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Fix-and-optimize approach for a healthcare facility location/network design problem considering equity and accessibility: A case study

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ABSTRACT

This study addresses a healthcare facility location/network design problem considering equity and accessibility. Locating the healthcare facilities, planning the capacity of healthcare facilities, and designing the transfer network are the primary goals of the given problem. The presented model aims to minimize system costs, maximize accessibility, and minimize inequality among all demand nodes. A real-world case study is presented to elucidate the performance and applicability of the proposed model. Moreover, a fix-and-optimize (FO) approach is proposed for tackling the problem on a large scale. The obtained results from experiments on several test problems indicate the efficiency of the developed FO.

1. Introduction

A facility location problem (FLP) is one of the most studied optimization problems, and it is being used in many real-world applications, such as healthcare systems, waste management, and transportation (see, e.g., [1–4]). The basic FLP involves facility location decisions on a given network. A closely related problem is the network design problem (NDP), which mainly focuses on the optimal selection of the links to be constructed on a network (see, e.g., [5–8]). As noted by many researchers, FLP and NDP are significantly related: the existing network configuration impacts facility location choices, and locations of the facilities drive network design decisions (see, e.g., [9–11]). In this study, we analyze an integrated facility location and network design problem (FLNDP) for a healthcare system design application.

A relatively more recent application of FLNDP is the healthcare system design. Healthcare systems play a significant role in promoting community health, and they are a vital issue in each country [12]. The growth in the number of patients, the aging population, increasing health care costs, technology shifts, and competition among service providers have intensely affected healthcare systems [13]. These changes encourage planners and policymakers to design efficient service networks considering equity and accessibility to provide high-quality healthcare services at the minimum possible cost. In light of this, healthcare system design objectives include minimizing costs, improving access to healthcare facilities (HFs), and reducing

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Table 1
Review of FLNDP studies.

Study	Network	Decision variables	Objective function	Period Single	Facility Multi	Link	Solution approach	Case study
Melkote and Daskin [9]	General	L, ND	Cost	√		ST, U	ST, U	CS
Drezner and Wesolowsky [18]	General	L, ND	Cost	√		ST, U	MT, U	SA, TS, GA
Cocking et al. [19]	General	L, ND	Cost	√		ST, U	ST, U	HA, LS, SA
Rahmaniani and Shafia [20]	General	L, ND	Cost	√		ST, U	ST, U	VNS, H-VNS
Contreras et al. [21]	General	L, ND	Max travel time	√		ST, U	ST, U	HA
Ghaderi [22]	General	L, ND	Max travel time		√	ST, U	ST, U	HAs, H-VNS
Pearce and Forbes [23]	General	L, ND	Cost		√	ST, U	ST, U	BD
Bigotte et al. [24]	General	L, ND	Travel time	√	MT, U	MT, U	HA	√
Melkote and Daskin [25]	General	L, ND	Cost	√		ST, C	ST, U	CS
Rahmaniani and Ghaderi [26]	General	L, ND	Cost	√		ST, C	ST, U	H-VNSs
Rahmaniani and Ghaderi [27]	General	L, ND	Cost	√		ST, U	MT, C	FO
Mortezaei and Jabalameli [28]	General	L, ND	Cost	√		ST, C	ST, C	H-SA
Shishebori et al. [29]	General	L, ND	Cost and covering	√		ST, C	ST, C	LR
Cocking et al. [35]	Healthcare	L, ND	Cost	√	ST, U	ST, U	CS	√
Shishebori et al. [36]	Healthcare	L, ND	Cost	√	ST, U	ST, U	CS	√
Ghaderi and Jabalamei [37]	Healthcare	L, ND	Cost	√	ST, U	ST, U	HA, FO	√
Shishebori and Babadi [38]	Healthcare	L, ND	Cost	√	ST, C	ST, C	CS	√
This study	Healthcare	L, ND, FC	Cost, accessibility and equity	√	MT, C	MT, C	FO	√

F: Facility; L: Link; ND: Network design; ST: Single-type; MT: Multi-type; U: Uncapacitated; C: Capacitated; FC: Facility capacity; H: Hybrid; SA: Simulated annealing; TS: Tabu search; LS: Local search; HA: Heuristic algorithm; FO: Fix-and-optimize; VNS: Variable-neighbor-search; GA: Genetic algorithm; LR: Lagrangian relaxation; BD: Benders decomposition; CS: Commercial solver.

the inequity in access to HFs. As the location of HFs and the design of the underlying networks have great importance in achieving these objectives, an FLNDP can be effectively used for healthcare system design, as is done in this paper for a real-world application.

Indeed, capacity planning is also a crucial aspect of establishing an efficient healthcare system (see, e.g., [14–16]). As noted by Zarrinpoor et al. [12] and Mousazadeh et al. [17], capacity planning affects service quality and should be considered while designing healthcare systems. For instance, the existence of a healthcare facility does not necessarily indicate high accessibility and usability. Furthermore, inappropriate resource allocation may result in unequal access and/or higher service costs in different regions at different time periods. Therefore, it is crucial to integrate capacity planning into FLNDP in healthcare system design while taking into consideration socioeconomic aspects, dynamic population requirements, service accessibility, and costs. As noted above, this study incorporates detailed capacity planning decisions in healthcare system design.

In this study, we contribute to healthcare FLNDP research by taking accessibility as well as equity into account, in addition to minimizing system design costs. Furthermore, we explicitly model facility capacity decisions in a dynamic setting.

The remainder of this study is structured as follows. Section 2 reviews studies conducted in FLNDP. Section 3 presents a problem statement describing accessibility and equity in the healthcare system design, followed by a mathematical formulation and a multi-objective optimization approach. Section 4 describes the solution method for the resulting problem. Section 5 presents the computational results of solving the problem by the proposed FO approach. Section 6 describes a real-world case study and its optimal solution. Section 7 provides managerial implications and insights. Concluding remarks and future research directions are noted in Section 8.

2. Literature review

An FLNDP has been studied under settings that mainly vary with respect to the types and capacities of facilities (F) and links (L) considered: single-type (ST) vs. multi-type (MT) and uncapacitated (U) vs. capacitated (C). Further variations include the objectives considered, additional constraints, the time horizon, and the solution approaches. Table 1 summarizes the FLNDP models with respect to such differences.

Particularly, Daskin et al. [10] introduced the FLNDP by investigating FLNDP-STUF/STUL; and they highlighted the trade-offs between facility location and link construction on a given network. Later, Melkote and Daskin [9] discussed the complexity of FLNDP-STUF/STUL, and they presented strong formulations for the problem. Drezner and Wesolowsky [18] proposed heuristic methods (simulated-annealing, tabu-search, and genetic-algorithm) for FLNDP-STUF/STUL, where a link can be one- or two-directional. Cocking et al. [19] studied FLNDP-STUF/STUL with a budget constraint and proposed heuristic and meta-heuristic methods, such as simulated annealing and greedy, local, and hybrid search methods to solve the resulting model. Rahmaniani and Shafia [20] also focused on FLNDP-STUF/STUL with a budget constraint; additionally, they accounted for the uncertainty of demand and costs. The authors proposed heuristic search algorithms. Similarly, Contreras et al. [21] investigated FLNDP-STUF/STUL with a budget constraint; however, instead of minimizing the total cost (facility location, link construction, and travel costs) as done in the studies cited above, the authors aimed at minimizing the maximum travel time. They formulated and compared two mixed-integer-programming (MIP) models for the problem. Ghaderi [22] and Pearce and Forbes [23] extended the budget-constrained FLNDP-STUF/STUL to settings with multiple periods (a so-called dynamic

FLNDP). Ghaderi [22] investigated the minimization of the maximum travel time and developed heuristic algorithms based on linear-relaxation and variable neighborhood search (VNS) methods, whereas Pearce and Forbes [23], with a cost minimization objective, proposed Benders decomposition and branch-and-cut methods. In addition to these studies that focus on FLNDP with single-type uncapacitated facilities and links, Bigotte et al. [24] investigated FLNDP with multi-type uncapacitated facilities and links. Specifically, the authors aimed at minimizing the total travel time on the network and proposed a heuristic method for solving the resulting FLNDP-MTUF/MTUL model.

The above studies consider uncapacitated FLNDPs. Melkote and Daskin [25] provided one of the earlier studies that incorporated capacities for single-type facilities in which the single-type links are assumed uncapacitated. They formulated the FLNDP-STCF/STUL and provided valid inequalities for the model. Rahmaniani and Ghaderi [26] proposed three VNS-based metaheuristic methods to effectively solve the MIP formulation of FLNDP-STCF/STUL with a cost minimization objective. In an earlier study, Rahmaniani and Ghaderi [27] investigated FLNDP-STUF/MTCL, which aimed to minimize the total construction and transportation costs. They assumed that various links could be constructed between two nodes, which are different in terms of capacity and cost. To solve the given problem, they proposed a fix-and-optimize (FO) heuristic method on the basis of the firefly algorithm. Mortezaei and Jabalameli [28] proposed a bi-objective MIP model for an FLNDP-STCF/STCL. They extended a two-stage hybrid algorithm to solve the proposed problem: in the first stage, the decisions about the facility locations and designing the underlying network were made; and in the second stage, the demands were allocated to the facilities. Similarly, Shishebori et al. [29] studied FLNDP-STCF/STCL, and they further incorporated investment budget constraints and uncertainty of demands and transportation costs in their model. Besides the traditional cost minimization objective, the authors also considered minimizing the total penalties of uncovered demand. They proposed a sub-gradient based Lagrangian relaxation algorithm to solve the proposed problem. Recently, Brahami et al. [30] proposed a bi-objective MIP model for a sustainable FLNDP-STCF/MTCL. They considered the environmental impacts of transportation as an objective function and assumed that links have different environmental impacts regarding their qualities. They developed NSGA-II, using mixed coding to solve the proposed model effectively. Sadat Asl et al. [31] studied a fuzzy FLNDP-MTCF/MTCL, aiming to minimize the total construction and transportation costs. They assumed that various facilities and links could be constructed, which differed in terms of capacity and cost. A metaheuristic algorithm, called hybrid firefly and invasive weed optimization, was developed to solve the proposed problem under demand uncertainty.

The above studies consider FLNDP problems either in the transportation domain or in a domain-independent manner. Despite the potential benefits of using FLNDP as a decision support tool in healthcare system design, to the best of our knowledge, there are only a few studies in the existing literature that investigated the FLNDP models in healthcare system design applications (most of the studies in the existing literature focus on the FLP and location-allocation models for healthcare system design, see, e.g., [3,32–34]). These studies are reviewed next.

Cocking et al. [35] proposed an FLNDP-STUF/STUL to improve access to HFs in Burkina Faso by minimizing the total travel cost to such facilities. Through solving the model with a commercial solver, they showed that by considering the road network configurations and facility locations simultaneously, the accessibility to HFs could be significantly improved. Shishebori et al. [36] proposed a reliable FLNDP-STUF/STUL considering investment budget constraints. They presented a practical case study to design a healthcare service network in the Kohkiloeihboyerahmad province of Iran and conducted sensitivity analyses using a commercial solver. Ghaderi and Jabalameli [37] presented a mathematical model for dynamic FLNDP-STUF/STUL considering periodic budget constraints for the network links and facilities separately. The model minimizes the total cost of the system design, and the authors proposed a FO approach to solve the resulting model. Even though accessibility to HFs is not explicitly accounted for in their model, the authors provided a practical case study to investigate the impact of their model on accessibility to HFs in the Illam province of Iran. Suggested future studies were proposed to take accessibility into account, which we do in this study. Shishebori and Babadi [38] presented a mathematical model for a robust and reliable budget-constrained FLNDP-STCF/STCL, which considers the parameter uncertainty and system disruption simultaneously. The authors used a commercial solver to solve the resulting model. To demonstrate the application of the proposed mathematical model, they presented a real-world case study in the healthcare system of the Chaharmahal-Bakhtiari province in Iran. More recently, Tavakkoli-Moghaddam et al. [39] developed a bi-objective mathematical model for healthcare FLNDP-MTCF/MTUL under uncertainty. The study's main goals were to minimize system costs and maximize the number of jobs created by establishing medical centers. Nevertheless, the goal of this problem is to minimize the total cost of the system without accessibility and equity considerations. Table 1 also summarizes the above FLNDPs in healthcare applications.

