities are required. Environmental and social criteria are improved more than 83% and 79%, respectively.

Despite the fact that Birjand is located in desert parts of Iran, with limited facilities and resources, current efforts to preserve them appears insufficient. Social criteria such as the social acceptability of the collection center and the possibility of creating new jobs are not currently considered by the authorities. These criteria can also be improved if the optimal solution proposed is implemented. To sum up, applying results of this paper can improve environmental and social conditions in the province in addition to reducing the cost of waste collection.

Table 10
Others to worst vectors.

Expert 8	Expert 7	Expert 6	Expert 5	Expert 4	Expert 3	Expert 2	Expert 1	**Experts**
Soc	*Env*	Soc	Soc	Soc	Soc	*Env*	Soc	**The worst criterion criterion**
9	9	9	9	9	9	9	9	Cost
8	1	3	4	4	5	1	5	*Env*
1	5	1	1	1	1	6	1	Soc

Table 11
Weights of the effective criteria in selecting the Pareto member.

Mean weights	**Experts**								**Criteria**
	Expert 8	Expert 7	Expert 6	Expert 5	Expert 4	Expert 3	Expert 2	Expert 1	
0.758	0.091	0.097	0.100	0.253	0.106	0.103	0.072	0.256	Cost
0.159	0.236	0.246	0.095	0.104	0.097	0.256	0.139	0.099	*Env*
0.083	0.091	0.101	0.129	0.029	0.034	0.077	0.096	0.033	Soc
0.043	0.038	0.044	0.043	0.046	0.039	0.051	0.038	0.041	ξ^{L^*}

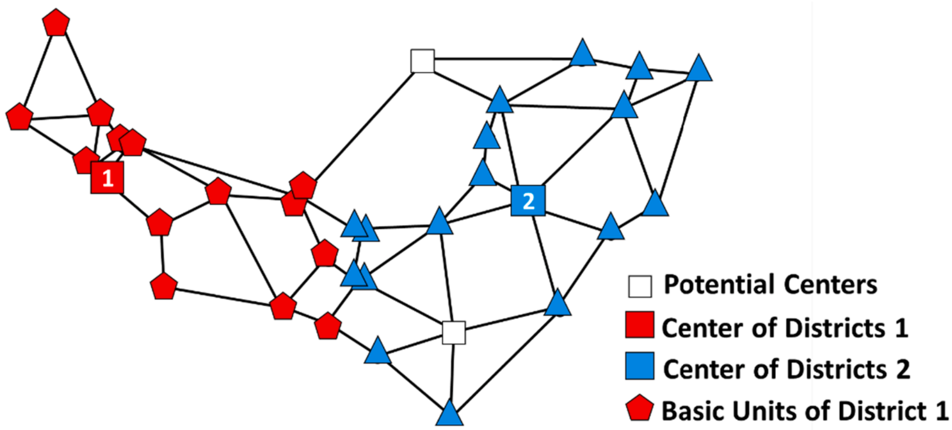

Fig. 11. The obtained districting structure based on the selected centers.

