Annals of Operations Research
https://doi.org/10.1007/s10479-023-05429-9

ORIGINAL RESEARCH

An optimization framework for the sustainable healthcare facility location problem using a hierarchical conflict resolution approach

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Accepted: 30 May 2023

Abstract
Optimal determination of healthcare facility locations is among critical strategic decisions that significantly impact long-term public health, well-being, and social welfare. In addition to the inherent complexities that arise from resource allocation and budget limitations in general facility location problems, this problem in the healthcare sector is even more complex. On one hand, since decision makers should consider various criteria in all aspects of sustainability in locating these facilities, this problem is a complex Multi-criteria decision-making problem. On the other hand, other objectives should also be considered in locating the mentioned facilities. As a result, this paper aims to develop a multi-objective mixed-integer linear programming (MOMILP) model, one aspect of which is the Multi-criteria decision-making (MCDM) aspect of the problem by considering sustainable criteria for the healthcare facility location problem. We defined total travel distance, equity, local covering, effectiveness, and overlap functions as the objective functions of the developed model. A novel hierarchical

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conflict-resolution approach is included to rank the sub-criteria as a guideline for the Best-Worst Method (BWM) to find the weights of the criteria. To examine the effectiveness of the proposed model, we applied it to a real-world problem of locating preventive healthcare centers in Iran. As the final stage of the study, a sensitivity analysis was carried out to test the performance of the proposed framework in different possible scenarios. The results indicated that the approach is robust and applicable to real-life facility-location problems.

Keywords Healthcare operations · Sustainability · Best-worst method (BWM) · Multi-criteria decision-making (MCDM) · Conflict resolution

1 Introduction

A global assessment of the World Health Organization (WHO) indicates that more than one-fifth of global deaths are attributable to modifiable environmental factors, such as physical, chemical, and biological factors external to a person (Prüss-Ustün et al. 2016). Enhancing the quality of life by increasing the health indicator could prevent 12.6 million deaths worldwide (Taymaz et al. 2020). Even though many health conditions are preventable, in practice, poor healthcare policies and interventions, inefficient healthcare systems, unbalanced resource planning, and limited access to healthcare services provide challenges to policymakers who can use the assistance of novel decision-making tools (Ali and Kannan 2022).

Healthcare decisions are inherently complex as they aim to maximize the health benefits, minimize the health risks, increase the patient choice, maximize physical involvement, satisfy the limitations on resources, and provide fair and equitable accessibility (Mardani et al. 2019; Haeri et al. 2021). Decisions about the location of healthcare facilities can be considered critical ill-structured decision problems, since the decisions need to consider stakeholders and conflicting objectives (Dell'Ovo et al. 2018). In healthcare, sub-optimal decisions about facility locations can have a profound impact on the community beyond economic and service measures. To elaborate, inequitable healthcare facilities are likely to result in increased morbidity and mortality rates. Thus, facility location modeling for healthcare is more critical than similar modeling for other areas (Ahmadi-Javid et al. 2017). For instance, spatial accessibility to healthcare services and facilities is important for public health and social welfare (Beheshtifar and Alimoahmmadi 2015).

Facility Location Problems (FLPs) are mainly solved by using various quantitative and qualitative techniques of Operations Research (OR), management science, and operations management. The objective functions are directly related to the application area and include minimizing travel distance, maximizing service level, minimizing waiting time, maximizing coverage, and minimizing transportation costs. The Healthcare Facility Location Problem (HFLP) has received increased attention in the last decade because of the increased demand generated by population growth and an aging population (Shariff et al. 2012). The recent literature of the problem shows that instead of single-objective models, scholars have increasingly started to define the locating of a healthcare facility as a multi-objective problem that commonly faces conflicting objective functions (Zhang et al. 2016).

It is not sufficient to consider only financial factors when determining the location of healthcare facilities; social impacts and environmental regulations must also be considered. This comprehensive concept, known as sustainability, can integrate these different elements in a structured way (Anvari and Turkay 2017; Celik Turkoglu and Erol Genevois 2020). The natural conflicts of criteria in facility location problems are even more complicated in the healthcare sector since they involve human factors in addition to technical aspects and economic aspects. Therefore, the intensified complexities and conflicts of interest make the healthcare facility location problem a Multi-Criteria Decision-Making (MCDM) problem in nature (Dell'Ovo et al. 2018). As a result, implementing MCDM techniques applicable to other application areas such as supply chain management (Soheilirad et al. 2018) is a promising methodological approach to address the problem.

Since stakeholders with a variety of expectations and priorities are present in healthcare facility location problems, these problems are inherently multi-objective. For instance, while the private sector (e.g., partnerships and privately owned corporations) and the public sector (e.g., hospitals, public health) share similar objectives such as maximizing their respective utility, they differ in the way that these objectives and constraints are formulated (Eriskin et al. 2022). In addition, although common financial objectives such as cost and covering should be included in the models, more novel concepts such as equity of healthcare services are significant in location strategies. Equity concerns naturally arise in many real-life applications (e.g., healthcare scheduling, facility location, disaster-response operations, and air-traffic control), and it is important to address these concerns so that the proposed solutions will be applicable, equitable, and acceptable (Shehadeh and Snyder 2021). Finally, HFLPs have strategic, long-term effects, since the facilities are required to maintain profitability for an extended period of time and be adaptable to changes in the environment and population demand (Celik Turkoglu and Erol Genevois 2020).

As a result, developing multi-objective approaches and models is a necessary task for evaluating the facility location problem related to the healthcare sector (Farahani et al. 2019). Since establishing new facilities will bring about certain financial and social prosperity to the selected locations, the combination of these locations and their coverage areas are important aspects of the facility location problem. Thus, the investigated problem is a multi-objective one, as well as a MCDM problem, and a multi-objective model is required to cover these specific sides of the problem.

This research proposes a multi-objective mixed-integer linear programming (MOMILP) method for solving the aforementioned features of the HFLP by including sustainable criteria as one of the objective functions for the location selection of preventive healthcare facilities. To formulate the MCDM aspect of the problem, 13 criteria are defined based on the literature and experts' opinions in three aspects of sustainability. The suggested model is tested on a real case of the Iranian healthcare sector in which 12 preventive healthcare facilities should be located all across the country in 31 provinces. The mathematical model is solved for the case study to select the best combination of locations for new preventive facilities. A sensitivity analysis is also used to analyze the behavior of the proposed model in different scenarios and to deal with possible changes in the configurations of the investigated problem.

The contributions of the current study can be summarized as follows:

- We identified and organized criteria related to the healthcare facility location problem in a structured hierarchical way.
- We incorporated the idea of sustainability in the selected criteria for the healthcare facility location problem.
- We developed a scalable approach to address large-scale problems.
- We considered covering objective functions from different viewpoints in the mathematical model.
- We included the dispersion concept as a separate objective function for the healthcare facility location problem.
- We combined the MCDM and multi-objective aspects of the facility location problem in an integrated framework.

- We developed a hierarchical conflict resolution approach to rank the sub-criteria as a guideline for decision-makers involved in the weight-determination phase.

The remainder of the paper is structured as follows. Section 2 presents a detailed literature review of the healthcare facility location problem. Section 3 describes the proposed conflict resolution approach along with the mathematical models for weight calculation and the facility location problem. Section 4 explains the case study in detail. Section 5 presents the computational results and relevant sensitivity analysis. Section 6.1 discusses the managerial implications of the proposed approach. Section 6 provides the conclusion and possible future research.

2 Literature review

This section reviews the literature relevant to the current study. The articles are organized based on their approach to investigating the healthcare facility location problem. Following that, the existing gaps in the literature are identified, and the role of this paper to address these gaps is discussed.

2.1 Mathematical approaches

Researchers have approached the facility location problem in healthcare through different methods. The problem's literature has mathematical formulations such as modeling with geographical considerations Harper et al. (2005), a Mixed Integer Non-Linear Programming (MINLP) approach Radman and Eshghi (2018), multi-objective optimization Zhang et al. (2016); Beheshtifar and Alimoahmmadi (2015), a network-based covering location problem (Net-CLP) approach Ye and Kim (2016), and a MO-MILP location model Dogan et al. (2020). Various objective functions have been considered in facility location problems. The most widely used objectives in this stream of research are minimizing travel distance, maximizing service level, minimizing waiting time, maximizing coverage, minimizing transportation costs, and avoiding placement next to hazardous facilities (Farahani et al. 2019). Muffak and Arslan investigated the maximum availability service facility location problem considering both stationary and mobile demand in an urban region. They presented a mixed-integer linear programming formulation and developed a Benders decomposition algorithm with several acceleration techniques (Muffak and Arslan 2023). Table 1 presents a summary of objective functions considered in the facility location problem in the healthcare sector.

2.2 MCDM approaches

There is another stream of papers in this area that address the facility location problem from a strictly MCDM point of view. A summary of these articles is organized in Table 2.

2.3 Heuristic and metaheuristic approaches

Using heuristic and metaheuristic methods to deal with real-life, large-scale problems is another approach to select the location of healthcare facilities. Mari'c et al. developed an efficient hybrid method based on combining the Evolutionary Approach (EA) with a modified Variable Neighborhood Search method (VNS) to determine the locations for long-term

Table 1 Summary of objective functions and solution approaches in related healthcare facility location problems

Study	Approach	Objective function(s)
(Beheshtifar and Alimoahmmadi 2015)	Hybrid GA and GIS analysis	Minimize transportation costs
		Minimize unequal access to healthcare center
		Maximize site land-use compatibility
		Minimize land purchase and establishment costs
(Mestre et al. 2015)	Stochastic optimization	Minimize the expected travel time
		Minimize the expected cost
(Guerriero et al. 2016)	Exact optimization	Maximize the covered demand
(Ye and Kim 2016)	Exact optimization	Minimize the total number of facilities.
(Zhang et al. 2016)	Multi-objective GA	Maximize population accessibility
		Minimize inequity of accessibility
		Minimize the people outside a travel distance
		Minimize the cost of building a new facility
(Radman and Eshghi 2018)	GA-based heuristic	Minimize total distance traveled by patients
		Minimize deviation in arrival rates
(Dogan et al. 2020)	Exact optimization	Minimize deviation in possible participation
		Minimize deviation in waiting time
		Minimize deviation in budget
(Muffak and Arslan 2023)	Benders decomposition	maximum availability service

care facilities among given potential sites (Marić et al. 2015). They considered minimizing the maximal number of patients assigned to established facilities as their objective function. Beheshtifar et al. developed a Non-dominated Sorting Genetic Algorithm (NSGA) II algorithm to select the locations of a number of clinics (Beheshtifar and Alimoahmmadi 2015). They analyzed the Pareto front obtained by TOPSIS to find the best solutions. Steine et al. proposed an integer-coded multi-objective genetic algorithm to address the multi-objective partitioning problem, to provide significant improvement to the map of the healthcare system of Parana State in Brazil (Steiner et al. 2015). Recently, Veenstra et al. addressed a simultaneous facility location and vehicle routing problem in healthcare logistics in the Netherlands; they proposed a fast hybrid heuristic to solve the problem (Veenstra et al. 2018). In this problem, the delivery of medication from a local pharmacy can occur via lockers (where patients

Table 2 MCDM approaches for location selection in healthcare

Study	Approach	Criteria
(Vahidnia et al. 2009)	FAHP	Distance from Arterial Routes
		Travel Time
		Contamination
		Land Cost
		Population Density
(Gu et al. 2011)	Integrated multi-criteria and GIS[a]	Efficiency
		Equity
		Accessibility
(Soltani and Marandi 2011)	Two-Stage fuzzy MCDM	Distance to Arterial roads
		Distance to existing hospitals
		Parcel area
		Population density
(Chatterjee and Mukherjee 2013)	FAHP	Cost
		Population Characteristics
		Location
(Eldemir and Onden 2016)	Hybrid AHP[b]-GIS	Competition
		Accessibility
		Environment
(Karamat et al. 2019)	Fuzzy extended ELECTRE[c]	Cost
		Proximity
		Population Characteristics
		Availability of Human Resource
		Accessibility
		Environment
(Senvar et al. 2016)	Hesitant Fuzzy TOPSIS[d]	Cost
		Demographics
		Market condition
		Business
		Transportation
		Workers
		Building structure
(Dell'Ovo et al. 2018)	Spatial decision support systems	Functional Quality
		Location Quality
		Environmental
		Quality
		Economic Aspect

Table 2 (continued)

Study	Approach	Criteria
(Niroomand et al. 2018)	Direct interval-based TOPSIS	Distance to the emergency center
		Time to the emergency center
		Distance to the emergency center
		Time to the emergency center
		Distance to the hospital
		Time to the hospital
		Population of the zone
		Expected emergency calls per semiannual
		Establishing cost
(Şahin et al. 2019)	AHP	Accessibility
		Demand factors
		Environmental conditions
		Government
		Related
		Competitors

[a] Geographic information system (GIS)
[b] Analytic hierarchy process (AHP)
[c] Elimination and choice translating reality (ELECTRE)
[d] Technique for order of preference by similarity to ideal solution (TOPSIS)

who are within the coverage distance of a locker can collect their medication) or by home delivery.