Based on the above review, one can note that current FLNDP research for healthcare system design is limited and does not address many practical and essential aspects of healthcare system design such as multiple periods, capacity planning, detailed accessibility, and equity modeling. We present a dynamic FLNDP-MTCF/MTCL, including facility capacity (FC) decisions, and address a real-world healthcare service network application considering equity and accessibility. The model aims to determine the optimal location of multiple types of HFs, their capacities at different time periods, the structure of the underlying network, and demand flow among the variously located HFs. We develop an FO approach to solve the resulting dynamic FLNDP-MTCF/MTCL on a large-scale. The main contributions of our study and the differences from other relevant studies can be summarized as follows:

- We formulate a novel MIP model for a dynamic FLNDP that simultaneously incorporates strategic decisions, including locations and capacities of HFs and the structure of their underlying network and tactical decisions, including dynamic demand allocation (i.e., demand flow between located HFs).

- We introduce two new health-oriented objectives, which are maximizing the total accessibility to HFs using an accessibility measuring function and minimizing the inequity of accessibility through a minimum p-envy function.
- We incorporate realistic settings such as the capacity limits for multi-type HFs and links, the minimum required population to establish new HFs, and the budget limits for constructing the HFs and links.
- We propose an FO approach based on an enhanced tabu search algorithm to solve large-scale instances.
- Furthermore, we present a real-world case study to illustrate the applicability and efficiency of the proposed model.

3. Problem description and formulation

In this section, we first describe the settings of the FLNDP for the healthcare service network design application, denoted by HFLNDP. After that, we take into account accessibility and equity. Following that, we present a mathematical formulation as a multi-objective optimization model, and the model is linearized. Finally, the augmented ε-constraint method is utilized to convert the resulting model into a single-objective model.

3.1. Description

In this study, we analyze a dynamic HFLNDP over $|T|$ periods indexed by $t \in T = \{1.2.....|T|\}$. There is a set of population centers considered as demand nodes (potential location) on the network and HFs in these population centers provide primary and preventive healthcare services under a customer-to-service system (i.e., patients go to the available HFs). Let these nodes be indexed by $i \in N$ and $j \in N$, where N defines the set of nodes. As the population and demographics might change over time as well as from zone to zone, we define pop_i^t as the population of node i during period t, and d_i^t as the demand for healthcare services at node i during period t. If healthcare service capacity is not sufficient within a zone during a period, patients might travel to other nodes for receiving healthcare services using the road network. There is a set of roadways that serve as transfer links between the nodes of the network. Let L denote the set of directed links such that $(i.j) \in L$ defines a link between nodes $i \in N$ and $j \in N$ and let dis_{ij} be the distance between node i and j. We note that, there might be existing HFs and existing transfer links (TLs) on the network, and without loss of generality, we are concerned with dynamically locating new HFs and TLs (as discussed later, our model can be easily modified to include existing HFs and TLs on the network) and we consider that there are multiple types of HFs and TLs. Also, set of existing HF and TR are considered in the network which are indexed by $i.j \in N_0 \subset N$ and $(i.j) \in L_0 \subset L$.

It is assumed that there are $|H|$ types of HFs indexed by $h \in H = \{1.2.....|H|\}$. When associated with a HF, we define f_{ih}^t as the cost of locating a type-h HF at node i in period t (a one-time construction cost with a default capacity). Let Z_{ih}^t be the binary variable such that $Z_{ih}^t = 1$ if an HF of type h is operated at node i at period t, $Z_{ih}^t = 0$ otherwise. In this regard, let us consider $\eta^t{}_i$ a variable, dependent on Z_{ih}^t, indicating that node i stays as a demand node at period t or not. To establish the dependence of $\eta^t{}_i$ on Z_{ih}^t, we define $\eta_i^t + \sum_h Z_{ih}^t = 1$. We assume that once an HF is built in period $t \in T$, it is available for service in period t and for future periods within the planning horizon; therefore, we have $Z_{ih}^t \geq Z_{ih}^{t-1}$ $\forall i.\forall h.\forall t > 0$, where $Z_{ih}^0 = 0$ if there is not a type-h HF at currently located at node i, and we have $Z_{ih}^0 = 1$ if there is already an existing type-h HF at node i (this definition captures the existing HFs on the network). Furthermore, we consider that there is a limited budget for HF construction in each period, and unutilized funds for HF construction can be used in future periods. Let B_1^t be the available budget for HF construction in period t. Then, we have $\sum_{t=1}^{t'} \sum_i \sum_h f_{ih}^t (Z_{ih}^t - Z_{ih}^{t-1}) \leq \sum_{t=1}^{t'} B_1^t$ as the HF construction budget restriction in period t'. Finally, we assume that each type of HF can only be established in potential locations with a population higher than a predefined value, in order to make a balance between demand and supply. Hence, let pop_{ih}^{min} be the minimum population required for opening an HF h at node i. Then, we have $Z_{ih}^t - Z_{ih}^{t-1} = 0$ $\forall i \in \{N pop_i^t < pop_{ih}^{min}\}.\forall h.\ \forall t > 0$ to meet this constraint.

In addition to HF location decisions, we consider that, after an HF is located, its capacity can be expanded over time. Specifically, when located at period t, a type-h HF's default capacity at node i is denoted by l_{ih} (this is the minimum capacity for a type-h HF at node i), and we consider that its capacity can be expanded up to $u_{ih} \geq l_{ih}$ in future periods. To avoid capacity extension in the same period of locating an HF, we define a binary variable δ_{ih}^t, such that $\delta_{ih}^t = 1$ if there is capacity expansion for the type-h HF already located at node i in period t, and $\delta_{ih}^t = 0$ otherwise. Note that one should have $\delta_{ih}^t \leq Z_{ih}^t$, because only an already located HF can have its capacity expanded; and we have $Z_{ih}^t - Z_{ih}^{t-1} + \delta_{ih}^t \leq 1$ so that capacity of an HF cannot be expanded in the period in which it is being located. Furthermore, let V_{ih}^t denote the capacity extension amount decided in period t for type-h HF at node i. Letting Q_{ih}^t be the available total capacity of the type-h HF at node i in period t, we can define $Q_{ih}^t = Q_{ih}^{t-1} + V_{ih}^t$ (again, one can define Q_{ih}^0 for the existing facilities accordingly). Also, it should be noted that $l_{ih} Z_{ih}^t \leq Q_{ih}^t \leq u_{ih} Z_{ih}^t$, so that overall capacity of an open HF will not exceed the maximum possible capacity. Finally, we consider that operating costs for an HF depend on its capacity and capacity expansion. Particularly, let o_{ih}^t and e_{ih}^t denote the unit operating cost (service providing cost per unit of available capacity) and the cost of unit capacity expansion for type-h HF at node i in period t. Then, the total HF operational costs over the planning horizon amount to $\sum_t \sum_i \sum_h (o_{ih}^t Q_{ih}^t + e_{ih}^t V_{ih}^t)$.

It is assumed that there are $|R|$ types of TLs indexed by $r \in R = \{1.2.....|R|\}$. When associated with a TL, we define c_{ijr}^t as the cost of constructing a type-r TL between nodes i and j in period t (a one-time construction cost with a default capacity). Let X_{ijr}^t be the binary variable such that $X_{ijr}^t = 1$ if a TL of type r is operated between nodes i and j at period t, $X_{ijr}^t = 0$ otherwise. We assume that once a TL is constructed in period $t \in T$, it is available for service in period t and for future periods within the planning horizon; therefore, we have $X_{ijr}^{t} \geq X_{ijr}^{t-1}$ $\forall i.\forall r.\forall t > 0$ where $X_{ijr}^{0} = 0$ if there is not a type-r TL at currently constructed nodes between nodes i and j, and we have $X_{ijr}^{0} = 1$ if there is already an existing type-r TL between nodes i and j (this definition captures the existing TLs on the network). Furthermore, we consider that there is a limited budget for TL construction in each period, and unutilized funds for TL construction can be used in future periods. Let B_2^t be the available budget for TL construction in period t. Then, we have $\sum_{t=1}^{t'} \sum_i \sum_j \sum_r c_{ijr}^{t} (X_{ijr}^{t} - X_{ijr}^{t-1}) \leq \sum_{t=1}^{t'} B_2^t$ as the TL construction budget restriction in period t'.

In addition to constraints pertinent to TL construction, some other constraints about network flow and TLs capacity should be formulated. Let Y_{ijr}^{t} be an integer variable denoting the amount of the demand that is transferred on a type-r TL between nodes i and j in period t. Also, we consider that the maximum capacity of a TL is cl_{ijr}. For a supply node, the summation of flow in, flow out and self-demand of the supply node should be equal to or less than the capacity of the located HF. Hence we have, $\sum_{(i.j)} \sum_r Y_{ijr}^{t} - \sum_{(i.j)} \sum_r Y_{jir}^{t} + d_j^t \leq Q_{jh}^{t} + M(1 - Z_{jh}^{t})$ $\forall j.\forall h.\forall t > 0$ as a flow conservation setup in a supply node. For a demand node, the summation of flow in and self-demand of the node should be equal to the flow out. So, we have $\sum_{(i.j)} \sum_r Y_{jir}^{t} - \sum_{(i.j)} \sum_r Y_{ijr}^{t} \leq d_j^t + \mathrm{M}(1 - \eta_j^t) \forall j.\ \forall t > 0$ and $\sum_{(i.j)} \sum_r Y_{ijr}^{t} - \sum_{(i.j)} \sum_r Y_{jir}^{t} + d_j^t \leq Q_{jh}^{t} + \mathrm{M}(1 - \eta_j^t) \forall j.\ \forall t > 0$ as a flow conservation in a demand node. As a logical constraint, it is assumed that only one TL can be constructed between two demand nodes; therefore, we have $\sum_r X_{ijr} \leq 1$. Furthermore, it should be noted that $Y_{ijr}^{t} \leq cl_{ijr} X_{ijr}^{t}$ and $Y_{jir}^{t} \leq cl_{ijr} X_{ijr}^{t}$, so that overall capacity of a constructed TL will not exceed the maximum possible capacity. These inequalities also represent the relationship between two decision variables and indicate that TLs are not directed.

The following nomenclatures are defined to mathematically formulate the proposed HFLNDP.

Sets	
N	Set of all the nodes in the network indexed by $i.j$
N^0	Set of existing facilities in the network indexed by $i'.j'$, $N^0 \subset N$
H	Set of the different types of HFs indexed by h
L	Set of the links in the network indexed by $(i.j)$
L^0	Set of existing links in the network indexed by $(i'.j')$, $L^0 \subset L$
R	Set of the different types of links indexed by r
T	Set of the periods indexed by t
Parameters	
d_i^t	Demand rate of patient zone i at period t
f_{ih}^t	Fixed cost of constructing an HF h at node i at period t
c_{ijr}^t	Fixed cost of constructing link $(i.j)$ of type r at period t
o_{ih}^t	Operating cost of an HF h at node i at period t (per unit demand)
g_{ijr}^t	Operating cost of link $(i.j)$ of type r at period t
dis_{ij}	Distance between node i and j
s_{ijr}	Average speed on link $(i.j)$ of type r
tr_{ijr}^t	Traveling cost of unit flow on link $(i.j)$ of type r at period t
e_{ih}^t	Serving capacity expansion cost of an HF h at node i at period t (per unit)
cl_{ijr}	Capacity of link $(i.j)$ of type r
B_1^t, B_2^t	Facilities and links construction budgets at period t
pop_i^t	Population of node i at period t
$pop_{ih}^{\min}$	Minimum population required for opening an HF h at node i
l_{ih}, u_{ih}	Minimum and maximum serving capacity of an HF h at node i
M	A large positive constant
Variables	
Z_{ih}^t	If an HF h is open at the beginning of period t (1), otherwise (0)
X_{ijr}^t	If link $(i.j)$ of type r is open at the beginning of period t (1), otherwise (0)
η_i^t	If node i stays as a demand node at period t (1), otherwise (0)
Y_{ijr}^t	Amount of the demand that is transferred on link $(i.j)$of type r at period t
δ_{ih}^t	If capacity expansion is placed for an HF h at node i at period t (1), otherwise (0)
Q_{ih}^t	Operating capacity of an HF h at node i at period t
V_{ih}^t	Amount of capacity expansion of an HF h at node i at period t
A_i^t	Accessibility of node i at period t
E_{ij}^t	The envy between nodes i and j at period t

3.2. Accessibility and equity

To improve accessibility of the healthcare system, which is one of the primary goals of governments, we propose a novel objective function. In healthcare system optimization problems, several objective functions, such as minimizing the total travel distance/time to facilities, minimizing the maximum travel distance/time to facilities, and maximizing the demand coverage to facilities, are generally used to improve accessibility to healthcare systems. These objective functions only consider one factor to formulate accessibility to facilities. However, accessibility to facilities depends on several factors, such as demand, travel time/distance to facilities, and capacity of facilities [40]. In this paper, we develop the formulation introduced by Wang and Tang [41], which simultaneously considers the capacity of HFs, the demand for HFs, and travel times to HFs.