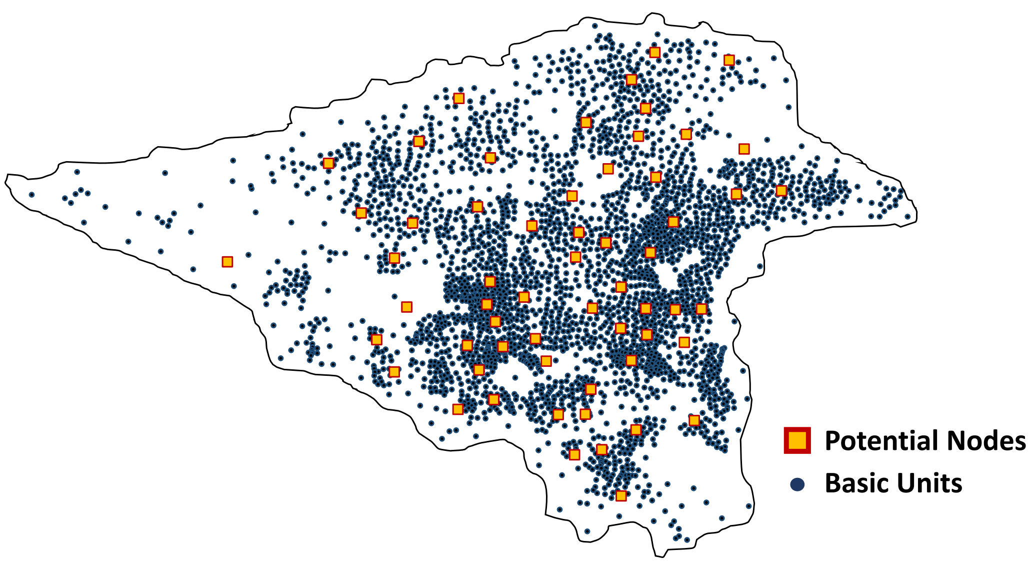

Fig. 12. Map of Tehran and the potential locations for construction of waste collection centers.

Table 12
The required information to calculate the objective functions, with Cost in millions of rial, Env in thousands of cubic feet per month, and SOC without units.

Location	Cost	Env	SOC	Location	Cost	Env	SOC
Gilan	8489	835	8	Golzar	7693	716	8
Ardakan	9476	722	4	Alian	8924	858	7
G-5	9212	898	4	Khoram	7885	758	4
Apadana	8037	729	5	Arg	8022	885	8
Pars	7228	708	4	SarSabz	6044	712	7
Ziba	9270	859	5	*Kurmesh*	5409	706	5
Sarder	7358	856	7	*Melal*	8350	899	4
Post	8379	745	4	*Alma*	6836	745	7
Keman	7474	740	9	*Asil*	7756	716	6
Farahi	5843	869	5	*Jordan*	9917	809	8
Monir	8611	795	7	*Behest*	9373	768	9
Tadim	7031	751	8	*Daani*	8600	702	7
Sareh	6025	813	8	*Pardew*	7967	776	4
Shandiz	8114	783	5	*Saei*	9308	849	6
Ab	6708	807	6	*Sadr*	7419	713	8

Regarding the second case study, Habibi et al. (2017) stated that there are currently only five waste collection centers in Tehran that meet the community's needs, according to statistics from the Tehran Waste Management Organization. There are some polluted areas in the southern parts of the city, and improper collection of municipal waste causes both urban environment pollution and social dissatisfaction. To tackle this problem, the Tehran municipality has set up some temporary waste collection centers in different parts of the city, most of which are located in urban traffic areas. This can also result in increased traffic and air pollution. Therefore, it is desirable that some permanent centers are established to collect waste.

To compare our obtained solutions with the existing system, we have assumed that each urban area is currently assigned to its nearest collection center. According to the calculations, if the numerical results of the second case study are implemented, about 21% improvement in collection costs, 47% improvement in environmental criteria, and 37% improvement in social criteria can be achieved. These results indicate significant improvements to the current situation, which indicates that not enough attention is currently devoted to sustainable development measures. Hence, the results of this research can be given to managers of responsible organizations as management decisions.