2.4 Multi-objective models for healthcare facility location

The nature of the facility location is a complex decision with multiple stakeholders, meaning multi-objective models can present a holistic viewpoint of the problem. Therefore, there are several studies in the literature that attempted to include conflicting objective functions in a variety of multi-objective mathematical models. Among others, Wichapa and Khokhajaikiat formulated a multi-objective model for the optimal location for infectious waste disposal in the waste management area. Based on a case study of 40 hospitals and 3 candidate municipalities in Thailand, they considered multiple factors such as infrastructure, geological, and social & environmental factors. They presented a new multi-objective facility location problem model which combines Fuzzy Analytic Hierarchy Process (FAHP) and Goal Programming (GP). The results showed that the proposed model could find suitable locations for infectious waste disposal by considering both total cost and final priority weight objectives Wichapa and Khokhajaikiat (2017). Zhang et al. considered diverse conflicting objective functions for location decisions for healthcare facilities to improve the equity of accessibility, raise the total accessibility, reduce the population outside the coverage range, and decrease the cost of building new facilities. By employing a genetic-based multi-objective optimization (MOO) approach to find a set of Pareto solutions, they argue that the planners can compare the features of each solution to analyze or select the solution that best supports their further decisions Zhang et al. (2016). Karatas and Yakıcı presented a novel methodology for solving multi-objective facility location problems with a focus on public emergency service stations. The model included the objectives of three well-known problems, the p-median problem, the maximal coverage location problem, and the p-center problem. They designed a sequential solution method to find a set of Pareto optimal solutions and a compromise solution for all three objectives. In specific, they combined branch and bound and iterative goal programming techniques. They validated the applicability and the performance of the algorithm with a set of numerical examples Karatas and Yakıcı (2018). Wang et al. developed a hierarchical programming model to incorporate four objective functions. They adopted a bi-level multi-objective particle swarm optimization (BLMOPSO) algorithm to tackle the binary location decision and capacity adjustment simultaneously. They evaluated the proposed method on a case study with 16 patient points with a maximum of 6 open treatment units. The results demonstrate that the proposed model is suitable to be considered as a useful planning tool for decision-makers to generate policies and strategies in healthcare and design other facility projects Wang et al. (2018). Karatas and Yakıcı presented a real-world multi-objective facility location model for determining the number and locations of Temporary Emergency Service Centers for a regional natural gas distribution company in Turkey. The model included three objectives, including p-median, maximal coverage, and p-center to minimize average and maximum transfer time. They developed an integrated and iterative branch and bound algorithm with goal programming to solve the model. They showed that the solution approach could provide decision-makers with a set of Pareto optimal solutions and a unique compromise solution for all objectives incorporated in the decision analytics model Karatas and Yakıcı (2021). In one recent work, Gargari and Sahraeian presented a new criterion space search algorithm to find all non-dominated points in a bi-objective nursing home location-allocation problem (Gargari and Sahraeian 2023). Wang et al. also developed a multi-objective location-allocation model for emergency supplies with timeliness and fairness. They presented a multi-objective hyper-heuristic (MOHH) optimization framework based on an evolutionary algorithm to solve the model (Wang et al. 2023).

2.5 Literature gaps

After reviewing and analyzing the publications that address the HFLP problem, we identified the following gaps. First, papers listed in Table 2 use a range of criteria from common economic criteria to rare social and environmental ones. However, there is no paper in which the criteria are defined in a structured hierarchy. To address this issue, we located the selected criteria in our problem in three aspects of sustainability. This organized scheme can help decision-makers to identify the role of each criterion in the selection process. Moreover, they can track the impact of possible changes in the result of the process. Second, a significant number of papers have considered common economic criteria. While environmental measures are present in a limited number of papers such as (Karamat et al. 2019), influential social aspects of these decisions are completely neglected in the previous studies. Although the sustainability concept has been adapted to other facility locations such as (Rao et al. 2015) in locating City Logistics Centers (CLC), this concept is absent in the healthcare sector. To overcome this trend, 13 criteria covering various aspects of establishing a preventive healthcare facility are identified and defined based on certain aspects of sustainability. Third, a majority of approaches have been applied to small-scale problems in the literature, such as locating one hospital (Şahin et al. 2019) or an emergency center (Niroomand et al. 2018). However, real-life problems are more complicated than these assumptions. To bridge this gap, the developed mathematical model can be easily modified for large-scale problems. This feature will increase the adaptability and applicability of the developed approach. Moving to the next gap, in papers such as (Guerriero et al. 2016) that considered covering as one of the objective functions, this concept is defined as a single parameter of the problem. However, in reality, the covering can be defined from various perspectives of the facility location problem. In the current study, a local covering is defined as a function of geographical and economic barriers of the candidate locations. Moreover, a technical covering function is also considered as a separate objective function to find the overlaps of the selected locations, which is related to standards of delivery of healthcare services. Another noteworthy gap in the literature of the problem is related to a concept known as dispersion. While many papers have been concerned with a covering function, the importance of the equal distribution of healthcare facilities is neglected. To address this aspect, a separated objective function is formulated in the section on sensitivity analysis to maximize the dispersion among the selected locations. This feature can help decision-makers to make a trade-off between the covering objective function and the dispersion objective function. Finally, all of the papers mentioned in the literature review addressed the location problem either from a strictly MCDM angle or from a purely mathematical viewpoint. However, since these aspects are interconnected, developing integrated models for the problem is an important effort overlooked in the literature. To address this gap, a combination of MCDM and mathematical objective functions form our proposed mathematical model. This characteristic will help to monitor the role of MCDM criteria as well as the mathematical aspects of the facility location problem in a well-structured way.

3 Methodology

In this section, we first present the proposed hierarchical conflict resolution approach for ranking the sub-criteria. Then, we present the compact formulation for the weight calculation of MCDM criteria. Finally, we provide a detailed description of the proposed mathematical model for healthcare facility location. Figure 1 shows the procedure of the proposed hybrid approach for the sustainable selection of the location of healthcare facilities.

3.1 Hierarchical conflict resolution framework for sub-criteria ranking

In this section, we demonstrate our proposed framework, which can be used for any hierarchical multi-criteria decision-making (HMCDM) problem. The idea behind a hierarchical multi-criteria decision-making problem is to decompose a complicated problem with several criteria and sub-criteria into a hierarchy.

The perspectives of experts are an important component of any HMCDM. There are two significant concerns that are frequently neglected in research studies. First, there is the potential for internal conflicts and prejudice among the group of decision-makers (or experts). Second, these specialists are not well educated about all of the criteria, and the majority of the time, an expert is knowledgeable only with regard to a single element of the problem. The suggested framework was primarily inspired by these two concerns. Here, we explain the notations used in our developed framework. Then, we discuss the steps of this framework. We conclude by outlining how the framework's output may be included in a BWM to determine

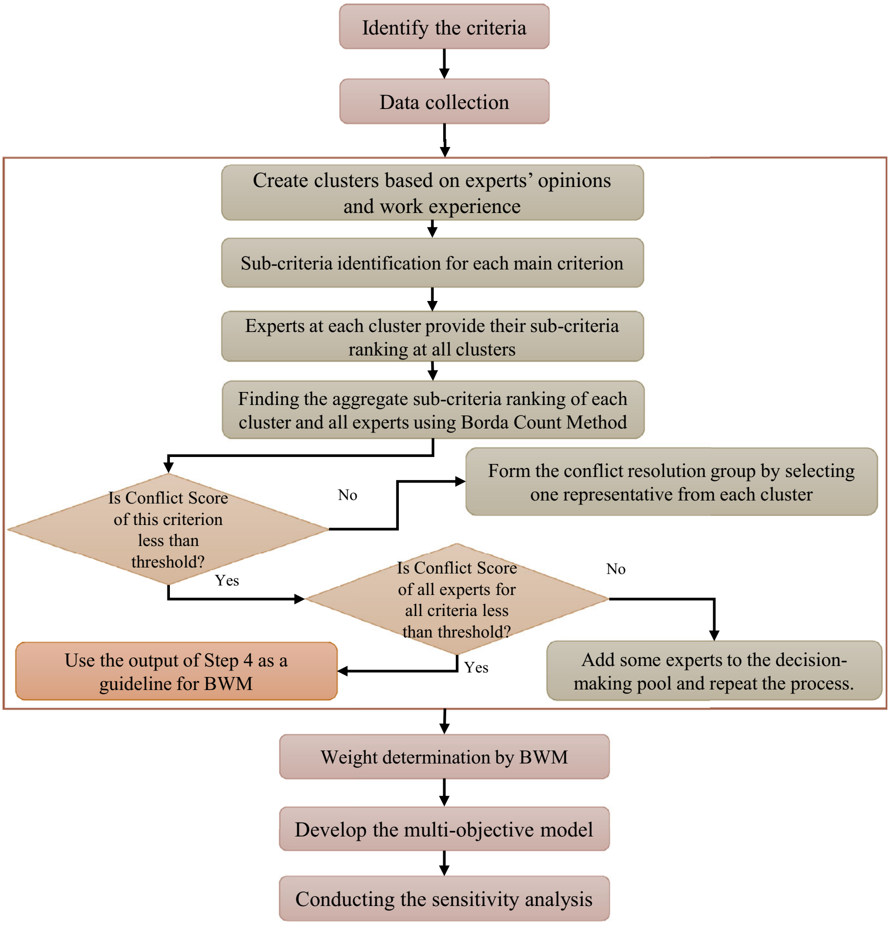


Fig. 1 Graphical summary of the proposed approach

the relative importance of each sub-criterion inside each cluster. Table 3 summarizes the notations used in this framework.

Step 1: Create J clusters among I experts for J main criteria that exist in the hierarchy. Each of the I experts will be assigned to one of these J clusters based on their work experience, education level, and familiarity level with respect to these J main criteria. We know that a_{ij} defines the cluster assignments for all experts. The following equations show the mathematical relationship between a_{ij}, N_j and I.

$$N_j = \sum_{i \in I} a_{ij}, \forall j \in J \tag{1}$$

$$I = \sum_{j \in J} N_j \tag{2}$$

Step 2: Each expert provides some sub-criteria for jth criterion.