The proposed problem is as follows:

$$A_i^t = \sum_{j \neq i} \sum_h \sum_r \frac{Q_{jh}^t f(\frac{dis_{ij}}{s_{ijr}}) X_{ijr}^t}{d_j^t} + \sum_h \frac{Q_{ih}^t}{d_i^t}, \quad \forall i, \ \forall t \tag{1}$$

Eq. (1) calculates the accessibility of node i at period t where f is a general distance-decay function. This function indicates the amount and speed of node access to HFs so that larger values indicate more access. The function consists of two parts. The first part is to calculate the access of a demand node to the existing capacities, and the second part shows the accessibility of a demand node in which an HF has been constructed. By increasing the capacity that a demand node has access to, the accessibility of that node increases. As can be seen, the demand for nodes is also included in the calculations so that if the demand of a node is high while it has low access to HFs, its accessibility will be very low. In addition, travel time directly affects accessibility. As the travel time to reach an HF increases, the general distance-decay function decreases, and consequently, the accessibility of that node decreases.

The various forms of general distance-decay are used in the measure of accessibility which can be categorized into three general forms including discrete, continuous, and hybrid types [41]. In this study, we use the gravity-based index, which has been widely applied in literature as follows:

$$f(\frac{dis_{ij}}{s_{ijr}}) = \left(\frac{dis_{ij}}{s_{ijr}}\right)^{-\beta} \tag{2}$$

In which s_{ijr} is the average speed on a type-r TL between nodes i and j, and β is a travel friction coefficient and usually takes a value within the range of [0.6, 1.8] [41].

Equity is one of the most appropriate principles that can be considered by policymakers in the healthcare system planning. This factor is generally defined as equal access to HFs and is measured using the deviation from the mean of actual accessibility [42]. In this study, we use a minimum envy criterion, which has been used in the past for considering equity in healthcare FLPs [43–45]. To use a minimum envy criterion, a function should be defined and considered as an envy function. Usually, this function is defined based on distance and time. In this study, we define a novel function based on the improved accessibility measure as follows:

$$E_{ij}^t = \max\left\{0, A_j^t - A_i^t\right\} \tag{3}$$

E_{ij}^t is the envy between node i and j in period t. Eq. (3) states that if the accessibility of demand node i is less than node j, the envy of demand node i for demand node j is equal to the difference between their accessibility and otherwise is equal to 0.

3.3. Mathematical model

With regard to the aforementioned descriptions, accessibility and envy functions, the mathematical model of a considered HFLNDP is formulated as follows:

$$Min\ obj_1 = \sum_t \sum_{(i,j):i<j} \sum_r g_{ijr}^t X_{ijr}^t \tag{4.1}$$

$$+ \sum_t \left(\sum_i \sum_h o_{ih}^t Q_{ih}^t + \sum_i \sum_h e_{ih}^t V_{ih}^t \right) \tag{4.2}$$

$$+ \sum_t \left(\sum_{(i,j)} \sum_r tr_{ijr}^t Y_{ijr}^t \right) \tag{4.3}$$

$$Max\ obj_2 = \sum_t \sum_i A_i^t \tag{5}$$

$$Min\ obj_3 = \sum_t \sum_i \sum_j E_{ij}^t \tag{6}$$

Subject to:

$$A_i^t = \sum_{j \neq i} \sum_h \sum_r \frac{Q_{jh}^t \left(\frac{dis_{ij}}{s_{ijr}}\right)^{-\beta} X_{ijr}^t}{d_j} + \sum_h \frac{Q_{ih}^t}{d_i}$$

$$\forall i, \ \forall t > 0 \tag{7}$$

$$E_{ij}^t = \max\left\{0, A_j^t - A_i^t\right\}$$

$$\forall i,\ j : i \neq j,\ \forall t > 0 \tag{8}$$

$$\sum_{(i,j)} \sum_r Y_{ijr}^t - \sum_{(i,j)} \sum_r Y_{jir}^t + d_j^t \leq Q_{jh}^t + M(1 - Z_{jh}^t)$$

$$\forall j,\ \forall h,\ \forall t > 0 \tag{9}$$

$$\sum_{(i,j)} \sum_r Y_{jir}^t - \sum_{(i,j)} \sum_r Y_{ijr}^t \leq d_j^t + M(1 - \eta_j^t)$$

$$\forall j,\ \forall t > 0 \tag{10}$$

$$\sum_{(i,j)} \sum_r Y_{jir}^t - \sum_{(i,j)} \sum_r Y_{ijr}^t \geq d_j^t - M(1 - \eta_j^t)$$

$$\forall j,\ \forall t > 0 \tag{11}$$

$$\eta_i^t + \sum_h Z_{ih}^t = 1$$

$$\forall i,\ \forall t \tag{12}$$

$$\sum_{t=1}^{t'} \left(\sum_i \sum_h f_{ih}^t \left(Z_{ih}^t - Z_{ih}^{t-1} \right) \right) \leq \sum_{t=1}^{t'} B_1^t$$

$$\forall t' > 0 \tag{13}$$

$$\sum_{t=1}^{t'} \left(\sum_{(i,j):i<j} \sum_r c_{ijr}^t \left(X_{ijr}^t - X_{ijr}^{t-1} \right) \right) \leq \sum_{t=1}^{t'} B_2^t$$

$$\forall t' > 0 \tag{14}$$

$$\sum_r X_{ijr}^t \leq 1$$

$$\forall (i,j) : i < j,\ \forall t \tag{15}$$

$$Y_{ijr}^t \leq cl_{ijr} X_{ijr}^t$$

$$\forall (i,j) : i < j,\ \forall r,\ \forall t \tag{16}$$

$$Y_{jir}^t \leq cl_{ijr} X_{ijr}^t$$

$$\forall (i,j) : i < j,\ \forall r,\ \forall t \tag{17}$$

$$Q_i^t = Q_i^{t-1} + V_i^t$$

$$\forall i,\ \forall t > 0 \tag{18}$$

$$l_{ih} Z_{ih}^{t} \le Q_{ih}^{t} \le u_{ih} Z_{ih}^{t}$$

$$\forall i,\ \forall h,\ \forall t > 0 \tag{19}$$

$$\left(Z_{ih}^{t} - Z_{ih}^{t-1}\right) + \delta_{ih}^{t} + \ \le 1$$

$$\forall i,\ \forall h,\ \forall t > 0 \tag{20}$$

$$\delta_{ih}^{t} \le Z_{ih}^{t}$$

$$\forall i,\ \forall h,\ \forall t > 0 \tag{21}$$

$$Z_{ih}^{t} \ge Z_{ih}^{t-1}$$

$$\forall i,\ \forall h,\ \forall t \tag{22}$$

$$X_{ijr}^{t} \ge X_{ijr}^{t-1}$$

$$\forall (i, j) : i < j,\ \forall r,\ \forall t \tag{23}$$

$$Z_{i'h}^{t-1} = 1$$

$$\forall i',\ \forall t = 1 \tag{24}$$

$$Z_{ih}^{t-1} = 0$$

$$\forall i \notin N_0,\ \forall t = 1 \tag{25}$$

$$X_{i'j'r}^{t-1} = 1$$

$$\forall (i', j') : i' < j',\ \forall t = 1 \tag{26}$$

$$X_{ijr}^{t-1} = 0$$

$$\forall (i, j) \notin L_0 : i < j,\ \forall t = 1 \tag{27}$$

$$Z_{ih}^{t} - Z_{ih}^{t-1} = 0$$

$$\forall i \in \left\{N | pop_{i}^{t} < pop_{ih}^{\min}\right\}, \forall h,\ \forall t > 0 \tag{28}$$

$$Z_{ih}^{t} \in \{0, 1\}$$

$$\forall i,\ \forall h,\ \forall t \tag{29}$$

$$\eta_{i}^{t} \in \{0, 1\}$$

$$\forall i,\ \forall t \tag{30}$$

$$X^t_{ijr} \in \{0, 1\}$$

$$\forall (i, j) : i < j,\ \forall r,\ \forall t > 0 \tag{31}$$

$$Y^t_{ijr} \geq 0,\ \text{integer}$$

$$\forall (i, j),\ \forall r,\ \forall t > 0 \tag{32}$$

$$\delta^t_i \in \{0, 1\}$$

$$\forall i,\ \forall t \tag{33}$$

$$Q^t_{ih}, V^t_{ih} \geq 0,\ \text{integer}$$

$$\forall i,\ \forall h,\ \forall t \tag{34}$$

The first objective function is given by Eqs. (4.1)–(4.3) is to minimize the total operational costs of healthcare systems over the planning horizon. This objective function consists of three components related to operating costs of TLs, operating and capacity expansion costs of HFs, and traveling costs of customers on TLs, respectively. The second objective function (5) maximizes accessibility for whole demand nodes over the planning horizon. The third objective function (6) minimizes the envy between all nodes over the planning horizon.

The presented model is a mixed-integer nonlinear programming (MINLP) in which Eqs. (7) and (8) are nonlinear. In order to linearize Eq. (7) a new variables, $W^t_{ijhr} = Q^t_{jh} X^t_{ijr}$, is defined and this equation is replaced by the following inequalities:

$$W^t_{ijhr} \leq Q^t_{jh} \tag{35}$$

$$W^t_{ijhr} \leq M X^t_{ijr} \tag{36}$$

$$W^t_{ijhr} \geq Q^t_{jh} - M\left(1 - X^t_{ijr}\right) \tag{37}$$

$$W^t_{ijhr} \geq 0 \tag{38}$$

where M is a large positive constant and is equal to the summation of demand. Also, in order to linearize Eq. (8), this equation is replaced by the following inequalities [43]:

$$E^t_{ij} \geq A^t_j - A^t_i$$

$$\forall i,\ j : i \neq j,\ \forall t > 0 \tag{39}$$

$$E^t_{ij} \geq 0$$

$$\forall i,\ j : i \neq j,\ \forall t > 0 \tag{40}$$

3.4. The equivalent single-objective model

This study looks at the augmented ε-constraint method, originally introduced by Mavrotas [46], to deal with the proposed MOPs. In an augmented ε-constraint method, one of the objective functions of the problem is optimized, and the rest of the objective functions are moved to constraints as follows:

$$\begin{aligned} &Max\ \ (g_1(x) + eps \times (s_2/r_2 + s_3/r_3 + \ldots + s_p/r_p)) \\ &s.t: \\ &g_k(x) - s_k = \varepsilon_k \quad k = 2, \ldots, p; \quad x \in S; s_k \in R^+; \quad \varepsilon_k \in R^+ \end{aligned} \tag{41}$$

In which x is the decision variables vector, and S is the solution space of the problem. $g_1(x). g_2(x)\ldots. g_p(x)$ denote the objective functions of the problem. $\varepsilon_1. \varepsilon_2\ldots. \varepsilon_p$ are the right-hand side values of the limited objective functions. $r_1. r_2\ldots. r_p$

denote the ranges of respective objective functions and $s_1.s_2.....s_p$ are the auxiliary variables of the relevant constraints. The *eps* is also in the interval [10^{-6},10^{-3}].