7. Conclusion

In this paper, a multi-objective sustainable location-districting

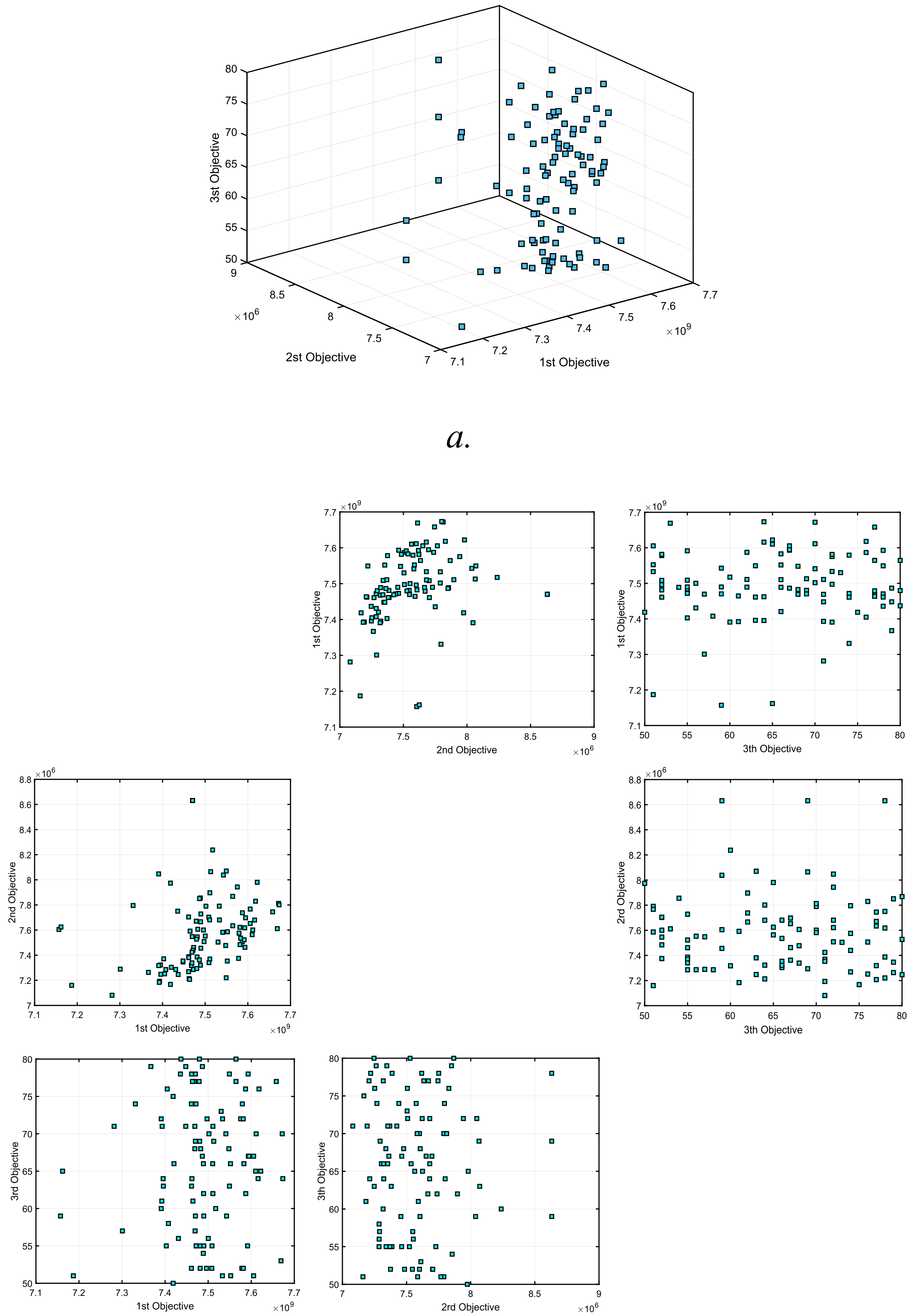

Fig. 13. The three-dimensional Pareto front (a.) and its two-dimensional image for the case study.

problem for MSW is presented. The proposed problem integrates location and districting for the first time. Three objective functions are defined to cover the minimization of the cost of establishing collection centers and collecting waste, the minimization of destructive environmental impacts caused by establishing collection centers and pollutant emission of waste collection, and the minimization of the social dissatisfaction caused by establishing collection centers. The workload balance in districts is modeled using explicit constraints, with another important set of constraints ensuring that the districts created are contiguous.