Step 3: Pick all the sub-criteria that are common among at least $\alpha\%$ of experts and form the sub-criteria pool at each cluster

Table 3 The notations of the conflict resolution framework

	Description
Sets	
i	Expert's index $i = 1, ..., I$
j, j', k	Criterion/Cluster index $j, j', k = 1, ..., J$
Parameters	
a_{ij}	Binary parameter: It takes one if i^{th} expert is assigned to j^{th} cluster
N_j	Number of experts assigned to j^{th} cluster
α	The threshold percentage for filtering the most important sub-criteria at each cluster
β	The acceptable conflict level among experts at different clusters
θ	The acceptable conflict level among all experts
m_j	Number of sub-criteria in j^{th} cluster
rc_{ij}	The provided ranking of i^{th} expert for j^{th}sub-criteria ranking in cluster
λ^{m_j}	maximum possible distance between two aggregate rankings with m_j sub-criteria
w_{jk}	The importance weight of j^{th} cluster's opinion about k^{th} main criterion
Framework's outputs	
ar_{jk}	The aggregate ranking of j^{th} cluster for sub-criteria of k^{th} main criterion
sr_j	The score representation of final aggregate ranking of sub-criteria of j^{th} cluster
fr_j	The final aggregate ranking of sub-criteria of j^{th} cluster
$d_{jj'k}$	The distance between aggregate sub-criteria ranking of cluster j and j' on k^{th} cluster
$cb_{jj'k}$	The conflict score between aggregate sub-criteria ranking of cluster j and j' on k^{th} cluster
cm_k	The conflict score among J clusters on k^{th} main criterion
cs	The total conflict score

Step 4: Each expert provides a strict ranking over all sub-criteria that exist at the jth cluster (i.e., rc_{ij}). Therefore, the initial ranking of inputs provided by all experts is equal to $I \times J$.
Step 5: Calculate the aggregated ranking by experts of all sub-criteria in the jth cluster using the tournament-style counting approach of the Borda Count Method (BCM).

Step 5.1: In the tournament-style counting approach of the Borda Count Method, the last choice would be worth zero points, and the point value for each of the higher options is one lower than in the traditional Borda count method. To be more exact, the score assigned to each sub-criterion at the j $^{\text{th}}$ cluster ranges from zero to $m_j - 1$.

Step 5.2: Calculate the summation of scores assigned to each sub-criterion.

Step 5.3: Convert the assigned scores to a ranking vector such that the highest score represents the most important sub-criterion, and the lowest score represents the least important sub-criterion (i.e., $\text{ar}_{jj'}$.)

Notice that the proposed framework calculates the aggregate ranking of all J clusters of experts for all J main criteria. Thus, at the end of Step 5, we will have J^2 aggregate rankings in total.

Step 6: The conflict score among these J groups of experts with regard to sub-criteria ranking at each cluster is calculated. In this step, we basically compare the aggregate ranking of clusters to examine if the existing conflict between clusters is tolerable. Equation 3 calculates the difference between the aggregate subcriteria ranking of clusters j and j' with respect to the k^{th} cluster

$$d_{jj'k} = \left(ar_{jk} - ar_{j'k}\right)^2 \quad \forall j, j', k = 1, \ldots, J \tag{3}$$

So, at each cluster, we have $(J - 1)!$ combinations of conflict degree, which means the framework generates $J\,!$ values of conflict degree in total. Now, we need to know the maximum possible difference between two ranking vectors to be able to calculate the conflict degree between two aggregate rankings. Define λ^{m_j} as the maximum possible distance between two aggregate rankings with m_j sub-criteria. It has been proven that the maximum difference between two ranking vectors happens when these two vectors are exactly the opposite of each other. For example, if we have 5 sub-criteria in the first cluster, the maximum deviation happens when have two vectors such as (1 2 3 4 5) and (5 4 3 2 1). In this example, the Euclidean distance between these two vectors is equal to 40. Equation 4 defines how the conflict score between the aggregate sub-criteria ranking of clusters j and j' with respect to the k^{th} cluster (i.e., $cb_{jj'k}$) is calculated.

$$cb_{jj'k} = \frac{d_{jj'k}}{\lambda^{m_j}} \quad \forall j, j', k = 1, \ldots, J \tag{4}$$

Step 7: The conflict score of each cluster is calculated. Equation 5 shows how the conflict score among J clusters on the k^{th} main criterion is calculated.

$$cm_k = \frac{\sum_{j \in J} \sum_{j' \in J} cb_{jj'k}}{2} \quad \forall k = 1, \ldots, J \tag{5}$$

Step 8: Conflict resolution at each cluster: if $\mathrm{cm}_k \leq \beta$ go to step 8.1., otherwise go to step 8.2.

Step 8.1: If any of the conflict scores of clusters is below the acceptable threshold (i.e., β), it means that there is enough consensus among the experts in different clusters with regard to sub-criteria ranking at each cluster. In this case, the aggregate ranking of sub-criteria at each cluster will be calculated using Eq. 6.

$$sr_k = \sum_{j \in J} w_{jk} ar_{jk} \quad \forall k \in K \tag{6}$$

Once the sr_k is calculated, in the same way as the Borda Count Method, the closest strict ranking will be identified as the aggregate sub-criteria ranking of all experts of the k^{th} main criterion. So w_{jk} will be calculated as a function of the knowledge, work experience, and education level of the experts assigned to the j^{th} cluster about the k^{th} main criterion.

Step 8.2: If any of the conflict scores of clusters is higher than the acceptable threshold (i.e., β), it means that there is not enough consensus among experts in different clusters with regard to sub-criteria ranking in the k^{th} cluster. In this scenario, our framework prescribes that each cluster determines a representative to discuss the conflict to reach a common ground via a consensus-reaching process. In case the representatives could not reach a common ground with regard to sub-criteria ranking, our framework suggests following the ranking of the cluster that has been assigned to that specific main criterion because they are the experts that have the most experience and knowledge with regard to that subject.

Step 9: Conflict resolution among all experts: Eq. 7 calculates the conflict score among all J clusters on all sub-criteria rankings.

$$cs = \sum_{k \in J} cm_k \tag{7}$$

if $\mathrm{cs} \leq \theta$ go to step 9.1., otherwise go to step 9.2

Step 9.1: In this case, the final aggregate ranking of the k^{th} cluster is the output of Step 8.

Step 9.2: In this case, our framework prescribes adding some new experts and repeating the process from Step 1. The rationale behind this prescription is that there is not enough consensus among all experts in the decision-making pool.

Step 10: The final aggregate ranking of all sub-criteria at each cluster will be used as a guideline for decision-makers who are involved in the weight determination phase using BWM.

3.2 Weight calculation for MCDM criteria

Rezaei introduced a novel MCDM technique known as the BWM (Rezaei 2015). Although this method is based on pairwise comparisons like AHP, it needs fewer pairwise comparisons and can produce more robust results. In specific, we selected this MCDM method since the statistical analysis of Rezaei (2015) showed that BWM performs significantly better than other MCDM options in terms of consistency ratio, minimum violation, total deviation, and conformity. In this method, the inconsistency rate (IR) is calculated to assess the consistency of the results. In the current study, a linear version of this approach is used. Equations 8 to 11 show the linear formulation of this method for a set of l criteria.

$$Min\mathcal{Z} = \sigma \tag{8}$$

$$|w_B - \alpha_{Bl} w_l| \leq \sigma, \forall l \tag{9}$$

$$|w_l - \alpha_{lW} w_w| \leq \sigma, \forall l \tag{10}$$

$$\sum_l w_l = 1, w_l \geq 0, \forall l \tag{11}$$

We use the set of w_c, the output of the BWM method, as the weights of criteria in Eq. 12 of the proposed mathematical model.

3.3 Mathematical model

In this section, the MOMILP model is presented in detail. Table 4 shows the notations of the developed model. The objective functions and constraints of the model are explained in detail in the following sections.

3.3.1 Objective functions

MCDM: As the first objective function, the MCDM objective function based on sustainable criteria is defined to maximize the weighted score.

$$\max z_1 = \frac{1}{12} \times \sum_{i=1}^{I} \sum_{l=1}^{L} x_i \times w_l \times c_{il} \tag{12}$$

Total travel distance: The second objective function minimizes the total travel distance of people in each node to the nearest-located screening facility.

$$\min z_2 = \sum_{j=1}^{J} nd_j \times pop_j \tag{13}$$

Table 4 The notations of the mathematical model

	Description
Sets	
l	Set of criteria $l = 1, ..., L$
i	Healthcare service center (i.e. potential locations) index $i = 1, ..., I$
j	Patients' node index (Number of cities with population more than 200000) $j = 1, ..., J$
k	Objective function index $k = 1, ..., K$
Decision variables	
x_i	It is one if we build the screening center at i^{th} location (binary variable)
ds_{ij}	Auxiliary decision variable for nearest distance between j^{th} node and selected locations
nd_j	The nearest distance between j^{th} node and the selected locations
lc_j	Binary decision variable that is one if the nd_j is no higher than a threshold
ol_{ij}	Binary decision variable that is one if the d_{ij} is no higher than a threshold
Parameters	
pop_j	The population of j^{th} node
d_{ij}	The distance between i^{th} location and j^{th} node
cp_i	The expected number of patients in i^{th} location
TL	The average desired threshold of local travel distance
TH	The standard threshold for healthcare services coverage
c_{il}	The value of criteria l for location i

Equity: This objective function is trying to minimize the maximum value of nd_j. In other words, the purpose of this objective function is to secure a more equitable distribution of the healthcare facilities across the country. To linearize this non-linear objective function, an auxiliary variable sv is defined to find the maximum value of nd_j to be minimized. Equation 15 shows the linear version of this objective function.

$$\min z_3 = \max\left(nd_j\right) \tag{14}$$

$$sv \geq nd_j, \forall j = 1, \ldots, J \Rightarrow \min z_3 = sv \tag{15}$$

Local coverage: The local covering objective function is defined in Eq. 16 to maximize the local coverage of the designated nodes of the network.

$$\min z_4 = \sum_{j=1}^{J} lc_j \tag{16}$$

Effectiveness: Providing healthcare services to locations with a higher prevalence of cancer is a crucial goal of the model. To do so, Eq. 17 is formulated to maximize the total number of new patients covered by the new facilities.

$$\min z_5 = \sum_{i=1}^{I} cp_i x_i \tag{17}$$

Overlap coverage: The final objective function, presented in Eq. 18, is trying to minimize the overlap among the selected locations for establishing new screening facilities. Since there are not enough resources to establish preventive healthcare facilities in all regions of a country, this objective is formulated to maximize the usage of available human resources so that less-developed sections are also covered in terms of having equal access to healthcare services.

$$\min z_6 = \sum_{j=1}^{J} u_j \tag{18}$$

Total objective function: Since the objective functions have different natures, they should be normalized before formulating the weighted total objective function. To normalize the objective functions, one approach is to minimize the distance between the objective function value (f) and the optimum point of that objective (f^*). f_k^* is the objective function value for solving the model as a single-objective model to optimize the kth objective function. After normalizing the objective functions, the total objective function can be defined to minimize the weighted distance of all objective functions from their optimal point, as stated in Eq. 19.

$$\min Z_{total} = \sum_{k=1}^{6} w_j \left(\frac{f_k^* - f_k}{f_k^*}\right) \tag{19}$$

3.3.2 Constraints

Allocation constraint: Constraint 20 is used to ensure that the total number of selected locations is equal to the desired number of facilities.

$$\sum_{i=1}^{I} x_i = 12 \tag{20}$$

Auxiliary constraint for nd_j: Constraint 21 is used to define an auxiliary variable that is the distance between the selected locations and the available nodes.

$$ds_{ij} = x_i d_{ij} \quad \forall i = 1, \ldots, I; \ j = 1, \ldots, J \tag{21}$$

Nearest distance constraint: The set of Eqs. 22 and 23 are defined to find the nearest distance between each node and the selected locations.

$$\text{Max nd}_j, \tag{22}$$

$$s_{i,j} \geq nd_j \quad \forall i = 1, \ldots, I, \ j = 1, \ldots, J \tag{23}$$

Local coverage constraint: Based on this set of constraints, if the distance of a node is higher than a predefined threshold, the local coverage is not satisfied.