In this method, determining the best values of ε_k is critical. To find these values, the best and worst values of objective functions considered should be obtained. To find the best value, we solve the problem considering the objective function we want to find the best value. The problem is solved with other objective functions for finding the worst value of an objective function, and the obtained values are stored. The worst value of the stored values is considered the worst value of that objective function. By finding the best and worst values of the objective functions, the appropriate value of ε_k can be determined. For this purpose, we change the ε_k between the best and worst obtained values and solve the problem. Then, the value of the first objective function at each level of the ε_k is analyzed to find the best one.

Regarding the above description, the multi-objective model now can be converted into an equivalent single-objective model as follows:

$$Min\ obj_1 = \sum_t \sum_{(i,j):i<j} \sum_r g^t_{ijr} X^t_{ijr} + \sum_t \sum_i \sum_h \left(o^t_{ih} Q^t_{ih} + \delta^t_{ih} e^t_{ih} V^t_{ih} \right) + \sum_t \left(\sum_{(i,j)} \sum_r tr^t_{ijr} Y^t_{ijr} \right) + \left(\sum_{s \in S-\{1\}} w^1_s \delta^1_s \right) - (eps \times (s_2/r_2 + s_3/r_3)) \tag{42}$$

Subject to:

$$\sum_t \sum_i \omega^t_i A^t_i + \left(\sum_{s \in S-\{1\}} w^2_s \delta^2_s \right) - s_2 = \varepsilon_2 \tag{43}$$

$$\sum_t \sum_i \sum_j \omega^t_i E^t_{ij} + \left(\sum_{s \in S-\{1\}} w^3_s \delta^3_s \right) + s_3 = \varepsilon_3 \tag{44}$$

$$s_k \in R^+ \tag{45}$$

Eqs. (9)–(40)

This single-objective model will be solved by a proposed solution method in the next section.

4. Solution method

The mathematical model proposed in the previous section comprises two well-known NP-hard problems, the FLP and the NDP. Also, the problem makes decisions on the capacity of HFs at each period, which can increase the complexity of the problem. Thus, traditional solvers such as CPLEX are not able to effectively solve the problem in large sizes. Hence, this section presents the design of an efficient FO approach based on the enhanced tabu search algorithm (ETSA) to solve large-scale instances.

4.1. Fix-and-optimize approach

Generally, in solving mixed-integer programming problems, the number of binary variables plays a vital role in the complexity of problems. It determines the majority of numerical efforts in the solving processes. Therefore, the proposed FO approach is composed of two main phases: fixing binary variables and optimizing the main problem; the ETSA is used for iteratively fixing the value of binary variables, and the CPLEX solver is applied to find the optimal solution of the subproblem at each iteration.

Two heuristic methods, including greedy initialization and hyper-heuristic selection methods, are applied to enhance TS's performance. The overall structure of the FO approach is shown in Fig. 1. As can be seen in the figure, the approach includes two main stages −the preparation and the main loop of ETSA. In the first stage, the input parameter of the problem and solution approach is set. After that, a greedy heuristic method (Heuristic I) is applied to generate an initial individual. In the second stage, a set of neighbor solutions is constructed using the different types of operators selected ¬through a hyper-heuristic selection method (Heuristic II). Following this, the main processes of ETSA are run. The solutions generated during the first and second stages of ETSA should be evaluated. As mentioned before, the binary variables of locating HFs, Z^t_{ih}, are fixed by ETSA. The fixed variables are exported to GAMS software as parameters, and the single-objective problem, presented in Section 3.4, is solved by the CPLEX solver. After the problem is solved, the obtained objective function is assigned to the imported solution and exported to MATLAB. This loop is used for evaluating the generated solutions in ETSA. More detailed descriptions of the solution approach are provided in the following subsections.

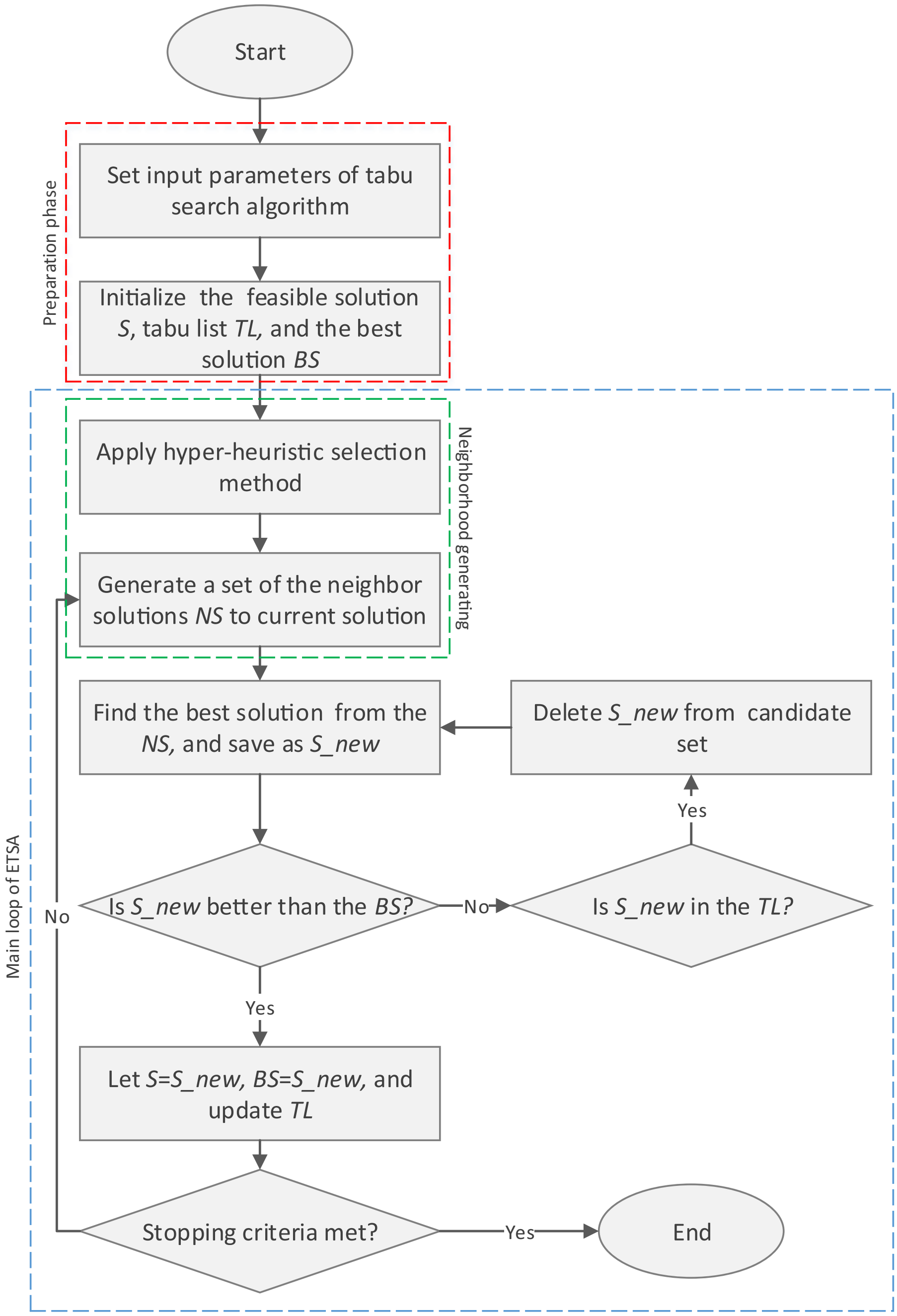

Fig. 1. Flowchart of the FO approach.

4.2. Solution representation

This study is based on seven sets of decision variables for determining the output of the problem. Only the decision variables related to locating the HFs at the first time period are considered in solution representation. The other decision variables that are made about the TLs and the capacity of HFs are obtained by solving the subproblems with the exact optimization method using the CPLEX solver within GAMS software. In general, each individual (solution) should be determined by the location and type of HFs. Hence, the individuals used in this study consist of two rows and N columns. Each column stands for a node and indicates a potential location. Each cell of the first row indicates whether a node is a facility node (1) or not (0). The type of the located HF is determined in the second row, such that each cell has a designation of 1, 2 or 3. Fig. 2 shows an example of the representation of a solution with eight nodes.

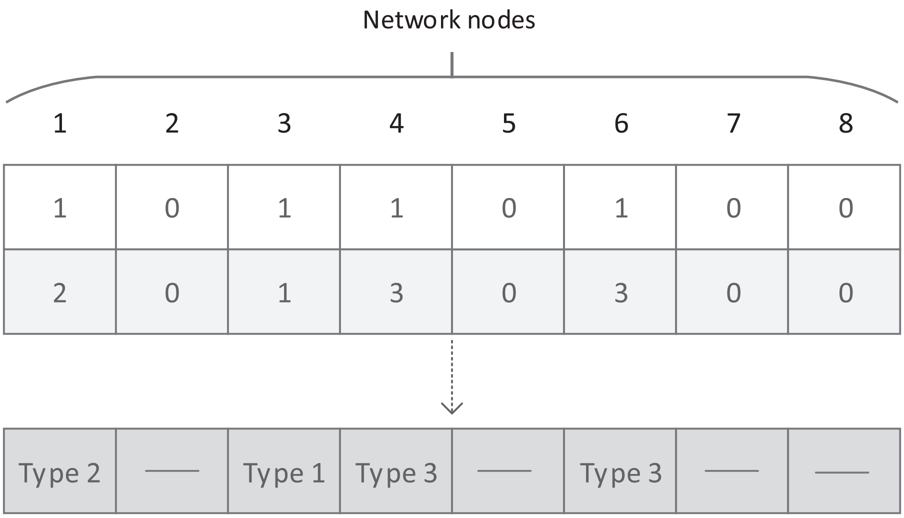

Fig. 2. The representation of a solution with eight nodes.

Set $t = 1$ and solve the SP_1 using CPLEX.

Fix binary variables, Z_{ih}^{t}, to the optimal solution obtained from solving SP_1 and solve the SP.

Fig. 3. Greedy heuristic approach for generating the initial solution.

4.3. Initial solution (heuristic I)

In metaheuristic algorithms, the initial solution has a significant effect on the efficiency of the algorithm. Generally, this solution is randomly generated, and this may lead to generating a low-quality initial solution. In this study, we use a greedy heuristic approach to generate the initial solution. In this approach, the problem is decomposed into two sub-problems, and an exact optimization algorithm separately solves each subproblem. The primary thought behind this method is that restricting the problem to just one period or fixing the binary variables that construct the HFs and TLs can solve the problem faster and easier. It is assumed that SP is a subproblem of the original problem in which the variables related to locating Hfs are fixed, and SP_1 is a subproblem of SP with $t = 1$. A pseudo-code of this approach is presented in Fig. 3.

4.4. Neighborhood generating producer (heuristic II)

The performance of the metaheuristic algorithms depends greatly on the operators used to generate the new solution. An efficient procedure for generating a neighborhood solution can lead to finding a better solution and improving the performance of algorithms. In single-based metaheuristic algorithms, several types of operators (e.g., swap, reversion, etc.) can be adopted to generate a new solution. Performing all the operators to make a neighborhood solution at each iteration significantly increases the algorithm's run time. Hence, this study uses a hyper-heuristic selection method to select between operators used to generate new solutions.

In the proposed selection of a hyper-heuristic procedure, a function was defined to evaluate the performance of each mentioned operator at each iteration that can be found in Maashi et al. [47], and was presented as follows:

$$EF(o) = \alpha f_1(o) - f_2(o) \tag{46}$$

In which, $f_1(o)$ denotes the performance of operator o, which is calculated based on the two-stage ranking procedure proposed by Maashi et al. [47]. The steps of the proposed ranking procedure are presented as follows:

Step 1. Generate an $O \times C$ matrix, in which O and C denote the number of the operators and comparison metrics, respectively.

Step 2. Apply all operators to generate a new solution.

Step 3. Calculate all evaluated functions for obtained solutions using Eq. (42).

Step 4. Rank the operators according to their performance against the evaluation function (the best and worst ranked are 1 and O.

Step 5. Record the rankings.