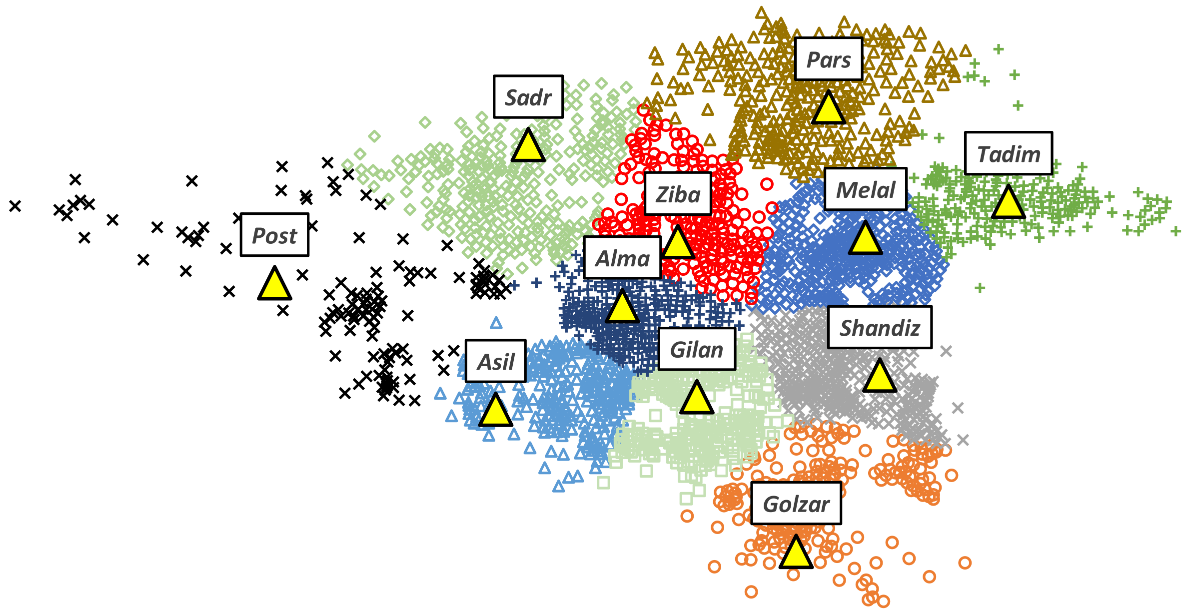

Fig. 14. The obtained location and districting structure of the case study.

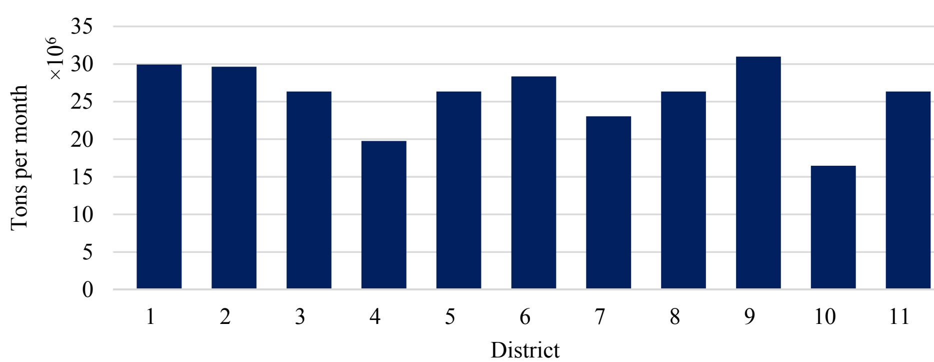

Fig. 15. The amount of waste assigned to each district.

Table 13
Values of the first objective function for different values of L^{MAX} and W^{MAX}.

	$L^{MAX}=3500$	$L^{MAX}=3000$	$L^{MAX}=2500$	$L^{MAX}=2000$
$W^{MAX}=0.25$	894.1	908.5	944.1	974.2
$W^{MAX}=0.2$	936.8	982.3	1021.7	1104.1
$W^{MAX}=0.15$	1039.6	1189.6	1219.3	*infeasible*
$W^{MAX}=0.1$	1078.9	1207.9	1277.8	*infeasible*
$W^{MAX}=0.05$	1099.8	1247.4	*infeasible*	*infeasible*

Table 14
Values of the second objective function for different values of L^{MAX} and W^{MAX}.