$$nd_j - T \leq M\left(1 - lc_j\right) \quad \forall j = 1, \ldots, J \tag{24}$$

$$nd_j - T \geq -M \times lc_j \quad \forall j = 1, \ldots, J \tag{25}$$

Overlap coverage constraint: This set of constraints is used to find whether there is a technical overlap between two selected locations for new screening. The overlap among centers is calculated by Eqs. 26 and 27, and Constraint 28 is defined to calculate the number of overlaps for each node j. Finally, Eq. 29 is used to eliminate the negative elements of v_j. In other words, this objective function does not differentiate between an uncovered node and a node that is covered by only one node. So, only the nodes covered by more than 1 node are counted in this equation.

$$d_{ij} - T \leq M\left(1 - ol_{ij}\right) \quad \forall i = 1, \ldots, I \quad and \quad \forall j = 1, \ldots, J \tag{26}$$

$$d_{ij} - T \geq -M \times ol_{ij} \quad \forall i = 1, \ldots, I \quad and \quad \forall j = 1, \ldots, J \tag{27}$$

$$v_j = \sum_{i=1}^{31} ol_{ij} - 1 \quad \forall j = 1, \ldots, J \quad \forall j = 1, \ldots, J \tag{28}$$

$$u_j = \max\left(0, v_j\right) \quad \forall j = 1, \ldots, J \tag{29}$$

4 Case study

To test the proposed approach for locating healthcare facilities, a real case study in the Iranian healthcare sector was selected. Healthcare in Iran is provided through a mixed public and private system. The government plays a significant role in the sector, providing healthcare services through public hospitals and clinics, as well as implementing health insurance programs. Access to healthcare has improved in recent years, with a focus on rural areas. However, there are still challenges, including inadequate infrastructure, shortages of medical supplies, and regional disparities. Iran has an extensive network of healthcare facilities, including public hospitals, private hospitals, clinics, and rural health centers. However, the infrastructure is often inadequate, especially in remote and rural areas, leading to disparities in access to healthcare services. The Iranian government operates a comprehensive public healthcare system, providing subsidized or free healthcare services to its citizens. Public hospitals and clinics offer a wide range of medical services, including primary care, specialized care, and emergency services. Iran faces several healthcare challenges, including non-communicable diseases such as cardiovascular diseases, cancer, and diabetes. In specific, Providing equal healthcare services is designated as among the most important missions of The Ministry of Health and Medical Education in Iran. Since cancer is categorized among the most fatal diseases in the country, we define the healthcare facilities in the case study as preventive centers for early-stage detection of cancer. Therefore, policy-makers are trying to intensify the early detection and prevention of cancer as much as possible. To do so, establishing new preventive healthcare facilities plays a key role. In this specific case, 12 new preventive healthcare facilities need to be located across the country. There are 31 provinces in Iran. The main goal of this comprehensive program is to provide equal cancer screening programs for people living in all parts of the country. There are contributing social and environmental factors as well as economic factors, and all of these factors should be considered in the decision-making process. Providing good coverage for cities surrounding the centers is equally important for the policy-makers. So, this case is a perfect example of the multi-objective sustainable facility location problem in healthcare. The other assumptions in the case are listed as follows:

- All facilities have the same capacity and can be assigned to all provinces.
- There are sufficient staff and specialists as well as medical equipment in all regions.
- There is enough public and government monetary support for building and supporting the facilities.

– The people living in cities with lower than 200,000 population will go to the nearest centers to receive screening services.

To gather the data, the formal annual report of the Statistical Centre of Iran in 2016 was used. Data related to the incidence of cancer in Iranian provinces was acquired from the website of the Non-Communicable Diseases Research Center (NCDRC). The mentioned real data was available for 11 of our chosen criteria. However, there was no comprehensive data available for two remaining criteria (pollution and related industry) in Iranian provinces. Therefore, we asked the qualified experts in these fields to assign a score to the provinces based on their knowledge and experience.

4.1 MCDM criteria

Reviewing the literature and getting feedback from experts in the healthcare sector led to selecting 13 criteria as most influential in selecting the location of a preventive healthcare facility in Iran. Table 5 shows these criteria, their unit measures, and their nature.

4.1.1 Economic criteria

Economic criteria can be classified into the following categories:

Cost: There are different kinds of costs in the selection process, including acquisition, construction, equipment, labor, and maintenance costs. To simplify the process, all costs are

Table 5 Selected criteria in sustainability pillars for the problem

Sustainability section	Criteria	Unit of measure	Nature
Economic	Cost Vahidnia et al. (2009), Soltani and Marandi (2011), Niroomand et al. (2018)	Rial	Negative
	Financial prospect	Rial	Positive
	Human resources Senvar et al. (2016)	Persons	Positive
	Related industries Senvar et al. (2016), Şahin et al. (2019)	Qualitative	Positive
Social	Income inequality Chatterjee and Mukherjee (2013)	Number	Positive
	Development impact	Index (0,1)	Positive
	Accessibility Vahidnia et al. (2009),Gu et al. (2011)	Persons	Positive
	Quality of healthcare services	Number	Negative
	Distance from capital Niroomand et al. (2018)	Kilometer	Positive
Environmental	Pollution Vahidnia et al. (2009), Şahin et al. (2019)	Qualitative	Negative
	Water resources Şahin et al. (2019)	Millimeter	Positive
	Waste disposal system	Number	Positive
	Local regulations Şahin et al. (2019)	Number	Negative

considered as a total number. Because of small variations in the design and financial status of different regions, establishing a similar preventive healthcare facility in two places can have different total expenses. However, to simplify the process, the average cost is used in these calculations.

Financial prospect: Even though constructing a healthcare facility is entirely different from manufacturing one, having a strong economy in the surrounding area can be helpful. This financial prosperity can help the facility to meet its financial needs for maintenance and salaries. In the current study, the Gross Domestic Product (GDP) is considered as an indication of a good economy.

Human resources: It is vital for decision-makers to know that the job market in the selected area is sufficient to staff the facilities. The number of unemployed people in the selected locations can indicate their potential in terms of human resources.

Related industries: Healthcare facilities need to have strong relationships with certain industries such as medical equipment and medicine. A greater presence of these sectors indicates a better location for a facility.

4.1.2 Social criteria

Social criteria include the following aspects:

Income inequality: The facilities are intended to be assigned to locations where social welfare is not well-established. A good indicator of this social aspect is the number of families at a low-income level in the selected areas.

Development impact: Assigning a facility to a specific province can bring serious benefits, one of which is the possible impact on improving the development situation of that area. The total value of this impact is important in the calculations.

Accessibility: Access to roads, public transportation, and air travel plays a key role in the facility location problem. To assess this aspect, the total number of people in the province using public transportation is considered in the study.

Quality of healthcare services: This criterion is defined to assure that the facilities are assigned to regions with lower available healthcare services. The total number of hospital beds in the selected provinces can accurately reflect this criterion.

Distance from the capital: Allocating facilities to less-developed areas is an integral part of the problem. The geographical distance of the selected regions from the capital of Iran can be seen as an indication of sustainable development in the country.

4.1.3 Environmental criteria

Environmental criteria include the following elements:

Pollution: Locating the facilities in regions with lower levels of air pollution and noise pollution is an important aspect of the defined problem. The total score of the selected locations is included in the proposed model.

Water resources: Having access to reliable water resources is very important for healthcare facilities. In this paper, the average long-term precipitation in a province is considered as an indication of good, consistent water resources.

Waste disposal systems: Handling the waste produced in the facilities is another concerning environmental facet of the problem. The total number of available waste disposal factories in each province can be used as a measure to evaluate the alternatives.

Local regulations: The proximity of facilities to natural habitats and the consequent required certificates can be a problematic factor. We consider the number of national protected areas in the chosen locations as a relevant indicator.

5 Computational results

As a first step, BWM is used to find the weights of the criteria. Then, the proposed MOMILP model is executed for the case study to find the optimal solution. A comprehensive sensitivity analysis is the final part of this section. The mathematical model was coded in GAMS optimization package and was executed on a system with a Core i5 CPU and 16.0 GB RAM. The computational time for the baseline model was around 300 s.

5.1 Conflict resolution approach

Within our case study, we used the conflict resolution approach framework. As a space-saving precaution, we only show the final, aggregate ranking of sub-criteria inside each cluster here. This is the final aggregate ranking for economic criteria: C4, C3, C3, and C1. This indicates that, from an expert's perspective, the related industry in various regions is the most important factor, whereas the setup cost of constructing a new clinic is the least important factor. According to expert opinions, the sub-criteria should be prioritized in this order in the social dimension of sustainability: C7, C5, C8, C9, and C5. Thus, accessibility is the primary consideration, and the quality of healthcare services available in the area is the least important criterion. Finally, when it comes to the environmental aspect of sustainability, local regulations are the most important criterion, and pollution level is the least important criterion. After local regulations, water resources happened to be slightly more important than waste disposal system from the experts' perspective.

5.2 Weights calculation

To find the weights of criteria in the MCDM objective function, calculations should be done at two levels: the top level, and the criteria level. Table 6 shows these calculations in detail. The final weights of the criteria can be obtained by multiplying the weights at the top level by the weights at the criteria level shown in Table 7.

5.3 Mathematical model output

In this section, the proposed mathematical model is solved for the specific case study. The model is coded in GAMS and is solved to optimality in about 150 s. The weights of the objective functions are considered equal in this configuration. Figure 2 shows the satisfaction percentage for each objective function separately. The satisfaction percentage is calculated as the value of each objective function divided by the optimal value of that objective function. A satisfaction percentage of 100 percent (such as for Z_6) means that the value of that objective function in the weighted and normalized model is equal to the value in the single-objective model. A satisfaction percentage lower than 100 for an objective function (such as for Z_5) indicates that its value is lowered by the model to make a trade-off between all objective

Table 6 Weight calculations for sustainability criteria

	Level	Calculations	Weights	
Criteria Level	Top Level	$\left.\begin{array}{l}A_B=(4,1,5)\\A_B=(5,1,4)\\A_B=(3,1,6)\end{array}\right\}\overset{Average}{\Longrightarrow}A_B=(4,1,5)$	Sustainability Aspect	Weight
			Economic	0.216
		$\left.\begin{array}{l}A_W=(4,5,1)\\A_W=(3,6,1)\\A_W=(5,4,1)\end{array}\right\}\overset{Average}{\Longrightarrow}A_W=(4,5,1)$	Environmental**	0.100
			Social*	0.683
				IR=0.183
	Economic level	$\left.\begin{array}{l}A_B=(1,2,5,5)\\A_B=(1,3,5,7)\\A_B=(1,4,5,6)\end{array}\right\}\overset{Average}{\Longrightarrow}A_B=(1,3,5,6)$	Criteria	Weight
			Cost*	0.560
		$\left.\begin{array}{l}A_W=(7,4,3,1)\\A_W=(5,4,3,1)\\A_W=(6,5,3,1)\end{array}\right\}\overset{Average}{\Longrightarrow}A_W=(6,5,3,1)$	Financial Prospect	0.229
			Human Resources	0.137
			Related Industry**	0.071
				IR=0.129
	Social	$\left.\begin{array}{l}A_B=(5,1,7,6,5)\\A_B=(6,1,7,7,3)\\A_B=(7,1,8,5,3)\end{array}\right\}\overset{Average}{\Longrightarrow}A_B=(6,1,8,6,4)$	Criteria	Weight
			Income Inequality	0.126
			Development Impact*	0.536
			Accessibility**	0.052
		$\left.\begin{array}{l}A_W=(4,7,6,1,5)\\A_W=(4,5,5,1,5)\\A_W=(4,6,6,1,5)\end{array}\right\}\overset{Average}{\Longrightarrow}A_W=(4,6,6,1,5)$	Quality of Healthcare Services	0.189
			Distance from Capital	0.094
				IR=0.221

Table 6 (continued)