Step 6. Calculate the $f_1(o)$ using Eq. (47)

$$f_1(o) = 2 \times (O + 1) \tag{47}$$

Set the parameter and give an initial solution; o indicates the index of the chosen operator; sol_{in} indicates the initial solution; sol_{new} indicates the newly generated solution;
Initialize ();
Run o, $\forall o \in O$;
Calculate EF(o) for o (Eq. (46)), $\forall o \in O$;
Assign a rank to o, $\forall o \in O$;
Select the o with the lowest $EF(o)$ as an initial operator;
while termination criterion not met, **do**
    Execute the selected o and generate sol_{new};
    Update $EF(o)$, $\forall o \in O$;
    Select the o with the lowest $EF(o)$;
end while

Fig. 4. Pseudo-code of the hyper-heuristic selection method.

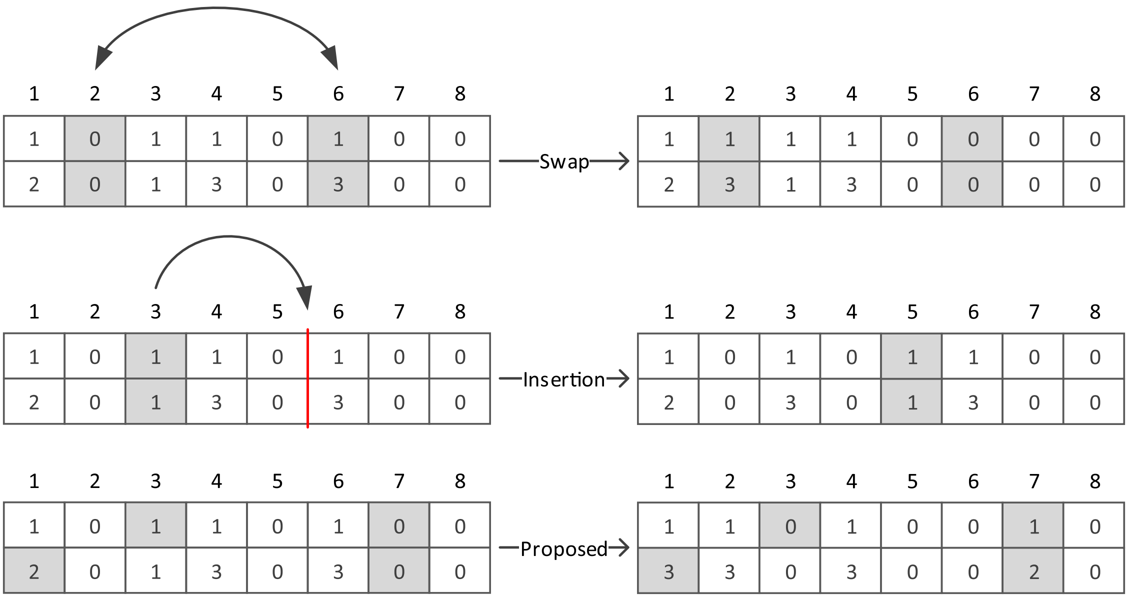

Fig. 5. An example of neighborhood generating operators.

In Eq. (46), $f_2(o)$ is the number of iterations performed since the operator o was last called. Using this function could increase the diversity of solutions by applying those operators that have not been used recently. α is a positive constant value used to strike a balance between $f_1(o)$and $f_2(o)$.

Fig. 4 represents a pseudo-code for a proposed hyper-heuristic selection method. A greedy algorithm was initially applied to find the best operator to make an offspring population in the first iteration of the algorithm. All operators were run and ranked based on the evaluation function defined in Eq. (42). The operator with a rank of 1, the lowest evaluation function, was selected as an initial operator. The selected operator was applied to make a new offspring population. After the first iteration, the evaluation function of all operators was calculated and updated. According to the updated evaluation function, the operator with the lowest evaluation function was selected for generating a new population in the next iteration. Until the termination criterion was met, the process was repeated. It should be noted that the greedy algorithm was applied only once to determine the operator that should be applied at the first iteration. After that, only one operator was selected at each iteration. This producer was applied for crossover and mutation operators separately.

This study applied swap, insertion, and a new proposed operator to explore new individuals in the solution space and generate a new neighborhood solution. An instance of mentioned operators is shown in Fig. 5.

Table 2
Different levels for the values of the problem's sets.

Notation	Description	Values
$\|N\|$	Number of nodes	10, 20, 40, 60 ,80 and 100
$\|L\|$	Number of links	$2\|N\|$ and $4\|N\|$
$\|T\|$	Number of time periods	5 and 10

Table 3
Dimension of test instances.

Problem dimension	Problem no.	Problem size			Time limitation
		$\|N\|$	$\|L\|$	$\|T\|$	
Small	1	10	20	5	2500
	2	10	40	10	5000
	3	20	40	5	5000
	4	20	80	5	5000
	5	20	80	10	10,000
Medium	6	40	80	5	10,000
	7	40	160	10	20,000
	8	60	120	5	15,000
	9	60	240	5	15,000
	10	60	240	10	30,000
Large	11	80	160	5	20,000
	12	80	320	10	40,000
	13	100	200	5	25,000
	14	100	400	5	25,000
	15	100	400	10	50,000

The unit of time is second.

5. Computational results

In this section, to evaluate the performance of the developed FO method, the results from this method were compared with the results from the CPLEX. The coding of the developed algorithm was done with MATLAB and GAMS software on a laptop with an Intel Core 7 CPU running a 2.20 GHz processor and providing 8 GB of memory.

5.1. Test instances and data generation

Because the proposed model has not been addressed in previous studies, there are no test instances available to evaluate the proposed method. Therefore, different test instances were generated and solved to investigate the performance of the FO approach. Solving the proposed model is highly dependent on the size of the network, including the number of nodes and links and the number of time periods. Hence, 15 test instances were generated using these mentioned factors. The different levels for the values of the problem sets are presented in Table 2. In addition, the types of facilities and links are constant and equal to three for all the test instances.

As mentioned before, the proposed model is solved by GAMS. Obviously, the CPU processing time of the test instances increases by increasing the problem dimension, such that the software would not be able to find the optimal solution in a specific amount of time. For example, numbers of variables, constraints and non-zero coefficient of test instance 6 are 8401, 2134, and 6477,449, respectively, which makes the problem difficult to solve in polynomial time. Therefore, the time limitation of $50|N||T|$ seconds is considered as one of the inputs of the GAMS for each test instance. The dimensions of the generated test instance are presented in Table 3 along with the CPLEX time limitation in seconds. It should also be noted that the time constraint of $10|N||T|$ seconds is considered to solve the sub problems using the CPLEX optimizer in the heuristic algorithm. The dimensions of a generated test instance are presented by vector $(|S|.|L|.\,|T|)$. The following features are considered in generating test instances as well.

- The locations of the patient zones, which are generated in random order, are uniformly distributed over a $200 * 200$ area.
- The fixed cost of constructing a TL and the cost of traveling on TL are proportional to the length of the TL.
- The operating cost of a TL is assumed to be proportional to the link construction cost.

5.2. Numerical results

The given problem is very complicated and finding the optimal solution in small dimensions demands a great amount of time. Even in some cases, the CPLEX optimizer cannot find a feasible solution in the specified time. Consequently, there is a need for other approaches with the ability to find optimal or near-optimal solutions. For this purpose, all test instances were solved by the proposed algorithm and their corresponding results were compared to the CPLEX algorithm.

Table 4
Computational results of test instances.

No.	Dimension	CPLEX		FO		Gap (%)	Ratio
		Objective	Time	Objective	Time		
1	(10,20,5)	1023.45	981	1023.45	423	0.00	0.43
2	(10,40,10)	2011.02	2983	2011.02	1534	0.00	0.51
3	(20,40,5)	1248.67	4621	1248.67	544	0.00	0.12
4	(20,80,5)	2077.03	5000	2083.75	789	0.32	0.16
5	(20,80,10)	2421.94*	10,000	2647.66	3327	9.32	0.33
6	(40,80,5)	3152.99	10,000	3085.68	2605	4.21	0.26
7	(40,160,10)	4612.15*	20,000	4953.10	12,806	7.39	0.64
8	(60,120,5)	4388.13*	15,000	4665.02	8225	6.31	0.55
9	(60,240,5)	5033.81*	15,000	5188.87	13,032	3.08	0.87
10	(60,240,10)	8783.90*	30,000	9269.64	23,948	5.53	0.80
11	(80,160,5)	8025.50*	20,000	8848.91	15,441	10.26	0.77
12	(80,320,10)	14,677.92*	40,000	15,159.35	31,848	3.28	0.80
13	(100,200,5)	10,182.33*	25,000	10,539.79	16,601	3.51	0.66
14	(100,400,5)	19,022.41*	25,000	19,773.79	23,473	3.95	0.94
15	(100,400,10)	24,333.09*	50,000	25,602.12	40,821	5.22	0.82
Average					13,027.8	4.16	0.58

*Lower bound: In these problems, CPLEX cannot solve the problem in the specified time; The unit of time is second.

The obtained results of solving the test instances by the proposed solution method and the CPLEX optimizer are presented in Table 4. The CPU processing time of algorithms, obtained objective functions and instances, and the gap related to the proposed FO approach are presented in this table separately for each test instance. The gap of the proposed FO approach was calculated as follows. "Objective" and "LB" indicate the best found solution and lower bound reported by CPLEX after the specified time limit, respectively.

$$\text{Gap} = \frac{\text{Objective} - \text{LB}}{\text{Objective}} \times 100 \tag{48}$$

According to Table 4, the first four problems were solved by CPLEX with a 0% error. In problem 6, the CPLEX reached near the lower bound after the time assumed for it ended. However, this algorithm was not able to solve the other problems in the specified time. The average amount of gaps reported for the test instances, which was solved by the proposed algorithm, was 4.16%. Moreover, the average time required for solving all the problems by the proposed algorithm was 13,027.8 s. The average ratio of the CPU processing time of the two algorithms was 0.58, which indicates that the proposed method improved the CPU processing time by 58 percent. The results indicated the high efficiency of the proposed algorithm in solving large-scale problems.

As one of the main motivations of this study is proposing greedy initialization and hyper-heuristic selection methods for improving the performance of TS, in this section, the impact of considering these methods on the solution approach is investigated by designing an experiment. In this experiment, four different modes were considered for ETSA. In the first mode, a simple TS without consideration for heuristic methods was applied in order to solve the problem. The second and third modes applied greedy initialization and hyper-heuristic selection methods for generating an initial solution and selecting the operators of TS, respectively. Finally, the last mode applied both mentioned heuristic methods. The computational results of comparing the mentioned modes are reported in Table 5. It should be noted that in the first mode, the initial solution was generated randomly, and TS operators were selected randomly at each iteration.

With regard to the obtained results, proposed heuristic methods improved the performance of TS in finding a better solution. As is clear from Table 5, the greedy initialization method reduced the average value of the objective function, which means that this heuristic method improved the performance of the TS. The reason behind this improvement is that the method generates a feasible solution, thereby helping the algorithm start the searching process in a feasible solution space. Likewise, the average value of objective function decreases when we use the hyper-heuristic selection, for this heuristic algorithm contributes to the FO approach to select the best operator at each iteration. Therefore, the FO can explore the solution space in an efficient way, and this increases the diversity of solutions.

6. A practical case study

In this section, the application of the proposed model is described as a real-world case study for improving accessibility to HFs in Ardabil province. The considered case study was modeled by MIP and solved by the CPLEX solver in GAMS optimization software v. 24.1.

6.1. Description

To elucidate the applicability and performance of the HFLND model under consideration, a real-world case study is provided for one of the mountainous regions in Iran, Ardabil province, which is located in the northwest region of the country.

Table 5
Comparison of designed modes.