	$L^{MAX}=3500$	$L^{MAX}=3000$	$L^{MAX}=2500$	$L^{MAX}=2000$
$W^{MAX}=0.25$	81.4	83.4	86.7	90.1
$W^{MAX}=0.2$	84.7	85.6	88.1	92.7
$W^{MAX}=0.15$	91.2	93.5	95.4	*infeasible*
$W^{MAX}=0.1$	99.3	104.8	107.2	*infeasible*
$W^{MAX}=0.05$	102.1	106.3	*infeasible*	*infeasible*

Since location and districting problems are NP-hard, a heuristic based on local search is proposed to solve real-world instances. This heuristic first considers an initial population in each iteration. A better population is then generated based on applying a local search on each member of the population. A new population for the next generation is generated using the non-dominated sorting method. To improve the diversity of solutions, a FCM is proposed.

To evaluate the efficiency of the proposed heuristic, the obtained results from CPLEX were compared to those of the heuristic on a set of twelve randomly generated instances. This confirmed the efficiency of the heuristic. Moreover, the sensitivity of the heuristic over W^{MAX} was investigated on a number of small, medium, and large instances.

A MSW problem in Birjand, Iran was studied as a first case study. For this case study 50 Pareto members were obtained by the augmented ε-constraint method. BWM, as a MCDM method, was then applied to select the final solution. In this method, each objective function is weighted as a criterion by experts. The second case study, determining the best locations for waste collection centers in Tehran, was solved by the heuristic. In addition, sensitivity analysis of the problem over some parameters was performed. Calculations showed the great effect of these parameters in the final structure of the location-districting problem.

While the model used in this study enforces districts to be compact and contiguous, thereby restricting the travel distances within each district, it does not explicitly consider the routing of vehicles to collect waste. A potential extension of this work could therefore be to include the design of collection routes as an explicit part of the problem. This

Table 15
Values of the third objective function for different values of L^{MAX} and W^{MAX}.

	$L^{MAX} = 3500$	$L^{MAX} = 3000$	$L^{MAX} = 2500$	$L^{MAX} = 2000$
$W^{MAX} = 0.25$	71	73	75	81
$W^{MAX} = 0.2$	75	77	78	84
$W^{MAX} = 0.15$	79	82	83	*infeasible*
$W^{MAX} = 0.1$	81	83	86	*infeasible*
$W^{MAX} = 0.05$	84	87	*infeasible*	*infeasible*

Table 16
Values of workload balance between districts for different values of L^{MAX} and W^{MAX}.

	$L^{MAX} = 3500$	$L^{MAX} = 3000$	$L^{MAX} = 2500$	$L^{MAX} = 2000$
$W^{MAX} = 0.25$	0.11	0.17	0.21	0.24
$W^{MAX} = 0.2$	0.09	0.14	0.18	0.2
$W^{MAX} = 0.15$	0.07	0.1	0.11	*infeasible*
$W^{MAX} = 0.1$	0.07	0.08	0.1	*infeasible*
$W^{MAX} = 0.05$	0.04	0.05	*infeasible*	*infeasible*

would enable us to study whether tactical decisions such as routing would influence the strategic decisions regarding districting and location of collection centers, and to consider elements such as fuel consumption (Tavares, Zsigraiova, Semiao, & da Graça Carvalho, 2008).

CRediT authorship contribution statement

Sobhan Mostafayi Darmian: Conceptualization, Validation, Methodology, Visualization, Writing - original draft. **Sahar Moazzeni:** Conceptualization, Validation, Methodology, Visualization, Writing - original draft. **Lars Magnus Hvattum:** Writing - review & editing, Project administration, Methodology.

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