Level	Calculations	Weights	
Environmental	$\left.\begin{array}{l} A_B = (7,5,1,7) \\ A_B = (6,6,1,8) \\ A_B = (5,6,1,8) \end{array}\right\} \overset{Average}{\Longrightarrow} A_B = (6,6,1,8)$	Criteria	Weight
		Pollution	0.146
		Water Resources	0.146
	$\left.\begin{array}{l} A_W = (5,7,8,1) \\ A_W = (5,6,8,1) \\ A_W = (6,6,8,1) \end{array}\right\} \overset{Average}{\Longrightarrow} A_W = (6,7,8,1)$	Waste Disposal System*	0.653
		Local Regulations**	0.053
			IR=0.226

* Best criterion, ** Worst criterion

Table 7 Final Weights of the criteria

Sustainability Aspect	Criteria	Notation	Weight
Economic	Cost	C1	0.121
	Financial prospect	C2	0.049
	Human resources	C3	0.029
	Related industry	C4	0.015
Social	Income inequality	C5	0.086
	Development impact	C6	0.366
	Accessibility	C7	0.035
	Quality of healthcare services	C8	0.129
	Distance from capital	C9	0.064
Environmental	Pollution	C10	0.014
	Water resources	C11	0.014
	Waste disposal system	C12	0.065
	Local regulations	C13	0.005

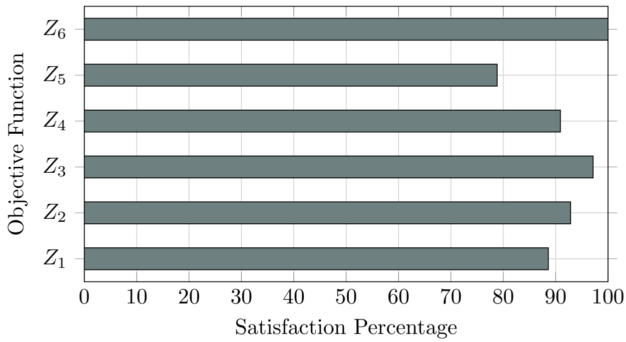


Fig. 2 The satisfaction percentage for each objective function

functions. Figure 3 shows the locations selected for the centers and the nodes they cover for the screening services in the case study.

5.4 Sensitivity analysis

Some elements of the investigated problem are prone to sudden changes. For example, a change in the preference of decision-makers will change the weights of the criteria and consequently the MCDM objective function of the problem. Likewise, decision-makers might be interested in assessing the alternative states of the problem in different settings. Thus, monitoring and evaluating the behavior of the proposed approach in different scenarios is informative. The sensitivity analysis is presented in separate sections; each section is concerned with a specific feature of the investigated problem.

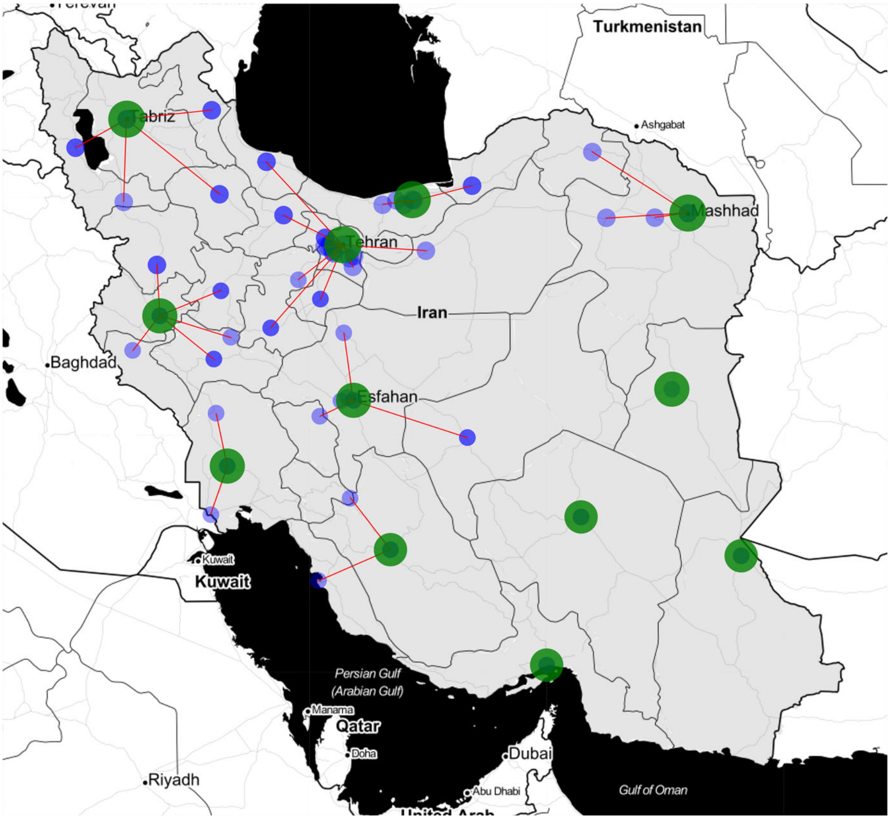


Fig. 3 Facility locations selected and the nodes they cover

5.4.1 Weight scenario

In the first section of sensitivity analysis, the impact of the weights of the sustainability criteria and the objective functions is investigated. To begin the process, each of four experts assigned a weight to each objective function (Table 8). Then, twenty scenarios are randomly generated in the obtained range for each objective function (Table 9), and twenty scenarios are

Table 8 Experts' opinions about weights of the objective functions

Expert	Objective function					
	1	2	3	4	5	6
Expert 1	0.2	0.2	0.1	0.1	0.2	0.2
Expert 2	0.1	0.3	0.1	0.1	0.3	0.1
Expert 3	0.05	0.15	0.35	0.2	0.2	0.05
Expert 4	0.3	0.1	0.08	0.4	0.05	0.07

Table 9 Weight scenarios for objective functions

Scenario	Objective function					
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6
1	0.191	0.152	0.318	0.141	0.112	0.082
2	0.102	0.127	0.089	0.328	0.265	0.087
3	0.239	0.178	0.155	0.159	0.140	0.127
4	0.126	0.199	0.260	0.232	0.075	0.104
5	0.153	0.172	0.171	0.252	0.124	0.126
6	0.120	0.199	0.112	0.256	0.248	0.062
7	0.090	0.101	0.333	0.185	0.197	0.090
8	0.122	0.239	0.291	0.172	0.126	0.048
9	0.172	0.214	0.153	0.205	0.153	0.099
10	0.081	0.244	0.197	0.144	0.270	0.060
11	0.152	0.204	0.287	0.136	0.155	0.063
12	0.117	0.147	0.116	0.289	0.210	0.119
13	0.195	0.184	0.245	0.248	0.047	0.079
14	0.088	0.208	0.112	0.186	0.208	0.195
15	0.151	0.079	0.262	0.308	0.063	0.134
16	0.195	0.187	0.123	0.246	0.141	0.106
17	0.092	0.180	0.161	0.282	0.175	0.108
18	0.110	0.130	0.246	0.319	0.088	0.103
19	0.146	0.202	0.120	0.240	0.163	0.126
20	0.208	0.138	0.233	0.124	0.184	0.110

randomly designed for the 13 criteria of the MCDM objective function (Table 10). Variations in the weights of the objective function and the sustainability criteria will directly affect the values of Z_{total} and Z_{MCDM}, respectively. The values of Relative Percentage Deviation (RPD), as calculated from Eq. 30, for these scenarios are shown in Table 11.

$$RPD_{Obj} = \frac{f_{sc} - f_{target}}{f_{target}} \times 100 \tag{30}$$

5.4.2 MCDM weight scenarios

In this part of the sensitivity analysis, the impact of the weights of three sustainability sections on the values of Z_total and Z_{MCDM} is evaluated. To do so, a number of scenarios with different weights for economic, social, and environmental sections are designed as in Table 12. Figure 4 shows the correlation test among the mentioned objective functions and the weights. As can be seen, the ratios of weights play a crucial part in affecting objective functions. The correlation between social and environmental weights is also significant. Changing the weight of the economic section is not as important as expected, though.

Table 10 Weight scenarios for sustainability criteria

Scenario	Criteria												
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
1	0.121	0.049	0.029	0.015	0.086	0.366	0.036	0.129	0.064	0.014	0.014	0.065	0.005
2	0.122	0.007	0.098	0.035	0.056	0.073	0.125	0.055	0.131	0.040	0.093	0.088	0.071
3	0.116	0.111	0.029	0.021	0.166	0.028	0.005	0.093	0.146	0.111	0.031	0.061	0.076
4	0.163	0.026	0.142	0.107	0.062	0.031	0.071	0.080	0.020	0.097	0.037	0.063	0.096
5	0.033	0.038	0.081	0.034	0.108	0.129	0.096	0.045	0.076	0.014	0.119	0.115	0.107
6	0.052	0.120	0.004	0.086	0.063	0.032	0.036	0.085	0.019	0.121	0.095	0.140	0.141
7	0.104	0.005	0.011	0.052	0.086	0.106	0.066	0.133	0.117	0.158	0.086	0.053	0.017
8	0.096	0.122	0.066	0.014	0.041	0.024	0.044	0.069	0.082	0.071	0.137	0.081	0.148
9	0.097	0.145	0.036	0.102	0.044	0.102	0.105	0.010	0.038	0.034	0.101	0.128	0.052
10	0.118	0.102	0.001	0.091	0.058	0.138	0.000	0.070	0.064	0.069	0.116	0.048	0.119
11	0.088	0.006	0.032	0.135	0.088	0.028	0.063	0.113	0.035	0.138	0.045	0.171	0.050
12	0.107	0.026	0.040	0.012	0.081	0.096	0.076	0.059	0.090	0.091	0.095	0.089	0.132
13	0.032	0.109	0.036	0.018	0.093	0.069	0.070	0.102	0.118	0.053	0.102	0.064	0.129
14	0.117	0.036	0.086	0.082	0.076	0.122	0.037	0.044	0.016	0.132	0.090	0.067	0.090
15	0.095	0.113	0.095	0.126	0.091	0.174	0.038	0.018	0.019	0.011	0.071	0.078	0.064
16	0.100	0.082	0.101	0.122	0.128	0.025	0.018	0.091	0.012	0.069	0.069	0.113	0.063
17	0.067	0.114	0.126	0.089	0.059	0.025	0.100	0.044	0.007	0.129	0.041	0.075	0.117
18	0.061	0.126	0.067	0.117	0.121	0.076	0.003	0.056	0.073	0.046	0.033	0.141	0.073
19	0.114	0.050	0.098	0.051	0.103	0.097	0.048	0.027	0.101	0.122	0.042	0.086	0.056
20	0.104	0.096	0.021	0.108	0.124	0.064	0.111	0.074	0.019	0.025	0.051	0.094	0.103

Table 11 The output of weight scenarios

Scenario	Objective value		RPD	
	Z_{Total}	Z_{MCDM}	Z_{Total}	Z_{MCDM}
1	0.107	0.446	2.523	17.100
2	0.112	0.479	3.023	10.966
3	0.110	0.482	2.872	10.408
4	0.092	0.445	0.767	17.286
5	0.097	0.486	1.290	9.665
6	0.113	0.508	3.139	5.576
7	0.097	0.461	1.313	14.312
8	0.108	0.405	2.639	24.721
9	0.095	0.52	1.139	3.345
10	0.110	0.485	2.802	9.851
11	0.097	0.491	1.313	8.736
12	0.108	0.483	2.639	10.223
13	0.091	0.488	0.604	9.293
14	0.101	0.453	1.802	15.799
15	0.093	0.452	0.848	15.985
16	0.120	0.449	3.953	16.542
17	0.101	0.464	1.848	13.754
18	0.090	0.464	0.5	13.754
19	0.110	0.458	2.837	14.869
20	0.102	0.504	1.906	6.319