NO.	Mode I		Mode II		Mode III		Mode IV	
	Objective	Time	Objective	Time	Objective	Time	Objective	Time
1	1115.561	346	1105.326	410	1074.62	372	1023.45	423
2	2171.902	1288	2151.791	1503	2091.46	1303	2011.02	1534
3	1323.59	440	1323.59	533	1286.13	462	1248.67	544
4	2208.775	639	2187.938	773	2167.1	702	2083.75	789
5	2859.473	2794	2859.473	3260	2727.09	2927	2647.66	3327
6	3394.248	2110	3301.678	2526	3178.25	2318	3085.68	2605
7	5299.817	10,244	5299.817	12,677	5101.69	11,269	4953.10	12,806
8	4944.921	6580	4898.271	8060	4851.62	6991	4665.02	8225
9	5655.868	11,077	5448.314	12,641	5344.53	11,207	5188.87	13,032
10	9825.818	19,397	9918.515	23,229	9640.42	21,553	9269.64	23,948
11	9379.845	12,816	9379.845	15,286	9202.86	13,742	8848.91	15,441
12	16,068.91	26,115	16,372.1	30,892	15,917.32	28,663	15,159.35	31,848
13	11,172.18	13,446	11,066.78	16,102	11,066.78	14,774	10,539.79	16,601
14	21,751.17	19,013	21,157.96	23,238	20,762.48	20,656	19,773.79	23,473
15	27,906.31	32,656	27,138.25	39,596	26,626.20	35,514	25,602.12	40,821
Average	8338.55	10,597.4	8240.64	12,715.07	8069.23	11,496.87	7740.05	13,027.8

The unit of time is second.

This province, with 17,953 Km^2 of area and a total population of 1268,173, is one of the deprived areas in Iran. Because of political divisions (information available on the Statistical Center of Iran website), this province has 25 population centers. Fig. 6 presents the geographical map of Ardabil province and its population centers numbered 1 to 25.

With respect to the classification of hospitals based on capacity, three types of HFs, including low-level, medium-level, and high-level hospitals that differ from each other in capacity, fixed construction costs, and fixed operating costs, are considered. All population centers are assumed as potential locations for establishing HFs. Additionally, some TLs in the network were conducted previously and classified into three categories− freeway, highway, and paved road− based on their quality. These types of TLs are characterized by different values of fixed costs, operating and transportation costs, average speed of transportation, and capacity. Fig. 7 depicts the existing HFs and underlying network of Ardabil province. As can be seen in this figure, in the current network, there are five HFs including one high-level hospital, one medium-level hospital and three low-level hospitals providing health services in the province, and 20 potential nodes (25–5) in which to open a new HF. Also, the underlying network consists of 33 existing and 18 potential TLs.

We tried to collect reliable data, as far as possible, for the given problem. Each population center in the province denotes a demand node with a different rate of demand which is calculated based on its population and the proposed planning horizon period. The fixed cost of establishing an HF depends on the node's population, and varies between [75,100], [200,292], and [500,729] monetary unit for different types of facilities according to their capacity. In addition, the operating costs of a facility per bed, are considered as 0.01, 0.02, and 0.03% of fixed construction costs for different types of facilities. The fixed cost of constructing a new TL depends on the link's quality and is equal to 6, 4 and 1 monetary units per kilometer. The operating costs of all types of TLs at each period are considered as 6% of the total fixed cost of constructing a TL. Moreover, the travel cost for each patient depends on the type of a TL and is equal to 0.001%, 0.003%, and 0.005% of the total fixed cost of constructing a freeway, highway, or paved road, respectively. The travel time between two population centers is calculated based on the road distance and average speed of travel on the constructed TL, which depends on the link's quality. The value of this parameter is equal to 110, 85, and 60 km/h for the freeway, highway, and paved road, respectively. The minimum population required to construct low-level, medium-level, and high-level hospitals is 5000, 20,000, and 50,000, respectively. It should be noted that the given values for these parameters are for the first period, and these values increase by a rate that is equal to 6% for each subsequent period. The planning horizon consists of four periods, each of which is two years.

6.2. The optimal solution

Fig. 8 schematically illustrates the optimal solution obtained by solving the single objective model. As shown in this figure, seven new HFs, including two high-level hospitals, two medium-level hospitals, and one low-level hospital, have been constructed in nodes Germi (5), Kowsar (13), Qeshlaqdasht (12), Hir (15), Moradlu (21), and Kuraim (24). As predictable, low-level hospitals have been constructed in less populous areas, and large and medium-sized hospitals have been constructed in populated areas. In addition, seven new lines have been constructed that connect nodes 1 to 14, 5 to 20, 11 to 12, 13 to 17, 24 and 25, 15 to 24, and 24 to 25. As shown in Fig. 8, patients in some areas should travel directly from their area to another area where HFs are available. While some of the other nodes are not directly connected to the node in which the HF is located, these patients must cross several nodes in order to reach the HF. The optimal values of the objective functions related to cost, access, and equity are 2729.17, 3.83, and 44.31, respectively. Details of the cost component are shown in Table 6. Also, the percentage of the total cost elements are compared to each other in Fig. 9. According to Table 6 and

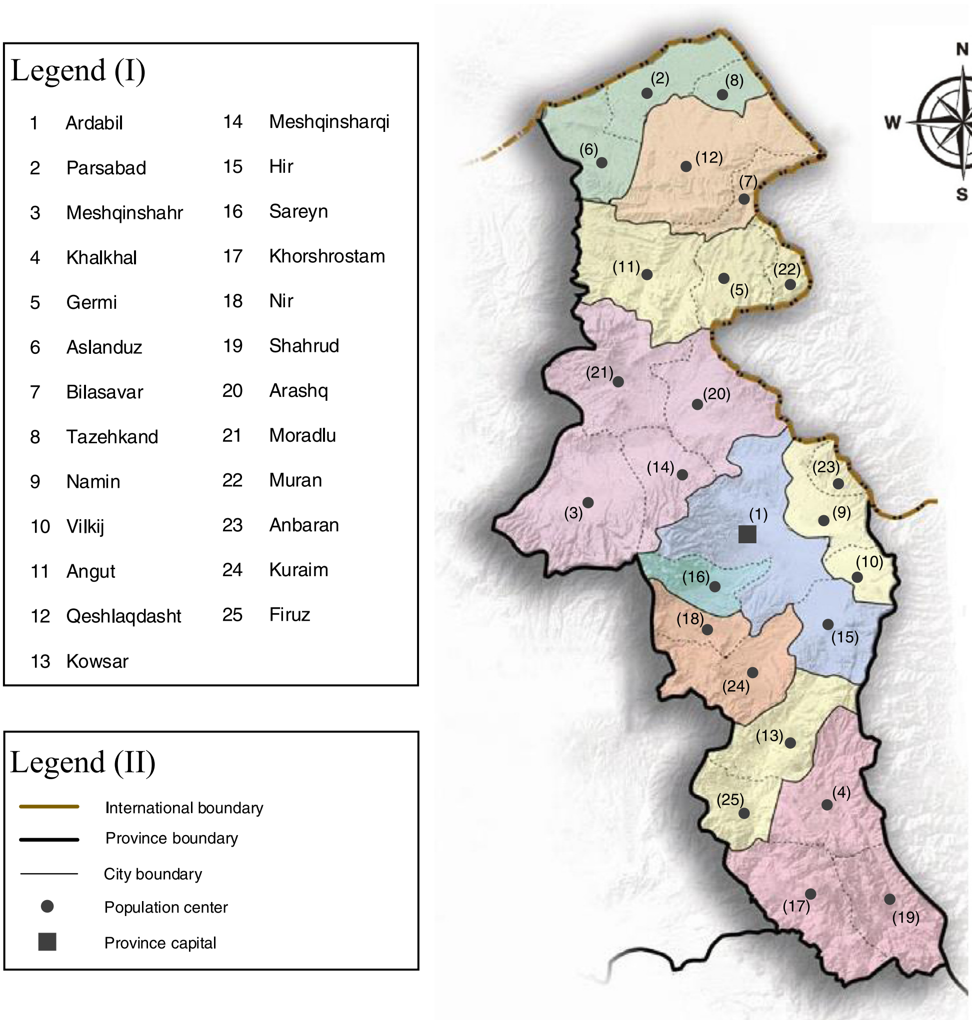

Fig. 6. The geographical map of Ardabil province.

Table 6
Cost components of the optimal solution.

Period	Fixed costs		Transportation	Operational costs		Capacity expansion	Total
	HFs	TLs		HFs	TLs		
1	2153	4912	104.77	201.63	301.73	0	7673.13
2	0	0	105.01	207.14	301.81	117.45	731.41
3	0	0	107.22	211.07	302.56	96.33	717.18
4	0	0	110.50	223.29	302.93	41.53	678.25
Total	2153	4912	435.50	826.94	1209.03	255.31	9799.97

Fig. 9, the construction costs of TLs have the greatest portion among these components. Additionally, the operating costs of the TLs have the greatest portion among the cost components of the objective function. Capacity expansion costs have the least portion among all cost elements. The obtained results indicate that all investments on the construction of HFs and TLs are made in the first period. Hence, it can be concluded that taking into account the dynamic capacity for facilities would avoid imposing additional fixed costs for constructing the HFs and TLs at other periods. Notably, this conclusion states the efficiency of the proposed HFLNDP.

6.3. Analytical results

In this section, two experiments were designed for investigating the impact of the capacity planning, accessibility and equity considered in the proposed HFLNDP.

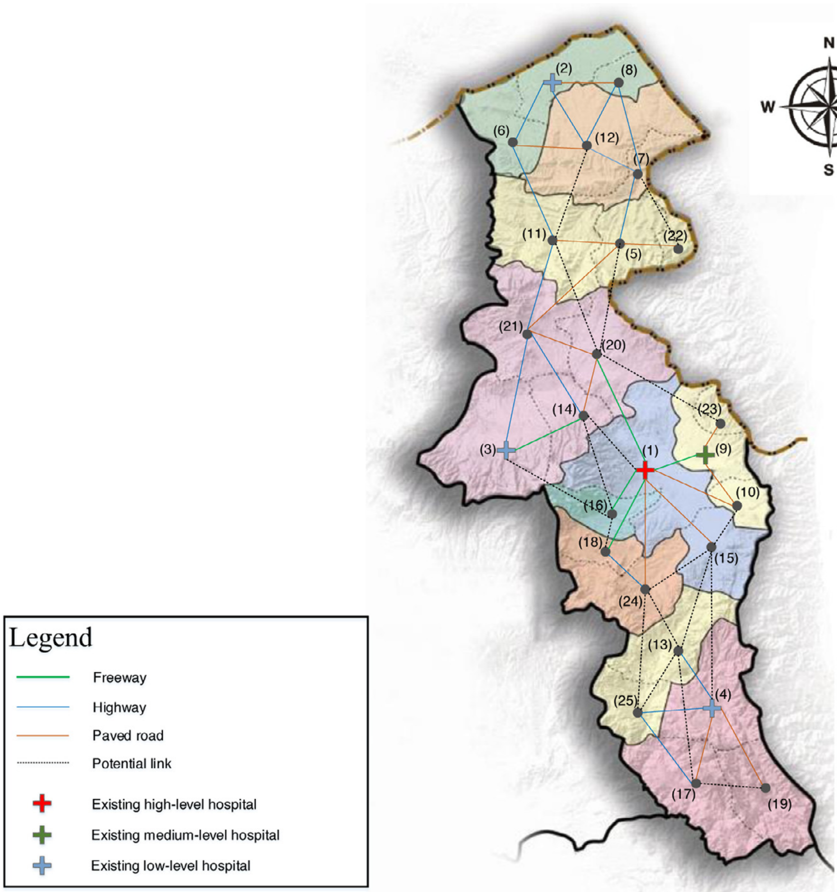

Fig. 7. Existing HFs and the underlying network of Ardabil province.

- *Impact of capacity planning on system's performance*

As mentioned before, the considered HFs in this study can increase their capacity over the planning horizons. The binary and integer variables were defined for decision making about increasing capacity of facilities. In addition, the specific upper and lower bounds of capacity were defined for the different types of HFs. To find the impact of capacity planning on the network, the related decision variables to the capacity planning are removed from the model, and the capacity of the HF is considered as a parameter. Then, the obtained results of solving the model are compared with the results obtained in terms of capacity planning consideration. The results show that in the condition in which capacity planning is not considered in the problem, the total cost of the system including construction, operation, and transportation costs is increased by 4%. This is because, in this case, one more facility, the medium-level hospital in node 16, is constructed. On the other hand, access to HFs is increased by 1% because of constructing one more HF. In addition, the third objective function of the problem (minimizing inequity in access) is increased by 2%. Because of this, the capacity expansion for nodes can no longer be used to improve accessibility. Consequently, equity in access to facilities is increased. Fig. 10 shows the rate of increase and decrease of cost components in this case, compared to the case in which capacity planning is considered. Finally, it can be concluded that considering capacity planning for facilities would avoid imposing additional construction costs and would improve system performance.