Table 12 MCDM weight scenarios

Scenario	Sustainability Section		
	Economic	Social	Environmental
1	0.2	0.4	0.4
2	0.2	0.2	0.6
3	0.2	0.6	0.2
4	0.4	0.4	0.2
5	0.4	0.1	0.5
6	0.4	0.5	0.1
7	0.6	0.2	0.2
8	0.6	0.1	0.3
9	0.6	0.3	0.1
10	0.8	0.1	0.1
11	0.1	0.8	0.1
12	0.1	0.1	0.8

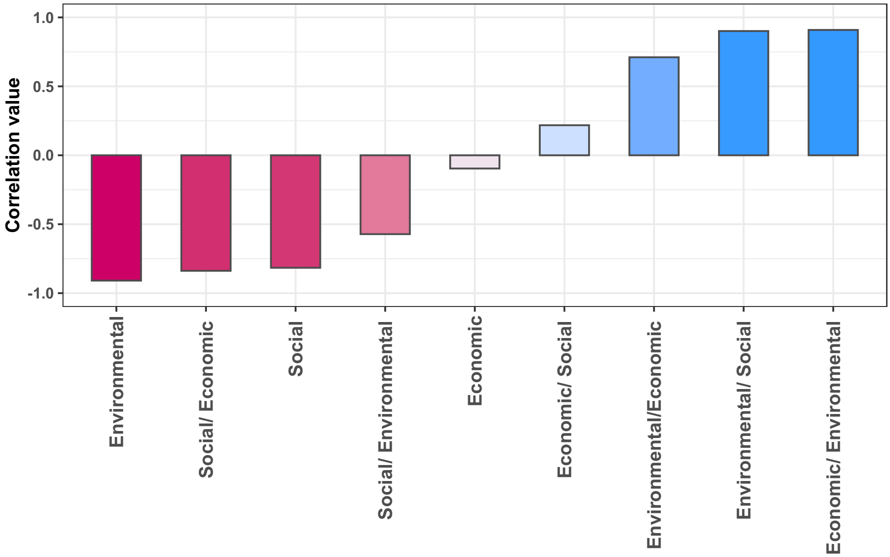


Fig. 4 The correlation test for MCDM scenarios

5.4.3 Dispersion model

Decision-makers might be interested in finding an allocation scheme in which the centers are distributed as widely as possible among the candidate locations. This idea can be attributed as dispersion and can be formulated as Eq. 31. To linearize the equation, an auxiliary binary variable r is defined as it is presented in Eqs. 32 to 34. Thus, the linear version of the objective function is Eq. 35. To assess the impact of this objective function, the model is run as a single-objective model to maximize the dispersion. In other words, other objective functions are excluded from the model to highlight the role of the dispersion objective. The centers are distributed more evenly in the presence of the dispersion concept, as visualized in the output of the model in Fig. 6.

$$\max z_{\text{ dispersion }} = \sum_{i=1} \sum_{k=1} x_i x_k d_{ik} \tag{31}$$

$$r_i \leq x_i, \forall i = 1, \ldots, I \tag{32}$$

$$r_k \leq x_k, \forall k = 1, \ldots, I \tag{33}$$

$$r_k \geq x_i + x_k - 1, \forall i = 1, \ldots, I, k = 1, \ldots, I \tag{34}$$

$$\max z_{\text{ dispersion }} = \sum_{i=1}^{I} \sum_{k=1}^{I} r_i d_{ik} \tag{35}$$

5.4.4 Alternative scenario

The investigated problem is subject to major modifications in the parameters and assumptions. For example, as an alternative scenario, a number of provinces (e.g., with large geographical

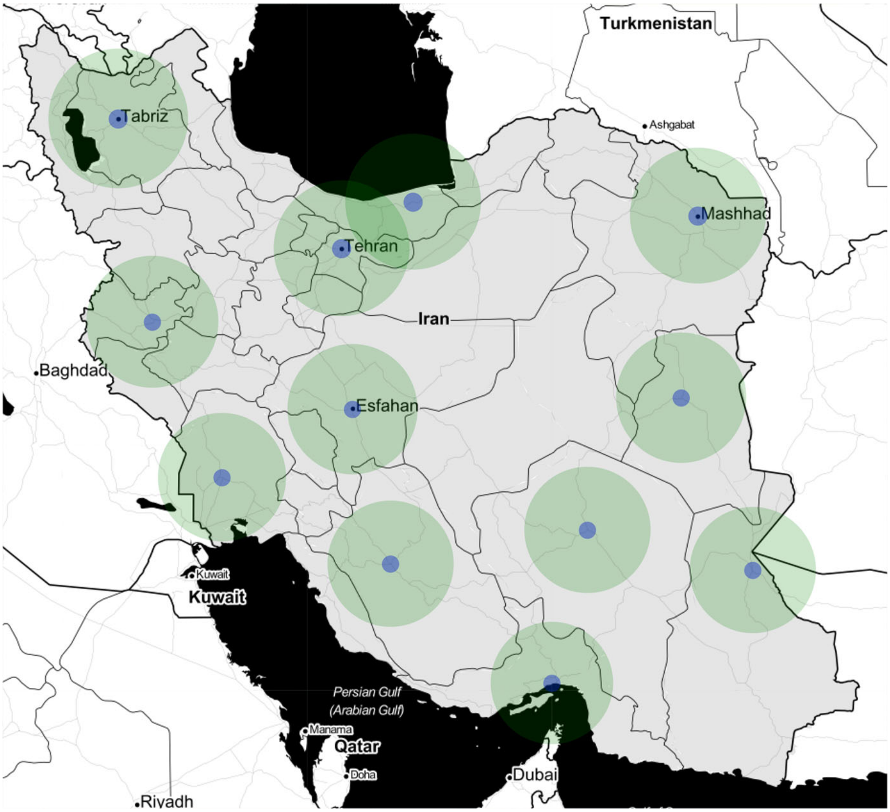


Fig. 5 Optimal solution in the base model settings

boundaries and wealth) may be omitted from the model due to budget limitations and environmental barriers. Similarly, threshold parameters are subject to change. For example, the local and standard thresholds may be required to be increased in order to cover the eliminated provinces. To test the performance of the model in this scenario, 4 provinces, colored in red in Fig. 7, are excluded from the model, and the threshold values are increased to compensate for the eliminated sections. Figure 5 also shows the output of the model in the main model scenario. The small circles show the radii of the local covering threshold, and the bigger circles show the limits of overlap coverage among the provisioned established centers.

5.4.5 Single-objective models

As another part of the sensitivity analysis, single-objective models are formed. To do so, only the master objective remains in the model, and other objectives are converted to constraints with lower and upper bounds. These bounds are obtained by solving the model separately for each objective function. Formulation 36 shows the reformulation of the model as single-objective models. Table 13 shows the RPD values for each objective function in each of the

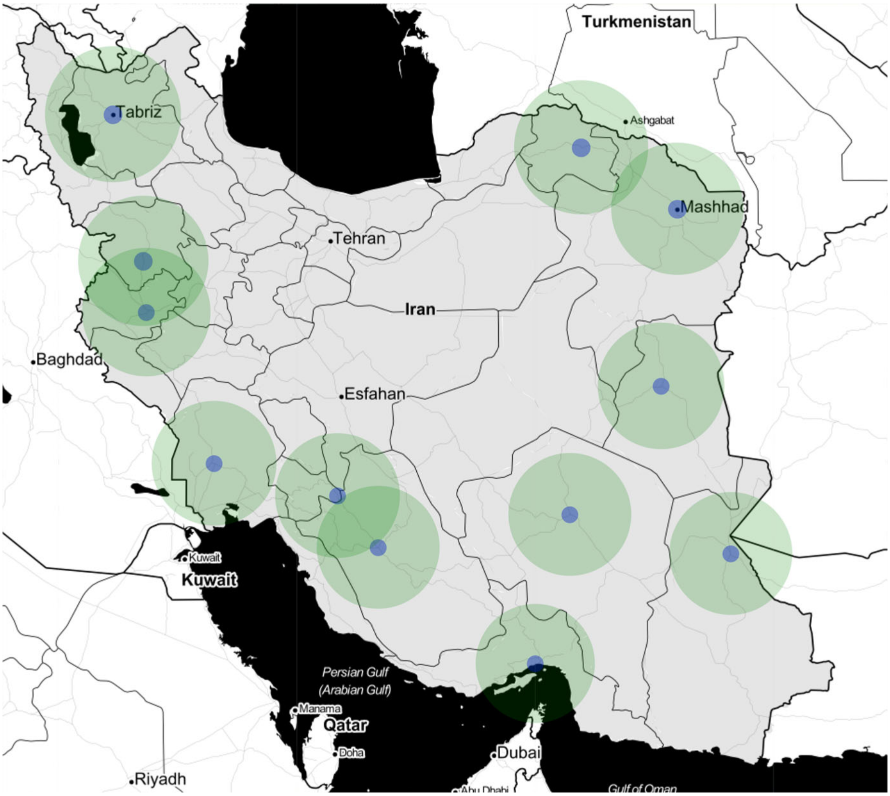


Fig. 6 Optimal solution in the dispersion model settings

single-objective models.

$$
\begin{aligned}
& \min(\max) z = f_i \\
& \text{s.t} \\
& f_k \leq UB_k, \forall f_k \text{ is maximization objective function}, k \neq i \\
& f_k \geq LB_k, \forall f_k \text{ is minimization objective function}, k \neq i
\end{aligned} \tag{36}
$$

5.4.6 Bi-objective model

As mentioned before, the problem is mainly composed of two parts: the MCDM section, and the multi-objective section. To evaluate the role of each section in the model, the model is reorganized as a two-objective MILP model. Formulation 37 shows this configuration in which the parts of the mathematical model have equal weights. Table 14 shows the defined weight scenarios for the new model, and Fig. 6 shows the share of each component in the $Z_t otsl$ value and the variations of each element in the scenarios. Since the value of the overlap coverage objective function is only affected by a change in threshold values, this objective

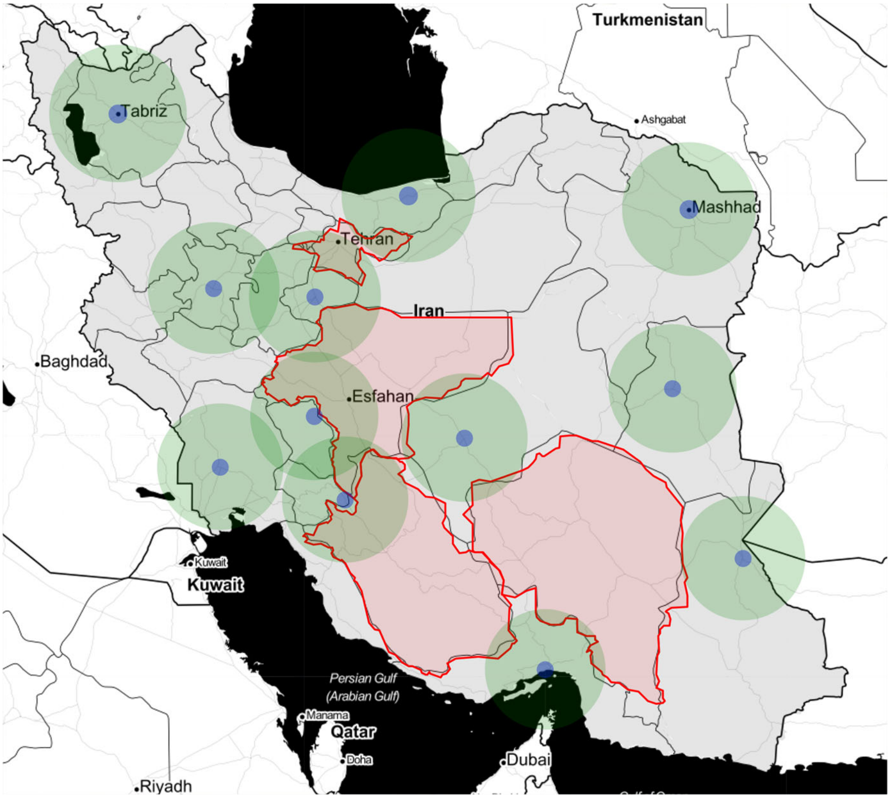


Fig. 7 Optimal solution in the alternative model settings

Table 13 RPD values of each objective function in single-objective models

Main Objective Function	RPD					
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6
Z_1	7.427	126.362	84.177	0	24.482	0
Z_2	11.067	78.385	95.886	0	24.213	0
Z_3	10.243	92.936	53.481	0	26.358	0
Z_4	12.055	136.655	0	0	24.278	0
Z_5	0.032	415.212	112.025	56.818	33.422	0
Z_6	9.584	96.567	95.886	0	25.843	0

Table 14 Weight scenarios for the two-objective model

Scenario	Weight		Scenario	Weight	
	MCDM	Mathematical		MCDM	Mathematical
1	0.05	0.95	11	0.55	0.45
2	0.10	0.90	12	0.60	0.40
3	0.15	0.85	13	0.65	0.35
4	0.20	0.80	14	0.70	0.30
5	0.25	0.75	15	0.75	0.25
6	0.30	0.70	16	0.80	0.20
7	0.35	0.65	17	0.85	0.15
8	0.40	0.60	18	0.90	0.10
9	0.45	0.55	19	0.95	0.05
10	0.50	0.50	20	0.99	0.01

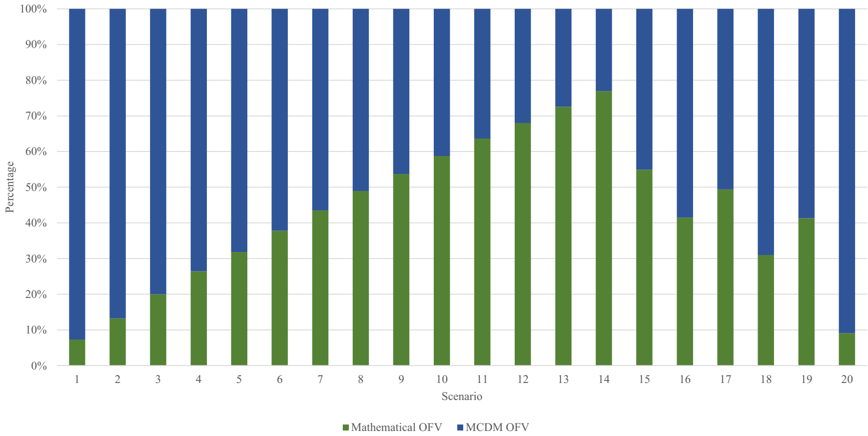
function is excluded from Fig. 8.

$$\begin{aligned} &\min z = w_1 y_1 + w_2 y_2 = \left(\frac{\left| f^*_{MCDM} - f_{MCDM} \right|}{f^*_{MCDM}} \right), \\ &y_2 = \sum_{k=1}^{5} w_k \left(\frac{\left| f^*_k - f_k \right|}{f^*_k} \right), \\ &w_1 = 0.5,\, w_2 = 0.5,\, w_k = \frac{w_2}{5} \end{aligned} \tag{37}$$

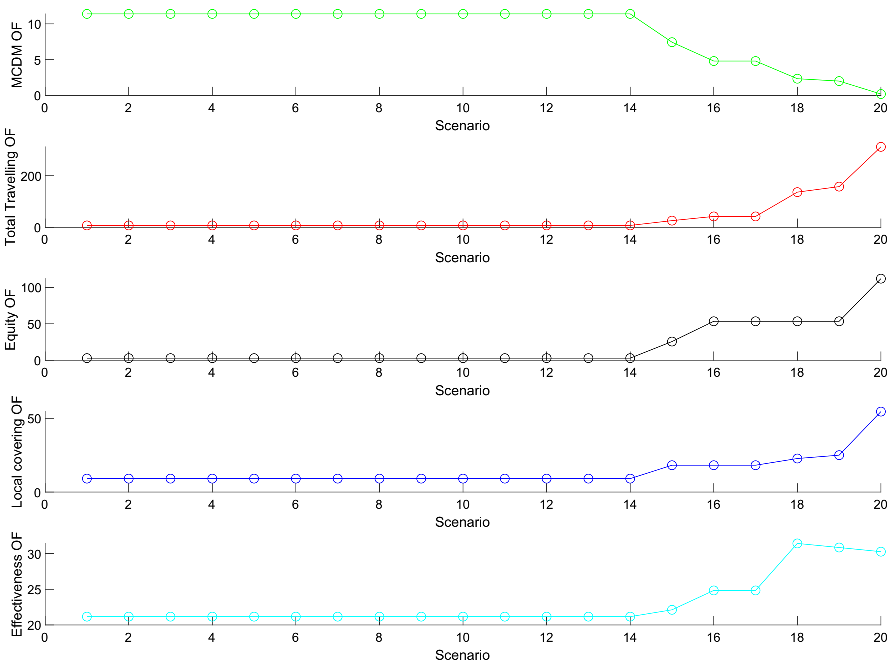
5.4.7 Threshold scenarios

Thresholds have an important role in the proposed model. These parameters affect the local coverage objective functions as well as the overlap coverage objective functions. To examine the effect of these thresholds on the output of the model, 15 scenarios are defined in Table 15. The main model is changed to a bi-objective covering model, as stated in Eq. 38. Figures 9 and 10 show the absolute percentage of deviation from the optimal value for each covering objective function and the number of new selected locations compared to the main model, respectively. Finally, Table 16 presents the correlations between the thresholds or their ratio and the covering objective functions.

$$\begin{aligned} &\min z = 0.5^* \left(\frac{f^{1*}_{\mathrm{lc}} - f^{1}_{\mathrm{lc}}}{f^{1*}_{\mathrm{lc}}}\right) + 0.5^* \left(\frac{f^{2*}_{\mathrm{lc}} - f^{2}_{\mathrm{lc}}}{f^{2*}_{\mathrm{lc}}}\right) \\ &\text{s.t} \\ &f_j \le UB_j, \forall f_j \text{ is maximization objective function,} \\ &j \ne \text{ coverage objective functions} \\ &f_j \ge LB_j, \forall f_j \text{ is minimization objective function,} \\ &j \ne \text{ coverage objective functions} \end{aligned} \tag{38}$$



(a). The share of objective functions in the Z_{total} value



(b). The deviation from the optimal point for objective functions

Fig. 8 The results of the bi-objective model

Table 15 Threshold scenarios

Scenario	Threshold		Scenario	Threshold	
	TL	TH		TL	TH
1	200	600	9	100	700
2	50	200	10	150	200
3	50	450	11	150	450
4	50	600	12	150	600
5	50	700	13	150	700
6	100	200	14	200	700
7	100	450	15	250	800
8	100	600	16	300	900

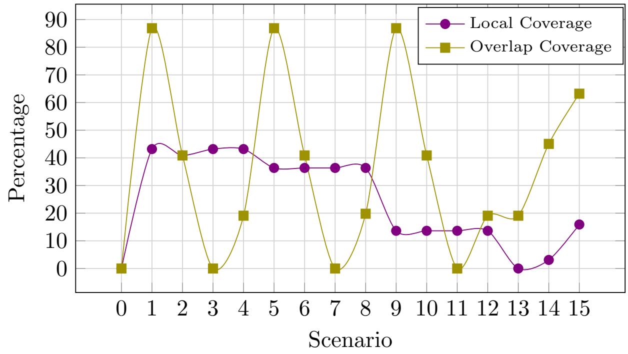


Fig. 9 The deviation percentage for threshold scenarios

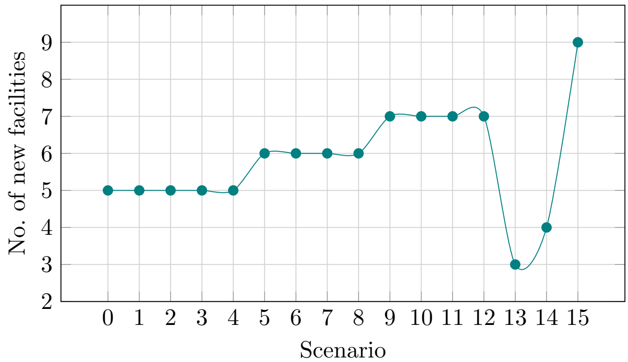


Fig. 10 Number of new selected locations for threshold scenarios

Table 16 Correlation table for threshold parameters

First variable	Second variable	P-value	Correlation
TL	Local coverage	0	−0.828
TL	Overlap coverage	0.847	0.052
TH	Local coverage	0.224	−0.322
TH	Overlap coverage	0.015	−0.596
$\frac{TH}{TL}$	Local coverage	0.008	0.637
$\frac{TL}{TH}$	Overlap coverage	0.070	−0.464

5.4.8 Number of facility scenarios

As the final part of sensitivity analysis, the effect of the number of new healthcare centers on the value of objective functions is assessed. The proposed model is solved for a different number of centers, from 6 to 18, and the value of each objective function is obtained. Figure 11 shows the trend of objective function values for different scenarios in this section. Since the sixth objective function (the overlap coverage function) is not affected by this parameter of the problem, this objective function is omitted in Fig. 11.

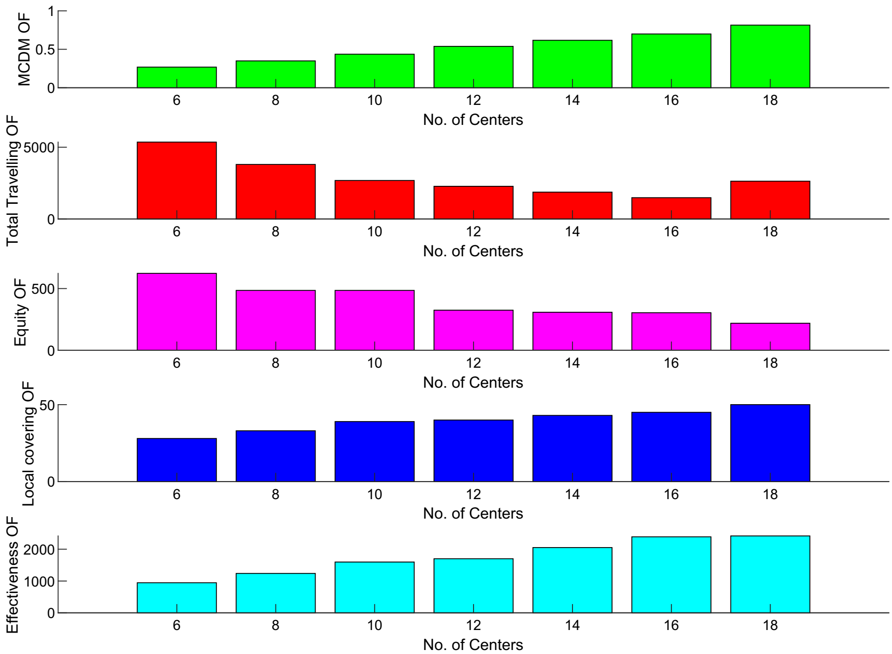


Fig. 11 Trend of objective function for different number of centers

6 Conclusion and future research

This paper investigated the sustainable facility location of healthcare facilities. The facility location problem is MCDM in nature. So, to address these aspects of the problem, 13 different criteria in all aspects of sustainability were identified. We developed a hierarchical conflict resolution approach to rank the sub-criteria in each sustainability section as a guideline for decision makers who are involved in the weight-determination phase. Then, the weights of these criteria were calculated by a BWM using experts' opinions. To address other features of the problem, several objective functions were considered to formulate a MOMILP model for the sustainable facility location problem in the healthcare sector. The proposed multi-objective model was tested for a case study in Iran's healthcare sector with actual data where 12 preventive facilities were to be assigned to 31 possible locations in the country. To find the overlaps in the network, cities with at least 200,000 population were considered as the nodes, and cities under this threshold were merged to the nearest node. Finally, a sensitivity analysis was carried out to test the performance of the model in various scenarios related to different elements of the problem. The results of this section help policy-makers to anticipate possible changes and to have contingency plans for managing those situations.