- *Impact of accessibility and equity on system's performance*

To find the impact of the social objective functions proposed in this problem, three different experiments were designed. In the first and second experiments, the proposed model was solved without considering the second and third objective function, respectively. In the third experiment, both of these objective functions were removed from the problem. The obtained results of these three experiments are shown in Fig. 11, which indicates that the reduction rate in the various cost components has been considered in the objective function. Fig. 11 also shows budget constraints in comparison to the main problem.

According to the results, all components of the costs except transportation costs are decreased when social objective functions are not considered in the problem. The rate of increase in the construction and operational costs of facilities are

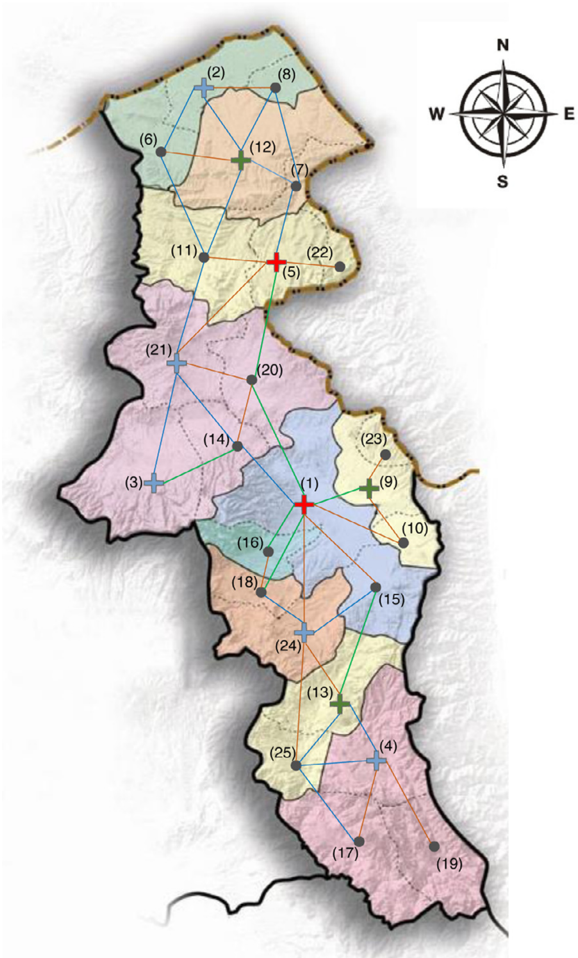

Fig. 8. The optimal solution obtained by solving the model.

higher than the rate of increase of other cost components. Therefore, it can be concluded that in order to improve the accessibility to facilities and reduce inequity in the system, more facilities should be constructed. Also, the transportation network is expanded when the social objective functions are considered in the problem. As can be seen in Fig. 11, only the transportation costs are increased in all problems relative to the main problem (negative percent on the graph shows an increase). In fact, because of establishing fewer facilities and fewer lines in these situations, the network is attempting to accommodate existing demands with further transportation demands. Total costs of the system in conditions without consideration of accessibility, without consideration of equity, and without consideration of accessibility and equity increase by 3, 17, and 22%, respectively.

6.4. Sensitivity analysis

In this section, we conducted different sensitivity analyses to investigate the impact of some critical parameters on the model results.

- *Impact of the budget constraints on the system's performance*

Fig. 12 illustrates the impact of the increase in the first-period facilities construction budget on the system costs. According to this figure, when B_1^1 increased, the operating and capacity expansion costs of facilities grew while the transportation and operating costs of links dropped. Due to the increase in B_1^1, more facilities were constructed, but the fewer the links are constructed, and fewer transports could be expected in the network. Also, the impact of the increase in the links construction budget on the system costs is presented in Fig. 13. As can be seen, the transportation and operating costs of links decreased as B_2^1 increased. The operating and capacity expansion costs of facilities showed no correlating trend by increasing B_2^1. This indicated that the number of constructed links increased, but the number of constructed facilities remained constant as B_2^1 increased. Because the number of facilities and construction budgets is the parameter that significantly impacts

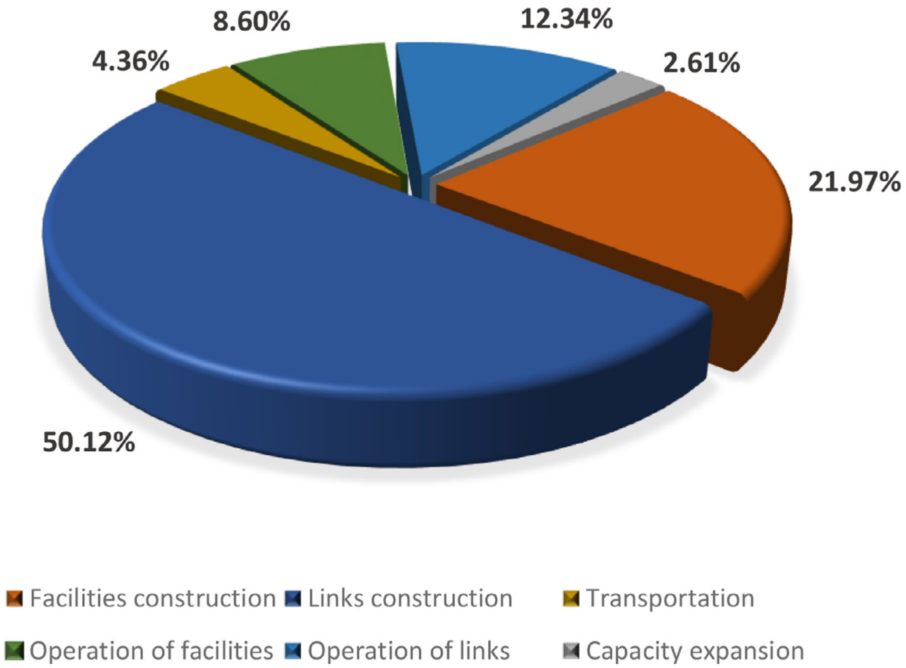

Fig. 9. Cost components of the optimal solution.

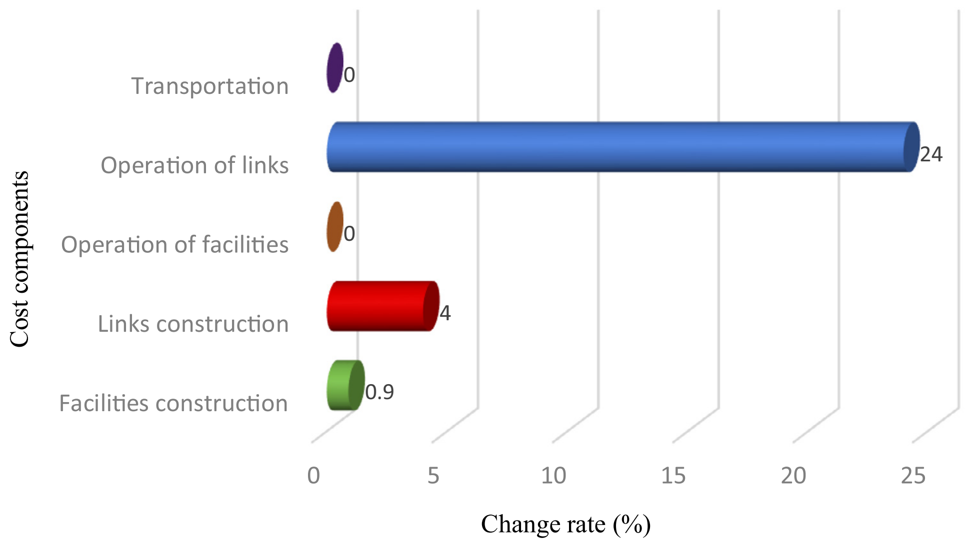

Fig. 10. Rate of increase and decrease of cost components when capacity planning is removed.

the optimal configuration of the network, the decision-maker should adjust the appropriate value of these parameters for designing the health services network.

Fig. 14 shows the impact of the increase in B_1^1 and B_2^1 on the accessibility of demand nodes. When the B_1^1 and B_2^1 increased, the accessibility of the system significantly grew. This was due to increasing the number of constructed facilities and links. As can be seen, accessibility is more sensitive to B_1^1. Therefore, we concluded that the increase in the facilities construction budget was more significant than the links construction budget for improving accessibility in the system.

- *Impact of the travel friction coefficient on the system's performance*

We designed sensitivity analysis to clarify the relationship between changing system costs change and changing the travel friction coefficient (β). The results of this analysis are shown in Fig. 15. It can be observed from Fig. 15 that the

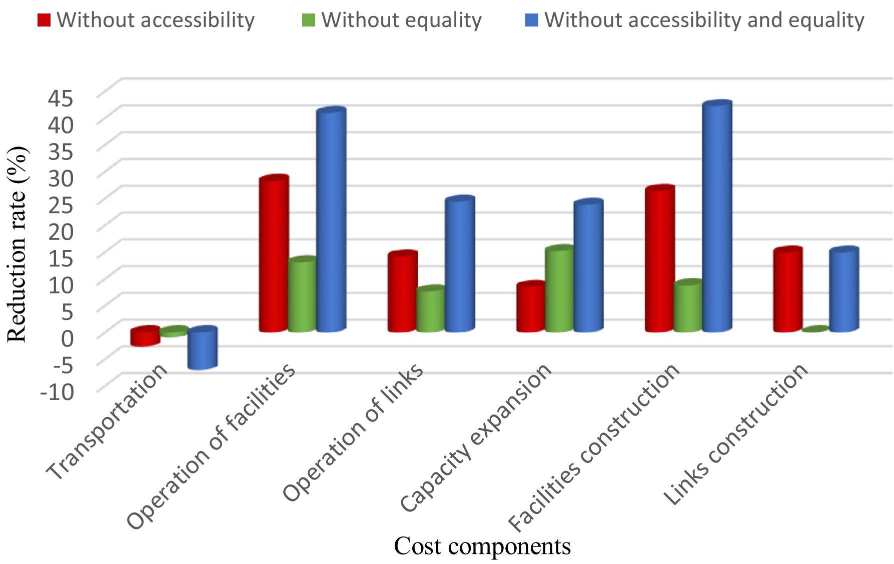

Fig. 11. Changes in cost components.

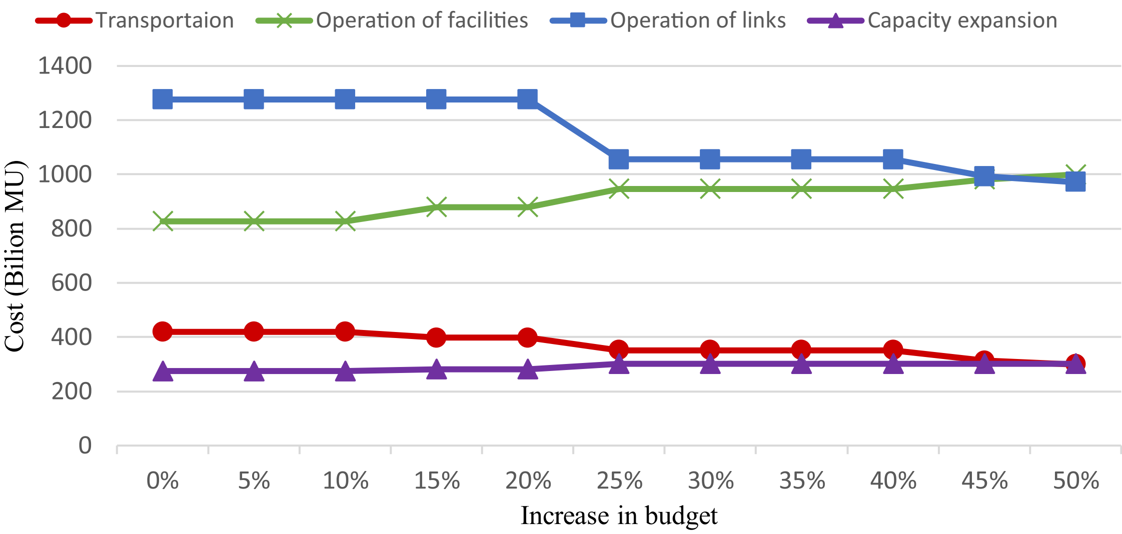

Fig. 12. Impact of increase in the facilities construction budget on the system's costs.

first objective function has an increasing trend. This is due to the increasing general-decay function presented in Eq. (1). By increasing this function, the first part of the accessibility function decreased. Hence, more facilities will be established to increase the accessibility (the second part of the accessibility function) of the system. Consequently, the costs related to the first objective function increased as the β increased. Also, the impact of the coefficient (β) on the second and third objective functions is shown in Fig. 16. Concerning this figure, the third objective function has a variable trend. Still, as can be seen, the accessibility of the system shows a decreasing trend that, according to the above-mentioned description, it was predictable.