6.1 Managerial implications

The current study can help managers and decision-makers in the healthcare sector in several ways:

- Decision-makers can incorporate their preferences for criteria in the proposed BWM for calculating the weights. This feature can help them readily adapt to new situations. For instance, in developing countries, social criteria are far more important than economic and environmental criteria. So, policy-makers can give higher weights to social criteria in order to reflect their specific concerns. In developed countries, environmental criteria are at the center of attention. So, the people in charge can assign higher weights to this section during the process.
- The management sector can obtain a set of alternatives as a result of the proposed hybrid approach. This flexibility will help managers dealing with unpredictable situations, since the proposed approach can be conveniently modified for new challenges. For example, there are various responsible sectors in these screening programs, and some of these sectors might object to one allocation strategy. So having a set of alternatives can be very helpful. As another example, political or geographical factors might lead to one location being omitted from the decision-making process. In such cases, the approach can be implemented with the new assumptions, and the new results will be available.
- Managers in the healthcare sector of developing countries have been facing perplexing challenges in recent years. On one hand, they should design and initiate their programs with limited budgets, most of which come from the government sector. On the other hand, they are responsible for improving the quality of services in all regions of a country simultaneously. To overcome this dilemma, they can adopt the approach proposed in this paper to address the mentioned aspects concurrently. The proposed method tries to distribute preventive healthcare facilities equally in all regions of the country, but it can also attempt to make a trade-off between the cost of establishing facilities and the financial prospects of the selected regions.
- Decision-makers can implement the proposed method with different assumptions. Locating the facilities in a small city or state can have an entirely different effect depending

on the country. For example, more than one facility can be assigned to each candidate location. Similarly, parameters can have different values in each cluster of a country. New assumptions like these can easily be added to the proposed model to tackle a specific facility location problem. Hence, the proposed approach can be seen as a useful decision-making tool for different configurations.

6.2 Limitations and future research

There are several technical and practical limitations in the current study. First, the limited availability of data for some criteria, especially the social ones, reflects the fact that there is a lack of understanding about the importance of data availability for healthcare facility location decisions. Second, there is no organized historical data to train predictive models to project the future patterns of diseases (e.g., cancers) to improve the practicality of the output provided by the proposed framework. The final technical limitation is that in the current framework, we assume that the demand for candidate nodes is constant over time, while there are external factors, like unprecedented pandemics, which can question this simplification. There are several future directions to extend this study. First, adapting the framework for other case studies (e.g., other countries) can be productive. Different countries have different criteria and priorities, and the model can be customized in several ways. Specifically, incorporating political criteria as a fourth pillar of sustainability can provide insight for decision-makers. Another future direction can be adapting the method for large-scale healthcare programs in a continent (e.g., HIV testing centers in Africa) or on a global scale (Sustainable Development Goals of UNICEF). Comparing the performance of the method on large-scale problems with the performance on the current problem can provide insight for policymakers. Developing a stochastic formulation of the problem and implementing fuzzy theory or grey theory to capture intrinsic uncertainty can extend the methodological boundaries. Finally, developing customized evolutionary algorithms such as biogeography-based optimization, ant colony optimization, or particle swarm optimization for large-scale instances can sustain the scalability of the proposed framework.

Declarations

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

Conflict of 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.

References

Ahmadi-Javid, A., Seyedi, P., & Syam, S. S. (2017). A survey of healthcare facility location. *Computers and Operations Research, 79*, 223–263.

Ali, I., Kannan, D. (2022). Mapping research on healthcare operations and supply chain management: A topic modelling-based literature review. Annals of Operations Research, 1–27

Anvari, S., & Turkay, M. (2017). The facility location problem from the perspective of triple bottom line accounting of sustainability. *International Journal of Production Research, 55*(21), 6266–6287.

Beheshtifar, S., & Alimoahmmadi, A. (2015). A multiobjective optimization approach for location-allocation of clinics. *International Transactions in Operational Research, 22*(2), 313–328.

Celik Turkoglu, D., & Erol Genevois, M. (2020). A comparative survey of service facility location problems. *Annals of Operations Research, 292*(1), 399–468.

Chatterjee, D., & Mukherjee, B. (2013). Potential hospital location selection using fuzzy-AHP: An empirical study in rural India. *International Journal of Innovative Technology and Research, 1*(4), 304–314.
Dell'Ovo, M., Capolongo, S., & Oppio, A. (2018). Combining spatial analysis with MCDA for the siting of healthcare facilities. *Land Use Policy, 76*, 634–644.
Dogan, K., Karatas, M., & Yakici, E. (2020). A model for locating preventive health care facilities. *Central European Journal of Operations Research, 28*(3), 1091–1121.
Eldemir, F., & Onden, I. (2016). Geographical information systems and multicriteria decisions integration approach for hospital location selection. *International Journal of Information Technology & Decision Making, 15*(05), 975–997.
Eriskin, L., Karatas, M., Zheng, Y.-J. (2022). A robust multi-objective model for healthcare resource management and location planning during pandemics. Annals of Operations Research, 1–48
Farahani, R. Z., Fallah, S., Ruiz, R., Hosseini, S., & Asgari, N. (2019). Or models in urban service facility location: A critical review of applications and future developments. *European Journal of Operational Research, 276*(1), 1–27.
Gargari, M. A., & Sahraeian, R. (2023). An exact criterion space search method for a bi-objective nursing home location and allocation problem. *Mathematics and Computers in Simulation, 206*, 166–180.
Gu, W., Wang, B., Wang, X. (2011). An integrated approach to multi-criteria-based health care facility location planning. In: Pacific-Asia conference on knowledge discovery and data mining, pp. 420–430. Springer
Guerriero, F., Miglionico, G., & Olivito, F. (2016). Location and reorganization problems: The Calabrian health care system case. *European Journal of Operational Research, 250*(3), 939–954.
Haeri, A., Hosseini-Motlagh, S.-M., Samani, M.R.G., Rezaei, M. (2021). An integrated socially responsible-efficient approach toward health service network design. Annals of Operations Research, 1–54
Harper, P. R., Shahani, A., Gallagher, J., & Bowie, C. (2005). Planning health services with explicit geographical considerations: A stochastic location-allocation approach. *Omega, 33*(2), 141–152.
Karamat, J., Shurong, T., Ahmad, N., Afridi, S., Khan, S., & Mahmood, K. (2019). Promoting healthcare sustainability in developing countries: Analysis of knowledge management drivers in public and private hospitals of Pakistan. *International Journal of Environmental Research and Public Health, 16*(3), 508.
Karatas, M., & Yakıcı, E. (2018). An iterative solution approach to a multi-objective facility location problem. *Applied Soft Computing, 62*, 272–287.
Karatas, M., & Yakıcı, E. (2021). A multi-objective location analytics model for temporary emergency service center location decisions in disasters. *Decision Analytics Journal, 1*, 100004.
Mardani, A., Hooker, R. E., Ozkul, S., Yifan, S., Nilashi, M., Sabzi, H. Z., & Fei, G. C. (2019). Application of decision making and fuzzy sets theory to evaluate the healthcare and medical problems: A review of three decades of research with recent developments. *Expert Systems with Applications, 137*, 202–231.
Marić, M., Stanimirović, Z., & Božović, S. (2015). Hybrid metaheuristic method for determining locations for long-term health care facilities. *Annals of Operations Research, 227*(1), 3–23.
Mestre, A. M., Oliveira, M. D., & Barbosa-Póvoa, A. P. (2015). Location-allocation approaches for hospital network planning under uncertainty. *European Journal of Operational Research, 240*(3), 791–806.
Muffak, A., & Arslan, O. (2023). A benders decomposition algorithm for the maximum availability service facility location problem. *Computers & Operations Research, 149*, 106030.
Niroomand, S., Bazyar, A., Alborzi, M., & Mahmoodirad, A. (2018). A hybrid approach for multi-criteria emergency center location problem considering existing emergency centers with interval type data: A case study. *Journal of Ambient Intelligence and Humanized Computing, 9*(6), 1999–2008.
Prüss-Ustün, A., Wolf, J., Corvalán, C. (2016). Preventing disease through healthy environments: A global assessment of the burden of disease from environmental risks. In: Preventing disease through healthy environments: A global assessment of the burden of disease from environmental risks, pp. 147–147.
Radman, M., & Eshghi, K. (2018). Designing a multi-service healthcare network based on the impact of patients' flow among medical services. *OR Spectrum, 40*(3), 637–678.
Rao, C., Goh, M., Zhao, Y., & Zheng, J. (2015). Location selection of city logistics centers under sustainability. *Transportation Research Part D: Transport and Environment, 36*, 29–44.
Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega, 53*, 49–57.
Senvar, O., Otay, I., & Bolturk, E. (2016). Hospital site selection via hesitant fuzzy topsis. *IFAC-PapersOnLine, 49*(12), 1140–1145.
Shariff, S. R., Moin, N. H., & Omar, M. (2012). Location allocation modeling for healthcare facility planning in Malaysia. *Computers & Industrial Engineering, 62*(4), 1000–1010.
Shehadeh, K.S., Snyder, L.V. (2021). Equity in stochastic healthcare facility location. arXiv preprint arXiv:2112.03760
Soheilirad, S., Govindan, K., Mardani, A., Zavadskas, E. K., Nilashi, M., & Zakuan, N. (2018). Application of data envelopment analysis models in supply chain management: A systematic review and meta-analysis. *Annals of Operations Research, 271*(2), 915–969.

Soltani, A., & Marandi, E. Z. (2011). Hospital site selection using two-stage fuzzy multi-criteria decision making process. *Journal of Urban and environmental engineering, 5*(1), 32–43.
Steiner, M. T. A., Datta, D., Neto, P. J. S., Scarpin, C. T., & Figueira, J. R. (2015). Multi-objective optimization in partitioning the healthcare system of Parana state in Brazil. *Omega, 52*, 53–64.
Şahin, T., Ocak, S., & Top, M. (2019). Analytic hierarchy process for hospital site selection. *Health Policy and Technology, 8*(1), 42–50.
Taymaz, S., Iyigun, C., Bayindir, Z., & Dellaert, N. (2020). A healthcare facility location problem for a multi-disease, multi-service environment under risk aversion. *Socio-Economic Planning Sciences, 71*, 100755.
Vahidnia, M. H., Alesheikh, A. A., & Alimohammadi, A. (2009). Hospital site selection using fuzzy AHP and its derivatives. *Journal of Environmental Management, 90*(10), 3048–3056.
Veenstra, M., Roodbergen, K. J., Coelho, L. C., & Zhu, S. X. (2018). A simultaneous facility location and vehicle routing problem arising in health care logistics in The Netherlands. *European Journal of Operational Research, 268*(2), 703–715.
Wang, Z., Leng, L., Ding, J., & Zhao, Y. (2023). Study on location-allocation problem and algorithm for emergency supplies considering timeliness and fairness. *Computers & Industrial Engineering, 177*, 109078.
Wang, L., Shi, H., & Gan, L. (2018). Healthcare facility location-allocation optimization for China's developing cities utilizing a multi-objective decision support approach. *Sustainability, 10*(12), 4580.
Wichapa, N., & Khokhajaikiat, P. (2017). Solving multi-objective facility location problem using the fuzzy analytical hierarchy process and goal programming: A case study on infectious waste disposal centers. *Operations Research Perspectives, 4*, 39–48.
Ye, H., & Kim, H. (2016). Locating healthcare facilities using a network-based covering location problem. *GeoJournal, 81*(6), 875–890.
Zhang, W., Cao, K., Liu, S., & Huang, B. (2016). A multi-objective optimization approach for health-care facility location-allocation problems in highly developed cities such as Hong Kong. *Computers, Environment and Urban Systems, 59*, 220–230.