7. Managerial insights

This section provides some insights into the way decisions are made regarding the healthcare system. More specifically, we explain some managerial insights based on our findings and model, which could be helpful to managers who make decisions about the location of healthcare facilities and about the underlying network of these locations. First, our model provides an opportunity for organizations responsible for transportation to see how their decisions affect the equity and

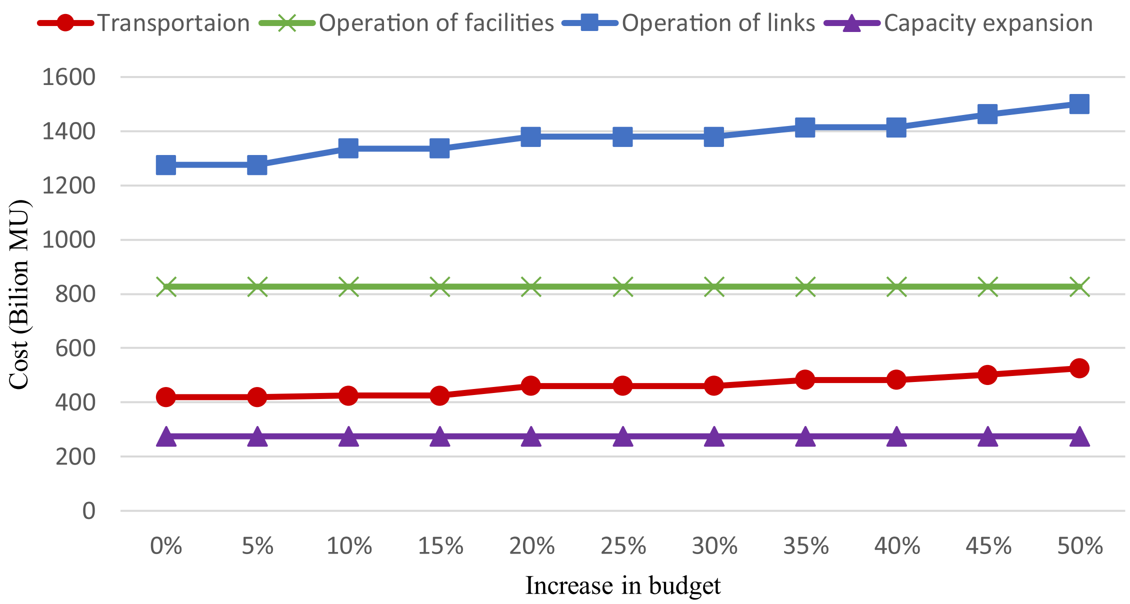

Fig. 13. Impact of increase in the links construction budget on the system's costs.

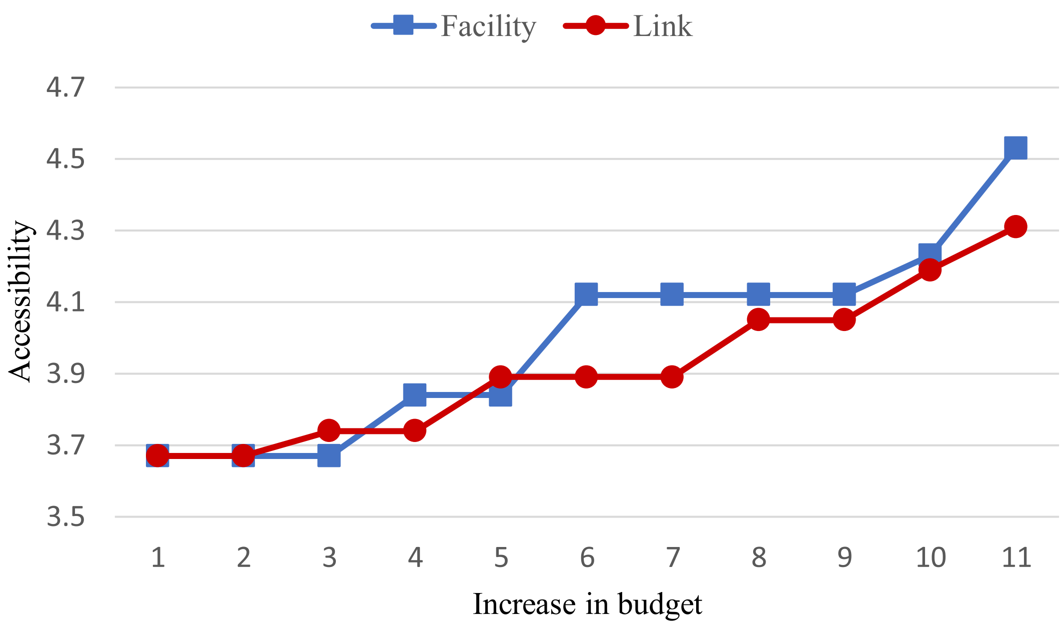

Fig. 14. Impact of increase in the facilities construction budget on accessibility.

accessibility in healthcare systems. Therefore, they will be able to make decisions about constructing roads to improve accessibility and equity. Second, our finding showed that considering accessibility and equity in designing a healthcare system would decrease the total costs of construction and design, which is a favorable outcome for decision-makers. Specifically, the construction and operating costs of healthcare facilities (HFs) would be decreased by considering equity and accessibility in the system. Hence, healthcare decision-makers could benefit from this model by improving accessibility and equity and by reducing the total costs. Finally, according to our obtained results, capacity planning could be considered a useful tool to reducing the number of links and HF construction costs. More importantly, the capacity planning used in this study was shown to significantly cut the operating costs of facilities. Given that, decision-makers could use capacity planning tools to reduce their costs.

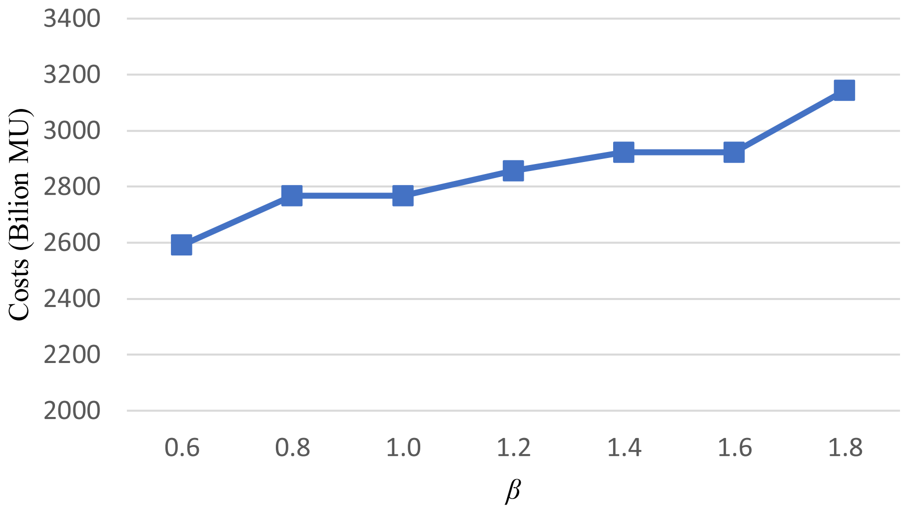

Fig. 15. Impact of the travel friction coefficient on the system's costs.

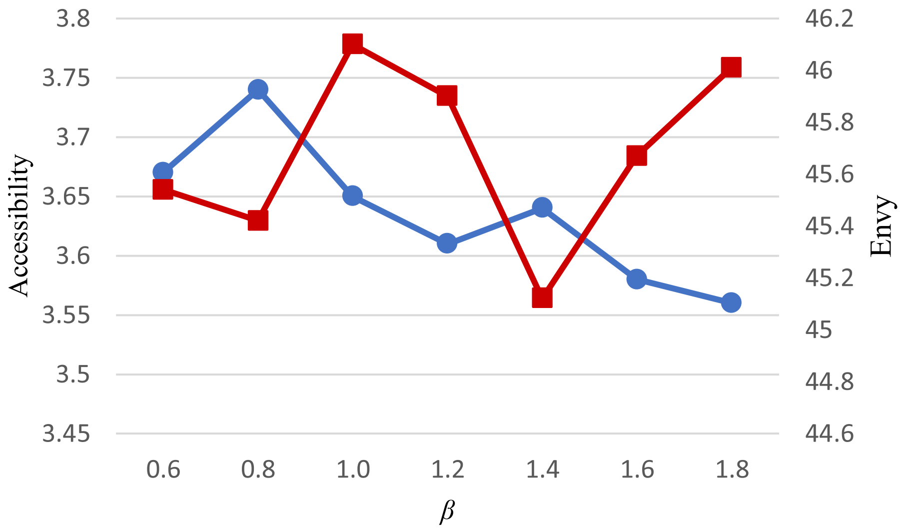

Fig. 16. Impact of the travel friction coefficient on accessibility and equity.

8. Conclusions

This study presented a dynamic FLNDP-MTCF/MTCL including facility capacity decisions addressing a real-world healthcare service network application considering equity and accessibility. The model aimed to determine the optimal location of multiple types of HFs, their capacities at different time periods, the structure of the underlying network, and demand flow among the located HFs. A multi-objective MINLP formulation was developed for the proposed problem, which was then converted to the linear model to be effectively solved. Two new health-oriented objective functions were proposed to formulate accessibility and equity in the system. The first one was utilized to maximize the accessibility for whole population centers and the second one to minimize the inequity of accessibility in the system. Furthermore, augmented ε-constraint was used to deal with the proposed MOP. An FO approach based on the ETSA was applied to solve this NP-hard problem for various test instances. In the ETSA, two heuristic methods including (greedy initialization and hyper-heuristic selection) were proposed to develop the performance of the algorithm. These heuristic methods were used for generating the initial solution and selecting the operators, respectively.

A real-world case study on the Ardabil province health services network was presented to illustrate the applicability and valuable efficiency of the developed mathematical model. Two experiments were designed to clarify the impact of the capacity planning and social factors on system performance. According to obtained results, it was observed that (i) capacity planning plays a key role in the health system's flexibility, and disregarding it may lead to imposing additional costs on the system; (ii) considering accessibility and equity would lead to expanding the health services network and imposing additional construction costs to the system. The results indicated the high efficiency of the proposed FO approach in solving large-scale problems. Also, our experimental results clearly illustrated that using proposed heuristic methods improved the performance of TS.

Finally, the current study can be extended by incorporating other features in future studies. We provide some future directions for interested researchers as follows:

- Developing a hierarchical structure for the concerned problem (see [12,13]).
- Considering the uncertainty as a fundamental element in HFLPs for different parameters of the problem and selecting novel approach to deal with it (see, e.g., [48,49]).
- Considering the disruptions for facilities and links.
- Furthermore, in terms of the solution approach, exact solution methods for large-scale instances such as decomposition methods could be applied to solve the proposed problem. Also, heuristics and metaheuristic algorithms could be applied as multi-objective optimization tools to solve the problem.

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